Tjalling C. Koopmans Research Institute

Discussion Paper Series nr: 04-01

The Effect of Home-ownership on Labor Mobility in The Netherlands

Michiel van Leuvensteijn
Pierre Koning

Universiteit Utrecht

Utrecht School of Economics

Tjalling C. Koopmans Research Institute
Utrecht School of Economics
Utrecht University

Vredenburg 138
3511 BG Utrecht
The Netherlands
telephone +31 30 253 9800
fax +31 30 253 7373
website www.koopmansinstitute.uu.nl

The Tjalling C. Koopmans Institute is the research institute and research school of Utrecht School of Economics.
It was founded in 2003, and named after Professor Tjalling C. Koopmans, Dutch-born Nobel Prize laureate in economics of 1975.

In the discussion papers series the Koopmans Institute publishes results of ongoing research for early dissemination of research results, and to enhance discussion with colleagues.

Please send any comments and suggestions on the Koopmans institute, or this series to P.vanDriel@econ.uu.nl

ontwerp voorblad: WRIK Utrecht

How to reach the authors.

Michiel van Leuvensteijn
The Netherlands Bureau for Economic Policy Analysis (CPB)
P.O. Box 80510
2508 GM, The Hague
The Netherlands
Tel: + 31703383488
Fax: +31703383350
Email: mvl@cpb.nl

Pierre Koning
The Netherlands Bureau for Economic Policy Analysis (CPB)
P.O. Box 80510
2508 GM, The Hague
The Netherlands
Tel: + 31703383489
Fax: +31703383350
Utrecht University
Utrecht School of Economics
Vredenburg 138
3511 BG Utrecht
The Netherlands.
E-mail: pwck@cpb.nl

Utrecht School of Economics
Tjalling C. Koopmans Research Institute
Discussion Paper Series 04-01

The Effect of Home-ownership on Labor Mobility in The Netherlands

Michiel van Leuvensteijn[a]
Pierre Koning[b]

[a] The Netherlands Bureau for Economic Policy Analysis (CPB)
[b] The Netherlands Bureau for Economic Policy Analysis (CPB) and Utrecht School of Economics

Januari 2004

Abstract
In various macro-studies, home-ownership is found to hamper job mobility and to increase unemployment. This paper addresses similar issues, but uses a micro-econometric framework where both individual job mobility, as well as the probability of being homeowner are modeled simultaneously. Using a panel of individual labor and housing market histories for the period 1989-1998, we estimate a nonparametric model of both job durations and home-ownership. We do not find homeowners to change less from jobs than tenants. Instead, our results suggest that the housing decision is driven by job commitment, and not the reverse. We do however find homeowners to be less vulnerable for unemployment.

Keywords: Duration Models, Labor Mobility (J6), Housing Market Analysis (R2).

Acknowledgements
The authors would like to thank Rob Alessie, Casper van Ewijk, Bas van der Klaauw, Jos van Ommeren, Gusta Renes, and two anonymous referees for valuable comments. Statistics Netherlands is gratefully acknowledged for providing access to the IPR data. Of course, the usual disclaimer applies.

1 Introduction

The European labor market is often characterized by its low mobility, both within as well as between countries. Since the introduction of EMU, this problem has become more prominent, as the mobility of labor is one of the few short-term adjustment mechanisms still left. One reason for the low labor mobility in Europe is that there are cultural and linguistic barriers. This, however, does not explain the differences in interregional mobility within a country, or changes in labor mobility through time. One of the explanations for this may be that home-ownership diminishes labor mobility and increases unemployment. The idea is that homeowners will not move to other regions when faced with an economic downturn, as they are more attached to their home. Also, they may be faced with decreases in housing prices. Thus, the probability of unemployment would be higher for homeowners.

Although the idea that home-ownership has a positive effect on unemployment is based on micro-economic assumptions, most studies addressing the effect of home-ownership on labor mobility and unemployment use macro- or meso-economic data. With aggregated data for the US, Green and Henderschott [3] show that home-ownership indeed constraints labor mobility, and thus increases unemployment for middle-aged classes, due to high transaction and moving costs involved. Using data of the OECD countries, Nickell [10] finds similar results. However, these studies do not reveal the

underlying behavior of individuals. For example, it may well be that lower job mobility of homeowners results from higher job commitment, also reducing the risk of unemployment. Obviously, this cannot be measured in meso- or macro-studies.

Instead of using macro- or meso-economic data, we will use longitudinal data of individual employees. This helps us to correct for spurious relationships and identify effects of home-ownership on labor mobility, and reverse. Both movements on the housing market and on the labor market are used to estimate the impact of home-ownership on job mobility as well as the probability of becoming unemployed. We use longitudinal data that are collected by the Dutch tax department (Income Panel Research data (IPR); for 1989-1998). In the IPR, about 75 thousand individuals are followed over time. These individuals can change between jobs, between unemployment and employment, between homes and between regions. In modeling these transitions, several variables in the IPR may be useful: age, income, the number of children, gender, home-ownership, job tenure, and housing duration.

Our analysis contributes to the literature on labor and housing market mobility in a number of aspects. First, the IPR provides us with a rather unique panel allowing us to link individual labor and housing market histories of a large sample of employees. The IPR data are comparable with the British Household Panel Survey, which also combines

both types of information (see e.g. Boeheim and Taylor [2]). Second, and in contrast to many other empirical studies on job mobility, we also explicitly model the probability of home-ownership, so as to correct for endogeneity bias. To minimize the biasing impact of distributional assumptions, this is done in a nonparametric fashion. Third, we do not only analyze the impact of home-ownership on job-to-job mobility, but also (and simultaneously) that on the risk of becoming unemployed or nonparticipant. This means we estimate a job duration model with multiple ('competing') risks.

The further structure of the paper will be as follows. Section 2 describes the literature on the relationship between the housing market and labor mobility. Section 3 presents the empirical model, whereas the data are described in Section 4. In Section 5 and 6, the estimation results and conclusions are presented.

2 Theory and Review

There are two strands of literature that describe the relation between the housing market and the labor market, depending on the macro or micro economic focus. Contributions in the first strand mostly try to explain labor migration. Here, the starting point is the Harris-Todaro model. In Harris and Todaro [4], a neoclassical model is developed in which (international) migration is caused by geographic differences in the supply and demand for labor. Regions with a limited supply of labor will have a relatively high expected wage, which is the product of the complement of the unemployment rate and the wage if employed. High expected wages will attract a large inflow of labor from low wage regions. This inflow of labor is mirrored by an outflow of capital.

Green and Henderschott [3] add to this the role of home-ownership to explain high unemployment and low labor migration. There are a number of ways in which home-ownership influences labor migration. First, in regions with an economic downturn homeowners are faced with a drop in house prices, making homes highly illiquid assets. Moving to another region to find a job may therefore be costly for homeowners. Second, high interest rates in times of recession may also result in a lock-in to below-market mortgages, with similar consequences for labor mobility. Third, high transaction costs may cause a decrease in labor mobility.

Various macro-studies address the relationship between home-ownership and unemployment empirically. For example, Nickell [10] analyzes the relationship between home-ownership and unemployment, using a panel of 20 OECD countries, from 1989 to 1994. With these data, Nickell shows that unemployment is (seemingly) positively correlated with home-ownership, with an elasticity of 0.13. This means that a rise of home-ownership with 10 percentage point results in an increase in unemployment of 1.3% point. Green and Henderschott [3] estimate an elasticity of 0.18, using aggregated data for the different states of the United States for the period 1970 -1990. This estimate is close to the estimate of Oswald [12], with an elasticity equal to 0.2. He analyzes the relationship between home-ownership and unemployment, using panel time series data of 19 OECD countries, from 1960 to 1990. This relationship is not only found between countries, but also between the regions of France, Italy, Sweden, Switzerland, the US and the UK.

For the Netherlands, Hassink and Curvers [5] show that regions with high home-ownership rates do not have high unemployment rates when tested on a meso-economic level. They estimate the relationship between unemployment rate and home-ownership for 348 regions for the period 1990-1998, and find home-ownership to have a negative impact on unemployment. This suggests a simultaneity problem: workers in regions with high economic growth and low unemployment will have higher

incomes, and therefore be more likely to buy a house. Apparently this is what is picked up in the estimation of the model.

Next to this, the relationship between labor mobility and the housing market is also studied on in a micro-economic context. Van Ommeren et al. [14] develop a theoretical search model in which the acceptance of a job offer not only depend on the direct gain in wage utility, but also on the once-only costs associated with moving residence and search costs. These on-the-job search costs are modest for most professions, compared to the once-only costs associated with moving residence. The once-only costs associated with moving to another residence depend strongly on housing status (see e.g. Van den Berg [13]).

Recently, various empirical studies have addressed the relationship between the housing market and labor mobility, making using of individual, longitudinal data. With the British Household Panel Survey, Henley [7] finds for the United Kingdom that unemployed are less likely to move than employed workers. Using the same data, Boeheim and Taylor [2] come to a similar result. Using Probit-models with pooled data for the United Kingdom, they find that regions with high unemployment show less home mobility. Also, they find that homeowners change less from jobs than tenants. For the Netherlands, Van Ommeren [15] estimates a search model for job movers with

(retrospective) panel data from the beginning of the nineties. He finds homeowners to be less likely to move to another home than tenants are. Also, he finds no evidence that job and residential moves are mutually related. Van der Vlist [16] concludes that homeowners are less likely to move to another home and to change jobs.

To sum up, the two strands of literature portray different, but not necessarily contradictory, pictures. Macro-studies, using variation between countries or regions over time, suggest that high home-ownership rates may lead to higher unemployment, in particular in periods of economic downturn. Micro-studies, using (longitudinal) data of individuals or households, find home-ownership to be associated with lower residential mobility and lower job-to-job mobility. This suggests that homeowners have more job commitment, and thus also may have a lower risk of unemployment. However, little is known on the exact causality of these effects. The question remains, to what extent home-ownership is driven by job commitment, and to what extent the reverse holds.

3 The Empirical Model

Our empirical model consists of two parts: the job duration model and the housing model. In the job duration model, we explain the individual labor market histories of a flow sample of employees. With this information, we identify the impact of various explanatory variables, including housing state on labor mobility. Also, since individuals are followed over time, we control for unobserved heterogeneity. Within the context of duration models, this means that we assume a (nonparametric) distribution of random effects. The same principle holds for the housing model. Here, we explain a sequence of housing states, measured on a yearly basis. These data allow us to estimate a Random Effects Logit model.

Initially, the job duration and the housing model are treated separately, and without the inclusion of random effects. As a result, the estimated impact of housing state on job mobility may be biased. Next, we estimate a simultaneous model where the job duration and the housing model are linked by the possible correlation of their random effects.

The job duration model

In this paper we use hazard rate or – stated differently – duration models to examine the impact of home-ownership on job spells. The hazard rate is defined as the rate at which an event takes place over a short period of time, given that this event has not occurred

so far. The hazard rate, θ, measures the probability of leaving a job or over a specific (small) time interval [T, $T+dt$], given that one occupies this job up to T:

(3.1) $$\theta = \Pr (T < t < T + dt \mid t \geq T$$

In the job duration model, the time interval dt is normalized to one month. Three types of transitions may take place: that into another job, of becoming unemployed, or of becoming nonparticipant. Therefore, the hazard rate out of employment is modeled into three possible competing risks. The impact of several exogenous variables, like age, sex or income, may vary with respect to these risks.

The competing risks have a *proportional* (or *loglinear*) structure (see e.g. Lancaster [9]). b denotes the index of a particular risk (b = 1,2.. B). Thus, the risk into b at time t can be described as:

(3.2) $$\theta_b (t \mid y_t , X_t) = \exp [\alpha_b y_t + \beta_b X_t + \Psi (t)]$$

with

b = 1,2,3

in which y_t equals one if the individual is a homeowner at time t (and zero if one rents a home) and X_t is a matrix representing individual covariates that may change over time t. Some of these characteristics do not vary over time, but are defined at the beginning of the duration spell. Obviously, the most relevant variable – that of the housing state $\boldsymbol{y}$ – is time-dependent. Ψ denotes the impact of duration dependence. In the estimation of the model, we use a (nonparametric) step function for Ψ. Further, take notice that the variables that change over time only do so on a calendar-year base. So residential transitions may coincide with job movements within a calendar year, whereas the exact sequence of events is unknown.

The housing model

We assume the housing state $\boldsymbol{y}$ to follow a Logit specification:

$$\text{(3.3)} \qquad \Pr(y_t = 1 \mid X_t, h_t) = \frac{\exp[\gamma X_t + \Phi(t) + \delta h_t]}{1 + \exp[\gamma X_t + \Phi(t) + \delta h_t]}$$

$$\Pr(y_t = 0 \mid X_t, h_t) = 1 - \Pr(y_t = 1)$$

As becomes apparent from (3.3), we assume the housing probability to be driven by the same, time varying covariates as the job duration model, X_t. In addition to this, we use the regional home-ownership rate h_t as an instrumental variable, only affecting the housing status. In our data, we have 538 regions. Also, since h_t pertains to average group behavior, it should be noted at this point that the assumptions for identification here are stronger than in models where instruments are measured on an individual basis (see Manski [11]). We will discuss these assumptions in detail in Section 5, when we come to the estimation results. Further, similar to (3.2), $\Phi(t)$ denotes a step function describing the impact of job tenure.

Unobserved heterogeneity

The IPR data we use provide us with a limited number of registered individual information. Obviously, more characteristics may be relevant in explaining the

differences in e.g. the risk of unemployment, or that of moving to another home. In particular, job commitment — which is approximated by the job tenure variable — may be measured imperfectly. The more important the impact of such unobserved heterogeneity, the larger the potential biasing impact of endogeneity effects. Endogeneity may arise if the choice of buying or renting a home is correlated with the risk of job transitions, becoming unemployed or nonparticipant.

Within the context of duration models, several methods have been developed to allow for unobserved heterogeneity. To minimize the impact of distributional assumptions, we adopt a nonparametric method which has been introduced by Heckman and Singer [6]. They assume that a sample consists of two (or more) (unobserved) subsamples with different levels of time invariant unobservable effects. Then, for all subsamples the corresponding weights are estimated, as well as the impact of unobserved differences on the hazard. This mass-point methodology is also used for the housing model. The unobserved differences in both models then can be linked, so as to allow for cross-correlation.

To allow for the presence of unobserved heterogeneity, we specify the risks (with index *b*) as a so called Mixed Proportional Hazard (MPH) structure. The mixing is with respect to ***v*,** which can be interpreted as a time invariant random effect:

(3.4) $$\theta_b (t \mid y_t , X_t , v_b) = \exp[\alpha_b y_t + \beta_b X_t + \Psi (t) + v_b]$$

where b = 1, 2, 3.

We also extend the housing model with random effects, u:

(3.5) $$\Pr (y_t = 1 \mid Z_t , u) = \frac{\exp[\gamma X_t + \Phi(t) + \delta h_t + u]}{1 + \exp[\gamma X_t + \Phi(t) + \delta h_t + u]}$$

$$\Pr (y_t = 0 \mid Z_t , u) = 1 - \Pr (y_t = 1)$$

To correct for endogeneity bias, we allow v_1 , v_2 , v_3 and u to be correlated. Similar to Heckman and Singer [7], we do this by modeling K combinations of mass points for { v_1 , v_2 , v_3 , u }, with probability weights, P_1, P_2 .. $1 - P_1 - .. - P_{k-1}$, respectively. Thus, the unknown distribution of { v_1, v_2 , v_3 , u } is represented by a nonparametric distribution with a finite number of points of support. The first point of support is normalized to {0 , 0, 0, 0}. Thus, in this specification one has to estimate the parameters {$\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, γ, P_1, $P_{2..}$ P_{K-1}} as well as K-1 combinations of {v_1, v_2 , v_3 , u}. We do this by using Maximum Likelihood estimation. We start by estimating the model without unobserved

heterogeneity (K=1; where there is only one point of support and P_1=1). Subsequently, we increase the number of points of support K iteratively, so as to improve the fit of the model. We perform a Likelihood Ratio test to determine the optimal K, that is, the number of points of support where the inclusion of an additional point of support, { v_1, v_2 , v_3 , u }, together with an additional weight, improves the likelihood significantly.

Correlation between the v's and u is not explicitly specified in the model, but follows from the combination of mass points. In principle, 4^{K-1} points of support allow us for all possible forms of correlation between the four random effects. However, this makes the empirical model computationally very burdensome. Therefore, with increasing K, we add a fixed point of support for { v_1, v_2 , v_3 , u }. For K=2, this means that we only allow the random effects of the v's and u to be fully correlated. For $K > 2$, however, the model becomes more flexible.

The mass-point methodology we use resembles that of Abbring [1] and Holm [8], who both estimate a bivariate model with limited dependent or duration data. Abbring [1] studies the impact of punitive sanctions on the job finding rate of unemployed employees. Both the job finding process, as well as the risk of being sanctioned, are influenced by random effects that may be correlated. Analogously, Holm [8] studies the effect of training on search durations. He also uses a random effect approach, both in the

training allocation model as well as in the hazard rate model of finding a job.

The likelihood

As stated before, if we do not allow for time invariant (unobserved) heterogeneity, the likelihood function of the model consists of two model parts that can be estimated separately. For ease of exposition, we first derive these two likelihood contributions, conditional on the unobserved components { v_1 , v_2 , v_3 , u }. Next, we integrate with respect to the unobserved mass points, so as to obtain the joint likelihood of the model.

Basically, our model explains two types of information:

Elapsed job durations:

- T = the elapsed job duration, starting from the moment of inflow in the IPR sample.
- d = a censoring indicator, which equals one if the job duration is right censored, and zero otherwise.
- b = the destination that follows the job duration spell. This destination can be another job (v = 1), unemployment (v = 2), or nonparticipation (v = 3).

Housing state:

- y_t = a dummy indicator, which equals one if a employee is a homeowner at time t, for

$t = 1..T$.

We assume that the censoring times are stochastically independent of the corresponding job durations, i.e. we assume that censoring is independent. Since the job durations are exponentially distributed, conditional likelihood of { T, b} of a particular individual can be described as:

$$(3.6) \qquad f_T\,(T, b \mid \boldsymbol{y}, \boldsymbol{X}, \boldsymbol{v}) = \exp[\,-\textstyle\sum_t^T \{\,\theta_1(t) + \theta_2(t) + \theta_3(t)\,\}\,] \times$$

$$\times \quad [\theta_1(T)^{I(b=1)} \times \theta_2(T)^{I(b=2)} \times \theta_3(T)^{I(b=3)}]^{(1-d)}$$

where I (b = 1,2,3) is an indicator function of the event between parentheses. In particular, this concerns the destination following the jobs spell. The first part of (3.6) represents the survival probability. Within the context of our model, this is the probability of not having found another job, having become unemployed or having become nonparticipant, up to time T. If T is censored (=1), the likelihood of { T, b } equals the survival probability. If T is uncensored (=0), equation (3.6) consists of two parts: the probability of survival until T, and the likelihood of a transition, either into another job (b=1), or unemployment (b=2), or nonparticipation (b=3).

The individual conditional likelihood of $\boldsymbol{y}$ – consisting of a sequence of housing states over the job spell of an individual – that follows from the (panel) Logit model (3.5) is:

$$(3.7) \quad \Pr(\boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{h}, u) = \prod_{t}^{T} \Pr(y_t = 1 \mid X_t, h_t, u)^{I(y(t)=1)} \times \Pr(y_t = 0 \mid Z_t, h_t, u)^{I(y(t)=0)}$$

The joint, individual likelihood of the observed variables – given the unobserved variables $\boldsymbol{v}$ and u – is obtained by multiplying (3.6) and (3.7). For the unobserved variables, we have K combinations of mass points for $\{ v_1, v_2, v_3, u \}$, with probability weights, $P_1, P_2 .. 1 - P_1 - .. - P_{k-1}$, respectively. Thus, the joint, integrated likelihood can be written as:

$$(3.8) \quad L = \sum_{i}^{K} \left[P_i \times f_T(T, b \mid \boldsymbol{y}, \boldsymbol{X}, \boldsymbol{v}_i) \times \Pr(\boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{h}, u_i) \right]$$

where i indicates the mass point combination. This expression is maximized with respect to $\{ \boldsymbol{\alpha}, \boldsymbol{\beta}, \gamma \}$, as well as K mass points of $\{ v_1, v_2, v_3, u \}$. Obviously, more combinations of mass points may help in increasing the fit of the model. As stated before, we use a likelihood ratio test to determine the optimal number of combinations.

4 Data

The IPR database consists of a sample of about 75000 individuals that are followed yearly by tax authorities, over the period 1989-1998. In the IPR, a number of possible housing and labor market states are distinguished. The states for the labor market are based on individual income states, like social assistance (SA) benefits, unemployment insurance (UI) benefits, income and no income. From these income states, one can derive the data at which a person becomes unemployed (SA or UI- benefit), or nonparticipant (no income or disability benefits). Further, since we know the identity of the employer, it is possible to keep track of job-to-job changes. Moving behavior can be derived from address changes. Housing market states consist of rental housing, home-ownership, or other types (for example, housing for the elderly). These are observed on a yearly basis. For each individual, we observe a complete or incomplete job spell, together with various individual characteristics.

Our data consist of a flow sample of employees. This means that we select upon individuals entering into a job, avoiding the problem of left censoring. This leaves us with 9426 observations of individual spells. The construction of a flow sample has one major advantage: for each employee we observe the exact job tenure. Obviously, this variable is crucial to identify the impact of job commitment, in particular the impact of (negative) duration dependence.

We also select upon employees that either are homeowners, and /or tenants during the time span covered by the interviews. Thus, employees living in “other house types” are left out of the sample. As the vast majority of individuals in this category are students or pensioned, this does not reduce the size of our sample (consisting of employees) substantially.

Given the IPR, the following variables are used in the empirical analysis:

(1) Age at time of moment of entry in the sample.

(2) Gender.

(3) Higher or university education. This (proxy) dummy variable indicates whether a person has received recently a scholarship for higher or university education at the moment of inflow in the sample. Thus, this level of education is not observed for older employees.

(4) Having children that receive child support, or not.

(5) Having a partner who earns income, or not.

(6) Marital state. Being married, or not.

(7) Wage in logs.

Table 1 over here

In Table 1 we present the characteristics of employees at the end of 1998. The majority of the employees is male (59%), 40 % has a working partner, 32 % has children, 7 % have studied recently. As we have a flow sample, a large fraction of the sample consists of employees that are more likely to switch jobs, and/or start their labor market career. Consequently, on average, employees are rather young (34 years), and job durations relatively short (almost twenty months). The mean percentage of homeowners is 53%. In the first year of a job spell, we observe a mean percentage of homeowners of about 25%. Thus, a large fraction of employees is observed to buy a home during their job spell.

As we have yearly observations of housing state (measured at the end of calendar years) and monthly observations of labor market state, this may cause measurement problems. For example, an employee becoming unemployed may be faced with a drop in income and therefore have to sell his home and move to a rental home. Suppose this employee is registered as being a tenant for the whole year, the new housing state may be misperceived as having caused an increase in job mobility. Similar problems arise if e.g. an employee decides to move to another region, and only temporarily moves to the rental sector. If then, after a while, the tenant becomes homeowner again, the new housing state may seem to have caused an increase in job mobility. Thus, measurement errors may

occur in some cases. However, there are no strong *a priori* beliefs that this will lead to a strong bias in our estimation results.

5 Estimation results

Initially – as we have stated before – the job duration model and the housing model are estimated separately, and without the inclusion of time invariant random effects. This is the model for K=1. Obviously, no possible interaction exists between the job duration and the housing model when unobserved heterogeneity is not included in the model. Thus, the comparison between the two models helps us to identify the possible impact of endogeneity effects. Endogeneity can be tested upon by examining the difference in the coefficient estimates of home-ownership in the two models – the null hypothesis being that this difference equals zero and there is no endogeneity (see e.g. Wooldridge [17]). In the end of this section, we will employ this endogeneity test.

We first assume that the hazard of leaving a job is not affected by duration in a job. Then, as we have a flow sample of employees, we allow for the presence of (negative) duration dependence in both models. The results of these two model versions are presented in the first two columns of Table 2.

From the first column, we may conclude that homeowners indeed experience fewer job-to-job transitions, but they also have a smaller risk of becoming either nonparticipant, or unemployed. Obviously, as will be shown in the sequel, these findings may be biased for various reasons.[1] Further, most coefficients are in line with economic intuition. That is, the probability of job-to-job transitions decreases with age and the wage level. Also, we find women, as well as married employees to show less job-to-job mobility than other employees do.

The risk into nonparticipation first decreases, and then increases with age. Students often have temporary jobs, which explains the relatively high inflow into nonparticipation of younger employees. On the other hand, older employees often enter into disability insurance, or in pre-retirement schemes. Remarkably, we find the 'higher education'-dummy to have a positive impact on the risk of becoming nonparticipant. This reflects the fact that this dummy is measured only for employees that are students, or have studied in the recent past. Again, this group often works in temporary jobs.

[1] For all model versions we also tested for possible biases stemming from the fact that job tenure is measured in months, and housing statuses on a yearly basis. In particular, we delayed the observed housing status with one year. This did not change our results substantially.

Less pronounced effects are found for the risk into unemployment. Here, the (negative) impact of home-ownership appears to be substantial, compared to the other variables. The higher the wage that is earned, the lower the probability of becoming unemployed. Employees with children have a significantly higher risk of becoming unemployed. It may be that these employees often work in part time jobs to combine formal and informal labor activities, and are more vulnerable for unemployment.

Table 2 over here

Generally, the estimation results of the housing model are in line with economic intuition: the probability of being home-owner increases with job duration, age and the wage level. In addition to this, individuals having children, being married or having a working partner are more likely to own a home. Students often live in rental homes. Remarkably, women are more likely to live more in owned homes than man are. It may well be that the female coefficient captures a difference in the education level — which we only observe to some extent — between men and women. In the Netherlands, the labor participation of women is still relatively low, compared to other countries and women that do participate are, on average, higher educated than men. As a result, the coefficient of women may be overestimated.

Duration dependence and job commitment

Until now, we have abstracted from the role of job tenure. Obviously, job commitment is crucial in understanding the decision of buying a home, as well as labor mobility. As job commitment and job security grow, individual employees will have a lower risk of becoming unemployed. Also, more and more they will be faced with the risk of losing the returns to job specific investments. Thus less time will be spent searching for other jobs. The attachment to a job also reduces the probability of moving, which makes buying a home more attractive.

The results in the first and second column of Table 2 illustrate the importance of job tenure as a proxy of job commitment, which is included as a (nonparametric) step function. The fit of the model increases dramatically, and all risks show that the job hazard strongly declines with tenure. A similar pattern is found in the housing model: the larger job commitment, the more likely it is that one owns a home. This indicates that the decision of buying a home is strongly influenced by job commitment. Using job tenure as a control variable helps in reducing the estimation bias: we no longer find a significant impact of home-ownership on job-to-job mobility. Also, the risk of nonparticipation is no longer affected by the home-ownership dummy. For the risk into unemployment, we still find a (smaller) significant negative impact. These findings

suggest that the housing market is affected by the labor market, in particular the tenure of workers, rather than the reverse.

The result that there is no impact of home-ownership on the risk of job changes may be quite particular for densely populated areas, where people can change jobs without changing residence. Also, moving costs may have been relatively low for homeowners. In the Netherlands, housing transactions are taxed by about 6%, but it may well be that — in the time span covered by the data — these costs were compensated by strong increases in housing prices. From the perspective of tenants, in particular those in the social renting sector, the costs of moving often are high: rental prices are kept artificially low, leading to long waiting lists. Once a new job in another region is accepted, and one has to move to another region, one may be faced with much higher rental prices in the private sector.

Thus, it seems that individual employees decide to change jobs without changing residence. In contrast to this, we do find a negative coefficient describing the effect of home-ownership on the risk of becoming unemployed. In a way, this is not surprising: the consequences of this event may lead to a far more substantial, and unanticipated decrease in income. Homeowners are not entitled to Social Assistance if they have own capital, and therefore have to break into their housing equity. Also, tenants are

(partially) insured against loss of income, as they may receive higher rent subsidies to compensate for this. Thus, homeowners have higher incentives to prevent unemployment by investing more in job specific capital.

The simultaneous model

Clearly, the inclusion of duration dependence helps in obtaining a better understanding of labor market dynamics, as well as the role of the housing market. Also, it helps us in disentangling duration dependence and the mixing distribution. If unobserved effects are important in the duration model, this means that the impact of genuine duration dependence is overestimated.

As becomes apparent from the third column of Table 2, unobserved time invariant effects indeed are important. The simultaneous model, which is estimated with three points of support (up to $K=3$, the likelihood of the model increases significantly), again shows a dramatic increase of the fit of the model. However, take notice that this increase is almost fully confined to the housing model; random effects are important in explaining housing state. This becomes apparent from size and the significance of the coefficients of the parameters u_1 and u_2 , the random effects in the housing model. Following the estimation results, three types of employees can be distinguished (at the three points of support), having unobservable characteristics that make them more or

less likely to own a home. As a result of these characteristics, 32% is very likely to own a home (P_2) and 29% very unlikely to own a home (P_1).

In contrast to this, in the job duration model the impact of unobserved time invariant characteristics is mostly found to be small. All coefficients, except for those of the risk into unemployment (which are denoted by v_{23} and v_{33}), are found to be insignificant. Moreover, for all risks the pattern of duration dependence seems to be unaffected. Not surprisingly, the estimated coefficients of the home-ownership dummy remain almost unchanged. Thus, following a Hausman test on the difference between the coefficients for the two model versions, the null hypothesis that there is no endogeneity cannot be rejected (with P-values of 0.252 and 0,343 for the home-ownership coefficient of the risks of job changes and into nonparticipation, respectively). These findings suggest that the potential biasing impact of unobserved, time invariant characteristics is not important.

Random effects however do matter with respect to the risk into unemployment. Employees with hidden characteristics that make them less (more) vulnerable for unemployment or nonparticipation , have a higher (lower) probability of owning a home. This seems to result in endogeneity effects: comparing the home-ownership coefficients for the unemployment risk in the two models, we find (weak) evidence that the

difference is significant (P = 0,074) – suggesting the presence of endogeneity effects. The intuition behind this result is that the lower the risk of a decrease in income, the higher the possibilities of buying a home. This effect may be reinforced by banks' selection criteria to grant mortgages. However, we still do find a significant (negative) impact of home-ownership on the risk of becoming unemployed. This means that the unemployment risk is affected negatively by home-ownership. As explained earlier, this can be driven by the stronger incentives homeowners have to invest in their jobs.

The regional home-ownership rate as an instrumental variable

In our model, the instrumental variable, regional home-ownership, serves as an important variable for identification, in particular for the simultaneous model. This rate is observed for 538 regions in the Netherlands. We find the regional home-ownership rate to have a strong impact on the individual housing status: the higher the regional proportion of home owners, the higher the individual probability of being a homeowner. However, there still are some conditions to be met for this variable to be used as a proper instrument. Clearly, the regional proportion of homeowners is a variable pertaining to average group behavior. As shown by Manski [11], the identification of causality effects with these variables may be problematic for various reasons. Three types of effects that may lead to estimation biases: endogenous effects, exogenous effects and correlated effects.

Endogenous effects occur when the propensity of an individual to behave in some way is influenced by the behavior of the group. Within the context of our model, individual homeowners may compare their social status with that of other homeowners in their neighborhood, and thus tend to invest in their careers. As a result, labor mobility of the individual homeowner may be small, as well as the unemployment risk. In that case, the regional proportion of homeowners would not be a valid instrument that is fully exogenous. However, in our model, such endogeneity effects are not likely to be important, as the proportion of homeowners is measured at the level of regions, and not at the level of (relevant) neighborhoods.

Exogenous (or contextual) effects occur if the propensity of an individual to behave in some way varies with exogenous characteristics of the reference group. Within the context of our model, these effects may result from individuals having a strong labor market position and earning a high income, moving to regions with high home-ownership rates. To a large extent, these exogenous effects are controlled for in our model, in particular by the income variable. Still, as far as some exogenous effects are not fully captured in our model, it is likely that most variation is between individuals within regions, and not variation between regions. Thus, exogenous effects will be considerably smaller for the instrumental variable.

Correlated effects arise if individuals in the same group tend to behave similarly because they face similar institutional settings. In the context of our model, this would mean that unobserved neighborhood characteristics affecting job mobility are correlated with the home-ownership rate. In particular, good employment perspectives may be concentrated in rich regions with a high proportion of home-owners. These effects are — by using income as a control variable — largely taken into account by the heterogeneity in our model. Further variation in job mobility between regions may be associated with differences in regional institutional settings, like property taxes set by local authorities, but these are not very likely to be related to the proportion of homeowners.

All in all, it seems that all three types of effects will not be substantial, as home-ownership is measured at the level of communities, and not (smaller) neighborhoods. Also, to a large extent the home-ownership rate is regulated by local authorities and we control for various variables, so as to avoid exogenous or correlated effects. Thus we conclude that this variable can be used as a valid instrument for identification.

6 Conclusions

To sum up, our estimation results suggest that the housing decision is strongly affected by job commitment; the estimated impact of home-ownership strongly decreases if we

control for this effect. Thus, the housing market is affected by the labor market, rather than the reverse. In particular, we do not find evidence of home-ownership affecting the risk of job changes, as well as the risk of nonparticipation. Also, and not surprisingly, endogeneity effects are not likely to be important for these risks. Individual employees decide to change jobs, irrespective of their housing status, and there are various explanations for this. First, given the population density in the Netherlands, people often change jobs without changing residence. Second, strong increases in housing prices may have compensated the moving costs of homeowners. And third, the regulation of the social renting sector may result in high moving costs for tenants.

Similar to the risk of job mobility, we find no impact of home-ownership on the outflow of the labor force. To a large extent, this concerns employees getting pensioned, or becoming disabled. It seems these transitions are not driven by housing state, and do not (directly) affect moving behavior.

In contrast to job-to-job changes and the probability of becoming nonparticipant, we do find a negative effect of home-ownership on the probability of becoming unemployed. The explanation for this is that the decrease in income that comes with unemployment is far more substantial for homeowners than for tenants. In principle, homeowners are not eligible for Social Assistance and have to break into their housing equity. Moreover,

tenants are (partly) insured against loss of income, due to the rent subsidy system. Thus, homeowners have a higher incentive to reduce the risk to become unemployed, in particular by investing more in job specific capital.

To conclude, home-ownership seems to stimulate job commitment in one way (lower risk of unemployment), but not at the cost of less job-to-job mobility. However, from these findings alone we cannot conclude that home-ownership does not affect labor market mobility at all. Institutional settings in the rental sector – in particular rental subsidies, and low prices in the social rental sector – may discourage labor mobility. From that perspective, labor mobility may be too low, both for homeowners and tenants.

References

[1] J.H. Abbring, “Essays in Labor Economics”, Thesis Publishers, Amsterdam (1997).

[2] R. Boeheim and M. Taylor, Residential Mobility, Housing Tenure and the Labour Market in Britain, Institute for Social and Economic Research and Institute for Labor Research, University of Essex, *Working paper* (2000).

[3] R. Green and P. Henderschott, Home-ownership and unemployment in the US, *Urban Studies*, 38, 1509-1520 (2001).

[4] J.R. Harris and M. P. Todaro, Migration, Unemployment and Development: A Two Sector Analysis, *American Economic Review*, 60, 126-142 (1970).

[5] W. Hassink and Ch. Kurvers, De invloed van woningbezit op werkloosheid: Oswald’s these voor Nederland bezien (The Influence of Home-ownership on Unemployment: Oswalds thesis analyzed for The Netherlands), *mimeo*, University of Utrecht (1999).

[6] J.J. Heckman. and B. Singer, A method for minimizing the impact of distributional assumptions in econometric models for duration data, *Econometrica*, 52, 271-320 (1984).

[7] A. Henley, Residential Mobility, Housing Equity and the Labour Market, *The Economic Journal*, 108, 414-427 (1998).

[8] A. Holm, The effect of training on search durations: a random effects approach, *Labor Economics*, 9, 433-450 (2002).

[9] T. Lancaster, "The econometric analysis of transition data," Econometric Society Monographs, no. 17, Cambridge University Press (1990).

[10] S. Nickell, Unemployment: Questions and Some answers, *Economic Journal*, 108, 802-816 (1998).

[11] C.F. Manski, Identification of endogeneous Social Effects: The Reflection Problem, *The Review of Economic Studies*, 60, 3, 531-542 (1993).

[12] A.J.Oswald, The Housing Market and Europe's Unemployment: A Non-technical Paper, *mimeo University of Warwick* (1999).

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

[14] J.N. Van Ommeren, P. Rietveld and P. Nijkamp, Job mobility, residential mobility and commuting: A theoretical analysis using search theory, *The Annals of Regional Science*, 34, 213-232 (2000).

[15] J.N. Van Ommeren, "Commuting and Relocation of Jobs and Residences," PhD-thesis, Tinbergen Institute Research Series (1996).

[16] A.J. Van der Vlist, “Residential Mobility and Commuting,” PhD-thesis, Tinbergen Institute Research Series (2001).

[17] J.M. Wooldridge, “Econometric analysis of cross section and panel data”, The MIT Press, Cambridge, Massachusetts (2002).

Table 1 Description of variables (mean and standard deviation)

	Employees Mean	Standard Deviation of Mean
	fractions*	
Job duration (including censored; in days)	596.25	7.44
Percentage of right-censored	0.232	0.004
Female	0.475	0.005
Working partner	0.345	0.005
Children	0.31	0.005
High Education	0.176	0.004
Age (years)	30.6	0.106
Married	0.41	0.005
Wage	4.47	0.05
Percentage of homeowners	0.53	
Number of observations	9426	

* unless defined otherwise,

Table 2A The (simultaneous) job duration and housing model – without columns and with unobserved heterogeneity (N=9426)

	Without unobserved effects; no job tenure included		**Without unobserved effects; job tenure included**		**With unobserved effects; job tenure included**	
	Estimates	Std. Err.	Estimates	Std. err.	Estimates	Std. err.
Parameters Job duration model:						
Risk of job changes						
Constant	-0.8905	0.0302	-0.1830	0.0406	-0.1747	0.0550
Homeowner	-0.3460	0.0374	0.0397	0.0459	-0.0084	0.0555
1-2 years tenure			-1.7229	0.0583	-1.7199	0.0585
3-5 years tenure			-2.2921	0.0660	-2.2853	0.0661
more than 5 years			-2.7514	0.1365	-2.7302	0.1356
Age 25– 35 years	-0.0575	0.0395	-0.2032	0.0512	-0.1903	0.0521
Age 35– 45 years	-0.3181	0.0522	-0.4333	0.0667	-0.4333	0.0678
Age>45 years	-0.5873	0.0691	-0.8013	0.0838	-0.8046	0.0849
Women	-0.1929	0.0310	-0.0988	0.0393	-0.0974	0.0395
Children	-0.2055	0.0380	-0.1682	0.0476	-0.1741	0.0478
Working partner	-0.0061	0.0389	-0.0482	0.0483	-0.0369	0.0484
High education	0.2504	0.0412	0.1184	0.0546	0.1139	0.0549
Log wage	-0.3727	0.0152	-0.1769	0.0182	-0.1757	0.0183
Married	-0.0356	0.0454	-0.0748	0.0562	-0.0727	0.0563
Random effects:	2nd point of support: v_{21}				0.0893	0.0624
	3rd point of support: v_{31}				-0.0820	0.0733
Risk into nonparticipation						
Constant	-1.6860	0.0455	-0.9838	0.0543	-0.9509	0.0758
Homeowner	-0.3392	0.0553	0.0119	0.0630	0.0529	0.0800
1-2 years tenure			-1.8735	0.0841	-1.8745	0.0841
3-5 years tenure			-2.2942	0.0941	-2.2983	0.0943
more than 5 years			-2.5341	0.1765	-2.5410	0.1774

Age 25– 35 years	-0.1669	0.6430	-0.2977	0.0737	-0.3073	0.0749
Age 35– 45 years	-0.4199	0.0800	-0.5153	0.0919	-0.5267	0.0932
Age>45 years	-0.1159	0.0878	-0.2640	0.1042	-0.2774	0.1062
Women	-0.0449	0.0443	0.0455	0.0515	0.0454	0.0515
Children	-0.0271	0.0514	0.0230	0.0607	0.0222	0.0608
Working partner	-0.1483	0.0584	-0.1505	0.0664	-0.1536	0.0664
High education	0.3523	0.0553	0.2045	0.0653	0.2075	0.0656
Log wage	-0.5847	0.0172	-0.4100	0.0201	-0.4103	0.0201
Married	0.1658	0.0708	0.1185	0.0807	0.1134	0.0809
Random effects:	2nd point of support: v_{22}				-0.0813	0.0838
	3rd point of support: v_{32}				-0.0580	0.1018
Risk into unemployment						
Constant	-2.2779	0.0655	-1.5910	0.0722	-1.3931	0.0926
Homeowner	-0.8687	0.0785	-0.5837	0.0844	-0.3745	0.1173
1-2 years tenure			-1.6169	0.1051	-1.6199	0.1051
3-5 years tenure			-2.1531	0.1211	-2.1690	0.1214
more than 5 years			-3.3230	0.3584	-3.3640	0.3585
Age 25– 35 years	0.2200	0.0802	0.0958	0.0868	0.0365	0.0885
Age 35– 45 years	0.1971	0.0960	0.1342	0.1042	0.0431	0.1078
Age>45 years	0.2077	0.1137	0.0447	0.1232	-0.0628	0.1275
Women	-0.0387	0.0646	0.0480	0.0692	0.0495	0.0694
Children	-0.0600	0.0746	-0.0247	0.0807	-0.0344	0.0810
Working partner	-0.2873	0.0786	-0.2796	0.0835	-0.2838	0.0836
High education	-0.0782	0.0960	-0.2122	0.1038	-0.1984	0.1045
Log wage	-0.2840	0.0383	-0.0941	0.0401	-0.0926	0.0402
Married	0.0366	0.0855	0.0180	0.0925	-0.0073	0.0926
Random effects:	2nd point of support: v_{23}				-0.3365	0.1119
	3rd point of support: v_{33}				-0.4086	0.1224
Unobserved heterogeneity: probability masses						
P_1 : 1st point of support					0.2863	0.0055
P_2: 2nd point of support					0.3184	0.0099
P_3 : 3rd point of support					0.3953	0.0100

Parameters of Housing model:

Constant	-3.2909	0.0175	-3.3851	0.0179	-9.1951	0.0904
1-2 years tenure			0.3334	0.0513	0.4922	0.0616
3-5 years tenure			0.7746	0.0297	1.4827	0.0475
more than 5 years			1.5174	0.0367	3.3260	0.0768
Age 25– 35 years	0.3752	0.0103	0.4036	0.0104	1.1249	0.0327
Age 35– 45 years	0.9179	0.0112	0.9332	0.0113	2.1337	0.0458
Age>45 years	0.9872	0.0123	1.0296	0.0124	2.5575	0.0558
Women	0.3133	0.0075	0.2991	0.0076	0.3186	0.0252
Children	0.1062	0.0079	0.1008	0.0079	0.0219	0.0329
Working partner	0.6068	0.0073	0.6115	0.0074	0.6808	0.0297
High education	-0.2631	0.0155	-0.2315	0.0157	-0.4934	0.0352
Log wage	0.2885	0.0038	0.2446	0.0039	0.1837	0.0132
Married	0.9347	0.0087	0.9405	0.0088	1.4555	0.0395
% homeowners	2.7560	0.0264	2.7399	0.0267	1.7655	0.0935
Random effects:	2nd point of support: u_2				7.6423	0.0685
	3rd point of support: u_3				4.8388	0.0585
Mean log likelihood	-7.1992		-6.8322		-5.0056	