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Paper in memoriam of Stephen Mayo

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Abstract: National housing markets differ in many aspects, making cross-national studies a fascinating subject. This article sheds light on housing demand in Germany and Japan. The primary task undertaken is to separate cross-national differences in the structure of housing demand by differing preferences and differing socioeconomic characteristics, exploiting the available cross-country variation in survey data from both countries. This study features the application of a mixed logit model that allows for a flexible substitution pattern among unobservable characteristics. This is an important feature in a comparison between countries since so many cultural and policy differences are impossible to model precisely.

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A full length version of this paper including an electronic data appendix can be found at `http://www.vwl.uni-mannheim.de/institut/e/papers.html`.

1. INTRODUCTION

The estimation of housing demand is a time-honored task. There are many reasons for this. Just to name a few, housing comprises usually 20% or more of a household's budget, making it the single most important budget item. Its longevity and its anchoring function for most household activities amplify the financial importance. Moreover, housing demand has traditionally been a target for large-scale government interference – understanding housing demand is therefore a prerequisite for enlightened housing policy.

The literature on housing demand is huge and this is not the place for an exhaustive review. We depart from Stephen Mayo's seminal survey of "theory and estimation in the economics of housing demand" written in 1981 and add two ingredients to the literature that has developed since. First, we exploit cross-national variation in order to identify the determinants of housing demand and to separate differences in preference parameters from household attributes and socio-economic characteristics. Second, we apply a very flexible discrete choice model in our econometric approach, the so-called mixed multinomial logit model popularized by McFadden and Train (2000) that accommodates both inter-alternative and inter-wave correlations. We argue that both ingredients will help us to better understand housing demand. Moreover, we argue that the combination of the two ingredients is more than the sum of its parts: their interaction makes this exercise particularly worthwhile.

We first look at the insights which cross national data may provide. We usually draw inferences about the determinants of housing demand by looking at differences and similarities across households. The empirical analysis of demand parameters in one country alone, however, most often suffers from the lack of a counter factual because "exogenous shocks" – usually precipitated by policy regime changes – are rare. This applies specifically to the estimation of price elasticities which can only be identified if proper price variation is present. In a purist sense, local housing markets feature no price variation at all since the definition of a local market implies the law of one price. Depending on the extent of intra-country mobility, cross-sectional data in a single country therefore features little variation. Even the time series data usually available in panels has little temporal variation, while the variation in longer series is frequently confounded by other historical changes.

In contrast, housing markets differ substantially across countries. As long as they share certain properties (such as a working market mechanisms that permits the application of standard demand functions in terms of income, prices, and "taste shifters" such as age and household size), cross-national comparisons can exploit the variation that has developed from past differences in preferences and policies.[1]

Of course, cross national comparisons suffer from confounding effects of cultural and attitudinal differences. The countries to be compared should therefore not be too unequal to make comparisons meaningless but still sufficiently different to feature policy and preference differences. This subtle balance restricts the choice of countries and requires a careful econometric analysis that controls for other confounding factors some of which are observable, others not.

Germany and Japan are two very suitable countries for a cross national comparison, see Börsch-Supan (1994).[2] They are both market economies with essentially private housing markets which share rather strong government intervention in the form of housing subsidies and market regulations (much more so than the United States). In turn, mechanisms and stringency of government intervention differs between the two countries, providing the necessary cross national variation. Germany and Japan have roughly comparable standards of living (comparable to that of the United States). They also have comparable demographics (both having a much higher share of elderly citizens than the United States). They have become somewhat "Americanized" after World War II, in particular with respect to consumption patterns.

Nevertheless, their histories and geographic features have led to very different housing outcomes, see Table 1. We first look at the official data that can be found in the statistical abstracts. Most notable are the differences in tenure choice and dwelling size. Ownership rates are high in Japan but very low in Germany: About 60% of households live in owner-occupied housing in Japan, but only about 40% in Germany. In turn, space consumption in Germany is much larger. In 1993, German dwellings had a floor space of about 86.8 m^2, Japanese dwellings only 51.8 m^2. This smallness of Japanese dwellings is amplified by the difference in household size. Japanese households have more members: 3.0 members on average rather

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[1] Stephen Mayo, in his work for the World Bank and other consulting institutions, was always interested in comparative housing demand analysis, see e.g. Mayo and Barnbrock (1985) for a comparative analysis of the effect of housing allowances on German and US housing demand, and Mayo and Malpezzi (1987) for a comparative analysis of housing demand in developing countries.

[2] This paper mainly refers to 1988 and 1993. This was before and only shortly after German unification. Since the East German housing market in these years cannot at all be described as the outcome of a market process, all figures and estimates refer to West Germany only.

than 2.25 members in Germany. Hence, a Japanese person consumes on average only about 17 m^2 of dwelling space, less than half of what a German person consumes.

These differences are echoed in our own samples, drawn from the German Socio-Economic Panel (GSOEP) and the Housing Demand Survey (JHDS) from the former Japanese Ministry of Construction (now Ministry of Land, Infrastructure and Transport). The samples are described in the electronic data appendix which also provides more detail on the two surveys.[3] To minimize endogeneity problems due to household formation (Börsch-Supan, 1986), our sample is restricted to married couples. This explains most of the differences vis-à-vis the official statistics. Among married couples, the ownership is higher, the total dwelling size larger, but – mainly due to relatively small children's rooms – the space consumed by each person is slightly smaller.

Table 1: Stylized facts

		West Germany		**Japan**	
		1988	**1993**	**1988**	**1993**
Ownership rate [%]	Official	39,1	40,9	61,1	59,6
	Sample	48,7	49,4	71,7	72,7
Dwelling size [sq.m.]	Official	86,2	86,8	50,5	51,8
	Sample	92,1	94,4	53,3	56,1
Household size	Official	2,28	2,25	3,2	3,0
	Sample	2,79	2,71	3,45	3,31
Dwelling size per house-hold member [sq.m.]	Official	37,8	38,6	15,8	17,3
	Sample	34,1	35,0	15,4	16,9

Sources: "Official" refers to the Statistical Yearbooks of Germany and Japan, respectively. "Sample" refers to our working samples which are restricted to married couples and described in the electronic data appendix.

We cannot even hope to "explain" these cross national differences in this small paper thoroughly and stringently.[4] How complicated this task is can be seen in the volume edited by

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[3] This electronic data appendix can be found at `http://www.vwl.uni-mannheim.de/institut/e/papers.html`.

[4] A description of further comparable cross-national statistics and their institutional background can be found in the electronic data appendix.

Noguchi and Poterba (1994), the policy analysis by Börsch-Supan (1994), and the forthcoming study by Börsch-Supan, Kanemoto and Stahl. We acknowledge the effects of these unmeasurable cultural and attitudinal differences – econometricians refer to them as "unobserved heterogeneity" – by our econometric methodology. This is the reason for the second new ingredient in this umpteenth paper on housing demand: we apply a mixed multinomial logit model that rather elegantly models unobserved preference features and other unobserved demand determinants and at the same time takes flexibly care of unobserved correlations across housing alternatives. Only after such modeling efforts can we interpret estimated preference differences between countries with reasonable confidence: we need an instrument to "soak up" the unexplained variation across the countries in a cross national comparison to correctly attribute the effects to observable characteristics.

The paper is structured as follows. Section 2 describes our methodology and its relation to the work of Stephen Mayo. Section 3 presents the details of our econometric model while Section 4 shows our estimation results. Section 5 concludes. An electronic appendix available under `http://www.vwl.uni-mannheim.de/institut/e/papers.html` presents data sources and auxiliary estimation results.

2. METHODOLOGY

A satisfactory estimation of housing demand requires a rather large technical apparatus. This is due to the well-known special characteristics of housing as pointed out succinctly in the seminal surveys by Mayo (1981) and Quigley (1979). Following these surveys, we address the durability of housing and our approach to permanent income estimation in the first subsection. We then stress the heterogeneity of housing and the need for hedonic price estimates. The last subsection is focussed on how to cope with unobserved heterogeneity and motivates our discrete choice approach to housing demand.

2.1 Durability of housing and permanent income

Housing differs from other consumption goods in many aspects. First of all, houses are extremely durable. Because of this, the consumption of housing during a period of time cannot be approximated by house purchases. The purchase of a house should be interpreted as an investment. If this house is owner-occupied afterwards, the investment good "house" supplies the owner with a return in form of the consumption good "housing services". If it is rented out, these housing services are sold on a regular basis and the return is transformed into money income. The renter consumes housing services without owning the investment good “house”. Since this paper deals with the consumption demand of housing, it tries to explain the decision which dwelling to *occupy*, not which ones to *purchase*.

Durability also means that current income can be a bad predictor of housing demand. Because households do not change their dwellings in response to short-frequency income changes, a measure of “permanent” or “normal” income is more appropriate. We follow the by now classical approach in constructing normal income from human capital estimates. In the German panel data, rich information on human capital variables is available, so that human capital regressions can be applied. We actually estimate a fixed effects model in order to account for unobserved heterogeneity. The regression fits well with an R^2 of 79% with and 35% without the fixed effects. The predicted values of these regressions are then used to predict individual income paths and a mean income over the life cycle. These values are then used as income measures in the set of explanatory variables in the housing demand estimation. The electronic data appendix and Heiss (2000) provide further details.

For Japan, we do not have such rich information on human capital variables and current income is only reported in intervals. We therefore regress income on the available information such as age of the head, number of earners and detailed information of the household composition using a maximum likelihood method that explicitly takes into account the intervals (see Ruud 2000, p. 758, and the data appendix). Income is then predicted conditional on the explanatory variables and the reported income interval.

Table 2 shows the correspondence between the reported current income and our measure of “normal income” in both countries, taking the example of 1993. Other years are similar.

Table 2: Current and Normal Household Income in Germany and Japan, 1993

		Quintile borders			
		1st	**2nd**	**3rd**	**4th**
Germany	Current	18,959	25,169	31,687	40,491
	Normal	20,419	25,175	29,653	35,547
Japan	Current	19,649	33,684	33,684	47,719
	Normal	19,806	33,307	34,144	47,119

Sources: Working samples of GSOEP and JHDS, see electronic data appendix, restricted to married couples and described in the data appendix. All amounts in US-$ 1993 converted by OECD PPP.

The quintile borders of normal income are compressed due to the smoothing effect by projecting income to the set of human capital variables. This effect is much stronger in Germany where we employ many human capital variables than in Japan where we use only demographic information to smoothen the bracketed income information.

2.2 Heterogeneity of housing I: hedonic price estimation

Another important aspect of housing as a good is its extreme heterogeneity. Since there is no such thing as a well-defined standard dwelling with a well-defined quality (and thus quantity of housing services) and a well-defined unit price, we have to define such a dwelling and its price. We follow the now classical hedonic approach identified by Mayo (1981) and Quigley (1979) and based on Rosen (1974) and Brown and Rosen (1982) as the method of choice.

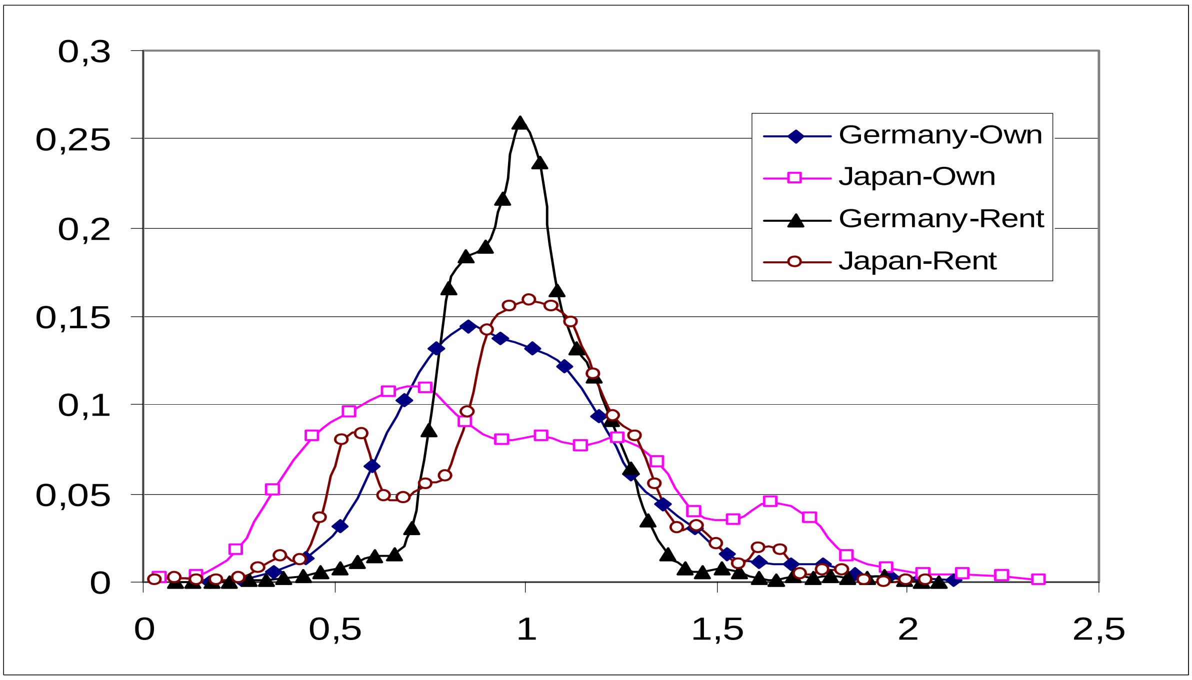
For rental housing the approach is straightforward. We interpret the predicted value of a regression of rents on dwelling characteristics as a quality measure. The price for each rental dwelling is then simply its observed rent divided by its predicted quality. Both the German and the Japanese data contain rich information on dwelling characteristics so that this well-known technique can be successfully applied. The identifying price variation (Brown and Rosen, 1982) is generated by pooling across regional submarkets and time, see further below. Coefficients of the hedonic estimation are reported in the electronic data appendix and are based on Heiss (2000) and Kohnz (2000). The goodness of fit (R^2) is 54,6% for Germany which is good, and 40.0% for Japan which is satisfactory. Attributing all the remainder to genuine price variation is of course a very strong identifying assumption which we will discuss in Section 4 in more detail.

For owner-occupied housing, the approach is a bit more complicated since neither the German nor the Japanese data carry reliable house values. For Germany, we therefore use the self-reported imputed rents ("If you were renting out your home, which rent do you think you could charge for it?") and then proceed as described for rental housing.[5] For Japan, we do not have this information. We therefore use the submarket-specific rental prices of an otherwise identical dwelling also for owner-occupied housing. Price elasticities are therefore identified by the variation across submarkets and across large/small and single/multiunit dwellings but not by variation across tenure types.

[5] We acknowledge that self-reported data may be subject to reporting bias. Unfortunately, we do not have reliable auxiliary data to gauge this potential bias or to correct for it.

By construction, the resulting rental and ownership prices have a mean of one. Figure 1 shows the distribution. Japanese unit prices have a wider distribution than German housing prices. This reflects the greater heterogeneity of land use in Japan, in particularly the differences between the Tokyo metropolitan area and other parts of Japan (Kanemoto, 1992). In Germany, imputed rents of owner-occupied housing vary more than the prices of rental housing. This may reflect a greater variety of owner-occupied housing as well as a larger reporting error of house values than rents[6]

Figure 1: Distribution of Unit Prices of Rental and Owner-Occupied Housing



Source: Working samples of GSOEP and JHDS, see electronic data appendix.

2.3 Heterogeneity of housing II: Housing demand as multidimensional choice

Our treatment of heterogeneity goes several steps further. We do not only normalize quality and quantity of a house by the use of the hedonic technique, but model housing demand as a selection among dwellings that differ in a large dimension of properties. The most prominent example of a dimension in which the type of consumption differs across households is tenure. Two other dimensions of housing attributes are dwelling size and structure type. A household simultaneously decides which kind of dwelling to inhabit and whether to rent or buy it.

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[6] By construction, price variation of owner-occupied and rental housing is identical in Japan.

Earlier studies used a continuous measure of the amount of "housing services" as the variable to be explained. The obvious advantage of this approach is its ease: the econometric analysis is straightforward since usual linear regression can be used to explain household behavior. However, for most policy purposes and housing demand projections, the heterogeneity in specific dimensions is of central interest and adds important aspects to the mere choice of the amount of a homogeneous good. For instance, a large low-quality dwelling may have the same rent and amount of "housing services" as a small luxury apartment, but they should not be regarded the same for many applications. The choice of tenure implies an important investment decision and has a significant impact on the portfolio composition of the household. Borrowing and down payment constraints may effectively prevent households from buying a house. At the same time, a dwelling can supply different kinds of service flows to the inhabitant depending on whether it is rented or owner-occupied.

For this reason, we model housing demand as the demand for different attributes of the occupied housing unit. We use a finite set of attributes since multi-dimensional joint discrete-continuous models quickly become very complex. This discrete choice approach "solves" many of the heterogeneity problems since it permits each of the alternatives to have a specific set of unobserved attributes, allowing more heterogeneity among housing alternatives than the single error term in a continuous "housing services" equation could absorb. At the same time, this set of error terms has to be carefully modeled. This is discussed at length in Section 3 below.

We follow Börsch-Supan (1985, 1987) and categorize housing demand in eight different housing types defined by the combination of three dimensions, for simplicity characterized by a binary description: tenure (own or rent), structure type (single family or multi family structure), and dwelling size ("small" or "large"). Table 3 shows the distribution of the eight housing alternatives in our sample.

Table 3: Distribution of Housing Alternatives (Percentages)

	Own				Rent			
	Single-Fam.		Multi-Fam.		Single-Fam.		Multi-Fam.	
	Large	Small	Large	Small	Large	Small	Large	Small
Germany 1988	21,5	19,6	4,0	3,6	2,3	11,5	9,7	27,8
Germany 1993	22,9	18,9	3,6	4,1	2,8	11,9	8,8	27,0
Japan 1988	55,6	9,7	2,1	3,7	1,9	4,7	1,6	20,8
Japan 1993	56,9	8,7	2,2	4,4	1,6	3,7	1,5	21,2

Source: Working sample of GSOEP and JHDS, see electronic data appendix.

As expected, the dominating housing alternatives are large single family houses and small rental apartments. We decided to use a common definition for "large" in the two countries. A dwelling is defined as "large" when it has four or more rooms. Since rooms are much smaller in Japan, this definition may be controversial. It leads to the strikingly large share of the first housing alternative in Japan. Instead, we could have used a different definition of "large" in each country. This would have led to a more "natural" distribution of the eight housing alternatives in Table 3. However, since we employ alternative-specific constants in all our demand equations, this alternate definition would change none of the estimated coefficients except for a shift in the shares in Table 3 and different estimates of the alternative-specific constants.

Models of a choice among alternatives require information on the explanatory variables for each alternative, including those which have not been chosen by the observed household. Knowing the prices for the alternative chosen by the household is not sufficient to identify the impact of prices on housing demand. We also have to impute the prices of the other alternatives that the household could have chosen as well. We assume that there are submarkets in time and location in which prices are constant, but that relative prices vary over these temporal and regional submarkets. For Japan, our data provide two points in time and 47 prefectures, leading to a total number of 94 submarkets over which prices may vary. In Germany, we have less regional variation (11 states) but this is offset by the additional variation across 7 community size classes and substantially more temporal variation (13 points in time), leading to a total of 1001 submarkets. We then define submarket-specific prices of the eight alternatives by taking the mean of the quality-adjusted prices for each alternative in the different submarkets, and assign to each household the mean prices of the submarket in which the household lives.

3. ECONOMETRIC SPECIFICATION

An important step in our treatment of heterogeneity is to employ an econometric model of discrete choice that is more flexible than the familiar multinomial logit (MNL) model (McFadden, 1974). The MNL model departs from the assumption that the utility of each of the housing alternatives (denoted by j=1...J) in Table 3 can be characterized for each individual household (denoted by n=1...N) by

$$u_n^j = x_n^j{}'\beta + \varepsilon_n^j \tag{1}$$

where the vector of explanatory variables x_n^j contains properties of alternative j (such as price) as well as characteristics of the household (such as size and income) interacted with alternative specific variables. A crucial assumption for the MNL model is that the error components ε_n^j which carry all unobserved heterogeneity are independent from each other. Together with the assumption of a Gumbel distribution, it leads to the well known choice probabilities

$$P_n^j = \frac{\exp(x_n^j{}'\beta)}{\sum_{k=1}^{J}\exp(x_n^k{}'\beta)} \tag{2}$$

The advantages of the MNL model are a closed form expression for the choice probabilities and a likelihood function which is globally concave in the unknown parameters. Therefore, estimation is straightforward.

These advantages, however, are not costless. Most notably, if some alternatives are more similar than others, the assumption of statistical independence of the error terms is counter factual; its violation, however, can lead to seriously biased parameter estimates. This is indeed the case for estimates of housing demand as shown by Börsch-Supan (1987). He therefore used the nested multinomial logit (NMNL) model. The drawback of the NMNL model is the necessity of specifying a fixed nesting structure.

These biases are amplified if the MNL model is applied to panel data where we have multiple observations of the same household with common unobserved characteristics over time. Börsch-Supan and Pollakowski (1990) have pointed out the importance of correcting for this additional unobserved heterogeneity to avoid biased estimates of housing demand determinants. They applied a conditional fixed effects multinomial logit (CFEMNL) model on housing demand in order to control for unobserved heterogeneity. This model conditions out time constant individual effects in panel data. The drawbacks of the CFEMNL-model are a substantial loss of information and the inflexible substitution pattern from the MNL model. Moreover, it allows only for time constant unobserved heterogeneity.

A newer branch of the literature tries to explicitly model housing demand in panel data as a dynamic decision process. This seems to be a promising approach since heterogeneity across individuals also arises from the difference between the time of housing choice and observation time. Households may have chosen a housing alternative when they were credit constraint but gained sufficient income when they were observed in our data. Since moving costs are high, they may not have adjusted their housing choice in between (Weinberg, Friedman, and Mayo, 1981). Goodman (1995) presents an intertemporal model of housing demand. VanderHart (1998) estimates a model that is based on the assumption that households solve a dynamic programming problem when deciding on their housing demand. However, since dynamic multinomial decision processes are very complicated, empirical applications must rely on quite restrictive assumptions on unobserved determinants of the decision process in order to obtain a tractable likelihood function.

One of the most elegant features of the mixed multinomial logit (MMNL) model applied in this paper is that it simultaneously allows for a flexible substitution pattern among alternatives, for unobserved heterogeneity in panel data, and for plausible dynamic interactions. It can be viewed as a pragmatic reduced form of a full-fledged structural dynamic model of a choice among many alternatives with correlated unobserved attributes.[7] The MMNL model is specified in the first subsection, the second subsection describes the nuts and bolts of practical estimation.

[7] We agree with an anonymous referee that the MMNL model (and the normal income approach) cannot fully account for the above-mentioned dynamic effects. We think, however, that given the current state-of-art in computing, the MMNL panel data model is preferable to a computationally tractable and therefore necessarily simplistic dynamic model of housing choice. This is likely to change in the future.

3.1 Specification of the mixed multinomial logit model

The MMNL model developed by McFadden and Train (2000) generalizes the MNL model by assuming that the stochastic part of the utility is a mixture of an i.i.d. random variable ε_n^j with extreme value type I distribution and a linear combination of other random variables. That is, utility can now be described as

$$u_n^j = x_n^j{}'\beta + \left(z_n^j{}'\gamma_n + \varepsilon_n^j\right) \tag{3}$$

where the stochastic part of the utility function $\left(z_n^j{}'\gamma_n + \varepsilon_n^j\right)$ has an error-components structure. The vector z_n^j contains characteristics of the alternative, and the γ_n will be specified as independent random variables with a parametric distribution $f(\gamma_n\,|\theta)$, the so-called mixing distribution, which gives the MMNL model its name. Its meaning will become clearer in equation (6) below.

The specification (3) can be motivated from a random parameters model. That is, unobserved heterogeneity is introduced into equation (1) by assuming that (some of) the parameters vary across the population. An example may help to clarify this point. Suppose, the only unobserved factor determining the choice is that some of the households have a propensity to favor owner-occupier alternatives, maybe because independence is important to them. To others, owner-occupation comes with too much effort or they are credit constrained. In this case, one would expect the error terms of the owner-occupying alternatives to be correlated as well as the error terms of the renting alternatives.

Let z_n^j in this example consist of two variables: d_o^j is an indicator for owner-occupying alternatives and d_r^j is an indicator for renting alternatives. Suppose γ_n follows a bivariate normal distribution with zero mean and zero covariance. Call the variances of its first and second element σ_o^2 and σ_r^2, respectively. So the alternative-specific constant c_j included in x_n^j of a random parameters model is associated with a parameter that is restricted to be equal to $\gamma_{no}\, d_o^j + \gamma_{nr}\, d_r^j$.

The covariance of the utilities of any two alternatives j and k conditional on z_n^j and z_n^k is equal to

$$E\left[\left(\gamma_n{}' z_n^j + \varepsilon_n^j\right)\left(\gamma_n{}' z_n^k + \varepsilon_n^k\right)\right] = z_n^j{}'\Omega z_n^k \tag{4}$$

where Ω is the covariance matrix of γ_n. For the above example, this means that $\text{cov}(u_n^j,u_n^k) = d_r^j \cdot d_r^k \cdot \sigma_o^2 + d_r^j \cdot d_r^k \cdot \sigma_r^2$. If j and k are both owner-occupying alternatives, their covariance is

σ_o^2; if both are renting alternatives, it is σ_r^2; otherwise, it is zero. This correlation structure is similar in spirit to the nested logit model: alternatives within "nests" are correlated. Estimated values for σ_o^2 and σ_r^2 are similarity parameters of the alternatives in the according "nest".

However, the mixed logit model allows for more. First and sticking with the above example, in addition to the indicator variables for owner-occupied and rental housing, we can also use indicators for the other dimensions of housing choice, i.e. dwelling size and structure type, thereby creating a correlation structure of "overlapping nests". This is not possible in the NMNL-model applied e.g. by Börsch-Supan (1987). We will estimate this model as our "basic mixed logit model", see Section 4.

Moreover, in addition to the dimension-specific constants we can also add substantive explanatory variables as weights z_n^j to the error structure in equation (4), say, housing prices. A helpful interpretation of this specification is that the estimated price coefficients vary by household. We will estimate this variant as our "price-weighted mixed logit model" in Section 4.

As a matter of fact, if certain weak regularity conditions apply, the choice probabilities of *any* random utility maximization model of discrete choice can be approximated arbitrarily closely by a MMNL model with an appropriate choice of the z_n^j and the distribution of the γ_n (McFadden and Train, 2000). This explains the great flexibility of the MMNL model.[8]

The mixed logit choice probabilities conditional on x_n^j, z_n^j, β and γ_n are conventional logit probabilities which makes the MMNL model convenient to estimate:

$$\overline{P}_n^j(\beta,\gamma_n) = \frac{\exp(x_n^{j}{}'\beta + z_n^{j}{}'\gamma_n)}{\sum_{k=1}^{J}\exp(x_n^{k}{}'\beta + z_n^{k}{}'\gamma_n)} \tag{5}$$

We do not estimate the individual γ_n. Instead, we estimate the parameters θ of its distribution $f(\gamma_n\,|\,\theta)$, the mixing distribution. The unconditional probability that household n chose its observed alternative y_n is therefore

$$P_n(\beta,\theta) = \int \overline{P}_n^{y_n}(\beta,\gamma_n) f(\gamma_n\,|\,\theta) d\gamma_n \tag{6}$$

[8] Brownstone and Train (1999) discuss the flexibility of the mixed logit model and compare it to alternative models such as the multinomial probit model.

which is the likelihood contribution of observation n. We assume that the distribution function of γ_n, which is mixed with the probability function $\overline{P}_n\left(\beta,\gamma_n^r\right)$, is normal.

3.6 Practical estimation of the mixed multinomial logit model

Since the errors are assumed to be independent over individuals, the likelihood function for the sample is the product over individuals of the probabilities in equation (6). In general, there is no closed-form solution to the multi-dimensional integral in this equation. In order to find an approximate maximum of the log likelihood function, numerical integration or simulation methods can be applied. In this paper, we use the maximum simulated likelihood method, as suggested by McFadden and Ruud (1994). Given start values β^0 and θ^0, a large number R of different values γ^r_n, r=1...R is drawn from the distribution $f(\gamma_n\,|\theta)$. For each draw r, the conditional probability $\overline{P}_n\left(\beta,\gamma_n^r\right)$ is calculated according to equation (5).

The simulated probability of this choice sequence is then equal to the mean over the draws: $P_n^s\left(\beta,\gamma_n^r\right)=\frac{1}{R}\sum_r \overline{P}_n\left(\beta,\gamma_n^r\right)$. Since the score and the hessian can be simulated accordingly, gradient based numerical maximization algorithms can be used to find values of β and θ, that (locally) maximize the likelihood function.[9]

The simulated probability is an unbiased estimator of the true marginal probability. The simulated log likelihood $L^s=\Sigma_n \ln(P_n^s)$ however is a biased estimate of the log likelihood, since it involves taking the logs of random variables. With a rising number of replications R, the variance of P_n^s falls and as a result the bias and the additional standard errors of the estimated parameters vanish (Börsch-Supan and Hajivassiliou, 1993). If number of draws for each observation rises with the number of observations, the maximum simulated likelihood estimator is consistent. If R rises faster than the square root of the observations, it is asymptotically equivalent to the infeasible maximum likelihood estimator (Hajivassiliou and Ruud, 1994).

In practice, the number of draws required to achieve these asymptotic results depends on the application. We use 200 draws in this application. As sensitivity checks with larger numbers of draws showed, the results do not change systematically beyond these 200 replications. Hence, we feel confident that our results do not suffer from simulation bias.

[9] At the estimation stage of this paper, we greatly benefited from GAUSS code that Kenneth Train provides for downloading on his homepage (`http://elsa.berkeley.edu/~train`).

Heteroscedasticity-consistent "sandwich" estimators of the standard errors of the parameters correct for the additional variance caused by simulation.

For our application to panel data, we also have to specify the error correlations over time. In the mixed logit model, this can be done in a straightforward way. Assuming that the individual γ_n are constant over time, the error terms "inherit" the temporal correlation of the z_n. Two alternatives become more correlated over time when their z_n^j become more similar.[10]

4. RESULTS

We apply our econometric methodology on housing demand equations of the following type: joint dependent variables are the probabilities of the eight housing alternatives of Table 3, explained by housing prices, household income, and a set of socio-economic characteristics such as the age of the household head and the size of the household. Age and household size enter with a quadratic term to accommodate nonlinearities. We also introduce a linear time trend to test whether housing demand changed over and above the general increase in affluence in the two countries during our panel period, and, of course, a set of alternative-specific constants. As always in discrete choice models, all variables except for the alternative-specific prices have to be interacted with dummies that carry variation across alternatives. We choose a full set of alternative constants but restrict the interaction of the other variables to the three dimensions tenure, structure type and dwelling size.

As pointed out in the introduction, we focus on two features of this housing demand estimation exercise. First, we want to learn from cross national variation. Second, we want to profit from the flexibility which the mixed logit model provides. Hence, we report two sets of six estimates. The first set refers to the simple MNL model, the second set to the mixed logit model (MMNL). As described in Subsection 3.1, we estimate two variants of the mixed logit model. The basic variant defines the mixing structure by the three dimensions of housing choice and introduces a very flexible correlation pattern across unobserved attributes of housing choices. The second variant adds prices as weights to this correlation pattern such that the estimated price coefficients vary by household. Both variants permit correlation of unobserved household characteristics across the panel waves in the German data, much in the way of random effects, but they are more flexible because correlations may change over time.

[10] In this case, equation (6) is modified such that the integration is done not over the conditional probabilities of a single observations, but over the conditional probability of the individual choice path.

In each set, we start with separate coefficient estimates in each country. This is equivalent to a full set of interactions with the two country-specific dummies for Germany and Japan. We then pool various sets of coefficients until we reach a fully pooled estimate. The structure of the various specifications is depicted in Table 4. Except for the pair of Model 3 and 4 (therefore indicated by dashes rather than solid lines), the models are nested consecutively and become more restrictive from the left to the right.

Table 4: Structure of Specifications

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Income, Age, Hh-size	Separate	Pooled	Pooled	Pooled	Pooled	Pooled
Prices	Separate	Separate	Pooled	Separate	Pooled	Pooled
Time trend	Separate	Separate	Separate	Pooled	Pooled	Pooled
Constants	Separate	Separate	Separate	Separate	Separate	Pooled

Source: Authors' calculations based on the GSOEP and JHDS working samples.

We first describe the goodness of fit of our MNL and MMNL regressions, and then turn to the substantive results.

4.1 Goodness of fit

Table 5 reports the likelihood value of the estimated models in order to obtain an idea of the goodness of fit of each specification.

Table 5: Likelihood values

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
MNL	-6208,9	-6273,8	-6380,4	-6286,0	-6383,0	-6616,3
MMNL (basic)	-4369,5	-4412,2	-4414,6	-4418,4	-4424,7	-4537,4
MMNL (with price weights)	-4323,9	-4368,0	-4370,1	-4371,2	-4384,6	-4509,0

Source: Authors' calculations based on the GSOEP and JHDS working samples.

There are four lessons from Table 5. First and quite clearly, the mixed logit model provides a much better fit than the conventional logit model. This is not too surprising, since the restrictive functional form of the MNL-model is well established. The magnitude of the improvement in the likelihood function, however, is impressive.

Second, pooling the German and Japanese data is rejected by far (Model 6 vs. Model 1). If we interpret the estimated coefficients as the parameters which describe the households' preferences, then we must conclude that German and Japanese households have significantly different preferences even after we have accounted for differences in the distribution of income, age, household size and housing prices. However, the story is more complicated. If we think that the variation in each single country is limited, then we have the choice between the Scylla of an estimate based on separate data with insufficient variation and the Carybdis of a pooled estimate which is based on sufficient variation in the explanatory variables but imposes a counterfactual equality of certain parameters. This is a good example where a priori knowledge must guide our decisions until we have richer data.

Third, pooling appears to hurt most in terms of the household characteristics (Model 2 vs. Model 1) and prices (Model 3 vs. Model 2 and Model 5 vs. Model 4) while pooling the time trends (Model 4 vs. Models 2 and Model 5 vs. Model 3) is significant but does not matter that much in terms of the likelihood value. We will come back to this result when we give the estimated price coefficients a closer look. Of course, pooling the alternative-specific constants reduces the likelihood dramatically (Model 6 vs. Model 5). This is to be expected as these constants describe all residual differences (conditional on the explanatory variables) in the baseline probabilities depicted in Table 3.

The fourth lesson pertains to the mixed logit model with prices as weights: while this kind of weighted mix does improve the fit significantly, the improvement is relatively small compared to the initial improvement. The structure of overlapping nests induced by the "basic variant" of the mixed logit model already fits the data well, while unobserved heterogeneity induced by differing reactions to price changes do not appear to play a major role.

4.2 Substantive Results

We now turn to the substantive results carried by the coefficient estimates. We concentrate on Models 1 and 5 which represent the fully interacted and the fully pooled (except for the constants) specifications, estimated by the conventional MNL and the basic mixed logit model.[11] Parameter estimates of Models 1 and 5 are displayed in Table A1 in the appendix to

[11] The results by the price-weighted mixed logits are very similar to the basic mixed logits and therefore not reported here – this is probably due to the relatively small magnitude of the price effects, see below.

this paper, while the full set of parameter estimates of all models including their translation into probability changes and elasticities is given in the electronic data appendix.

Since coefficients in discrete choice models carry little intuitive information, we convert the coefficient estimates first into finite changes in the predicted probabilities, increasing and decreasing each variable by 10% (first line in Tables 6 through 10), and second into the corresponding elasticities (in italics, second line in Tables 6 through 10). Since the effects are roughly symmetric, we only report the effects of an increase in the respective variable. For those variables which enter quadratically (age and household size), the effects are actually slightly stronger for a decrease than for an increase. This is to be expected since both age and household size have a concave effect on housing demand because elderly rarely move in larger dwellings, and larger households have usually more children. Again, the full matrices of changes and elasticities are relegated to the data appendix.

We order our presentation by variable, starting with income and prices, and ending with household size and age. If not indicated otherwise, we only comment on results that are based on coefficient estimates which are significant at least at the 5% level. The reader is referred to the appendix table which indicates the significance levels of all estimated coefficients.

Income has the expected positive effect on owner-occupancy, on choosing a large dwelling, and on living in a single family home, see Table 6. It is the magnitudes that are of special interest. They must be interpret with care since they refer to a change in the "normal" or "permanent" income. According to the conventional logit model applied to separate samples of the German and Japanese data, having a permanent income 10% above the average increases the probability to own in Germany by 5.3 percentage points (from 48.6%), in Japan only by 2.8 percentage points (from 72.0%), pointing to a certain saturation in Japan.

We argue that these conventional estimates are likely to be on overestimate for three reasons. First, they are based on relatively little income variation, particularly in the German GSOEP sample of married couples. Second, the estimates are based on the inflexible logit model with its counterfactual independence of irrelevant alternatives (Börsch-Supan, 1987). Finally, conventional estimates ignore unobserved household characteristics correlated with income.

By pooling cross nationally, our housing demand estimates address the first point. Indeed, the large German estimates are now substantially reduced, and the estimates look much more similar between the two countries. Note that pooling the data does not mean that we impose the same elasticities – the implicit interactions in the discrete choice model permit a richer variation in these effects. Going one step further, the mixed logit model takes care of objections two and three – heterogeneity in unobserved attributes of the eight housing alternatives as well as of the unobserved characteristics of the households, mainly in the German true panel data (remember, that we have only two unlinked waves in the Japanese data). Hence, the last row in Table 6 are our preferred estimates where we both exploit the cross national variation and account for unobserved heterogeneity. Both steps reduce the coefficient estimates. While this may be a sorry outcome for economists, it appears that the large and cross nationally unequal income elasticities were an artifact of misspecification and unaccounted heterogeneity.

Table 6: Effects of Increasing Household Income

	Germany			**Japan**		
	Own	**Large**	**Home**	**Own**	**Large**	**Home**
Baseline	**48,6%**	**38,2%**	**55,7%**	**72,0%**	**61,9%**	**72,1%**
Model 1, MNL	5,26%	3,78%	3,72%	2,76%	2,69%	1,62%
	1,08	*0,99*	*0,67*	*0,38*	*0,43*	*0,22*
Model 5, MNL	3,33%	2,08%	1,48%	3,61%	3,26%	2,47%
	0,67	*0,54*	*0,26*	*0,51*	*0,53*	*0,35*
Model 1, MMNL	4,01%	2,83%	1,92%	2,83%	2,74%	1,63%
	0,82	*0,75*	*0,35*	*0,40*	*0,45*	*0,23*
Model 5, MMNL	2,06%	1,52%	0,48%	1,94%	1,60%	1,30%
	0,42	*0,40*	*0,09*	*0,27*	*0,26*	*0,18*

Source: Authors' calculations based on the GSOEP and JHDS working samples.

The reaction to price changes tells us a very similar story, see Tables 7 and 8. We first model a 10% increase in the unit rental price (Table 7), then a 10% increase in the unit price of owner-occupied housing (Table 8). As expected, increasing the price of rental housing decreases the demand for it, and subsequently raises the demand for owner-occupied housing, while this is reversed for an increase in the price of owner-occupied housing. Note that we refer to quality-corrected unit prices based on our hedonic estimation in Section 2.

According to the estimates by the conventional logit model, the price effects are rather large in Germany and relatively small in Japan (and highly significant in both countries). 10% higher rental prices increase ownership by almost 8 percentage points in Germany, from 49% to 57%. This does appear very large in relation to the actual price variation which Germany has experienced during the last ten years: prices changed more than 10% while the tenure balance remained largely unchanged. The MNL-estimates also indicate a substantial spillover towards large dwellings, and an expected increase in the demand for single family homes.

It indeed appears that these effects are grossly misleading. In the country-separated mixed logit model, the prices are essentially insignificant; they are significant at the 10% (owner-occupied) and 5% level (rental housing) but very small in the pooled model. Housing demand turns out to be rather inelastic in particular with respect to changes in owner-occupied house prices, and this in both countries (see last row of Table 8).

This findings are disconcerting at first sight. While they are certainly subject to errors-in-variables critique due to the many imputations and auxiliary regressions described in Section 2, we think that they do make sense and point out the often underestimated problems in estimating housing price elasticities from survey data. The construction of price indexes by the time-honored hedonic method described in Section 2 attributes all measurable differences in housing characteristics to the quality index, leaving the remainder for the price index. This is, however, a mixture of true price signals and noise from unmeasured housing attributes. The mixed logit model filters out unobserved heterogeneity across the eight housing alternatives, hence reduces the price effect to the true mostly cross sectional signal. It appears that we have very little actual price variation in our data, and most part in the hedonic remainder is actually noise from unmeasured housing attributes.

This finding also offers a solution to the often discussed puzzle that cross sectional price elasticities are much larger than time-series elasticities: the former may actually be based on misleading “noise” as indicated by the “filter effect” of the mixed logit model.

Table 7: Effects of Increasing the Unit Price of Rental Housing

	Germany			**Japan**		
	Own	**Large**	**Home**	**Own**	**Large**	**Home**
Model 1, MNL	7,56%	2,18%	4,30%	1,70%	1,21%	1,22%
	1,56	*0,57*	*0,77*	*0,24*	*0,20*	*0,17*
Model 5, MNL	5,25%	1,50%	3,02%	4,19%	2,94%	2,99%
	1,06	*0,39*	*0,54*	*0,59*	*0,48*	*0,42*
Model 1, MMNL	0,27%	0,05%	0,17%	1,65%	1,15%	1,16%
	0,06	*0,01*	*0,03*	*0,23*	*0,19*	*0,16*
Model 5, MMNL	0,23%	0,05%	0,15%	0,37%	0,28%	0,27%
	0,05	*0,01*	*0,03*	*0,05*	*0,04*	*0,04*

Source: Authors' calculations based on the GSOEP and JHDS working samples.

Table 8: Effects of Increasing the Unit Price of Owner-Occupied Housing

	Germany			**Japan**		
	Own	**Large**	**Home**	**Own**	**Large**	**Home**
Model 1, MNL	-7,54%	-2,21%	-4,37%	-0,10%	-0,07%	-0,06%
	-1,55	*-0,58*	*-0,78*	*-0,01*	*-0,01*	*-0,01*
Model 5, MNL	-3,67%	-1,06%	-2,16%	-2,89%	-2,03%	-1,90%
	-0,74	*-0,28*	*-0,39*	*-0,41*	*-0,33*	*-0,27*
Model 1, MMNL	-0,21%	-0,11%	-0,09%	-0,10%	-0,07%	-0,06%
	-0,04	*-0,03*	*-0,02*	*-0,01*	*-0,01*	*-0,01*
Model 5, MMNL	-0,04%	-0,02%	-0,01%	-0,03%	-0,01%	-0,02%
	-0,01	*0,00*	*0,00*	*0,00*	*0,00*	*0,00*

Source: Authors' calculations based on the GSOEP and JHDS working samples.

The effects of the age of the householder and of household size are a less dramatic story. The nonlinear effect of age on the three dimensions of housing demand is summarized in Table 9. Households with an older head are more often owners, have on average larger dwellings, and, as a consequence, more often a single family home. The tenure effect is slightly but not significantly stronger in Germany than in Japan where ownership rates are already higher (except for the third estimation variant). The probability that household heads who are 10% older than the average household head (i.e., 55 years rather than 50 years) own their dwellings is in the order of 7 percentage points higher in Germany and 6 percentage points higher in Japan than the probability for the average household head. Needless to say that the effects of age on housing demand are highly significant.

Table 9: Effects of Increasing the Average Age of Household Heads

	Germany			**Japan**		
	Own	**Large**	**Home**	**Own**	**Large**	**Home**
Model 1, MNL	8,46%	5,61%	5,65%	6,54%	6,11%	5,98%
	1,74	*1,47*	*1,01*	*0,91*	*0,99*	*0,83*
Model 5, MNL	7,33%	4,63%	5,24%	6,54%	6,18%	5,79%
	1,48	*1,21*	*0,94*	*0,92*	*1,01*	*0,81*
Model 1, MMNL	3,81%	2,27%	2,16%	6,72%	6,22%	6,08%
	0,78	*0,60*	*0,39*	*0,94*	*1,01*	*0,85*
Model 5, MMNL	6,96%	4,97%	2,31%	4,85%	3,94%	3,84%
	1,42	*1,32*	*0,41*	*0,68*	*0,64*	*0,54*

Source: Authors' calculations based on the GSOEP and JHDS working samples.

Also household size enters as a quadratic function. Large households have a slightly higher propensity to own or live in a single-family home, but these effects are only marginally significant. Mainly and as expected, larger households have larger dwelling sizes, see Table 10. The latter effects are highly significant.

The effects are computed for a 10% change. About a threefold change of those reported in Table 10 corresponds to one more person in the household. Hence, households with one more person than the average have a about a 15 percentage point higher probability to live in large dwellings. Note that this effect is about twice as large in Japan than in Germany – here, also the difference between the two countries is highly significant.

Table 10: Effects of Increasing the Average Household Size

	Germany			Japan		
	Own	**Large**	**Home**	**Own**	**Large**	**Home**
Model 1, MNL	1,97%	5,04%	2,55%	3,88%	4,59%	3,87%
	0,40	*1,32*	*0,46*	*0,54*	*0,74*	*0,54*
Model 5, MNL	1,52%	2,84%	1,64%	2,95%	4,08%	3,08%
	0,31	*0,74*	*0,29*	*0,42*	*0,67*	*0,43*
Model 1, MMNL	1,12%	1,77%	0,93%	3,97%	4,64%	3,91%
	0,23	*0,47*	*0,17*	*0,56*	*0,76*	*0,55*
Model 5, MMNL	1,65%	1,71%	0,70%	2,45%	2,53%	2,21%
	0,34	*0,45*	*0,13*	*0,34*	*0,41*	*0,31*

Source: Authors' calculations based on the GSOEP and JHDS working samples.

As opposed to the income and price effects, the results are very stable across all four estimation methods although the mixed logit model – by estimating a flexible random effects model – has the capacity to filter out unobserved household characteristics. This stability for well-measured household characteristics helps to obtain confidence in the estimated models.

7. CONCLUSIONS

Departing from the conventional approach to estimate housing demand, we added two new ingredients: we explored the usefulness of cross national variation, and we experimented with a relatively new type of discrete choice models, the flexible mixed logit model.

The possibility to pool the data from two countries with very different cultural and historical backgrounds offered us more variation in the explanatory variables. This helped us to achieve more precise estimates of the income, age and household size effects. Since one has to normalize hedonic price indices, this approach does not help to obtain better price estimates.

The application of the mixed logit model offered quite a few surprises. Needless to say that the flexible model fits much better than the conventional logit approach. More importantly, it discovered quite systematic biases of the conventional approach. By filtering out much of the unobserved heterogeneity, it reduced income and price effects dramatically. In particular, it laid bare the lacking cross sectional variation in prices by the hedonic price construction method. Put less favorably, the MMNL makes the errors-in-variables problem much more visible than the conventional MNL model (although it is present in both specifications!).

The income effects, although much reduced, are still highly significant and of plausible magnitude, since they are fairly close to estimates from long time series: an increase in permanent income by 10% increases owner-occupancy by 2 percentage points, and the demand for large dwellings by 1.5 percentage points. These effects are remarkably similar in both countries.

The obvious extension of our work is to include a third country. Based on the nested logit model, Börsch-Supan (1985) compared housing demand in Germany and the United States. Work is under way to apply the methodology of the current paper to the triangle of Germany, Japan, and the United States.

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APPENDIX TABLE A1: Full Regression Results for Models 1 and 5

		Multinomial Logit		Basic Mixed Logit	
		Model 1	**Model 5**	**Model 1**	**Model 5**
Log Likelihood		-6208.9	-6383.0	-4369.5	-4424.7
Price_Rental		-3.039 **	-1.466 **	-0.688	-0.129 *
	× Japan	2.987 **		0.637	
Price_Owner-Occupied		-3.101 **	-2.149 **	-1.525 +	-0.972
	× Japan	2.230 **		0.653	
Age ×	Home	0.004	-0.041	0.540 **	0.000
	× Japan	-0.036		-0.572 **	
	Large	0.119 **	0.121 **	0.626 *	0.695 **
	× Japan	0.019		-0.487 *	
	Own	0.158 **	0.127 **	1.368 **	1.096
	× Japan	-0.055		-1.260 **	
Age^2 ×	Home	0.007	0.052 +	-0.423 *	0.049
	× Japan	0.042		0.472 **	
	Large	-0.083 *	-0.091 **	-0.577 *	-0.490 *
	× Japan	-0.025		0.467 *	
	Own	-0.094 *	-0.074 **	-1.087 **	-0.653
	× Japan	0.042		1.033 **	
Hh-size ×	Home	0.855 +	0.277	-0.065	0.412
	× Japan	-0.616		0.301	
	Large	1.740 **	0.505 *	2.878 +	1.077
	× Japan	-2.053 **		-3.189 +	
	Own	0.992	-0.083	0.300	0.001
	× Japan	-0.869		-0.175	
$Hh\text{-}size^2$ ×	Home	-0.085	-0.015	0.225	0.020
	× Japan	0.079		-0.229	
	Large	-0.160 **	-0.016	-0.166	0.070
	× Japan	0.230 **		0.235	
	Own	-0.179 +	0.013	-0.115	0.182
	× Japan	0.185		0.122	
Income ×	Home	0.016	-0.009 +	0.094 **	-0.024 +
	× Japan	-0.035 *		-0.112 **	
	Large	0.036 **	0.018 **	0.084 **	0.093 **
	× Japan	-0.014		-0.062 **	
	Own	0.054 **	0.047 **	0.351 **	0.216 **
	× Japan	-0.015		-0.311 **	

[continued on next page]

APPENDIX TABLE A1 (continued)

		Multinomial Logit		Basic Mixed Logit	
		Model 1	Model 5	Model 1	Model 5
Time Trend ×	Home	-0.009	-0.016	-0.156 *	-0.023
	× Japan	-0.010		0.138 +	
	Large	-0.011	-0.011	0.191 *	0.037
	× Japan	0.007		-0.195 *	
	Own	0.052 *	0.021	0.110 +	-0.098
	× Japan	-0.066		-0.124	
Parameters of mixing distribution (standard deviations of γ_n):					
Germany:	Single-Fam.			9.462 **	10.070 **
	Multi-Fam.			3.925 **	-0.184
	Large			1.390 **	5.057 **
	Small			11.288 **	8.335 **
	Own			1.490 **	-1.026
	Rent			13.725 **	9.675 **
Japan:	Single-Fam.			0.131	2.894
	Multi-Fam.			0.156	1.046 *
	Large			0.081	7.572 **
	Small			0.196	-1.405 *
	Own			0.171	9.544 *
	Rent			0.328	6.084 *

**,*,+: Statistically different from zero at the 1% ,5% ,10% significance level, respectively.

Source: Authors' calculations based on the GSOEP and JHDS working samples. Note: Regression results for the other models and a translation of the parameters into finite differences and elasticities can be found in the electronic appendix at `http://www.vwl.uni-mannheim.de/institut/e/papers.html`.