

# Structural Empirical Analysis of Vacancy Referrals with Imperfect Monitoring and the Strategic Use of Sickness Absence

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## Abstract

This paper provides a structural analysis of the role of job vacancy referrals (VRs) by public employment agencies in the job search behavior of unemployed individuals, incorporating institutional features of the monitoring of search behavior by the agencies. Notably, rejections of VRs may lead to sanctions (temporary benefits reductions) while workers may report sick to avoid those. We estimate models using German administrative data from social security records linked with caseworker recorded data on VRs, sick reporting and sanctions. The analysis highlights the influence of aspects of the health care system on unemployment durations. We estimate that for around 25% of unemployed workers, removing the channel that enables strategic sick reporting reduces the mean unemployment duration by 4 days.

*Keywords:* unemployment, wage, sanctions, moral hazard, sickness absence, physician, structural estimation, counterfactual policy evaluation, unemployment duration.

*JEL classification:* J64, J65, C51, C54

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# 1 Introduction

Unemployment insurance (UI) benefit recipients in OECD countries typically receive job search assistance by the public employment service (PES) via employment agencies and they are required to fulfill prespecified job search requirements. Benefit recipients who do not comply with these requirements risk receiving a sanction in the form of a temporary or permanent benefit reduction. Perhaps the most prominent example is provided by job vacancy referrals (VRs) by the PES (see Immervoll and Knotz 2018, and Knotz 2018). Typically, a VR involves an obligation of the unemployed to apply at a prespecified vacancy, where noncompliance may lead to a sanction. Like with other active labor market policies, the aim is to increase the reemployment rate and to counteract moral hazard.

As shown by e.g. van den Berg and van der Klaauw (2006), policies designed to combat moral hazard in UI systems may give rise to complicated interactions between the agency and the unemployed. As the monitoring of the unemployed workers' search behavior is imperfect, the latter have incentives to develop strategic responses to the monitoring. In such settings, the empirical evaluation of counterfactual policy designs is served well by a structural analysis.<sup>1</sup> After quantifying the role of job vacancy referrals in the job search decisions by the unemployed while taking institutional features of the monitoring system into account, we can carry out counterfactual evaluations that fully incorporate strategic responses.

A specific institutional feature of active labor market policy assignments is that they cannot be imposed if the unemployed individual is declared sick. In our setting, while rejections of VRs may lead to sanctions, such sanctions are not imposed if the worker has reported sick in the time interval in which (s)he is supposed to apply for the vacancy. To put this differently, if the worker does not deem the VR attractive, (s)he may decide not to apply and to report sick to avoid a sanction. A key parameter in the model is therefore the probability that a worker is successful in obtaining a sick permit from the relevant health care worker (typically a physician).

Our study is among the first to focus on the influence of aspects of the health care system on realized unemployment durations. Notably, we estimate the elasticity of the mean unemployment duration with respect to the ease of obtaining a sick permit. More in general, we contribute to

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<sup>1</sup>Structural empirical analyses of active labor market policies include Fougère, Pradel, and Roger (2009), Lise, Seitz, and Smith (2015), Launov and Wälde (2016), Gautier et al. (2018), Cockx et al. (2018), Wunsch (2013) and van den Berg and van der Klaauw (2019). The pioneering study by Fougère, Pradel, and Roger (2009) estimates a model to examine effects of job contacts through the public employment services on job seekers' search effort. Our paper is the first to structurally analyze the interplay of vacancy referrals and sanctions and the role of strategic sick reporting in a monitoring system.

the literature that connects health care policy design with unemployment policy design.

We estimate our model using administrative register data on employment and earnings combined with caseworker-recorded data. The data are from Germany and include detailed information on unemployment and employment durations, benefit receipt, the arrival of VRs, imposed sanctions, sickness absence during unemployment and daily wages during employment. Empirical model specifications allow for unobserved heterogeneity of the structural parameters across individuals. We use the joint distribution of various intermediate and final outcomes (including unemployment durations and accepted wages) to estimate the models. Counterfactual policies include changes in the ease of obtaining a sick permit, the VR arrival rate, the sanction enforcement rate and the length of the sanction. In addition, the results provide an understanding of the underlying mechanisms.<sup>2</sup>

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, sickness absence and sanctions in the observation window. Section 3 develops the structural model. Section 4 describes the data. Section 5 derives the likelihood function and describes how the model is estimated. Section 6 presents estimation results. Section 7 presents the evaluation of counterfactual policies and section 9 concludes.

## 2 Institutional Background

### 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, who are below age 45 and 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-

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<sup>2</sup>Starting with van den Berg, van der Klaauw, and van Ours (2004), a large number of reduced-form duration-model studies has documented positive effects of sanctions and monitoring on exit rates out of unemployment. Reduced-form evidence on positive effects of VRs on exit rates includes van den Berg, Hofmann, and Uhlendorff (2019) and Bollens and Cockx (2017). The former additionally find a positive association between receiving a VR and the probability of reporting sick. Using data from Sweden, Engström, Hesselius, and Holmlund (2012) find that intensifying monitoring increases the fraction of VRs that result in job applications.

Zingerle 2010).

## 2.2 Vacancy Referrals and Sanctions

With a vacancy referral, a caseworker asks an unemployed worker to apply for a specific job vacancy. The caseworker has learned about the vacancy either because it was registered by the employer at the agency or because of informal networks or investigations by the caseworker. The VR usually contains information about the occupation, the working hours and the starting date of the job, but not the wage. The time lag between a VR and the completion 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. A sanction is not given if the rejected job is not deemed to be “suitable”. During our observation period this included jobs that would involve a huge commuting time or jobs with a wage that is substantially below the previous wage or below the UI benefits level.

Not applying to a job after receiving a corresponding VR and refusing to accept a suitable job offer are among the justifications for a sanction. With a sanction, the UI 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. However, this may be detected through commonly used communication channels between the caseworker and the employer posting the vacancy. Also, the sanction can be avoided by strategically claiming sickness (see the next subsection).

Other reasons for “long” sanctions of 12 weeks are refusing to participate in or dropping out of active labor market policy measures. If a 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%.<sup>3</sup>

After the imposition of a sanction, the unemployed job seeker is supposed to continue with his or her 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

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<sup>3</sup>Voluntary job quits are among the other justifications for a long sanction. In this case, individuals do not receive any benefits in the first 12 weeks of their unemployment spell. We exclude individuals who experience this from our analysis.

unemployed loses all claims for UI benefits. Qualitative evidence based on expert interviews<sup>4</sup> suggests that the conduct of monitoring the unemployed worker and the frequency at which VRs are used remain unchanged after a sanction. Sanctioned unemployed can apply for unemployment assistance (UA, or “welfare”) benefits during the sanction period. These benefits are typically much lower than UI benefits. Their level does not depend on the previous wage. Instead, they are means-tested – i.e., they depend on the household income and savings – and on the household composition.

The employment agency’s observation of non-compliance with job search requirements is imperfect. First, during our observation period, each single caseworker handled on average over 400 unemployed workers at any given point in time. With such a caseload, caseworkers cannot monitor individual job search efforts closely. Second, even with intense monitoring after the receipt of a VR, infringements may go undetected if there is a communication fault between the caseworker and the human resources department of the employer that opened the vacancy.

Besides that, caseworkers have discretionary power regarding whether to impose a sanction (Müller and Oschmiansky 2006). After the detection of a violation of the job search requirements, the unemployed worker has the opportunity to explain and justify his behavior. At this stage, the caseworker has some leeway to decide whether or not this justification is sufficient.<sup>5</sup> The discretionary space that caseworkers have may be used relatively often if sanctions are severe, as they were in Germany in our observation window. Caseworkers may feel reluctant to impose such harsh punishments, especially if they feel that the infringement is modest while the punishment leads to long-run hardship (see van den Berg and Vikström, 2014, for an exposition).

### 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. During the first six weeks of sickness, the unemployed continues receiving UI benefits and the remaining UI entitlement duration continues to decline.<sup>6</sup> In this case there are no direct financial incentives to report sick during UI benefit

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<sup>4</sup>The IAB research institute of the Federal Employment Agency has access to a number of designated experts of the usage of active labor market policies in practice and the day-to-day activities by caseworkers and functionings of local employment agencies. For our study, a number of these experts held in-depth interviews with caseworkers from different agencies to find out details about practicalities of monitoring and sanctions in the years from which our data originate.

<sup>5</sup>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.

<sup>6</sup>If an unemployed is sick with the same diagnosis for more than 6 weeks, the unemployed enters sickness benefits (Ziebarth and Karlsson 2010). This benefit scheme requires a specific medical certificate. This certificate can be

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 or in case of a VR that 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. The unemployed can freely choose their personal physician or house doctor and can switch physician at any time. This allows them to search for one who is lenient and willing to hand out sick notes.<sup>7</sup>

### 3 A Structural Model of Job Search, Vacancy Referrals, Sanctions and Sick Notes

Our model extends the sequential partial search model framework of, e.g., Mortensen (1986) by incorporating various policy features. The model shares features of (and generalizes) earlier sequential partial search models with different types of job offers and/or sanctions, such as the models in Fougère, Pradel, and Roger (2009) and van den Berg and Vikström (2014).

Consider a population of newly unemployed workers who are risk neutral and discount the future at the discount factor  $\beta$ . 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. Whenever a job offer arrives, the decision has to be taken whether to accept it or reject it and search further. We allow for two kinds of job offers: regular job offers and 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 may try to obtain a sick note and, if successful, is released of the duty to apply for the referred vacancy. Moreover, our model includes terminal sanctions and reflects that unemployed workers can renew their benefit eligibility if they find a job and stay employed sufficiently long. We now discuss the model parts in more detail.

**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

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verified by a doctor of the medical service of the health insurance. In this paper, we focus on short-term sickness.

<sup>7</sup>Carlsen, Lind, and Nyborg (2020) develop a theoretical model of medical doctor's decision-making, and show that in equilibrium doctors often tend to diagnose and treat patients based on subjectively stated symptoms, rather than verifying that the patient indeed suffers the stated symptoms.

real sickness, the worker receives a sick note with probability one and thus never receives a sanction. If 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 decide on job offers and on whether to try to obtain a sick note in case of a VR. 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 the exogenous per-period probability  $\lambda_J$ . A regular job offer is characterized by a random draw from the wage offer distribution  $F_J$ . If the unemployed worker accepts it, he becomes employed at the offered wage, starting in the next time period. If he rejects it, he remains unemployed. Formally, the expected value of receiving a regular job offer is

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

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  $\lambda_V$ . 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 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 not applying to this referred vacancy. For the unemployed worker the expected value of receiving a VR equals

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

where  $B_V(w, s, P)$  is the value of applying for a VR with attached wage  $w$ .

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 for his dealings with the VR. We denote the probability that a job offer is received upon applying for a VR by  $\psi$  (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.<sup>8</sup> 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 discretionary leeway in deciding whether a sanction is actually imposed or not.<sup>9</sup> If the unemployed worker does receive a sanction, no benefits are paid out to him for the next  $K$  time periods.<sup>10</sup> 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 offer  $w$  equals

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

**Terminal Sanctions** Whenever an unemployed worker receives a sanction, it may happen that his accumulated number of sanctions exceeds the terminal sanction threshold,  $P \geq \bar{P}$ . 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.<sup>11</sup> The value function of a terminally sanctioned unemployed worker is

$$\Phi = \beta \left( (1 - p_{sick}) \lambda_J \int \max\{E(w, \bar{P}), \Phi\} dF_J(w) + (1 - \lambda_J(1 - p_{sick})) \Phi \right).$$

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

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

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<sup>8</sup>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.

<sup>9</sup>In the theoretical model, the event of a real sickness is realized at the onset of the period, so that an onset of real sickness directly after not having received a sick note and before applying to the VR (all within the same time period) is ruled out. See the discussion of the value of unemployment below.

<sup>10</sup>In the German UI system during our observation period  $K = 3$  (see Section 2).

<sup>11</sup>In the German UI system during our observation period  $\bar{P} = 2$  (see Section 2).

if  $P < \bar{P}$ . 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  $P \geq \bar{P}$ , 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  $\delta$ . 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 the utility loss resulting from a terminal sanction. However, if  $P$  is reset to 0 after any period of employment (no matter how short this period is), the threat of receiving a terminal sanction is strongly understated relative to the real institutional setting. We stick as close to the real world 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  $\bar{\tau}$  time periods.<sup>12</sup> The value of employment thus becomes dependent on employment duration. We define  $\tau$  as number of employment periods necessary to establish a new claim to unemployment benefits, i.e., after  $\tau$  periods in employment  $P$  is set to 0. The value of being employed at wage  $w$ , given  $P$  and  $\tau$  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

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

**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. As long as  $s > 0$ ,  $s$  depreciates by one after each time period. Upon arrival of a new sanction,  $s$  is increased by  $K$  units, i.e., the unemployed worker is sanctioned by a benefit reduction for the subsequent  $K$  time periods. The other state variable  $P$

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<sup>12</sup>In the German UI system during our observation period  $\bar{\tau} = 12$  (see Section 2).

counts the number of sanctions received in the past. If an unemployed worker’s accumulated past sanctions cross a threshold value  $\bar{P}$ , 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  $\bar{w}_J(s, P)$  and for job offers obtained through VRs  $\bar{w}_V(s, P)$  for each combination of state variables  $s \in \{0, \dots, K\}$  and  $P \in \{0, \dots, \bar{P}\}$  and a reservation wage  $\bar{w}_\Phi$  that characterizes decision-making of terminally sanctioned individuals. In Appendix A we solve for the system of reservation wage equations that characterizes the model solution.

## 4 Data

Estimation is based on administrative records from the German PES (Bundesagentur für Arbeit). The data contain daily information about employment and unemployment spells, earnings, and UI benefits from social security registers. As is common for this type of data, we do not observe information about self-employment, inactivity, and civil servants (Dundler 2006). These data are linked with data on participation in active labor market policy measures, including the receipt of VRs, sickness absence, and sanctions. The latter data were recorded by the caseworker as part of the regular processing of each and every administrative act and event. The data also include sociodemographic variables on education, family status and health restrictions. The latter captures health impediments that were present at the moment of entry into unemployment and that are deemed by the caseworker to complicate the search for a job. The impediments need to be ex ante validated by a medical expert. We use a binary indicator of this as a proxy of general health status.

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 and public employment programs played an important role in the East. We select unemployed workers who are between 25 and 57 years old. The first age restriction is motivated by the labor market policy regime being different for those aged below 25, and the second one by early-retirement schemes. We omit individuals who passed the highest secondary school exam (“Abitur”) or have a university degree because they virtually never receive a sanction. As a result,

we characterize the level of education by a dummy “medium/high education” which indicates if the individual completed a vocational training consisting of education and practice. In our setting this can be regarded to be the highest of the two levels of education. In 2003, several labor market reforms were introduced. Therefore, we right-censor observations at December 31, 2002.<sup>13</sup> Our final estimation sample consists of 97,356 individuals.

The transitions from unemployment to work and the accepted wages after such a transition are the main outcome variables. Our data do not contain information about working hours. Hence, the wage variable captures daily gross wages.<sup>14</sup> We only count transitions to work if they involve a regular job without subsequent receipt of any form of benefits from the PES. Unemployment spells with transitions into inactivity, subsidized work or programs with training measure benefits (Unterhaltsgeld) are right-censored at these transitions. As the model is in discrete time, we time-aggregate the data into monthly observations. One may argue that this is problematic in the light of the fact that multiple VRs may arrive per month. However, in practice such multiplicity is exceedingly rare (across workers in around 1% of the relevant months). The data do not specify the occupation or the sector of VRs.

We observe the intended length and the starting dates of sanctions. In our analysis, we focus on sanctions lasting 12 weeks. We do not observe information about the reason for long sanctions that are imposed after the start of the unemployment spell. However, the majority of the observed sanctions are related to VRs. Following statistics of the German PES, sanctions related to VRs were about four times as common as sanctions due to refusing or dropping out of a training measure (Bundesagentur für Arbeit 2004). In our structural estimation we assume that a sanction observed in the same month or in the month after a VR has been received is motivated by VR noncompliance. Regarding sickness absence periods, we only consider those of 13 days or more, as the application period for referred vacancies typically does not exceed two weeks. Obviously, we do not observe whether sickness absence is due to a VR. Moreover, we do not observe whether a job found after receiving a VR is the one which the unemployed had been referred to.

Table 1 provides some summary statistics of the sample. Clearly, sickness absence is more common after a VR than if no VR was issued. Still, the difference between the two fractions appears rather small. To shed more light on this we estimate a descriptive linear-probability

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<sup>13</sup>To avoid outliers, we impose a few additional sampling restrictions. Specifically, we omit individuals with monthly UI benefits below 500 euro and/or with an accepted wage that is missing or that has a value below the 2nd percentile in the data.

<sup>14</sup>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.

regression equation with sickness absence in a given month on the left-hand side and VR receipt as a binary indicator on the right-hand side, controlling for individual covariates  $X$ . The results (see Table 2) indicate that a VR is a highly significant determinant of sickness absence.

The limited use of sanctions as reported in Table 1 confirms the information from Section 2 that the monitoring scheme was rather weak. A major advantage of the structural approach is that the estimation results can be applied to infer the effects of stricter regimes.

In Table 1, not surprisingly, exits to work are more common upon a VR. At first sight, jobs accepted upon a VR pay less on average than those accepted in other months. The former type of jobs seem to be more stable, although it should be kept in mind that job separations are rarely observed in our relatively short observation window. Figure B.1 in the Appendix displays histograms of accepted wages, separately for jobs that were taken up in a month in which a VR occurred and for jobs taken up in a month without a VR. Figure B.2 shows a histogram of UI benefits.

Table 1: Summary statistics

Variable	Mean	Std. Dev.
Age	37.5	8.4
UI benefits level	910.8	233.7
Medium/high education	0.609	0.488
Health restricted	0.176	0.381
VR rate	0.202	0.401
Sick rate given no VR received	0.033	0.179
Sick rate given VR received	0.035	0.184
Job finding rate	0.086	0.280
Job finding rate given VR received	0.157	0.364
Sanction rate given VR received	0.004	0.063
Separation rate, VR jobs	0.074	0.262
Separation rate, non-VR jobs	0.070	0.253
Accepted wages, VR jobs	2031.0	571.2
Accepted wages, non-VR jobs	2110.2	609.2

*Notes:* Summary statistics based on a sample of 97,356 individuals observed for up to 36 months. Time unit: month. Monetary unit: euro. For brevity, and with some abuse of language, a “rate” is meant to signify the fraction of times an event occurs in a month conditional on presence in the relevant state at the onset of the month. The sanction rate, however, counts the fraction in the VR month as well as the subsequent month. “Job finding” means: making a transition into employment. “VR job” means: a job taken up in a month in which a VR occurred.

Table 2: Linear-probability regression: the association between VR receipt and sickness absence

Outcome: Sickness absence > 2 weeks	
VR	0.0048*** (0.00043)
Age	0.0005*** (0.00002)
Medium/high education	-0.0030*** (0.00035)
Health restricted	0.0191*** (0.00041)
UI benefits	-0.0022*** (0.00075)

*Notes:* The table displays coefficient estimates from a linear probability model, estimated outside of the structural model. Standard errors are in parentheses. \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5% and 10%, respectively. The sample restrictions described in Section 4 apply. The regressions are based on the 1,082,613 time periods (months) in our sample that begin within unemployment.

## 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,  $w_{it}^{acc}$ .<sup>15</sup>

**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 mean and standard deviation  $m_J, s_J$  and  $m_V, s_V$ , respectively.<sup>16</sup>

<sup>15</sup>To be more formally precise we could include an additional element  $w_{it}^{acc} \cdot \mathbf{1}(e_{it+1} > e_{it})$  in  $Z_{it}$ .

<sup>16</sup>Note that the log-normal distribution is often parameterized by the mean and standard deviation of the underlying normal distribution,  $\mu$  and  $\sigma$ . Instead, we choose to parameterize by the mean and standard deviation of

**Measurement Error** We allow for measurement error in accepted wages. Note that this reduces the sensitivity of our estimates to the lowest observed accepted wage in the data as it can reconcile low observed wage levels with reservation wage levels that are higher. 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, some residual error is known to exist and, moreover, monthly wages are obtained by scaling up daily payments. 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  $\epsilon$  is normally distributed with mean zero and variance  $\sigma_\epsilon^2$ . The measurement error variance  $\sigma_\epsilon^2$  is an unknown parameter to be 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  $b$ .<sup>17</sup> All remaining parameters are estimated. The complete vector of unknown parameters is

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

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

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

For a derivation of the likelihood contributions  $g_{it}(Z_{it} | \theta)$  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 the means of the wage offer distributions,  $m_J$  and  $m_V$ , which take only positive values, we specify the dependence on  $X_i$  by

$$m_J = \exp(\zeta_1' X_i), \quad m_V = \exp(\zeta_2' X_i).$$

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the log-normal variable itself,  $m$  and  $s$ , for ease of interpretation. The relationship between the two parameterizations is  $\mu = \ln(m) - \ln(\sqrt{1 + \frac{s^2}{m^2}})$ ,  $\sigma^2 = \ln(1 + \frac{s^2}{m^2})$ .

<sup>17</sup>How we make use of the benefit data is described in more detail below in the section on observed heterogeneity.

For  $\lambda_J$ ,  $\lambda_V$ ,  $\psi$ , and  $\delta$ , which take values in  $[0, 1]$ , we specify dependence on  $X_i$  by

$$\begin{aligned}\lambda_J &= (1 + \exp(-\zeta'_3 X_i))^{-1}, & \lambda_V &= (1 + \exp(-\zeta'_4 X_i))^{-1}, \\ \psi &= (1 + \exp(-\zeta'_5 X_i))^{-1}, & \delta &= (1 + \exp(-\zeta'_6 X_i))^{-1}.\end{aligned}$$

For the estimation we include in  $X_i$ , age, dummy variables which indicate health restrictions and medium/high education, 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  $\nu$  that takes values in a discrete set  $\{v_1, \dots, v_M\}$ . The probability that  $\nu$  takes realization  $v_m$  in the inflow into unemployment is denoted by  $\pi_m$ . We impose a normalization on  $\nu_M$  such that  $\mathbb{E}[\nu] = 0$ . The latent factor  $\nu$  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

$$p_{doc} = (1 + \exp(-X'_i \zeta_8 - \gamma_{doc} \nu))^{-1}, \quad (4)$$

$$p_{sanc} = (1 + \exp(-X'_i \zeta_9 - \gamma_{sanc} \nu))^{-1}. \quad (5)$$

The motivation for adopting a discrete distribution for unobserved heterogeneity is twofold. First, in duration analysis it is known to act well as an approximation for continuous heterogeneity distributions, in the sense that the parameters of interest are estimated robustly even if the true distribution is continuous (see van den Berg, 2001, for an overview). Secondly, with maximum likelihood estimation of highly nonlinear models it has major computational advantages over continuous distributions. For future purposes it is important to point out that the discreteness should not be taken too literally. Rather, the estimated shape of the distribution of  $\nu$  provides a rough indication of unobserved variation of determinants of  $p_{doc}$  and  $p_{sanc}$  among the individuals flowing into unemployment.

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  $\gamma_{doc}$  and  $\gamma_{sanc}$  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.<sup>18</sup>

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

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

where the dependence of the structural parameters  $\theta$  on  $X_i$  and  $\nu$  is governed by the parameters  $\zeta_1, \zeta_2, \dots, \zeta_9$  and  $\gamma_{doc}$  and  $\gamma_{sanc}$  respectively. We subsume these parameters into vectors  $\zeta$  and  $\gamma$  and denote by  $\pi$  the vector containing the probabilities  $\pi_1, \dots, \pi_M$ . Maximum likelihood estimation for the specification with observed and unobserved heterogeneity is performed by maximizing  $\mathcal{L}$  over  $\zeta, \gamma, \pi, \sigma_J, \sigma_V$  and  $\sigma_e$ .

**Identification** To provide intuition on how the structural model parameters are identified, we present equations that link the parameters of our model to empirical moments of the observed data. If a set of empirical moments uniquely maps into model parameter values then the structural model is identified in the formal econometric sense (see, e.g., French and Taber 2011). Also, the links between the observed data and the model parameters may provide some intuition on which variation in the data is informative on which parameter.

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 identification argument, the lowest sampled wage accepted by an unemployed worker in state  $(s, P)$  after receiving / not receiving a VR, identifies the reservation wages  $\bar{w}_V(s, P)$  and  $\bar{w}_J(s, P)$ , respectively. Given identification of the reservation wages, the wage offer distributions,  $F_J$  and  $F_V$ , are identified from the respective distributions of accepted wages, provided  $F_J$  and

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<sup>18</sup>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 models based on mixed proportional hazards.

$F_V$  are recoverable.<sup>19</sup>

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  $sick_t$  dummy variables that indicate arrivals of VRs, sanctions and sickness absences, respectively, in period  $t$ . Conditional on the state  $(s_t, P_t)$ , the model implies the following relationships between data moments and structural parameters.

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

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

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

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

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

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

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

It is straightforward to show that in 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. The extent to which the empirical distributions of outcomes deviate from the corresponding specifications in the model without unobserved heterogeneity is informative on such heterogeneity. For example, if the empirical hazard rate of the unemployment duration distribution displays a different shape as a function of the elapsed duration than the shape in a model without unobserved heterogeneity then this suggests heterogeneity in  $\nu$  affecting the parameters  $p_{doc}$  and  $p_{sanc}$ .

We estimate the model by maximum likelihood, i.e., we fit the whole joint distribution of the observed outcomes conditional on  $X$ . The above empirical moments capture a subset of the

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<sup>19</sup>For estimation we restrict  $F_J$ ,  $F_V$  to be log-normal. The log-normal distribution has the recoverability property (see Flinn and Heckman 1982).

likelihood contributions that show up in the likelihood function (see Appendix A.4).

## 6 Estimation Results

We provide estimates for a basic empirical specification that does not account for parameter heterogeneity as well as a full specification that does include both observed and unobserved parameter heterogeneity.<sup>20</sup> Table 3 presents parameter estimates for the basic specification without heterogeneity, Table 4 presents estimates for the full specification. For ease of interpretation of our parameter estimates for the full specification, Tables 5 and 6 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  $\nu$ .<sup>21</sup>

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.

Another common result 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,  $\lambda_J$ , and  $\lambda_V$ , do not have equivalent interpretations. Regular job offers that arrive at rate  $\lambda_J$ , if accepted, result in a job that can be taken up immediately. VRs arrive at rate  $\lambda_V$ , 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  $\lambda_V$ .

In the full specification, the impact of  $X_i$ , i.e., of age, health restrictions, and medium/high education, is significantly different from zero for all model parameters, indicating that it is relevant

<sup>20</sup>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.

<sup>21</sup>The parameter estimates of the unobserved heterogeneity distribution warrant some discussion. Notice from Table 6 that four of the six implied estimates of  $p_{doc}$  and  $p_{sanc}$  are close to the boundary of their support (i.e., 0 and 1) for any value of  $X_i$ . We have performed an extensive search for other optima of the likelihood function, using a range of different starting values, but did not find a higher likelihood value. Imposing that the above-mentioned four values of  $p_{doc}$  and  $p_{sanc}$  are at the closest boundary value and subsequently estimating the other parameters does lead to a higher likelihood value. However, it is not difficult to show that this model is not nested in our parameterized specification (except for limiting cases, where the likelihood values are actually substantially lower). These results suggest that it may be interesting to consider a more flexible specification for the unobserved heterogeneity distribution; e.g. a two-factor loading specification. However, that would increase the computational burden substantially. In addition, the key results of interest (the implied structural parameter values, their dependence on  $X_i$ , the model fit in terms of mean observables, and the policy implications) appear to be insensitive to this. In particular, when imposing that the above-mentioned four values of  $p_{doc}$  and  $p_{sanc}$  are at their closest boundary values and when subsequently estimating the other parameters, the implications of the resulting estimated model are virtually identical to those presented for the full specification in the paper.

to account for observed heterogeneity. For all parameters that additionally include the unobserved factor  $\nu$ , 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.

Table 3: Parameter Estimates, Basic Specification.

Parameter	Estimate	SE
$m_J$	1848	$3.7 \times 10^{-4}$
$m_V$	1851	$1.5 \times 10^{-6}$
$s_J$	283	$8.5 \times 10^{-8}$
$s_V$	581	$1.0 \times 10^{-7}$
$\lambda_J$	0.090	$1.5 \times 10^{-7}$
$\lambda_V$	0.211	$1.8 \times 10^{-6}$
$p_{sick}$	0.018	$1.6 \times 10^{-7}$
$p_{doc}$	0.003	$2.7 \times 10^{-5}$
$p_{sanc}$	0.571	$1.4 \times 10^{-5}$
$\psi$	0.379	$4.9 \times 10^{-8}$
$\delta$	0.043	$8.4 \times 10^{-8}$
$\sigma_\epsilon$	0.307	$1.9 \times 10^{-6}$

*Notes:* Displayed are parameter estimates based on our estimation sample of 97,356 individuals observed between 2000 and 2002. The sample restrictions described in Section 4 apply. Asymptotic standard errors are computed using the outer product of the score and the delta method.

Table 4: Parameter Estimates, Full Specification

Parameter	Estimate	SE	Parameter	Estimate	SE
<i>m<sub>J</sub></i> :			<i>m<sub>V</sub></i> :		
Intercept	7.578	$8.4 \times 10^{-7}$	Intercept	7.411	$16.8 \times 10^{-7}$
Age (divided by 10)	0.007	$2.2 \times 10^{-7}$	Age (divided by 10)	0.023	$26.0 \times 10^{-8}$
Medium/ high education	0.013	$4.8 \times 10^{-7}$	Medium/ high education	0.034	$5.9 \times 10^{-7}$
Health restrictions	-0.065	$5.4 \times 10^{-7}$	Health restrictions	-0.079	$1.3 \times 10^{-6}$
<i>s<sub>J</sub></i> :	140	$9.1 \times 10^{-4}$	<i>s<sub>V</sub></i> :	515	$10.6 \times 10^{-4}$
<i>σ<sub>ε</sub></i> :	0.294	$1.8 \times 10^{-7}$			
<i>λ<sub>J</sub></i> :			<i>λ<sub>V</sub></i> :		
Intercept	-2.231	$8.6 \times 10^{-6}$	Intercept	-0.194	$191.7 \times 10^{-7}$
Age (divided by 10)	-0.114	$7.0 \times 10^{-7}$	Age (divided by 10)	-0.303	$488.8 \times 10^{-8}$
Medium/ high education	-0.026	$8.5 \times 10^{-6}$	Medium/ high education	0.243	$124.2 \times 10^{-7}$
Health restrictions	0.031	$8.5 \times 10^{-6}$	Health restrictions	-0.248	$151.9 \times 10^{-7}$
<i>p<sub>sick</sub></i> :			<i>ψ</i> :		
Intercept	-4.101	$346.3 \times 10^{-7}$	Intercept	-0.474	$208.9 \times 10^{-7}$
Age (divided by 10)	0.143	$799.6 \times 10^{-8}$	Age (divided by 10)	-0.181	$504.2 \times 10^{-8}$
Medium/ high education	-0.170	$308.4 \times 10^{-7}$	Medium/ high education	0.203	$143.4 \times 10^{-7}$
Health restrictions	0.455	$283.7 \times 10^{-7}$	Health restrictions	-0.170	$169.5 \times 10^{-7}$
<i>δ</i> :					
Intercept	-3.286	$29.4 \times 10^{-8}$			
Age	0.002	$55.5 \times 10^{-9}$			
Medium/ high education	-0.092	$27.3 \times 10^{-8}$			
Health restrictions	0.002	$24.1 \times 10^{-8}$			
<i>p<sub>sanc</sub></i> :			<i>p<sub>doc</sub></i> :		
Intercept	0.299	$2.0 \times 10^{-4}$	Intercept	-5.990	$2.9 \times 10^{-5}$
Age (divided by 10)	0.084	$2.9 \times 10^{-6}$	Age (divided by 10)	0.250	$2.8 \times 10^{-5}$
Medium/ high education	-0.014	$2.5 \times 10^{-4}$	Medium/ high education	-0.490	$3.0 \times 10^{-4}$
Health restrictions	-0.028	$2.0 \times 10^{-4}$	Health restrictions	0.384	$2.3 \times 10^{-4}$
<i>γ<sub>sanc</sub></i>	2.639	$5.4 \times 10^{-6}$			
<i>ν</i> :			<i>π</i> :		
<i>v<sub>1</sub></i>	2.657	$2.3 \times 10^{-6}$	<i>π<sub>1</sub></i>	0.326	$2.9 \times 10^{-7}$
<i>v<sub>2</sub></i>	-1.901	$2.7 \times 10^{-6}$	<i>π<sub>2</sub></i>	0.394	$5.5 \times 10^{-7}$
<i>v<sub>3</sub></i>	-0.419		<i>π<sub>3</sub></i>	0.280	

*Notes:* Displayed are parameter estimates based on our estimation sample of 97,356 individuals observed between 2000 and 2002. The sample restrictions described in Section 4 apply. Standard errors are computed using the outer product of the score.

Table 5: Average structural parameters

Parameter	Population avg.	Population std. dev.
$m_J$	1960	68
$m_V$	1773	88
$\lambda_J$	0.06	0.007
$\lambda_V$	0.21	0.060
$p_{sick}$	0.03	0.010
$p_{doc}$	0.03	0.045
$p_{sanc}$	0.44	0.419
$\psi$	0.24	0.044
$\delta$	0.03	0.002

*Notes:* The table displays means and standard deviations of the estimated structural model parameters, numerically integrating over the empirical distribution of observables,  $X_i$ , and the estimated distribution of the unobserved factor,  $\nu$ .

Table 6: Implied structural parameters

$\nu$	medium/ high education	0	0	1	1
	health restricted	0	1	0	1
	$m_J$	2007	1881	2034	1906
	$m_V$	1802	1665	1865	1723
	$\lambda_J$	0.065	0.067	0.064	0.066
	$\lambda_V$	0.206	0.169	0.249	0.206
	$p_{sick}$	0.028	0.043	0.023	0.037
	$\psi$	0.238	0.209	0.277	0.245
	$\delta$	0.036	0.036	0.033	0.033
$\nu_1 = 2.657$ ( $\pi_1 = 0.326$ )	$p_{doc}$	0.084	0.119	0.053	0.076
	$p_{sanc}$	1.000	0.999	1.000	0.999
$\nu_2 = -1.901$ ( $\pi_2 = 0.394$ )	$p_{doc}$	0.001	0.001	0.001	0.001
	$p_{sanc}$	0.012	0.012	0.012	0.012
$\nu_3 = -0.419$ ( $\pi_3 = 0.280$ )	$p_{doc}$	0.004	0.006	0.003	0.004
	$p_{sanc}$	0.380	0.373	0.376	0.370

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

We may use the estimated model to simulate statistics of outcome variables. A number of these are reported in Table C.1 and Figure C.1 in the Appendix.<sup>22</sup>

**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 1 displays reservation wages for regular job offers and job offers obtained through VRs as a 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  $s > 0$ .<sup>23</sup>

Figure 1 shows that for unemployed workers who have never been sanctioned ( $s = 0, P = 0$ ) the reservation wage for regular job offers,  $\bar{w}_J$ , is slightly higher than the reservation wage for VR offers,  $\bar{w}_V$ . In contrast, for unemployed workers who have previously been sanctioned, there is a persistent sizable positive gap between  $\bar{w}_J$  and  $\bar{w}_V$ . 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.

## 7 Labor Market Policy Simulations

We use the estimated model to study how counterfactual policy changes impact job search outcomes and sick reporting. In the first part of this section, we focus on changes in sanction enforcement and changes in the VR rate. Increasing sanction enforcement corresponds to instructing caseworkers to use their discretionary leeway less and to 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 rollout of VRs may have on firms' vacancy posting behavior and on the wage offer distribution, i.e., our model abstracts from 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.

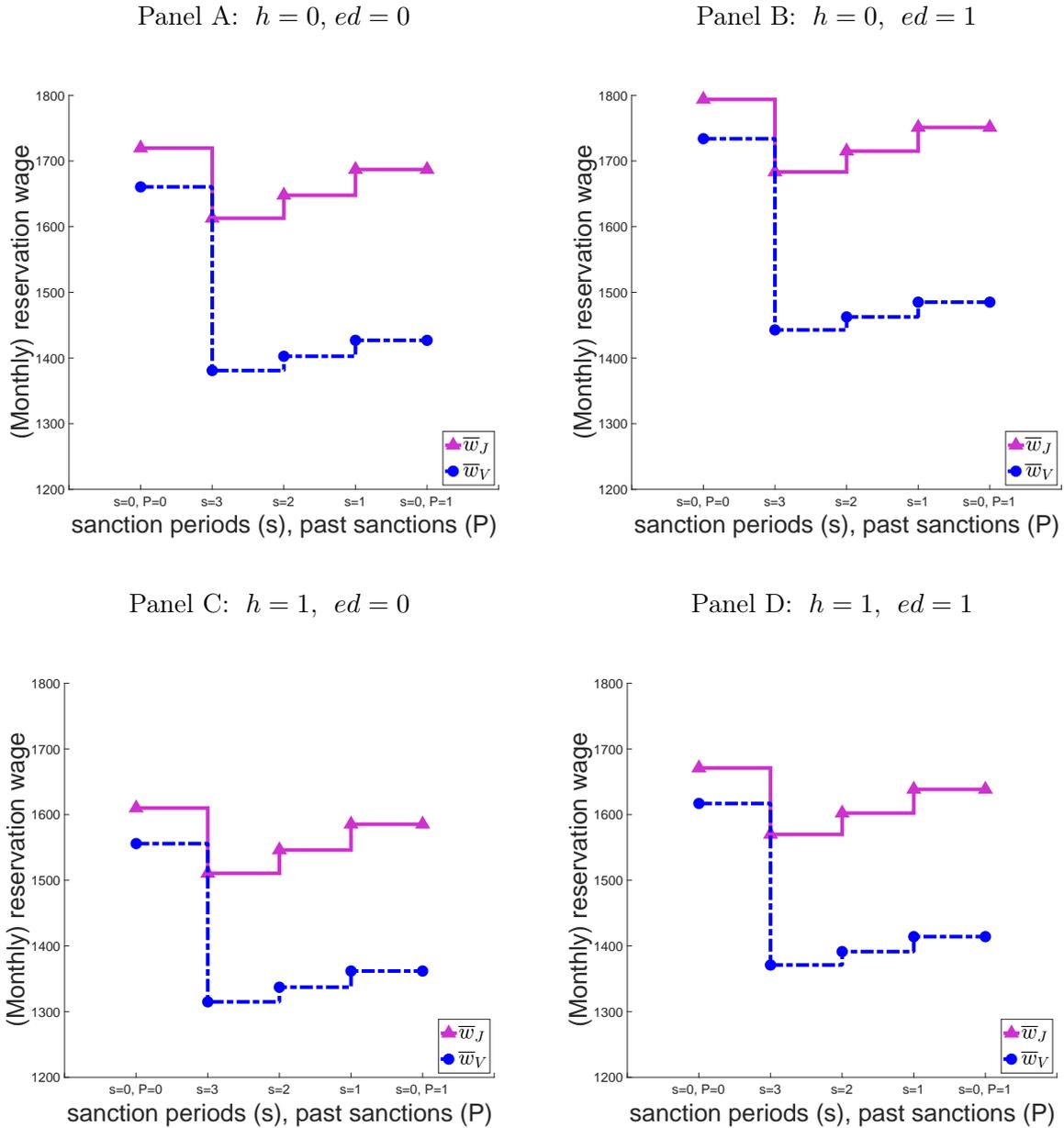
For each counterfactual policy change, we examine effects on job finding rates, average un-

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<sup>22</sup>Assessing the model fit by comparing them to observed outcomes is hampered by the fact that outcome variables and their observability in the actual data depend on earlier events and on unobserved heterogeneity. For example, observed accepted wages are not drawn from a simple truncated version of a wage offer distribution but depend on truncation points that vary over time and depend on unobserved determinants of model parameters and on censoring of earlier events. Moreover, the length of the observation window varies across individuals in the sample.

<sup>23</sup>Recall that in the institutional setting that we study, the second sanction already is a terminal sanction, so that  $P \in \{0, 1\}$ .

Figure 1: Implied reservation wages,  $h$ : health restrictions,  $ed$ : medium/high education



*Notes:* Reservation wages by current sanction status,  $s$ , and past sanctions,  $P$ , plotted separately for regular job offers and VRs. Plotted are reservation wages for agents with median benefit level (1000 Euro) and of median age (38) and for the median unobserved type,  $\nu = -0.419$ . Each panel corresponds to a different observable type in terms of health restrictions,  $h$ , and education,  $ed$ .

employment 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.<sup>24</sup>

Table 7 displays results on the impact of changing sanction enforcement on job search outcomes. The results presented in Table 7 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 0.27 months (around 8 days). Moving to full enforcement ( $p_{sanc} = 1$ ), would reduce the average unemployment duration by 1 month. We find that accepted wages respond only slightly to changes in sanction enforcement. Moving to full enforcement, leads to a small decrease by 2.7% (56 Euro) in the mean accepted wage.

Table 7: Changing sanction enforcement

$\tilde{p}_{sanc}$	0	$p_{sanc}$	$2p_{sanc}$	$3p_{sanc}$	1
<i>All unemployed</i>					
Job finding rate	8.54%	9.26%	9.43%	9.50%	10.18%
Avg. accepted wage	2103	2058	2046	2041	2002
Avg. unemp. duration (months)	11.67	10.77	10.58	10.50	9.80
<i>VR received</i>					
Job finding rate	12.79%	16.33%	17.17%	17.53%	21.06%
Sanction	0.0%	0.62%	0.67%	0.71%	0.98%

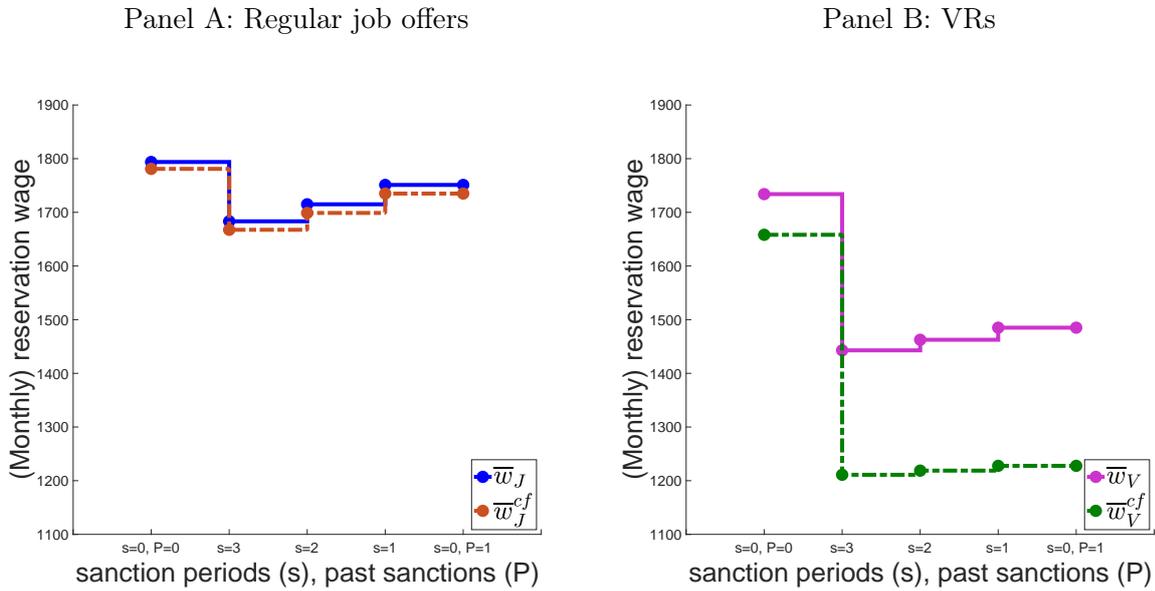
*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

To shed light on the underlying mechanism, we examine how reservation wages respond to changes in sanction enforcement. Figure 2 displays the magnitude by which unemployed workers with median characteristics adjust their reservation wages when sanction enforcement is tripled. Figure 2 shows that tripling sanction enforcement leads to a minimal reduction in reservation wages for regular wage offers ( $\bar{w}_J$ ) and a strong reduction in reservation wages for offers obtained

<sup>24</sup>Recall that sanction enforcement at baseline is, on average, at 44%, but substantially dispersed in the population. For the fraction of the population for whom doubling or tripling  $p_{sanc}$  yields values greater than 1, we fix counterfactual sanction enforcement at 1 (full enforcement).

through VRs ( $\bar{w}_V$ ). 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  $\bar{w}_V$  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.

Figure 2: Increasing sanction enforcement, reservation wages



*Notes:* Reservation wages by current sanction status,  $s$ , and past sanctions,  $P$ . Plotted for the status quo policy and a counterfactual scenario where sanction enforcement is tripled. Panel A and B display reservation wages for regular job offers and VRs, respectively. Plotted are reservation wages for individuals with median benefit level (1000 Euro), of median age (38), of the modal type with respect to education and health restrictions (i.e., with medium/high education and no health restrictions), and of the median unobserved type,  $\nu = -0.419$ .

**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 by 25% or decreased by 25% or 50% of its status quo value.

Table 8 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 0.74 months (23 days). Furthermore, the overall

job finding rate increases by 0.69, while the job finding rate for months when a VR was received falls by 0.24 percentage points as the VR rate is increased by a factor of 1.25.

Table 8: Changing the VR rate

$\tilde{\lambda}_V$	$0.5\lambda_V$	$0.75\lambda_V$	$\lambda_V$	$1.25\lambda_V$
<i>All unemployed</i>				
VR	9.89%	14.75%	19.56%	24.36%
Job finding rate	7.78%	8.54%	9.26%	9.95%
Avg. accepted wage	2053	2056	2058	2062
Avg. unemp. duration (months)	12.81	11.67	10.77	10.03
<i>VR received</i>				
Job finding rate	16.80%	16.59%	16.33%	16.09%
Sanction	0.51%	0.57%	0.62%	0.72%

*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

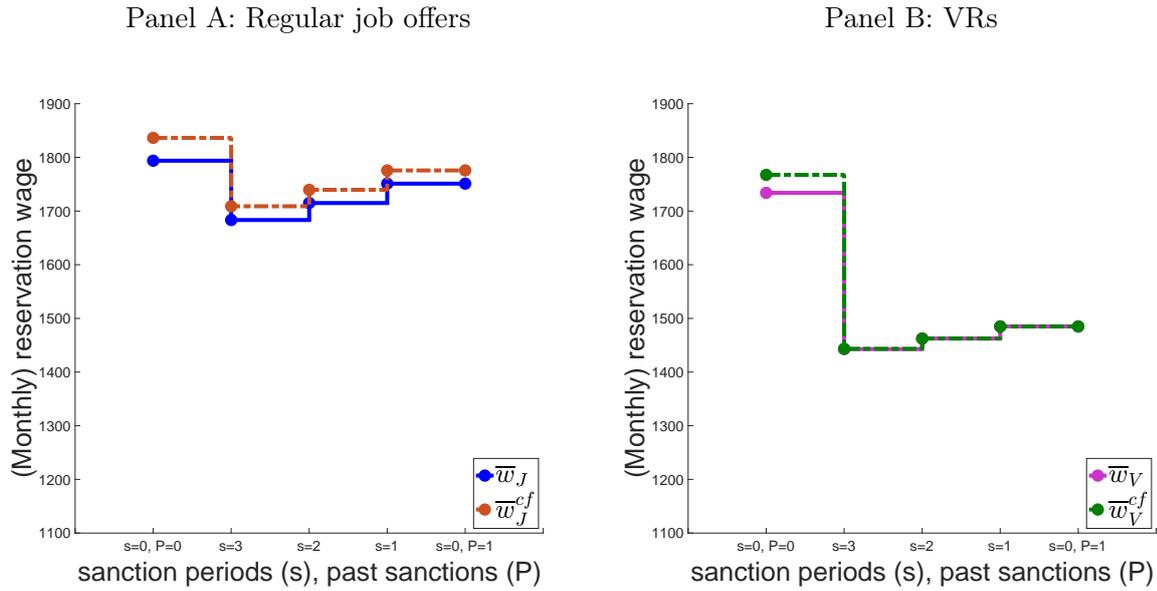
It may seem counterintuitive that VRs elevate overall job finding while reducing job finding in months when a VR is received. The explanation is that VRs have two counteracting effects on job search behavior. On the one hand as the VR rate is increased the risk of receiving a sanction in the future increases. 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.

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 3 displays reservation wages for unemployed workers with median characteristics. 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  $\lambda_V$  is increased: unemployed job seekers reject resulting

Figure 3: Increasing the VR rate, reservation wages



*Notes:* Reservation wages by current sanction status,  $s$ , and past sanctions,  $P$ . Plotted for the status quo policy and a counterfactual scenario where the VR rate is increased by 25%. Panel A and B display reservation wages for regular job offers and VRs, respectively. Plotted are reservation wages for individuals with median benefit level (1000 Euro), of median age (38), of the modal type with respect to education and health restrictions (i.e., with medium/high education and no health restrictions), and of the median unobserved type,  $\nu = -0.419$ .

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  $\lambda_V$  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 given job offers obtained through VRs are accepted.

**Jointly Varying Sanction Enforcement and the VR Rate** Another aspect that can be studied using our model is to what degree increasing sanction enforcement and increasing the VR rate complement each other in reducing the unemployment duration. To this end, we run simulations in which sanction enforcement and the VR rate are jointly varied. The results, displayed in Table 9, imply that there is considerable complementarity between the two policies. The effect of increasing the VR rate by a factor of 1.5 is 17.5% greater under full sanction enforcement than under the status quo. Without any sanctions (under  $p_{sanc} = 0$ ) the effect of this policy change would be 26% smaller than under the status quo. Similarly, the impact of increasing sanction enforcement from its status quo value to full enforcement is 25% larger if the VR rate is fixed at  $1.5\lambda_V$ , and 41% smaller if it is fixed at  $0.5\lambda_V$ . Jointly switching to full sanction enforcement

and increasing the VR rate to  $1.5\lambda_V$  reduces the average unemployment duration by 2.6 months (24%).

Table 9: Jointly varying sanction enforcement and VR rate, impact on unemployment duration

$\tilde{p}_{sanc}$	$\tilde{\lambda}_V$				
	$0.5\lambda_V$	$0.75\lambda_V$	$\lambda_V$	$1.25\lambda_V$	$1.5\lambda_V$
0	13.27	12.37	11.67	11.13	10.66
$p_{sanc}$	12.81	11.67	10.77	10.03	9.40
$2p_{sanc}$	12.70	11.22	10.58	9.83	9.18
$3p_{sanc}$	12.63	11.08	10.50	9.74	9.09
1	12.24	11.02	9.80	8.92	8.19

*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

**Varying Sanction Duration** We now simulate the effects of changing the sanction duration,  $K$ . The results in Table 10 show that increasing the sanction duration from its status quo value  $K = 3$  unambiguously reduces the average unemployment duration and increases the unconditional job finding rate, as well as the job finding rate conditional on VR receipt. Increasing sanction duration from three to nine months results in a comparable yet slightly greater reduction in average unemployment duration compared to doubling sanction enforcement. Note, however, that increasing sanction enforcement generally increases the rate at which job seekers who receive a VR are sanctioned while increasing sanction duration (slightly) reduces this rate.

Table 10: Changing sanction duration

$\tilde{K}$	1	3	9	18
<i>All unemployed</i>				
Job finding rate	9.24%	9.26%	9.51%	9.60%
Avg. accepted wage	2065	2058	2050	2044
Avg. unemp. duration (months)	10.81	10.77	10.51	10.43
<i>VR received</i>				
Job finding rate	15.85%	16.33%	16.71%	16.97%
Sanction	0.64%	0.62%	0.53%	0.48%

*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

## 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. The model allows for a decomposition of the per-period sickness absence probability into a baseline (real sickness) probability and a VR-induced (feigned sickness) probability. Conditional on agent type (i.e., conditional on  $X_i$  and  $\nu$ ), the overall probability to report sick for a particular individual in a given period equals

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

where all right-hand side parameter values are implicitly conditioned on  $X_i$  and  $\nu$ .

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

$$\begin{aligned} &\frac{P(\text{ VR-induced sick report})}{P(\text{ sick report } )} \\ &= \frac{\sum_{m=1}^M \sum_{x \in \mathbf{X}} \pi_m P(X_i = x) P(\text{ VR-induced sick report } | X_i = x, \nu_i = v_m)}{\sum_{m=1}^M \sum_{x \in \mathbf{X}} \pi_m P(X_i = x) P(\text{ sick report } | X_i = x, \nu_i = v_m)} \\ &= 5.95\%, \end{aligned} \quad (8)$$

i.e., according to our estimated model, about 6% of all observed sick reports among unemployed individuals occur because individuals try to circumvent a VR.

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 11 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 5.9% (roughly in line with the decomposition described above). This

overall effect is entirely driven by reduced sick reporting in months when a VR is received. Sick reporting in these months drops by 26% (from 4.41% to 3.27%), when VR-induced sick reporting is eliminated.

Table 11: Eliminating VR induced sick reporting

$\tilde{p}_{doc}$	$p_{doc}$	0
<i>All unemployed</i>		
VR	19.56%	19.56%
Sickness absence ( $\geq 2$ weeks)	3.76%	3.54%
Job finding rate	9.26%	9.30%
Avg. accepted wage	2058	2055
Avg. unemp. duration (months)	10.77	10.72
<i>VR received</i>		
Sickness absence	4.41%	3.27%
Job finding rate	16.33%	16.51%
Sanction	0.62%	0.62%

*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

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 0.05 months (1.5 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.

Although average effects of eliminating VR-induced sick reporting on job search outcomes are small, the magnitude of these effects varies substantially across individuals in the heterogeneous population and is more 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,  $P(\text{VR-induced sick report} \mid X_i, \nu)$ .

Counterfactual outcomes for this subpopulation are displayed in Table 12. The presented results show that VR-induced sick reporting constitutes 18% of overall sick reporting within this subpopulation. Moreover, we find that VR-induced sick reporting does have a more sizable impact on job search outcomes. In particular, eliminating VR-induced sick reporting leads to a 0.13 months (4 days) reduction in average unemployment duration. The share of individuals who

receive a sanction is virtually the same.

In Table C.2, 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 6 days, while the sanction rate increases from 0.89% to 0.93%.

Table 12: Eliminating VR induced sick reporting, top 25%

$\tilde{p}_{doc}$	$p_{doc}$	0
<i>All unemployed</i>		
VR	17.39%	17.38%
Sickness absence ( $\geq 2$ weeks)	4.60%	3.90%
Job finding rate	7.23%	9.34%
Avg. accepted wage	1988	1980
Avg. unemp. duration (months)	10.81	10.68
<i>VR received</i>		
Sickness absence	7.80%	3.73%
Job finding rate	18.61%	19.24%
Sanction	0.96%	0.97%

*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

We end this section by returning to the difficulty of implementing  $p_{doc} = 0$  in practice. It seems unrealistic to assume that physicians or other gatekeepers in the health care system can be induced to apply more stringent verifications of sickness claims if the claim comes shortly after a VR. One might relegate verifications for all unemployed individuals to a specific body that applies a more stringent policy than that used for employed individuals or for the population as a whole. However, it is not clear if this is cost-effective. In the end, the costs of such a policy should be taken into consideration, as should be done with the costs of more intensive monitoring of unemployed job seekers.

## 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 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 considerable share of overall sick reporting. 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% (or 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 4 days (or 6 days, respectively).

An interesting extension would be to study equilibrium effects of VRs and sanctions. It can be conjectured that some of these policies have effects on wage setting and vacancy posting behavior. Moreover, increasing the VR rate may crowd out other workers who applied for the referred vacancies. We view these as interesting extensions 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

$$\tilde{E}(w, 0, 0) = w + \beta((1 - \delta)E(w, 0, 0) + \delta U(0, 0)) \quad (9)$$

$$= \frac{w + \beta\delta U(0, 0)}{1 - \beta(1 - \delta)}, \quad (10)$$

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

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

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

$$E(\bar{w}_J(s, P), P) = U(\max\{s - 1, 0\}, P), \quad (12)$$

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

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

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

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

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

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

## A.2 Terminal Sanctions, Value Function

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

$$\Phi = b_{\text{low}} + \beta \left( \lambda_J \int \max\{E(w, \bar{P}), \Phi\} dF_J(w) + (1 - \lambda_J)\Phi \right). \quad (16)$$

Rearranging and inserting (11) into (16) yields

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

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

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

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

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

Note that the reservation wage for regular job offers of unemployed workers with no past sanctions,  $\bar{w}_J(0, 0)$ , enters this equation. The reservation wage of terminally sanctioned unemployed workers,  $\bar{w}_\Phi$ , 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

$$E(\bar{w}_J(s, P)) = U(\max\{s - 1, 0\}, P), \quad (20)$$

and moreover for the reservation wages after receipt of a VR

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

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

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

$$U(s, P) = \beta(1 - p_{sick}) \left( \lambda_J \int_{\bar{w}_J(s, P)}^{+\infty} \frac{w - \bar{w}_J(s, P)}{1 - \beta(1 - \delta)} dF_J(w) + \lambda_V A_V(s, P) \right. \\ \left. + (1 - \lambda_V)E(\bar{w}_J(s, P), P) \right) + \beta p_{sick}E(\bar{w}_J(s, P), P).$$

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

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

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

$$\int B_V(w, s, P) dF_V(w) = \psi \int \max\{E(w, P), E(\bar{w}_V(s, P), P)\} dF_V(w) \\ + (1 - \psi) E(\bar{w}_J(s, P), P) \\ = \psi \int_{\bar{w}_V(s, P)}^{+\infty} \frac{w - \bar{w}_V(s, P)}{1 - \beta(1 - \delta)} dF_V(w) + \psi E(\bar{w}_V(s, P), P) \\ + (1 - \psi) E(\bar{w}_J(s, P), P)$$

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

thus yields

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

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

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

Note from (3) that it holds that

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

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

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

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

$\bar{w}_V(s, P)$  for (for  $s = 0, \dots, K$  and  $P = 1, \dots, \bar{P} - 1$ ) and  $\bar{w}_\Phi$ . Taken together, we thus obtain a system of  $2 \times K \times (\bar{P} - 1) + 1$  reservation wage equations that we solve numerically 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  $g_t^{uu} = g_t(e_t = 0, vr_t, sick_t, sanc_t, e_{t-1} = 0 | \theta)$  is given by

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

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

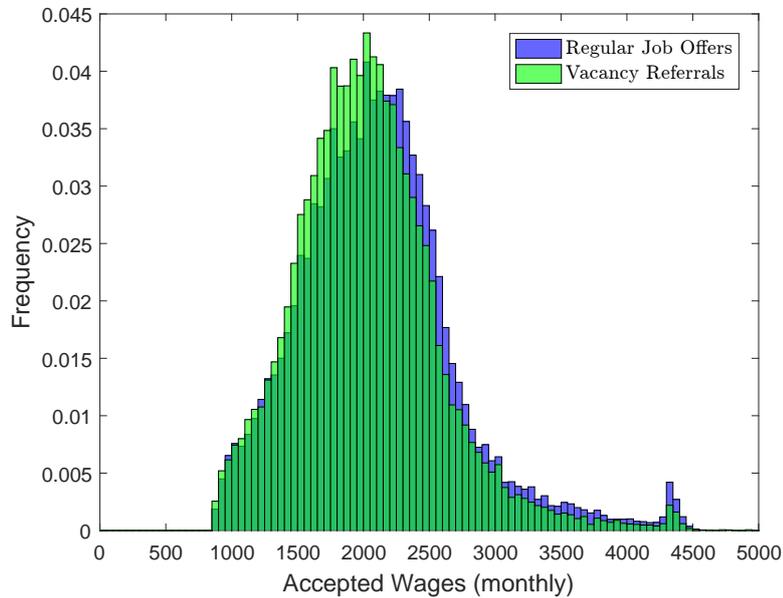
$$g_t^{ue} = \begin{cases} (1 - p_{sick})\lambda_J \int f_J(w) \mathbf{1}\{w \geq \bar{w}_J(s, P)\} \frac{1}{\sigma_\epsilon} \phi\left(\frac{w - \tilde{w}^{acc}}{\sigma_\epsilon}\right) dw & \text{if } (vr_t = 0, \tilde{w}_t^{acc}, s_t = s, P_t = P) \\ (1 - p_{sick})\lambda_V \psi \int f_V(w) \mathbf{1}\{w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

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

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

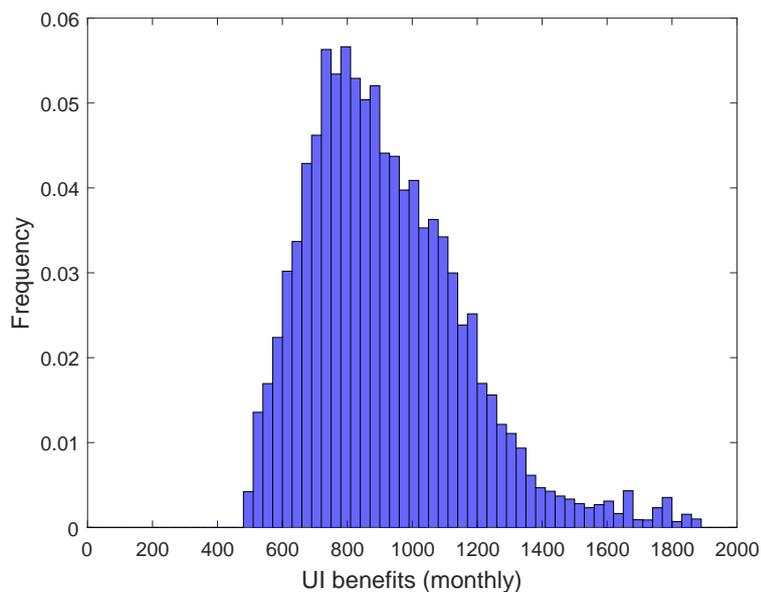
## B Additional Figures

Figure B.1: Empirical distribution of accepted wages



*Notes:* Accepted (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 our estimation sample of 97,356 individuals observed between 2000 and 2002. The sample restrictions described in Section 4 apply.

Figure B.2: Empirical distribution of UI benefits



*Notes:* Monthly UI benefits in Euro. Based on our estimation sample of 97,356 individuals observed between 2000 and 2002. The sample restrictions described in Section 4 apply.

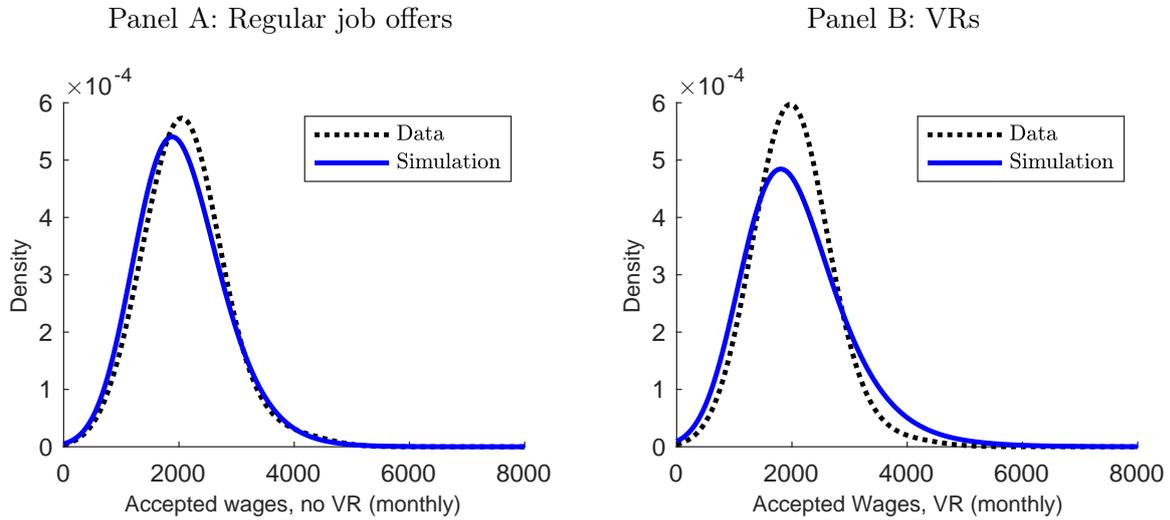
## C Additional Implications of the Estimated Model

Table C.1: Observed outcomes and simulated observable outcomes

	Data	Simulation
<i>All unemployed</i>		
VR	20%	20%
Sickness absence ( $\geq 2$ weeks)	3.4%	3.8%
Job finding rate	8.6%	9.3%
Accepted wage	2110	2058
<i>VR received</i>		
Sickness absence ( $\geq 2$ weeks)	3.5%	4.4%
Job finding rate	16%	16%
Sanction	0.4%	0.6%

*Notes:* Data fractions and averages are computed from monthly observations based on our estimation sample of 97,356 workers observed between 2000 and 2002. The sample restrictions and definitions as described in Section 4 apply. Simulated numbers are based on simulation draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.

Figure C.1: Observed accepted wages and simulated observable accepted wages



*Notes:* Simulated monthly accepted wages are based on simulation draws for 20,000 workers. We simulate histories of 3600 time periods for each worker. Displayed are accepted wages, 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).

**Remarks about Table C.1 and Figure C.1.** As explained in Section 6 of the paper, the comparison of observed outcomes and simulated observable outcomes should not be viewed as a test of the model fit. Amongst other issues, the simulations do not include right-censoring that may originate from data imperfections. In a highly nonlinear model with heterogeneity it is difficult to relate a particular discrepancy between observed outcomes and simulated observable outcomes to some specific model feature. As a general remark, one may expect the fit to improve by making job offer probabilities dependent on the elapsed duration, but this may involve a formidable computational cost. An alternative extension concerns the inclusion of other sanction types which could influence the discretionary propensity of caseworkers to issue a sanction for rejecting a VR offer.

The simulated observable accepted wages in Figure C.1 do take wage measurement errors  $\epsilon$  into account. Its variation is not negligible. The estimated standard deviation  $\sigma_\epsilon$  of the error in observed log wages equals 0.31 in the basic model specification; this can be contrasted to the estimated standard deviation of 0.15 for log wages of regular offers. The sizeable role of wage measurement errors explains why the simulated densities on Panels A and B in Figure C.1 are not widely different despite the substantial difference between the estimated  $F_J$  and  $F_V$ .

Table C.2: Eliminating VR induced sick reporting, top 10%

$\tilde{p}_{doc}$	$p_{doc}$	0
<i>All unemployed</i>		
VR	12.41%	12.37%
Sickness absence ( $\geq 2$ weeks)	10.33%	4.72%
Job finding rate	7.25%	7.36%
Avg. accepted wage	1987	1976
Avg. unemp. duration (months)	13.74	13.55
<i>VR received</i>		
Sickness absence	9.65%	2.52%
Job finding rate	15.08%	16.04%
Sanction	0.89%	0.93%

*Notes:* Computed from simulations draws for 20,000 workers. We simulate histories of 3600 time periods for each worker.