An analysis of housing expenditure using semiparametric models and panel data

Erwin Charlier\textsuperscript{a,b}, Bertrand Melenberg\textsuperscript{a}, Arthur van Soest\textsuperscript{a,*}

\textsuperscript{a}Department of Econometrics, Tilburg University, P.O. Box 90153, 5000 LE, Tilburg, Netherlands
\textsuperscript{b}NIB Capital Asset Management, P.O. Box 8285 3503 RG, Utrecht, Netherlands

Received 1 April 1997; received in revised form 1 March 2000; accepted 5 July 2000

Abstract

In this paper we model expenditure on housing for owners and renters by means of endogenous switching regression models for panel data. We explain the share of housing in total expenditure from a household specific effect, family characteristics, constant-quality prices, and total expenditure, where the latter is allowed to be endogenous. We consider both random and fixed effects panel data models. We compare estimates for the random effects model with estimates for the linear panel data model in which selection only enters through the fixed effects, and with estimates allowing for fixed effects and a more general type of selectivity. Differences appear to be substantial. The results imply that the random effects model as well as the linear panel data model are too restrictive. © 2001 Elsevier Science S.A. All rights reserved.

\textit{JEL classification:} C14; C33; R21

\textit{Keywords:} Sample selection; Engel curves; Semiparametric models; Panel data

1. Introduction

In most industrialized countries housing is one of the main categories of household expenditure. Its understanding is, therefore, crucial for analyzing...
household consumption. The decision how much to spend on housing is strongly related to the choice between renting and owning. The standard reference is Lee and Trost (1978), who explain annual family expenditure on housing taking the decision to own or to rent explicitly into account. They use cross-section data and apply a switching regression model with endogenous switching and normally distributed error terms, which is also referred to as Tobit V by Amemiya (1984). A recent application of this model is, for example, given by Megbolugbe and Cho (1996), who explain racial differences in housing demand of US families.

Several authors have focused on different aspects of the demand for housing. Ioannides and Rosental (1994) analyze the choice between renting and owning in relation to consumption and investment demand for housing. Zorn (1993) models the fact that some households cannot obtain a mortgage due to mortgage constraints, which results in a kinked budget set. Haurin (1991) also considers mortgage constraints, and analyzes how the intertemporal variation in income affects tenure choice. Ermisch et al. (1996) use cross-section data to analyze housing demand in Britain, using a switching regression model for recent movers vs. nonmovers. These authors focus on estimating price and income elasticities, and also compare their findings with earlier results for the US and the UK. They find income elasticities of around 0.5, which is rather low compared to the range of earlier estimates for the US (0.7–1.5) or the UK (0.5–1.1). The price elasticities they find are about \(-0.4\), which is again somewhat low compared to US findings (a range of \(-0.8\) through \(-0.5\)), but in line with earlier UK findings. They emphasize the sensitivity of their elasticity estimates for selectivity issues and the income measure.

In a series of studies, Axel Börsch-Supan and various coauthors analyze both cross-section and panel data models for housing choice in the US and Germany. See, for example, Börsch-Supan (1986, 1987), Börsch-Supan and Pitkin (1988), and Börsch-Supan and Pollakowski (1990). They focus on discrete choice models, using generalizations of the multinomial logit model. For example, Börsch-Supan and Pollakowski (1990) estimate a fixed effects multinomial logit model for the choice between four types of dwelling, distinguishing owner occupied vs. rental dwellings, and large vs. small dwellings.

In this paper we focus on housing expenditure and not on housing assets, housing equity or mortgage constraints. Thus, our dependent variable is continuous instead of discrete, so that we cannot use Börsch-Supan’s discrete choice type of panel data models. We will combine the model of Lee and Trost (1978), henceforth referred to as LT model, with the consumer demand literature on expenditure on goods. We extend the LT model in two ways. First, we use panel data, and can therefore allow for time constant unobserved household specific effects which can be correlated with the regressors. In other words, we will allow
for fixed effects, which would be impossible in the cross-section context. The usual cross-section model imposes independence between individual effects and regressors or instruments, which, in a panel data context, leads to the more restrictive random effects model. There are two types of fixed effects models that we consider: a linear model in which selectivity only enters through the fixed effects, and a model similar to that of Kyriazidou (1997), which incorporates more general selectivity effects than the linear model. We will compare results for these two fixed effects models with those of a random effects model.

Following the two-stage budgeting consumption literature (Blundell and Walker, 1986), we will explain housing expenditure from total expenditure rather than income. A second generalization compared to the LT model, is that we take account of potential endogeneity of total expenditure. We test for this and present estimates allowing for it. Our main focus is the sensitivity of housing expenditure for total expenditure and for prices. We construct and incorporate prices along the lines of Börisch-Supan (1987) and Börisch-Supan and Pollakowski (1990), exploiting price variation across time and across space.

Our main findings are that the random effects model, the model in which selectivity enters through the fixed effects only, and the model which assumes that total expenditure is exogenous, are all rejected against the more general fixed effects model. Moreover, the models lead to different conclusions about aggregate elasticities of housing expenditure with respect to total expenditure and prices.

The remainder of this paper is organized as follows. In Section 2 we describe the data, drawn from the Dutch Socio Economic Panel, 1987–1989. In Section 3 we discuss various parametric and semiparametric panel data models and report our estimation and testing results using these models in order to explain housing. Section 4 concludes.

2. Data

We will use data from the waves 1987–1989 of the Dutch Socio-Economic Panel (SEP). Although this panel exists since 1984, information concerning housing is only present since 1986 and wealth data are available as of 1987. We will use a cleaned subsample for each year with information on family characteristics (including marital status, number of children living with the family, age of the head of household, education level and region of residence), and labor market characteristics (including hours of work, gross and net earnings). The labor market characteristics are used to construct household income which consists of labor earnings, other family income (mainly from letting rooms or child allowances), benefits and pensions. Personal income of children is
excluded. Asset income and capital gains are also excluded, because this type of income is strongly related to the home ownership decision. Wealth data\(^1\) are used to construct savings.\(^2\) For issues on cleaning the savings data we refer to Camphuis (1993). Income and savings are used to construct total expenditure. Expenditure and income are reported in *Dutch guilders per month*.

The budget share spent on housing is defined as the fraction of total expenditure spent on housing. Housing expenditure for renters is the amount of money spent on rent by the family (i.e., excluding gas/water/electricity/heating as well as rental subsidy). For owners expenditure on housing consists of the following components: net interest costs on the mortgage,\(^3\) net rent paid if the land is not owned, taxes on owned housing,\(^4\) costs of insuring the house, opportunity costs of housing equity, maintenance costs, and minus the increase of the value of the house. The latter three costs components are not observed in the data. The opportunity cost of the foregone interest on housing equity is set equal to 4\% of the value of the house minus the mortgage value. Maintenance costs and the increase of the value of the house are set equal to 2\% and 1\% of the value of the house, respectively. In Appendix A, we shall investigate the sensitivity of the results with respect to these choices. It appears that most results are hardly affected.

Appendix A contains some further details on the construction of the sample and the variables of interest, and a comparison with macro-data on housing expenditure. Given this sample, we excluded households with item nonresponse on wealth or income, implying that total expenditure is missing, and we also excluded a few households with housing budget share larger than 0.6. For the 1987 wave this reduces the dataset from 3006 to 2273 observations. In addition to the data derived from the SEP, we also included constant-quality prices of owned and rented housing, constructed along the lines of Börsch-Supan (1987) and Börsch-Supan and Pollakowski (1990). These prices vary over time and space; Appendix A contains the details.

Variable definitions and summary statistics for the three resulting panel waves are presented in Table 1. The average budget share of housing is 0.21 for

---

\(^1\) Net wealth is constructed using checking accounts, savings and deposits accounts, saving certificates, certificates of deposits, bonds and mortgage bonds, shares, options and other securities, antiques, jewels, coins, etc., real estate other than one’s own residence, one's own car, claims against private persons, other assets, life-insurance with saving elements, personal loan or revolving credit, hire-purchase and other loans.

\(^2\) We also corrected for donations, bequests, and capital gains.

\(^3\) Mortgage interest payments are tax deductible. See Appendix A for computation of the marginal tax rate.

\(^4\) This refers to a direct tax on housing property and to extra income tax due to adding the imputed rental value of the house to household income.
Table 1
Overview of variables and summary statistics for 1987, 1988 and 1989 (standard deviations in parentheses)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean 1987</th>
<th>Renters</th>
<th>Mean 1988</th>
<th>Renters</th>
<th>Mean 1989</th>
<th>Renters</th>
<th>Mean 1987</th>
<th>Owners</th>
<th>Mean 1988</th>
<th>Owners</th>
<th>Mean 1989</th>
<th>Owners</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of obs.</td>
<td></td>
<td>1144</td>
<td>1201</td>
<td>1125</td>
<td>1129</td>
<td>1178</td>
<td>1246</td>
<td>1129</td>
<td>1246</td>
<td>1129</td>
<td>1246</td>
<td>1129</td>
<td>1246</td>
</tr>
<tr>
<td>BS0, BS1</td>
<td>Budget share (i.e. monthly expenditure on housing divided by monthly total expenditure)</td>
<td>0.21</td>
<td>0.21</td>
<td>0.21</td>
<td>0.20</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>DOP2</td>
<td>Dummies for education level</td>
<td>0.24</td>
<td>0.26</td>
<td>0.26</td>
<td>0.15</td>
<td>0.16</td>
<td>0.17</td>
<td>0.16</td>
<td>0.17</td>
<td>0.16</td>
<td>0.17</td>
<td>0.16</td>
<td>0.17</td>
</tr>
<tr>
<td>DOP3</td>
<td></td>
<td>0.37</td>
<td>0.36</td>
<td>0.38</td>
<td>0.48</td>
<td>0.45</td>
<td>0.48</td>
<td>0.45</td>
<td>0.48</td>
<td>0.45</td>
<td>0.48</td>
<td>0.45</td>
<td>0.48</td>
</tr>
<tr>
<td>DOP4</td>
<td></td>
<td>0.09</td>
<td>0.08</td>
<td>0.11</td>
<td>0.19</td>
<td>0.18</td>
<td>0.20</td>
<td>0.18</td>
<td>0.20</td>
<td>0.18</td>
<td>0.20</td>
<td>0.18</td>
<td>0.20</td>
</tr>
<tr>
<td>DOP5</td>
<td></td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.07</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
<td>0.07</td>
</tr>
<tr>
<td>AGE</td>
<td>Age of the head of the household in decennia</td>
<td>4.01</td>
<td>3.94</td>
<td>4.00</td>
<td>4.08</td>
<td>4.07</td>
<td>4.10</td>
<td>4.08</td>
<td>4.07</td>
<td>4.10</td>
<td>4.10</td>
<td>4.08</td>
<td>4.07</td>
</tr>
<tr>
<td>AGE2</td>
<td>And its square</td>
<td>17.54</td>
<td>16.96</td>
<td>17.43</td>
<td>17.63</td>
<td>17.47</td>
<td>17.74</td>
<td>17.63</td>
<td>17.74</td>
<td>17.47</td>
<td>17.74</td>
<td>17.47</td>
<td>17.74</td>
</tr>
<tr>
<td>LINC</td>
<td>Logarithm of monthly family income and</td>
<td>7.71</td>
<td>7.71</td>
<td>7.76</td>
<td>8.06</td>
<td>8.08</td>
<td>8.14</td>
<td>8.06</td>
<td>8.08</td>
<td>8.14</td>
<td>8.14</td>
<td>8.06</td>
<td>8.08</td>
</tr>
<tr>
<td>L2INC</td>
<td>Its square (in guilders)</td>
<td>59.64</td>
<td>59.69</td>
<td>60.38</td>
<td>65.16</td>
<td>65.49</td>
<td>66.40</td>
<td>65.16</td>
<td>65.49</td>
<td>66.40</td>
<td>66.40</td>
<td>65.16</td>
<td>65.49</td>
</tr>
<tr>
<td>EXP</td>
<td>Monthly total family expenditure</td>
<td>2370</td>
<td>2479</td>
<td>2552</td>
<td>3307</td>
<td>3549</td>
<td>3662</td>
<td>3307</td>
<td>3549</td>
<td>3662</td>
<td>3662</td>
<td>3307</td>
<td>3549</td>
</tr>
<tr>
<td>LEXP</td>
<td>Logarithm of monthly total family expenditure</td>
<td>7.67</td>
<td>7.71</td>
<td>7.74</td>
<td>8.01</td>
<td>8.08</td>
<td>8.11</td>
<td>8.01</td>
<td>8.08</td>
<td>8.11</td>
<td>8.11</td>
<td>8.01</td>
<td>8.08</td>
</tr>
<tr>
<td>L2EXP</td>
<td>And its square</td>
<td>59.09</td>
<td>59.75</td>
<td>60.15</td>
<td>64.37</td>
<td>65.51</td>
<td>66.00</td>
<td>64.37</td>
<td>65.51</td>
<td>66.00</td>
<td>66.00</td>
<td>64.37</td>
<td>65.51</td>
</tr>
<tr>
<td>DMAR</td>
<td>Dummy for married</td>
<td>0.74</td>
<td>0.70</td>
<td>0.70</td>
<td>0.94</td>
<td>0.93</td>
<td>0.94</td>
<td>0.94</td>
<td>0.93</td>
<td>0.94</td>
<td>0.94</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>NCH</td>
<td>Number of children living with the family</td>
<td>0.84</td>
<td>0.81</td>
<td>0.79</td>
<td>1.22</td>
<td>1.23</td>
<td>1.16</td>
<td>1.22</td>
<td>1.23</td>
<td>1.16</td>
<td>1.16</td>
<td>1.22</td>
<td>1.23</td>
</tr>
<tr>
<td>LRP</td>
<td>Logarithm of constant quality price of rental housing</td>
<td>6.05</td>
<td>6.08</td>
<td>6.09</td>
<td>6.06</td>
<td>6.09</td>
<td>6.10</td>
<td>6.06</td>
<td>6.09</td>
<td>6.10</td>
<td>6.10</td>
<td>6.06</td>
<td>6.09</td>
</tr>
<tr>
<td>LOP</td>
<td>Logarithm of constant quality price of owner occupied housing after tax</td>
<td>5.79</td>
<td>5.78</td>
<td>5.83</td>
<td>5.75</td>
<td>5.75</td>
<td>5.80</td>
<td>5.75</td>
<td>5.75</td>
<td>5.80</td>
<td>5.80</td>
<td>5.75</td>
<td>5.75</td>
</tr>
<tr>
<td>LRELPR</td>
<td>LRP – LOP</td>
<td>0.25</td>
<td>0.30</td>
<td>0.26</td>
<td>0.31</td>
<td>0.34</td>
<td>0.30</td>
<td>0.31</td>
<td>0.34</td>
<td>0.30</td>
<td>0.30</td>
<td>0.31</td>
<td>0.34</td>
</tr>
</tbody>
</table>

renters and about 0.20 for owners. For owners, this share decreased slightly over time.

Figs. 1 and 2 describe the 1987 data in some more detail. In Fig. 1, nonparametric density estimates for the budget shares BS0 for renters and BS1 for owners are shown, as well as nonparametric regressions of these budget shares on log(total expenditure). Both budget share distributions are skewed to the right. The regression estimates suggest that the housing budget share is nonlinear in log(total expenditure), but can be approximated reasonably well by a quadratic function. This is similar to what Banks et al. (1994) find for many commodity groups.

In Fig. 2, the result of a nonparametric regression of the probability of owning a house as a function of log(total income) is presented together with the frequency distribution of log(total income). Families with higher total income tend to have a higher probability of owning a house for the main part of the income range.
3. Models

The panel data models we consider allow for household specific effects which are either assumed to be independent of the explanatory variables (random effects), or allowed to be correlated with the explanatory variables (fixed effects). Starting point is the following system of equations:

\[ d_{it} = 1(\pi' x_{it} + \eta_i - u_{it} \geq 0), \]
\[ y_{0it} = \beta_0' x_{it} + \omega_{0i} + \varepsilon_{0it} \quad \text{if } d_{it} = 0, \]
\[ y_{1it} = \beta_1' x_{it} + \omega_{1i} + \varepsilon_{1it} \quad \text{if } d_{it} = 1. \]

Here the indices \(i\) and \(t\) refer to household \(i\) in period \(t\) (\(t = 1, \ldots, T\)). \(d_{it}\) is a sector selection dummy variable, representing the tenure choice between owning and renting, which is 1 for owners and 0 for renters, \(x_{it}\) is a vector of explanatory
Fig. 2. Nonparametric estimates of the probability of owning a house as a function of log household income (LINC), and distribution of LINC.
variables (log total expenditure and its square, prices, and taste shifters), $y_{0it}$ and $y_{1it}$ are the budget shares spent on housing for renters and owners, respectively. $x_{0i}$, $x_{1i}$, and $\eta_i$ are unobserved household specific time-invariant effects, and $\varepsilon_{0it}$, $\varepsilon_{1it}$, and $u_{it}$ are the error terms. $\beta_1$, $\beta_0$ and $\pi$ are vectors of unknown parameters. $I(\cdot)$ stands for the usual indicator function.

3.1. Random effects

In a random effects model, where $x_{0i}$, $x_{1i}$, $\eta_i$, $\varepsilon_{0it}$, $\varepsilon_{1it}$, and $u_{it}$ are normally distributed and independent of $x_{it}$, we could apply the estimation procedure proposed by Vella and Verbeek (1999). However, their estimation procedure relies on the normality assumptions. An alternative approach to estimate the slope parameters in the random effects panel data model is to consider each wave of data separately (i.e., three cross-sections). Considering a particular wave, we can drop the $t$-subscript, and include the random effects in the error terms which then become $v_i = (x_{0i} + \varepsilon_{0i}, x_{1i} + \varepsilon_{1i}, \eta_i - u_i)$; subsequently, we can use existing estimation techniques for a cross-section endogenous switching regression model. A semi-parametric cross-section model estimator gives consistent estimates for the slope parameters in the three equations (for each wave), without requiring normality of the errors.

Even if the error terms in a cross-section endogenous switching regression model are independent of the regressors, identification of the parameters of this model, without further distributional assumptions, requires that at least one component of both $\beta_1$ and $\beta_0$ are equal to zero (possibly the same), while the corresponding components of $\pi$ are not equal to zero. Such exclusion restrictions are not required if normality of the errors is imposed, but are generally needed in a semi-parametric framework. Therefore, we will impose them throughout.

From an economic point of view, it is natural to exclude the price of rented housing from the housing demand equation for owners, and to exclude the price of owned housing from the demand equation for renters. Once the choice between renting and owning is made, the price of the alternative which is not chosen is no longer relevant. Another exclusion restriction we use is that the head of household’s education level is not included in the budget share equations. Education level may affect the family’s information set and interest in financial matters, and may, therefore, influence the family’s portfolio choice, of which the choice between owning and renting is an important component. However, it is not clear why education should have a direct impact on housing

---

5 The only exception we know of is given by Chen (1999). He relaxes the exclusion restriction and imposes an additional symmetry condition on the errors.
consumption, given the ownership decision. Finally, we exclude the number of children from the share equations. Although there is no a priori reason for this, the number of children was always insignificant in the share equations at any conventional level.

As mentioned above, $x_i$ will include the log of total expenditure and its square, which might be endogenous. For example, according to the two-stage budgeting literature, a household first decides how much to spend in total in each period and, given this decision, it decides how much of this to spend on food, clothing, housing, etc. Thus, total expenditure per period is a decision variable and could be endogenous. In the model, where error terms arise due to future uncertainty only, total expenditure is exogenous to the share equations. However, introducing random preferences in a life-cycle consistent way will lead to a model in which the resulting error term is correlated with total expenditure so that total expenditure may be endogenous.

To the best of our knowledge, computationally convenient semi-parametric estimators of the model allowing for endogenous regressors in the binary choice selection equation are not available yet. Therefore, we shall assume that the log of total expenditure and its square are not present in the selection equation. Instead, this equation includes the log of household income and its square, which can be seen as instruments for the total expenditure variables.

We decompose $x_i$ into $x_{ai}$, containing log total expenditure and its square, $x_{bi}$, containing log household income and its square, and $x_{di}$, containing prices and taste shifters. Exclusion restrictions yield $x_{cl}$ as a subvector of $x_{di}$. $x_{bi}$ and $x_{di}$ are included in the selection equation, and $x_{ai}$ and $x_{ci}$ are included in the budget share equations. The random effects assumption implies that the error terms $x_{0i} + \varepsilon_{0i}$, $x_{1i} + \varepsilon_{1i}$ and $\eta_i - u_i$ are assumed to be independent of $(x_{bi}', x_{di}')$, whereas $x_{ai}$ is allowed to be endogenous.

A detailed analysis of various cross-section models is given in Charlier et al. (2000). Since in that paper, the normality assumption on $(x_{0i} + \varepsilon_{0i}, x_{1i} + \varepsilon_{1i}, \eta_i - u_i)'$ is strongly rejected, we here only report the results based on the approach of Newey (1988). This approach yields consistent estimators under weaker distributional assumptions than normality, and has the advantage of computational convenience. Newey’s approach consists of two steps. The first step is to estimate the binary choice selection equation by maximum likelihood. In our search for a flexible enough specification for this, we have experimented

---

6See Blundell and Walker (1986), for example.
7Not all semiparametric estimators developed so far are also computationally convenient, in particular not those estimators which require optimization of a heavily nonlinear objective function with possibly many local optima.
with several single index generalizations of a probit model (see Appendix C), and found the following one-parameter extension:

\[ P\{d_i = 1|x_{bi}, x_{di}\} = \Phi(\pi'_b x_{bi} + \pi'_d x_{di} + \tau[\pi_b x_{bi} + \pi_d x_{di}]^2). \]

We also estimated the model with higher-order polynomials or rational functions of the single index, but these higher-order terms turned out to be insignificant.

The second step is to estimate the budget share equations, taking account of selectivity bias and potential endogeneity of expenditure variables. Selection is accounted for by adding an extra regressor which can be seen as a correction term. This correction term is an unknown function of the index \( \pi'_b x_{bi} + \pi'_d x_{di} \). The unknown function is replaced by a polynomial with coefficients to be estimated, and the parameters \( \pi_b \) and \( \pi_d \) are replaced by their first round estimates. Newey shows that, for the case of exogenous regressors, OLS on the two subsamples with the terms of the polynomials added as additional regressors, leads to consistent estimates if the order of the polynomial tends to infinity with the number of observations. He also derives the asymptotic covariance matrix of the estimator and a consistent estimate for it.

Potential endogeneity of \( x_{ai} \) can be accounted for by using IV (with \( x_{ci} \) and log family income and its square as instruments) instead of OLS in the second step. This is described extensively in Charlier et al. (2000). To make the current paper self-contained, we have included the details of this estimator and its implementation (choice of smoothing parameters, etc.) in Appendix C.

Results on the selection equation are presented in Table 2. In the left panel we present the ML estimates of the selection equation for each of the three waves separately. The estimate of \( \tau \), the coefficient of \( (\pi'_b x_{bi} + \pi'_d x_{di})^2 \), is always negative, and significant at the 5% level in the first and third wave. The results for the three waves are quite similar to each other. We find that the probability \( P\{d_i = 1|x_{bi}, x_{di}\} \) increases with the index \( \pi'_b x_{bi} + \pi'_d x_{di} \) over the sample range.\(^8\) The income pattern is U-shaped, and the probability of ownership increases with income over most of the income range. The education effect is also positive, significant, and much stronger than the income effect. The age pattern is inversely U-shaped with a maximum probability of ownership at about 45 years of age. Being married increases the probability of ownership; the number of children is insignificant. The regional dummies imply that ownership is higher in other regions than in the west of the country, where house prices are higher than elsewhere.

---

\(^8\) LM tests similar to those in Chesher and Irish (1987), reject normality in the extended probit model only for 1987. Homoskedasticity, however, is rejected for all waves, suggesting that the single index specification might be inadequate, despite the seemingly high flexibility. Because Newey’s estimator applies only to a single-index selection equation, alternative single-index semiparametric estimators are unlikely to perform much better.
Table 2
Estimation results for the selection equation (standard errors in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>33.506b (4.569)</td>
<td>9.669b (3.528)</td>
<td>15.552b (5.846)</td>
<td>12.897b (1.981)</td>
<td>54.583b (7.598)</td>
<td></td>
</tr>
<tr>
<td>DOP2</td>
<td>0.170c (0.081)</td>
<td>0.071 (0.086)</td>
<td>0.274b (0.091)</td>
<td>0.166b (0.049)</td>
<td>0.288c (0.137)</td>
<td></td>
</tr>
<tr>
<td>DOP3</td>
<td>0.480b (0.074)</td>
<td>0.361b (0.075)</td>
<td>0.548b (0.085)</td>
<td>0.460b (0.044)</td>
<td>0.802b (0.125)</td>
<td></td>
</tr>
<tr>
<td>DOP4</td>
<td>0.566b (0.126)</td>
<td>0.527b (0.113)</td>
<td>0.616b (0.118)</td>
<td>0.580b (0.067)</td>
<td>0.952b (0.210)</td>
<td></td>
</tr>
<tr>
<td>DOP5</td>
<td>0.483c (0.224)</td>
<td>0.280 (0.169)</td>
<td>0.594c (0.207)</td>
<td>0.478b (0.110)</td>
<td>0.835c (0.371)</td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>1.185b (0.225)</td>
<td>1.443 (0.231)</td>
<td>1.456b (0.233)</td>
<td>1.358b (0.131)</td>
<td>2.024b (0.380)</td>
<td>16.875c (5.942)</td>
</tr>
<tr>
<td>AGE2</td>
<td>−0.126b (0.026)</td>
<td>−0.160b (0.027)</td>
<td>−0.160b (0.027)</td>
<td>−0.149b (0.015)</td>
<td>−0.217b (0.044)</td>
<td>−2.091c (0.739)</td>
</tr>
<tr>
<td>LINC</td>
<td>−10.591b (1.215)</td>
<td>−4.515b (0.919)</td>
<td>−6.017b (1.521)</td>
<td>−5.282b (0.524)</td>
<td>−17.304b (2.026)</td>
<td>6.590 (13.318)</td>
</tr>
<tr>
<td>L2INC</td>
<td>0.743b (0.080)</td>
<td>0.352b (0.061)</td>
<td>0.443b (0.099)</td>
<td>0.398b (0.035)</td>
<td>1.214b (0.134)</td>
<td>−0.496 (0.838)</td>
</tr>
<tr>
<td>DMAR</td>
<td>0.485b (0.090)</td>
<td>0.576b (0.099)</td>
<td>0.649b (0.095)</td>
<td>0.572b (0.054)</td>
<td>0.839b (0.156)</td>
<td></td>
</tr>
<tr>
<td>NCH</td>
<td>0.045 (0.034)</td>
<td>0.049 (0.031)</td>
<td>0.016 (0.033)</td>
<td>0.038b (0.018)</td>
<td>0.071 (0.056)</td>
<td>−0.200 (0.497)</td>
</tr>
<tr>
<td>LRELPR</td>
<td>1.255b (0.296)</td>
<td>0.504 (0.282)</td>
<td>0.801c (0.306)</td>
<td>0.713b (0.162)</td>
<td>2.006b (0.496)</td>
<td>2.010 (2.604)</td>
</tr>
<tr>
<td>τ</td>
<td>−0.215b (0.021)</td>
<td>−0.036 (0.061)</td>
<td>−0.114c (0.049)</td>
<td>−0.111b (0.027)</td>
<td>−0.130b (0.014)</td>
<td></td>
</tr>
<tr>
<td>Dummy87</td>
<td>−2.682b (0.680)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy88</td>
<td>−1.468b (0.459)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

aColumns 2–6 are based on (pooled) cross-section data, column 7 is based on panel data and a model with fixed effects.
bSignificant at the 1% level.
cSignificant at the 5% level.
We have imposed that the coefficients of the log prices for rented and owned housing add up to zero, implying that only the price ratio matters. The log of the price ratio of rental housing and owner occupied housing (LRELPR) has a positive effect, implying that a higher relative price of renting increases the probability of owning. This is in line with what one might expect.

For the sake of comparison we also included in Table 2 estimates based on pooled data for the three waves. We considered the cases without and with time dummies included. Since the time dummies turned out to be insignificant, we only report the estimation results without the time dummies. The estimates are always in the range of the estimates based on the three separate waves. Standard errors are generally lower than those for the three waves separately, and all pooled estimates are significant at the 5% level. The conclusions do not change.

In Table 2 we also make a comparison with a logit specification instead of probit. We present the results for the 1987 wave. Taking into account the differences in normalization, the estimation results turn out to be quite similar.9

Results on the budget share equations are presented in Tables 3 and 4. Table 3 contains the results ignoring selection, while Table 4 presents the results taking selection into account. These tables also contain corresponding results for the fixed effects models, to be discussed in the next subsection. The semiparametric estimates based upon Newey (1988) are presented in the upper panel of Table 4. We distinguish between the case in which LEXP and L2EXP are assumed to be exogenous, and the case where they are allowed to be endogenous.10 In both cases we calculated the series approximation of the correction term up to nine terms. Generally, for both owners and renters, the results did not change much after including seven terms in the series approximation.

The estimated standard errors, which take into account the first stage estimation error in the parameters of the selection equation, appear to differ substantially from the standard OLS standard error estimates, but are similar to the Eicker-White standard errors. This indicates that the first stage errors hardly affect the standard errors of the second stage estimates, but that taking into account heteroskedasticity due to the selection correction term is crucial.

The results based on the pooled data are presented in Table 3 (no selection correction) and the bottom panel of Table 4 (with selection correction). When selectivity was taken into account we used seven terms in the series approximation. We find that the standard errors increase substantially when endogeneity of LEXP and L2EXP is taken into account. Still, in the model which does not account for selectivity, all parameters remain significant. Taking account of selectivity also leads to higher estimated standard errors. When both selectivity

---

9 The final column of Table 2 will be discussed in the next subsection.
10 Results in Appendix B show that the results of the Newey (1988) estimates are not sensitive with respect to the definition of the expenditure measure for owners.
Table 3
Estimation results for the budget share equations without correction for selection (standard errors in parentheses)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled random effects</th>
<th>Pooled IV random effects</th>
<th>Linear Model fixed effects</th>
<th>Linear Model IV fixed effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BS owners</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>4.102b (0.238)</td>
<td>4.939b (0.712)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>0.045b (0.009)</td>
<td>0.029b (0.010)</td>
<td>-0.073 (0.041)</td>
<td>-0.063 (0.044)</td>
</tr>
<tr>
<td>AGE2</td>
<td>-0.005b (0.001)</td>
<td>-0.003b (0.001)</td>
<td>0.009b (0.004)</td>
<td>0.009c (0.004)</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.977b (0.059)</td>
<td>-1.271b (0.178)</td>
<td>-0.769b (0.049)</td>
<td>-1.345b (0.269)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.052b (0.003)</td>
<td>0.073b (0.011)</td>
<td>0.036b (0.003)</td>
<td>0.070b (0.016)</td>
</tr>
<tr>
<td>DMAR</td>
<td>0.036b (0.004)</td>
<td>0.027b (0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy87</td>
<td>-0.001 (0.003)</td>
<td>-0.000 (0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy88</td>
<td>-0.002 (0.001)</td>
<td>-0.001 (0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOP</td>
<td>0.068b (0.010)</td>
<td>0.108b (0.010)</td>
<td>0.065b (0.016)</td>
<td>0.050b (0.018)</td>
</tr>
<tr>
<td>BS renters</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>2.914b (0.236)</td>
<td>3.056b (0.421)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AGE</td>
<td>0.038b (0.007)</td>
<td>0.027b (0.007)</td>
<td>0.114b (0.034)</td>
<td>0.108b (0.035)</td>
</tr>
<tr>
<td>AGE2</td>
<td>-0.004b (0.000)</td>
<td>-0.003b (0.001)</td>
<td>-0.009b (0.004)</td>
<td>-0.009b (0.004)</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.772b (0.055)</td>
<td>-0.820b (0.106)</td>
<td>-0.800b (0.062)</td>
<td>-0.653b (0.219)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.040b (0.003)</td>
<td>0.045b (0.006)</td>
<td>0.039b (0.004)</td>
<td>0.031c (0.014)</td>
</tr>
<tr>
<td>DMAR</td>
<td>0.011b (0.002)</td>
<td>0.001b (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy87</td>
<td>-0.004 (0.003)</td>
<td>-0.003 (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy88</td>
<td>-0.002 (0.002)</td>
<td>-0.002 (0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LRP</td>
<td>0.119b (0.017)</td>
<td>0.112b (0.017)</td>
<td>0.057b (0.020)</td>
<td>0.060b (0.020)</td>
</tr>
</tbody>
</table>

*In IV estimation AGE, AGE2, LINC, L2INC, Dummy87, Dummy88 and either LOP (for owners) or LRP (for renters) are used as instruments.

bSignificant at the 1% level.

Significant at the 5% level.

and endogeneity are taken into account, few parameters remain significant. This also occurred in the random effects models for the three separate waves.

We tested exogeneity of LEXP and L2EXP by means of Hausman-type tests, based on the difference between the non-IV and the IV random effects share equation estimates in Tables 3 and 4. The realization of the test statistics ranges from 2.11 to 11.17, which is always less than the critical value of a chi-square distribution with six degrees of freedom at 5%. We thus cannot reject exogeneity of LEXP and L2EXP.

Focusing on the case of exogenous LEXP and L2EXP, we see that the effect of LEXP and L2EXP is insignificant in the 1987 wave, but significant in both equations in the other waves. In all these cases the parameter estimates imply that, ceteris paribus, the budget share spent on housing responds negatively to a change in total expenditure.
Table 4
Estimation results for the budget share equations using panel data models taking selection into account (standard errors in parentheses)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>BS owners</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>1.657(^e)</td>
<td>-4.536(^e)</td>
<td>4.260(^e)</td>
<td>12.072(^e)</td>
<td>2.615(^e)</td>
<td>-5.000(^e)</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.023</td>
<td>(0.021)</td>
<td>0.036</td>
<td>(0.033)</td>
<td>-0.030</td>
<td>(0.023)</td>
</tr>
<tr>
<td>AGE2</td>
<td>0.002</td>
<td>(0.002)</td>
<td>0.004</td>
<td>(0.004)</td>
<td>0.003</td>
<td>(0.002)</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.336</td>
<td>(0.213)</td>
<td>1.223</td>
<td>(1.484)</td>
<td>-1.041</td>
<td>(0.165)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.010</td>
<td>(0.013)</td>
<td>-0.087</td>
<td>(0.093)</td>
<td>0.054(^e)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>DMAR</td>
<td>0.014</td>
<td>(0.011)</td>
<td>-0.004</td>
<td>(0.022)</td>
<td>0.009</td>
<td>(0.012)</td>
</tr>
<tr>
<td>LOP</td>
<td>0.106(^e)</td>
<td>(0.021)</td>
<td>0.102(^e)</td>
<td>(0.022)</td>
<td>0.142(^e)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>BS renters</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CONSTANT</td>
<td>1.177(^e)</td>
<td>-0.003(^e)</td>
<td>3.890(^e)</td>
<td>3.057(^e)</td>
<td>3.395(^e)</td>
<td>2.960(^e)</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.015</td>
<td>(0.019)</td>
<td>0.015</td>
<td>(0.020)</td>
<td>-0.043(^d)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>AGE2</td>
<td>0.004</td>
<td>(0.002)</td>
<td>0.001</td>
<td>(0.002)</td>
<td>0.005(^d)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.235</td>
<td>(0.170)</td>
<td>0.048</td>
<td>(0.458)</td>
<td>-0.910(^e)</td>
<td>(0.157)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.004</td>
<td>(0.011)</td>
<td>-0.013</td>
<td>(0.030)</td>
<td>0.047(^e)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>DMAR</td>
<td>-0.011</td>
<td>(0.008)</td>
<td>-0.016</td>
<td>(0.009)</td>
<td>-0.023(^d)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>LOP</td>
<td>0.104(^e)</td>
<td>(0.023)</td>
<td>0.109(^e)</td>
<td>(0.023)</td>
<td>0.102(^e)</td>
<td>(0.035)</td>
</tr>
</tbody>
</table>

Variable | Pooled random effects | Pooled IV random effects | Kyriazidou 'OLS' estimates | Kyriazidou IV\(^d\) estimates
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>2.595(^e)</td>
<td>3.370(^e)</td>
<td>0.083</td>
<td>0.359(^e)</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.040(^e)</td>
<td>(0.013)</td>
<td>0.020</td>
<td>(0.015)</td>
</tr>
<tr>
<td>AGE2</td>
<td>0.004(^e)</td>
<td>(0.001)</td>
<td>0.002</td>
<td>(0.001)</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.594(^e)</td>
<td>(0.142)</td>
<td>0.821</td>
<td>(0.814)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.026(^e)</td>
<td>(0.008)</td>
<td>0.042</td>
<td>(0.050)</td>
</tr>
<tr>
<td>DMAR</td>
<td>0.006</td>
<td>(0.007)</td>
<td>0.012</td>
<td>(0.007)</td>
</tr>
<tr>
<td>LOP</td>
<td>0.126(^e)</td>
<td>(0.012)</td>
<td>0.121(^e)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Dummy87</td>
<td>-0.006</td>
<td>(0.007)</td>
<td>-0.013</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Dummy88</td>
<td>-0.004</td>
<td>(0.004)</td>
<td>-0.008</td>
<td>(0.004)</td>
</tr>
</tbody>
</table>
**BS renters**

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>2.679(^a)</th>
<th>1.856(^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGE</td>
<td>-0.037(^a) (0.012)</td>
<td>-0.027(^d) (0.012)</td>
<td>0.127(^d) (0.051)</td>
</tr>
<tr>
<td>AGE2</td>
<td>0.004(^a) (0.001)</td>
<td>0.003(^d) (0.001)</td>
<td>-0.018(^a) (0.006)</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.601(^c) (0.091)</td>
<td>-0.417 (0.233)</td>
<td>-0.882(^c) (0.087)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.027(^a) (0.005)</td>
<td>0.016 (0.015)</td>
<td>0.044(^c) (0.005)</td>
</tr>
<tr>
<td>DMAR</td>
<td>-0.021(^c) (0.005)</td>
<td>-0.019(^c) (0.005)</td>
<td>0.051 (0.028)</td>
</tr>
<tr>
<td>LOP</td>
<td>0.105(^a) (0.016)</td>
<td>0.106(^c) (0.016)</td>
<td>0.024(^c) (0.007)</td>
</tr>
<tr>
<td>Dummy87</td>
<td></td>
<td></td>
<td>0.009(^d) (0.004)</td>
</tr>
<tr>
<td>Dummy88</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Series approximation using single-index ML probit in estimating the selection equation.

\(^b\) IV using AGE2, LINC, L2INC, DMAR and either LOP (for owners) or LRP (for renters) as instruments.

\(^c\) Estimates include the estimate for the constant term in the series approximation.

\(^d\) Significant at the 5% level.

\(^e\) Significant at the 1% level.

\(^f\) In IV estimation AGE, AGE2, LINC, L2INC, Dummy87 and Dummy88 are used as instruments.

<table>
<thead>
<tr>
<th>Year</th>
<th>(s_1)</th>
<th>(s_1^*)</th>
<th>(s_0)</th>
<th>(s_0^*)</th>
<th>(s_1)</th>
<th>(s_1^*)</th>
<th>(s_0)</th>
<th>(s_0^*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>87/88</td>
<td>0.6</td>
<td>0.76</td>
<td>0.6</td>
<td>0.60</td>
<td>0.6</td>
<td>0.63</td>
<td>0.6</td>
<td>0.61</td>
</tr>
<tr>
<td>87/89</td>
<td>1.0</td>
<td>1.28</td>
<td>1.1</td>
<td>1.04</td>
<td>1.1</td>
<td>1.13</td>
<td>1.1</td>
<td>1.10</td>
</tr>
<tr>
<td>88/89</td>
<td>0.4</td>
<td>0.40</td>
<td>0.6</td>
<td>0.73</td>
<td>0.6</td>
<td>0.63</td>
<td>0.6</td>
<td>0.55</td>
</tr>
</tbody>
</table>
The price effect, measured by LOP for owners and by LRP for renters, is always positive and strongly significant, implying that housing demand is inelastic, conditional on the ownership decision. The implied estimate of the price elasticity for the average owner\(^{11}\) varies from about \(-0.5\) to \(-0.2\) for owners, and is always about \(-0.5\) for renters. For owners, it increases over time.

For the random effects and fixed effects panel data models (see also next subsection) we present for each wave implied elasticities of housing expenditure with respect to total expenditure (conditional on the ownership decision) in Table 5. We present means of these elasticities for owners and renters separately, weighted with housing expenditure. These can be interpreted as aggregate elasticities (see Banks et al., 1994).\(^{12}\) Apart from the means and their standard errors, we also present the fraction of households for which the elasticity estimate is larger than zero.\(^{13}\) In the pooled random effects models with LEXP and L2EXP assumed to be exogenous, the elasticities are positive but much smaller than one, suggesting that housing is a necessity. The standard errors, however, are sometimes quite large, yielding means which are insignificantly different from zero. If LEXP and L2EXP are allowed to be endogenous, the elasticities are sometimes negative, though never significantly so.

### 3.2. Fixed effects

Using simultaneously more than one wave for estimation requires that we explicitly include the time period in the notation. As in the previous model, we decompose \(x_{it}\) into \(x_{ait}\), containing log total expenditure and its square, \(x_{bit}\), containing log household income and its square, and \(x_{dit}\), containing the prices and taste shifters. Exclusion restrictions again yield \(x_{cit}\) as a subvector of \(x_{dit}\). The selection equation contains \(x_{bit}\) and \(x_{dit}\), while the budget share equations contain \(x_{ait}\) and \(x_{cit}\). The household specific effects will be (formally) treated as time-invariant nuisance parameters, which, therefore, allows for correlation between fixed effects and regressors and errors. Throughout, we shall allow

---

\(^{11}\) This elasticity is computed as \(-1 + \beta/\bar{y}\), where \(\beta\) is the parameter of the log price, and \(\bar{y}\) is the average budget share.

\(^{12}\) The elasticity of housing expenditure for a given household \(i\) is \(e_i = 1 + [\beta_1 + 2\beta_2 \text{LEXP}_i]/s_i\), where \(\beta_1\) and \(\beta_2\) are the coefficients of LEXP and L2EXP in the share equation, respectively, LEXP\(_i\) is log total expenditure of household \(i\), and \(s_i\) is the predicted budget share (this is done separately for owners’ and renters' budget shares; the index for owning or renting is suppressed in the notation). The aggregate elasticity is given by \(\sum_i \text{HE}_i e_i / \sum_i \text{HE}_i\), where \(\text{HE}_i\) is household \(i\)'s predicted housing expenditure (either renting or owning). This elasticity can be interpreted as the percentage change of total expenditure on (either rented or owner-occupied) housing if all households' total expenditures rise by 1%.

\(^{13}\) The median elasticities (not reported) were very close to zero in all cases.
Table 5
Housing expenditure elasticities for the panel data models (standard errors in parentheses)

<table>
<thead>
<tr>
<th></th>
<th>Owners</th>
<th>fr &gt; 0</th>
<th>Renters</th>
<th>fr &gt; 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Effects, exogenous LEXP and L2EXP</td>
<td>1987</td>
<td>0.015 (0.056)</td>
<td>0.51</td>
<td>0.084* (0.042)</td>
</tr>
<tr>
<td></td>
<td>1988</td>
<td>0.145* (0.052)</td>
<td>0.61</td>
<td>0.124* (0.041)</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>0.092 (0.047)</td>
<td>0.58</td>
<td>0.065 (0.042)</td>
</tr>
<tr>
<td>Random Effects, exogenous LEXP and L2EXP</td>
<td>1987</td>
<td>-0.162 (0.319)</td>
<td>0.50</td>
<td>0.138 (0.116)</td>
</tr>
<tr>
<td></td>
<td>1988</td>
<td>0.749* (0.181)</td>
<td>0.75</td>
<td>0.184* (0.095)</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>-0.176 (0.387)</td>
<td>0.51</td>
<td>0.200* (0.103)</td>
</tr>
<tr>
<td>Linear, exogenous LEXP and L2EXP</td>
<td>1987</td>
<td>-0.002 (0.017)</td>
<td>0.49</td>
<td>-0.004 (0.019)</td>
</tr>
<tr>
<td></td>
<td>1988</td>
<td>-0.029 (0.020)</td>
<td>0.43</td>
<td>-0.003 (0.021)</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>-0.009 (0.020)</td>
<td>0.45</td>
<td>0.001 (0.022)</td>
</tr>
<tr>
<td>Linear, endogenous LEXP and L2EXP</td>
<td>1987</td>
<td>-0.072 (0.046)</td>
<td>0.38</td>
<td>0.100* (0.049)</td>
</tr>
<tr>
<td></td>
<td>1988</td>
<td>-0.074 (0.050)</td>
<td>0.35</td>
<td>0.099 (0.054)</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>-0.040 (0.052)</td>
<td>0.37</td>
<td>0.101 (0.058)</td>
</tr>
<tr>
<td>Kyriazidou, exogenous LEXP and L2EXP</td>
<td>1987</td>
<td>0.020 (0.031)</td>
<td>0.50</td>
<td>-0.040 (0.026)</td>
</tr>
<tr>
<td></td>
<td>1988</td>
<td>-0.006 (0.030)</td>
<td>0.47</td>
<td>-0.037 (0.028)</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>0.015 (0.035)</td>
<td>0.47</td>
<td>-0.032 (0.029)</td>
</tr>
<tr>
<td>Kyriazidou, endogenous LEXP and L2EXP</td>
<td>1987</td>
<td>-0.138* (0.049)</td>
<td>0.36</td>
<td>-0.033 (0.046)</td>
</tr>
<tr>
<td></td>
<td>1988</td>
<td>-0.174* (0.053)</td>
<td>0.42</td>
<td>-0.040 (0.048)</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>-0.151* (0.053)</td>
<td>0.30</td>
<td>-0.034 (0.050)</td>
</tr>
<tr>
<td>Kyriazidou IV BS12</td>
<td>1987</td>
<td>0.114* (0.043)</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>BS10</td>
<td>1987</td>
<td>-0.413* (0.054)</td>
<td>0.16</td>
<td></td>
</tr>
</tbody>
</table>

*a* Significant at the 5% level.

*b* Significant at the 1% level.

*c* Based upon separate estimates for each wave (top panel Table 4).

*d* Based upon the estimates in the fourth column of Table 3.

*e* Based upon the estimates in the fifth column of Table 3.

*f* Based upon the estimates in the fourth column of the bottom panel of Table 4.

*g* Based upon the estimates in the fifth column of the bottom panel of Table 4.

Let $x_{ait}$ to be endogenous. Estimation can be based on taking differences between periods $t$ and $\tau, t \neq \tau$. This yields, for households with $d_{it} = d_{i\tau}$,

$$y_{pit} - y_{pit} = \beta'_{pa}(x_{ait} - x_{ait}) + \beta'_{pc}(x_{cit} - x_{cit}) + (\varepsilon_{pit} - \varepsilon_{pit})$$

if $d_{it} = d_{i\tau} = p, p = 0, 1$

with

$$d_{is} = 1(\pi_{b, s} x_{bis} + \pi_{d} x_{dis} + \eta_i - u_{is} \geq 0), s = t, \tau.$$ 

Thus, if $d_{it} = d_{i\tau} = p, p = 0, 1$, we can write

$$y_{pit} - y_{pit} = \beta'_{pa}(x_{ait} - x_{ait}) + \beta'_{pc}(x_{cit} - x_{cit}) + \eta_{pit} x_{bit}, x_{bit}, x_{dit}, x_{dit} + \varepsilon_{pit},$$
where the functions $g_{pt}$, $p = 0, 1$, are given by

$$g_{pt}(x_{bit}, x_{dit}, x_{bit}, x_{dit}, d_{it} = d_{it} = p) = E\{e_{pit}^{pt} - e_{pit}|x_{bit}, x_{dit}, x_{bit}, x_{dit}, d_{it} = d_{it} = p\}$$

and where $\tilde{e}_{pit}$ satisfies

$$E\{\tilde{e}_{pit}|x_{bit}, x_{dit}, x_{dit}, d_{it} = d_{it} = p\} = 0, p = 0, 1.$$

The assumptions with respect to the error terms $(e_{0it}, e_{1it}, u_{it})$ determine the functions $g_{0t}$ and $g_{1t}$ and the way to estimate the parameters. We discuss the two that will be applied.

3.2.1. Linear panel data model

If we assume that no selection bias is present after differencing, i.e., $g_{pt} \equiv 0, p = 0, 1$, standard panel data estimation procedures can be used. In this case there is no reason to estimate the auxiliary selection equation. Only the budget share equations need to be estimated. This corresponds to the assumption that $\eta_{it} - u_{it}$ is independent of $e_{0it}$ and $e_{1it}$, for all $t$, implying that possible selection effects on the budget share equations only enter through correlation between $z_{it}$ and $(\eta_{it}, u_{i1}, \ldots, u_{iT})$. This assumption is often used in applications. An example is the study of Pedersen et al. (1990) of wage differentials between public and private sector.

Estimation results for the linear fixed effects estimator are included in Table 3, both under the assumption that LEXP and L2EXP are exogenous (OLS), and allowing for their endogeneity (IV). A Hausman-type test comparing these two leads to rejecting exogeneity for renters but not for owners. The wave dummies are always insignificant. The other variables (except AGE for owners) are always significant. The estimated parameters of the variables LEXP and L2EXP imply a negative effect, ceteris paribus. The price effects are significantly positive around 0.06, implying price elasticities of about $0.08$ for both renters and owners. These elasticities are now not only conditional upon the exogenous variables and the choice between renting and owning, but also on the household specific fixed effects.

The same applies to the elasticities of housing expenditure with respect to total expenditure. They can be calculated in the same way as in the random effects panel data model. The aggregate elasticities for each panel wave are presented in Table 5. For owners the aggregate elasticities are insignificantly negative. For renters the elasticities are positive but small when allowing for endogeneity for LEXP and L2EXP, and significant only for the 1987 wave. Comparing the results with those for the random effects model, the fairly large standard errors do not allow general conclusions concerning differences in sign or magnitude.
3.2.2. Semi-parametric model

For a panel with two time periods Kyriazidou (1997) proposes an estimator requiring weaker assumptions than those in the model discussed above. Her main assumption is exchangeability of the error terms. For the share equation of owners, this means that, conditional on \((x_{bit}, x_{dit})\), all \(t\), \(\eta_i\), \(\varepsilon_{0i}\), and \(\varepsilon_{1i}\), the vectors with error terms \((\varepsilon_{1it}, \varepsilon_{1ir}, u_{it}, u_{ir})\) and \((\varepsilon_{1it}, \varepsilon_{1ir}, u_{it}, u_{ir})\) are identically distributed. It implies that for households for which \(d_{it} = d_{ir}\) and \(\pi'_b x_{bit} + \pi'_d x_{dit} = \pi'_b x_{bit} + \pi'_d x_{dit}\), the effect of selection on the budget share equation (i.e., the \(g\)-functions) is the same in periods \(t\) and \(r\). For such observations, differencing will not only eliminate the fixed effect, but also the selection effect. Note the difference with the linear model introduced above, where we could use all the observations, since the assumptions implied that correction terms were zero. Now, we only use that the correction terms are scarce, all observations for which the difference between these two values is sufficiently close to zero are used. This leads to weighted IV or weighted LS estimators for \((\beta'^{0}_{1a}, \beta'^{0}_{0c})\) and \((\beta'^{1}_{1a}, \beta'^{1}_{1c})\). We present the IV estimation procedure for the owners’ share equation; the procedure applied to the other cases is very similar.

Denote the regressors in the budget share equations by \(\tilde{x}_{it} = (x'_{ait}, x'_{cit})\), and the corresponding instruments by \(w_{it} = (x'_{bit}, x'_{dit})\) (of the same dimension as \(\tilde{x}_{it}\)). Let

\[
\hat{S}_{wx} = \sum_{i=1}^{n} \hat{\omega}_i (w_{it} - w_{it})(\tilde{x}_{it} - \hat{x}_{it})d_{it}d_{it},
\]

\[
\hat{S}_{wy1} = \sum_{i=1}^{n} \hat{\omega}_i (w_{it} - w_{it})(y'_{1it} - y'_{1it})d_{it}d_{it},
\]

\[
\hat{\omega}_i = \frac{1}{s_{1n}} K \left( \frac{\hat{\pi}_b(x_{bit} - x_{bit}) + \hat{\pi}_d(x_{dit} - x_{dit})}{s_{1n}} \right),
\]

where \(\hat{\pi}_b\) and \(\hat{\pi}_d\) are estimates of \(\pi_b\) and \(\pi_d\) (to be discussed below), and \(K\) is a kernel with bandwidth satisfying \(s_{1n} \to 0\) as \(n \to \infty\). Then the IV estimator for \((\beta'^{1}_{1a}, \beta'^{1}_{1c})\) is \(\hat{S}_{wx}^{-1} \hat{S}_{wy1}\). The estimator is asymptotically normal with an asymptotic bias and an asymptotic covariance matrix that can be estimated consistently, see Kyriazidou (1997, Theorems 1 and 2). The rate of convergence is \((ns_{1n})^{1/2}\).

We use the standard normal density function for the kernel. For choosing the bandwidth, we use the plug-in procedure given by Horowitz (1992): first, some initial value for the bandwidth is chosen and the parameter estimates, the estimate of the asymptotic bias, and the estimate of the covariance matrix are
computed. These estimates are used to compute the MSE minimizing bandwidth, and then the bias and the covariance matrix are re-estimated.\footnote{Details on this procedure are available upon request from the authors. We also experimented with various different smoothness parameters, in particular, in case of the tests we employ (see remainder of this section). It turns out that in most cases the conclusions do not really differ, although in a few cases, where the test results are close to the corresponding critical value, the conclusions change.}

The approach for two time periods can easily be generalized to the case of more than two time periods. Given some estimates for the selection equation, the budget share equations can be estimated using the IV approach for each combination of panel waves \((t, \tau)\). Minimum distance, preferably with the optimal weighting matrix, can then be applied to combine these estimates. Details can be found in Appendix D. To estimate the optimal weighting matrix, an estimate for the covariance matrix of the estimators for the different time periods is required. These covariances converge to zero due to the fact that the bandwidth tends to zero. The proof is similar to that in Charlier (1994) and is included in Appendix D. The minimum distance estimator is, therefore, a weighted average of the estimators for each pair \((t, \tau), (t \neq \tau)\), with weights given by the inverse of the corresponding covariance matrix estimate.

The above estimator requires a first-stage estimator \((\hat{\pi}_b^t, \hat{\pi}_d^t)'\) for \((\pi_b^t, \pi_d^t)'\). This can be, for instance, smoothed maximum score (see Charlier et al., 1995, or Kyriazidou, 1997) or conditional logit, depending on the distributional assumptions for the selection equation. Kyriazidou proposes to use smoothed maximum score. Both estimators only use transitions from owning to renting and from renting to owning. Such transitions are scarce in our data, however. Consequently, it is impossible to estimate a very flexible specification. Therefore, we will impose the stronger assumptions that the \(u_i (t = 1, \ldots, T)\) are iid with a logistic distribution, and use the conditional logit ML estimator to estimate the selection part of the model (see Chamberlain, 1980). Since this estimator for \((\hat{\pi}_b^t, \hat{\pi}_d^t)'\) converges at a faster rate than those for \((\beta_1^t, \beta_0^t)'\) and \((\beta_1^0, \beta_0^0)'\), the former will not affect the limit distribution of the latter. This is similar to the result in Kyriazidou (1997).

In order to retain as many observations as possible, we extend the conditional logit estimator to the case of unbalanced panels. Let \(c_i = (c_{i1}, \ldots, c_{iT})\) denote a vector of zeros and ones, with \(c_{it} = 1\) indicating that all the variables are observed for household \(i\) in time period \(t\). Assuming independence between \(y_i\) and \(c_i\) conditional on \(x_i\), it is easy to show that \(c_i\) can be treated as exogenous. The conditional likelihood contribution of an observation then only depends on observed values of \((y_{it}, x_{it})\).

We estimate the selection equation using the unbalanced panel for the years 1987–1989, consisting of 3917 households, with 2324 present in all three years,
953 in two years, and 640 in only one year.\textsuperscript{15} This leads to 3063, 3274 and 3181 observations in the three waves. Important for the precision of the estimates, however, is the number of households that switch at least once between the two states renting and owning. This number is 168.

In the fixed effects logit model, only the coefficients corresponding to the time-varying regressors are identified. This implies that, due to little or no time variation in these variables, the constant term and the parameters of the education dummies, the dummy for being married, and the regional dummies cannot be estimated. Only the log price ratio (LRELPR), AGE, AGE2, LINC, L2INC and NCH remain. We added time dummies for each wave, two of which can be estimated; the coefficient for the dummy for 1989 is normalized to zero.

The results of the selection equation are included in the final column of Table 2. The estimates for the time dummies show that the ownership rate increases over time, ceteris paribus. The age variables imply an inversely U-shaped pattern of the probability of owning similar to the other results in Table 2. LINC and L2INC are jointly insignificant. When L2INC is excluded, LINC remains insignificant. This result is different from that for the random effect panel data model, where income had a significant impact on the probability of home ownership. That finding was probably due to the relation between permanent income and home ownership. In the fixed effects model, permanent income is part of the fixed effect, and the interpretation of our result is that transitory income components do not affect the home ownership decision significantly.

Regarding the home-ownership decision, generally housing theorists would expect a positive relationship between the probability of owning and transitory income. One possible reason for this is that mortgage lender imposed down-payment constraints prohibit ownership for some low wealth households. Positive transitory income could then be used to overcome the downpayment constraint, resulting in a positive relationship.\textsuperscript{16} In the Dutch situation, such an effect does not seem to be present: in the Netherlands mortgage lenders generally do not impose downpayment restrictions; instead, they base their mortgage decisions mainly on (their estimate of) the permanent part of the borrower’s income.

The results on the budget share equations are included in the lower panel of Table 4.\textsuperscript{17} The bias in the first step Kyriazidou estimates (see Kyriazidou, 1997,

\textsuperscript{15} Since total expenditure does not play a role in the selection equation, observations with missing information on total expenditure are also used.
\textsuperscript{16} See, for instance, Englehardt (1994), and Haurin et al. (1996). We thank the anonymous referee for pointing this out to us.
\textsuperscript{17} Results in Appendix B show that most parameters tend to change slightly but not significantly with the different definitions for housing expenditure for owners.
Theorem 1) was generally large for AGE, AGE2, LOP and LRP, while it was small for the time dummy, LEXP and L2EXP (± 9% of the parameter estimates) using 87/88 or 88/89 in estimation. However, the bias for these parameters was much larger for 87/89 (± 35%). The parameters related to AGE, AGE2, LEXP, L2EXP, and the prices are substantially different from their random effects counterparts based on IV. The price effects remain positive, but are always insignificant. This implies that price elasticities are not significantly different from − 1. Their point estimates are very close to − 1 for owners, and − 0.8 (‘OLS’ estimates) or − 0.9 (IV estimates) for renters.

The coefficients of LEXP and L2EXP are strongly significant. They imply that, ceteris paribus, the budget share spent on housing responds negatively to a change in total expenditure. The age effect is significant for owners in case of IV, and for renters for ‘OLS’. In both cases the pattern is inversely U-shaped, with a maximum at age 35 and 54 for renters and owners, respectively.

To test for exogeneity of LEXP and L2EXP, we compare the Kyriazidou estimates using a Hausman test. Since the covariance between the estimators tends to zero asymptotically (see Appendix D), this test is easy to perform. The resulting chi-square test statistic is 10.31 for owners and 2.23 for renters. Both are smaller than the critical value of the $\chi^2_3$ at the 5% significance level. Hence, the null of exogeneity of LEXP and L2EXP cannot be rejected.

To test the assumption of no selectivity bias in the linear panel data model, we perform a Hausman-type test comparing the IV parameter estimates in Tables 3 and 4. Because the Kyriazidou estimator converges slower than the linear panel data estimator, the limit distribution of the difference between the estimators is determined by the limit distribution of the Kyriazidou estimator only. The resulting values for the test statistics are 88.2 for owners and 23.7 for renters. Both are larger than the critical value of the $\chi^2_3$ at any conventional significance level. This indicates that the model that does not allow for correlation between the error terms in the share equations and the error term or fixed effect in the selection equation is misspecified.

To test the assumption of no correlation between the household specific effects and $(x_{hi}, x_{di})'$ we perform a Hausman-type test based on the difference between the Newey IV and the Kyriazidou IV estimates for those explanatory variables present in both estimates (AGE, AGE2, LEXP, L2EXP, and LOP or LRP). The limit distribution of the difference between the estimators is again determined by the limit distribution of the Kyriazidou estimator only. The resulting values for the test statistics are at least 232.1 for owners and at least 37.8 for renters. These exceed the critical $\chi^2_3$ value at any conventional significance level, indicating that the random effects panel data model that does not allow for correlation between the household specific effects and the explanatory variables is misspecified. This result continues to hold when we compare the estimates for owners and renters simultaneously.
To test whether the coefficients of the common variables in the budget share equation for owners and renters are the same we use a Wald test. Because $T = 3$, no household can both own a house for two periods or more and rent a house for two periods or more. As a consequence, the covariance between the estimates for $\beta_0$ and $\beta_1$ in Table 4 is zero, which makes it straightforward to perform the Wald test. The value of the test statistic is 11.74 which is below the 5% critical value of the $\chi^2_6$ distribution. This implies that we cannot reject the hypothesis that the coefficients for the common variables are the same.

In Table 5 we include the weighted elasticity estimates for the Kyriazidou model, i.e., the aggregate elasticities of housing expenditure with respect to total expenditure. For owners the results are negative and insignificant under exogeneity of LEXP and L2EXP, and become significantly negative when LEXP and L2EXP are endogenous. For renters the elasticity estimates are mostly negative and insignificant; only the 1987-wave results under exogeneity shows significantly negative effect.

Again, the importance of the fixed effects for the interpretation of these results should be emphasized. Permanent income effects enter through the fixed effect. The negative elasticities condition on these fixed effects, and, therefore, say nothing about the effects of permanent income. The negative estimates imply that transitory shocks on total expenditure tend to be negatively correlated to changes in housing expenditure. We have no economic explanation for this.

Under endogeneity, the significant elasticities for owners thus seem to have the wrong sign. To see whether this is due to an inappropriate choice of instruments, we also replaced the instruments by the lagged values of log(household income) and its square.\footnote{We used the balanced panel. Due to the extra time lag in the instruments we can only compute the estimates for the 1988 and 1989 waves of the panel so no minimum distance step is required.} The parameter estimates change: the elasticity estimate equals 0.006 with standard error 0.38; thus, it is insignificant with a much higher standard error than those reported in Table 5. The choice of current income variables as instruments, therefore, could explain the negative sign for the elasticities.

The final panel of Table 5 contains the estimates for the elasticities when different measures of housing expenditure for owners are used (see Appendix B). The elasticities appear to be sensitive to the chosen measure.\footnote{The elasticity estimates for the other models are much less sensitive to the definition of expenditures for owners (results not presented.).}

Since the Kyriazidou-model can be seen as our final model, we performed a specification test on this model. A natural approach here is to perform a test on overidentifying restrictions in the minimum distance step. The realizations of the
test statistics are 41.50 for renters and 20.77 for owners, which both exceed the $\chi^2_{11}$ critical value distribution at the 5% level.\textsuperscript{20}

4. Conclusions

We have modelled expenditure on housing for owners and renters using endogenous switching regression models for panel data. In choosing the model assumptions we were guided by economic theory, but to a large extent also by the availability of suitable estimators and the nature of the data. We extended the standard switching regression model in several directions. We used (unbalanced) panel data instead of cross-section data, and considered random effects and fixed effects models. For the random effects case, cross-section models and data can be used to obtain consistent estimates, but the fixed effects models require different techniques. We used two of them, allowing for different types of selection effects. Where possible, we tried to avoid normality assumptions and relied on semiparametric techniques. Finally, we focused on estimation techniques which allow some of the explanatory variables in the budget share equations to be endogenous.

The sample we used consists of three waves of the Dutch Socio-Economic Panel, combined with constant-quality prices, varying over time and space. We estimated the slope coefficients in the random effects model using the cross-section data for each wave in a semiparametric model. We have compared results which do and do not take account of potential endogeneity of the variables related to total expenditure. Differences between these two sets of estimates mainly concern the parameter estimates related to the total expenditure variables themselves.

For the fixed effects panel data case we estimated two models. The first one is the linear panel data model which can be estimated using standard techniques. The alternative estimator based on weaker assumptions was proposed by Kyriazidou (1997). Here we estimated the parameters in the selection equation using conditional logit. The parameters in the budget share equations are estimated in a second step, making use of the conditional logit estimates. The models were compared using Hausman-type tests. The results indicate that both the random effects and the linear panel data model are too restrictive. Exogeneity of total expenditure variables is not always rejected. Finally, we also applied a test on overidentifying restrictions in the Kyriazidou (1997) model, the most

\textsuperscript{20} There are 7 parameters to be estimated. Using one pair of waves, only the difference of the two corresponding time dummies is identified. Therefore we have $5 \times 3 + 3 = 18$ constraints in the minimum distance step. This yields $18 - 7 = 11$ degrees of freedom.
general model that we considered. The results suggest that even the flexible Kyriazidou (1997) model is misspecified.

Our overall conclusion is that standard models with random effects which can be estimated with cross-section data, and linear panel data models which only allow for very specific selection mechanisms, are rejected against the flexible semi-parametric fixed effects model of Kyriazidou (1997). The various models also lead to diverging conclusions on the elasticities of interest. The price elasticities for renters and owners (conditional on the choice between owning and renting and taste shifters and income) are about $-0.5$ in the random effects models, but are closer to $-1$ (owners) or $-0.8$ (renters) in the fixed effects models. Compared to the estimates in the literature for the UK and the US, the latter are somewhat large. The estimates of total expenditure elasticities vary from significantly positive in the random effects models to insignificantly (renters) or even significantly (owners) negative in the most general fixed effects model, though the latter result for owners is sensitive to the way in which housing expenditures for owners are defined. Part of the difference can be explained by a positive impact of permanent income on housing demand, an effect which is controlled for in the fixed effects model but not in the random effects model. The estimated total expenditure elasticities are quite low compared to estimates of income elasticities in the literature. This comparison may not be valid, however, since the elasticities in the literature are defined differently and, for example, typically do not condition on the choice between renting and owning.

Acknowledgements

We thank two anonymous referees, Marno Verbeek and seminar participants at Rice University for helpful comments. Research of the third author was possible due to a fellowship of the Netherlands Royal Academy of Arts and Sciences (KNAW). We are grateful to Statistics Netherlands (CBS) for providing the data.

Appendix A. Data appendix

In this appendix we give some details on the construction of the variables for 1987–1989, used in the application. For 1989, macro-data are available which will be compared to our data.

A.1. Housing

Initial dataset: 3613, 3818, 3896 households for 1987, 1988 and 1989, respectively.
Dropped from the analysis are:

- families that live for free (± 0.8%);
- families with a total income below Dfl. 1,- per month (± 200 obs);
- families that receive a so-called huurgewenningsbijdrage (i.e., a governmental allowance for people who experienced a large rent increase because of renovation of their dwelling or who had to search for a different dwelling after pull down of their previously rented dwelling). The reason for this latter drop is that the amount is a substantial part of the housing expenditure (16% on average) and it is not clear from the data whether this amount is included in the answers on rent payments or not (± 1.2% of the renters).

A.2. Housing consumption for owners

\[(1 - \text{tax}) \text{erfpacht} + \text{tax huurwaardeorfait} + (1 - \text{tax}) \text{interest payment} + \text{foregone interest} - \text{increase in the value of the house} + \text{maintenance costs} + \text{eigenaarsgedeelte onroerend goedbelasting} + \text{opstalverzekering}.\]

Here erfpacht is the amount of money you have to pay if you do not own the land on which your dwelling is built (which is partly deductible), tax is the marginal tax rate of the most earning adult in the household, huurwaardeorfait is tax levied on the value of the house of owners, eigenaarsgedeelte onroerend goedbelasting is municipal tax for house owners and opstalverzekering is a house insurance for fire, broken windows etc. Expenditure on gas/water/electricity/heating is excluded.

A.3. Computation of the variables in expenditure for owners

Approximately 140 house owning families dropped out because the value of the house is not known, which is necessary to correct for, among other things, huurwaardeorfait. In the data we have either the amount spent on interest payments on the mortgage or the interest rate on the mortgage. If we only have the interest rate on the mortgage we computed the interest payments by multiplying this percentage with the mortgage value. If the mortgage value is not reported we used 149,000, 155,000 and 163,000 (the average value of a house for 1987, 1988 and 1989). The numbers of observations affected are 22, 27 and 22, respectively. Foregone interest is set equal to 0.04 times the difference in the value of the house and the mortgage value. Maintenance costs are defined as 2% of the value of the house. In the main text we investigate the sensitivity of the results with respect to the percentage increase in the value of a house and the percentage used in the maintenance costs. Because the eigenaarsgedeelte onroerend goedbelasting can differ per municipal it is calculated as follows: we have data over 1986–1989 on Tilburg and we will consider Tilburg to be representative for its province. Per province we have the amount of tax that was
paid to the local government per inhabitant of the municipality (CBS, 1987, Statistiek der gemeentebegroting). The eigenaarsgedeelte onroerend goedbelasting per province is calculated as the figure for Tilburg times the relative tax per inhabitant of the province. The relative tax for the provinces is approximately constant over time. The opstalverzekering is simply 12.95 times the value of the house divided by 100,000 (Budgethandboek NIBUD, 1987).

A.4. Computation of marginal tax rate

In the SEP we only observe net income like net wages, net unemployment benefits, net pensions, etc. To calculate the marginal tax rate we need gross income of the spouse that earns most because he/she will have to report the tax related issues of owning a house (like e.g. huurwaardeforfait). From the net income we could try to invert the tax system and infer gross income. However, this is a very cumbersome approach. Therefore, we will follow Euwals and van Soest (1999). Gross income is already available for individuals with a paid job. We now estimate a net wage equation using the households in which at least one individual has a paid job. An important variable to be included is the tax free allowance (TFA). Constructing this for married couples involves the gross income of the other spouse. All the households for whom we could determine the TFA were included in estimation. The equation estimated is the same as in Euwals and van Soest (1999), i.e. without a constant term. Without making differences between men and women we got an $R^2$ of 0.9955 and the parameter estimates are fairly similar. Given the net income we can now estimate gross income by inverting the relationship. By taking derivatives of net income with respect to gross income we can estimate the marginal tax rate.

A.5. After tax constant quality prices of housing

In the budget share equations, after tax constant quality prices of housing are used. After tax prices are used to take into account tax deduction of housing for owners and hence tax effects are only relevant for owners. Constant quality prices of housing for both renters and owners are constructed as follows:

- Define regions and house-categories. For each combination of (renter, region, house-category) and (owner, region, house-category) we determine the fraction of houses in it, based on our 1987 sample. We also determine the median rent (for renters) and the median house price (for owners), based on the sample for 1987, 1988 and 1989.

- Constant quality prices of housing are then computed by multiplying the fraction for each combination with the median rent or median house price, respectively. The resulting constant quality prices of housing vary for renters and owners and by regions.
To limit the number of combinations we distinguish 11 regions\textsuperscript{21} and two house categories.\textsuperscript{22} Together with the owners/renters distinction this results in 44 categories. To obtain the weights and prices the sample consists of about 2000 observations (the reduction is mainly due to the absence of information on house-category), so on average 45 observations are available for each cell. To reduce the influence of outliers the median rent and house price are used. For owners, the constant quality prices of housing are multiplied by 1 minus the marginal tax rate for the household in the particular year.

A.6. General remarks concerning the data

The following data cleaning operations have been applied:

- People who got married or divorced are left out in the analysis to avoid dependence between households in the sample (± 140 households per year);
- Households that spend more than 0.6 times their monthly income on housing (± 130 households per year) are also left out.

In general, we lose approximately 670 households per year. If we use only the observations with income budget shares smaller than 0.6 we end up with 2936, 3157 and 3261 observations.

A.7. Comparing the data with macro-data

We will compare the 1989 with the figures in Woningbehoeftenonderzoek 1989/1990 reported by Statistics Netherlands (CBS). Their definitions for rent and income are the same as the ones we use. For renters the CBS tabulates rent, net annual income and budget shares. The definition of expenditure on housing for owners differs from our measure. The CBS measure of housing expenditure includes expenditure on the mortgage, erfpacht, opstalverz., eigenaarsgedeelte onroerend goed belasting, rijksbijdrage eigen woning bezit and tax issues like interest, erfpacht, huurwaardeforfait en rijksbijdrage eigen woning bezit. We constructed this measure without opstalverz., eigenaarsgedeelte onroerend goed belasting, rijksbijdrage eigen woning bezit and related tax issues. For owners the CBS tabulates net yearly income and budget shares.

Comparing the 1989 data with the statistics in the Woningbehoeftenonderzoek 1989/1990 we conclude that:

\textsuperscript{21} The regions are the 12 Dutch provinces; however, Overijssel and Flevoland are grouped together because the latter is very small, yielding 11 regions.
\textsuperscript{22} The first type consists of detached, semi-detached or corner houses and the second type consists of row houses and apartments.
House owners are overrepresented in our sample. We see two reasons for this: the group of one-person households is underrepresented and 75% of this group rents, and the owners are overrepresented in the more-than-one-person households.

For renters our rent data follow the results of the CBS, but low income households ( < 26,000 net per year) are underrepresented. Furthermore, the higher budget shares are overrepresented yielding an average budget share of 0.20 instead of 0.18.

The distribution of net annual income for owners with a mortgage has higher fractions in the higher income brackets. The distribution of budget shares has the same property and the average budget share is 0.148 instead of 0.137.

Households owning a house without a mortgage are underrepresented.

In general the data have the following features:

- the density of income shifts a little bit to the right over time;
- the density of the budget shares for renters remains approximately the same over time;
- the density of the budget shares for owners is slightly shifted to the right when compared to the 1989 macro-data;
- the density of the interest payments on mortgages looks the same for all years. However, the average value is increasing (slightly) over 1987−1989.

Although the 1986 data are not used in the main text, we also compared them to the macro-data for 1986. The results are similar to those for 1989.

Appendix B

In this appendix we will investigate the sensitivity of the cross-section Newey IV results for 1987 and the panel data Kyriazidou IV results with respect to the maintenance costs and the mortgage costs in housing consumption for owners. Let BS1ab denote the budget share spent on housing for owners with a% increase of the value of a house (a = 0, 1, 2, 3, 4) and b% of the value of the house as the maintenance costs (b = 1, 2). In the main text a equals 1 and b equals 2. From the definition of housing costs for owners it follows that BS1ab = BS1a + 1, b + 1 so, for example, BS121 = BS132. Because the averages for BS142, BS132 (and hence BS131 and BS121) are very low compared to the average for renters we only consider BS122, BS112 and BS102. The last digit can then be dropped, because it is fixed at 2, so that we write BS1a, a = 2, 1, 0. Thus, BS11 is used throughout the main text. The means for BS12, BS11 and BS10 are, respectively, 0.15, 0.20 and 0.24 with standard errors of 0.08, 0.09 and 0.11.
Table 6
Sensitivity of the estimation results with respect to the measure for housing expenditure of owners, cross-section*

<table>
<thead>
<tr>
<th>Variable</th>
<th>BS12 Newey IV(^{b,c})</th>
<th>BS11 Newey IV(^{b,c})</th>
<th>BS10 Newey IV(^{b,c})</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>3.652(^d)</td>
<td>4.536(^d)</td>
<td>5.419(^d)</td>
</tr>
<tr>
<td>AGE</td>
<td>0.024 (0.027)</td>
<td>0.036 (0.033)</td>
<td>0.045 (0.077)</td>
</tr>
<tr>
<td>AGE2</td>
<td>0.002 (0.003)</td>
<td>0.004 (0.004)</td>
<td>0.005 (0.009)</td>
</tr>
<tr>
<td>LEXP</td>
<td>0.863 (1.168)</td>
<td>1.223 (1.484)</td>
<td>1.459 (2.241)</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.062 (0.073)</td>
<td>0.087 (0.093)</td>
<td>0.104 (0.144)</td>
</tr>
<tr>
<td>DMAR</td>
<td>0.026 (0.018)</td>
<td>0.004 (0.022)</td>
<td>0.004 (0.028)</td>
</tr>
<tr>
<td>LOP</td>
<td>0.079(^e) (0.018)</td>
<td>0.102(^e) (0.022)</td>
<td>0.124(^e) (0.018)</td>
</tr>
</tbody>
</table>

\(^a\)The results for renters and for the selection equation are the ones presented in the second and third column of Table 3.
\(^b\)Series approximation using single index ML probit in estimating the selection equation.
\(^c\)IV using AGE, AGE2, LINC, L2INC, DMAR and either LOP (for owners) or LRP (for renters) as instruments.
\(^d\)Estimates include the estimate for the constant term in the series approximation.
\(^e\)Significant at the 1% level.

In Table 6 we indicate the sensitivity of the parameter estimates of the Newey IV estimates with respect to the measure for housing expenditure for owners. The number of terms used in the series approximation is the same for all measures. The coefficients related to LEXP, L2EXP, DMAR, and LOP tend to change somewhat, but the main conclusions remain the same. The standard errors remain rather large such that we do not find significant differences in most of the parameter estimates when varying housing expenditure for owners. The parameter related to LOP seems to be most sensitive to the measure for housing expenditure used. However, the conclusions for the price elasticity remain the same.

In Table 7 we indicate the sensitivity of the parameter estimates of the Kyriazidou IV panel estimates with respect to the measure for housing expenditure for owners. Most coefficients change somewhat but the main conclusions remain the same.

Appendix C

In this appendix we discuss some details of implementing the Newey (1988) estimator discussed in Section 3.1. Starting point is the random effects model which, for one cross-section, can be written as

\[ d_i = 1(\pi'x_i - v_{it} \geq 0), \]
Table 7

Sensitivity of the estimation results with respect to the measure for housing expenditure of owners, panel

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kyriaz. IV BS12</th>
<th>Kyriaz. IV BS11</th>
<th>Kyriaz. IV BS10</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGE</td>
<td>0.253</td>
<td>(0.072)</td>
<td>0.359</td>
</tr>
<tr>
<td>AGE2</td>
<td>-0.021</td>
<td>(0.007)</td>
<td>-0.033</td>
</tr>
<tr>
<td>LEXP</td>
<td>-0.560</td>
<td>(0.120)</td>
<td>-0.801</td>
</tr>
<tr>
<td>L2EXP</td>
<td>0.025</td>
<td>(0.007)</td>
<td>0.036</td>
</tr>
<tr>
<td>Dummy87</td>
<td>-0.005</td>
<td>(0.007)</td>
<td>-0.013</td>
</tr>
<tr>
<td>Dummy88</td>
<td>-0.005</td>
<td>(0.004)</td>
<td>-0.008</td>
</tr>
<tr>
<td>LOP</td>
<td>-0.016</td>
<td>(0.026)</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*The results for the selection equation are the ones presented in the second and third column of Table 6 and the results for renters are the ones in the sixth and seventh column of Table 6. Because the smoothing parameters are related to the index of the first step estimates only, the smoothing parameters are the ones reported in Table 6.

bSignificant at the 1% level.

\[ y_{0i} = \beta_0 x_i + v_{0i} \text{ if } d_i = 0, \]
\[ y_{1i} = \beta_1 x_i + v_{1i} \text{ if } d_i = 1. \]

Compared to the notation in Section 3.1, the time index \( t \) is omitted and the random effects are incorporated in the error terms \( v_i = (v_{0i}, v_{0i}, v_{1i}) \), which is independent of \( x_i \). Let \( \tilde{x}_i = (x'_{0i}, x'_{1i})' \) and \( f_i = \pi' x_i = \pi' x_{0i} + \pi' x_{1i} \). Newey uses the fact that the independence assumption implies that the distribution of \( v_i \) depends on \( z_i = (x_{0i}, x_{1i}) \) only through the index \( f_i \). Although several aspects vary with the subsample used (either \( d_i = 0 \) or \( 1 \)), we suppress this in the notation and hence

\[ y_i = \beta \tilde{x}_i + g(z_i) + \tilde{e}_i \]

with

\[ g(z_i) = E\{e_i|z_i, d_i\} \quad \text{and} \quad E\{\tilde{e}_i|z_i, d_i\} = 0. \]

Note that \( \beta \) and \( g \) vary with the subsample used, whereas \( \pi \) does not. The functions \( g \) can then be written as \( g(z_i) = \tilde{g}(f_i) \).

To estimate the budget equations, \( \tilde{g} \) is approximated by \( \sum_{k=0}^{K} x_k f_1^k \), with \( K = K(d_i, n) \) (\( n \) is the number of observations) and in which \( x \) varies with the subsample used. The following regression equations can now be used for a given subsample (renters or owners):

\[ y_i = \beta \tilde{x}_i + \sum_{k=0}^{K} x_k f_1^k + \tilde{e}_i, \quad (C.1) \]
where \( \hat{\beta}_i = \hat{\pi}_b y_{hi} + \hat{\pi}_d x_{di} \) and where \( \hat{\pi}_b \) and \( \hat{\pi}_d \) denote estimates of \( \pi_b \) and \( \pi_d \), respectively (to be discussed below). If \( x_{di} \) and hence \( \hat{x}_i \) is exogenous, a consistent and asymptotically normal estimator for \( \beta \) can be obtained by applying OLS to Eq. (C.1) for each subsample. This was shown by Newey (1988), who also derives a consistent estimator for the asymptotic covariance matrices of the estimators.

We apply Newey’s procedure to the case that \( x_{ni} \) is allowed to be endogenous by replacing OLS with IV. Denote the regressors in Eq. (C.1) for a given subsample by \( \hat{x}_i^s \), i.e. \( \hat{x}_i^s = (\hat{x}_i^1, 1, \hat{f}_i, \ldots, \hat{f}_i^K)' \) (with now \( K = K(1, n) \)) and let \( \hat{X}^s = (\hat{x}_1^s, \ldots, \hat{x}_n^s)' \) where \( n1 \) is the number of observations with \( d_i = 1 \). Furthermore, let \( \hat{w}_i^s \) be the vector of instruments, i.e. \( \hat{x}_i^s \) with \( x_{ni} \) replaced by \( x_{hi} \) (hence \( \hat{w}_i^s \) is of the same dimension as \( \hat{x}_i^s \)), and let \( \hat{W}^s = [\hat{w}_1^s, \ldots, \hat{w}_n^s]' \). The parameters \( \beta_1 \) and \( x_{1} \) to \( x_{K} \) can now be estimated by applying IV to Eq. (C.1). Under appropriate regularity conditions 23 the IV-estimator for \( \beta \) will be consistent and asymptotically normal: \( \sqrt{n}(\hat{\beta} - \beta') \to^d N(0, V) \). Notice, however, that the constant term in the regression equation cannot be estimated separately, since the series approximation also includes a constant term. 24 The asymptotic covariance matrix \( V \) can be estimated consistently by

\[
[I, 0](\hat{W}^{s'}\hat{X}^s)^{-1}\left\{ \sum_{i=1}^{n1} \hat{w}_i^s \hat{w}_i^s \hat{e}_i^2 + \hat{H}_W \hat{V}(\hat{\pi}_b, \hat{\pi}_d)\hat{H}_W' \right\}(\hat{X}^{s'}\hat{W}^s)^{-1}[I, 0]',
\]

where \( \hat{e}_i \) is the IV residual and

\[
\hat{H}_W = \sum_{i=1}^{n1} \left\{ \hat{w}_i^s \hat{z}_i^2 \left( \sum_{k=1}^{K} k\hat{x}_k \hat{f}_i^k \right)^{-1} \right\},
\]

where \( \hat{x}_k, k = 1, \ldots, K \) are the IV estimates of the \( x_k \). The expressions in Newey (1988) are a special case with \( \hat{W}^{s} \) replaced by \( \hat{X}^s, \hat{e}_i \) by the OLS residuals and \( \hat{x}_k, k = 1, \ldots, K \) by the OLS estimates. See also Newey (1984) for a discussion of deriving limit distributions in a two-step estimation framework.

The smoothing parameter in the estimation procedure is the number of terms in the series approximation, which is chosen such that adding more terms in the series approximation no longer affects the parameter estimates for the regression

---

23 Appropriate regularity conditions should include conditions guaranteeing consistency of the IV estimates of \( \beta_{1s} \) and \( \beta_{1t} \), and conditions that allow one to derive the presented limit distribution. The former conditions will be different from Newey’s, since identification should now be based on moment restrictions. Given identification (and consistency) the latter conditions will be comparable to Newey’s conditions.

24 Andrews and Schafgans (1998) show how the constant term can be estimated if observations with selection probability close to one are available. Since, however, we do not have many observations with probability of ownership close to zero or one, this approach is practically infeasible for both renters and owners.
coefficients. In practice, often only a few terms in the series approximation turn out to be required.

The Newey approach for estimating $\beta$, requires estimation of a single index binary choice model to obtain estimates for $(\pi_b, \pi_d)$. Ahn and Powell (1993) allow for a more general model, in which the probability of ownership is estimated completely nonparametrically. Due to the large number of explanatory variables in the selection equation, such an approach is practically infeasible for our purposes. Klein and Spady (1993) have proposed an estimator which is semiparametrically efficient under weak regularity assumptions. This estimator, however, is difficult to compute. Instead, we started with the probit ML estimates for $(\pi_b', \pi_d')$. We tested for normality and heteroskedasticity of exponential form using tests described in Chesher and Irish (1987). Both normality and homoskedasticity were rejected. Therefore, we experimented with the following specification, in which the single index assumption is retained:

$$P(d_i = 1|z_i) = \Phi(m(\tau, f_i)/\exp\{\sigma(\gamma, f_i)\}).$$

Here $m$ and $\sigma$ are power series in $f_i$ with coefficients $\tau$ and $\gamma$, respectively. This can be seen as a series approximation to an arbitrary single index model. Let $\tau_j$ and $\gamma_j$ denote the coefficients related to $f_j$. The normalizations imposed are $\tau_0 = 0$, $\tau_1 = 1$ and $\gamma_0 = 0$. We estimated this model for several lengths of the two power series, and found one significant term in $m$, namely $f_i^2$.

Appendix D

In this appendix we derive the limit distribution of the minimum distance estimator for the Kyriazidou panel data model with more than two time periods. The estimators used in the first step are the Kyriazidou estimators based on two time periods. They play a major role in determining the limit distribution of the minimum distance estimator. Particularly, we will show that the asymptotic covariance between the Kyriazidou estimators based on a different combination of two different time periods is asymptotically zero. For notational convenience we will show the results comparing the estimator based on time periods one and two with the one based on the periods two and three. The result can be easily extended including more estimators in the first step.

Let $\tilde{\beta}_{1,ts}$ denote the estimator for $(\beta_{1a}, \beta_{1c})$ based on time periods $s$ and $t$. It is easy to show that for the second step minimum distance estimator, $\beta_1$, say, we can write

$$\sqrt{n_{3n}} (b_1 - \beta_1) = \underline{b_{1,21}} - \beta_1$$

(D.1)
for some matrix $A_n$ converging in probability to $A$,\textsuperscript{25} say, when $n \to \infty$, and some smoothing parameter $s_{3n}$. Hence the limit distribution of the minimum distance estimator is determined by the limit distribution of

$$
\sqrt{n s_{3n}} \begin{bmatrix} \hat{\beta}_{1,21} - \beta_1 \\ \hat{\beta}_{1,32} - \beta_1 \end{bmatrix}.
$$

From Kyriazidou (1997) we have

$$
\sqrt{(n s_{1n})(\hat{\beta}_{1,21} - \beta_1)} \to ^d N(AB_1, V_1)
$$

and

$$
\sqrt{(n s_{2n})(\hat{\beta}_{1,32} - \beta_1)} \to ^d N(AB_2, V_2),
$$

with $AB_1, AB_2$ the asymptotic bias, and $V_1, V_2$ the asymptotic covariance matrices.

Using the optimal estimators (i.e. minimizing asymptotic MSE) in the first round it follows that $s_{1n} = O(n^{-\nu})$ and $s_{2n} = O(n^{-\nu})$ for some $0 < \nu < \frac{1}{2}$. Therefore also $s_{3n} = O(n^{-\nu})$.

Now define

$$
\lim_{n \to \infty} \frac{ns_{3n}}{ns_{1n}} = c_{31}, \text{ and } \lim_{n \to \infty} \frac{ns_{2n}}{ns_{2n}} = c_{32}
$$

with $0 < c_{31} < \infty$ and $0 < c_{32} < \infty$.

Then

$$
\sqrt{ns_{3n}} \begin{bmatrix} \hat{\beta}_{1,21} - \beta_1 \\ \hat{\beta}_{1,32} - \beta_1 \end{bmatrix} = \begin{bmatrix} \sqrt{ns_{1n}} (\hat{\beta}_{1,21} - \beta_1) \\ \sqrt{ns_{2n}} (\hat{\beta}_{1,32} - \beta_1) \end{bmatrix} \begin{bmatrix} \frac{ns_{3n}}{ns_{1n}} \\ \frac{ns_{3n}}{ns_{2n}} \end{bmatrix}
$$

$$
\to ^d N \left( \begin{bmatrix} AB_1 \sqrt{c_{31}} \\ AB_2 \sqrt{c_{32}} \end{bmatrix}, \begin{bmatrix} c_{31} V_1 & \text{cov} \\ \text{cov} & c_{32} V_2 \end{bmatrix} \right)
$$

We will now show that $\text{cov} = \text{cov}(\sqrt{(ns_{3n})(\hat{\beta}_{1,21} - \beta_1)}, \sqrt{(ns_{3n})(\hat{\beta}_{1,32} - \beta_1)})$ tends to zero as $n$ tends to infinity. Because the first round estimator for $\pi$ converges at a faster rate, the limit distribution of the estimators can be analyzed assuming we know the true value for $\pi$ (analogously to Kyriazidou,

\textsuperscript{25} A is equal to $(L \Sigma^{-1} L)^{-1} L \Sigma^{-1}$, where $\Sigma$ is the covariance matrix of the first round estimators and where $L$ is the derivative of the linear moment restrictions imposed in the minimum distance step. $\Sigma$ is estimated using the estimator of the covariance matrix of the first step estimators. Details are presented in the remainder of this appendix.
Define \( f_{it} = \pi_b x_{bit} + \pi_d x_{dit} \) and suppress the first subscript on \( y \). Then \( \tilde{\beta}_{1,21} \) and \( \tilde{\beta}_{1,32} \) are

\[
\tilde{\beta}_{1,21} = \left[ \sum_{i=1}^{n} \frac{1}{S_{1n}} K \left( \frac{f_{i2} - f_{i1}}{s_{1n}} \right) (w_{i2} - w_{i1}) (\tilde{x}_{i2} - \tilde{x}_{i1})' d_{i1} d_{i2} \right]^{-1} \\
= \beta_1 + [S_{w21,x21}]^{-1} S_{w21,e21},
\]

\[
\tilde{\beta}_{1,32} = \left[ \sum_{i=1}^{n} \frac{1}{S_{1n}} K \left( \frac{f_{i3} - f_{i2}}{s_{1n}} \right) (w_{i3} - w_{i2}) (\tilde{x}_{i3} - \tilde{x}_{i2})' d_{i2} d_{i3} \right]^{-1} \\
= \beta_1 + [S_{w32,x32}]^{-1} S_{w32,e32}.
\]

Because the inverted matrices in (D.5) and (D.6) converge in probability they will be ignored in the remainder.

Analogous to Kyriazidou (1997, proof of Lemma 1) one can show that

\[
\sqrt{nS_{3n}} S_{w21,e21} = \frac{\sqrt{nS_{3n}}}{\sqrt{s_{1n}}} \sqrt{nS_{1n}} S_{w21,e21} = \frac{1}{\sqrt{nS_{1n}}} \sqrt{nS_{3n}} = \frac{1}{\sqrt{nS_{1n}}} \sqrt{n} \sum_{i=1}^{n} \tilde{\xi}_{i21n},
\]

where

\[
\tilde{\xi}_{i21n} = \frac{1}{\sqrt{s_{1n}}} K \left( \frac{f_{i2} - f_{i1}}{s_{1n}} \right) (w_{i2} - w_{i1}) A v_{i21} d_{i1} d_{i2}
\]

and \( A v_{i21} = v_{i2} - v_{i1} \). \( v_{it} = \varepsilon_{it} - E \{ \varepsilon_{it} | d_{i1} = d_{i2} = 1, x_{bi1}, x_{di1}, x_{bi2}, x_{di2}, \varepsilon_{i1} \} \) and a similar expression holds for \( S_{w32,e32} \). Now drop the subscript \( i \) and define \( A v_{21} = v_{21}, A v_{32} = v_{32}, G_{21} = f_{i2} - f_{i1} \) and \( G_{32} = f_{i3} - f_{i2} \). Using that \( \tilde{\xi}_{i21n} \) and \( \tilde{\xi}_{i32n} \) have expectation zero it follows that (suppressing \( i \) subscripts)

\[
\text{cov}(\sqrt{nS_{1n}} S_{w21,e21}, \sqrt{nS_{2n}} S_{w32,e32}) = E \{ \tilde{\xi}_{21n} \tilde{\xi}'_{32n} \}
\]

\[
= \frac{1}{\sqrt{s_{1n}s_{2n}}} K \left( \frac{G_{21}}{s_{1n}} \right) K \left( \frac{G_{32}}{s_{2n}} \right) f_{G_{21},G_{32}}(G_{21}, G_{32}) dG_{21} dG_{32}
\]

\[
= \sqrt{s_{1n}s_{2n}} \int \int E \{ A v_{21} A v_{32} A v_{21} A v_{32} | G_{21} = v_{21} s_{1n}, G_{32} = v_{32} s_{2n} \} K(v_{21})
\]

\[
K(v_{32}) f_{G_{21},G_{32}}(v_{21}, v_{32}) d\nu_{21} d\nu_{32}
\]

\[
\rightarrow 0 * f_{G_{21},G_{32}}(0,0) E \{ A v_{21} A v_{32} A v_{21} A v_{32} | G_{21} = G_{32} = 0 \} \left[ \int K(v) d\nu \right]^2
\]

\[
= 0 (n \rightarrow \infty).
\]
Using (D.3) and (D.8) it now follows that

\[
\sqrt{ns_3n} \begin{bmatrix} \hat{\beta}_{1.21} - \beta_1 \\ \hat{\beta}_{1.32} - \beta_1 \end{bmatrix} \xrightarrow{d} N \left( \begin{bmatrix} AB_1 \sqrt{c_{31}} \\ AB_2 \sqrt{c_{32}} \end{bmatrix}, \begin{bmatrix} c_{31} V_1 & 0 \\ 0 & c_{32} V_2 \end{bmatrix} \right). \tag{D.9}
\]

In practice, we need to estimate

\[
\begin{bmatrix} AB_1 \sqrt{c_{31} / ns_1n} \\ \sqrt{ns_1n} \\ AB_2 \sqrt{c_{32} / ns_2n} \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} V_1 & c_{31} ns_1n \\ ns_1n & ns_3n \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 0 \\ V_2 & c_{32} ns_2n \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 0 \\ ns_2n & ns_3n \end{bmatrix}. \tag{D.10}
\]

The quantities \( AB_1 / \sqrt{(ns_1n)} \), \( AB_2 / \sqrt{(ns_2n)} \), \( V_1 / (ns_1n) \) and \( V_2 / (ns_2n) \) are what we estimate in the first step of the estimation procedure, so the question is how to estimate the other quantities. A possible way to do this is to assume that \( s_{jn} = c_j n^{-\gamma} \) for some \( c_j, j = 1, 2, 3 \). Then it follows that all the remaining quantities in (D.10) are equal to 1 and hence we only need the bias and variance estimates from the first step. We use this choice in the main text. For \( s_{jn}, j = 1, 2 \), Kyriazidou (1997) assumes the structure mentioned before. However, the assumption that \( s_{3n} = c_3 n^{-2} \), although natural, can be restrictive in small samples. Therefore, we also investigated the sensitivity of the results when the remaining quantities in (D.10) are slightly different from 1.

References


Camphuis, H., 1993. Checking, editing and imputation of wealth data of the Netherlands socio-economic panel for the period 87–89. VSB-CentER Savings Project discussion paper.
Charlier, E., 1994. A smoothed maximum score estimator for the binary choice panel data model with individual fixed effects and application to labour force participation. CentER discussion paper no. 9481, Tilburg University.