Employer search and employment subsidies

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Employer search and employment subsidies

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In this paper insights into the literature on employment subsidy evaluation and that on employer search are merged to explore uncharted territory: the firm and job characteristics leading to deadweight loss in employment subsidy schemes. A model is developed which integrates various arguments found in the existing employer search literature. Using a survey of Dutch firms for 1999, the model predictions are confirmed. The richness of the data set enables one to construct some measures of deadweight loss which are new to the existing literature. It turns out that firms which experience low screening costs (large firms), firms that forego substantial production due to unfilled jobs (vacancies for full-time jobs) and firms operating in slack labour market conditions cause significantly more deadweight loss.

I. Introduction

A decade ago, Calmfors (1994) summarized the potential relevance of marginal employment subsidies – which focus on temporarily subsidizing employers who hire long-term unemployed – to fight long-term involuntary unemployment. A few years later Fay (1996), Friedlander et al. (1997) and Martin (1998) reviewed the employment subsidies employed in the OECD countries and found disappointing results: the subsidy wastage is immense. Hence the optimism to fight unemployment using employment subsidies in the early nineties was moderated considerably within a few years after its widespread introduction.

The empirical literature in this field can be divided into two parts: micro econometric and macro econometric evaluations. Micro econometrics focuses on the so-called ‘treatment’ effects of subsidy schemes. In order to do so, the job find probability of participants is compared to job find probabilities of non-participants controlling for individual characteristics. To measure treatment effects two routes are available. Lalonde (1996) gives an overview of the literature on experimental data; Heckman and Hotz (1996) demonstrate how cross-section or panel data can be used to determine treatment effects. Macro econometrics extents the analysis into another direction in an attempt to incorporate the general equilibrium effects of the subsidy. Calmfors et al. (2001) give a clear overview of this strand of literature.

Although different in many respects, both micro and macro econometric empirical evaluations apply the concept of deadweight loss. This loss is a measure for subsidy wastage, as it consists of the share of participants in the employment subsidy scheme that would have also found a job in the absence of the subsidy.

Much of the empirical attention focuses on a precise measurement of deadweight loss – see Dar and Tzannatos (1999). Surprisingly hardly any attention has been paid to the characteristics of firms and jobs associated with deadweight loss. That is, which firms (and for what jobs) hire subsidized unemployed

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they would have hired without the subsidy? The answer to that question is relevant, as insight on the characteristics contributing to deadweight loss is a necessary step in reducing its disappointingly large extent.

In this paper the first steps are taken to answer that question, combining the literature on employment subsidy evaluation and employer search. We employ an employer search model with unemployment duration as a screening device. The firm uses this duration to split the job seekers pool in two parts: those who are taken into consideration for the vacancy and those who are not. The threshold value of the screening device standard depends on firm, job and sector characteristics, as the employer search literature predicts. The higher duration a firm allows for, the more it recruits from long-term unemployed and hence the more likely the firm hires subsidized long-term unemployed it would have also hired in the absence of the subsidy, i.e. the firm causes deadweight loss.

Section II of this paper outlines the employer search model. We utilize this model to sketch the conditions under which employers are willing to recruit from (subsidized) long-term unemployed and to analyse the potential incidence of deadweight loss. Section III discusses the existing employer search literature. Section IV focuses on the data on a survey of Dutch firms from 1999 and the resulting hypotheses, which is tested in Section V. Section VI concludes.

II. A Sequential Employer Search Model

We use a sequential employer search model of an employer attempting to fill a vacancy. The employer posts a vacancy, which draws a periodical arrival rate of job seekers. Imperfect information prevents the employer from observing the productivity of job seekers free of costs. Following Omori (1997), we assume the employer to use unemployment duration as a screening device. If the job candidate experiences an unemployment spell shorter than the screening device standard \( r \), the employer decides to assess the job candidate. Otherwise the job candidate is rejected. During the assessment the – otherwise hidden – applicant’s productivity level, \( p_j \), is revealed. The employer employs a minimum productivity standard, \( p^* \). If the job candidate meets the productivity standard \( (p_j \geq p^*) \) she is hired and the search process closes; if not, the employer waits for the next applicant to arrive.

The determinants of hiring costs

Assessing applicants is not free of costs: each assessment costs \( b \). The same holds for a vacancy: each period it is not filled, the firm foregoes productivity, \( c \). As a result firms try to generate a high arrival rate of high productive applicants, which ensures a quick filling of the vacancy so that few assessments are needed. The firm has two instruments to influence the arrival rate and the quality of applicants. On the one hand, the firm can shift the screening device standard. Reducing \( r \) increases the average quality of applicants who are entitled to an assessment, as both skill obsolescence (Albrecht et al. (1998) or Arthur et al. (1998)) and loss of work attitude (Layard et al. (1991)) ensure a negative link between productivity and unemployment duration. However, a lower unemployment spell will reduce the arrival rate of applicants, as more job seekers are excluded from the recruitment procedure. On the other hand, the firm can use the type of recruitment channel to influence the arrival rate and the quality of applicants. We concentrate on recruitment via the labour exchange offices and advertisements. These channels have typical characteristics as regards their ability to generate a high arrival rate and high productive applicants. The firm’s choice of a recruitment channel can therefore be seen as an investment decision, where costs of operating a recruitment channel depend positively on the channel’s ability to generate both a high arrival rate and high productivity applicants.

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1 The model employed is a partial equilibrium model, implying that we cannot model the full macroeconomic consequences of an employment subsidy scheme. Since we only focus on firm behaviour following the availability of an employment subsidy scheme, a partial equilibrium model is sufficiently rich to answer our research question.

2 Van Ours and Ridder (1992) and Gorter et al. (1996) show that recruitment from lower educated usually involves sequential recruitment. Since the burden of (long-term) unemployment and subsequently the use of employment subsidies is predominantly devolved on lower or non-educated, we apply sequential search in our model.

3 Recruiting from long-term unemployed – which is a prerequisite in this paper – restricts the number of relevant recruitment channels to two: advertisements and the labour exchange office. It is typical of long-term unemployed that they do not have a social network, which makes recruiting via informal contacts difficult; see for example Gorter et al. (1996). Private employment agencies are often reluctant to mediate long-term unemployed, as profit margins on mediating them are generally low. Self-confidence of long-term unemployed is, generally speaking, low – cf. Layard et al. (1991), which diminishes the relevance of recruiting via open application.
Van Ours (1994) shows that the probability to find a qualified applicant from a public employment agency is usually low. Gorter et al. (1996) and Russo et al. (1997a) show that firms prefer advertisements to the labour exchange office as a recruitment channel when job requirements are high. Moreover, Russo et al. (1997b) and Russo et al. (2000) show that advertisements produce both a higher response rate and a higher average quality pool of applicants than recruiting via the labour exchange office.

Consequently, advertisements outperform the labour exchange office as a recruitment channel in terms of the former’s ability to attract both more and better applicants. We proceed on the assumption that the cost of the cheapest recruitment channel \((r = 0)\) is \(e.\) The mark-up factor, \(\zeta,\) on the costs of the cheapest recruitment channel of the channel \(r\) chosen is then positive in \(r,\) hence \(\zeta(0) = 1\) and \(\zeta > 0.\)

The firm operates in a competitive labour market and minimizes hiring costs in order to make a competitive wage offer. Hiring costs have three origins: assessment costs, recruitment channel costs and the costs of periodically foregone productivity. The cost of foregone productivity per assessment consists of two factors. On the one hand, it depends on the average number of periods between two successive candidates, \(\psi -\) the latter is inverse to the arrival rate of job seekers, consequently \(\psi\) is positive in labour market tightness, \(\theta,\) hence \(\psi(\theta)\) and \(\psi > 0.\) On the other hand, the cost of foregone productivity depends on the average number of candidates, \(\varphi,\) needed to find a candidate who is entitled to enter the assessment procedure. This average depends negatively both on the screening device standard, as a higher \(t'\) allows more applicants to enter the assessment, and on the chosen recruitment channel as advertisements generate higher quality candidates than the labour exchange office. Hence, \(\varphi(t', r)\) and \(\varphi < 0\) and \(\varphi_r < 0.\) The product of \(\varphi\) and \(\psi\) equals the average number of periods between two candidates who are entitled to enter the assessment procedure.

Finally, the average number of assessments, \(\chi,\) needed to find a qualified candidate who meets the productivity standard \(p^*\), is positive in \(t'\) and negative in \(r.\) Raising \(t'\) decreases the average quality of applicants, which reduces the success rate of an assessment; raising \(r\) increases the quality of applicants. Hence, \(\chi(t', r)\) and \(\chi_t > 0\) and \(\chi_r < 0.\) Hiring costs are then given by:

\[
HC(t', r, \theta) = \chi(t', r)[b + \psi(t', r)\psi(\theta)c] + \zeta(r)e
\]

Equation 1 intuitively yields an appealing outcome. Costs \(\zeta(r)e\) are needed to generate an arrival rate of job seekers with a certain average quality. Between brackets we find the direct and indirect costs of each assessment. Direct costs of an assessment are costs \(b;\) indirect costs originate from the unproductive period in between the arrivals of two assessable candidates. Multiplying these assessment costs with the number of assessments needed to find a qualified candidate and adding the costs of activating the recruitment channel yield total hiring costs.

The screening device standard and deadweight loss

To minimize hiring costs, the firm sets optimal values for \(t'\) and \(r.\) Before turning to the comparative statics of the model, we first link the firm’s choice of \(t'\) to the incidence of deadweight loss. To keep the design of the employment subsidy simple, governments usually apply a uniform subsidy start value, \(t'^*\), entitling every employer who wants to participate, regardless of, for example, labour market, and sector or job characteristics. That is, an employer is subsidy entitled if he hires a job seeker who is out of employment for more than \(t'^*\) periods. Consequently, deadweight loss might arise when the firm sets \(t' > t'^*\) since in such conditions the firm’s recruitment behaviour (recruiting up to \(t'\)) overlaps the government’s subsidy granting. Since firms may experience different exogenous values of the variables, \(b, c, \theta\) and \(e\) in Equation 1, \(t'\) is essentially sector, firm or even job specific. To analyse the incidence of deadweight loss, the relationship between the screening device standard \(t'\) and these exogenous variables should therefore be scrutinized.

Comparative statics

To derive the optimal hiring standard \(t',\) we rewrite Equation 1 as follows:

\[
HC(t', r, \theta) = \chi(t', r)[b + \varphi(t', r)\psi(\theta)c] + \zeta(r)e
\]

\(4\) We treat the recruitment channel \(r\) as a continuous variable. The cheapest recruitment channel \((r = 0)\) is the labour exchange office, which yields a base level arrival rate of applicants and a basic quality level of applicants.

\(5\) We ignore here the possibility that the firm lowers its productivity standard, \(p^*\) – this possibility, which implies that employees may need additional training, is elaborated in Welbers and Muysken (2004).

\(6\) Labour market tightness is defined as \(\theta = \sqrt{u},\) where \(v\) represents vacancies and \(u\) unemployment. Its impact on the arrival rate of job seekers is elaborated in Pissarides (2000).

\(7\) Partial derivatives of a variable \(x\) with respect to \(t'\) are for the sake of simplicity denoted by \(x_t.\)

\(8\) Signs below arguments indicate the sign of the (partial) derivative.
where \( \varphi^* = \chi \varphi \), and \( \varphi^*_e, \varphi^*_r < 0 \). Since the firm minimizes hiring costs, we find that both \( HC_r \) and \( HC_{rr} \) are positive and \( HC_r HC_{rr} - (HC_{rr})^2 > 0 \). We assume that the effectiveness of \( t^r \) to reduce hiring costs increases for higher levels of \( r \), i.e. \( HC_{rr} < 0 \). The reason is that a higher \( r \) increases the average quality of the applicants and as a result increases the success rate of the assessment therefore moderates the impact of the assessment procedure in order to limit the effects of increased costs. The reason is that raising \( t^r \) on applicant quality and subsequently on the success rate of the assessment therefore moderates for a higher value of \( r \). This makes raising \( t^r \) more effective to reduce hiring costs. **Using the implicit function theorem we derive the four partial derivatives \( (\partial t^r/\partial c, \partial t^r/\partial b, \partial t^r/\partial e, \partial t^r/\partial \theta) \) we are interested in. For the impact of costs of foregone productivity on the screening device standard we find:**

\[
\frac{\partial t^r}{\partial c} = \frac{\varphi_e^* HC_r - \varphi_r^* HC_{rr}}{HC_{rr} HC_{rr} - (HC_{rr})^2}
\]  

(3)

The properties of \( HC \) imply that the numerator of Equation 3 is positive; the conditions for a relative minimum ensure that the denominator is also positive, which together imply that \( \partial t^r/\partial c > 0 \). This is also consistent with empirical evidence of Barron et al. (1997) and Burdett and Cunningham (1998) – who show that firms take more time to fill a vacancy when \( c \) is low – because raising \( t^r \) speeds up the recruitment procedure. **10**

The intuition behind Equation 3 is that firms have two instruments to speed up the recruitment procedure in order to limit the effects of increased foregone productivity costs: increase \( t^r \) and/or \( r \). Increasing the screening device standard \( t^r \) speeds up the recruitment procedure and hence limits foregone productivity \( (\varphi_r^* < 0) \). The impact of this effect is captured by the second term in the numerator of Equation 3, where \( HC_{rr} \) measures the effectiveness of using the alternative, the recruitment channel \( r \). The higher the current level of \( r \), the less effective a change in \( r \) will be (\( HC_{rr} > 0 \)). Subsequently, the more the firm must rely on \( t^r \) and hence the more sensitive \( t^r \) is to changes in \( c \).

The first term in the numerator of Equation 3 shows an indirect effect on \( t^r \) due to changes in foregone productivity \( c \) through \( r \). Increasing \( r \) speeds up the recruitment procedure and hence limits foregone productivity \( (\varphi_r^* < 0) \) and will therefore be used in continuation of an increase in \( c \). Subsequently, an increase in \( r \) reduces the negative effect that raising \( t^r \) has on the quality of applicants and as a result its effect on hiring costs \( (HC_{rr} < 0) \). Consequently, the firm increases \( t^r \) indirectly following an increase in \( r \). The impact of the indirect effect of \( r \) on \( t^r \) depends on \( HC_{rr} \). Both the direct and indirect effects of a change in \( c \) on \( t^r \) are positive, which ensures \( \partial t^r/\partial c > 0 \).

The impact of assessment costs on the hiring standard follows from:

\[
\frac{\partial t^r}{\partial b} = \frac{\chi_e HC_{rr} - \chi_r HC_{tr}}{HC_{rr} HC_{rr} - (HC_{rr})^2}
\]  

(4)

Firms facing high costs \( b \) try to limit the number of assessments needed to find a qualified candidate. Upgrading the quality of applicants is the answer, for which two instruments are available: raising \( r \), which has an indirect positive effect on \( t^r \) (as described under \( \partial t^r/\partial c \)), or decreasing \( t^r \), which raises the quality level of applicants \( (\varphi_r^* > 0) \). Assuming the direct effect to dominate the indirect effect, an increase in assessment costs leads to a lower \( t^r \): \( \partial t^r/\partial b < 0 \).

The impact of recruitment channel costs on the hiring standard follows from:

\[
\frac{\partial t^r}{\partial e} = \frac{\chi_e HC_{rr} - \chi_r HC_{tr}}{HC_{rr} HC_{rr} - (HC_{rr})^2}
\]  

(5)

Since the cost of using advertisements as a recruitment channel is modelled as a mark-up on the costs, \( e \), of using the labour exchange office, an increase in costs \( e \) widens the recruitment channel cost gap between advertisements and the labour exchange office. Hence an increase in \( e \) makes advertisements a relatively more expensive recruitment channel than the labour exchange office. Consequently, to limit costs \( e \) the firm has only one instrument at its disposal: avoid using advertisements – which explains why the numerator of Equation 5 contains only one factor. Or formally, the firm reduces \( r \) and subsequently (through \( HC_{rr} < 0 \)) decreases \( t^r \) indirectly, which explains why we find \( \partial t^r/\partial e < 0 \).

Finally Equation 6 presents \( \partial t^r/\partial \theta \):

\[
\frac{\partial t^r}{\partial \theta} = \frac{\varphi^*_r HC_{rr} - \varphi^*_e HC_{tr}}{HC_{rr} HC_{rr} - (HC_{rr})^2}
\]  

(6)

A change in labour market tightness influences the effectiveness of \( t^r \) and \( r \) to reduce hiring costs. From the properties of \( \varphi^* \), we know that both \( \varphi^*_e \) and \( \varphi^*_r \) are negative. \( \varphi^*_e < 0 \) means that the effectiveness of using the screening device standard to reduce the

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9 See Welters (2005) for the mathematical proof for \( \varphi^*_r < 0 \).

10 We use the condition that the denominator is positive to interpret \( \partial t^r/\partial b, \partial t^r/\partial e \) and \( \partial t^r/\partial \theta \), which have identical denominators.
length of the hiring period increases for higher levels of tightness. If tightness increases, more time evolves between the arrival of two applicants, which lengthens the hiring period. Consequently, the reduction in the length of the hiring period following an increase in \( r' \) is more pronounced when this mark-up is high, i.e. in tight labour market conditions.

We explain \( \psi_{r'} < 0 \) in similar fashion as \( \psi_{\theta^t} < 0 \). Moreover, there is an additional empirical argument – which is not captured in our model – why \( \psi_{r'} < 0 \), which is related to on-the-job search. Burgess (1993) and Burda and Wyplosz (1994) show that on-the-job search is pro-cyclical. Since advertisements are the main search channel of employed job seekers, searching through advertisements becomes more effective to fill jobs as both the arrival rate of applicants and the quality of job seekers are boosted in tight labour market conditions, advertisements become required to employ job seekers, searching through advertisements, not to look for low paid jobs – cf. Holzer (1996).

Nonetheless both the direct effect of an increase in \( \theta \) on \( r' \) and the indirect effect through \( r \), suggest \( \partial r'/\partial \theta > 0 \).

Since we found \( \partial r'/\partial e > 0 \), \( \partial r'/\partial b < 0 \), \( \partial r'/\partial c < 0 \) and \( \partial r'/\partial \theta > 0 \), our model predicts that firms facing low costs \( b \), high costs \( c \), low costs \( e \) and high levels of \( \theta \) set a high screening device standard and subsequently have a higher incidence of deadweight loss.

III. Empirical Employer Search Literature

We take the insights gained from the analysis in Section II as starting point for our empirical analysis on the explanatory power of employer search behaviour in the composition of deadweight loss. We distinguish three variables in our model related to deadweight loss: assessment costs \( b \), foregone productivity costs \( c \) and labour market tightness \( \theta \). Since we cannot measure the variables directly, we use insights arising from the empirical employer search literature to link these variables to firm and job characteristics. The richness of our data set allows us to approximate the variables \( b, c \) and \( \theta \) beyond the current level applied in the literature. In Section V we will use these insights to test whether there is a link between deadweight loss incidence and firm and job characteristics, as our model predicts.

Our model implies the following hypotheses:

The assessment cost hypothesis \( (\partial e / \partial b < 0) \): if assessment costs are high, firms are reluctant to weaken the screening device standard, which reduces the probability that such firms hire subsidized unemployed they would have hired in the absence of the subsidy.

The empirical literature splits assessment costs into two parts: intensive and extensive costs. Intensive costs refer to the intensity with which firms assess candidates (costs \( b \) in our setting). Extensive costs refer to the number of candidates the firm assesses per job offer it makes. We focus on the intensive costs in our analysis.\(^{12}\)

Table 1 summarizes four variables that are typically employed in empirical studies to explain intensive search cost differences between firms. The main theoretical rationale is that firms will increase intensive search when the job task is complicated (e.g. training or experience is required), the costs of monitoring employees are high (e.g. in large firms) or when it is costly to fire employees (e.g. employees on a fixed contract). Careful assessment of candidates is necessary in such situations, which increases intensive screening costs.

The empirical results of the effect of the level of monitoring costs (e.g. high in large firms) on intensive search are inconclusive and, if any, predict a negative effect. Barron et al. (1987) argue that firms applying assessments on a regular basis, experience economies of scale and employ an internal assessment centre, which is a cost saving activity. This argumentation would suggest that large firms

\(^{11}\) We do not have data that relate costs \( e \) to firm, sector and/or job characteristics; hence we leave costs \( e \) out of the analysis.

\(^{12}\) Since our model is sequential, we disregard extensive search costs.

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<table>
<thead>
<tr>
<th>Table 1. Effects on intensive search costs(^{a})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training required</td>
</tr>
<tr>
<td>Barron and Bishop (1985)</td>
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<tr>
<td>Barron et al. (1985)</td>
</tr>
<tr>
<td>Barron et al. (1987)</td>
</tr>
<tr>
<td>Holzer (1990)</td>
</tr>
<tr>
<td>Barron et al. (1997)</td>
</tr>
<tr>
<td>Burdett and Cunningham (1998)</td>
</tr>
</tbody>
</table>

Notes: \(^{a}\) An asterisk indicates the coefficient is significantly different from zero at the 0.10 significance level.
could economize on intensive search costs, which offsets the monitoring argument that monitoring costs are high in large firms.

The foregone productivity hypothesis \((\partial r^f / \partial c > 0):\) If per period foregone productivity costs are high, firms are more willing to weaken the screening device standard, which increases the probability that such firms hire subsidized unemployed they would have hired in the absence of the subsidy.

In comparison to providing indicators for assessment costs, the empirical literature on measuring costs of foregone productivity is less abundant. Barron et al. (1997) and Burdett and Cunningham (1998) use advance notice of a vacancy as an indicator of costs \(c.\) That is, a firm that knows in advance that a job will be broken up and hence needs to be filled at a future date can search for a new employee while the job is still productive. In such circumstances foregone productivity costs are absent.

The tightness hypothesis \((\partial r^f / \partial \theta > 0):\) if tightness increases, the screening device standard becomes more effective to fill vacancies quickly, which leads to a higher \(r^f.\) The indirect effect through \(r^f\) reinforces the direct effect of tightness on \(r^f.\)

To measure labour market tightness the empirical literature generally applies year, sector, or regional dummies – cf. Russo et al. (2000) or Gorter et al. (2003). If the dataset provides alternative indicators, these are used. Barron and Bishop (1985) exploit a data set, which comprises information on the number of applicants who came and had a look or phoned for a job, which they use as a proxy for tightness.

IV. Data and Hypotheses

To test our model predictions, we use a dataset of a study on the employment effects of a Dutch employment subsidy scheme (VLW), conducted in 1999 by the Netherlands Economic Institute (NEI) – Van Polanen Petel et al. (1999).¹³ The VLW was introduced in 1996 and closed in 2003. The scheme aimed at increasing the employment opportunities of long-term unemployed. An employer who hired an unemployed facing an uncompleted unemployment spell of at least one year was entitled to a subsidy of 2 160 euros at most, if he paid the unemployed wages amounting to no more than 130% of the legal minimum wages.¹⁴

NEI sent 1 966 questionnaires to employers who had hired or continued to hire employees in the period 1996 to 1999 inclusive and for whom they had received a VLW employment subsidy. The response rate was 18.6% resulting in a dataset of 365 cases. The VLW subsidy was also applied to finance relief jobs for long-term unemployed. This type of application of VLW employment subsidies has been left out in the analysis, which further reduces the firm sample to 129.

Description of the data

In Table 2 below we mention the variables in the data set that we use in our analysis. Most variables are categorical variables; some are continuous variables.

Participant and job related variables do not measure a specific characteristic of the participant population or the pool of employed jobs. Instead they indicate employer behaviour regarding the type of participants they hire and the type of jobs they offer to participants. Consequently, the variable ‘workload’ does not represent the share of participants that hold a part-time rather than a fulltime subsidized job, but instead the share of firms that offer only part-time jobs to participants (39%), the share of firms that offer both part and fulltime contracts to participants (13%) and the share of firms that offer only fulltime contracts to participants (48%). The workload variable is split at 36 working hours a week.

The ‘job activity’ variable divides jobs activity in supportive and main activity. A supportive job is not considered by the firm to be its main or core activity. The variable ‘relevance of the job’ refers to the priority attached to the work the subsidized participant does. The job is considered non-relevant if the employer would have decided to drop the workload (now done by the participant) in case capacity constraints had forced him to decide which workload was crucial and which was not.

Next, we consider some firm/sector related characteristics. The survey contains a continuous variable measuring employment growth between 1996 and 1998. We add ‘tightness’ to the data as a continuous variable specified by sector on a yearly basis. The variable is constructed as the

¹³ VLW is an abbreviation of afdrachtsVermindering Langdurig Werklozen (Tax Deduction Long-term Unemployed).

¹⁴ Employers situated in regions facing high unemployment rates (typical of large cities and northern provinces) could obtain a subsidy for unemployed experiencing at least 6 months of unemployment. Hence, \(r^f\) is not uniform as we claim. Still this does not disqualify our claim, as \(r^f\) is not demand side determined but supply side determined instead.
Table 2. Descriptive statistics

<table>
<thead>
<tr>
<th>Categorical variables</th>
<th>Description</th>
<th>Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Group 1, participant related characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>Share of firms whose participants are men only/both men and women/women only</td>
<td>0.45 0.21 0.34</td>
</tr>
<tr>
<td>Age</td>
<td>Share of firms whose participants are below 25 only/both below and above 25/above 25 only</td>
<td>0.11 0.13 0.76</td>
</tr>
<tr>
<td><strong>Group 2, job related characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload</td>
<td>Share of firms whose participants hold a part-time/both part and fulltime/fulltime contract only</td>
<td>0.39 0.13 0.48</td>
</tr>
<tr>
<td>Job activity</td>
<td>Share of firms whose participants work in supportive only/both supportive and main/main activity only</td>
<td>0.36 0.12 0.52</td>
</tr>
<tr>
<td>Relevance of work</td>
<td>Share of firms employing participants at important jobs/unimportant jobs</td>
<td>0.87 0.13</td>
</tr>
<tr>
<td><strong>Group 3, employer related characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fulfilling expectations</td>
<td>Share of employers who selected/do not know yet/did not select high quality long-term unemployed</td>
<td>0.40 0.20 0.40</td>
</tr>
<tr>
<td>Recruitment difficulties</td>
<td>Share of firms experiencing no severe difficulties/severe difficulties to fill low paid vacancies</td>
<td>0.32 0.68</td>
</tr>
<tr>
<td>Unemployment record</td>
<td>Share of employers for whom ltu plays a decisive/non-decisive/no role at all in a hiring decision</td>
<td>0.15 0.62 0.22</td>
</tr>
<tr>
<td><strong>Group 4, firm/sector related characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sector</td>
<td>Share of firms operating in the private/public sector</td>
<td>0.63 0.37</td>
</tr>
<tr>
<td>Firm size</td>
<td>Small firm/medium sized/large firm (number of regular employees)</td>
<td>0.30 0.27 0.43</td>
</tr>
<tr>
<td>Autonomy firm</td>
<td>Share of firms not part of a larger entity/part of a larger entity</td>
<td>0.76 0.24</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Continuous variables</th>
<th>Description</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment growth (mean)</td>
<td>Percentage increase in employment between 1996 and 1998</td>
<td>0.32</td>
</tr>
<tr>
<td>Tightness (mean)</td>
<td>Vacancy/employment ratio × 100</td>
<td>1.86</td>
</tr>
</tbody>
</table>

| Shares | | |
|--------|--------|--------|--------|
| **Deadweight loss construct** | Description | Shares |
| DWL1 | Share of employers that would have hired all subsidized/less than all employees in the absence of the subsidy | 0.47 0.53 |
| DWL2 | Share of employers that expect all/50%-100%/0%-50%/none of their subsidized employees to have found unsubsidized employment | 0.39 0.09 0.16 0.36 |
vacancy/employment ratio, using data from Statistics Netherlands.\textsuperscript{15} Firm size refers to the number of employees within the firm, which is divided into three categories in which 10 and 50 employees are the thresholds.

Additionally we consider some employer related characteristics. The variable ‘fulfilling expectations’ is a construct of two other variables. First, employers was asked whether the productivity of subsidized participants was comparable to that of regular employees. Next employers were asked whether they expected the participants to be as productive as they turned out to be. Employers answering both questions positively, have found a high quality long-term unemployed without being surprised to have found such an employee within the pool of long-term unemployed. These employers constitute a separate category. Next there is a category of employers who are not (yet) able to assess the qualities of the subsidized participants and finally there is a category of employers who answered at least one of both questions negatively.

The variable ‘unemployment record’ entails firms who reject long-term unemployed in hiring decisions categorically, employers who use long-term unemployment next to other screening devices and employers for whom long-term unemployment is no criterion in hiring decisions.

**Deadweight loss construct**

We use two measures of deadweight loss, which we present in Table 3: $DWL_1$, the share of employers who would have hired all subsidized employees in the absence of the subsidy; and $DWL_2$, the share of employers who expect all their subsidized employees to have found unsubsidized employment.\textsuperscript{16} Since the first measure relates to the unsubsidized job find probability within the firm and the second to the unsubsidized job find probability both within and outside the firm, one would expect $DWL_1$ to be strictly smaller than $DWL_2$. Table 3 shows that this is not the case, which might indicate that responding firms have not interpreted $DWL_2$ as the overall

\begin{table}[h]
\centering
\caption{Overlap between two constructs to measure deadweight loss}
\begin{tabular}{lccc}
\hline
 & \textit{DWL1} & \textit{DWL2} & \textit{Total (row)} \\
\hline
All of them & 32\% & 7\% & 39\% \\
Some of them & 5\% & 4\% & 9\% \\
Total (row) & 47\% & 53\% & 100\% \\
\hline
\end{tabular}
\end{table}

‘unsubsidized job find probability’ but as the ‘unsubsidized job find probability’ outside the firm.

In Table 3 we also show the overlap between both measures. There are two main groups of employers. One group (32\%) who admit that the subsidized employee would have found a job without the subsidy and one group (30\%) who indicate that the subsidized employee would not have found a job in the absence of the subsidy. The less certain firms are that the participant(s) would have found a job without the subsidy, the less often they argue that they would have hired the participant(s) even without a subsidy. This expected tendency follows clearly from Table 3.

Since the definition of deadweight loss contains the unsubsidized job find probability both inside and outside the firm, the deadweight loss indicator we want to use in our regression should contain both elements. Therefore we need to amalgamate $DWL_1$ and $DWL_2$. The overlap between both measures suggests a first potential amalgamation, $DWL_3$, which consists of three (ordered) categories. The northwest and the southeast partition in Table 3 (32\% and 30\% respectively) belong to the pure deadweight loss and to the no deadweight loss at all category respectively; the six remaining partitions are classified into the middle category. Furthermore we develop two alternative indicators, $DWL_4$ and $DWL_5$, in which we exploit the informational value of the matrix in Table 3, to reclassify the six partitions out of the middle category of $DWL_3$. Though reclassified, the ordinal structure remains intact in $DWL_4$ and $DWL_5$.\textsuperscript{17}

\textsuperscript{15} Ideally we would like to use the $u/v$ ratio, but then we need unemployment rates specified to sector, which leads to problems on defining as to what sector the unemployed belong to. We decided to abstain from this definition problem and to rely on vacancies over total employment within a sector.

\textsuperscript{16} Bear in mind that these shares do not measure deadweight loss percentages comparable to the typical shares found in the empirical literature. The latter deadweight loss shares refer to the share of participants that would have found an unsubsidized job. Here we measure the share of firms that expect its subsidized employees to have found an unsubsidized job. Since the vast majority of participating firms employ one subsidized employee only, both shares only differ marginally.

\textsuperscript{17} $DWL_4$ and $DWL_5$ differ from each other and from $DWL_3$ with respect to the allocation of the grey elements in Table 3. The elements ‘50–100\%, all of them’ and ‘100\%, some of them’ are included in the top category of $DWL_4$ and in a separate category between top and middle category of $DWL_5$. The element ‘0–50\%, some of them’ is included in the bottom category of $DWL_4$ and in a separate category between middle and bottom category in $DWL_5$. 

Preservation of the ordinal structure of the DWL-construct prevents the development of more variants of the DWL-construct. Since there is no theoretical argument to prefer one of the three mentioned constructs over the others, the eventual choice we will make, is empirically motivated – see Section V.

**Predicted deadweight loss**

We distinguished three variables in our model related to deadweight loss: assessment costs ($b$), foregone productivity costs ($c$) and labour market tightness ($\theta$). We found that firms facing low costs $b$, high costs $c$ and high levels of $\theta$ set a high screening device standard and subsequently have a higher incidence of deadweight loss. Now we relate variables included in our data set to variables $b$, $c$ and $\theta$ which we subsequently link – using insights arising from Section III – to firm and job characteristics. In Section V we will use these insights to test whether there is a link between deadweight loss incidence and firm and job characteristics, as our model predicts.

**The assessment cost hypothesis**

From the factors discussed in Section III, our data set contains only one: ‘firm size’, to indicate (intensive) search costs. We include this variable in the regression. Moreover, to separate the economies of scale argument from the monitoring effect, we include the variable ‘autonomic firm’. Firms that are part of a larger conglomerate can borrow screening expertise from its partners, which means that they exploit economies of scale regardless their size.

As additional variables, we include ‘supportive job’, ‘meeting (high) expectations’ and ‘unemployment record’ to indicate assessment costs $b$. A supportive job is of less strategic value to the firm than a job in its main activity – compare the positive impact of experience and/or training required mentioned in Section III. Consequently, to fill a supportive job, screening can be less strict and consequently cost $b$ is lower. Moreover we include the share of employers who anticipated the participants’ productivity levels correctly, as their levels equaled those of regular employees. This variable shows the firm’s awareness of the qualities of long-term unemployed and hence indicates low screening costs. Finally, we include the use of the unemployment record as a screening device. A firm assigning a decisive role to the unemployment record in hiring decisions finds it difficult or costly to apply more sophisticated recruitment methods. This firm apparently faces high costs $b$.

The above discussion of how variables in our data set are related to screening costs is summarized in Table 4. Since screening costs are negatively related to the hiring standard $r$, we expect firms who have high screening costs $b$ to cause less deadweight loss. The variables, which are supposed to correlate positively with $b$, are then supposed to decrease deadweight loss, whereas the negatively correlated variables increase deadweight loss. Table 4 also contains a first glimpse of the results resulting from the regression analysis, which we discuss in more detail in Section V.

**The foregone productivity hypothesis**

Our data set does not contain a direct measure for advance notice. However, we try to measure it indirectly by ‘employment growth’. Vacancies can arise for two reasons: filling a vacant position or extending the workforce. In the case of the former, costs $c$ are low since the firm has advance notice of that particular job opening, however when expanding this need not be the case. As firms experiencing employment growth have relatively more often extension vacancies, we expect employment growth to be more correlated with costs of foregone productivity $c$.

Because a vacancy for a ‘part-time’ job only leads to limited production loss, we expect foregone productivity costs also to increase with the size of the job in terms of hours worked per week. Moreover, vacancies for which subsidized employees have been recruited, but which would not have been filled in the absence of a subsidy, are typically ‘non-priority’ jobs. For these jobs the same holds as for part-time vacancies.

Again Table 4 summarizes the impact of the variables discussed above on costs of foregone productivity $c$. The variables which are supposed to cause higher costs will then also induce a tighter $r$ and therefore it is less likely that firms, showing such characteristics, cause deadweight loss.

**The tightness hypothesis**

We include the variables ‘difficulty filling low wage job’ and ‘tightness’ in our equation. Both variables directly measure tightness. From the analysis above it follows that they are expected to correlate negatively with deadweight loss.

The variables ‘youngsters’, ‘male participants’ and ‘profit sector’ in Table 4 are control variables, for which we do not have a clear theoretical indication about their sign and hence no predicted sign in the regression.
V. Empirical Results

To test the hypotheses spelled out in Section IV above, we specify five equations. All five are ordered probit regressions – cf. McCullagh (1980). The first two equations – see Table 5 – are devoted to the two available deadweight loss indicators in the data set (DWL and DWL2). Though the regressions that we will present all have the same structure in terms of independent variables, they differ with respect to the structure of the dependent variable in terms of the number of ordinal categories. This implies we cannot rely on the likelihood ratio statistic for model selection, instead we rely on the Akaike, the Schwarz and the Hannan–Quinn criteria.

It is not surprising that all three model selection criteria predict the first equation to yield a superior fit. DWL refers to the behaviour of the firm in the absence of the subsidy, whereas DWL2 refers to the behaviour of participants and other firms in the absence of the subsidy, which is more difficult to judge by the firm hiring the subsidized participant. Deadweight loss is defined as the share of subsidized employees that would have found an unsubsidized job. Since this unsubsidized job could have been found both within and outside the current firm, both DWL and DWL2 should be taken into consideration in our analysis. Therefore, we expect the most pregnant results to come from DWL3, DWL4 or DWL5 – which are amalgamations of DWL and DWL2 – and consequently we restrict the analysis to these three regressions.

Though slightly different, all three model selection criteria indicate that the DWL4 specification yields the best model fit, which implies that our decision to reallocate the six middle partitions in Table 3 paid off.

### Table 4. Set of independent variables to test for deadweight loss

<table>
<thead>
<tr>
<th>DWL</th>
<th>b</th>
<th>c</th>
<th>θ</th>
<th>Predicted DWL</th>
<th>Estimated DWL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participant related characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Youngsters (control variable)</td>
<td></td>
<td></td>
<td>?</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>Male participants (control variable)</td>
<td></td>
<td></td>
<td>?</td>
<td>-**</td>
<td></td>
</tr>
<tr>
<td>Job related characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Part time work</td>
<td></td>
<td></td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>
| Supportive job | | | + | + | -**
| Relevance of work | | | + | + | +***
| Firm/sector related characteristics | | | | | |
| Profit sector (control variable) | | | ? | | |
| Employment growth | | | + | + | +***
| Tightness | | | + | + | +**
| Firm size (number of employees) | | | +/− | −/+ | +*
| Autonomic firm | | | + | | −*
| Employer related characteristics | | | | | |
| Expectations fulfilled and requirements met | | | − | + | +**
| Difficulties to fill low wage jobs | | | + | + | −**
| Unemployment record | | | + | | −**

Note: * 10% significance, ** 5% significance, *** 1% significance.

18 Except for DWL1, which has only two categories and hence boils down to a binary probit regression.
19 More generally one could question the ability of employers to assess the employment probabilities of unemployed in an unsubsidized world, which would endanger the validity of using survey studies to test for deadweight loss patterns, as we do. Calmfors et al. (2001) find that macro econometric studies used to measure additional employment effects of employment subsidies lead to slightly lower estimates of additional employment than survey studies. This indicates that employers somewhat overestimate the unsubsidized employment probabilities of participants. Calmfors et al. (2001) put this difference down to external displacement, i.e. subsidized employment leads to a reduction in employment elsewhere due to competition in goods markets. Controlling for external displacement brings the outcomes of survey and macro econometric studies into line, which leads us to the conclusion that deadweight loss estimates firms provide are accurate.
20 We have considered selectivity bias, as employers are reluctant to report causing deadweight loss, which, from a social point of view, is an unsatisfactory answer. Therefore we expect employers causing deadweight loss to be over-represented in the non-response, which causes a selectivity bias. However, the dataset does not contain any variable related to non-responding firms, which blocks testing for selectivity bias. Still, we think selectivity bias is no major problem to our empirical results, as our interest is not in the share of employers causing deadweight loss, but in the difference in characteristics between deadweight loss provokers and non-provokers. Table 2 shows that our data do not suffer from a lack of firms that admit they provoked deadweight loss. As long as characteristics of non-responding deadweight loss provoking firms do not differ from responding deadweight loss provoking firms, the analysis does not suffer from selectivity bias. We do not have any reasons to assume this variation exists.
## Table 5. Ordinal probit regressions of deadweight loss in VLW

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>DWL1</th>
<th>DWL2</th>
<th>DWL3</th>
<th>DWL4</th>
<th>DWL5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold 1a</td>
<td>-2.39** (0.99)</td>
<td>-1.82** (0.88)</td>
<td>-2.02** (0.92)</td>
<td>-2.25** (0.91)</td>
<td>-2.15** (0.87)</td>
</tr>
<tr>
<td>Threshold 2</td>
<td>-1.26 (0.87)</td>
<td>-0.58 (0.88)</td>
<td>-1.70* (0.89)</td>
<td>-1.67* (0.86)</td>
<td>-1.17 (0.84)</td>
</tr>
<tr>
<td>Threshold 3</td>
<td>-0.91 (0.86)</td>
<td>-0.68 (0.84)</td>
<td>-1.17 (0.84)</td>
<td>-0.68 (0.84)</td>
<td>-1.17 (0.84)</td>
</tr>
<tr>
<td>Threshold 4</td>
<td>-0.89 (0.87)</td>
<td>-0.68 (0.84)</td>
<td>-0.68 (0.84)</td>
<td>-0.68 (0.84)</td>
<td>-0.68 (0.84)</td>
</tr>
</tbody>
</table>

### Participant related characteristics

| Young                   | -0.76 (0.58) | 0.10 (0.34) | -0.40 (0.34) | 0.36 (0.34) | -0.17 (0.34) |
| Mixed                  | 1.35*** (0.50) | 0.76 (0.52) | 0.88 (0.52) | 1.50*** (0.52) | 0.90* (0.52) |
| Older Reference        | -1.10*** (0.37) | -0.46 (0.34) | -0.54* (0.34) | -0.87** (0.34) | -0.62** (0.34) |
| Male                   | -1.33*** (0.50) | -1.09*** (0.41) | -1.09*** (0.42) | -1.80*** (0.46) | -1.23*** (0.40) |
| Female Reference       | -0.24 (0.35) | 0.29 (0.31) | 0.24 (0.31) | -0.05 (0.33) | 0.19 (0.26) |
| Supportive job         | -0.62 (0.54) | -0.04 (0.42) | 0.03 (0.45) | -0.50 (0.54) | -0.12 (0.45) |
| Mixed                  | -0.89 (0.45) | -0.79** (0.36) | -0.77** (0.38) | -0.73** (0.45) | -0.79** (0.38) |
| No important job       | -0.38 (0.42) | -0.79** (0.33) | -0.77** (0.34) | -0.73** (0.36) | -0.79** (0.32) |
| Important job Reference| -0.23 (0.38) | -0.21 (0.36) | 0.11 (0.40) | 0.11 (0.34) | -0.12 (0.34) |

### Job related characteristics

| Part time              | -1.14*** (0.38) | -0.10 (0.34) | -0.25 (0.32) | -0.78** (0.34) | -0.41 (0.31) |
| Mixed                  | -1.32*** (0.45) | -0.67* (0.36) | -0.76** (0.38) | -0.99** (0.45) | -0.80** (0.38) |
| Full time Reference    | -0.24 (0.35) | 0.29 (0.31) | 0.24 (0.31) | -0.05 (0.33) | 0.19 (0.26) |
| Supportive job         | -0.62 (0.54) | -0.04 (0.42) | 0.03 (0.45) | -0.50 (0.54) | -0.12 (0.45) |
| Mixed                  | -0.89 (0.45) | -0.79** (0.36) | -0.77** (0.38) | -0.73** (0.45) | -0.79** (0.38) |
| No important job       | -0.38 (0.42) | -0.79** (0.33) | -0.77** (0.34) | -0.73** (0.36) | -0.79** (0.32) |
| Important job Reference| -0.23 (0.38) | -0.21 (0.36) | 0.11 (0.40) | 0.11 (0.34) | -0.12 (0.34) |

### Firm/sector related characteristics

| Employment growth (1996–1998) | 0.01*** (0.00) | 0.00 (0.00) | 0.00 (0.00) | 0.01*** (0.00) | 0.01* (0.00) |
| Small firm               | -1.23*** (0.41) | -1.27*** (0.38) | -1.35*** (0.36) | -1.27*** (0.41) | -1.28*** (0.34) |
| Medium firm              | 0.23 (0.42) | 0.13 (0.38) | -0.21 (0.36) | 0.11 (0.40) | -0.12 (0.34) |
| Large firm               | -0.33 (0.39) | -0.46 (0.34) | -0.34 (0.31) | -0.61* (0.31) | -0.42 (0.30) |
| Autonomic firm           | -0.45* (0.26) | -0.27 (0.17) | -0.20 (0.18) | -0.38* (0.21) | -0.24 (0.18) |
| Firm being part of larger entity | -0.57* (0.34) | 0.17 (0.31) | -0.05 (0.31) | -0.02 (0.33) | -0.05 (0.30) |
| Collective sector        | -0.34 (0.39) | -0.42* (0.24) | -0.13 (0.23) | -0.59** (0.28) | -0.26 (0.23) |
| Private sector           | -0.91* (0.48) | 0.92** (0.40) | 1.09*** (0.39) | 0.86** (0.36) | 0.95*** (0.36) |

### Employer related characteristics

| Expectations not fulfilled and/or requirements not met | -0.34 (0.29) | -0.42* (0.24) | -0.13 (0.23) | -0.59** (0.28) | -0.26 (0.23) |
| Unclear       | 0.91* (0.48) | 0.92** (0.40) | 1.09*** (0.39) | 0.86** (0.36) | 0.95*** (0.36) |

(Continued)
the marginal differences between the outcomes of all five equations as evidence for the cogency of our results.\footnote{Moreover, we respecified $DWL_4$ using an ordered logit regression to analyse the sensitivity of our results for potential outliers. The logit and probit specifications differ only marginally, which we interpret as further evidence for the cogency of our results.}

The assessment cost hypothesis. Four out of five variables included in testing the assessment cost hypothesis yield the expected effect; only the variable ‘supportive job’ is not significantly different from zero.

Deadweight loss is positively correlated to firm size. That is, small firms cause significantly less deadweight loss than large firms. The firm size effect disappears for medium sized firms, whose incidence of deadweight loss does not significantly deviate from large sized firms, which implies that also medium sized firms enjoy economies of scale. In order to test the existence of economies of scale in screening decisions in a different way we included the variable ‘autonomic firm’. The assessment cost hypothesis is confirmed as autonomous firms (controlling for firm size) cause less deadweight loss. Therefore we conclude that the moderating effect of economies of scale on screening costs $b$ dominates the elevating effect of increased monitoring on screening costs.

Firms that correctly anticipate the productivity of subsidized participants whose productivity equals that of regular employees cause significantly more deadweight loss. This finding is also in line with our theoretical considerations. Finally, the same holds for the variable ‘unemployment record’: firms attaching decisive value to unemployment status as a cheap screening device cause – as expected – significantly less deadweight loss.

The foregone productivity hypothesis. All three variables used in testing the foregone productivity hypothesis produce the expected effect. The variable ‘part time work’ negatively correlates with deadweight loss; important jobs lead to more deadweight loss. Finally, firms facing strong employment growth cause significantly more deadweight loss.

The tightness hypothesis. The two variables included in testing the tightness hypothesis both yield the (significant) opposite effect as expected. Apparently, the screening device standard becomes less effective when used to reduce the length of the hiring period (in order to reduce hiring costs), as tightness goes up. Consequently firms reduce $t$ in tightening conditions. Explanations for this unambiguous finding must lie

---

**Table 5. Continued**

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>$DWL_1$</th>
<th>$DWL_2$</th>
<th>$DWL_3$</th>
<th>$DWL_4$</th>
<th>$DWL_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>No difficulties to fill low wage jobs</td>
<td>0.94*** (0.32)</td>
<td>0.41 (0.28)</td>
<td>0.61** (0.28)</td>
<td>0.63** (0.30)</td>
<td>0.61** (0.28)</td>
</tr>
<tr>
<td>Difficulties to fill low wage jobs</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Long-term unempl. decisive screening device</td>
<td>$-1.23^{**}$ (0.54)</td>
<td>$-1.04^{**}$ (0.43)</td>
<td>$-1.27^{***}$ (0.45)</td>
<td>$-0.82^{**}$ (0.41)</td>
<td>$-1.16^{***}$ (0.42)</td>
</tr>
<tr>
<td>Long-term unempl. non-decisive screening device</td>
<td>$-0.74^*$ (0.42)</td>
<td>$-0.23$ (0.34)</td>
<td>$-0.41$ (0.32)</td>
<td>$-0.20$ (0.31)</td>
<td>$-0.35$ (0.30)</td>
</tr>
<tr>
<td>Long-term unempl. no screening device</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Akaike criterion</td>
<td>1.22</td>
<td>2.30</td>
<td>1.97</td>
<td>1.73</td>
<td>2.79</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>1.69</td>
<td>2.81</td>
<td>2.46</td>
<td>2.22</td>
<td>3.33</td>
</tr>
<tr>
<td>Hannan-Quinn criterion</td>
<td>1.41</td>
<td>2.51</td>
<td>2.17</td>
<td>1.93</td>
<td>3.01</td>
</tr>
<tr>
<td>Likelihood ratio statistic</td>
<td>62.57</td>
<td>70.17</td>
<td>72.04</td>
<td>76.77</td>
<td>76.08</td>
</tr>
<tr>
<td>Probability (LR statistic)</td>
<td>$2.8 \times 10^{-6}$</td>
<td>$1.7 \times 10^{-6}$</td>
<td>$8.4 \times 10^{-8}$</td>
<td>$1.4 \times 10^{-8}$</td>
<td>$1.8 \times 10^{-8}$</td>
</tr>
<tr>
<td>LR index (pseudo $R^2$)</td>
<td>0.35</td>
<td>0.22</td>
<td>0.26</td>
<td>0.30</td>
<td>0.20</td>
</tr>
<tr>
<td>$N$</td>
<td>129</td>
<td>129</td>
<td>128</td>
<td>128</td>
<td>128</td>
</tr>
</tbody>
</table>

Notes: $^*$ The threshold values indicate the cumulative probits when all independent variables equal zero. The negative values, e.g. for threshold 2 (i.e. $DWL_2 = 2$) in specification $DWL_2$ means that the predicted probability of scores of 2 or less on the dependent variable are smaller than for scores greater than 3. The thresholds are necessary for calculating predicted values but are relatively uninteresting. Hence we leave them unmentioned.

Standard errors in parentheses.

* $10\%$ significance, ** $5\%$ significance, *** $1\%$ significance.
outside our model. One potential explanation is that $\chi$ – the average number of assessments needed to find a qualified candidate – is not only a function of $r^*$ and $r_0$, but also of $\theta$, where $\chi_0 < 0$. If the most able unemployed profit more than proportionally from improving labour market conditions, they have left the unemployment pool in tight conditions. This implies that in tight conditions the unemployment pool consists predominantly of low ability unemployed, which raises the failure rate of assessments. If this effect through $\chi$ is large enough, firms will reduce the screening device standard in tight conditions, which explains the decline in deadweight loss incidence in such conditions.

The estimation results presented in Table 5 support our theoretical analysis presented in Section II above partly. The regressions confirm our predicted effects of assessment costs and foregone productivity costs. The predicted effect of tightness on deadweight loss incidence is not confirmed. In contrast, we find that tightness is correlated negatively to deadweight loss. Overall, it turns out that assessment costs, costs of foregone productivity and labour market tightness can be considered important factors in determining deadweight loss and indirectly the screening device standard.

VI. Conclusions

In this paper we have questioned the government’s implicit assumption that, in designing employment subsidy schemes, firms apply a uniform screening device standard. Based on that assumption the government justifies a uniform start value of subsidy entitlement. We show that this notion is invalid and forms an important source of the deadweight loss shares found in employment subsidy schemes.

Differences in firm, job and labour market characteristics induce firms to apply different optimal values of the screening device standard. Thus a government that wants to minimize deadweight loss should set a differentiated start value of subsidy entitlement. It is obvious that such a differentiation might have the unwanted side effect of complicating the design of a employment subsidy. Nonetheless, we think it would be worth while to consider two deviations.

First, our results show that large firms (in terms of employees) cause substantially more deadweight loss than small firms. Most employment subsidy schemes are dealt with by tax authorities, who have the number of employees at a firm readily available. This makes differentiating the start value of subsidy entitlement to firm size a feasible option. In that case large firms should be required, in order to obtain a employment subsidy, to recruit from unemployed facing a longer spell of unemployment than unemployed in small firms do.

Second, our results show that low levels of labour market tightness lead to more deadweight loss. This finding should make policy makers conscious of the fact that, if a government wants to reserve entry into the subsidy scheme only to unemployed who will not find employment without help, the government has to be alert, especially in tight labour market conditions. As the interest to participate is large in slack labour market conditions, the entrance condition should be strict. In tight labour market conditions the need to use unemployment duration as a selection mechanism is less urgent. In such conditions anyone unemployed willing to participate may be considered unable to find a job without help. In addition, a government that brings the start value of subsidy entitlement in line with labour market conditions lowers deadweight loss shares.

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