



# VU Research Portal

## Job search and commuting time

van den Berg, G.J.; Gorter, C.

1996

### **document version**

Early version, also known as pre-print

[Link to publication in VU Research Portal](#)

### **citation for published version (APA)**

van den Berg, G. J., & Gorter, C. (1996). *Job search and commuting time*. (Research Memorandum; No. 1996-1). Vrije Universiteit Amsterdam.

### **General rights**

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal ?

### **Take down policy**

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

### **E-mail address:**

[vuresearchportal.ub@vu.nl](mailto:vuresearchportal.ub@vu.nl)

ET

iteit der Economische Wetenschappen en Econometrie

05348

1996

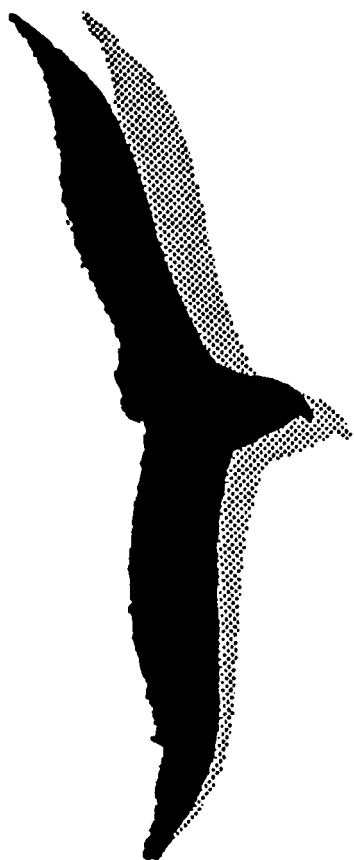
001 Serie research memoranda

Job Search and Commuting Time

Gerard J. van den Berg  
Cees Gorter

Research Memorandum 1996-1

January 1996



|a|l|e|r|t|

applied  
labour  
economics  
research  
team

*vrije* Universiteit

*amsterdam*



# Job Search and Commuting Time

Gerard J. van den Berg \*

Cees Gorter †



January 8, 1996

## Abstract

We structurally analyze a job search model for unemployed individuals that allows jobs to have different wage/commuting-time combinations. The structural parameter of interest is the willingness to pay for commuting time. We use a unique dataset containing subjective responses on the optimal search strategy by unemployed individuals in order to estimate this structural parameter without the need to rely on strong functional form assumptions. We pay special attention to specification errors in the model and to measurement errors in the data. The estimation results identify certain types of individuals who have a very low willingness to pay for (i.e. a very high disutility of) commuting time.

---

\* Free University Amsterdam, Tinbergen Institute and CEPR.

† Free University Amsterdam and Tinbergen Institute.

Address: Department of Economics, Free University Amsterdam, De Boelelaan 1105, NL-1081 HV Amsterdam. The Netherlands.

Keywords: structural estimation, job search model, commuting time, reservation wage, willingness to pay.

This research was stimulated by a discussion with Ken Wolpin. Also thanks to Guido Imbens, Wilbert van der Klaauw and colleagues at the Free University for their comments. The Netherlands Organization for Strategic Labour Market Research allowed us to use the data. Gerard J. van den Berg acknowledges the Royal Netherlands Academy of Arts and Sciences for financial support.

# 1 Introduction

During the last decade, a structural approach has become prominent in the empirical analysis of individual unemployment durations and search behavior. In this approach, the framework of job search theory is used explicitly in the empirical analysis. In particular, the structural parameters of the job search model (i.e. the parameters of the utility function and the distribution functions of the stochastic events faced by the searcher) are estimated. The results enable a distinction between choice and chance components of the exit rate out of unemployment. Moreover, the parameter estimates can be used to estimate elasticities of this exit rate with respect to its determinants. These in turn can be used for policy analyses. Mortensen (1986) contains a survey of job search theory. See Flinn and Heckman (1982), Wolpin (1987) and Van den Berg (1990a) for examples of structural empirical analyses. Wolpin (1992) surveys the empirical literature.

In virtually all of the models used, jobs are characterized by a single variable (the wage). This implies that the optimal strategy of an unemployed individual can be characterized by a one-dimensional reservation wage. Blau (1991) is a notable exception. In his model, jobs are allowed to have different wage/hours combinations, and the optimal strategy compares utility levels associated with different combinations. There are other relevant job characteristics that are not taken account of in the literature. In particular, none of the studies in the literature addresses the fact that potential jobs differ with respect to the commuting time (i.e. the time needed to travel between the present home and the location at which the work is done). Unit commuting costs may be an important determinant of behavior. If it is high, then the individual may prefer to reject an offer of a far-away job in favor of a job around the corner even if the former job offers a much higher wage. In that case these costs may affect the allocation process on the labor market. A structural analysis of a job search model allowing jobs to have different wage/commuting-costs combinations provides estimates of the effect of commuting costs on job search behavior. This in turn helps to address the effect of subsidizing these costs.

Recently, in The Netherlands, there has been a growing interest in interactions between geographical mobility and mobility on the labor market. The Netherlands is the third most densely populated country in the world. Most of its population is located in the Western part of the country. During rush hours, there is an extremely large amount of traffic congestion in this part of the country. This has stimulated investments in infrastructure. At the same time, there is a growing political awareness that commuting traffic harms the environment. In

1989 the national government fell over the issue of tax deductions for commuting costs.

In order to predict the effects of policy changes, it is essential to know how these changes would affect individual behavior regarding acceptance and rejection of job offers. In this paper we structurally analyze a job search model allowing jobs to have different wage/commuting-time combinations. It is well known that the results of structural empirical analyses of partial job search models based only on unemployment duration data and data on characteristics of accepted jobs, are dependent on functional-form assumptions on the wage offer distribution (see Flinn & Heckman (1982)). One way to deal with this is to use information from subjective responses on aspects of search behavior or the environment facing the searcher (see for example Lancaster & Chesher (1983), Van den Berg (1990a) and Van den Berg (1995)). Here we use a unique dataset containing subjective responses by unemployed respondents on (i) their reservation wage for jobs requiring virtually no commuting time, and (ii) their reservation wage for jobs requiring an hour of commuting time per home-to-work trip.<sup>1</sup>

We specify a job search model with the following distinguishing characteristics. First, job offers are characterized by random drawings from a bivariate distribution of wages and commuting times. These variables are not necessarily independent, nor are potential jobs necessarily uniformly distributed over the universe. Second, individuals are allowed to change their residence at a certain cost upon accepting a job offer. Third, instantaneous utility depends on income and on commuting time. Fourth, the model is nonstationary. In particular, the unemployment benefits level, the job offer arrival rate and the distribution of wages and traveling times are allowed to change over the duration of unemployment.

In this paper, the parameter of interest is the utility trade-off between the wage and the commuting time, or, in other words, the willingness to pay for commuting time. (Note that “willingness to pay” is used here in a slightly different context than in a traditional static model framework, since we have a dynamic model with stochastic arrivals of opportunities. It does however refer to a parameter of the instantaneous utility function.) We characterize the optimal strategy in the model and derive the expressions for the theoretical equivalents of the two subjective responses mentioned above. By taking the difference of these, a number of nuisance factors cancel, and the parameter of interest is identified in a

---

<sup>1</sup>In the empirical literature on job search, subjective reservation wage data have been used both in reduced-form regressions and in structural analyses; see Devine and Kiefer (1991) and Wolpin (1992) for surveys. None of the subjective reservation wage data used in the literature distinguishes between jobs with different characteristics.

straightforward way. We estimate this parameter for different types of individuals. The prime methodological contribution of the paper thus consists of showing that responses on basic quantitative characteristics of the search strategy can be fruitfully used to estimate structural parameters of job search models, without the need to rely on strong functional form assumptions. In particular, in this way one can estimate utility function parameters of search models with multiple job characteristics.

Contrary to many other analyses that use subjective responses on the search process, we pay considerable attention to measurement errors in such responses. In the estimation procedure we deal with different types of such errors. It is not uncommon that part of the respondents fail to understand questions on reservation wages (see e.g. Lancaster & Chesher (1983) and Ridder & Gorter (1986)), or do not bother to give precise answers. This problem may be even more prominent in case such questions refer to jobs with different non-wage characteristics. Respondents may return a zero reservation wage difference for two types of jobs if the real difference is very small, and they may round off the probability of a very unlikely event to zero. We adopt a specification of the measurement error distribution that allows for these errors. As a result, the empirical model has a limited-dependent variable specification. This empirical model bears a remote formal resemblance to a disequilibrium controlled-prices trading model with unobserved prices (see Maddala (1983)). We develop a Hausman specification test to test whether a qualitative categorization of responses is in accordance to quantitative responses within some of these categories.

As noted above, there is a growing interest in interactions between geographical mobility and job mobility in The Netherlands. References relevant for our purposes include Rouwendal & Rietveld (1994a), who use a cross section of wages and commuting distances of employed individuals to estimate some parameters of a search model that allows for stochastic commuting distances. They assume that the wage offered is independent of the commuting distance, and they take parametric distributions for both variables. HCG (1990) contains a descriptive study on subjective valuation of commuting time in The Netherlands (this study is summarized in Bates & Glaister (1990) and in Waters (1992)). Below we compare our results to those in the literature. Gorter (1994) surveys the Dutch literature on spatial aspects of labor market behavior. Most of the qualitative implications of our theoretical model are in accordance to the stylized facts in this literature.

The outline of the paper is as follows. In Section 2 we present the job search model sketched above. In Section 3 we discuss the data, and in Section 4 we

propose a method to estimate the parameters of interest from the data at hand. The approach is fairly general, in the sense that it can be fruitfully applied to estimate utility trade-offs between any two different job characteristics, provided that appropriate subjective responses on the optimal strategy are available. In Section 4 we also address identification of the parameters of the empirical model specification. Section 5 contains the results. We also examine some implications of the estimates, and we test the model specification, both by testing theory-based exclusion restrictions and by applying general model specification tests like the Hausman test. Section 6 concludes.

## **2 The job search model with stochastic commuting times**

### **2.1 The general model**

Job search theory tries to describe the behavior of unemployed individuals in a dynamic and uncertain environment. In this section we develop a job search model that takes account of positive commuting times associated with potential jobs, and that allows these times to be dispersed over potential jobs. The model is nonstationary and in continuous time. It can be regarded as a generalization of the nonstationary job search model as developed by Van den Berg (1990a). Because of that, we avoid technicalities.

Job offers arrive at random intervals following a possibly non-homogeneous Poisson process with arrival rate  $\lambda(t)$ , in which  $t$  denotes the elapsed duration of unemployment. A job offer at time  $t$  is a random drawing (without recall) from the joint distribution of net wages  $w$  and commuting times  $h$ , with distribution function  $F(w, h|t)$ . Several comments are in order. First of all, we take the wage to be net of pecuniary commuting costs and possible refunds for these costs by the employer, so that the value of  $h$  does not reflect pecuniary aspects of the job offer. Later on we return to this issue. Secondly, in line with the theoretical and empirical literature on search theory, we assume that all jobs are full-time jobs. Thirdly, we allow commuting times to be non-uniformly distributed over space. For example, for an individual living in a village, most job offers may originate from a nearby larger town, so they will have approximately the same commuting time. Finally, we allow the wage offers to be dependent on the associated commuting times. This is just for reasons of generality. For example, one may live close to a few small firms offering low wages and far from a large firm offering a

higher wage.

Every time an offer arrives, the decision has to be made whether to accept the offer or reject it and search further. Initially, we assume that once a job is accepted it will be kept forever at the same wage. This means that we exclude job-to-job transitions. Later on we will examine the consequences of relaxing this assumption. Upon accepting a job offer, the individual has the possibility of changing his residence at a fixed cost  $c$ , in order to reduce commuting time to zero. In that case the individual borrows the amount of  $c$ , and returns the money flow  $\rho c$  to the bank for the rest of his life. (The exact terms of the mortgage are inessential for the remainder.) During the spell of unemployment, unemployment benefits  $b(t)$  are received.

Nonstationarity arises if  $b(t)$ ,  $\lambda(t)$  or  $F(w, h(t))$  change as a function of  $t$ . Such changes may be due to business cycle effects, policy changes, institutional features of the environment facing the searcher, or stigma effects. We assume that job searchers have perfect foresight in the sense that they correctly anticipate changes in the values of these functions of  $t$ . Individuals do not know in advance when job offers arrive, or which  $w$  and  $h$  are associated with them.

Unemployed individuals aim at maximization of their own expected present value of utility over an infinite horizon. We assume that utility is intertemporally separable. The instantaneous utility function equals  $u(w, h)$  in case one works at a wage  $w$  and commuting time is equal to  $h$ , whereas it equals  $v \cdot u(b, 0)$  in case one is unemployed and benefits are equal to  $b$ . We assume that  $u$  strictly increases (strictly decreases) in its first (second) argument. The parameter  $v$  represents the non-pecuniary component of instantaneous utility in unemployment relative to employment. Empirical studies on other data sets have found this to be smaller than one (see e.g. Van den Berg (1990a) and Van den Berg (1990b) and references therein).

Let  $\rho$  be the rate of discount, and let  $R(t)$  denote the expected present value of search if unemployment duration equals  $t$ , when following the optimal strategy. Analogous to Van den Berg (1990a) it can be shown that, under regularity conditions, there is a unique continuous solution to the Bellman equation for  $R(t)$ . This equation then implies the following differential equation for  $R(t)$  at points at which  $R(t)$  is differentiable in  $t$ ,

$$\rho R(t) = \frac{dR(t)}{dt} + v \cdot u(b(t), 0) + \lambda(t) \cdot E_{w,h|t} \max \left\{ 0, \frac{u(w, h)}{\rho} - R(t), \frac{u(w - \rho c, 0)}{\rho} - R(t) \right\} \quad (1)$$



In this equation, the expectation is taken over the distribution with c.d.f.  $F(w, h|t)$ . Equation (1) has a familiar structure. The return of the asset  $R(t)$  in a small interval around  $t$  equals the sum of the appreciation of the asset in this interval, the instantaneous utility flow in this interval, and the expected excess value of finding a job in this interval. When an offer of  $w, h$  arrives at  $t$  then there are three options: (i) to reject it (excess value zero), (ii) to accept it and spend commuting time  $h$  in the future (excess value  $u(w, h)/\rho - R(t)$ ), and (iii) to accept it and move to a residence at the location of the job (excess value  $u(w - \rho c, 0)/\rho - R(t)$ ). It is clear that the optimal policy is to choose option (ii) if  $u(w, h) > \rho R(t)$  and  $u(w, h) > u(w - \rho c, 0)$ , to choose option (iii) if  $u(w - \rho c, 0) > \rho R(t)$  and  $u(w, h) < u(w - \rho c, 0)$ , and to choose option (i) in all other cases.

Figure 1 depicts the areas associated with each choice for a typical case. The optimal strategy can be characterized by three reservation wage type functions, as follows. First, suppose one cannot change residence. Then a job offer of  $w, h$  at  $t$  is acceptable if and only if  $w$  exceeds the reservation wage for offers at  $t$  of jobs with  $h$  hours of commuting time. This reservation wage is denoted by  $\phi(h|t)$  and is implicitly defined by

$$u(\phi(h|t), h) = \rho R(t) \quad (2)$$

Now suppose changing residence is allowed. Then, upon acceptance of an offer of  $w, h$  using the criterion  $\phi(h|t)$ , the individual decides to change residence if and only if  $h$  exceeds the "moving threshold" commuting time for jobs with wage  $w$ . The moving threshold is denoted by  $\xi(w)$  and is implicitly defined by

$$u(w, \xi(w)) = u(w - \rho c, 0) \quad (3)$$

Note that  $\xi(w)$  does not depend on the unemployment duration  $t$ .

Finally, some jobs are acceptable if changing residence is possible, while they are unacceptable if changing residence is not possible. In that case  $w, h$  fails to satisfy  $w \geq \phi(h|t)$ , while it does satisfy  $w > \zeta(t)$ , with  $\zeta(t)$  implicitly defined by

$$u(\zeta(t) - \rho c, 0) = \rho R(t) \quad (4)$$

Note that  $\zeta(t)$  does not depend on  $h$ .

From equations (2) and (3) one can derive simple comparative statics, like

$$\frac{\partial \phi(h|t)}{\partial h} > 0 \quad \text{and} \quad \frac{\partial \xi(w)}{\partial c} > 0. \quad (5)$$

Other comparative exercises can be carried out analogous to Van den Berg (19904).

For the sequel it is important to note that the values of the function  $\phi(h|t)$  depend on the values of all the deep structural parameters and functions  $\lambda, F, b, c, u, v$  and  $\rho$ .

## 2.2 Reservation wage differences

As stated in the introduction, the data provide information on the reservation wages given two possible realizations of commuting time. In particular, the data provide subjective responses on  $\phi(1|t)$  and  $\phi(0|t)$ , with commuting time measured in hours, and with  $t$  denoting the elapsed unemployment duration of the respondent. We therefore now examine  $\phi(h|t)$  more closely in the theoretical model. Note that  $\phi(h|t)$  is sensibly defined even if  $h$  is so large that it is always optimal to change residence upon accepting a job. In the latter case the value of  $\phi(h|t)$  is irrelevant for actual behavior, but it does correctly describe the optimal strategy in case a zero-probability offer comes along of a job on commuting time  $h$  for which changing residence is forbidden.

Let  $u_1$  and  $u_2$  denote the partial derivatives of  $u$  with respect to their first and second argument, respectively. By differentiating equation (2) with respect to  $h$  we obtain

$$\frac{\partial \phi(h|t)}{\partial h} = -\frac{u_2(\phi(h|t), h)}{u_1(\phi(h|t), h)} \quad (6)$$

Somewhat informally, this states that if  $h$  increases then the increase of the reservation wage is such that at the new reservation wage the decrease in utility due to the increase of  $h$  is exactly offset. Note that minus the right-hand side of equation (6) defines the (negative) marginal willingness to pay for commuting time  $h$  when the reservation wage equals  $\phi(h|t)$ . From the equation it is clear that information on the behavior of  $\phi(h|t)$  as a function of  $h$  allows identification of  $u_2/u_1$ .

From equation (2) it follows that for all  $t$  and all  $h$  there holds that

$$u(\phi(h|t), h) = u(\phi(0|t), 0) \quad (7)$$

We now make the assumption that preferences are additive in  $w$  and  $h$ , i.e. that there are functions  $k, g$  and  $U$  such that for every  $w, h$  there holds that

$$u(w, h) = U(k(w) + g(h)) \quad (8)$$

By substituting this into equation (7) it follows that

$$k(\phi(h|t)) - k(\phi(0|t)) = g(0) - g(h) \quad (9)$$

The right-hand side of this equation can be interpreted as an indicator of the *ceteris paribus* difference in utility for commuting time 0 and commuting time  $h$ .

Several comments are in order. First, note that the only way in which  $t$  enters this equation is as an argument of the reservation wage function. Given values of  $\phi(h|t)$  and  $\phi(0|t)$ , nothing in the equation changes with  $t$ . Secondly, the latter is also true for the structural parameters other than the utility function. Given values of  $\phi(h|t)$  and  $\phi(0|t)$ , nothing in the equation changes with  $\lambda, F, b, c, v$  or  $\rho$ . These properties are of importance for the empirical implementation below.

Note that in the special case in which both  $k$  and  $g$  are linear, equation (9) specifies  $\phi(h|t) - \phi(0|t)$  as a linear function of  $h$ . Consequently, in that case the utility function  $u$  can be completely identified (up to a monotone transformation) from information on  $\phi(1|t) - \phi(0|t)$ .

It may be clear from the derivation above that the form of equation (9) is robust with respect to numerous generalizations c.q. misspecifications of the model. Basically, this equation follows from a comparison of the lifetime utilities of jobs with different commuting times. Since the search technology in unemployment and the instantaneous utility of unemployment do not affect the lifetime utility of a job, the part of the model describing the former can be generalized substantially at no cost.

On the other hand, if employed individuals search optimally to obtain better jobs, then the lifetime utility of a job with given  $w, h$  depends on the parameters of the search technology in employment. It can be shown that then these parameters directly enter the equivalent of equation (7) (that is, in addition to the effect they have on  $\phi(h|t)$  and  $\phi(0|t)$ ). This is also true for the right-hand side of the equivalent of equation (9). So, if the job offer arrival rates in employment and unemployment are the same, then the right-hand side of the equivalent of (9) depends on  $\lambda$ . Similarly, if preferences do not satisfy equation (8) then the right-hand side of the equivalent of equation (9) (which would be some kind of difference of  $\phi(1|t)$  and  $\phi(0|t)$ ) includes all structural parameters of the model. An empirical analysis in the context of these extended models would require the joint estimation of all the structural parameters. (Note that the extension in which employed individuals are allowed to search is fundamentally more complex than the model we developed, since the reservation wage of an employed individual depends on (i) his present wage and (ii) commuting time, and on (iii) the commuting time associated with the offer at hand.) Nevertheless, the results of

this paragraph suggest that our model specification can be tested by examining whether the right-hand side of the reservation wage difference equation (9) depends on observable variables representing structural determinants of the model (like  $b$  and  $X$ ). In such a case it should be clear *a priori* that such variables do not affect the true utility function.

A similar result follows by extending the model to allow for habit formation. Suppose that the willingness to pay for commuting time  $g(h)$  depends on unemployment duration  $t$ . Then the right-hand side of equation (9) depends on  $t$  (under the condition that the optimal strategy still has the reservation wage property). This can be tested, taking into account that  $t$  is an endogenous variable.

In Section 4 we discuss the empirical implementation of the model developed in this section. As noted in the introduction, we pay substantial attention to the modeling of different types of measurement errors in the data. We therefore first describe the data we use, in Section 3.

### 3 The data set

For the empirical analysis, we use data from the OSA (Netherlands Organization for Strategic Labour Market Research) Labor Supply Panel Survey. In this survey, a random sample of households in The Netherlands is followed over time. The study concentrates on individuals who are between 15 and 61 years of age, and who are not full-time students. Therefore only households with at least one person in this category are included. All individuals (and in all cases the head of the household) in this category are interviewed. The first wave consists of 4020 individuals (in 2132 households), and has been collected in April 1985. The length of the time interval between two consecutive interviews is generally about two years.

At the first interview, respondents were asked to recall their labor market history from January, 1980 until the date of the interview. They were also asked to provide information on their income at the date of the interview. In addition, a number of time-constant individual characteristics is recorded.

The data set contains unique quantitative information on the strategy used by unemployed job searchers. At the first interview, individuals who were unemployed at the date of that interview were asked for their lowest acceptable net wage offer. Responses on this question are interpreted as the observed counterpart of the reservation wage  $\phi(0|t)$ , in which  $t$  is the elapsed duration of unemployment at the first interview. Immediately after this question, the respondent is asked

for his lowest acceptable net wage offer *if the time needed to travel from home to the work location as well as the time needed for the reverse route would be one hour, and if all pecuniary commuting costs would be reimbursed by the employer.* Responses on the latter question are interpreted as the observed counterpart of the reservation wage  $\phi(1|t)$ . These questions were not repeated at subsequent interviews. In the sequel, we use  $\tilde{\phi}(h|t)$  ( $h = 0, 1$ ) to denote the answer to the question on  $\phi(h|t)$ .

One might argue that the first question can also be interpreted as referring to the mean reservation wage  $E_h(\phi(h|t))$  over all commuting times, rather than to  $\phi(0|t)$ . However, the question refers to the **lowest** acceptable offer, and the lowest possible acceptable wage offer is  $\phi(0|t)$ , since  $\phi(h|t)$  increases in  $h$ . Moreover, it may be reasonable to assume that for most unemployed individuals the “standard” job is a job around the corner. (Note that this may not be true for employed individuals.)

For our analysis, we have selected individuals who reported to be unemployed and searching for a job in the first wave of the survey (272 cases). After eliminating observations with missing information, a sample of 238 individuals remains.

When answering the question on  $\phi(1|t)$ , the respondent has the option of stating that at the time of the interview he would never accept a job with the characteristics described in the question. In that case, the respondent states that  $u(w, 1) < \rho R(t)$  for all  $w$  in the support of  $F(w, 1|t)$  (see equation (2)). This will happen when commuting costs are extremely high. In any case, we can denote this by  $\tilde{\phi}(1|t) = \infty$ .

Consequently, we can distinguish between three types of answers. Given an answer  $\tilde{\phi}(0|t)$ , the respondent supplies either  $\tilde{\phi}(1|t) = \tilde{\phi}(0|t)$ , or  $\tilde{\phi}(0|t) \neq \tilde{\phi}(1|t) < \infty$ , or  $\tilde{\phi}(1|t) = \infty$ . We denote these as Cases 1, 11 and 111, respectively. According to Table 1, they hold for 54%, 31% and 15% of the respondents, respectively. For those in the second group, the average difference between  $\tilde{\phi}(1|t)$  and  $\tilde{\phi}(0|t)$  equals about US \$ 130 per month. Figure 2 summarizes the sample distribution of  $\tilde{\phi}(1|t) - \tilde{\phi}(0|t)$  for the second group. We postpone a discussion of the empirical model specification for the Cases 1 and 111 until the next section.

We use information from the first interview on personal characteristics (like gender and age) and household characteristics (married or living together, number of children at home). We also include variables reflecting differences in the regional environment. First, an indicator is created to measure the condition of the regional labor market for each individual in the sample. For this purpose, the OSA labor market survey was extended with data on unemployment rates in regional-occupational labor market segments. We distinguish between 40 regions.

For each of these regions, unemployment rates have been calculated for groups defined by occupation (we distinguish between 46 types), age (5 categories) and gender. Secondly, we use the degree of urbanization to control for behavioral differences of individuals in urban and peripheral areas. Table 1 contains an overview of variables and their sample means.

## 4 The empirical implementation

### 4.1 A basic empirical specification

In this section we discuss how to use equation (9) in conjunction with the data discussed in the previous section, to estimate the parameter of interest. First of all, we assume for the moment that the function  $k$  is linear,

$$k(w) = k_0 + k_1 w \quad (10)$$

This assumption will be relaxed later on. By substituting (10) into equation (9) it follows that

$$\phi(1|t) - \phi(0|t) = \frac{g(0) - g(1)}{k_1} \quad (11)$$

The right-hand side of this equation can be interpreted as the pecuniary equivalent of the *ceteris paribus* difference in utility between commuting time 0 and commuting time  $h = 1$ . In other words, it is minus the (negative) willingness to pay for commuting time  $h = 1$ . Note that  $k_0$  (including all the variables that only affect the *level* of the reservation wage as a function of  $h$ ) has canceled from this equation. Because the right-hand side of equation (9) does not depend on  $t$ , we will suppress the dependence of  $\phi(h|t)$  on  $t$  in the notation below.

The empirical implementation has to deal with at least three different issues. First, it has to deal with the way in which the model specification is allowed to vary over observed explanatory variables, and with the role of omitted explanatory variables and related specification errors. Secondly, it has to deal with the modeling of the three cases we distinguished concerning the response to the questions on  $\phi(1)$  and  $\phi(0)$ . Thirdly, it has to deal with possible measurement errors in the case in which the respondent supplies answers  $\tilde{\phi}(0) \neq \tilde{\phi}(1) < \infty$ .

Consider the first issue. For obvious reasons, it is likely that  $(g(0) - g(1))/k_1$  differs among different types of individuals. Let  $x$  denote the observed explanatory variables. We make the following parameterization,

$$\frac{g(0) - g(1)}{k_1} = x'\beta + e \quad (12)$$

with  $E(e) = 0$  and  $e \perp x$ . We take  $e$  to be i.i.d.  $\text{Normal}(0, \sigma_e^2)$  across individuals. The variable  $e$  is assumed to capture the effects of unobserved (omitted) explanatory variables on  $(g(0) - g(1))/k_1$ , i.e. it is a specification error.

In Section 3 we observed that a positive fraction of the respondents give exactly the same answer to the question on  $\phi(1)$  as to the question on  $\phi(0)$ . Probably, respondents do not bother to give a different answer if the difference in values is very small. Such observations then provide information on the parameter of interest. The data seem to confirm this in the sense that the proportion of respondents in Case 1 is smaller for groups of individuals for which we a priori expect a larger disutility of commuting (e.g. females). Also, note from Figure 2 that the sample distribution of the observed difference of  $\phi(1)$  and  $\phi(0)$  is heavily skewed to the right and that the left-hand tail ends rather abruptly at about Dfl 50 per month. (Later on we formally test whether this interpretation of Case 1 responses is correct.) We assume that

$$\tilde{\phi}(1) = \tilde{\phi}(0) \Leftrightarrow \phi(1) - \phi(0) < c_0 \quad (13)$$

In Section 3 we also observed that a positive fraction of the respondents basically states that the value of  $\phi(1)$  is so large that a transition to a job with commuting time  $h = 1$  is precluded (Case 111). Probably respondents, when giving such an answer, ignore the highly unlikely event of an arrival of an extremely large wage offer that would induce them to accept the corresponding commuting time  $h = 1$ . Again, such observations provide information on the parameters of interest, and the data confirm this in the same sense as in the previous paragraph. We therefore take

$$\tilde{\phi}(1) = \infty \Leftrightarrow \phi(1) - \phi(0) > c_1 \quad (14)$$

In the light of the fact that this group of respondents consists only of 36 individuals, we do not attempt to estimate a more sophisticated model for this case.

At this stage it is instructive to examine the model without measurement errors in the Case 11 answers  $\tilde{\phi}(1) - \tilde{\phi}(0)$  (i.e., when these satisfy  $\tilde{\phi}(1) - \tilde{\phi}(0) = \phi(1) - d(0)$ ). In this case

$$\begin{aligned} \tilde{\phi}(0) \neq \tilde{\phi}(1) < \infty \quad \Leftrightarrow \quad c_0 < \phi(1) - \phi(0) < c_1 \quad \text{and} \\ \tilde{\phi}(1) - \tilde{\phi}(0) = x'\beta + e \end{aligned} \tag{15}$$

Suppose one were to estimate this model. This model can be called a two-limit Tobit model with quantitative observations for the middle group and with unknown threshold values. The unknown parameters are  $\beta$ ,  $\sigma_e$ ,  $c_0$  and  $c_1$ . The likelihood contains the restrictions that for all individuals in Case 11 there holds that

$$c_0 < \tilde{\phi}(1) - \tilde{\phi}(0) < c_1 \tag{16}$$

Denote the numbers of respondents in Cases 1, 11 and 111 by  $n_1$ ,  $n_2$  and  $n_3$ , respectively. Apart from the restrictions in equation (16), the log likelihood is as follows (with  $\Psi$  denoting the cumulative distribution function of the Standard Normal distribution):

$$\begin{aligned} \log L = \sum_{n_1} \log \Psi \left( \frac{c_0 - x'\beta}{\sigma_e} \right) + \sum_{n_3} \log \Psi \left( \frac{x'\beta - c_1}{\sigma_e} \right) + \\ -n_3 \log \sigma_e - \frac{1}{2\sigma_e^2} \sum_{n_2} (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta)^2 \end{aligned} \tag{17}$$

The first term on the right-hand side is based on the probability that the event described in equation (13) occurs, using equations (11) and (12) and using the normal distribution of  $e$ . Similarly, the second term is based on the probability that the event described in equation (14) occurs. The last terms are based on product of (i) the probability that the event described in equation (15) occurs and (ii) the density of  $\tilde{\phi}(1) - \tilde{\phi}(0)$  conditional on the event described in equation (15).

The expression on the right-hand side of equation (17) is increasing in  $c_0$  and decreasing in  $c_1$ . This means that the maximum likelihood estimates of these parameters are determined by the inequality restrictions (16). Specifically, the estimate of  $c_0$  ( $c_1$ ) equals the smallest (largest) observed  $\tilde{\phi}(1) - \tilde{\phi}(0)$  among Case 11 respondents. Thus, the likelihood is discontinuous and the ML estimators have non-standard properties. (There is an analogy to the estimation of job search models in case the reservation wage is estimated as the smallest observed accepted wage offer (see Flinn & Heckman (1982)). Basically, the ML estimates



of  $c_0$  and  $c_1$  can be considered as being exactly correct when estimating the other parameters by ML.) It is clear that such estimates are extremely sensitive to measurement errors in the  $\tilde{\phi}(h)$  data. For example, if only one respondent erroneously supplies a value of  $\tilde{\phi}(1)$  which is extremely large, and larger than his true  $\phi(1)$ , then the estimate of  $c_1$  will be substantially biased in an upward direction, and this will affect the other estimates.

This suggests that it is necessary to account for measurement errors in the model specification. There is actually another way to argue that the specification of the model above is restrictive. Note that the model can be thought of as consisting of two stages: (1) an ordered probit stage describing the allocation of respondents over the Cases I, II and 111, and (2) a regression stage describing the quantitative values of the endogenous variable of the respondents in Case 11. The model states that the stochastic variation governing the first stage is the same as the stochastic variation governing the second stage: the only source of variation consists of specification errors. Clearly, this is restrictive. We will now present two model extensions that deal with this. The first one will turn out to be the empirically superior one.

## 4.2 More sophisticated empirical specifications

The first extension of the basic specification of the previous subsection concerns the inclusion of measurement errors in the values of  $\tilde{\phi}(1) - \tilde{\phi}(0)$  of the Case 11 respondents. First of all, note that any systematic measurement error, equally affecting the supplied values of  $\phi(1)$  and  $\phi(0)$  of a Case 11 respondent, cancels from the equation for  $\tilde{\phi}(1) - \tilde{\phi}(0)$ . Now suppose that there are measurement errors  $v$  in the values of  $\tilde{\phi}(1) - \tilde{\phi}(0)$  supplied by Case 11 respondents, in the following way,

$$\tilde{\phi}(1) - \tilde{\phi}(0) = \phi(1) - \phi(0) + v \quad (18)$$

These may be due to calculation errors. They do not cancel e.g. if on average the error made in calculating  $\phi(1)$  exceeds the error made in calculating  $\phi(0)$ , which is plausible. As a consequence, equation (15) is replaced by

$$\begin{aligned} \tilde{\phi}(0) \neq \tilde{\phi}(1) < \infty \quad \Leftrightarrow \quad c_0 < \phi(1) - \phi(0) < c_1 \quad \text{and} \\ \tilde{\phi}(1) - \tilde{\phi}(0) = x'\beta + e + v \end{aligned} \quad (19)$$

in which  $\phi(1) - \phi(0)$  is still described by equations (11) and (12). We assume that  $E(v) = 0$  and  $e \perp v \perp x$ . We take  $v$  to be i.i.d.  $\text{Normal}(0, \sigma_v^2)$  across individuals.

In this model, the unknown parameters are  $\beta, \sigma_e, \sigma_v, c_0$  and  $c_1$ . Now there are no inequality restrictions for the unknown parameters in terms of the data (like (16)). This is basically because for any Case 11 respondent there are positive probabilities on  $\tilde{\phi}(1) - \tilde{\phi}(0) < c_0$  and on  $\tilde{\phi}(1) - \tilde{\phi}(0) > c_1$ .

To derive the likelihood contributions of respondents in Case 11, it is necessary to derive the density  $w$  of  $\tilde{\phi}(1) - \tilde{\phi}(0)$  conditional on being in Case 11, that is the density of  $x'\beta + e + v$  conditional on  $c_0 - x'\beta < e < c_1 - x'\beta$  (and conditional on  $x$ ). By applying results in Pudney (1989) we obtain (with  $\psi$  denoting the p.d.f. of the Standard Normal distribution):

$$\omega(\tilde{\phi}(1) - \tilde{\phi}(0) | c_0 < \phi(1) - \phi(0) < c_1) = \frac{1}{\sqrt{\sigma_e^2 + \sigma_v^2}} \psi \left( \frac{\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta}{\sqrt{\sigma_e^2 + \sigma_v^2}} \right) \quad (20)$$

$$\frac{\Psi \left( \frac{c_1 - x'\beta - (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta) \frac{\sigma_e^2}{\sigma_e^2 + \sigma_v^2}}{\frac{\sigma_e \sigma_v}{\sqrt{\sigma_e^2 + \sigma_v^2}}} \right) - \Psi \left( \frac{c_0 - x'\beta - (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta) \frac{\sigma_e^2}{\sigma_e^2 + \sigma_v^2}}{\frac{\sigma_e \sigma_v}{\sqrt{\sigma_e^2 + \sigma_v^2}}} \right)}{\Psi \left( \frac{c_1 - x'\beta}{\sigma_e} \right) - \Psi \left( \frac{c_0 - x'\beta}{\sigma_e} \right)}$$

If  $\sigma_v = 0$  then the numerator of the ratio forming the last part of equation (20) reduces to the indicator function of the event described by (16), so then the density above reduces to the doubly truncated Normal density for the basic specification of the previous paragraph. For  $\sigma_v > 0$  the density above has thinner tails than Normal densities. Note that if  $\tilde{\phi}(1) - \tilde{\phi}(0)$  gets very large or very small, then the ratio forming the last part of equation (20) goes to zero. In sum, the density described by equation (20) is a sort of average between a Normal density and a doubly truncated Normal density.

By invoking equation (20) it can be shown that the log likelihood equals

$$\log L = \sum_{n_1} \log \Psi \left( \frac{c_0 - x'\beta}{\sigma_e} \right) + \sum_{n_3} \log \Psi \left( \frac{x'\beta - c_1}{\sigma_e} \right) + \quad (21)$$

$$-\frac{n_2}{2} \log(\sigma_e^2 + \sigma_v^2) - \frac{1}{2(\sigma_e^2 + \sigma_v^2)} \sum_{n_2} (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta)^2 +$$

$$+ \sum_{n_2} \log \left[ \Psi \left( \frac{c_1 - x'\beta - (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta) \frac{\sigma_e^2}{\sigma_e^2 + \sigma_v^2}}{\frac{\sigma_e \sigma_v}{\sqrt{\sigma_e^2 + \sigma_v^2}}} \right) + \right. \\ \left. - \Psi \left( \frac{c_0 - x'\beta - (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta) \frac{\sigma_e^2}{\sigma_e^2 + \sigma_v^2}}{\frac{\sigma_e \sigma_v}{\sqrt{\sigma_e^2 + \sigma_v^2}}} \right) \right]$$

This is a well-behaved likelihood function; therefore the ML estimators have standard properties. Like the basic model specification of the previous subsection, the present model can be thought of as consisting of two stages: (1) an ordered probit stage describing the allocation over Cases 1, 11 and 111, and (2) a regression stage for the endogenous variable in Case 11. The present model states that the stochastic variation governing the second stage is larger than the stochastic variation governing the first stage. The additional variation in the second stage consists of measurement errors in the endogenous variable in Case II.<sup>2 3</sup>

We now present a second model extension. It may be that in reality the variation in the second stage is smaller (rather than larger) than the variation in the first stage. The following model extension generates this prediction. Consider again the basic specification of the previous subsection, and suppose that the specification of the threshold values  $c_0$  and  $c_1$  is incorrect in the sense that in reality these values are not the same for every individual. The latter is plausible as some individuals may put more efforts in quantifying a value of  $\phi(1)$  close

<sup>2</sup>It should be noted that the model extension above bears a formal resemblance to a disequilibrium trading model with controlled prices (see Maddala (1983) for a brief survey of applications of disequilibrium models). Consider a model in which there is only trade if the equilibrium price  $P$  at which supply and demand meet lies between lower and upper threshold values  $P_1$  and  $P_2$ . Suppose that we only observe whether  $P$  is larger or smaller than these values, and that in addition we observe the traded quantity  $Q$  if positive (which is only the case if  $P_1 < P < P_2$ ). This model can be translated to our model if we interpret  $P_1$  and  $P_2$  as  $c_0$  and  $c_1$ ,  $P$  as  $\phi(1) - \phi(0)$ , and  $Q$  as  $\tilde{\phi}(1) - \tilde{\phi}(0)$ . In addition, some exclusion restrictions in the demand and supply functions are necessary. To our knowledge, such models have not been estimated.

<sup>3</sup>The empirical implementation of our model is remotely related to the methodology developed by Cameron (1988) for analyzing subjective responses on the acceptance or rejection of prices for a certain leisure activity. In her setup, respondents are confronted with (randomly assigned) given prices, whereas we basically ask for the threshold price. Cameron & James (1987) contains an empirical analysis. Our empirical model can be formally reduced to Cameron's model by taking  $c_0 = c_1$  and by taking this to be the observed offered price. Note that in that case there is no equivalent of Case 11. This, as well as the fact that for each respondent a threshold value is observed, simplifies the empirical specification considerably.

to  $\phi(0)$  than others, and some individuals may have more trouble quantifying a very large value of  $\phi(1)$ . For simplicity, we assume for the moment that there is a single random variable describing the variation in both  $c_0$  and  $c_1$ , and that this variable is orthogonal to  $e$ . In particular,

$$\begin{aligned} c_0 &= \gamma_0 + u \\ c_1 &= \gamma_1 + u \end{aligned} \tag{22}$$

We take  $u$  to be i.i.d.  $\text{Normal}(0, \sigma_u^2)$  across individuals. In this model, the unknown parameters are  $\beta$ ,  $\sigma_e$ ,  $\sigma_u$ ,  $\gamma_0$  and  $\gamma_1$ . Again, there are no inequality restrictions like (16) for unknown parameters in terms of data. This is basically because now for any observation  $\tilde{\phi}(1) - \tilde{\phi}(0)$  there is a positive probability that  $\tilde{\phi}(1) - \tilde{\phi}(0)$  lies between  $c_0$  and  $c_1$ .

The likelihood function for this specification can be derived analogous to above.

$$\begin{aligned} \log L &= \sum_{n_1} \log \Psi\left(\frac{\gamma_0 - x'\beta}{\sqrt{\sigma_e^2 + \sigma_u^2}}\right) + \sum_{n_3} \log \Psi\left(\frac{x'\beta - \gamma_1}{\sqrt{\sigma_e^2 + \sigma_u^2}}\right) + \\ &\quad - n_2 \log \sigma_e - \frac{1}{2\sigma_e^2} \cdot \sum_{n_2} (\tilde{\phi}(1) - \tilde{\phi}(0) - x'\beta)^2 + \\ &\quad + \sum_{n_2} \log \left[ \Psi\left(\frac{\gamma_1 - \tilde{\phi}(1) + \tilde{\phi}(0)}{\sigma_u}\right) - \Psi\left(\frac{\gamma_0 - \tilde{\phi}(1) - \tilde{\phi}(0)}{\sigma_u}\right) \right] \end{aligned} \tag{23}$$

Again, this likelihood function is well-behaved and the ML estimators have standard properties. Note that it is therefore not necessary to include measurement errors into the model in order to get a standard estimable specification.

The present model version states that the stochastic variation governing the ordered probit stage of the model is larger than the stochastic variation governing the “regression” stage. The additional variation in the first stage consists of specification errors in the boundaries of the probit categories. This variation does not affect the values of the endogenous variable in the second stage for Case 11 respondents.

When estimating the latter model version, the estimate of  $\sigma_u^2$  invariably went to zero. This means that the variation in the first stage is smaller than in the second stage. We therefore did not pursue analyses of more elaborate model extensions along this line.

Clearly, one may think of yet other ways to link the data to the model. For example, one may adopt a specification of the utility function such that individuals are completely indifferent between values of  $h$  within the sets  $[0, h_*]$  and  $[h^*, \infty)$  (in the latter case, utility is minus infinity). Then Case 1 and Case 111 answers can be interpreted as evidence that  $1 < h_*$  and  $1 > h^*$ , respectively. In such models, Case 1 and 111 respondents do not round off their answers. However, it can be shown that the resulting empirical models are similar to the models we estimate. Another type of models follows from assuming that Case 1 and 111 respondents have not understood the question on  $\phi(1)$  at all. We return to this in the next subsection.

### 4.3 Identification

As noted above, the model version allowing for measurement errors  $v$  in the Case 11 responses is the preferred empirical specification. In this subsection we examine the identifiability of this model, and we propose some specification tests.

So consider the model defined by equations (11), (12), (13), (14) and (19) and by the corresponding distributional assumptions. Because of the small number of observations we do not attempt to generalize this model any further. For ease of exposition we redefine  $x$  such that  $x'\beta$  can be rewritten as  $\beta_0 + x'\beta_1$ , in which the latter  $x$  does not contain a constant. Thus, the parameters are  $\beta_0, \beta_1, c_0, c_1, \sigma_e$  and  $\sigma_v$ .

The ordered probit on the Case 1, 11 and 111 categories allows identification of  $(c_0 - \beta_0)/\sigma_e, (c_1 - \beta_0)/\sigma_e$  and  $\beta_1/\sigma_e$ . The mean of  $\tilde{\phi}(1) - \tilde{\phi}(0)$  conditional on being in Case 11 (and conditional on  $x$ ) equals

$$\begin{aligned} & E(\tilde{\phi}(1) - \tilde{\phi}(0) | c_0 < \beta_0 + x'\beta_1 + e < c_1) \\ & = \beta_0 + x'\beta_1 + \sigma_e \cdot \frac{\psi\left(\frac{c_0 - \beta_0 - x'\beta_1}{\sigma_e}\right) - \psi\left(\frac{c_1 - \beta_0 - x'\beta_1}{\sigma_e}\right)}{\Psi\left(\frac{c_1 - \beta_0 - x'\beta_1}{\sigma_e}\right) - \Psi\left(\frac{c_0 - \beta_0 - x'\beta_1}{\sigma_e}\right)}. \end{aligned} \tag{24}$$

This means that a “second stage” regression on these data allows identification of the parameters  $\beta_0$  and  $\beta_1$  of the unconditional mean of  $\phi(1) - \phi(0)$ , and of  $\sigma_e$ . By implication,  $c_0$  and  $c_1$  are identified. The remaining parameter  $\sigma_v$  is then

identified from the variance of the “second stage” regression. If  $\beta_1 = 0$  then higher moments are needed for identification.

This identification argument is not crucially dependent on the assumed functional form of the error distributions (i.e. on Normality), in the sense that it also holds for other distributions for which the mean is zero and the only unknown parameter is a scale parameter. However, it is clear that the estimates of  $\beta_0$  and  $\sigma_e$  are not robust with respect to the assumption of symmetrically distributed specification errors. Because of this the results are not suitable for predicting individual levels of  $\phi(1) - \phi(0)$ .

Intuitively, it is likely that the estimates of  $c_0$  and  $c_1$  will be affected by the shape of the empirical density of  $\tilde{\phi}(1) - \tilde{\phi}(0)$  among Case 11 respondents, in the sense that these estimates will be close to the points at which the density sharply increases and decreases, respectively. The size of the tails outside these points will affect the estimate of  $\sigma_v$ . This estimate will also be affected by the amount of heaping in the Case 11 reservation wage difference data.

We distinguish between two types of specification tests in our application. The first type tests whether the theory leading to equation (11) is correct. We use the theoretical framework of Section 2 to generate exclusion restrictions on the variables included in  $x$ . This idea has been discussed in Subsection 2.2. For example, we will use the respondent’s unemployment benefits level  $b$  as an additional regressor. If the corresponding coefficient is significant then this is interpreted as evidence that the theoretical model is incorrect, in the sense that on-the-job search is an important determinant of search behavior of unemployed individuals, or in the sense that instantaneous utility is not additive in  $w$  and  $h$ .

Secondly, we test the specification of the empirical limited-dependent variable model (see equation (21)). In addition to straightforward goodness of fit tests we will also carry out Hausman tests (see Godfrey (1991) for a survey on Hausman tests). As noted above, the parameters  $(c_0 - \beta_0)/\sigma_e$ ,  $(c_1 - \beta_0)/\sigma_e$  and  $\beta_1/\sigma_e$  can be estimated by an ordered probit analysis on the Case 1, 11 and 111 categories. These parameters can also be estimated by performing ML on the whole data set. If the model is correct then these estimates should not be significantly different. Now suppose that the  $\beta_1/\sigma_e$  estimates are significantly different. Then this is evidence that the quantitative responses in the Case 11 group are governed by a different behavior than the qualitative self-classifications of the respondents over the three cases. This may occur if an answer  $\tilde{\phi}(1) - \tilde{\phi}(0)$  does not mean that the true difference  $\phi(1) - \phi(0)$  is very small, but rather means that the respondent has not understood the question on  $\phi(1)$  at all. It is less clear what it means if the estimates of  $(c_0 - \beta_0)/\sigma_e$  and  $(c_1 - \beta_0)/\sigma_e$  are different. Intuitively, this may

indicate that the distribution of  $e$  is misspecified.

## 5 Results

Table 2 presents the parameter estimates for the analysis based on the whole dataset. The observed explanatory variables  $\mathbf{x}$  are classified into categories describing personal characteristics, household characteristics and characteristics of the environment, respectively. We first discuss the results for  $\beta$  in the first column of Table 2.

In the part of  $\beta$  corresponding to the first two categories, the only significant element is the element associated with the number of children for females. (A similar variable for males turned out to be completely insignificant.) The larger the number of children, the lower the willingness of females to pay for commuting time. An additional child implies that the willingness to pay for two hours of commuting time per day is about Dfl 140 per month lower (this is about US \$ 80). Apparently, the value of leisure is relatively large for females with children. Another explanation is that the pecuniary cost of child care is increasing with (i) the number of hours in which such facilities are used, and (ii) the number of children, and that females are more concerned with this. Finally, a working woman having children may want to work close to the child care location in order to be able to move quickly to that location in case of an emergency, and also perhaps in order to be able to have lunch with the children.

Note that the value of  $\phi(1) - \phi(0)$  for a woman having a couple of children can be very large. For example, a woman having three children has a value of  $\phi(1) - \phi(0)$  that *ceteris paribus* is about Dfl 500 per month higher than the corresponding value for a male. For most occupations this would mean that, given any plausible value of  $\phi(0)$ , the value of  $\phi(1)$  exceeds the maximum possible offered wage (this is even more so if the baseline reservation wage  $\phi(0)$  for females is larger than for males.) In other words, such females would restrict job search to jobs located within a very small distance. The disutility of commuting time can therefore be identified as a(nother) factor having a negative impact on the labor market performance of females.

The regional unemployment rate does not have a significant “effect” on the willingness to pay for commuting time. Note that if it were significant then this might indicate a misspecification of the model. In unemployment duration analyses, the regional unemployment rate is often used as an explanatory variable indicating labor market tightness, i.e. as a proxy for the job offer arrival rate  $\lambda$  (see Section 2). As argued in Subsections 2.2 and 4.3, if the job offer arrival rate

is significant in the parameter  $\beta$  of the utility function then this suggests that the theoretical model is incorrect.

The degree of urbanization does have a significant “effect” on the willingness to pay for commuting time. *Ceteris paribus*, an individual living in a large city (degree of urbanization = 13) is willing to pay about Dfl 290 per month more for two hours of commuting per day than an individual in a very rural area (degree of urbanization = 3). One explanation for this is that commuting trips in highly urbanized areas are often multi-purpose trips, in the sense that traveling to work can easily be combined with traveling to friends, shops, child-care centers, leisure activity centers and so on.

Other explanations are based on the observation that commuting trips usually take place during rush hours. In highly urbanized areas there will often be traffic congestion during rush hours, implying that the distance reached in a given time period is smaller during rush hours than at other times of the day. So, even when it takes one hour to reach a given work location during rush hours, it will take less time to travel from home to work during e.g. lunch hours. This phenomenon will not occur in rural areas. This gives jobs on a one hour commuting distance in urbanized areas an advantage over similar jobs in rural areas. Finally, there may be a self-selection effect in the sense that individuals with a strong dislike of being in unknown places and being among unknown people may be over-represented in rural areas. Note that there may also be a self-selection effect working in the other direction: individuals who dislike commuting may choose to live close to where most jobs are, i.e. in highly urbanized areas. The latter is not supported by our result. To overcome these endogeneity problems, data with much longer labor market histories as well as locational choice histories may be needed.

The other coefficients in  $\beta$  are insignificant (note that the sample size is quite small). Since there is no established literature on the effects of personal characteristics on the disutility of commuting time, some specification search over such characteristics seems justified.<sup>4</sup> We performed additional analyses to investigate

---

<sup>4</sup>Rouwendaal & Rietveld (1994a) specify a search model for unemployed individuals in which jobs are characterized by a wage and a commuting distance, and in which wage offers are assumed to be independent from the associated commuting distances. They use a cross section of realized wages and commuting distances of *employed* individuals in order to estimate parameters of the offer distribution and the pecuniary costs of commuting per distance measure. The values of the other parameters (like  $\lambda, \rho$  and  $b$ ) are fixed numerically prior to the estimation procedure. They estimate models for four parts of the country, and they find that the disutility of commuting a kilometer is slightly larger for the most densely populated part. This is not in conflict with our results on the “effect” of the degree of urbanization, since the time needed to travel one kilometer is larger in more urbanized areas.



the “effects” of nationality and years of work experience, and we allowed for nonlinearities in the education variable. We also investigated whether a preference for temporary jobs has any “effect”. It turns out that all personal characteristics are invariably insignificant. Because of this, we also present in Table 2 the estimates for the model in which all personal characteristics are excluded as explanatory variables. The other estimates are highly insensitive to this exclusion.

The results for  $c_0$  and  $c_1$  are very plausible. When the difference between  $\phi(1)$  and  $\phi(0)$  is less than Dfl 157 per month then individuals do not bother to quantify  $\phi(1)$ . About 54% of the sample consists of Case 1 respondents, so the estimated population median of  $\phi(1) - \phi(0)$  is smaller than Dfl 57 per month. This finding is robust with respect to the assumed distribution of  $e$ .

When the difference between  $\phi(1)$  and  $\phi(0)$  exceeds Dfl 525 per month then respondents simply state that they would never accept a job with  $h = 1$  at the date of the interview. Note that by estimating  $c_1$  we have in effect quantified the expression “never”, albeit only in this specific context. The model predicts that if the respondents who give such an answer are offered a job with  $h = 1$  and a monthly wage exceeding their reservation wage for jobs around the corner by say Dfl 600, that then some of them would then accept this job.

The estimated standard deviation  $\sigma_e$  of the specification error is substantial. The pseudo- $R^2$  for the equation  $\phi(1) - \phi(0) = x'\beta + e$  equals 0.53. The standard deviation  $\sigma_v$  of the measurement error is significantly positive, but small. This is plausible, given that there are almost no data points either far below  $c_0$  or far above  $c_1$ , and given that there is some heaping in the  $\tilde{\phi}(1) - \tilde{\phi}(0)$  data. In any case, this result justifies the approach followed in Subsection 4.2.

We also estimated a model in which  $k(w)$  in the utility function (see equation (8)) is linear in  $\log w$  rather than in  $w$ . In that case, equations (11) and (12) are replaced by  $\log \phi(1|t) - \log \phi(0|t) = (g(0) - g(1))/k_1 = x'\beta + e$ . We redefine Cases I-III by replacing  $\phi(h)$  by  $\log \phi(h)$  in the appropriate equations in Section 4. The resulting estimate of  $\beta$  reflects proportionate “effects” of  $x$  on the willingness to pay for commuting time. It turns out that this model fits the data almost equally well and that the estimation results do not provide new insights. This also holds

---

Rouwendaal & Rietveld (1994) estimate a parameterized reduced-form model for the distribution of commuting distances of employed individuals, using the same data as in their paper mentioned above. They find that (*ceteris paribus*) individuals with children and older individuals have significantly smaller commuting distances. The former is consistent with our findings. HCG (1990) contains a descriptive study of subjective valuations of commuting time in the whole population (see also Bates & Glaister (1990) and Waters (1992)). They also conclude that the disutility of commuting time is relatively large for individuals with children and for younger individuals.

for other alternative additive utility function specifications we tried.

Finally, we estimated the model of Section 4 using the likelihood function (17), taking account of (16). In this case,  $c_0$  and  $c_1$  are estimated to be Dfl 50 and Dfl 542, respectively, which are the smallest and largest observed  $\tilde{\phi}(1) - \tilde{\phi}(0)$  among Case 11 respondents. These estimates do not differ much from those in Table 2, which is not surprising given the (small) magnitude of the  $\sigma_v$  estimate in Table 2. However, some of the  $\beta_1$  estimates do differ. Notably, the gender coefficient goes from 0.78 to -0.81 while the “degree of urbanization” coefficient goes from -0.28 to -0.15 (it remains significant).

We now turn to the additional specification tests proposed in Subsection 4.3. First of all, we re-estimated the model with the unemployment benefits level  $b$  included in  $x$ , using a number of different ways to measure  $b$ . The corresponding coefficient invariably turned out to be insignificant, which supports our structural model. This is also true if the elapsed unemployment duration  $t$  is included in  $x$ , taking account of the endogeneity of  $t$  by using an ancillary equation for  $t$ .

In order to apply the Hausman tests we need the estimates of the ordered probit analysis. These are presented in Table 3 along with the corresponding scaled ML estimates for the whole data set. The latter are merely transformations of the estimates in Table 2 and are reproduced here to facilitate a comparison with the ordered probit estimates. At first glance it seems that the differences between the two sets of estimates are very small. The Hausman test statistic for the comparison of the two sets of  $\beta_1/\sigma_e$  estimates has a  $\chi^2_{10}$  distribution under the null hypothesis of a correct model specification. The value of this statistic equals 0.4, which is way below the 90% critical value of this distribution (which is 16.0). The Hausman test statistic for the comparison of the two complete sets of estimates (that is, the  $\beta_1/\sigma_e$ ,  $(c_0 - \beta_0)/\sigma_e$  and  $(c_1 - \beta_0)/\sigma_e$  estimates) has a  $\chi^2_{12}$  distribution under the null hypothesis. The value of this statistic equals 1.5, which again is much smaller than the 90% critical value of this distribution (which is 18.5). So these tests support our model specification. In particular, the quantitative responses in the Case 11 group are governed by the same behavior as the qualitative self-classifications of the respondents over the three cases.

## 6 Conclusion

In this paper we have used subjective responses on the optimal search strategy of unemployed individuals to estimate structural parameters. These responses concern the reservation wage for jobs around the corner and the reservation wage for jobs on a one-hour commuting distance. The structural parameters we esti-

mate are the parameters of the utility function that represent the utility trade-off between the wage and the commuting time. The relation between these parameters and the observed reservation wages follows from a general nonstationary job search model in which jobs have multiple characteristics. Such an estimation procedure avoids the need to make the strong functional form assumptions usually made in structural analyses of job search.

When specifying the empirical model specification we have paid substantial attention to measurement errors and specification errors. Some of the estimation issues may be of more general interest, notably for the analysis of limited-dependent variable models with unknown threshold values.

The results indicate that the disutility of commuting time is particularly high for females with children. Indeed, their reservation wage for jobs requiring two times one hour of commuting time a day often exceeds the maximum possible offered wage. In that case job search will be restricted to jobs located within a very small distance. The disutility of commuting time can therefore be identified as a factor having a negative impact on the labor market performance of females with children. It may be that this effect can be reduced by subsidizing the costs of child care. Child care facilities in The Netherlands were notoriously bad in the mid-eighties, which is the period in which our data were collected. However, it is clear that, to address this policy issue, additional research would be necessary.

The results also indicate that the disutility of commuting is larger in rural areas than it is in highly urbanized areas. This may have to do with the fact that commuting trips in highly urbanized areas can be combined more easily with trips for other purposes. It may also be a consequence of the fact that the physical distance that can be reached in a one hour commuting trip during rush hours is smaller in an urbanized area than in a rural area.

The specification tests all support the model specification. It may be interesting to examine whether other observed variables that, according to the job search model, are endogenous (notably unemployment duration), can be used to extract additional information on the parameters of interest. Gronberg & Reed (1994) use data on job durations and transitions from one type of job to another to estimate the willingness to pay for certain job characteristics. The integration of such an analysis with the analysis of the present paper is beyond the scope of this paper, but seems to be an interesting topic for further research.

We finish this paper by making some remarks on the use of subjective responses on reservation wages for different types of jobs. First of all, the idea of using of such responses for the estimation of the willingness to pay for commuting

time can be fruitfully extended to other job attributes. In that case, responses must be available on reservation wages for jobs differing in the degree in which the attribute is provided. It is obviously important to phrase the questions in such a way that it is clear which characteristics the job one refers to has. In our case, it would be better if the question that we refer to as the question on  $\tilde{\phi}(0)$  would explicitly refer to a job on a zero commuting time distance. However, it is also important that the type of job one refers to is a conceivable kind of job, so it would be even better if this question would refer to jobs on a fixed minimal commuting time distance (like 15 minutes).

In our application, the response we denote by  $\tilde{\phi}(1)$  is quite often the same as the response we denote by  $\tilde{\phi}(0)$ . To investigate whether this is due to a misunderstanding of the question concerning jobs on a one hour distance, or whether the respondent's utility would only be substantially affected by commuting times exceeding one hour, it would be helpful if the respondent would be asked additional reservation wage questions concerning jobs requiring other commuting times (say, 1.5 hours). This would also enable the estimation of non-linearities in the willingness to pay as a function of commuting time (or, more general, the job characteristic). However, the latter can also be achieved by random assignment over respondents of questions referring to different commuting times.

Figure 1 OPTIMAL STRATEGY

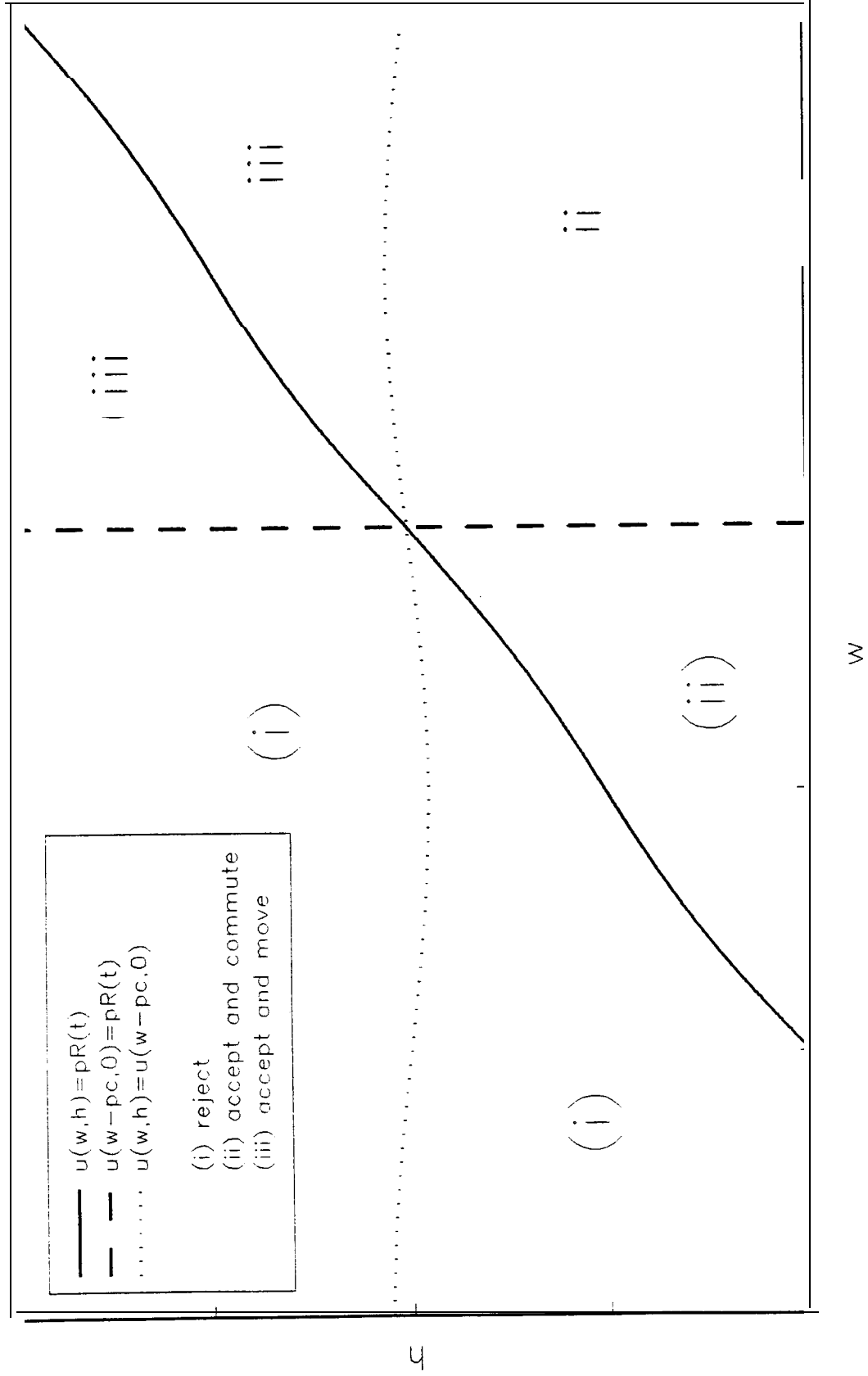
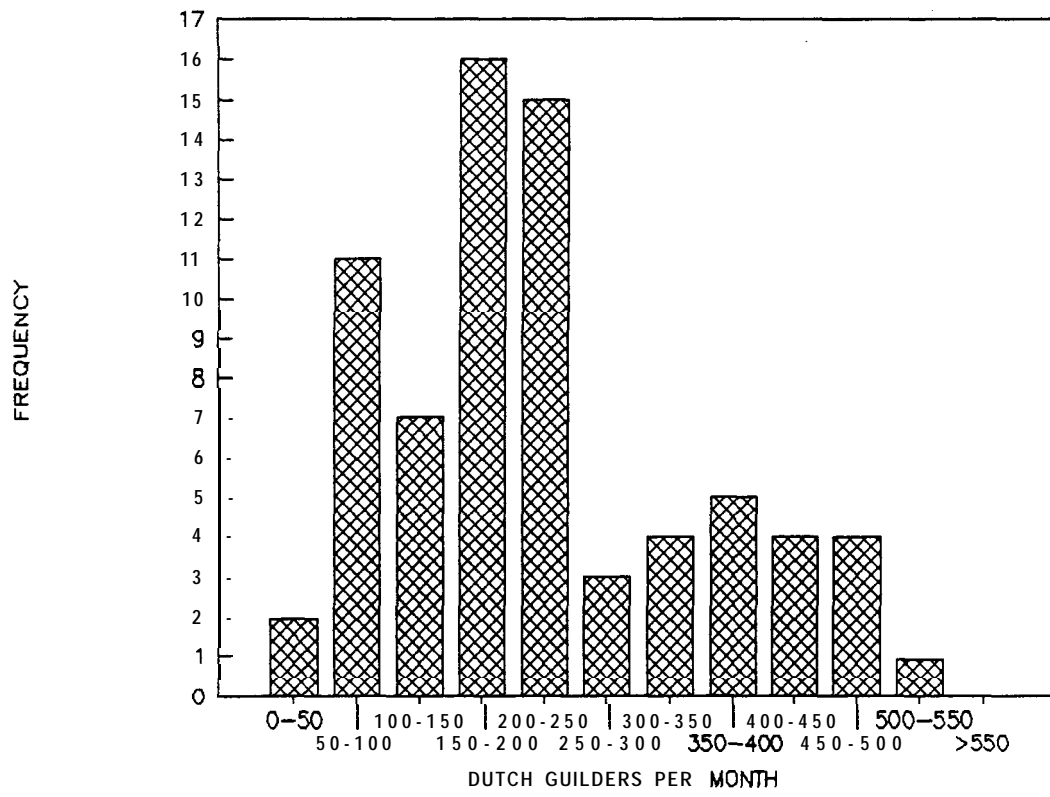


FIGURE 2 RESERVATION WAGE DIFFERENCES  
FOR THE SECOND GROUP (CASE II)



**Table 1.** Sample Means

variable	mean
<b>Independent variables</b>	
gender (female= 1)	0.43
age (in years)	34
educational level1 (1,..,6)	3.2
married or living together	0.53
number of children at home (when female)	0.34
regional unemployment rate (in %)	19
degree of urbanisation	9.5
<b>Dependent variables</b>	
qualitative, for $d; l) - \tilde{\phi}(0)$ :	
• no difference	0.54
• positive difference	0.31
• infinite difference	0.15
continuous, for positive difference:	
$\tilde{\phi}(1) - \tilde{\phi}(0)$ (in Dfl per month)	235.8
sample size	238

**Note:** the value of the variable educational level1 denotes the highest attained level according to the traditional classification of the Dutch educational system into six levels of ascending advancement: 1) less than completed primary education; 2) completed primary education; 3) lower secondary education, either in the general stream (MAVO or at most 3 years of HAVO or VWO) or the vocational stream (LBO); 4) secondary education, again either in the general stream (completed HAVO or VWO) or the vocational stream (MBO); 5) higher vocational (HBO) or incomplete college training; and 6) university graduation.

**Table 2.** Estimates for the Full Model

variable/parameter	estimate (s.e.)		estimate (s.e.)	
<b>Disutility of commuting time (<math>\beta</math>)</b>				
<i>person-specific characteristics:</i>				
gender (female= 1)	0.78	(0.83)	—	—
age (in years)	-0.038	(0.033)	—	—
educational level (1,...,6)	-0.16	(0.32)		
<i>household-specific characteristics:</i>				
married or living together	1.10	(0.73)	0.78	(0.70)
number of children at home (when female)	1.42	(0.52)	1.67	(0.44)
<i>environment-related features:</i>				
regional unemployment rate (in %)	-0.035	(0.024)	-0.027	(0.023)
degree of urbanisation	-0.29	(0.11)	-0.29	(0.11)
constant	3.80	(1.96)	2.33	(1.27)
<b>Threshold values</b>				
lower threshold ( $c_0$ )	0.57	(0.12)	0.57	(0.12)
upper threshold ( $c_1$ )	5.25	(0.16)	5.25	(32.8)
<b>Error standard deviations</b>				
specification error ( $\sigma_e$ )	4.41	(0.48)	4.49	(0.49)
measurement error ( $\sigma_v$ )	0.19	(0.085)	0.19	(0.086)

**Note:** standard errors are in parentheses.

**The** monetary unit **is** Dfl 100 (**which is** about US \$ 60),  
**and the time unit is** one month.



**Table 3.** Estimates for the Ordered Probit Model and Corresponding Scaled Estimates for the Full Model

variable/parameter	ordered probit estimate (s.e.)	full model estimate (s.e.)
<b>Disutility of commuting time (<math>\beta_1/\sigma_e</math>)</b>		
<i>person-specific characteristics:</i>		
gender (female= 1)	0.22 (0.20)	0.18 (0.19)
age (in years)	<b>-0.009</b> (0.008)	-0.009 (0.008)
educational level (1, . . .,6)	-0.051 (0.075)	-0.037 (0.071)
<i>household-specific characteristics:</i>		
married or living together	0.23 (0.17)	0.25 (0.16)
number of children at home (when female)	0.30 (0.11)	0.32 (0.11)
<i>environment-related features:</i>		
regional unemployment rate (in %)	-0.008 (0.005)	-0.008 (0.005)
degree of urbanisation	-0.075 (0.027)	-0.065 (0.024)
<b>Threshold values</b>		
lower threshold ( $(c_0 - \beta_0)/\sigma_e$ )	-0.91 (0.51)	-0.73 (0.44)
upper threshold ( $(c_1 - \beta_0)/\sigma_e$ )	0.13 (0.58)	0.33 (0.45)

*Note: standard errors are in parentheses. The estimates for the full model in the last two columns are calculated from the results reported in Table 2.*

## References

- Bates, J. and S. Glaister (1990), "The valuation of time savings for urban transport appraisal for developing countries: a review", Working paper, World Bank, Washington D.C.
- Blau, D.M. (1991), "Search for nonwage job characteristics: a test of the reservation wage hypothesis", *Journal of Labor Economics*, 9, 186-205.
- Cameron, T.A. (1988), "A new paradigm for valuing non-market goods using referendum data: maximum likelihood estimation by censored logistic regression", *Journal of Environmental Economics and Management*, 15, 355-379.
- Cameron, T.A. and M.D. James (1987), "Efficient estimation methods for "closed-ended" contingent valuation surveys", *Review of Economics and Statistics*, 69, 269-276.
- Devine, T.J. and N.M. Kiefer (1991), *Empirical Labor Economics*, Oxford University Press, Oxford.
- Flinn, C.J. and J.J. Heckman (1982), "New methods for analyzing structural models of labor force dynamics", *Journal of Econometrics*, 18, 115-168.
- Godfrey, L.G. (1991), *Misspecification tests in econometrics*, Cambridge University Press, Cambridge.
- Gorter, C. (1994), "Regional labor market research in The Netherlands", in H. Scholten and S.C. de Groot, editors, *Labor market and social security (in Dutch)*, IVA, Tilburg.
- Gronberg, T.J. and W.R. Reed (1994), "Estimating workers' marginal willingness to pay for job attributes using duration data", *Journal of Human Resources*, 29) 911-931.
- HCG (1990), *The Netherlands value of time*, HCG, The Hague.
- Lancaster, T. and A.D. Chesher (1983), "An econometric analysis of reservation wages", *Econometrica*, 51, 1661-1676.
- Maddala, G.S. (1983), *Limited-dependent and qualitative variables in econometrics*, Cambridge University Press, Cambridge.
- Mortensen, D.T. (1986), "Jobsearch and labor market analysis", in O. Ashenfelter and R. Layard, editors, *Handbook of Labor Economics*, North-Holland, Amsterdam.
- Pudney, S. (1989), *Modelling individual choice*, Basil Blackwell, Oxford.

- Ridder, G. and C. Gorter (1986), "Unemployment benefits and search behaviour, an empirical investigation" , Working paper, University of Amsterdam, Amsterdam.
- Rouwendal, J. and P. Rietveld (1994a), "A structural model of commuting distances and spatial job search", Working paper, Wageningen University, Wageningen .
- Rouwendal, J. and P. Rietveld (1994b), "Changes in commuting distances of Dutch households", *Urban Studies*, 31, 1545-1557.
- Van den Berg, G.J. (1990a), "Nonstationarity in job search theory", *Review of Economic Studies*, 57, 255-277.
- Van den Berg, G.J. (1990b), "Search behaviour, transitions to nonparticipation and the duration of unemployment", *Economic Journal*, 100, 842-865.
- Van den Berg, G.J. (1995), "Wage dispersion and mobility", *Economic Modelling*, 12, 15-27.
- Waters, W.G. (1992), "The value of time savings for the economic evaluation of highway investments in British Columbia" Working paper, University of British Columbia, Vancouver.
- Wolpin, K.I. (1987), "Estimating a structural job search model: the transition from school to work", *Econometrica*, 55, 801-818.
- Wolpin, K.I. (1992), "A survey of empirical methods for the study of labor force dynamics" , Working paper, University of Minnesota, Minneapolis.