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Hidden Unemployment in Disability Insurance in the Netherlands

An Empirical Analysis Based on Employer Data

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Abstract in English

In this paper, we construct and estimate a (semi-) structural model, so as to uncover the fraction of hidden unemployment in the Disability Insurance (DI) enrolment rate. For this purpose, we use longitudinal administrative data of Dutch employers for 1994-2003. We find the (average) fraction of hidden unemployment in DI enrolment to amount to about 11%. This corresponds to 2.6% of the ‘true’ unemployment insurance (UI) enrolment rate of employers. Over the years, we observe a strong decrease in this fraction, from 5.4% in 1995, to 0.7% in 2003. In addition, our estimates suggest that most of correlation that is observed between the UI and DI enrolment rates can be explained by substitution effects, and not by ‘true’ correlation between the schemes that is exogenous to the firm. In the model, the fraction of hidden unemployment in the DI scheme is (over-)identified from various restrictions imposed by the data. First, identification follows from exclusion restrictions obtained from the coefficient estimates of variables that are assumed to influence the UI enrolment rate only. For this purpose, we use information on the wage distribution of workers employed at the firms in our sample, and sectoral growth rates. Second, identification of substitution effects follows from the observed correlation between both enrolment rates.

Keywords: Firm behaviour (D21), social security (H55), disability (I12), employment determination (J2).

Abstract in Dutch

In dit paper onderzoeken we het aandeel van verborgen werkloosheid (WW) in de WAO-instroom. Op basis van longitudinale administratieve UWV-gegevens van werkgevers van 1994-2003 schatten we dit aandeel op gemiddeld 11% van de WAO-instroom. Dit komt overeen met 2,6% van de ‘werkelijke’ WW-instroom. Kijken we naar het aandeel van de instroom over de tijd, dan zien we een sterke daling van de verborgen werkloosheidscomponent, van 5,4% van de WW-instroom in 1994 tot 0,7% in 2003. Daarnaast vinden we dat het grootste deel van de correlatie tussen WW- en WAO-instroom in de UWV-gegevens is toe te rekenen aan substitutie-effecten, en niet correlatie waar werkgevers geen invloed op hebben.

Steekwoorden: werkgeversgedrag (D21), sociale zekerheid (H55), arbeidsongeschiktheid (I12), werkgelegenheid (J2)

Een uitgebreide Nederlandse samenvatting is beschikbaar via www.cpb.nl.

Contents

Summary

By now, there is a substantial body of empirical research that addresses the effects of social insurance on labour supply (see Krueger and Meyer (2002) for a survey). This strand of research seems of particular interest to Western European countries, where relatively generous social security arrangements have caused substantial hidden unemployment. More recently, however, such effects also have become more prevalent in the US. Autor and Duggan (2003) find that, as a result of DI program liberalisation in 1984, DI enrolmentrates have become two to three times more responsive to labour demand shocks. For the Netherlands, the evidence suggests that – in particular in the eighties – the inflow of (hidden) unemployed into the Dutch disability scheme has caused the supply of labour to decrease substantially (Roodenburg and Wong Meeuw Hing (1985), Aarts and De Jong (1992) and Van Vuren and Van Vuuren (2005)). In all of these studies, the implicit assumption is that disability and unemployment risks may be related and therefore hard to disentangle. When workers have become incapable to perform their current tasks, determination of the degree of worker disability, as well as the responsibility of the employer, may be a complex task. In these cases, the substitute pathway hypothesis is particularly relevant: employers (and workers) might opt for the scheme which is most attractive.

Riphahn (1997) and Hassink et al. (1997) present empirical models where the maginitude of substitution effects is addressed explicitly. Riphahn (1997) tests the hypothesis that variables affecting the risk of early retirement affect the risk of disability retirement similarly. Rather than testing the hypothesis that the inflow in schemes are full substitutes, Hassink et al. (1997) model the extent of subtitution as a parameter that can be estimated. Identification of this parameter hinges upon exclusion restrictions – that is, variables that, when substitution is absent, are supposed to affect the inflow in either DI or UI exclusively.

In this paper, we investigate empirically the extent to which DI and UI are used as substitute pathways. For this purpose, we use administrative longitudinal employer data on the inflow into DI and UI from 1993 to 2003. Similar to earlier work in this field, the identification of substitution effects hinges upon the use of exclusion restrictions. Using these variables, we are able to identify and estimate the 'true' underlying share of DI enrolment that can be typed as hidden unemployment. This paper, however, extends and diversifies the analysis in two aspects. First, the panel setup of the data helps us to control for estimation biases that potentially affect our substitution coefficient estimates. In particular, we exploit the panel character by using the method proposed by Wooldridge (2002) – that is, we include average values of variables in the (Tobit) regressions of the UI and DI enrolment rates, so as to correct for potential estimation biases. Second, in our analysis we distinguish between correlation that results from 'true' correlation that is exogenous to the firm, and correlation that results from substitution effects.

Exogenous effects may arise if e.g. low productivity workers with both high UI and DI risks are concentrated within particular firms. The neglect of such effects may cause substitution effects estimates to be biased upwards.

Our estimation results suggest that substitution effects are the major determinant of the observed correlation of UI and DI enrolment rates of firms. In terms of (expected) values, we estimate 11% of the observed DI enrolment rate in 1994-2003 to exist of hidden unemployment. When estimating the model for separate years, we find this a dramatic increase in this share, from 38% in 1994 to about 3% of the inflow into the DI scheme in most recent years. From this, we conclude that various policies have been effective in discouraging the inflow into DI from the UI scheme. Our estimates are robust with respect to the choice of identifying restrictions that are used in our model. More specifically, in the model the fraction of hidden unemployment in the DI scheme is (over-)identified by restrictions imposed on the data. In particular, we use wage distribution quartiles of workers employed at the firms in our sample, and sectoral business cylce indicators as exclusion restrictions. We show that these restrictions yield comparable estimates of the hidden unemployment in the DI enrolment rate.

1 Introduction

By now, there is a substantial body of empirical research that addresses the effects of social insurance on labour supply (see Krueger and Meyer (2002) for a survey). This strand of research seems of particular interest to Western European countries, where relatively generous social security arrangements have caused substantial hidden unemployment. More recently, however, such effects also have become more prevalent in the US. Autor and Duggan (2003) find that, as a result of DI program liberalisation in 1984, DI enrolmentrates have become two to three times more responsive to labour demand shocks. For the Netherlands, the evidence suggests that – in particular in the eighties – the inflow of (hidden) unemployed into the Dutch disability scheme has caused the supply of labour to decrease substantially (Roodenburg and Wong Meeuw Hing (1985), Aarts and De Jong (1992) and Van Vuren and Van Vuuren (2005)). In all of these studies, the implicit assumption is that disability and unemployment risks may be related and therefore hard to disentangle. When workers have become incapable to perform their current tasks, determination of the degree of worker disability, as well as the responsibility of the employer, may be a complex task. In these cases, the substitute pathway hypothesis is particularly relevant: employers (and workers) might opt for the scheme which is most attractive.

So far, only few studies have addressed the interplay between DI and UI schemes explicitly. This may be of particular interest for policy analyses, as changes in one scheme are likely to affect the use of other schemes as well. Typically, in this literature multiple social insurance schemes are modelled within the context of early retirement. In these models, the decision to retire consists of a choice between various schemes – or, stated differently, substitute pathways into unemployment. For instance, Kapteyn and De Vos (2002), Kerkhofs et al. (1999) and Heyma (2004) show that the substitute pathways hypothesis cannot be rejected. That is, the inflow into early retirement programs, disability insurance and unemployment insurance are driven by relative benefit conditions. Still, from this information alone it is hard to determine the absolute size of substitution effects. Obviously, other factors – e.g. firing costs of employers – may also be important determinants of substitution effects.

Riphahn (1997) and Hassink et al. (1997) present empirical models where the maginitude of substitution effects is addressed explicitly. Riphahn (1997) tests the hypothesis that variables affecting the risk of early retirement affect the risk of disability retirement similarly. For some characteristics, like age, wage and job characteristics, risk structures appear to be very similar. However, the effects do not coincide with respect to the individual health and aggregate employment measures – indicating that both schemes are not complete substitutes. Rather than testing the hypothesis that the inflow in schemes are full substitutes, Hassink et al. (1997) model the extent of subtitution as a parameter that can be estimated. Identification of this parameter hinges upon exclusion restrictions – that is, variables that, when substitution is absent, are supposed to affect the inflow in either DI or UI exclusively. With employer survey data, Hassink et al. (1997) use variables like (lagged) quits and dismissals, as well as the training period per firm as exclusion restrictions for the inflow into UI. In a similar vein, working conditions and the number of workers on sick leave are assumed to affect the inflow into DI only. With this information, they find between 6 and 9% of the 'desired' dismissal rate to be directed to the DI scheme.

In this paper, we investigate empirically the extent to which DI and UI are used as substitute pathways. For this purpose, we use administrative longitudinal employer data on the inflow into DI and UI from 1993 to 2003. Similar to earlier work in this field, the identification of substitution effects hinges upon the use of exclusion restrictions. Using these variables, we are able to identify and estimate the 'true' underlying share of DI enrolment that can be typed as hidden unemployment. This paper, however, extends and diversifies the analysis in two aspects. First, the panel setup of the data helps us to control for estimation biases that potentially affect our substitution coefficient estimates. In particular, we may expect the inflow into DI to be driven by the health conditon of employees at a particular firm. As health measures are unobserved in our data, the estimated impact of various correlated variables – like age, education level and income – are subject to severe omitted variable biases. Such biases are likely to affect exclusion variable coefficients as well, yielding improper estimates of the substitution effect. Both Riphahn (1997) and Hassink et al. (1997) ignore the potential effects of omitted variable bias. By contrast, we exploit the panel character of our data to circumvent this. Following Wooldridge (2002), we include average values of variables in the (Tobit) regressions of the UI and DI enrolment rates, so as to correct for potential estimation biases.

Second, in our analysis we distinguish between correlation that results from 'true' correlation that is exogenous to the firm, and correlation that results from substitution effects. Exogenous effects may arise if e.g. low productivity workers with both high UI and DI risks are concentrated within particular firms. The neglect of such effects may cause substitution effects estimates to be biased upwards.

Our estimation results suggest that substitution effects are the major determinant of the observed correlation of UI and DI enrolment rates of firms. In terms of (expected) values, we estimate 11% of the observed DI enrolment rate in 1994-2003 to exist of hidden unemployment. When estimating the model for separate years, we find this share to have decreased dramatically, from 38% in 1994 to about 3% of the inflow into the DI scheme in most recent years. From this, we conclude that various policies have been effective in discouraging the inflow into DI from the UI scheme. Our estimates are robust with respect to the choice of identifying restrictions that are used in our model. More specifically, in the model the fraction of hidden unemployment in the DI scheme is (over-)identified by restrictions imposed by the data. In particular, we use wage distribution quartiles of workers employed at the firms in our sample, and sectoral business cylce indicators as exclusion restrictions. We show that these restrictions yield comparable estimates of the hidden unemployment in the DI enrolment rate.

The remainder of this paper starts by discussing the major characteristics of the Dutch DI and UI system. Section 3 discusses the data. The model specification and estimation results are presented in Sections 4 and 5, respectively. Finally, Section 6 concludes.

2 DI and UI in the Netherlands

2.1 The DI system

In the Netherlands, the provision of DI and UI is mandatory and financed by pay-as-you-go contribution rates. One of the key distinctive features of the Dutch DI scheme it that it covers all workers against all income losses that result from injuries (‘loss of earnings capacity’). This, combined with the public monopoly provision of DI, makes the disability determination system rather susceptible to moral hazard problems. Moral hazard problems are further aggravated by the generosity of the DI system, which is based on the individual earnings capacity. This means that disability is measured as a percentage, rather than an all or nothing condition.

Over the years, the Dutch DI system has repeatedly been subject of public debate. Expressed as a percentage of the insured population, DI enrolment peaked at 16% in the mid eighties, and since then declined and stabilised at about 13%. There is strong evidence that the DI scheme has been used as a substitute pathway into both unemployment and early retirement. Using medical information of DI recipients in the eighties, Aarts and De Jong (1992) estimate a structural share of hidden unemployment of 33 to 51%. Westerhout (1996) estimates this share to have been equal to 50% in the period 1973-1992. Finally, using employer data for 1990, Hassink et al. (1997) find 6 to 9% of the ‘desired dismissals’ rate to be directed towards the DI scheme.

Various reform plans have been introduced to reduce the inflow into DI in the Netherlands. In 1996, the sickness benefit program has been privatised, making employers fully responsible for these costs. As from 1998, employer incentives have been further enhanced by the system of DI experience rating. This means that, in principle, employers bear the costs of the first five years of DI benefits.[1] Finally, in 2002, the (potential) impact of incentives was further enhanced by a more stringent system of gatekeeping and an extension of the sickness benefit period from one to two years. In order to be eligible for a medical DI assesment, both workers and employers have to meet several conditions during the sickness benefit period. [2] In sum, employer incentives to reduce the inflow into sickness benefits and the DI scheme have increased substantially, particularly since 1998. In recent years, these incentives seem to have become effective in reducing the DI enrolment rate (see e.g. Koning (2004)).

[1] Using a dif-in-dif approach, Koning (2004) finds the effect of experience rating to amount to 16% of the DI enrolment rate.

[2] As of 2006, a regime change of the Dutch DI system has taken place. The major ingredient of this plan will be the distinction between a public DI scheme for fully and permanently disabled, and a mixed (public and private) DI scheme for partially and temporarily disabled. Benefit conditions for the partial disability program will become less generous.

2.2 The UI system

In contrast to the DI scheme, UI entitlement is restricted to workers who meet minimal work history conditions. In particular, there are two criteria that determine eligibility, as well as the entitlement period of UI. In order to become eligible to the UI scheme, workers must have earned wages in at least 26 of the 39 past weeks. However, if the worker has not earned wages in at least four out of the five most recent calendar years, the UI benefit scheme is virtually equivalent to the social assistance benefits, and the entitlement period is 6 months. If the worker meets the four-out-of-five condition, the scheme is wage-related and equals 70% of the wage in the job previous to unemployment, where the entitlement period is a step function of the work history. At present, the minimal entitlement period equals 6 months, whereas the maximum entitlement period equals five years for workers. Together with the nonstatutory arrangements made by social partners, this makes the UI scheme rather attractive as an exit route into early retirement. In particular, some collective agreements supplement the UI scheme to 90% or 80% of the previous wage earnings and extend the entitlement spell. Although the UI scheme may be seen as a particularly attractive exit device for older workers, benefit and entitlement conditions have remained stable since 1987. [3]

Similar to the UI benefit conditions, the Dutch dismissal system has remained more or less unchanged. Dismissals occur if labour contracts are dissolved unilaterally by a firm. Like most European countries, in the Netherlands the employer must justify the dismissals. That is, the worker either fails to perform his/her tasks, the relationship between worker and employer may have become untenable, or jobs may have become redundant. The Dutch dismissal law is governed by a ‘dual system’: employers either choose to request a Civil Court to dissolve a regular employment contract, or they dismiss the worker by requesting prior permission from local employment offices. The court procedure is less time consuming, and there is no risk that the contract will not be dissolved – employers essentially buy off this risk in the form of severance payments.[4] Choosing the employment office route is less costly for employers, at least in the short run, but dismissals will not always be approved and judgements are binding. Employment offices may do so if they suspect that both the employer and employee already have come to an agreement to end the contract, and need approval by the employment office for the worker to become eligible for the UI scheme.

[3] Recently, social partners have proposed to change the entitlement conditions for the UI scheme. This proposal entails a lengthening of the entitlement period for workers with a relatively short work history, and shortening the entitlement period for workers with relatively a long work history. Until now, the government has not implemented these plans.

[4] In this case, the so called ‘ABC-formula’ is mostly used to determine the amount of severance pay. This means that the reference pay increases with worker tenure, the current wage earnings and the extent to which the employer and worker can be blamed for the dismissal.

In practice, most large firms use the Civil Court to dissolve employment contracts, whereas small firms mostly prefer the employment office. In 2004, there were about 162,000 dismissal requests by Dutch employers. Of these requests, 90,000 (56%) were directed towards the employment offfices, and 72,000 (44%) to the Civil Court (SZW (2005)). In the same year, 82,000 dismissal requests have been settled by the employment offices. 84%, of these requests were approved, 8% were not approved, and 8% of the requests were withdrawn. Moreover, 21% of the dismissal requests (and 24% of the dismissal approvals) of the employment offices were by reason of incapacity to continue their work. Some of these workers have entered the UI scheme, others may have applied for, and subsequently entered the DI scheme.

3 Data

For our analysis, we use administrative data from the Dutch UI and DI social benefit administration (UWV) for 1994-2003. For this period, we observe an unbalanced panel of 41,050 private employers in the industrial and services sector with more than 25 workers, corresponding to 246,474 employer-year observations. Table 3.1 summarises the main characteristics of this panel data set. For each employer, we observe the number of workers, the sectoral code, as well as information on the composition of the workforce. In addition, we observe the inflow of workers into the UI and DI scheme that can be assigned to them. For each year, refreshment samples are drawn from new employers. As we can see from the distribution of observations over the years, the effect of attrition dominates this effect, albeit slightly. On average, we have 7.4 yearly observations per employer.

We define the DI and UI employer enrolment as the percentage of workers that directly enters into the DI or UI scheme, and are contracted by this firm up to this moment. This results in underreporting. For instance, a worker may first receive UI benefits, but subsequently be admitted to the DI scheme. For short UI benefit spells, this worker can still be assigned to an employer, but now as an DI recipient. However, as we assume that the event of DI and UI enrolment occurs at the moment of contract termination, we leave out these observations. Similarly, we do not report workers with combined DI and UI benefits, amounting to 0.17% of the employee fractions of firms. Including these observations would lead to the overestimation of substitution effects: as DI and UI enrolment rates are measured in terms fractions of workers in firm observations, the correlation between both rates that results from combined benefits would be biased upwards, yielding an upward bias in the substitution effect as well.

Table 3.1 shows the yearly fraction of workers that enter into DI and UI schemes, averaged over employers. As both UI and DI enrolment constitute only a small fraction of the workers, we do not observe any enrolment in both schemes for 36% of the yearly employer observations. Also, note that we observe positive rates for both schemes for 26% of the observations. Obviously, firms with large employer size will be overrepresented in this group. In the table, we have clustered sectors at the level of one digit, resulting in seven categories.[5]

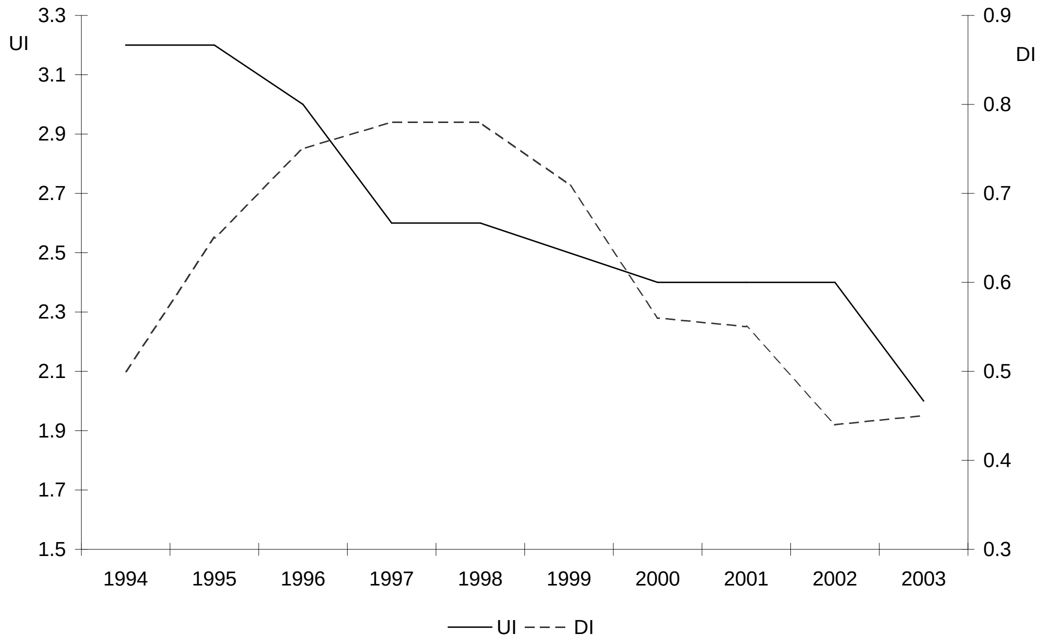
[5] In the UWV-data, sectors are measured at the level of two digits, resulting in about 70 sectors.

Table 3.1 Sample statistics UWV-panel dataset, 1994-2003 (N=246,040)

	Mean	Std.dev.	Minimum	Maximum
DI enrolment	0.63%	1.4%	0%	92%
partial	0.24%	0.48%	0%	28%
full	0.39%	0.64%	0%	83%
UI enrolment = 0 ; DI enrolment = 0	0.36			
UI enrolment = 0 ; DI enrolment > 0	0.091			
UI enrolment > 0; DI enrolment = 0	0.34			
UI and DI enrolment > 0	0.21			
Workforce composition				
Age 15-24	0.27	0.22	0	1
Age 25-34	0.32	0.14	0	0.96
Age 35-44	0.22	0.11	0	0.80
Age 45-54	0.10	0	0.88	
Age 55-65	0.054	0	1	
Female	0.30	0.23	0	1
First Quartile wage dist. (ln)	7.7	1.3	− 1.43	11.8
Third Quartile wage dist. (ln)	9.3	1.0	0.80	12.3
Firm size				
<50 employees	0.51	0.50	0	1
51-100 employees	0.26	0.44	0	1
101-250 employees	0.15	0.35	0	1
251-1000 employees	0.060	0.24	0	1
>1000 employees	0.014	0.12	0	1
Sector				
Industry	0.31	0.46	0	1
Harbour, fishery	0.024	0.15	0	1
Transport	0.078	0.27	0	1
Horeca	0.13	0.33	0	1
Finance, insurance	0.028	0.16	0	1
Tertiary services	0.35	0.48	0	1
Temporary employment	0.047	0.21	0	1
Business cycle measure				
Sectoral wage sum growth	0.12	0.48	− 1.5	2.2

Figure 3.2 shows the evolvement of UI and DI enrolment rates over time. During the period of investigation, UI enrolment rates have gradually decreased, from 3.3% in 1994, to 2.0% in 2003. In contrast, up to 1998 DI enrolment rates first have increased, and then decreased substantially. Thus, at first sight, there is mixed evidence for the substitute pathway hypothesis: DI enrolment rates have varied substantially, but this variation does not (fully) mimic the pattern of the UI enrolment rates. We return to this issue when discussing the yearly parameter value estimates for substitution between the schemes.

Figure 3.1 Mean UI and DI enrolment rates over time



4 Model and empirical implementation

4.1 The model

The model we propose resembles that of Hassink et al. (1997). The basic idea underlying this model is that firms have a desired dismissal rate and a 'true' disability rate. Both rates are unobserved, as part of the 'true' disability rate is directed to the UI scheme. We classify this approach as 'semi-structural' – that is, we uncover the size of substitution effects by imposing (exclusion) restrictions, but we do not present a model that explains the determinants of these substitution effects. We extend the model of Hassink et al. (1997) by allowing UI and DI risks to be correlated – apart from correlation that results from substitution effects. We label this correlation as 'true' correlation, or effects that are exogenous to the firm.

Our starting point is the following specification in which a firm's desired layoff rate f^0 and 'true' disability rate d^0 are specified as linear functions of sets of variables x_0, x_f, and x_d:

$$f^0 = \beta_{0f}' x_0 + \beta_f' x_f + u_f \tag{4.1a}$$

$$d^0 = \beta_{0d}' x_0 + u_d \tag{4.1b}$$

$$u = \begin{pmatrix} u_f \\ u_d \end{pmatrix} \sim N(0,\Sigma), \text{ with } \Sigma = \begin{pmatrix} \sigma_f^2 & \rho_{fd}\sigma_f\sigma_d \\ \rho_{fd}\sigma_f\sigma_d & \sigma_d^2 \end{pmatrix} \tag{4.1c}$$

where x_0 is a vector of common covariates, x_f is a vector of covariates affecting the layoff rate but not the disability enrolment rate. The slope parameters of our model are organised in the vectors β_{0f}, β_f, β_{0d}.

In our model substitution effects are characterised by λ ($\lambda \geq 0$). This variable represents the fraction of desired layoffs that is directed to the disability scheme. Consequently, the DI enrolment rate that can be classified as hidden unemployment equals λf^0: [6]

$$f = (1-\lambda) f^0 \tag{4.2a}$$

$$d = d^0 + \lambda f^0 \tag{4.2b}$$

[6] An obvious extension of this specification would be the inclusion of 'reverse' substitution effects – that is, disabled employees ending up in the unemployment scheme. With the data at hand, however, we cannot identify such effects. In Koning and Van Vuuren (2006), we however do extend the model in such a way, using variables that can be used to identify reverse substitution effects as well.

The combination of (4.1) and (4.2) yields

$$f = \gamma_{0f}' x_0 + \gamma_{ff}' x_f + v_f \tag{4.3a}$$

$$d = \gamma_{0d}' x_0 + \gamma_{fd}' x_f + v_d \tag{4.3b}$$

$$v = \begin{pmatrix} v_f \\ v_d \end{pmatrix} \sim N(0, \Sigma), \text{ with } \Sigma_v = \begin{pmatrix} \tau_f^2 & \rho_v \tau_f \tau_d \\ \rho_v \tau_f \tau_d & \tau_d^2 \end{pmatrix} \tag{4.3c}$$

with the following parameter restrictions:

$$\gamma_{0f} = (1-\lambda)\beta_{0f} \tag{4.4a}$$

$$\gamma_{ff} = (1-\lambda)\beta_f \tag{4.4b}$$

$$\gamma_{0d} = \beta_{0d} + \lambda\beta_{0f} \tag{4.4c}$$

$$\gamma_{fd} = \lambda\beta_f \tag{4.4d}$$

$$\tau_f^2 = (1-\lambda)^2\sigma_f^2 \tag{4.4e}$$

$$\tau_d^2 = \sigma_d^2 + \lambda^2\sigma_f^2 + 2\lambda\rho_{fd}\sigma_f\sigma_d \tag{4.4f}$$

$$\rho_v = \frac{\lambda\sigma_f + \rho_{fd}\sigma_d}{\sqrt{\lambda^2\sigma_f^2 + \sigma_d^2 + 2\lambda\rho_{fd}\sigma_f\sigma_d}} \tag{4.4g}$$

where τ_f^2, τ_d^2 and ρ_v represent the (observed) variances, as well as the correlation between, v_f and v_d. For both ρ_{fd} and λ close to zero, the (observed) correlation coefficient ρ_v can be rewritten as a first order Taylor series expansion: $\rho_v \approx \rho_{fd} + \frac{\sigma_f}{\sigma_d}\lambda$. This expression makes apparent that the correlation coefficient between v_f and v_d can be approximated by two components. The first one relates to the correlation between the error terms in the underlying model ('true' effects), whereas the second corresponds with the substitution parameter λ.

4.2 Identification and exclusion restrictions

In our model, the vector x_f identifies our key parameter of interest, λ. We therefore refer to these variables as exclusion restrictions. More specifically, λ can be derived from the parameter estimates of γ_{ff} and γ_{fd} in the following way:

$$\hat{\lambda} = \frac{\gamma_{fd}}{\gamma_{fd} + \gamma_{ff}} \tag{4.5}$$

This expression makes apparent that only one exclusion restriction suffices to identify λ. In the UWV data, a number of variables can be used as exclusion restrictions. First, in the absense of substitution effects, we may expect the employee wage distribution not to affect the inflow in the DI scheme. More specifically, workers are insured against any loss of income that is due to the risk of (partial) disability. Thus, in the absence of substitution effects, the absolute level of wages does not affect the DI enrolment rate. [7] We therefore use wage quartiles as exclusion

[7] Obviously, we may expect the wage distributions variables we use (i.e. first and third quartile of the distribution) to be

restrictions in our benchmark model. Second, the sectoral wage sum growth can be considered as an indicator of the business cycle, only affecting the 'true' UI enrolment rate. We will use this variable to check for the robustness of our results.

From the equations (4.4.e)-(4.4.g) we see that the number of (remaining) structural parameters describing the variance and correlation between the UI and DI rates (σ_f, σ_d and ρ_{fd}) matches the number of parameter estimates (τ_f, τ_d and ρ_{fd}). This however does not imply that our structural parameters are identified for all possible combinations of observed parameter values. To clarify this point, let us concentrate on the restriction described in equation (4.4.g), relating the observed correlation coefficient to the structural parameters of the model. In order to have unique and tractable outcomes for this coefficient, two conditions should be met. First, the observed correlation coefficient should be monotically and positively related to the 'true' correlation coefficient ρ_{fd} for $-1 \leq \rho_{fd} \leq 1$. Second, the support of ρ_{fv} should map all possible outcomes of ρ_v ($-1 \leq \rho_v \leq 1$). Both conditions are satisfied iff

$$\sigma_d > \lambda \sigma_f \tag{4.6}$$

The intuition behind this condition is as follows. Suppose we observe high and positive correlation between the DI and UI rates. Now, if substitution effects dominate the (observed) variation in disability rates ($\lambda \sigma_f \geq \sigma_d$), the underlying 'true' correlation between DI and UI rates can be either positive or negative. Obviously, one may think of positive 'true' correlation to be most likely, with substitution effects that further increase the (observed) correlation. However, as variation in the DI risk is dominated by UI risk variation, a priori 'true' negative correlation may be washed out, thus reversing the sign of (obserevd) correlation.

4.3 Reduced form estimation

As the stuctural parameters in our model can be expressed in terms of reduced form coefficients (see equations (4.4)), our estimation strategy consists of a two step procedure: we estimate the reduced form parameters (γ_{0f}, γ_{0d}, γ_{fd}, τ_f, τ_d and ρ_v) and then use these coefficients to estimate the structural parameters (β_{0f}, β_{0d}, β_f, λ, σ_f, σ_d and ρ_{fd}) by Minimum Distance Estimation.

In the first step, we use a Bivariate Tobit specification for the reduced form model. As we have argued in the previous section, many firms have no inflow into the UI and DI scheme, rendering a Tobit version of equations (4.3) most appropriate. We extend this specification by allowing for

endogenous (e.g. workers may be compensated for high employer specific DI risks by higher wages) but we correct for this by employer specific effects.

unobserved, employer specific, effects c_f and c_d:

$$f_{it} = \max\left(0, \gamma_{0f}' x_{0,it} + \gamma_{ff}' x_{f,it} + c_{f,i} + v_{f,it}\right) \tag{4.7a}$$

$$d_{it} = \max\left(0, \gamma_{0d}' x_{0,it} + \gamma_{fd}' x_{f,it} + c_{d,i} + v_{d,it}\right) \tag{4.7b}$$

$$v = \begin{pmatrix} v_f \\ v_d \end{pmatrix} \sim N(0, \Sigma_v), \text{ with } \Sigma_v = \begin{pmatrix} \tau_{vf}^2 & \rho_v \tau_{vf} \tau_{vd} \\ \rho_v \tau_{vf} \tau_{vd} & \tau_{vd}^2 \end{pmatrix} \tag{4.7c}$$

with i indicating the employer code, t as time indicator, and c_f and c_d. In the literature, applications of Tobit models with fixed effects are limited, particularly when applied to datasets with large numbers of groups. Honoré (1992) proposes a method for which consistency does not require any assumptions on the individual specific effects, basically by using transformations to eliminate c_f and c_d. As a disadvantage, however, estimation of this model does not provide us with the parameters needed for calculating marginal effects. Moreover, this approach does not enable us to exploit information on the correlation structure of the UI and DI enrolment rates. We therefore follow a random effects approach for which consistency does not require any additional distributional assumptions, but does require a correct specification of the correlation between the individual specific effects and the explanatory variables. Thus, we follow Wooldridge (2002) by assuming x_0 and x_f to be strictly exogenous conditional on c_f and c_d, i.e. the employer specific effects. [8] This means we specify the employer specific effects as

$$c_{f,i} = \psi_f + \xi_{0f} \overline{x}_{0,i} + \xi_{ff} \overline{x}_{f,i} + a_{fi} \tag{4.8a}$$

$$c_{d,i} = \psi_d + \xi_{0d} \overline{x}_{0,i} + \xi_{fd} \overline{x}_{f,i} + a_{di} \tag{4.8b}$$

$$a = \begin{pmatrix} a_f \\ a_d \end{pmatrix} \sim N(0, \Sigma_a), \text{ with } \Sigma_a = \begin{pmatrix} \tau_{af}^2 & \rho_v \tau_{af} \tau_{ad} \\ \rho_v \tau_{af} \tau_{ad} & \tau_{ad}^2 \end{pmatrix} \tag{4.8c}$$

with $\overline{x}_i$ denoting employer averaged variables over time, ψ_f and ψ_d as constants, and ξ the vector describing the effect of these averages on the employer specific effect. Note that the total variances of f and d are defined as $\tau_f^2 = \tau_{vf}^2 + \tau_{af}^2$ and $\tau_d^2 = \tau_{vd}^2 + \tau_{ad}^2$, respectively. The correlation between the random effects (a_f and a_d) is restricted to be equal to the correlation of the residuals in equation (4.7). This means that we assume 'true' correlation between the random effects of the enrolment rates, as well as between residuals of the enrolment rates to be identical. Using equation (4.8) as an auxiliary regression for (4.7), our model is equivalent to a bivariate random effects Tobit model, with $\overline{x}_0$ and $\overline{x}_f$ as an additional set of of time-constant explanatory variables. Including averages as controls for unobserved heterogeneity is intuitive: the effect of changing x_0 and x_f is estimated, holding the time average constant. Thus, we solve the unobserved heterogeneity problem and obtain unbiased estimates of γ_{0f}, γ_{ff}, γ_{0d} and γ_{fd}.

[8] Kalwij (2003) builds upon the approach of Wooldridge (2002) by using a first-differencing approach. This approach is less sensitive to misspecification of the parameterisation of correlated random effects.

Wooldridge (2002) shows that it suffices to estimate the model parameters by pooled estimation, which facilitates the estimation procedure considerably. As a result, we estimate τ_f and τ_d, and not the random effects and residual variance separately.

When estimating the bivariate random effects Tobit model, we increase the flexibility of the error structures of UI and DI enrolment rates in two aspects. First, in order to allow for serial correlation we use a two-step-estimation approach: we first obtain maximum likelihood estimates of the model for each separate year, and then use Minimum Distance Estimation where all parameter values are restricted to be constant over time (Wooldridge (2002). Second, we allow for heteroscedasticity in the error terms by specifying τ_f and τ_d as functions of employer size: $\tau_f = \tau_{f0} N^{\eta}$ and $\tau_d = \tau_{d0} N^{\eta}$, where N is the employer size. Note that the parameter value of η is restricted to be equal for both UI and the DI enrolment rate regressions, so as to obtain constant relative values of τ_f and τ_d and ensuring ρ_v to be constant with respect to employer size (equation 4.4.g).

4.4 Structural model estimation

We have argued that for the identification of the structural model parameters – in particular in order to obtain a (unique) value for ρ_{fd} (the 'true' correlation) – we need the condition (4.6) to be satisfied. Thus, when estimating our structural parameter coefficients by MDE, we impose (4.6) as an maximization constraint, together with $\lambda > 0$. We define θ as the vector of the structural parameters to be estimated:

$$\theta = \left(\beta_{0f}, \beta_{0d}, \beta_f, \lambda, \sigma_f, \sigma_d, \rho_{fd}\right) \tag{4.9}$$

and γ as the vector of reduced form parameters obtained from the first estimation stage:

$$\gamma = \left(\gamma_{0f}, \gamma_{0d}, \gamma_{fd}, \gamma_{ff}, \tau_f, \tau_d, \rho_v\right) \tag{4.10}$$

The restrictions presented in equation (4.4) can be summarised by $g(\theta) = \gamma$. MDE estimation of θ now follows from minimising

$$\Psi(\theta) = [\hat{\gamma} - g(\theta)]\hat{\Omega}^{-1}[\hat{\gamma} - g(\theta)]'. \tag{4.11}$$

The resulting parameter estimates $\hat{\theta}$ are consistent and asymptotically normally distributed with covariance matrix

$$\hat{C} = [\ \hat{\Gamma}'\hat{\Omega}^{-1}\hat{\Gamma}\ ]^{-1}$$

where $\hat{\Gamma} = [\frac{\partial g(\theta)}{\partial \theta'}]_{\theta=\hat{\theta}}$.

When following the two-step-estimation procedure on the full sample, we assume the structural parameter estimates to be constant in the time period under consideration. Basically, the parameter value of λ is then identified from the (time constant) reduced form coefficients of the exclusion restriction (i.e. the wage income quartiles), whereas the 'true' correlation (ρ_{fd}) is identified from the reduced form correlation coefficient (ρ_v). In principle, a similar estimation procedure can be followed for separate years, which may be particularly informative from a policy perpective. In order to obtain such results, we assume the coefficient estimates of the auxiliary regressions (equation 4.8) to be contant, while allowing all coefficients in equations (4.7) to be year-specific. When estimating the structural model coefficients, we allow all structural parameters to be year-specific as well, with ρ_{fd} (the 'true' correlation) as the only time constant. In contrast to substitution effects, we argue that this correlation cannot be affected by business cycle conditions, or policies affecting the relative attractiveness of the UI vis-à-vis the DI scheme. As a result, variation in λ over time is not only identified from the (yearly) parameter coeffcients of the exclusion restriction, but also from (the time variation in) the correlation between UI and DI enrolment rates.

5 Estimation results

Table 5.1 presents the Maximum Likelihood estimation results of the reduced form bivariate Tobit model, where parameters are restricted to constant over time. [9] The UI enrolment rate decreases with respect to age, and increases with respect to firm size. Note however that we have not included firm size averages in the regression (the variation of firm size within firms was too small to allow for this), so that these firm size effects may be biased – that is, either the type of workers at firms, or firm specific characteristisc may explain the employer size effect. When looking at the calendar time effects, we find the UI enrolment rate to have decreased substantially. This can be explained by favourable labour market conditions during the period of investigation, causing the unemployment rate to decrease from about 7% in 1993 to about 4% in 2003.

For the DI enrolment rate, we do not find a clear, monotonic impact of the age composition of firms. Similar to the UI scheme, DI enrolment rates are lower for firms with a high fraction of women, and firms with low employer size. Furthermore, calendar time effects are an important determinant of the DI enrolment rate. From 1994 to 1998, the DI enrolment rate has gradually increased, and then dropped substantially. Potential explanations for this pattern may be the introduction of experience rating in 1998, and stricter gatekeeping requirements in 2002. Furthermore, the estimated correlation coefficient of the UI and DI enrolment rate is equal to 0.12. The heteroscedasticity coefficient η has the expected sign – that is, the size of variance in enrolment rates decreases in employer size per firm.

Table 5.2 reports the structural parameter estimates that are obtained from MDE, based upon the reduced form estimates obtained in the first step (Table 5.1). We find the estimate of ρ_{fd} – representing the 'true' correlation – to be equal to 0.040. We estimate λ to be equal to 0.026, implying that 2.6% of the desired dismissals is through enrolment into the DI scheme. This estimate is substantially lower than Hassink et al. (1997) (6 to 9%). Recall from Section 4.1 that, for λ and ρ_{fd} close to zero, the correlation that results from substitution effects can be approximated by $\lambda \frac{\sigma_f}{\sigma_d}$. This yields an estimate of 0.078, which is about two thirds of the 'observed' correlation (ρ_v) that is obtained from the reduced form model. The importance of subsitution effects is also mirrored by the other parameter estimates, in particular of the regression for the DI enrolment rate. In contrast to the reduced form estimates, we now find 'true' DI enrolment rate to increase with age. Particularly young employers have high UI enrolment rates, and therefore constitute an important fraction of the 'hidden component' in the inflow into DI.

[9] In order to obtain MLE of the bivariate Tobit model, we employed the QLIM code in SAS.

Table 5.1	Estimation results for 1994-2003: Reduced Form Parameters of Bivariate Tobit Model for UI and DI Enrolment			
	UI		DI	
	Coefficient	St.error	Coefficient	St.error
Constant	− 0.065	0.0021	− 0.089	0.00087
Age 25-34	0.039	0.0039	0.0071	0.00015
Age 35-44	− 0.042	0.0043	0.0023	0.00016
Age 45-54	− 0.055	0.0055	0.0037	0.00020
Age >=55	− 0.11	0.0079	0.0053	0.00028
Female	− 0.042	0.0040	0.00015	0.00015
26-50 employees	0.028	0.00049	0.0015	0.00020
51-100 employees	0.041	0.00050	0.0027	0.00021
101-250 employees	0.044	0.00054	0.0033	0.00022
>250 employees	0.052	0.00055	0.0037	0.00022
First Quartile ln(wage)	0.0039	0.00046	0.00093	0.00017
Third Quartile ln(wage)	0.020	0.00058	− 0.00024	0.00022
Year = 1995	0.0015	0.00067	0.0038	0.00025
Year = 1996	− 0.021	0.00072	0.0054	0.00027
Year = 1997	− 0.025	0.00071	0.0066	0.00026
Year = 1998	− 0.027	0.00073	0.0069	0.00027
Year = 1999	− 0.029	0.00075	0.0056	0.00027
Year = 2000	− 0.036	0.00079	0.0029	0.00029
Year = 2001	− 0.038	0.00081	0.0037	0.00029
Year = 2002	− 0.053	0.00090	− 0.00010	0.00033
Year = 2003	− 0.073	0.00092	− 0.0030	0.00032
Age 25-34, average	0.099	0.0020	− 0.0064	0.00076
Age 35-44, average	0.064	0.0026	0.014	0.00095
Age 45-54, average	0.040	0.0034	0.028	0.0012
Age >=55, average	0.0071	0.0052	0.010	0.0017
Female, average	− 0.0027	0.00084	0.0046	0.00030
First Quartile ln(wage), average	− 0.0061	0.00033	0.00039	0.00012
Third Quartile ln(wage), average	0.0069	0.00034	0.0050	0.00013
τ_{f0}	0.36	0.0022		
τ_{d0}	0.11	0.0066		
ρ_v	0.12	0.0026		
η	− 0.66	0.0026		

Basically, our estimate of λ for 1994-2003 is identified from the exclusion restrictions imposed on the wage quartile coefficients. The reduced form estimates for UI enrolment indicate that find high wage firms are more likely to dismiss workers. For DI enrolment, we find the reduced form coefficients to be less pronounced – that is, only for the first wage quartile, we find the effect on DI enrolment to be positive and significant. This suggests that substitution effects are most prevalent for low wage workers.

Table 5.2 Minimum Distance Estimates for whole sample (1994-2003): structural parameters				
	UI		DI	
	Coefficient	St.error	Coefficient	St.error
Constant	− 0.067	0.0021	− 0.088	0.00085
Age 25-34	0.040	0.0040	0.0082	0.0014
Age 35-44	− 0.043	0.0044	0.026	0.0015
Age 45-54	− 0.056	0.0056	0.041	0.0019
Age >=55	− 0.11	0.0081	0.058	0.0027
Female	− 0.044	0.0041	0.0021	0.0014
26-50 employees	0.028	0.00050	0.015	0.00019
51-100 employees	0.042	0.00052	0.026	0.00020
101-250 employees	0.045	0.00055	0.032	0.00021
>250 employees	0.053	0.00056	0.036	0.00022
Age 25-34, average	0.10	0.0021	− 0.0090	0.00074
Age 35-44, average	0.066	0.0027	0.0012	0.00093
Age 45-54, average	0.041	0.0035	0.0026	0.0011
Age >=55, average	0.0073	0.0054	0.0010	0.0016
Female, average	− 0.0028	0.00087	0.0047	0.00030
First Quartile ln(wage), average	− 0.0062	0.00033	0.00013	0.00028
Third Quartile ln(wage), average	0.0071	0.00034	− 0.00011	0.00029
Year = 1995	0.0015	0.00069	0.00055	0.00012
Year = 1996	− 0.021	0.00074	0.0048	0.00013
Year = 1997	− 0.025	0.00073	0.0037	0.00024
Year = 1998	− 0.028	0.00075	0.0060	0.00024
Year = 1999	− 0.030	0.00077	0.0073	0.00025
Year = 2000	− 0.037	0.00081	0.0076	0.00025
Year = 2001	− 0.039	0.00083	0.0063	0.00026
Year = 2002	− 0.054	0.00093	0.0038	0.00027
Year = 2003	− 0.075	0.00095	0.0047	0.00027
Exclusion restrictions (x_f)				
First Quartile ln(wage)	0.0039	0.00048		
Third Quartile ln(wage)	0.020	0.00059		
ρ_{fd}	0.040	0.015		
λ	0.026	0.00081		
σ_f	0.36	0.0022		
σ_d	0.12	0.00071		

Table 5.3 reports the key structural parameter estimates for DI enrolment into full and partial disability, and years separately. For the yearly estimates, we re-estimated the reduced form as well as the structural model for separately, while restricting the ‘true’ correlation coefficient ρ_{fd} and the average value parameters to be constant over time. [10] Note that the condition described

[10] We also estimated the model for separate sectors. We find hidden unemployment to be highest in the hotel and catering industry (7% of the desired dismissal level). We also find the fraction of desired dismissals directed to the DI

in (4.6) is not binding for all of these subsets of the data – that is, the coefficient estimate of λ does not exceed the estimated value of $\frac{\sigma_d}{\sigma_f}$, and we have unique values for our structural parameters. For the inflow into the full DI scheme, the estimated fraction of hidden unemployment is 15%. For the partial scheme, we find similar effects (18%). Here, it should be noted that the sum of parameter estimates of λ for partial and full disability enrolment rates exceeds that of the parameter estimate for the joint DI enrolment rate. From this, we conclude that the partial and full disability scheme act as substitute pathways: high inflow in the full (partial) DI scheme is accompanied by low inflow in the partial (full) DI scheme.

Table 5.3 also makes apparent that the hidden component in DI enrolment has decreased substantially over time. In 1994, almost 40% of the DI enrolment rate is estimated to consist of hidden unemployment, whereas for 1999-2003 this percentage was only 2 to 4%. This decrease can mainly be attributed to a lower proportion of layoffs that is directed to DI, and has further been agravvitated by a lower (total) desired layoff rate. Our results suggest that various policies aimed at discouraging substitution from UI to DI have indeed been effective. Particularly in the time intervals 1994-1996, and 1998-1999, the hidden UI component in DI enrolment has decreased substantially. In a way, these results are surprising, as DI enrolment rates in our sample started to decrease not earlier than in 1998. We therefore conclude that, with constant substitution rates, DI enrolments rate would have been substantially higher until 1999. Moreover, decreases in the DI enrolment rates in more recent years cannot be explained by a lower inflow of desired dismissals. Rather than subsitution between the schemes, it seems preventative measures by employers have lowered the 'true' DI enrolment rate substantially. (see e.g Koning (2004)).

An obvious way to check for the robustness of our estimation results is to use an alternative exclusion restriction. For this purpose, we have re-estimated the model for 1996-2002, but now using the yearly average wage sum growth per sector as an exclusion restriction.[11] The second column of Table 5.4 ('Model (i)') presents the resulting yearly estimates of λ. For all years, we find our results not to differ with respect to the benchmark model.

As a second robustness check, we tested our model against a more flexible specification for the employer fixed effects. In doing this, we followed Zabel (1992), who proposes to include higher

scheme (λ) to be relatively high for the financial sector, but the number of dismissals is relatively low as well, resulting in a low share of DI enrolment that can be classified as hidden unemployment. More generally, low sectoral UI enrolment rates coincide with a high fraction of hidden unemployment.

[11] Obviously, we also could have included this variable as an additional exclusion restriction in the 'benchmark' model. As a disadvantage, however, we then lose two years of employer observations, as the sectoral business cycle variable is obtained from two lagged observations of wage sums in our sample. Moreover, in contrast to previous years, sectoral codes are not observed for about 30% of the employer observations in 2003.

Table 5.3 **Key parameter estimates and implied variable values for various subsamples of the data (standard errors between parentheses)**

	λ	σ_f	σ_d	ρ_{fd}	$\frac{\lambda Ef}{\lambda Ef+Ed}$ % Hidden UI in DI
Total	0.026	0.36	0.12	0.040	0.11
	(0.00081)	(0.0022)	(0.00071)	(0.015)	(0.0035)
Full disability	0.021	0.36	0.11	0.045	0.15
	(0.00084)	(0.0023)	(0.00073)	(0.017)	(0.0060)
Partial disability	0.016	0.32	0.090	0.036	0.18
	(0.00086)	(0.0021)	(0.00064)	(0.027)	(0.0097)
1994	0.054	0.37	0.12	0.040	0.38
	(0.0025)	(0.0066)	(0.0023)	(0.015)	(0.018)
1995	0.033	0.35	0.12	0.040	0.17
	(0.0024)	(0.0061)	(0.0021)	(0.015)	(0.012)
1996	0.023	0.40	0.14	0.040	0.098
	(0.0024)	(0.0069)	(0.0025)	(0.015)	(0.010)
1997	0.018	0.38	0.14	0.040	0.069
	(0.0025)	(0.0067)	(0.0024)	(0.015)	(0.010)
1998	0.019	0.33	0.11	0.040	0.064
	(0.0025)	(0.0059)	(0.0020)	(0.015)	(0.0084)
1999	0.010	0.32	0.11	0.040	0.035
	(0.0026)	(0.0064)	(0.0020)	(0.015)	(0.0091)
2000	0.0069	0.39	0.11	0.040	0.034
	(0.0024)	(0.0082)	(0.0023)	(0.015)	(0.012)
2001	0.0075	0.43	0.12	0.040	0.039
	(0.0024)	(0.0094)	(0.0025)	(0.015)	(0.012)
2002	0.0058	0.44	0.11	0.040	0.041
	(0.0023)	(0.010)	(0.0025)	(0.015)	(0.016)
2003	0.0067	0.35	0.10	0.040	0.023
	(0.0026)	(0.0088)	(0.0025)	(0.015)	(0.0089)

order polynomials of the value averages in the auxiliary regression(s). The third column of Table 5.4 presents the estimates of λ that result from this approach. Generally, we find the inclusion of quadratic terms of our value averages (of age categories, gender and wage quartiles) to increase the fit of our (bivariate) reduced form model substantially, but this does not affect the size of the coefficients decribing the effect of our exlcusion restrictions. Consequently, our parameter estimates of λ do not change significantly as well.

Table 5.4 Testing the robustness of λ vis-a-vis alternative specifications

	Model (i): 'Benchmark model'	Model (ii): Sectoral business cycle as exclusion restriction	Model (iii) Flexible parameterisation of employer fixed effects
1994	0.054	–	0.049
	(0.0025)		(0.0025)
1995	0.033	–	0.028
	(0.0024)		(0.0025)
1996	0.023	0.027	0.020
	(0.0024)	(0.0025)	(0.0026)
1997	0.018	0.021	0.015
	(0.0025)	(0.0025)	(0.0026)
1998	0.019	0.020	0.014
	(0.0025)	(0.0025)	(0.0025)
1999	0.010	0.012	0.0053
	(0.0026)	(0.0026)	(0.0024)
2000	0.0069	0.0083	0.0023
	(0.0024)	(0.0024)	(0.0021)
2001	0.0075	0.0091	0.0032
	(0.0024)	(0.0024)	(0.0021)
2002	0.0058	0.0052	0.0025
	(0.0023)	(0.0023)	(0.00019)
2003	0.0067	–	0.013*
	(0.0026)		(0.0021)

* Indicates a coefficient estimate of λ that is significantly different from Model (i) (P > .01).

6 Conclusions

In this paper, we construct and estimate a (semi-) structural model, so as to uncover the size of hidden unemployment in the DI enrolment rate. For this purpose, we use longitudinal administrative data for the Netherlands over the period 1994-2003. In principle, the estimation procedure we propose can be applied to various types of data sets, ranging from survey data to (large) administrative data. In the first stage of the estimation, standard estimation techniques can be used to obtain reduced form estimates. These estimates can then be used to obtain Minimum Distance estimates of the structural parameters of our model. The estimates are particularly informative on the potential size of policies that aim to diminish moral hazard problems – for instance, the use of DI experience rating systems.

We find the average fraction of hidden unemployment in DI enrolment in 1994-2003 to be equal to about 11%. This corresponds to 2.6% of the 'true' UI enrolment rate of employers. We find this result to be robust to our choice of exclusion restrictions. More specifically, using wage distribution quartiles on the one hand, and sectoral business cycle indicators on the other hand, we obtain similar estimates for the size of substitution effects. Our estimates suggest that most of the correlation that is observed between the UI and DI enrolment rates can be explained by substitution effects, and not by ('true') correlation that is exogenous to the firm. For the period of investigation, we find the hidden component in DI enrolment to have decreased substantially, from 38% in 1994 to 2-4% from 2000 onwards. This means that, with constant substitition effects, DI enrolments rate would have been substantially higher until 1999. Moreover, the decreases in the DI enrolment from 2000 and onwards cannot be explained by a lower inflow of desired dismissals. Instead, it may well have been that preventative measures by employers, in particular the experience rating plan that started in 1998, have lowered the DI enrolment rate substantially.

The estimation method we propose in this paper offers interesting avenues for further research. First, one way to extend the model is by also addressing substitution between DI enrolment and (early) retirement schemes. Taking this into account – as suggested by Kerkhofs et al. (1999) – would probably imply a higher share of false claimants of DI benefits. Second, substitution effects can also be modelled between the enrolment rate into the partial disability scheme and into the full disability scheme. Our estimation results suggest the presence of such effects, but a more explicit model is needed to determine its importance.

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