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

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September 17, 2023

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

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.[1] 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.

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.[2]

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

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

receipt. However, during sickness absence, the unemployed does not have to comply with the job 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 λ_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 λ_V. A VR is characterized by a wage draw from the offer distribution F_V. We assume that the unemployed worker learns the wage offer attached to a referred vacancy immediately when he receives the VR. After observing the wage offer, he decides whether to try to get a sick note 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 (i.e., the probability of being rejected by the employer is 1). 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 o□ered the job.[8] If he indeed receives a job o□er, he may accept and start the job at the o□ered 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.[9] If the unemployed worker does receive a sanction, no benefits are paid out to him for the next K time periods.[10] 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 o□er w equals

$$B_V(w; s; P) = \max \quad E(w; P); p_{sanc} U(K; P + 1)$$

$$+ (1$$

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

Value of Employment The expected discounted lifetime utility of an employed worker depends on the per period wage and an exogenous job destruction rate . 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

counts the number of sanctions received in the past. If an unemployed worker's accumulated past sanctions cross a threshold value $\overline{P}$, a terminal sanction is imposed on him, i.e., he completely loses benefit eligibility.

Reservation Wages It is straightforward to show that the value of employment is strictly increasing in w. It follows that the unemployed worker adopts a reservation wage strategy when deciding whether to accept or reject job offers. The worker's strategy is completely characterized by reservation wages for regular job offers $\overline{w}_J(s;P)$ and for job offers obtained through VRs $\overline{w}_V(s;P)$ for each combination of state variables $s \in \{0;\ldots;K\}$ and $P \in \{0;\ldots;\overline{P}\}$ and a reservation wage $\overline{w}$ 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.[13] 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.[14] 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

[13] 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.

[14] 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.

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 reconciliate 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., $ln(w^{acc}) = ln(w^{acc}) +$, where is normally distributed with mean zero and variance ^{2}. The measurement error variance ^{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 $= 0.997$. Note that we observe the exact unemployment benefits that an individual receives and thus we do not need to estimate b.[17] All remaining parameters are estimated. The complete vector of unknown parameters is

$$= \; _J; \; _J; \; _V; \; _V; \; _J; \; _V; \; ; p_{sick}; p_{doc}; p_{sanc}; \; ; \; :$$

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

$$L = \prod_{i=1}^{N} \prod_{t=1}^{T_i} g_{it} \; Z_{it} j$$

For a derivation of the likelihood contributions $g_{it} \; Z_{it} j$ 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

$$m_J = \exp \; {}^0_1 X_i \; ; \quad m_V = \exp \; {}^0_2 X_i \; :$$

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

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

For $_J;$ $_V;$, and , which take values in $[0;1]$, we specify dependence on X_i by

$$_J = 1 + \exp({}^{0}_{3}X_i) \;^{1}; \qquad _V = 1 + \exp({}^{0}_{4}X_i) \;^{1};$$

$$= 1 + \exp({}^{0}_{5}X_i) \;^{1}; \qquad = 1 + \exp({}^{0}_{6}X_i) \;^{1}:$$

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 that takes values in a discrete set $f v_1; :::; v_M g$. The probability that takes realization v_m in the inflow into unemployment is denoted by $_m$

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 $_{doc}$ and $_{sanc}$ 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.[18]

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

$$L = \prod_{i=1}^{N} \sum_{m=1}^{M} {}_m \left(\prod_{t=1}^{T} h_{it}\left(Z_{it} \mid (v_m; X_i) \right) \right); \tag{6}$$

where the dependence of the structural parameters on X_i and is governed by the parameters $_1; _2; \ldots; _9$ and $_{doc}$ and $_{sanc}$ respectively. We subsume these parameters into vectors and and denote by the vector containing the probabilities $_1; \ldots; _M$. Maximum likelihood estimation

F_V are recoverable.[19]

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

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.[20] 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 .[21]

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 ($_J$ < $_V$). Note, however, that the two arrival rates, $_J$, and $_V$, do not have equivalent interpretations. Regular job offers that arrive at rate $_J$, if accepted, result in a job that can be taken 7(eometer)-326(estimates)-b.364 -at the two20ts7(eomeJ/F25 7.9

to account for observed heterogeneity. For all parameters that additionally include the unobserved factor , 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	$3.7 \quad 10^{4}$
m_V	1851	$1.5 \quad 10^{6}$
s_J	283	$8.5 \quad 10^{8}$
s_V	581	$1.0 \quad 10^{7}$
$_J$	0.090	$1.5 \quad 10^{7}$
$_V$	0.211	$1.8 \quad 10^{6}$
p_{sick}	0.018	$1.6 \quad 10^{7}$
p_{doc}	0.003	$2.7 \quad 10^{5}$
p_{sanc}	0.571	$1.4 \quad 10^{5}$
	0.379	$4.9 \quad 10^{8}$
	0.043	$8.4 \quad 10^{8}$
	0.307	$1.9 \quad 10^{6}$

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

Table 4: Parameter Estimates, Full Specification

Parameter	Estimate	SE	Parameter	Estimate	SE
m_J :			m_V :		
Intercept	7.578	8.4 10^{7}	Intercept	7.411	16.8 10^{7}
Age (divided by 10)	0.007	2.2 10^{7}	Age (divided by 10)	0.023	26.0 10^{8}
Medium/ high education	0.013	4.8 10^{7}	Medium/ high education	0.034	5.9 10^{7}
Health restrictions	-0.065	5.4 10^{7}	Health restrictions	-0.079	1.3 10^{6}
s_J :	140	9.1 10^{4}	s_V :	515	10.6 10^{4}
:	0.294	1.8 10^{7}			
$_J$:			$_V$:		
Intercept	-2.231	8.6 10^{6}	Intercept	-0.194	191.7 10^{7}
Age (divided by 10)	-0.114	7.0 10^{7}	Age (divided by 10)	-0.303	488.8 10^{8}
Medium/ high education	-0.026	8.5 10^{6}	Medium/ high education	0.243	124.2 10^{7}
Health restrictions	0.031	8.5 10^{6}	Health restrictions	-0.248	151.9 10^{7}
p_{sick} :			:		
Intercept	-4.101	346.3 10^{7}	Intercept	-0.474	208.9 10^{7}
Age (divided by 10)	0.143	799.6 10^{8}	Age (divided by 10)	-0.181	504.2 10^{8}
Medium/ high education	-0.170	308.4 10^{7}	Medium/ high education	0.203	143.4 10^{7}
Health restrictions	0.455	283.7 10^{7}	Health restrictions	-0.170	169.5 10^{7}
:					
Intercept	-3.286	29.4 10^{8}			
Age	0.002	55.5 10^{9}			
Medium/ high education	–0.092	27.3 10^{8}			
Health restrictions	0.002	24.1 10^{8}			
p_{sanc} :			p_{doc} :		
Intercept	0.299	2.0 10^{4}	Intercept	-5.990	2.9 10^{5}
Age (divided by 10)	0.084	2.9 10^{6}	Age (divided by 10)	0.250	2.8 10^{5}
Medium/ high education	-0.014	2.5 10^{4}	Medium/ high education	-0.490	3.0 10^{4}
Health restrictions	-0.028	2.0 10^{4}	Health restrictions	0.384	2.3 10^{4}
$_{sanc}$	2.639	5.4 10^{6}			
:			:		
v_1	2.657	2.3 10^{6}	$_1$	0.326	2.9 10^{7}
v_2	-1.901	2.7 10^{6}	$_2$	0.394	5.5 10^{7}
v_3	-0.419		$_3$	0.280	

<u>*Notes*</u>

Table 5: Average structural parameters

Parameter	Population avg.	Population std. dev.
m_J	1960	68
m_V	1773	88
$_J$	0.06	0.007
$_V$	0.21	0.060
p_{sick}	0.03	0.010
p_{doc}	0.03	0.045
p_{sanc}	0.44	0.419
	0.24	0.044
	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, .

Table 6: Implied structural parameters

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.[22]

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 $s > 0$.[23]

Figure 1 shows that for unemployed workers who have never been sanctioned $(s = 0; P = 0)$ the reservation wage for regular job offers, $\overline{w}_J$, is slightly higher than the reservation wage for VR offers, $\overline{w}_V$. In contrast, for unemployed workers who have previously been sanctioned, there is a persistent sizable positive gap between $\overline{w}_J$ and $\overline{w}_V$. Facing the risk of receiving a terminal sanction upon rejecting a VR makes these individuals accept much lower wage offers for VR offers than for regular job offers.

7 Labor Market Policy Simulations

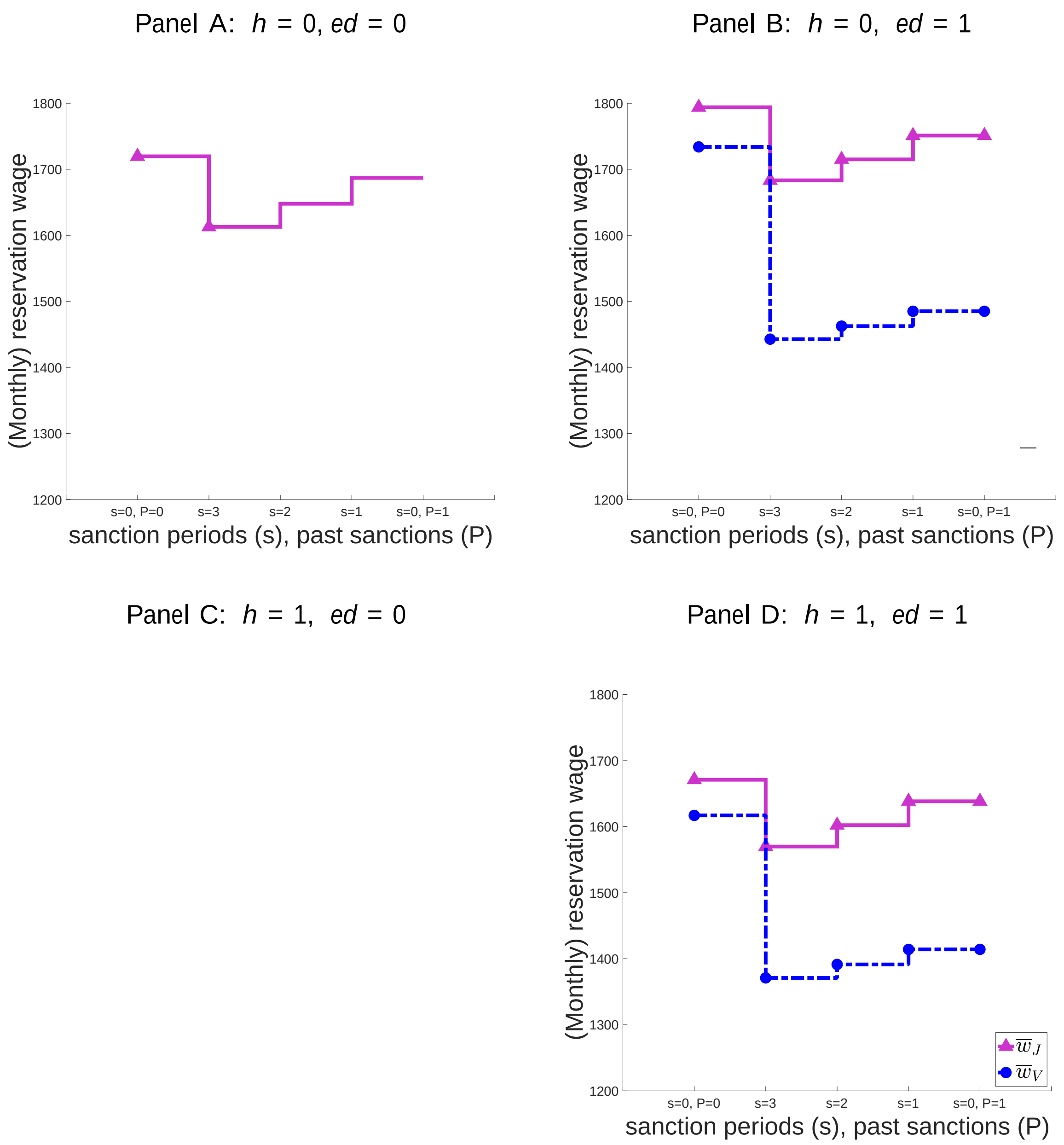
We use the estimated model to study how counterfactual policy changes impact job search outcomes and sick reporting. In the first part of this section, we focus on changes in sanction enforcement and changes in the VR rate. Increasing sanction enforcement corresponds to instructing caseworkers to use 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-

[22] 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.

[23] 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, $= 0.419$. 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.[24]

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

p_{sanc}	[illegible]	[illegible]	$2p_{sanc}$	$3p_{sa}$[illegible]	[illegible]
All unemployed					
[illegible]b finding rate	[illegible]8.54%	9.26%	[illegible]3%	9[illegible]	10.18%
[illegible]g. accepted wage	2103	2058	[illegible]046	2[illegible]	2002
[illegible] unemp. durat[illegible] months)	11.67	10.77[illegible]	[illegible]0.58	10.[illegible]	9.80
[illegible]ceived					
Jo[illegible]ding rate	12.79%[illegible]	[illegible]33%	17.17%	17[illegible]	21.06%
San[illegible]	0.[illegible]	0.62%	0.67%	[illegible]	0.98%

Notes: Compute[illegible] s[illegible]tions draws for 20[illegible]owkthn4023o1(7)]Tervtnemploy[illegible]e28(t)-330(du 0 Td-[illegible]ed)-401([illegible]

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

$\tilde{}_V$	$0.5\ {}_V$	$0.75\ {}_V$	${}_V$	$1.25\ {}_V$
All unemployed				
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
VR received				
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.

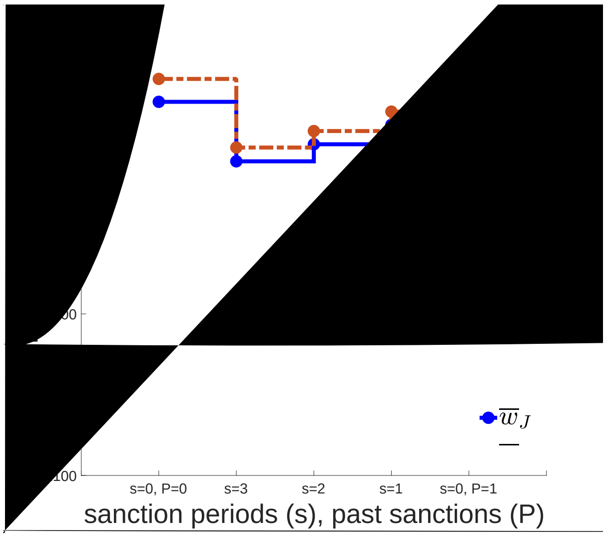
Figure 3 displays reservation wages for unemployed workers with median characteristics. The figure shows that reservation wages rise as the VR rate is increased, meaning that the force pushing towards a higher option value of search, because more job offers are sampled, dominates.

The fact that increasing the VR rate leads to higher reservation wages explains the declining job finding rates in months when a VR as ${}_V$ is increased: unemployed job seekers reject resulting

Figure 3: Increasing the VR rate, reservation wages

Panel A: Regular job offers

Panel B: VRs



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, $= 0{:}419$.

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 $_V$ 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.[illegible] is 17.[illegible]% greater under fud [(0o8(undceme57)28(-8(fue57)28implyn(e

VRs

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

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

	$\tilde{\ }_V$				
$\tilde{p}_{sanc}$	$0.5\ {}_V$	$0.75\ {}_V$	${}_V$	$1.25\ {}_V$	$1.5\ {}_V$
0	13.27	12.37	11.67	11.13	10.66
p_{sanc}	12.81	11.67	10.77	10.03	9.40
$2\,p_{sanc}$	12.70	11.22	10.58	9.83	9.18
$3\,p_{sanc}$	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
All unemployed				
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
VR received				
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), the overall probability to report sick for a particular individual in a given period equals

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

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

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

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

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

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%

$\bar{p}_{doc}$	p_{doc}	0
All unemployed		
VR	17.39%	17.38%
Sickness absence (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
VR received		
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.

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A Derivations

A.1 Value of Employment

For the value of employment, $\bar{E}(w;P; \quad)$, we have

$$\bar{E}(w;0;0) = w + \quad (1 \quad)E(w;0;0) + \quad U(0;0) \tag{9}$$

$$= \frac{w + \quad U(0;0)}{1 \quad (1 \quad)}; \tag{10}$$

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

$$\begin{aligned}
\bar{E}(w;P; \quad) &= w \sum_{l=0}^{1} {}^{l}(1 \quad)^{l} + \quad U(0;P) \sum_{l=0}^{1} {}^{l}(1 \quad)^{l} + \quad (1 \quad) \bar{E}(w;0;0) \\
&= w \frac{1 \quad (1 \quad)}{1 \quad (1 \quad)} + \quad U(0;P) \frac{1 \quad (1 \quad)}{1 \quad (1 \quad)} + \quad (1 \quad) \bar{E}(w;0;0) \\
&= \frac{w}{1 \quad (1 \quad)} + \quad U(0;P) \frac{1 \quad (1 \quad)}{1 \quad (1 \quad)} + \quad (1 \quad) \frac{U(0;0)}{1 \quad (1 \quad)}
\end{aligned} \tag{11}$$

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

$$E \;\; \overline{w}_J(s;P);P \;\; = U(\max f s \quad 1;0 g;P); \tag{12}$$

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

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

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

$$U(0;P) = \frac{(1 \quad)\overline{w}_J(0;P) + \quad ^{+1} \; (1 \quad) \;\; \overline{w}_J(0;0)}{(1 \quad) \; 1 \qquad + \quad ^{+1} \; (1 \quad)}: \tag{14}$$

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

$$\bar{E}(w;0;0) = \frac{w}{1 \quad (1 \quad)} + \frac{\overline{w}_J(0;0)}{(1 \quad)(1 \quad (1 \quad))}: \tag{15}$$

A.2 Terminal Sanctions, Value Function

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

thus yields

$$
\begin{aligned}
p_{doc} & \int \max\{E(\overline{w}_J(s;P);P) \quad B_V(w;s;P);0\}dF_V(w) \\
&= p_{doc} \int_0^{\overline{w}_J(s;P)} E(\overline{w}_J(s;P);P) \quad B_V(w;s;P)dF_V(w) \\
&= p_{doc} \quad F_V(\overline{w}_J(s;P)) \;\; E(\overline{w}_J(s;P);P) \quad E(\overline{w}_V(s;P);P) \\
& \qquad \int_{\overline{w}_V(s;P)}^{\overline{w}_J(s;P)} \frac{w \quad \overline{w}_V(s;P)}{1 \quad (1 \quad)} dF_V(w)
\end{aligned}
$$

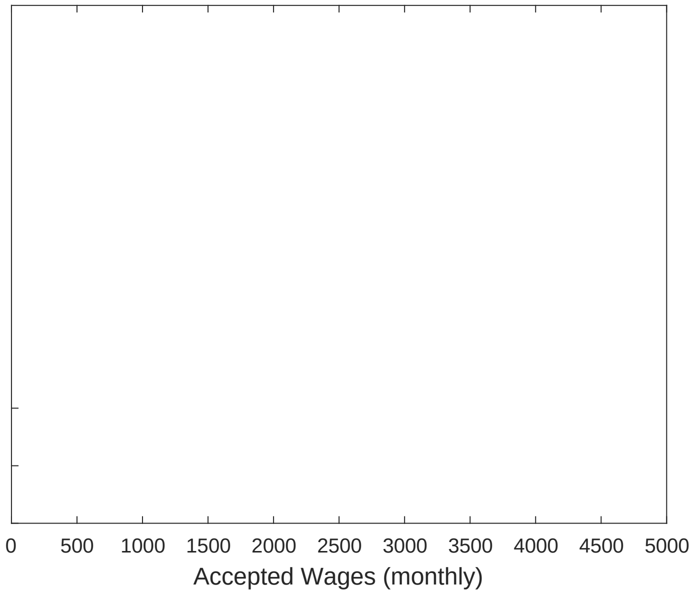
$\overline{w}_V(s;P)$ for (for $s = 0;\ldots;K$ and $P = 1;\ldots;\overline{P} \quad 1)$ and $\overline{w}$. Taken together, we thus obtain a system of $2 \quad K \quad (\overline{P} \quad 1) + 1$ reservation wage equations that we solve numerically for the same number of reservation wages.

A.4 Likelihood Contributions

In the following the individual subscript i

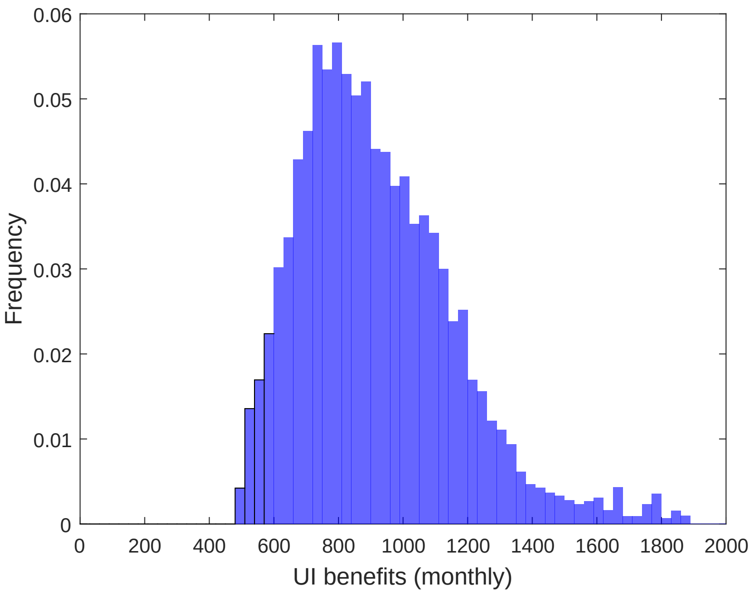
B Additional Figures

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

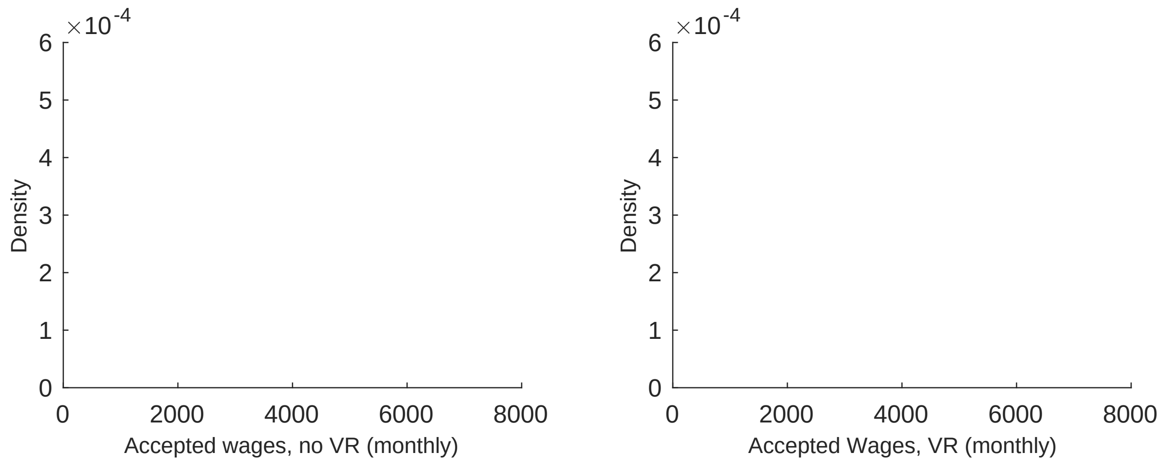
Table C.1: Observed outcomes and simulated observable outcomes

	Data	Simulation
All unemployed		
VR	20%	20%
Sickness absence (2 weeks)	3.4%	3.8%
Job finding rate	8.6%	9.3%
Accepted wage	2110	2058
VR received		
Sickness absence (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

Panel A: Regular job offers   Panel B: VRs



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 into account. Its variation is not negligible. The estimated standard deviation 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
All unemployed		
VR	12.41%	12.37%
Sickness absence (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
VR received		
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.