Workers' marginal costs of commuting

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Abstract. *This paper applies a dynamic search model to estimate workers' marginal costs of commuting, including monetary and time costs. Using data on workers' job search activity as well as moving behaviour, for the Netherlands, we provide evidence that, on average, workers' marginal costs of one hour of commuting are about 17 euro.*

Keywords: On-the-job search; Job moving; Commuting time; Commuting cost; Willingness-to-pay

JEL code: R20, J32

1. INTRODUCTION

In the current paper, we aim to estimate workers' marginal costs of commuting. These costs include mainly travel *time costs* and *monetary costs*, but they may also include other costs that affect the utility of travel (e.g., stress, risk of accidents). Commuting costs play an important role in hundreds of studies that contribute to urban economics theory (e.g., Wheaton, 1974; Fujita, 1989). In the Alonso-Muth-Mills monocentric model, commuting costs not only determine urban spatial structure – by influencing the size of the city – they also determine whether a city is monocentric at all (Ogawa and Fujita, 1980; Fujita and Ogawa, 1982), and generally they will determine land, and therefore house, prices, as well.[1] However, it turns out that we know surprisingly little about the size of these commuting costs.

A large number of transport economics studies focus on the *time component* of commuting costs (e.g., Small et al., 2005). Estimates of the time component of commuting costs vary by a large margin, but studies tend to find that the value of travel time is 20% to 100% of the hourly (gross) wage (Small, 1992). De Borger and Fosgerau (2008) find strong reference-point effects in stated preference data and suggest a way to correct for this effect. Revealed preference studies tend to find substantially higher values than stated preference studies.[2]

[1] Commuting costs are also relevant to other economics fields, such as labour economics, because these costs affect the cost of being employed, and therefore workers' labour supply (e.g., Wales, 1978; Cogan, 1981; Parry and Bento, 2001), as well as workers' reservation and realised wages (e.g., Van den Berg, 1992; Van den Berg and Gorter, 1997, Manning, 2003a; 2003b).

[2] The majority of (transport economics) studies that assess the costs associated with travel time are based on *actual* commuters' mode and route choices (Miller, 1989; Small, 1992; Hensher, 1997 and Small et al., 2005). There are likely, however, some serious problems with these studies, with regard to correlation between travel time and cost, and the difficulty of measuring the travel time and cost associated with different travel alternatives. A related technique avoids these problems by exploiting subjective response data on choices among hypothetical trip or mode alternatives that differ in time and cost components (see

Although the time component is an important part of the commuting costs, the other components are not negligible, and may therefore not be ignored (Cogan, 1981). For commuters, the monetary costs are thought to be about 30% to 40% of the time costs (e.g., Fujita, 1989; Small, 1992). Furthermore, workers may vary the speed of their commute through their choice of travel mode, so the share of the time costs as part of the total commuting costs is endogenously determined. As a consequence, information on the costs of the time component is not necessarily informative about the total commuting costs.

For all travel modes except car use, the marginal *monetary* costs are easy to determine. For non-motorized transport (bicycling, walking), the marginal monetary costs are (close to) zero; for public transport (train, bus, metro), the marginal monetary costs can be derived from the price paid for the ticket. For car users, however, who are the majority of commuters, the marginal monetary costs associated with commuting are not so straightforward to determine. These costs of car use comprise not only the variable costs of car use (fuel, depreciation of the car due to its use), but also costs that are related to the ownership of the car (interest, insurance, etc). The latter cost component is frequently treated as *fixed,* and it is therefore assumed not to affect workers' marginal costs of travel. This may be argued to be a relevant assumption in the United States, where car availability is high and almost all workers commute by car. Outside the United States, the proportion of workers who commute by car is much smaller. For example in the Netherlands, approximately 50% of workers commute by car. Car ownership decisions will frequently depend on the length of the commuting distance, which constitutes about one third of a car's mileage (De Jong, 1990). Consequently, even though treating car ownership costs as fixed

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Hensher, 1997; Verhoef et al., 1997; Calfee and Winston, 1998; Fosgerau, 2005). With such data, the problems of revealed preference data are eliminated by design. However, this advantage is gained at the cost of introducing a range of biases related to the hypothetical nature of data (McFadden 1999).

may make sense with respect to some travel decisions, these costs are clearly not fixed with respect to commuting.[3]

Workers' marginal commuting costs can be derived in various ways. One method, familiar to labour economists, is to use the trade off between wages and the length of the commute, using hedonic wage models, as developed by Rosen (1986), see for example Zax (1991). But such a method has a number of disadvantages, as it relies on the (implicit) assumption that workers have full information about availability of jobs and do not have to search for jobs (Hwang et al., 1992; Hwang et al., 1998; Gronberg and Reed, 1994). A number of studies have shown that estimates of valuation of job attributes, such as commuting time, are likely seriously downward-biased if hedonic wage models are used (Gronberg and Reed, 1994; Van Ommeren et al., 2000; Villanueva, 2007). An alternative method is to rely on the trade off between house prices and commuting (which implicitly also relies on Rosen, 1986). For certain relatively simple spatial structures of cities with well-defined workplace centres, such as Hong Kong, this method seems promising (see Tse and Chan (2003) and Yiu and Tam (2007)). For complex urban structures, such as in the Netherlands, application of this method seems difficult.

In this paper, we estimate commuting costs based on *actual on-the-job search,* as well as

[3] In addition to monetary and time commuting cost, there are other cost components. For example, given the presence of a car in the household, the use of the car for commuting imposes *opportunity* costs on other members within the same household who do not have simultaneous access to the use of the car. There is also a large literature in psychology that suggests that the psychological costs of travel are substantial (for a review, see Koslowsky et al., 1995). For example, long commutes increase blood pressure, physical disorders and anxiety. Further, long commutes are thought to have adverse effects on a worker's mood, as well as on cognitive performance. Economics literature on the psychological costs of commuting indicates that these costs are relevant (Kahneman et al., 2004; Stutzer and Frey, 2004). As most of the psychological costs of travel increase with travel *time*, it is not necessary to deal with these costs separately.

job moving, behaviour. Workers' marginal commuting costs will be derived from data on job search and job moving behaviour, employing a *dynamic* job search approach.[4] Our paper relates to a number of studies that have estimated the implied value of job attributes using data on job moving behaviour (Herzog and Schlottmann, 1990; Gronberg and Reed, 1994; Manning, 2003b; Dale-Olsen, 2006) and job search behaviour (Van Ommeren and Hazans, 2008).[5] It is also loosely related to the approach introduced by Bartik et al. (1992) who estimated the value of residential characteristics based on residential moving behaviour.

The dynamic job search approach assumes that workers are not in their preferred (welfare-maximising) job due to imperfect information about other jobs, but workers are able to improve their welfare over time by *searching* for other jobs, and by *moving to other jobs* if a job is found that increases welfare. This approach uses the implicit trade off between commuting time and wage, which affects both on-the-job-search and job moving behaviour, to determine workers' marginal costs of travel.[6]

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[4] This approach avoids some strong assumptions underlying discrete choice-based estimates based on actual route or mode choices, including the assumption that the choice set of the worker is accurately observed, and that the characteristics of the travel alternatives not chosen by the commuter are accurately observed. It also avoids the fundamental assumption, common in transport studies, that a change in mode affects only the costs and times associated with these modes. Such an assumption may be very restrictive, as it ignores, for example, changes in convenience (see, e.g., Calfee and Winston, 1998).

[5] Isacsson and Swärdh (2007) estimate the value of commuting time based on the duration of employment, using strong assumptions regarding the choice of transport mode and the related costs.

[6] The reader may wonder whether a method that relies on the trade off between wages and commuting time, and therefore measures the long-run marginal costs of commuting, generates results that are comparable to methods, common in transport economics, that measure the short-run marginal costs of the time component. At least theoretically, the answer is yes. One of the standard micro-economics results is that long-run and short-run marginal costs are equal (because the long-run and short-run average curves are tangent, see Varian, 1992). Our dynamic search model has the same property.

Our study is related to studies that focus on the compensation workers receive, in the labour market, for commuting (e.g., Zax, 1991; Van Ommeren et al., 2000; Manning, 2003a; Van Ommeren and Hazans, 2008). Typically, these studies use either commuting *time* or *distance* as an approximation for commuting costs. This is not justified, but is seen as a restriction of the available data set. Intuitively, if commuting costs mainly consist of time costs, then the use of commuting time is preferred. On the other hand, if there exist large (unobserved) differences in speed, for example due to congestion, then commuting distance may be the preferred measure. The two measures are equivalent only if the commuting speed is fixed and constant across the population. In the current paper, we apply a dynamic search model approach, and measure commuting costs based on commuting time. The use of commuting time, when commuting distance is not observed, will be justified theoretically by allowing for endogenously chosen speed. Hence, we will measure the costs of commuting in terms of time.[7]

Although the dynamic search model approach has a number of fundamental advantages, it has also a number of disadvantages (Gronberg and Reed, 1994; Manning, 2003b). One of the main drawbacks of the dynamic search model approach is that one must assume identical utility functions across workers, and the literature remains suspicious as to what extent this assumption biases the results (e.g., see the seminal paper by Gronberg and Reed, 1994). This criticism can be (partially) addressed by means of panel data techniques; these techniques have not been applied previously in this context. In the current paper, we will show that the results remain robust, using panel data techniques.

Note that although we are aware of various studies that use either the *job mobility* or the

[7] We believe that such a measure is generally more useful than a measure in terms of distance, for international comparisons. One notable characteristic of commuting time (and not of distance) is that the nationwide average commuting time is hardly time-varying (see Van Ommeren and Rietveld, 2005).

job search approach to estimate the value of job attributes, this is the first study that applies both approaches to the same data set. Both approaches rely on the same underlying dynamic search model, so they should (if applied correctly) generate the same estimate of the value of job attributes. Another potential advantage is to estimate joint models of job search and mobility. In our application, though, it turns out that joint models of job search and mobility generate identical results to separate models of job search and mobility, without any gain in the efficiency of the estimates. Throughout the paper, we will provide the results for the separate models, and, discuss soon the estimates of the joint model, when discussing the robustness of the analysis.

Although the underlying assumptions of the search and mobility approaches are the same, the job search approach is easier to apply, since the job mobility approach requires information on voluntary job mobility – information that is frequently not available in surveys. One may avoid this issue by making the additional assumption that the job attribute does not affect the involuntary job-quitting rate (see Van Ommeren and Hazans (2008) for details). In the context of our study, this does not turn out to be problematic, because it seems reasonable to assume that the length of the commute does not affect the involuntary job-quitting rate. Hence, given estimates from both approaches, we are able to test whether the two approaches are consistent with each other in their empirical implementation. Given consistency, estimates of the different approaches can be pooled, enabling one to reduce the standard errors of the pooled estimate.

The outline of the paper is as follows. In section 2, we introduce a job search model (allowing for commuting costs), specify the appropriate utility function, and derive workers' marginal willingness-to-pay for commuting costs. The empirical results are discussed in section 3. Section 4 concludes the paper.

2. THEORETICAL MODEL

2.1 Short-run behaviour

Consider an employed individual who lives forever. In the short run, the worker's residence and workplace locations, and therefore the commuting distance *D,* are exogenously given. Also, in the short run, she derives utility from job attributes *X* by the quasi-concave *instantaneous* utility function *v*(*X*). The estimation method we use to estimate workers' value of job attributes applies to any quasi-concave utility function *v(X)*. However, in the context of commuting, for estimation and interpretation purposes, it is useful to specify *v(X)* in more detail.

We assume that *v(X) = v(Y,L)*, where Y is income and L denotes leisure time. Income Y is equal to *wH-c*, where *w* is the hourly wage, H is the number of hours worked and c denotes the monetary commuting costs.[8] Leisure time is equal to $\bar{L}-H-t$, where $\bar{L}$ is the total time available and *t* is the commuting time.[9] We presume that commuting speed, and, therefore, commuting time *t*, as well as hours of work *H,* are optimally chosen.

We consider commuting distance to be produced according to the production function *d*, which takes money and travel time as inputs. We assume that this production function is strictly increasing and strictly concave, such that the isoquants are strictly convex. Since the commuting distance is exogenously given, we require that:

$$D=d(c,t), \tag{1}$$

where $d_c>0$ and $d_t>0$.

The commuter's utility maximisation problem is now to maximise $v(wH-c,\bar{L}-H-t)$ with respect to H and *t*, subject to (1), which has the following first-order conditions: $wv_Y=v_L$,

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[8] Hence, in this model, the individual consumes leisure time, pays for the costs of the commute, *c*, and spends *wH-c* on other consumption goods.

[9] In this specification, we impose that travel time has no leisure time component. Including such a component, so that leisure time is equal to $\bar{L}-H-t\gamma$, where $0<\gamma\leq 1$, does not change the results.

$v_Y=\lambda d_c$, and $v_L=\lambda d_t$, where λ is the Lagrange multiplier associated with the distance constraint.[10] Together, these first-order conditions imply that $wd_c=d_t$. Further, it appears that, by the envelope theorem, $\partial v/\partial w=v_Y H$. Consider, now, the optimally-chosen cost and time to be a function of the distance and differentiate (1); thus, we find that $1=d_c c_D+d_t t_D$. This also implies that $\partial v/\partial D=-v_Y/d_c$. The marginal willingness-to-pay (MWP), to reduce *optimally-chosen* commuting time, is now defined as:

$$MWP=\frac{\partial v/\partial D}{\partial v/\partial w}\frac{1}{t_D}=-\frac{1}{Hd_c t_D}=-\frac{w}{H}\frac{1}{d_t t_D}\,. \tag{2}$$

Hence, the MWP is negative and numerically greater than w/H, provided that $0<1/(d_t t_D)<1$. The latter constraint holds when both $c_D>0$ and $t_D>0$ (because $d_c>0$ and $d_t>0$). This is a requirement on the expansion path of d; the curve formed by points (c,t), satisfying $wd_c(c,t)=d_t(c,t)$, can be represented by $(c(t),t)$, where $c(t)$ is an increasing function of t. Another way of stating this is that increasing distance, and maintaining a constant marginal rate of technical substitution between cost and time, requires increasing input of *both* cost and time.[11]

In summary, we have $-MWP=\alpha w/H$, where $\alpha=1/(d_t t_D)>1$. This measure may be interpreted as the *total* marginal costs of commuting associated with commuting time. It measures the increase in wage that is necessary to compensate for an optimally-chosen increase in commuting time, given an increase in distance. An optimally-chosen increase in commuting time corresponds to an increase in distance, as well as in monetary costs. Hence, as implied by (2), this measure exceeds the MWP for commuting time that ignores monetary commuting costs.

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[10] These first-order conditions are standard. For example, the condition $wv_Y=v_L$ implies that wage is the opportunity cost of leisure.

In fact, fixing monetary commuting costs, and given optimal working hours (as, for example, assumed by Manning, 2003a), the $MWP = -v_L/(v_Y H) = -w/H$, which is smaller (in absolute value) than $-\alpha w/H$, as $\alpha>1$.

We have described distance as being produced according to a *continuous* production function, which is in contrast to the discrete models typically used in the transport literature (the main exception is DeSalvo and Huq, 2005). In favour of the continuous formulation stands the fact that the choice of how to go to work, and hence the time and cost, involves, in general, much more than a simple discrete-mode choice. There are a multitude of choices – including some continuous choices. Consider, e.g., the possibilities for combining different modes (Van Exel and Rietveld, 2004), choosing departure time in situations of peak-hour congestion, choosing between slow and fast routes, car drivers choosing speed and driving style, choosing between cars with different costs, etc. (Rouwendal, 1996; Rienstra and Rietveld, 1996; Verhoef and Rouwendal, 2001; Gander, 1985; Rotemberg, 1985). It should be noted, however, that the result that $-MWP=\alpha w/H>w/H$ may also be derived under the antithetical assumption that commuting cost and time are fixed as functions of commuting distance, as long as commuting cost and time increase in distance.[12] Thus the analysis in this paper remains valid also for this case where the commuter is restricted to just one transport mode with a given cost and speed.

Given an optimally-chosen combination of commuting time and working hours, the

[11] A necessary and sufficient condition for this property to hold, for any w, is that $d_{jj}d_i<d_{ij}d_j$ for $i\neq j$, $i,j=c,t$. These conditions imply convexity and hence are stronger. Proof of these assertions is available from the authors upon request.

[12] This is easy to show, using the same argument as above. We require that cost and time are increasing differentiable functions of distance.

expression for instantaneous utility may be rewritten as $v(wH-\alpha wt)$.[13] Therefore, instantaneous utility depends on the daily wage *wH,* as well as on the *interaction* between the *hourly wage w* and the *commuting time t*. Our main interest is to estimate the unknown coefficient α, as it determines workers' MWP, given information on *H* and *w*. We will see now that the MWP can be derived from both observations of on-the-job search and from observations of job moving.

2.2 Long-run behaviour: search and moving decisions

The worker either searches ($s = 1$) or does not search ($s = 0$), in the labour market. Search costs are equal to $k(s)$, and jobs arrive at rate $p(s)$. When searching, $p(1) = p > 0$ and $k(1) = k > 0$, when not searching, $p(0) = 0$ and $k(0) = 0$. Job attribute offers X_0 are drawn randomly from a given distribution, which is independent of current job attribute *X*. Pooling of offers is not allowed: job offers are either refused or accepted before other offers arrive. For convenience, we ignore involuntary job mobility into unemployment. Van Ommeren and Hazans (2008) show how the results are affected when allowing workers to become unemployed. In the current application, allowing for unemployment does not change the results, as it seems reasonable to assume that commuting time does *not* determine involuntary job mobility.

The individual is assumed to maximise lifetime utility *V*, discounting future utility at the rate ρ. The expected lifetime utility $V(X)$, conditional on the current job, includes the possibility of job offers in the future. The decision whether to accept a job offer accounts for expected future offers. Discounted lifetime utility can then be written as the sum of the instantaneous utility and the expected benefit of accepting a job offer during the next time period. It is assumed

[13] Note that $\partial v/\partial w=v_Y H$ and $[\partial v/\partial D]/t_D=-v_Y w\alpha$, so $v=v(wH-\alpha wt)$ is consistent with these first-derivatives. Note further that $v(wH-\alpha wt)$ represents the same preferences as, for example, $v(log(wH-\alpha wt))$, where *log* denotes the natural logarithm. This issue will be addressed later on.

that each period is infinitely small, so calendar time is continuous. This leads to the following well-known equation:

$$\rho V(X) = v(X) - k(s) + p(s)E\max[V(X_0) - V(X),0], \tag{3}$$

where expectation is formed with respect to the distribution of the *job offer* attribute X_0. The interpretation of this formula is well known (see, e.g., Mortensen, 1986). Current utility equals $v(X)\text{-}k(s)$. A job offer will be received at a rate $p(s)$ and the offer will be accepted if the value of the new job exceeds that of the current one. Hence, the optimal acceptance strategy is to accept a job offer only if $V(X_0)\text{-}V(X) > 0$.

The optimal-choice search decision is obtained by maximising (2), with respect to s. It can easily be seen that:

$$\begin{aligned} &s = 1 \quad \text{if } pE\max[V(X_0) - V(X),0] \geq k; \\ &s = 0 \quad \text{otherwise.} \end{aligned} \tag{4}$$

Hence, if s = 1, then the expected benefits of search exceed the search costs.

In the previous subsection, we have shown that X includes two job attributes: the wage w as well as the commuting time t. Workers' MWP for commuting time is defined as the ratio of the marginal instantaneous utility of commuting time t over the marginal instantaneous utility of wage w, so $MWP = [\partial v(X)/\partial D.t_D^{-1}]/[\partial v(X)/\partial w]$. Note that k and p are not observed, and (4) can be rewritten as s = 1 if $E\max[V(X_0)\text{-}V(X),0] \geq k/p$, so k/p can be considered (unobserved) random error from the point of view of the econometrician.[14] It can then be demonstrated that (using the same steps as Van Ommeren and Hazans, 2008):

$$MWP = \frac{\partial \Pr(s=1)}{\partial D} t_D^{-1} / \frac{\partial \Pr(s=1)}{\partial w}, \qquad \textbf{(5)}$$

where Pr(s = 1) denotes the probability that the worker is searching for another job. Hence, workers' MWP is equal to the ratio of the marginal effects of commuting time and wage on the probability of job search. This result is intuitive: commuting time and wage both affect the utility of the worker. Workers use the trade-off between commuting time and wage to determine their optimal search – and therefore moving – behaviour.

Job offers will only be accepted if $V(X_0)-V(X) > 0$, otherwise the job offer will be rejected. The moving rate, θ, is equal to the job arrival rate *p(s)* times the probability that the job offer will be accepted. In our application, as is quite common, we only observe if *at least one* job move occurs during a fixed time interval (in our application, two years). So, it is more straightforward to use the job moving probability, for a fixed interval, than the job-moving rate.[15] Define $m = 1$ when a worker moves at least once, and $m = 0$ when the worker does not move during a fixed interval. When the interval is short, then $Pr(m = 1) = 1-exp[-\theta]$, where $Pr(m = 1)$ denotes the probability of job moving at least once. The ratio of the derivatives of the job moving probability $Pr(m = 1)$, with respect to two job attributes (in our application, *w* and *t*), and

[14] Note that *k/p* may take any positive value.

[15] The job moving rate θ is defined, in the theoretical model, for an infinitely small period. With respect to job mobility, few workers move more than once during a month, so monthly data are ideal. Given bi-annual data, as will be used in our application, multiple job moves during a fixed period cannot be distinguished from single job moves.

the ratio of the derivatives of instantaneous utility flow *v,* with respect to these two job attributes, can be shown to be equal to each other. Gronberg and Reed (1994) and Van Ommeren et al. (2000) derived this result for job moving rate θ, but it can easily be shown to extend to job moving probabilities, as there is a one-to-one relationship between job moving rates and job moving probabilities. Hence:

$$MWP = \frac{\partial \Pr(m=1)}{\partial D} t_D^{-1} / \frac{\partial \Pr(m=1)}{\partial w} . \quad \textbf{(6)}$$

Equation (5) implies that workers' *MWP* equals the ratio of the marginal effects of commuting time and wage on *job moving* behaviour. The intuition of this result is similar to the intuition for on-the-job search. Consequently, (5) and (6) imply that:

$$MWP = \frac{\partial \Pr(s=1)}{\partial D} t_D^{-1} / \frac{\partial \Pr(s=1)}{\partial w} = \frac{\partial \Pr(m=1)}{\partial D} t_D^{-1} / \frac{\partial \Pr(m=1)}{\partial w} . \quad \textbf{(7)}$$

In conclusion, workers' MWP for commuting time can be derived from the marginal effects of wage and commuting time on on-the-job *search* behaviour as well as on job *moving* behaviour, using the same underlying assumptions.

2.3 Estimation method

In our data, workers report whether they search or not for another job. It is then useful to introduce the latent variable search intention s^*, where s and s^* are related by: s = 1 if $s^* > 0$ and s = 0 if $s^* \leq 0$. We relate the search intention to explanatory variables by $s^* = \beta' X_s + u_s$, where β is a vector of unknown coefficients, X_s is a vector of explanatory variables and u_s is an independent random variable with expectation 0. For job moving, a similar latent-variable framework can be used, so $m^* = \eta' X_m + u_d$, and $m = 1$ if $m^* > 0$ and $m = 0$ if $m^* \leq 0$.

The specifications of X_s and X_m are determined by theoretical considerations. Recall that the utility function v can be written as $v(wH-\alpha wt)$. This indicates that X_s and X_m may include the *daily wage, wH,* and the *commuting time interacted with the hourly wage, wt.* Let β_t and η_t be the parameters associated with the interaction of commuting time and hourly wage in the job search and the job mobility model. Let β_w and η_w be the parameters associated with the *daily wage*. The ratio of the marginal effects of the interaction between the hourly wage and commuting time and the daily wage on *search,* as well as *job moving,* behaviour is then equal to β_t/β_w and η_t/η_w, respectively, and thus, using (7):

$$MWP = (\beta_t / \beta_w) w / H = (\eta_t / \eta_w) w / H = -\alpha w / H \ . \qquad \textbf{(8)}$$

Estimates of $(\beta_t/\beta_w)w/H$, as well as $(\eta_t/\eta_w)w/H$, can therefore be interpreted as workers' MWP for commuting. To interpret the results, we will follow the literature, by defining workers' marginal commuting costs (*MCC*) as the number of hours H times MWP, so $MCC = (\beta_t / \beta_w) w = (\eta_t / \eta_w) w$ and $MCC/w = \beta_t/\beta_w = \eta_t/\eta_w$. Workers' *MCC* is easier to interpret than MWP, as it shows how much, at the margin, a worker is willing to pay *per day* to reduce his/her *daily* commute.

3. EMPIRICAL RESULTS

3.1 Data

We have seen that workers' valuation of commuting time can be derived from data on job search, as well as job moving, behaviour. The data requirements to estimate job search and job moving models are similar, but not identical. Job search behaviour relates to an activity, which may, or may not, result in a job move. Job moving is usually preceded by a job search activity (but not always, as employers also approach workers, see Mekkelholt, 1993), but this job search activity will frequently not be recorded in the survey available to the analyst (as it falls outside the search period defined by the survey).

In case of on-the-job search, one needs data about job search at a certain moment in time (or about search during a short interval); for job moving, one needs to follow workers over time, so one has to observe a worker at least twice. This implies that there is usually less information about job mobility than about job search.

Our data derive from the biannual Dutch labour supply panel survey (OSA). We select seven waves of data (for the years 1990 to 2002) containing the information that we require. In total, we have 18,450 annual observations on job search activity for 8,937 different workers. Job search is defined here as any job search activity in the month before the interview. To observe job moving, we use information about workers observed in the consecutive surveys. We have 9,513 valid observations on job moving for 4,544 different workers. The mean net hourly wage in our sample is € 9.17. For males, the mean net wage is € 9.57, whereas for females the mean net wage is € 8.61.

In our data set, we do not observe the daily number of working hours (but only the weekly number of hours). From other data sources (WBO, 2002), we find the national mean of daily working hours, which is 7.8 for males, 6.0 for females and 7.0 for the whole sample. In particular, for males the variation in *daily* working hours is small, but, also, for females this variation is small, with few female workers working less than 5 or more than 8 hours (see Hamermesh, 1996, who reports similar results for Germany). Hence, we may impute the gender-specific national means of the daily working hours, for the individual daily working hours, as the effect of the measurement error is small.[16] Given the imputed daily working hours, and information about the monthly wage and weekly working hours, which are both available in the survey, the daily wage has been calculated.

We measure on-the-job search (defined as occurring in the month before the interview) and job moving as dichotomous variables. The mean (monthly) on-the-job search rate is 0.08, the annual job moving rate is 0.10 and the daily commuting time is 0.77 hours (which corresponds to a 23 minutes one-way commute, in line with other studies for the Netherlands). In our data, the correlation between job moving and search, in a certain month during the same year, is only 0.19, whereas the correlation between search in year *t* and job moving in year *t+2* (the next

[16] Note that random measurement error in the number of hours worked per day induces a downward bias in the estimate of β_w, and therefore an upward bias in MCC. Note that β_w refers to the product of *H*, which is observed with error, and the hourly wage *w*, which is *observed*, so we therefore assume to be observed without measurement error. In this case, the bias in the estimated β_w (as a proportion of the true value) is equal to $\sigma_H^2 / (\sigma_H^2 + \sigma_w^2)$ approximately, where σ_H^2 and σ_w^2 refer to the variances of hours and wage, respectively (the approximation is exact, given the absence of other control variables, see Verbeek, 2001, p. 121). In our data, σ_w^2 = 9.67 (9.92 for males; 8.82 for females), whereas, according to the WBO (2002), σ_H^2 = 0.83 (0.64 for males; 1.04 for females). Hence, the bias is only 8.5% of the true value (6.4% for males; 12% for females). As we control for other variables, it is plausible that the bias is less; we control for the presence of a partner, children, and industry, which likely strongly reduces unobserved variation in working hours per day, but these variables are known not to have as much explanatory power for the wage rate.

period available in our data) is even lower (0.08). This indicates that job search and moving data are statistically quite different concepts.

Figure 1 shows the bivariate relationship between on-the-job search and commuting time. It appears that there is a strong, positive relationship between search and commuting time: search intensity almost doubles when the commute increases from less than 0.6 hours to more than 2 hours per day. The bivariate relationship between job moving and commuting time is similar.

3.2 Empirical results

On-the-job search

We have estimated a range of discrete choice models for job search. A large number of explanatory variables are available and are used as control variables. We will provide here the results based on a standard probit and random-effects probit model. In the standard probit model, the panel structure of the data is ignored. However, it may be the case that some workers are more likely to search, for reasons not included in the model. This is potentially problematic as the theoretical model assumes homogeneous individuals. For this reason, we also estimate a random effects model, which allows for a correlation ρ between the random errors of the same individual. The results are presented in Table 1. We will focus on the estimates of β_w and $\beta_{h,}$ as well as the estimate for *MCC*, summarised in Table 4. For the standard probit model, we find that β_w = -0.0055 and β_h = 0.011, so *MCC/w* = 2.01. For the random effects model, *MCC/w* = 2.06, so, essentially, the same result is obtained. This suggests that the empirical results, obtained for a sample of heterogeneous workers, are not so sensitive to the assumption of homogeneity. This is important because the dynamic search approach, and therefore the derivation of *MCC/w*, assumes that workers have identical utility functions.[17]

We find that, at the margin, workers' costs associated with commuting time are about twice the net wage. Evaluated at the mean wage, this implies a *MCC* of € 18 (see Table 4), with a standard error (s.e.) of € 3 to € 4, depending on the type of model used.[18] In our data, the mean commuting time is 0.73 hours, with a standard deviation of 0.58. Hence, a one standard-deviation increase in the commuting time increases the *MCC* by about € 10.80, on average.

We have estimated all models separately by gender (Table 2), also. In the standard probit, for males, β_w = -0.0052 and β_h = 0.0074, so the value of *MCC/w* = 1.41(standard error = 0.48). In the random effects model, for males, we find *MCC/w* = 1.43. For females, *MCC/w* is equal to 2.24 and 2.25, respectively.[19] These estimates imply that workers' *MCC* is around € 14 for males and around € 19 for females, suggesting that the *MCC* is higher for females than for males. However, the difference in these estimates is statistically insignificant at the 5% level.[20]

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[17] We have also estimated *worker* fixed-effects logit models, which identify the coefficients of interest by controlling for unobserved worker characteristics, so the homogeneity assumption is even less problematic. However, given fixed effects, there is too little variation in the data to estimate β_t/β_w precisely, because the standard error of β_t is large, relative to its point estimate (t = 0.740). However, the point estimate has the correct sign (negative).

[18] The standard error is calculated using the delta method, see Goldberger (1991).

[19] Note that measurement error in the number of daily working hours, H, is more present for females than for males (for whom variation in H is much smaller). Random measurement error in H decreases the estimate of β_w. This suggests that the larger value of *MCC* for females may be partially due to measurement error in H. Our investigation of this issue, based on data for job mobility, as discussed later on, suggests however that this is *not*, or hardly, the case.

[20] The (weighted) average of these gender-specific estimates is € 15.40, so the (weighted) average of the models, estimated separately for gender, is (slightly) lower than the point estimate of the model, based on the pooled observations.

According to the labour economics literature, it is plausible that females with children and an employed (male) partner have higher *MCC* (e.g., Wales, 1978). The main reason is that these females have a higher value of non-working time. This is consistent with the stylised fact that females with children and an employed husband are less likely to work and, if they work, they are more likely to work part-time. We have therefore re-estimated the same model, based on a sample of females with children (and with an employed partner)(see Table 3). We find that *MCC/w* is 3.35 (with a standard error of 1.18). So, in line with this hypothesis, the *MCC* is substantially higher for this group, but the estimate is rather imprecise due to the limited number of observations. We have therefore re-examined this result by estimating the same model for the whole sample, and including interaction effects for females with children. According to these results, the *MCC/w* for this group of females is about 50% larger, but this difference is not statistically different. Hence, our results suggest that the *MCC* of this group is in the range of € 9 to € 30.

On-the-job mobility

We have also estimated models of *job mobility,* in order to estimate η_t and η_w. The full results are given in Tables 5 and 6, and summarised in Table 7. In essence, the results are the same as for on-the-job search. Estimates of *MCC* vary from between € 13 and €17. Again, allowing for worker-specific unobserved heterogeneity does not change the results. The only difference is that the results based on mobility data suggest that females have a slightly lower *MCC* than males, but this difference is far from statistically significant. Similar to the results for on-the-job search, we have also examined whether females with children and an employed partner have a higher *MCC*. This appears to be the case, but the difference is far from being statistically significant.

Combining the MCC estimates of search and mobility

We have estimated separate models using information on *on-the-job search* as well as information on *job moving* behaviour. Both models give information on the size of *MCC*. It appears that the difference in the *MCC* estimates of the job search and job mobility models is small and statistically insignificant. For example, given the model where observations of males and females are pooled, the difference in the estimates is € -2.19 for the standard probit model and € -2.21 for the random-effects probit model. Hence, the estimates based on the *job search* and *job-moving* approaches are consistent with each other, and differ only due to random error. The mean size effect can therefore be calculated by the weighted average of the two estimates, where the weights are based on the inverse of the variance of the estimates.[21] The mean effect based on the standard probit models is €17.09 with a standard error of € 2.31, whereas for the random-effects probit model, the *MCC* is only slightly higher (€ 17.60; s.e. € 2.59). Hence, as before, a one standard-deviation increase in the commuting time increases the *MCC* by about € 10.

Using the same methodology but distinguishing now between females with children (and an employed husband) and the rest of the sample, we find that the *MCC* for females with children is € 18.46 (s.e. 2.71) and for the rest of the sample is € 15.68 (s.e. 2.36). Hence, the results suggest that females with children have a higher *MCC* than other workers, but a larger sample of observations is needed to clarify this issue, as the difference between these estimates is not statistically significant.

3.3 Robustness analyses

We have repeated the analyses many times with different sets of control variables, and found that the results remain robust.[22] We have also re-estimated models for observations for a selected range of the reported hourly wage, to reduce potential measurement error in the reported wage. The results remain robust. Furthermore, we have re-examined the functional form of the two main variables of interest: the daily wage wH and the commuting time t. Recall that theory suggested that $v = v(wH\text{-}\alpha wt)$, so, in the empirical specification of the model, wH as well as wt have been used. Note, however, that $v(wH\text{-}\alpha wt)$ represents the same preferences as, for example, $v(log(wH\text{-}\alpha wt))$, where *log* denotes the natural logarithm. The latter can be approximated by $v(log(wH)\text{-}\alpha t/H)$, for $\alpha t/H$ much smaller than one. The latter approximation amounts to the assumption that daily commuting costs are small, relative to the daily wage. Hence, the instantaneous utility depends, then, on the *logarithm* of the daily wage and the level of commuting time (relative to the number of working hours H). Hence, we have re-estimated all models using a specification based on the *logarithm of the daily wage* and the *level of commuting time,* as well as models that include the daily wage, the logarithm of the wage, commuting time interacted with wage, and commuting time. We find now that point estimates of *MCC*, evaluated

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[21] These weights are optimal when the difference in the estimates is entirely due to random error. The standard error of this mean is computed as the square root of the sum of the inverse variance weights.

[22] We have excluded a range of regressors, as well as included additional regressors such as elapsed job duration and region (12 provinces), but the results remain robust. Note that the control variables in the search model control for *two* types of confounding effects: firstly, workers face different wage distributions, and, depending on the level of the current wage relative to the expected wage of the new job, they will decide to search; secondly, workers face different arrival rates $p(s)$, even for the same level of search effort, which will affect their search decision. Hence, each control variable controls both for differences in the wage distribution and for differences in the job arrival rates. To address this issue, we have estimated a standard hedonic wage model and have used the difference between the observed and

at the mean, are systematically *larger* (about 10% to 32% in absolute value) than reported above, but these new point estimates are all within the 95% confidence interval of the results presented above. We have compared the fitness criteria of the estimated models with those reported in section 3.2, but the fitness criteria are very similar.[23]

Finally, we have estimated bivariate probit models, which allow for correlation between the unobserved error terms in the two equations for job search and job moving. It appears that the results are almost identical: workers' *MCC* changes only slightly, whereas the standard errors are hardly reduced. In conclusion, our results are robust, and we have reported the point estimates that are the most conservative.[24]

Our estimates for α are lower than the implied value obtained by Manning (2003a) using information on on-the-job mobility in the U.K.[25] Our point estimates, however, exceed the point estimates obtained by Van Ommeren and Hazans (2008) using information on job search for

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the expected wage, viz. the residuals of the hedonic wage model, instead of the observed wage. It appears that the results are almost identical.

[23] For most models, the fitness criteria are slightly better for the model specification reported in the tables above than for the alternative specification. It appears however that the alternative specification is consistently less appropriate for females.

[24] We have found that estimates of workers' MCC are about €17 per hour. Our findings, therefore, indicate that the costs associated with commuting are substantial. It is plausible that workers will be compensated in the labour and/or housing market. In case of *full* compensation (via higher wages and house prices), commuting time should *not* have any effect on on-the-job activity or on-the-job mobility *when one does not control for wages and house prices* (Manning, 2003a). Indeed, estimates not shown here imply that on-the-job search activity, as well as job mobility, strongly increase with commuting time, when one does *not* control for wages (and house prices). So, on average, workers are *partially* compensated for their commuting costs. This result is in line with the common result: that estimates based on hedonic wage models find that wages are not so responsive to the length of workers' commuting time.

[25] Our estimates are also lower than those obtained by Stutzer and Frey (2004), who estimate, for Germany, that α is equal to 0.4, using subjective information on well being.

Lithuania. In Van Ommeren and Hazans (2008), it was argued that to determine a worker's value of job attributes via information on job search would be more accurate than using information about job mobility. In particular, it was argued that if the job attribute was correlated to involuntary job mobility, then the use of information on job mobility will bias the results. In that study, the authors suggested that the relative high value for α, obtained by Manning (2003a), may be due to the use of job mobility data (instead of job search data). Since we find almost identical results for α in our study, given information about job mobility and job search, it appears that, at least in the case of commuting time, there is no fundamental difference with respect to the choice of analysing job search or job move data. We do not have an explanation why our estimates are in between those of Manning (2003a) and Van Ommeren and Hazans (2008), although it should be emphasised that those studies focus on the U.K. and Lithuania, respectively.

Our findings are not so straightforward as to compare with those of transport studies that focus on the time component of commuting costs. In that literature, it is hotly debated whether time costs are small or large, relative to the wage rate. A usual finding is that the disutility of one hour of commuting is less than the net gross hourly wage (Small, 1992).[26] Our estimates indicate that the *overall* marginal costs of commuting are about twice the net wage, suggesting that other costs (monetary costs, opportunity costs of car use, etc.) play an important role at the margin.

4. CONCLUSION

In this paper, we have estimated workers' marginal costs associated with the length of the commute. We have argued, in the introduction, that these costs play an important role in economic theory regarding the spatial structure of the economy. Perhaps surprisingly, there is little known about the level of these costs. We used a dynamic model approach, which allows us to estimate the total marginal costs associated with commuting time. The approach has been applied to observations on job moving, as well as job search, behaviour in the Netherlands, using panel data. The application of panel data approaches partially addresses one of the limitations of the dynamic model approach used, which requires that individuals have identical utility functions (Gronberg and Reed, 1994). We demonstrate that workers' marginal costs associated with commuting time are about € 17 per hour, and that these results are hardly sensitive to the specification used.

Our estimates imply that, at the margin, workers' commuting costs are substantial. For example, when the marginal costs of commuting are € 17 per hour, then an employed worker is indifferent to a job offer that increases his daily commute by one standard deviation (35 minutes), yet, at the same time, increases his daily net wage by about € 9.91, so about the net wage for one hour of work.

Our finding of substantial marginal costs of commuting is consistent with the observation that workers' average commuting time is short, whereas, at the same time, there is a large labour economics literature which argues that there is a large variation in wages offered to job seekers, and that non-wage characteristics may be relevant (Burdett and Mortensen, 1998). If the costs associated with commuting were small, as, for example, implied by Calfee and Winston (1998), workers would be willing to accept, at least temporarily, much longer commuting times than observed in the data. In our (representative) sample, the average commuting time is 23 minutes (one-way), and only 8% of workers commute more than 60 minutes (one-way). This suggests

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[26] However, Kahneman et al. (2004) show that, on average, workers feel slightly *better* during work than

that the marginal costs associated with commuting are indeed substantial.

Our estimation approach is consistent with search-theoretical approaches applied in the 'wasteful commuting' literature, and it is interesting to apply our results to that literature. For example, the study by Van Ommeren and Van der Straaten (2008) uses a theoretical model similar to that used in the current paper. In that paper, as in this one, it is also argued that workers have to search for jobs, and it is shown that, due to a *finite* job arrival rate, workers are *not* able to minimise the length of their commute. Their empirical results imply that, on average, about 40% of the daily commuting time (46 minutes per day) is due to job search frictions. Using a marginal commuting cost of € 17 per hour, this implies that the daily costs of 'wasteful commuting' are, on average, € 5 per commuter.

during commuting, which is considered stressful, suggesting the opposite.

LITERATURE

Bartik, T.J., J.S. Butler and J.T. Liu (1992), Maximum score estimates of the determinants of residential mobility: Implications for the value of residential attachment and neighbourhood amenities, *Journal of Urban Economics*, 32, 233-256

Burdett, K. and D.T. Mortensen (1998), Wage differentials, employer size, and unemployment, *International Economic Review*, 39, 2, 257-293

Calfee, J. and C. Winston (1998), The value of automobile travel time: implications for congestion policy, *Journal of Public Economics*, 69, 83-102

Cogan, J.F. (1981), Fixed costs and labor supply, *Econometrica*, 49, 945-963

Dale-Olsen, H. (2006), Estimating workers' marginal willingness to pay for safety using linked employer-employee data, *Economica*, 73, 99-127

De Borger, B. and Fosgerau, M. (2008), The trade-off between money and time: A test of the theory of reference-dependent preferences, *Journal of Urban Economics*, 64 (1), 101-115

De Jong, G.C. (1990), An indirect utility model of car ownership and private car use, *European Economic Reviews*, 34, 5, 971–985

DeSalvo, J.S. and M. Huq (2005), Mode choice, commuting cost, and urban household behavior, *Journal of Regional Science*, 45, 3, 493-517

Fosgerau, M. (2005), Investigating the distribution of the value of travel time savings, *Transportation Research Part B: Methodological,* 40, 8, 688-707

Fujita, M. (1989), *Urban economic theory*, Cambridge University Press, Cambridge, UK

Fujita, M. and H. Ogawa (1982), Multiple equilibria and structural transition of non-monocentric urban configurations, *Regional Science and Urban Economics*, 12, 161-196

Gander, J.P. (1985), A utility-theory analysis of automobile speed under uncertainty of enforcement, *Transportation Research B*, 19, 3, 187-195

Goldberger, A.S. (1991), *A course in econometrics*, Harvard University Press, Cambridge, Massachusetts

Greene, W.H. (2000). *Econometric analysis*: Prentice Hall International, Upper Saddle River, New Jersey, 4th edition.

Gronberg, T.J. and W.R. Reed (1994), Estimating workers' marginal willingness to pay for job attributes using duration data, *Journal of Human Resources*, 24, 911-931

Hamermesh, D.S. (1996), Workdays, workhours and work schedules: evidence for the United States and Germany, Kalamazoo, MI, USA, The W.E. Upjohn Institute

Hensher, D.A. (1997), Behavior and resource values of travel time savings: a bicentennial update. In: Oum, T.H., J.S. Dodgson, D.A. Hensher, S.A. Morrison, C.A. Nash, K.A. Small and W.G. Waters II, (eds.), *Transport Economics, Selected Readings,* Amsterdam: Harwood Academic Publishers, pp.653-665

Herzog, H.W. and A.M. Schlottmann (1990), Valuing risk in the workplace: market price, willingness to pay, and the optimal provision of safety, *Review of Economics and Statistics*, 72, 463-470

Hwang, H. D., W.R. Reed and C. Hubbard (1992), Compensating wage differentials and unobserved productivity, *Journal of Political Economy*, 100, 4, 835-858

Hwang, H.D., D.T. Mortensen and W.R. Reed (1998), Hedonic wages and labour market search, *Journal of Labor Economics*, 16, 4, 815-847

Isacsson, G. and Swärdh, J.-E. (2007), Empirical on-the-job search model with preferences for relative earnings: How high is the value of commuting time? Working paper, Swedish National Road & Transport Research Institute (VTI)

Kahneman, D., A.B. Krueger, D.A. Schkade, N. Schwarz and A.A. Stone (2004), A survey method for characterizing daily life experience: the day reconstruction method, *Science*, 306, 1776-

1780

Koslowsky, M., A.N. Kluger and M. Reich (1995), *Commuting stress: causes, effects, and methods of coping,* New York: Plenum Press

Manning, A. (2003a), The real thin theory: monopsony in modern labour markets, *Labour Economics*, 10, 105-131

Manning, A. (2003b), *Monopsony in motion*, Princeton University Press, Princeton, NJ

McFadden, D. (1999), Rationality for economists?, *Journal of Risk and Uncertainty*, 19, 1-3, 73-105

Mekkelholt, E.W. (1993), *Een sequentiele analyse van de baanmobiliteit in Nederland*, PhD thesis, Amsterdam

Miller, T. (1989), The value of time and benefits of time savings, Working Paper, Urban Institute, Washington, DC

Mortensen, D.T. (1986), Job search and labor market analysis. In: O.C. Ashenfelter and R. Layard (eds.), *Handbook of Labor Economics*, Amsterdam: North-Holland

Ogawa, H. and M. Fujita (1980), Land use patterns in a monocentric city, *Journal of Regional Science*, 20, 4, 455-475

Parry, I.W.H. and A. Bento (2001), Revenue recycling and the welfare effects of road pricing, *Scandinavian Journal of Economics*, 103, 4, 645-671

Rienstra, S.A and P. Rietveld (1996), Speed behaviour of car drivers: a statistical analysis of acceptance of changes in speed policies in the Netherlands, *Transportation Research D*, 1, 2, 97-110

Rosen, S. (1986), The Theory of Equalizing Differences. In: O.C. Ashenfelter and R. Layard (eds.), *Handbook of Labor Economics*, Amsterdam: North-Holland

Rotemberg, J.J. (1985), The efficiency of equilibrium traffic flows, *The Journal of Public Economics*, 26, 191-205

Rouwendal, J. (1996), An economic analysis of fuel use per kilometre by private cars, *Journal of Transport Economics and Policy*, 30, 3-14

Small, K.A. (1992), *Urban Transportation Economics*, Chur: Harwood

Small, K. A., Winston, C. and Yan, J. (2005), Uncovering the distribution of motorists' preferences for travel time and reliability, *Econometrica,* 73, 4, 1367-1382

Stutzer, A. and B.S. Frey (2004), Stress that doesn't pay: the commuting paradox, *IZA Discussion Paper*, 1278

Tse, C.Y. and A.W.H. Chan (2003), Estimating the commuting cost and commuting time property price gradients, *Regional Science and Urban Economics*, 33, 745-767

Van den Berg, G.J. (1992), A structural dynamic analysis of job turnover and the costs associated with moving to another job, *The Economic Journal*, 102, 1116-1133

Van den Berg, G.J. and C. Gorter (1997), Job search and commuting time, *Journal of Business and Economic Statistics*, 15, 2, 269-281

Van Exel, N.J.A. and P. Rietveld (2004), Travel choice-sets: determinants and implications, Free University, Amsterdam, mimeo

Van Ommeren, J.N., G.J. Van den Berg and C. Gorter (2000), Estimating the marginal willingness to pay for commuting, *Journal of Regional Science*, 40, 3, 541-563

Van Ommeren, J.N. and M. Hazans (2008), The workers' value of the remaining employment contract duration, *Economica*, 75, 297, 116-136

van Ommeren, J.N and P. Rietveld (2005), The commuting time paradox, *Journal of Urban Economics,* 58, 3,437-454

Van Ommeren, J.N and W. Van der Straaten (2008), The effects of search imperfections on commuting behavior: evidence from employed and self-employed workers, *Regional Science and Urban Economics*, 38, 2, 127-147

Varian, H.R. (1992), *Microeconomic Analysis*, *Third Edition*, Norton & Company, New York

Verbeek, M. (2001), *A Guide To Modern Econometrics*, John Wiley & Sons, Chichester

Verhoef, E.T., P. Nijkamp and P. Rietveld (1997), The social feasibility of road pricing, a case study for Randstad area, *Journal of Transport Economics and Policy*, 31, 255-276

Verhoef, E.T. and J. Rouwendal (2001), A structural model of traffic congestion, Tinbergen Institute Discussion Paper 26, 3

Villanueva, E. (2007), Estimating compensating wage differentials using voluntary job changes: evidence from Germany, *Industrial and Labor Relations Review*, 4, 544-561

Wales, T.J. (1978), Labour supply and commuting time; an empirical study, *Journal of Econometrics*, 8, 215-226

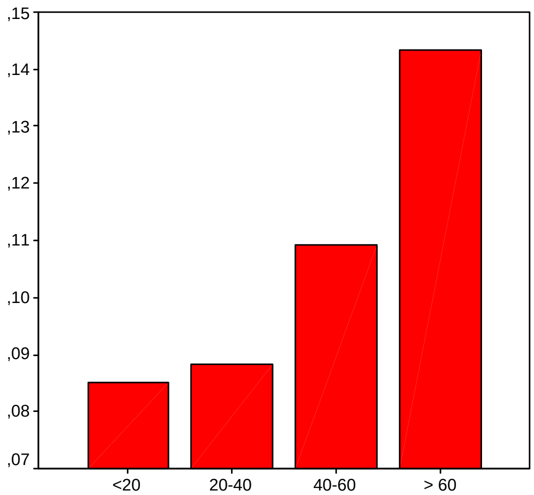
WBO (2002), Woning Behoefte Onderzoek, 2002

Wheaton, W.C. (1974), A comparative static analysis of urban spatial structure, *Journal of Economic Theory*, 9, 223-237

Yiu, C.Y. and C.S. Tam (2007), House price gradient with two workplaces – An empirical study in Hong Kong, *Regional Science and Urban Economics*, 37, 413-429

Zax, J.S. (1991), Compensation for commutes in labor and housing markets*, Journal of Urban Economics*, 30, 192-207

On-the-job search



commuting time

Figure 1

Table 1. Probit estimates of on-the-job search

	Standard probit			Random effects probit	
Variable	Coefficient	St. err.		Coefficient	St. err.
Daily wage	-0.0055	0.0009		-0.0061	0.0010
Hourly wage*commute	0.0110	0.0025		0.0125	0.0027
Very low education	-0.1780	0.0738		-0.2064	0.0898
Low education	-0.1213	0.0339		-0.1439	0.0421
High education	0.2654	0.0376		0.3081	0.0466
Very high education	0.3107	0.0604		0.3757	0.0734
Hours per week	-0.0064	0.0020		-0.0081	0.0023
Male	0.1940	0.0409		0.2176	0.0494
Age	0.2948	0.0708		0.3237	0.0840
Age^2	-0.0852	0.0123		-0.0957	0.0150
Children	0.0014	0.0139		-0.0050	0.0167
Partner	-0.2215	0.0449		-0.2511	0.0531
Employed partner	0.0766	0.0464		0.0943	0.0553
Monthly wage partner	-0.0265	0.0298		-0.0349	0.0344
ρ				0.2554	0.0255
MCC/w	-2.01	0.39		-2.06	0.44
Number of observations	18,450			18,450	

Note: industry and year controls are not reported.

Table 2. Probit estimates of on-the-job search by gender

	Males				Females			
	Standard		Random effects		Standard		Random effects	
Variable	Coeff.	St. err.	Coeff.	St. err.	Coeff.	St. err.	Coeff.	St. err.
Daily wage	-0.0052	0.0011	-0.0058	0.0012	-0.0082	0.0017	-0.0089	0.0019
Hourly w.*commute	0.0074	0.0027	0.0083	0.0035	0.0184	0.0038	0.0202	0.0045
Very low edu	-0.1866	0.0913	-0.2012	0.1161	-0.1084	0.1267	-0.1414	0.1415
Low edu	-0.0706	0.0439	-0.0799	0.0562	-0.2101	0.0545	-0.2348	0.0646
High edu	0.2161	0.0520	0.2676	0.0666	0.3232	0.0555	0.3520	0.0641
Very high edu	0.2531	0.0792	0.3231	0.0995	0.3811	0.0959	0.4309	0.1121
Hours per week	-0.0131	0.0040	-0.0159	0.0048	-0.0107	0.0027	-0.0120	0.0030
Age	0.4418	0.0993	0.5096	0.1232	0.1696	0.1071	0.1700	0.1205
Age^2	-0.1109	0.0170	-0.1293	0.0216	-0.0635	0.0192	-0.0670	0.0220
Children	0.0058	0.0183	-0.0019	0.0229	-0.0060	0.0239	-0.0105	0.0271
Partner	-0.1266	0.0594	-0.1441	0.0726	-0.3699	0.0812	-0.3978	0.0924
Employed p.	0.0301	0.0575	0.0517	0.0683	0.0395	0.0986	0.0427	0.1154
Monthly wage p.	0.0628	0.0530	0.0544	0.0588	0.0080	0.0418	0.0081	0.0488
ρ			0.2925	0.0332			0.1797	0.0422
MCC/w	-1.41	0.48	-1.43	0.55	-2.24	0.49	-2.25	0.53
Number of obs.	10,748		10,748		7,702		7,702	

Note: industry and year controls are not reported.

Table 3. Probit model of on-the-job search: females with children and employed husband

	Coefficient	Standard error	Coefficient	Standard error
Daily wage	-0.0071	0.0026	-0.0081	0.0032
Hourly wage*commute	0.0239	0.0066	0.0274	0.0084
Very low education	-0.0889	0.1923	-0.0992	0.2438
Low education	-0.2257	0.0893	-0.2692	0.1149
High education	0.2661	0.0906	0.2973	0.1111
Very high education	0.2269	0.1806	0.2576	0.2319
Hours per week	-0.0019	0.0047	-0.0024	0.0057
Age	0.1811	0.3250	0.1385	0.3700
Age^2	-0.0529	0.0544	-0.0500	0.0628
Children	0.0461	0.0466	0.0446	0.0593
Monthly wage partner	0.0135	0.0538	0.0075	0.0667
ρ			0.2685	0.0736
MCC/w	-3.35	1.18	-3.39	1.30
Number of observations	3,195		3,195	

Note: industry and year controls are not reported.

Table 4. Summary based on *job search*

	All observations		Males		Females	
	(1)	(2)	(3)	(4)	(5)	(6)
	probit	r.e. probit	probit	r.e. probit	probit	r.e. probit
β_w	-0.0055	-0.0061	-0.0052	-0.0058	-0.0082	-0.0089
s.e.	(0.0009)	(0.0010)	(0.0011)	(0.0012)	(0.0017)	(0.0019)
β_t	0.0110	0.0125	0.0074	0.0083	0.0184	0.0202
s.e.	(0.0022)	(0.0027)	(0.0027)	(0.0035)	(0.0038)	(0.0045)
MCC/w	-2.01	-2.06	-1.41	-1.43	-2.24	-2.25
s.e.	(0.39)	(0.44)	(0.48)	(0.55)	(0.57)	(0.56)
MCC	-18.43 €	-18.89 €	-13.49 €	-13.68 €	-19.29 €	-19.24 €
s.e.	(3.57 €)	(4.03 €)	(4.59 €)	(5.26 €)	(4.91 €)	(4.85 €)

Note: MCC is calculated at the gender-specific mean wage *w*.

Table 5. Probit estimates of *job moving*

	Standard probit		Random effects probit	
Variable	Coefficient	Standard error	Coefficient	Standard error
Daily wage	-0.0098	0.0014	-0.0108	0.0016
Hourly wage * commute	0.0174	0.0033	0.0198	0.0040
Very low education	-0.1566	0.1059	-0.1573	0.1181
Low education	-0.1595	0.0475	-0.1639	0.0555
High education	0.0451	0.0571	0.0371	0.0681
Very high education	0.1154	0.0983	0.0805	0.1174
Hours per week	-0.0021	0.0030	-0.0013	0.0034
Male	0.1652	0.0616	0.1410	0.0724
Age	-0.1937	0.1100	-0.2272	0.1281
Age^2	-0.0163	0.0193	-0.0124	0.0228
Children	0.0098	0.0205	-0.0757	0.0116
Partner	-0.0580	0.0686	0.0099	0.0242
Employed p.	-0.0645	0.0662	-0.0874	0.0807
Monthly wage p.	0.0792	0.0437	-0.0654	0.0749
ρ			0.2783	0.0528
MCC/w	-1.76	0.33	-1.82	0.37
Number of observations	9,513		9,513	

Note: industry and year controls are not reported.

Table 6. Probit estimates of job move by gender

	Males				Females			
	Standard		Random effects		Standard		Random effects	
Variable	Coeff.	St. err.	Coeff.	St. err.	Coeff.	St. err.	Coeff.	St. err.
Daily wage	-0.0073	0.0017	-0.0081	0.0021	-0.0183	0.0028	-0.0197	0.0029
Hourly w.*commute	0.0132	0.0041	0.0141	0.0052	0.0284	0.0056	0.0330	0.0068
Very low education	-0.1680	0.1330	-0.1936	0.1484	-0.0081	0.1833	-0.0030	0.2054
Low education	-0.1158	0.0625	-0.1310	0.0745	-0.1706	0.0760	-0.1955	0.0845
High education	0.0381	0.0803	0.0430	0.0965	0.0462	0.0845	0.0433	0.1006
Very high education	-0.0920	0.1319	-0.0904	0.1630	0.3152	0.1561	0.3518	0.1739
Hours per week	0.0058	0.0069	0.0045	0.0074	-0.0061	0.0040	-0.0070	0.0044
Age	-0.2097	0.1536	-0.2400	0.1836	-0.1785	0.1684	-0.1908	0.1897
Age^2	-0.0105	0.0263	-0.0111	0.0323	-0.0181	0.0304	-0.0205	0.0345
Job duration	-0.0698	0.0141	-0.0601	0.0152	-0.1027	0.0175	-0.0976	0.0187
Children	-0.0271	0.0277	-0.0305	0.0339	0.0523	0.0351	0.0518	0.0402
Partner	0.0592	0.0912	0.0447	0.1061	-0.1801	0.1258	-0.1900	0.1456
Employed partner	-0.0916	0.0842	-0.0852	0.0969	-0.2020	0.1454	-0.2128	0.1644
Monthly wage p.	0.1687	0.0837	0.1671	0.0982	0.1321	0.0601	0.1329	0.0659
ρ			0.2830	0.0508			0.2460	0.0687
MCC/w	-1.82	0.55	-1.76	0.63	-1.55	0.30	-1.67	0.34
Number of obs.	5,725				3,788			

Note: industry and year controls are not reported.

Table 7. Summary based on *job moving*

	All observations		Males		Females	
	(1)	(2)	(3)	(4)	(5)	(6)
	probit	r.e. probit	probit	r.e. probit	probit	r.e. probit
η_w	-0.0098	-0.0108	-0.0073	-0.0081	-0.0183	-0.0197
s.e.	(0.0014)	(0.0016)	(0.0017)	(0.0019)	(0.0028)	(0.0029)
η_t	0.0174	0.0198	0.0132	0.0141	0.0284	0.0330
s.e.	(0.0033)	(0.0040)	(0.0041)	(0.0052)	(0.0056)	(0.0068)
MCC/w	-1.76	-1.82	-1.82	-1.76	-1.55	-1.67
s.e.	(0.33)	(0.37)	(0.55)	(0.63)	(0.30)	(0.34)
MCC	-16.14 €	-6.68 €	-17.42 €	-16.84 €	-13.34 €	-14.38 €
s.e.	(3.03 €)	(3.39 €)	(5.26 €)	(6.03 €)	(2.58 €)	(2.93 €)

Note: MCC is calculated at the gender-specific mean wage *w*.