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Prevalence and substitution effects in tobacco consumption:
A discrete choice analysis of panel data

Abstract:
This paper analyzes tobacco demand within a discrete choice framework. Using binomial and multinomial logit models with random effects, and an unbalanced panel data set of Norwegian households over a twenty year period, we first consider the decisions a) whether to smoke or not, and b) given the choice is to smoke, whether to smoke hand rolled or manufactured cigarettes. Next, we consider a multinomial logit framework, in which the households choose between no tobacco, only manufactured cigarettes, only hand rolled cigarettes, and a combination of manufactured and hand rolled cigarettes. In this process, we utilize the potential offered by panel data to investigate unobserved heterogeneity, which is crucial for commodities where consumers have different tastes and where users tend to become addicted. Using Maximum Likelihood in combination with bootstrap estimation of standard errors, we find that income and prices influence the 'type of tobacco choice probabilities' at least as strongly as the 'smoking/non-smoking probabilities'. Cet.par., an increase in the price of manufactured cigarettes could lead consumers to switch to hand rolled cigarettes, rather than quit smoking. Socio-demographic variables seem to be at least as important in explaining the discrete aspects of tobacco consumption as income and prices. Finally, we find significant unobserved household specific effects in the smoking pattern.

Keywords: Tobacco. Discrete choice. Panel data. Logit analysis. Heterogeneity. Bootstrapping.

JEL classification: C33, C35, D12, I18

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1 Introduction

The increased risk of severe disease and premature death associated with tobacco smoking is well-known. As a response to this fact, but also for fiscal reasons, several countries have imposed taxes on tobacco products. The economic literature has given attention to several aspects of tobacco consumption, but relatively little attention has been given to its composition. Tobacco is far from a homogeneous commodity, but shows large variability both in price and consumer perceived quality. In addition, medical research has found a nearly doubled risk of lung cancer amongst users of hand rolled cigarettes compared with users of manufactured cigarettes, see Engeland *et al.* (1996). If one wants to evaluate the efficency of tobacco taxes as policy instruments, one needs to understand the disaggregate behaviour as correctly as possible. This knowledge would also clarify how tobacco tax rates are connected with revenue, and how they affect economic welfare in different socio-economic groups.

In this paper we focus on discrete aspects of tobacco consumption – that is, the decision whether to smoke or not and whether to smoke manufactured or hand rolled cigarettes. We find this approach appealing since households seem to leap between different choices, depending on exogenous variables, rather than adjust smoothly. We expect that a similar framework may be useful for other, non-tobacco, commodities which are closely related and for which we may observe discrete jumps when income, prices and socio-economic variables change.

Chaloupka and Warner (2000), in an overview of some important economic aspects of tobacco consumption, mention in particular (p. 1565) four articles which treat the substitution between manufactured cigarettes and other types of smoking tobacco (hand rolled cigarettes and pipe tobacco): Thompson and McLeod (1975), Leu (1984) and Pekurinen (1989, 1991). Pekurinen, using Finnish data, reports significant substitution effects, while Thompson and McLeod find a slight substitution effect in Canadian data. On the other hand, Leu finds an insignificant substitution effect in Swiss data. Considering the fact that all types of smoking tobacco contain nicotine, the vague, and somewhat ambiguous, results regarding substitution in these studies are quite surprising. However, all of them use aggregate per capita data. Since the year-to-year variation in prices usually is rather small, and the demographic structure and distribution of income are fairly stable, aggregation will conceal most of the micro behaviour. Indeed, traces of such an explanation are pointed out by Leu (1984, p. 110): "The failure of cigar and pipe tobacco prices to be significant implies that the different tobacco products are not really substitutes, probably because cigarette smokers differ in their characteristics from pipe and cigar smokers."

Unlike Leu, we interpret the impact on the tobacco consumption of changes in household characteristics as substitution. We then interpret the term 'substitution' more widely than in standard theory. According to standard theory, based on well-behaved utility functions, consumers are usually assumed to choose interior solutions – that is positive quantities of all available goods – and their substitution consists in smoothly adjusting the consumption bundle as a response to price changes. A notable exception is the case of perfect substitutes, where the theory predicts corner solutions for all but one set of relative prices. However, this theory does not explain why households with the same characteristics, facing the same set of prices and income, choose different consumption bundles. Nor does it explain how a household will respond to changes in its characteristics. For instance, this theory does not offer a way of modeling situations in which a household smoking manufactured cigarettes switches to less expensive hand rolled cigarettes as a response to reduced per capita income when receiving a new-born child.

We find that the framework offered by discrete choice models are better suited to handling this type of behaviour. We distinguish, using logit parameterizations of the choice probabilities, up to four alternative consumer choices: (i) not to use tobacco at all, (ii) to use manufactured cigarettes only, (iii) to use hand rolled cigarettes only, and (iv) to use both commodities. The variables assumed to affect the choice probabilities are first, pecuniary variables, *i.e.*, income and prices, second, household composition, third, socio-demographic characteristics of the main income earner, like age, cohort, gender, and, fourth, a set of dummy variables representing geographic location. All of these variables can be said to account for observed heterogeneity. Furthermore, we explore, by including random household specific effects in the choice probabilities, how unobserved heterogeneity affects the choice pattern.

Our data base is from the Norwegian expenditure surveys 1975–1994, and constitutes a rotating panel of more than 25 000 observations, where some households are observed twice, at a one year interval, and some are observed only once. We expect the variation in relative prices along the time dimension to be sufficient for making estimation of price effects possible.

Our results indicate that income and prices are more important factors in the decision of whether to smoke manufactured or hand rolled cigarettes than in the decision of whether to smoke or not. Another major finding is that households smoking cigarettes differ significantly in their demographic and socio-economic characteristics from households smoking hand rolled cigarettes. We also find clear evidence of unobserved household specific heterogeneity in the choice pattern.

Norwegian tobacco taxes are exceptionally high by international standards and the *per cigarette* tobacco tax on manufactured cigarettes is nearly twice the tax on hand rolled cigarettes.[1] This is most likely due to the politicians' distributional concerns with respect to economic variables rather than with respect to health variables. Due to this particular tax structure, the Norwegian tobacco tax policy can be expected to make within-tobacco substitution in the above mentioned wide sense more easily detectable than in most other countries. Thus, our data should be well suited to studying both price induced substitution, and substitution induced by variations in demographic variables.

In a related paper, Wangen and Biørn (2001), we analyze consumed quantities of both types of cigarettes in a continuous setting. In principle, an integration of the two approaches might have been more efficient. However, since a full multi-equation discrete-continuous choice model for unbalanced panel data with unobserved random heterogeneity would involve heavy computer programming and calculation, we decided to leave this integration for future research. An additional argument for treating the discrete analysis separately is measurement errors. It is well known that measurement errors in the endogenous variables of discrete or limited dependent variable models will yield inconsistent estimates, but it is easier to obtain good measurements of the qualitative status of zero or positive consumption than for the exact consumed quantity. Recently, the probability that a smoker will purchase tobacco within a one-week period, is estimated to about 98 % based on frequency of purchase in a cross section from the Spanish Expenditure Survey, see Miles (2000). This implies that only 2 % of the smokers will be erroneously labeled as non-smokers. Since our data are collected over a two-week period, the fraction of erroneously labeled households can be expected to be even lower, that is if Miles' results are applicable to Norwegian data. An inspection of the transition between different choices for households observed twice (Table 4) suggests that the share may be higher than indicated by Miles' results. We find that only 89 % of non-smoking households in the first period were non-smokers in the second period, and vice versa; only 86 % of non-smokers in the second period were non-smokers in the first period. A thorough investigation of this issue is left for future studies.

The rest of the paper is disposed as follows. The model framework, which includes several variants of the multinomial logit, the maximum likelihood (ML) estimation procedure, and computational procedures are described in Section 2. Bootstrap procedures used in simulating the distribution of the ML estimators and in calculating standard errors are in particular described. Section 3 describes the data set and data manipulations.

[1] In December 1994, the average retail prices per cigarette for manufactured and hand rolled cigarettes were 31.5 cents and 16.5 cents, respectively. Of these amounts, the tobacco tax constituted 16.9 cents and 9.1 cents per cigarette. On top, tobacco is also subject to value added tax, at a rate of 22 % in 1994.

The empirical results are discussed in Section 4. Section 5 concludes.

2 Models, estimation, and computational procedures

In this section, we describe a general multinomial logit model of discrete choice with individual specific heterogeneity, of which special cases will be considered in the empirical applications.

The classical theory of the utility maximizing consumer leads to demand functions for the commodities, including the tobacco commodities, which express the quantities demanded as continuous variables. However, for commodities like tobacco, corner solutions in practice often arise. This issue is discussed in Wangen and Biørn (2001, section 2). It may then be more convenient to apply a discrete choice framework, by for instance assuming that each tobacco alternative has its stochastic utility specified as a linear function of certain covariates. It is well known that if the respondents choose the alternative in the choice set which gives maximal utility and the stochastic disturbance components of the utility function follow a multivariate extreme value distribution, then the derived choice probabilities will have the multinomial logit form [see McFadden (1984, section 3)]. This is one way of rationalizing the approach we take in this paper. As arguments in the stochastic utility functions we select variables assumed to affect the utilities of the respective alternatives.

We model the household's smoking decisions as qualitative choices by means of a multinomial logit model with $J+1$ mutually exclusive alternatives, denoted by $j = 0, 1, \ldots, J$. In all cases but one, $j=0$ refers to the non-smoking case, $j = 1, \ldots, J$ refer to various smoking alternatives. The last case is characterized by $J = 1$, where $j = 0$ and $j = 1$ refer to two smoking alternatives. Let the households be indexed by i and the observation periods by t, N is the index set of households observed at least once, $i \in N$, and T_i is the set of periods during which household i is observed, $t \in T_i$. Let

$$(1) \quad y_{jit} = \begin{cases} 1 & \text{if household } i \text{ in year } t \text{ chooses alternative } j, \\ 0 & \text{otherwise,} \end{cases} \qquad \begin{array}{c} j = 0, 1, \ldots, J, \\ i \in N,\ t \in T_i, \end{array}$$

and

$$(2) \qquad p_{jit} = P(y_{jit} = 1), \qquad i \in N,\ t \in T_i,\ j = 0, 1, \ldots, J.$$

We specify the response probabilities, conditionally on x_{it} and α_i, as

$$p_{jit} = \frac{\exp(v_{jit})}{\sum_{k=0}^{J} \exp(v_{kit})}, \qquad v_{jit} = \begin{cases} x_{it}\beta_j + \alpha_i, & j = 1, \ldots, J, \\ 0, & j = 0, \end{cases}$$

where x_{it} is a row vector of covariates, to be specified in Section 4, β_j is the column vector of coefficients specific to alternative j, α_i is a common random household specific effect related to alternatives j ($j = 1, \dots, J$) for household i, assumed to be normally distributed with zero mean and standard deviation σ_α. By this formulation, we assume (i) that all coefficients are the same for all households in all periods, (ii) that the explanatory variables are the same for all alternatives, and (iii) that the random heterogeneity α_i is specific to household i, but independent of which of the smoking alternatives $j = 1, \dots, J$ is chosen. Equivalently, we may interpret $(-\alpha_i)$ as a random effect associated with the non-smoking alternative.

The above assumptions imply that the household's decisions with respect to the different smoking categories are non-nested and satisfy the IIA axiom [cf. McFadden (1984, section 3.5)]. This may be somewhat unrealistic, since, say, the conditional probability of non-smoking given either non-smoking or manufactured cigarette smoking, may not be invariant to whether or not hand rolled cigarette smoking or mixed smoking exist as possible choices. A way of generalizing the model by allowing the J smoking alternatives to be nested, and relaxing the IIA axiom, would be the following: Assume that the probability that household i in observation year t chooses smoking alternative j, given that it is a smoker, is

$$q_{jit} = \frac{p_{jit}}{1 - p_{0it}} = \frac{e^{v_{jit}/\theta}}{\sum_{k=1}^{J} e^{v_{kit}/\theta}}, \quad i \in N,\ t \in T_i, j = 1, \dots, J,$$

and that the probability of non-smoking is

$$p_{0it} = \frac{e^{v_{0it}}}{e^{v_{0it}} + \left(\sum_{k=1}^{J} e^{v_{kit}/\theta}\right)^{\theta}}, \quad i \in N,\ t \in T_i,$$

where θ is a positive scalar constant. This would imply

$$p_{jit} = (1 - p_{0it}) q_{jit} = \frac{\left(\sum_{k=1}^{J} e^{v_{kit}/\theta}\right)^{\theta}}{e^{v_{0it}} + \left(\sum_{k=1}^{J} e^{v_{kit}/\theta}\right)^{\theta}} \frac{e^{v_{jit}/\theta}}{\sum_{k=1}^{J} e^{v_{kit}/\theta}}, \qquad i \in N,\ t \in T_i,\ j = 1, \dots, J.$$

The case $\theta = 1$ corresponds to the multinomial logit model that we assume, whereas $\theta \in (0, 1)$ gives a *nested logit model* with alternatives $1, \dots, J$ 'related'. They are the more strongly 'related' the closer to zero θ is, 'unrelatedness' corresponding to $\theta = 1$ [cf. McFadden (1984, section 3.10) for an overview of hierarchical multinomial logit models]. We do not pursue the estimation of this extension of our model here, but consider the case where θ is a free parameter, to be estimated jointly with $\beta_1, \dots, \beta_J$ and σ_α, as a topic for further research.

Let $g(\alpha_i;\sigma_\alpha)$ be the density function of α_i and let $\mu_i = \alpha_i/\sigma_\alpha$. We then have

$$g(\alpha_i;\sigma_\alpha) = \phi\left(\frac{\alpha_i}{\sigma_\alpha}\right)\frac{1}{\sigma_\alpha} = \phi(\mu_i)\frac{1}{\sigma_\alpha}, \qquad d\alpha_i = \sigma_\alpha d\mu_i,$$

where $\phi(\cdot)$ is the density function of the standardized normal distribution. Assuming that all observations are independent, conditionally on the v_{jit}'s, across households and time periods, the joint likelihood function of the y_{jit}'s, conditionally on the v_{jit}'s, can be written as

$$\prod_{i\in N}\prod_{t\in T_i}\prod_{j=0}^{J} p_{jit}^{y_{jit}},$$

where

$$p_{jit} = \frac{\exp(v_{jit})}{\sum_{k=0}^{J}\exp(v_{kit})}, \qquad v_{jit} = \begin{cases} x_{it}\beta_j + \mu_i\sigma_\alpha, & j = 1,\dots,J, \\ 0, & j = 0. \end{cases} \tag{3}$$

The likelihood function of the y_{jit}'s conditional of the x_{it}'s, but marginal with respect to the μ_i's, then becomes

$$\mathcal{L} = \prod_{i\in N}\int_{-\infty}^{\infty} g(\alpha_i;\sigma_\alpha)\prod_{t\in T_i}\prod_{j=0}^{J} p_{jit}^{y_{jit}}\,d\alpha_i = \prod_{i\in N}\int_{-\infty}^{\infty}\phi(\mu_i)\prod_{t\in T_i}\prod_{j=0}^{J} p_{jit}^{y_{jit}}\,d\mu_i. \tag{4}$$

The ML estimation of $\beta_1,\dots,\beta_J,\sigma_\alpha$, *i.e.*, the maximization of $\mathcal{L}$ with respect to these parameters, is discussed in the Appendix, in which we derive the first and second order derivatives of $\mathcal{L}$ with respect to the parameters. In order to solve this problem numerically, we approximate the integral in (4) by a simple step function [see Nielsen and Rosholm (1997, p. 10)]. Let M be a set of points symmetric around zero, with equal distance, *e.g.*,

$$M = \{-1.5, -0.9, -0.3, 0.3, 0.9, 1.5\},$$

and define a set of discreticized probabilities $f(m)$ by

$$f(m) = \frac{\phi(m)}{\sum_{m\in M}\phi(m)}, \qquad m \in M.$$

Using (3), the approximate log of the maximand then becomes

$$\begin{aligned} \ln(\mathcal{L}) &= \sum_{i\in N}\ln\sum_{m\in M} f(m)\prod_{t\in T_i}\prod_{j=0}^{J} p_{jit}^{y_{jit}} \\ &= \sum_{i\in N}\ln\sum_{m\in M} f(m)\prod_{t\in T_i}\prod_{j=0}^{J}\frac{\exp(v_{jit}y_{jit})}{\sum_{k=0}^{J}\exp(v_{kit})} \\ &= \sum_{i\in N}\ln\sum_{m\in M} f(m)\prod_{t\in T_i}\prod_{j=1}^{J}\frac{\exp[(x_{it}\beta_j + m\sigma_\alpha)y_{jit}]}{1+\sum_{k=1}^{J}\exp(x_{it}\beta_k + m\sigma_\alpha)}, \end{aligned} \tag{5}$$

since $\sum_{j=0}^{J} y_{jit} = 1, \; \forall \, i, t$.

Most of the numerical calculations are performed by means of a program utilizing the E04UCF procedure in NAG's library of Fortran77 routines (Mark 16). In the ML estimation, we used $\sigma_\alpha = 1$ and $\beta_j = 0$ as starting values. Other starting values did not result in solutions with higher likelihood. The parameter estimates reported in Tables 5 – 7 and 9–11 are ML estimates, while the standard errors are obtained from bootstrapping; see Efron and Tibshirani (1993). For each model, 1000 bootstrap samples were drawn randomly, with replacement, from the original data set, and ML was performed on each sample, using the original ML estimates as starting values. The reported standard errors are the empirical standard deviation of the resulting distribution of the parameter estimates, which we use, *inter alia*, in judging the significance of the point estimates. Note that the estimators of the β vector and their standard deviations are not 'asymptotically pivotal statistics', *i.e.*, not asymptotically independent of unknown population parameters. Hence, their bootstrap distributions have the same accuracy as first-order asymptotic approximations, but do not provide higher-order approximations; see Horowitz (1997, sections 1 and 2.2).

The method of approximating the likelihood function is simple, but results from a few Monte Carlo simulations showed that it performed quite well. More accurate methods for numerical integration are available, see for instance Crouch and Spiegelman (1990) who compare Gaussian quadrature and trapezoidal-rule-like integration techniques in a logistic-normal application. However, these methods are computationally more costly as the likelihood function must be evaluated in more than our six points (usually twenty or more), and the bootstrap procedure already strained the available computer resources. Moreover, the assumption of normally distributed random effects is chosen for convenience in the first place. Our approximation can be interpreted as if the random effects were generated by a discrete distribution, and it is not obvious that this is a less adequate assumption than normality.

3 Data

The data set is taken from the Norwegian Surveys of Consumer Expenditures, collected by Statistics Norway, for the years 1975 – 1994 and detailed official Consumer Price Indexes for the same period.

The consumer survey data consist of a rotating panel in which roughly 30 % of the households participate in two subsequent years and the rest is observed once. The expenditure data are collected almost evenly throughout the year. Roughly 1/26 of the households participate between the 1st and the 14th of January, roughly 1/26 participate between the 15th and the 28th of January, and so on. Most of the expenditure data are reported in two-week accounting periods, and yearly expenditure is estimated simply by multiplying the two-week amount by 26. Expenditure on goods with a low purchase frequency (*e.g.*, certain durables), are reported in annual interviews.

Tables 1 – 4 contain summary information on the data set. Table 1 gives an overview of definitions, abbreviations, and some descriptive statistics for the variables.[2] Table 2 contains the user frequencies for the two tobacco commodities. Table 3 reports the number of households observed once and twice in the data set, classified by year. Hence, it describes the rotating character of the data set, formally combining 19 balanced two-wave panels with 20 year specific cross-sections. In the different years, on average about 900 households are observed once and about 200 households are observed twice, giving a total average of about 1300 reports from about 1100 households for each year in the 20 year data period.

We use total consumption expenditure excluding durables as our *income measure*. The exclusion of durables is mainly done in order to reduce the number of extreme observations, since in the official definition of total consumption expenditure, purchases of durables are treated as any other commodity, and symmetrically, revenues from selling such commodities are counted as a negative expenditure. This, in fact, causes the total consumption expenditure including transactions in durables to be negative for several households which have sold durables and to be extremely high for several households which have had large expenditures on such commodities during the observation period. In any case, our exclusion of durables should give a better proxy as an income measure. The total Consumer Price Index (CPI) is used as deflator of the total consumption expenditure excluding durables.

The *price indexes* are from the monthly official CPI and subindexes. Following a simple set of rules, the monthly price indexes are converted to fit into the two-week periodization in the consumer survey.[3] The CPI and its subindexes are reported only for the whole country, implying that all households are assumed to face the same set of prices. However, this assumption may not be as strong as it seems; due to a recommended price policy there was very little, if any, inter-monthly dispersion of tobacco prices until

[2] Total consumption expenditure, age, and cohort have been rescaled to get a mean value of an order of magnitude equal to unity, in order to reduce round off errors in the calculations. Confer the explanations to Table 1.

[3] For two-week periods which belong entirely to one calendar month, the respective months' indexes are applied directly. For periods overlapping two months the indexes are calculated as weighted arithmetic means of the two months' indexes, using the relative number of days in each month as weights.

early 1991. Probably, most of the variation after 1991 is caused by differences in vendors' mark-up. As far as we know, there is very little difference in prices between brands (within each group of the two tobacco goods) and no particular geographical variation. The neglect of inter-monthly variation in prices is appropriate for the period until 1991, but probably less accurate thereafter.[4]

The *household size* is represented by the number of household members in four age intervals, $0-15$ years, $16-30$ years, $31-60$ years, and $61-99$ years. Four *characteristics of the head of household* are included. Age is measured in the observation year, cohort is (rescaled) year of birth, gender is one for females and zero otherwise, and activity is one if the head of household is economically inactive and zero otherwise. Finally, two sets of *geographical dummies* are included. The first set (west, mid, north, east) indicates the trade region in which the household is located, and the second set (rural, densely (except Oslo, Trondheim or Bergen), city (Oslo, Trondheim or Bergen)) indicates the population density in the residence municipality.[5]

Estimation results from logit models, like discrete models in general, are sensitive to mis-specification. Clearly, the linear structure imposed on the exponents in the logit probabilities will be better approximations if the range of variation of the exogenous variables is limited. Also, even if the approximation is good, extreme observations on the exogenous variables may have a disproportionate influence on the estimation. For this reason, we have excluded observations with outlying values of the exogenous variables. Table 1 indicates, in italics, some of the truncation points. For instance, the minimum value of the Age variable indicates that households with values below 2.0 (which is 20 years) are excluded. In addition, we deleted households with 9 or more members and panel households whose number of members in any age group, or the total number of persons, changed by more than one person. Finally, to ensure that households have the same head in both periods, households with changes in Cohort or Gender are also deleted.

4 Empirical results

Overview

We divide the explanatory variables, contained in the vector x_{it}, into four categories: (i) total expenditure and prices, (ii) household size variables, (iii) characteristics of the head of household (main income earner), and (iv) geographic dummy variables (see Ta-

[4]Since brand differences in quality are not reflected in prices, these two groups are quite homogeneous along the price dimension at each moment of time, and homogenous in quality over the entire period.

[5]In order to avoid the dummy trap, one category of each set is excluded ('east' and 'city' – which means Oslo).

ble 1). The specification chosen as the basic model, is a model in which all variables under (i) – (iv) are included and are untransformed. We label this specification Model LLLL, where the four characters refer to the groups of variables (i) – (iv), L symbolizing that the variable group enters linearly in the logit probabilities; cf. (3). Omission of a variable group is symbolized by O, so that, for instance, Model LLLO excludes all geographic dummies from an otherwise linear specification.

Three models within the general logit model class described in Section 2 are considered, all assuming that the households' choices are determined by the covariate vector x_{it} and most of them also by a random household specific effect α_i. The interpretation of the latter effect differs across models. The models are:

Model A: Binomial model of smoking prevalence. This model focuses on the smoking/non-smoking decision, but pays no regard to the kind of tobacco used. It is characterized by $J = 1$ and σ_α free, where $j = 0$ represents non-smoking and $j = 1$ represents smoking. The parameter σ_α measures the dispersion in the individual, latent attraction towards tobacco in general. Results for this model are given in Tables 5 and 9.

Model B: Binomial model of smoking composition. This model confines attention solely to the manufactured/hand rolled cigarette decision, *conditional on using one of the commodities only in the cross section part of the sample and conditional on using one of the commodities only in both periods in the panel part of the sample.* It is characterized by $J = 1$ and σ_α free, where $j = 0$ represents manufactured cigarettes and $j = 1$ represents hand rolled cigarettes. The parameter σ_α for this model measures the dispersion in the individual, latent attraction towards hand rolled cigarettes as opposed to manufactured cigarettes. Results for this model are given in Tables 6 and 10.

Model C: Multinomial logit model of combined smoking prevalence and composition. This model puts in a sense the pieces in Models A and B together, although Model B is estimated from a substantially smaller sample than Models A and C. We specify four alternative choices, $J = 3$, where $j = 0$ represents non-smoking and $j = 1$, $j = 2$, and $j = 3$ represent, respectively, smoking of manufactured cigarettes, of hand rolled cigarettes, and of both kinds of cigarettes. Results for this model are given in Tables 7, 8, 11, 12, and 13. The parameter σ_α for this model measures the dispersion in the household specific, latent attraction towards tobacco in general. Some versions of this model are estimated with $\sigma_\alpha = 0$ or with the panel property of the data set neglected.

Models A, B, and the versions of Model C with σ_α free are estimated by ML, see Section 2 for details. The versions of Model C with σ_α set to zero are estimated by means of the Limdep 7 software [see Greene (1998)]. One of these versions is also estimated separately for each vintage of data, disregarding its panel property, in order to detect possible trends or cyclical patterns in the coefficients over the twenty year data period, during which substantial changes can be assumed to have taken place in the smoking habits in Norway.[6]

When comparing the different models, we focus on the partial derivatives of the probabilities with respect to the covariates, denoted as the *PD of probability*, for short, evaluated at the sample means and $\alpha_i = 0$. Parameter estimates are not so easily comparable. The main attention is given to the LLLL versions of Models A, B, and C, and typically we will first comment on the two former before comparing them with the latter. The results for the binomial model of composition, Model B, are less reliable than the other two, owing to the quite rigid restriction imposed when selecting the sample of one-commodity users – especially for households observed twice. For instance, users of manufactured cigarettes in the first period who stop smoking (as a response to price increases) are excluded. Clearly then, this sample is non-randomly selected, as this selection procedure favours panel households with strong persistence in consumption. Thus, the panel households will tend to have small within variation, possibly giving the between variation too high influence. Table 4 gives the frequencies of the endogenous variables for the households observed twice. Of the 867 panel housholds in the subsample of one-commodity smokers, only 29 change their category from the first period to the second (16 go from manufactured to hand rolled, while 13 go from hand rolled to manufactured).

Income effects

According to the binomial model of prevalence, total expenditure has a positive and significant effect on the probability of being a smoking household (Table 9), and in the binomial model of composition, total expenditure has a significantly[7] positive effect on the probability of smoking manufactured cigarettes (Table 10). Thus, the binomial models suggest that high income households, *cet.par.*, tend to smoke more often than low income households, and when they smoke they tend to prefer manufactured cigarettes to hand rolled ones. These results are in accordance with those from the multinomial model (Table 11). All four PDs are significant; increased total expenditure reduces the probability of non-smoking and of smoking hand rolled cigarettes and increases the probability of smoking manufactured cigarettes and choosing mixed consumption. The

[6] In the latter estimations, no constant term was included since the sum of age and cohort is constant in a cross section.

[7] A 5 % significance level based on the standard errors calculated from the bootstrap ML estimates, or from the Limdep 7 output (for Model C), is assumed throughout.

evidence is thus that increased income (total expenditure) makes the households shift towards the more 'exclusive' tobacco category, or to a mix of the two.

Tables 5 and 6, which report parameter estimates for the binomial models with different sets of covariates, enables us to examine how the estimated income coefficients depend on omission or inclusion of other variables. For both models, all four versions give the same sign of the income coefficient. The PD of the probabilities for the multinomial models reported in Tables 11 and 12 give the same sign conclusions, but the size of the estimates differs. The largest difference shows the PD of the probability of non-smoking, which is -13.3 percentage points in the version using panel information, but only -1.1 percentage point in the version neglecting the panel aspect (Table 12).

Price effects

The two binomial models and the multinomial model have different price variables. In the model of prevalence, only their aggregated price is included, in the model of composition, the relative price of the two commodities is the appropriate price variable. In the multinomial model, both real prices are included.

According to the three models, all but two PDs of probabilities are insignificant. In Model C, the price of manufactured cigarettes has a positive effect and the price of hand rolled cigarettes has a negative effect on the probability of smoking hand rolled cigarettes (Table 11). In this model, the two prices have opposite effect on all probabilities: An increased price on manufactured cigarettes reduces the probability of smoking manufactured cigarettes, increases the probability of hand rolled cigarettes and reduces the probability of mixed consumption and the probability of being non-smokers, while the signs are reversed for the price on hand rolled cigarettes. Strictly interpreted, this implies that some households will respond to a price increase on manufactured cigarettes by substituting towards handrolling tobacco, but also that some will start smoking. The latter result seems unlikely, and may indicate that the estimated price effects should be interpreted with care. In the binomial model of composition, the relative price has a negative effect on the probability of smoking manufactured cigarettes (Table 10), indicating that an increased price on manufactured cigarettes would induce smoking households to switch to hand rolled cigarettes. Although the latter sign is reasonable, this effect is barely statistically significant (t-statistic=1.75).

From Tables 5 and 6, we find that the sign of the price coefficients are not sensitive to which background variables are included. The results for the multinomial model (Tables 11 and 12) give mainly the same qualitative conclusions. The only exception is the PD of the probability of mixed consumption with respect to the price of hand rolled cigarettes, which is negative in the panel version (-0.8 percentage points) but positive in the version neglecting the panel aspect (6.9 percentage points), neither of these PDs are significant, however.

Effect of household size

All four household size variables are statistically significant in the binomial model of prevalence. If the number of children is increased by one, the probability of being a non-smoking household increases by roughly 11 percentage points at the sample mean (Table 9). This effect may be due to a higher awareness of health risk on the part of the child, but it probably also represents a kind of 'per capita income effect'. The latter interpretation applies to all of the household size variables, as the household becomes relativly 'poorer' when the household size increases (*cet.par.*). In addition, a newcoming adult smoker may change a household's smoking status from non-smoking to smoking, or a non-smoking newcomer may persuade the smoking household members to quit. The total of these effects is estimated to having a positive effect on the smoking probability, varying between 24 and 35 percentage points for the different age groups. All household size variables have a negative effect on the probability of smoking manufactured cigarettes, and only the number of persons in the oldest age group is not statistically significant. The magnitude of the effects are modest, but reasonable, varying between 1.1 and 3.7 percentage points (Table 10).

In the multinomial model, all sixteen PDs of probabilities are significant (Table 11). Increasing the family by one child will increase the non-smoking probability by 10 percentage points, reducing the probabilities of all three smoking alternatives with 3-4 percentage points. If the household gets an adult newcomer, the probability of non-smoking is reduced by between 24 and 37 percentage points, depending on the newcomer's age group. The corresponding increase in the probability for the three smoking alternatives is largest for hand rolled cigarettes, followed by mixed consumption and manufactured cigarettes. The latter is rather low compared with the effect on the non-smoking alternative, between 3.2 and 4.8 percentage points, depending on the age group. These results are consistent with a 'reduced per capita income' interpretation. *A priori*, it is an open question whether or not the effect of increasing the number of potential smokers is stronger than the effect of reduced *per capita* income. Our results indicate that the former dominates.

The sign of the coeffcent estimates for Model B are not sensitive to which background variables are included (Table 6). For Model A, versions LLLL and LLLO give very similar estimates for the household size variables, but the LLOO version gives opposite signs for children and the oldest age group. Comparing the multinomial model versions in Table 11 and 12, we find that the signs of the PDs are mainly the same.

Effect of characteristics of the head of household

It is not straightforward to interpret the impact of characteristics of a particular household member on the smoking probability of the whole household – unless it is a one-person household. Economic inactivity of the head of household (main income earner) surely has a strong influence on the household income; the effects of gender, age, and cohort are less predictable. To some extent age is also related to economic inactivity. The inactivity dummy has a statistically significant effect in both binomial models, Models A and B. Switching from activity to non-activity increases the smoking probability (+21.4 percentage points), and given smoking, increases the probability of smoking hand rolled cigarettes (+3.0 percentage points). This pattern is also found in the multinomial model, Model C (Table 11); inactivity reduces the non-smoking probability and increases the probability of all smoking alternatives. The qualitative pattern is consistent across the three models, but the size differs substantially. Briefly, households with inactive heads have a higher propensity to consume tobacco, and given that they smoke, they tend to choose the cheaper alternative.

Regarding the gender dummy, there is a correspondence in the qualitative conclusions of the three models. In the multinomial model, households with female heads have a lower propensity to consume tobacco than other households (PD of probability equals -21.3 percentage points) (Table 11). They are less likely to smoke hand rolled cigarettes or to have a mixed consumption, but have almost the same propensity for smoking manufactured cigarettes. In the binomial model of composition, the gender dummy have a positive significant PD of manufactured cigarettes. Briefly, households with female heads have a lower propensity to consume tobacco, and given that they smoke, they tend to use manufactured cigarettes.

Age and cohort are interesting variables in explaining the smoking probabilities, as tobacco consumption may vary over the life-cycle and individuals born in the same year share a common history (including the impact of anti-smoking campaigns etc.). Their estimated effects in the binomial model of prevalence, which are significant, indicate that both increasing age, conditional on cohort, and increasing cohort, conditional on age, affect the smoking probability negatively (Table 9). Conditional on being a one commodity smoker, both increasing age and cohort affect the probability of smoking manufactured cigarettes positively and hand rolled cigarettes negatively (Table 10), although the age effect is barely insignificant (t-statistic=1.74). Hence, households headed by older persons have, *cet. par.*, a lower smoking probability than younger ones, and given that they smoke, they tend to use manufactured rather than hand rolled cigarettes. Likewise, households with heads belonging to later cohorts have, *cet. par.*, a lower smoking probability than those with heads born earlier, and given that they smoke, they tend to use manufactured rather than hand rolled cigarettes.

The ML estimation of the multinomial logit model, Model C, in Table 12 has been rerun separately for all the twenty years in the sample period, proceeding as if each vintage of data is a cross section. The PD of the probability of age, cohort, the gender dummy, and the inactivity dummy are reported in Tables 13A – D, respectively. Not unexpectedly, several estimates are insigificant, due to the smaller number of observations underlying each set. The age variable have a positive effect on non-smoke in all years, and mainly negative effect on the three smoking alternatives. For all four probabilities, the cohort variable have varying signs over the years. The effect of the gender dummy on the probability of non-smoking is positive (and often significant) in the first sixteen years of the sample period and negative (although insignificant) in the last four years. Maybe this indicates a change in women's attitude towards tobacco smoking in Norway during the last part of our sample period (1991 – 1994). It is also worth noting that the gender dummy affects the smoking probability of hand rolled cigarettes negatively in all years except the last, the probability of smoking manufactured cigarettes positively in seventeen of the twenty years. Inactivity affects the non-smoking probability negatively in all years except one and affects the probability of smoking hand rolled cigarettes positively in all years except two. For manufactured cigarettes the effect is negative in ten of the twenty years.

Effect of geographic region

The estimated effects of all geographical dummies on the probability of smoking manufactured cigarettes are significantly negative in the binomial model of composition (Table 10), clearly indicating that the smoking of hand rolled cigarettes relative to manufactured ones is more common outside the largest cities. In the model of prevalence, the estimates indicate that the highest prevalence occurs in the northern region (Table 9). All these results agree with those based on the multinomial model (Table 11).

The inclusion of geographical dummies hardly affects the coefficients of the other covariates in the model of prevalence (compare versions LLLL and LLLO in Table 5). In the model of composition, on the other hand, the inclusion of geographical dummies affects all coefficient estimates, but to a varying degree (Table 6). The coefficients of cohort, gender, and inactivity are the least sensitive. The version of the multinomial model neglecting the panel aspect (Table 12) give mostly identical signs as the panel model (Table 11).

Unobserved heterogeneity

Estimates of the variance of the latent household effect α in Model A (prevalence model), Model B (composition model) and Model C (multinomial model) are given in the first rows of Tables 5, 6, and 7, respectively. The former and the latter represents, *inter alia*, the dispersion in the household 'attraction' towards tobacco in general unexplained by the specified covariates. For Model B, σ_α^2 measures the latent household 'attraction' towards either of the smoking alternatives given that one of them has been chosen. In all the models versions considered, both variance estimates are significantly positive according to the standard errors in the bootstrap distribution of the ML estimates of σ_α^2, except for version LOOO of Model B. The standard error in the bootstrap distribution is substantially smaller in Model A than in Model B, reflecting, *inter alia*, that the former estimation is based on a considerably larger data set.

The standard errors of the latent household specific effects, *i.e.*, the square root of the σ_α^2 estimates, are substantial when compared with the product of the average size of the dummy variables and their coefficients (compare Table 1 with Tables 5 and 6). This gives evidence of non-negligible latent heterogeneity in the households' preferences for tobacco and its composition – indicating addiction – which supports the findings in Wangen and Biørn (2001, pp. 18 – 19). The σ_α^2 estimates in Models A and C are fairly insensitive to the selection of covariates (Table 5). For Model B (Table 6), however, the estimate of this parameter tends to increase when the demographic and geographic covariates are successively excluded. Some of the systematic heterogeneity is then 'transmitted' to the σ_α^2 estimates.

5 Concluding remarks

The focus of this paper has been on households' discrete choice behaviour with respect to tobacco commodities. Binomial logit models with random effects, and an unbalanced panel data set of Norwegian households for a twenty year period have been used, in which we have distinguished up to four alternative choices: (i) not to use tobacco at all, (ii) to use manufactured cigarettes only, (iii) to use hand rolled cigarettes only, and (iv) to use both commodities. Exploiting the panel property of the data, we have also made attempts to explore how unobserved heterogeneity affects the choice pattern.

We have found that characteristics related to the welfare of households, such as household size and economical inactivity, have significant effects both on the decision of whether to smoke or not, and on the decision of which type of cigarettes to smoke. The two-commodity approach has improved our understanding of the effects of economic variables. The results for these two specific tobacco commodities might also carry over to other close substitutes, for instance cigarettes and smokeless tobacco; cf. Chaloupka and Warner (2000, p. 1565) and maybe to closely related non-tobacco commodities as well.

The estimated price effects indicate that prices are more important when choosing between alternatives of smoking, than when choosing whether to smoke or not. This may explain some of the patterns which can be found in the aggregate consumption. In Norway, hand rolled cigarettes have a share of total tobacco consumption which is higher than any other country, cf. WHO (1997, p. 20), but the smoking prevalence and the per capita tobacco consumption are 'normal' by international standards. The high levels of taxation, mentioned in the introduction, may have motivated smokers to substitute towards hand rolled cigarettes rather than quit smoking.

The estimated price response is not so clear-cut and significant as might be expected. This may be due to at least two circumstances: The first is closely related to the dangers of extrapolation, since the price level of the two commodities may exhibit too little variation across the observation period to reveal the price induced substitution. This is perhaps best illustrated by a hypothetical policy experiment: Suppose the tobacco taxes were changed so that the *per cigarette* price of handrolled cigarettes was roughly twice the price of manufactured ones, rather than the opposite. In such a situation we find it likely that the share of households smoking hand rolled cigarettes (and also the share of hand rolled cigarettes of total cigarette consumption) would be low, perhaps close to zero. At this hypothetical price level, it is also likely that only a few households would respond to small changes in relative prices. Yet, somewhere between the observed price levels and the hypothetical ones, large scale substitution must have taken place. It is possible that much of the substitution would take place close to the point where the price levels are equal. Second, if the price effects differ across households types, our models, which disregard interaction beween prices and demographic variables, suffer from specification errors, and we cannot disregard the possibility that the demographic variables 'steal' explanatory power from the price effects.

Socio-demographic variables appear to be at least as important explanatory variables for the discrete aspects of tobacco consumption as income and prices. We find clear evidence that an increase in the number of children reduces the smoking probability, while an increase in the number of adults increases it. Given that a household contains smokers, an increase in the number of persons, regardless of age, tends to reduce the probability of smoking manufactured cigarettes and to increase the probability of smoking hand rolled cigarettes. Households with inactive heads are more likely to consume tobacco than active ones, and given that they smoke, they tend to choose the cheaper alternative, hand rolled cigarettes. Households with female heads have a lower propensity to consume tobacco, and given that they smoke, they tend to use manufactured cigarettes. Lastly, we find clear indications that the highest prevalence of tobacco smoking occurs in the northern region of Norway and that smoking of hand rolled cigarettes relative to manufactured ones is more common outside the largest cities.

Table 1: Descriptive statistics				
	Mean	**Std**	**Min**	**Max**
Texp	0.67	0.41	***0.01***	***2.69***
P_man	1.21	0.18	0.88	1.65
P_hand	1.23	0.21	0.88	1.90
P_tob	1.22	0.19	0.88	1.77
P_rel	0.98	0.03	0.87	1.07
Dem1	0.73	1.01	0	***5***
Dem2	0.66	0.83	0	***4***
Dem3	1.07	0.88	0	***3***
Dem4	0.42	0.71	0	***3***
Age	4.86	1.62	***2.0***	***8.5***
Coho	5.61	1.76	***1.6***	***9.1***
Gend	0.22	0.42	0	1
Inac	0.27	0.44	0	1
West	0.24	0.43	0	1
Cent	0.14	0.35	0	1
Nor	0.08	0.27	0	1
East	0.54	0.50	0	1
Rur	0.24	0.43	0	1
Dens	0.56	0.50	0	1
City	0.20	0.40	0	1

Numbers given in italics in the columns for minimum and maximum are effective truncation points. Other truncation rules are explained in Section 3.

Explanation of exogenous variables

Group 1

Texp = 0.001*((total expend.)-(expend. on durables))/(Total CPI[a])
P_man = CPI for manufactured cigarettes/Total CPI
P_hand = CPI for hand rolled cigarettes/Total CPI
P_tob = CPI for manufactured and hand rolled cigarettes combined/Total CPI
P_rel = CPI for manufactured cigarettes/CPI for hand rolled cigarettes

Group 2

Dem1 = Number of persons in age group [0,16)
Dem2 = Number of persons in age group [16,31)
Dem3 = Number of persons in age group [31,61)
Dem4 = Number of persons in age group [61,99)

Group 3

Age = 0.1*(age of head of household)
Coho = 0.1*((year of birth, head of household)-1880)
Gend = 1 if head is female, 0 otherwise
Inac = 1 if head is economically inactive, 0 otherwise

Group 4

West = 1 if residence is in the western trade region, 0 otherwise
Cent = 1 if residence is in the central trade region, 0 otherwise
Nor = 1 if residence is in the northern trade region, 0 otherwise
East = 1 if residence is in the eastern trade region, 0 otherwise
Rur = 1 if residental municipality is rural (with less than 50% of residents in densely populated area), 0 otherwise
Dens = 1 if residental municipality is densely populated (with 50% or more of residents in densely populated area (except Oslo, Bergen and Trondheim)), 0 otherwise
City = 1 if resident in a city (Oslo, Bergen or Trondheim), 0 otherwise

[a] All CPI equals 100 in July 1979.

Table 2: User status by year. Relative frequency, per cent				
Year	**None**	**Hand roll only**	**Man. Cig. only**	**Both**
1975	43.7	30.8	7.4	18.1
1976	42.5	29.5	7.6	20.4
1977	47.8	22.8	8.6	20.7
1978	51.4	20.9	8.3	19.4
1979	49.5	24.3	7.8	18.3
1980	51.0	23.3	8.3	17.3
1981	50.9	24.6	7.1	17.4
1982	51.4	26.2	7.8	14.6
1983	49.9	27.0	7.6	15.5
1984	51.0	24.8	7.8	16.4
1985	50.0	23.3	10.3	16.3
1986	49.9	20.8	12.5	16.8
1987	51.1	19.3	12.3	17.3
1988	52.6	19.0	11.9	16.5
1989	51.2	17.8	13.8	17.2
1990	53.0	18.0	12.0	17.0
1991	54.1	16.4	14.1	15.4
1992	52.4	15.8	13.7	18.1
1993	49.9	18.4	13.7	17.9
1994	56.0	15.5	14.1	14.4

Table 3: Number of observations in different cross-sections and panels			
Cross sections		**Two-year panels**	
Year	**obs.**	**Panel**	**obs.**
1975	889	-	-
1976	700	**1975-1976**	374
1977	533	**1976-1977**	426
1978	531	**1977-1978**	390
1979	1026	**1978-1979**	394
1980	720	**1979-1980**	390
1981	1113	**1980-1981**	374
1982	1002	**1981-1982**	404
1983	1019	**1982-1983**	460
1984	1079	**1983-1984**	378
1985	1110	**1984-1985**	404
1986	1094	**1985-1986**	376
1987	891	**1986-1987**	288
1988	1058	**1987-1988**	296
1989	794	**1988-1989**	322
1990	811	**1989-1990**	356
1991	860	**1990-1991**	330
1992	938	**1991-1992**	382
1993	881	**1992-1993**	354
1994	1117	**1993-1994**	316
Sum	18166	**Sum**	7014
Total	25180		

Table 4: Transition between different choices, households observed twice						
Freq Pct of total Pct of row sum Pct of col. sum		**Second period**				
		Non-smoke	**Manuf. cigarette**	**Hand rolled**	**Both**	**Total**
First period	**Non-smoke**	1595 45.48 89.41 86.83	78 2.22 4.37 21.91	84 2.4 4.71 9.98	27 0.77 1.51 5.72	1784 50.87 100.00 ..
	Manuf. cigarette	86 2.45 23.89 4.68	211 6.02 58.61 59.27	16 0.46 4.44 1.9	47 1.34 13.06 9.96	360 10.27 100.00 ..
	Hand rolled	123 3.51 13.99 6.7	13 0.37 1.48 3.65	627 17.88 71.33 74.47	116 3.31 13.2 24.58	879 25.06 100.00 ..
	Both	33 0.94 6.82 1.8	54 1.54 11.16 15.17	115 3.28 23.76 13.66	282 8.04 58.26 59.75	484 13.8 100.00 ..
	Total	1837 52.38 .. 100.00	356 10.15 .. 100.00	842 24.01 .. 100.00	472 13.46 .. 100.00	3507 100 .. ..

Table 5: Model A. Binomial Logit models of prevalence. ML coefficient estimates and standard errors obtained from bootstrap distribution. Y=1 for smokers. No. of obs. = 25,180								
	LLLL		LLLO		LLOO		LOOO	
	Param	St.err.	Param	St.err.	Param	St.err.	Param	St.err.
σ_α^2	6.2249	0.2956	6.2170	0.2872	6.1665	0.2775	5.8821	0.2087
Const	11.9134	1.7549	11.6088	1.6740	0.5710	0.3593	1.2030	0.3312
Texp	0.6827	0.1427	0.7548	0.1420	0.9466	0.1429	2.4114	0.1504
P_tob	-0.3933	0.6230	-0.4298	0.6022	-2.2866	0.2858	-2.3978	0.2707
Dem1	-0.4312	0.0661	-0.4513	0.0614	0.0813	0.0619		
Dem2	0.9452	0.0862	0.9190	0.0882	1.2248	0.0966		
Dem3	1.4163	0.1149	1.4048	0.1107	0.7999	0.0877		
Dem4	1.0471	0.1624	1.0344	0.1615	-0.5241	0.1026		
Age	-1.9545	0.2432	-1.9454	0.2298				
Cohort	-0.8283	0.2239	-0.8029	0.2151				
Gend	-0.8032	0.1418	-0.7474	0.1384				
Inac	0.8585	0.1453	0.8787	0.1486				
West	-0.5985	0.1418						
Cent	0.2758	0.1478						
Nor	0.5388	0.1781						
Rur	-0.4674	0.1714						
Dens	0.0225	0.1440						

Table 6: Model B. Binomial Logit models of composition. ML coefficient estimates and standard errors obtained from bootstrap distribution. Y=1 for manufactured cigarettes. No. of obs. = 8,136								
	LLLL		LLLO		LLOO		LOOO	
	Param	St.err.	Param	St.err.	Param	St.err.	Param	St.err.
σ_α^2	7.9639	1.1519	8.3354	0.9533	8.4655	0.9784	9.3522	11.8603
Const	1.0035	11.8776	-0.7763	9.5801	32.2481	5.6390	42.0675	9.1752
Texp	5.9759	0.9147	7.5256	0.8769	7.9230	0.9037	5.6255	0.6304
P_rel	-14.4019	8.4988	-12.8212	6.3711	-34.8124	5.8563	-51.0166	10.7287
Dem1	-0.5940	0.1713	-1.2601	0.2077	-1.1830	0.2024		
Dem2	-0.7329	0.2664	-1.5027	0.2719	-1.6905	0.2837		
Dem3	-1.7970	0.3955	-2.4738	0.3804	-3.4716	0.4243		
Dem4	-0.5488	0.4669	-1.2155	0.4761	-3.5438	0.5505		
Age	0.9595	0.4811	0.5131	0.4194				
Cohort	1.4981	0.4425	1.2130	0.3998				
Gend	2.9361	0.5945	3.0989	0.4620				
Inac	-1.4540	0.4062	-1.3141	0.3797				
West	-2.8561	0.4536						
Cent	-2.8709	0.5012						
Nor	-4.9320	0.8369						
Rur	-5.3037	0.7233						
Dens	-3.6545	0.5664						

Table 7: Model C. Multinomial Logit. ML coefficient estimates and standard errors obtained from bootstrap distribution. Non-smoke is basis alternative						
	Manuf. cig.		**Hand roll cig.**		**Both types**	
	Param.	**St.err.**	**Param.**	**St.err.**	**Param.**	**St.err.**
σ_α^2	6.4261	0.3011	6.4261	0.3011	6.4261	0.3011
Const	6.7070	1.8177	11.2345	1.7662	11.8235	1.7866
Texp	1.4559	0.1532	-0.1669	0.1512	1.1257	0.1511
P_man	0.2883	2.0752	3.1237	2.0122	0.6094	2.0822
P_hand	-0.8292	1.7478	-3.0427	1.6859	-0.9447	1.7616
Dem1	-0.5245	0.0689	-0.3405	0.0658	-0.5059	0.0673
Dem2	0.7718	0.0910	0.9636	0.0868	1.1339	0.0878
Dem3	1.1192	0.1214	1.5646	0.1216	1.6294	0.1230
Dem4	0.9852	0.1766	1.0945	0.1703	1.1813	0.1764
Age	-1.5753	0.2410	-1.9846	0.2383	-2.2575	0.2380
Cohort	-0.3687	0.2226	-0.9208	0.2185	-0.9203	0.2192
Gend	-0.4579	0.1501	-1.1465	0.1523	-0.6545	0.1567
Inac	0.6157	0.1663	0.9280	0.1583	0.9058	0.1626
West	-1.0264	0.1502	-0.3848	0.1450	-0.6946	0.1513
Cent	-0.1937	0.1630	0.5239	0.1550	0.2132	0.1633
Nor	-0.2854	0.2060	0.9116	0.1909	0.3542	0.2035
Rur	-1.2977	0.1825	-0.0152	0.1779	-0.6818	0.1848
Dens	-0.4336	0.1527	0.3665	0.1518	0.0363	0.1529

Table 8: Model C, $\sigma_\alpha = 0$. Multinomial Logit. ML coefficient estimates and standard errors. No panel structure imposed. No. of obs. = 25,180						
	Manuf. cig. only		**Hand rolled cig. only**		**Both types of cig.**	
	Coeff.	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
Const	-1.8441	0.7543	2.4226	0.5694	3.0809	0.6793
Texp	0.8472	0.0590	-0.5914	0.0562	0.5784	0.0555
P_man	-0.7615	0.9073	1.9628	0.7491	-0.3982	0.8655
P_hand	0.3093	0.7197	-1.7878	0.6352	0.1721	0.7065
Dem1	-0.2099	0.0268	-0.0446	0.0199	-0.1886	0.0235
Dem2	0.0974	0.0331	0.2551	0.0246	0.4377	0.0275
Dem3	0.0984	0.0418	0.4931	0.0311	0.5627	0.0375
Dem4	0.2069	0.0687	0.2481	0.0466	0.3297	0.0654
Age	-0.1183	0.1015	-0.4999	0.0753	-0.7731	0.0917
Cohort	0.2212	0.0972	-0.2923	0.0722	-0.3173	0.0873
Gend	0.1780	0.0553	-0.6049	0.0487	-0.0006	0.0550
Inac	0.0449	0.0658	0.3504	0.0481	0.3421	0.0612
West	-0.4958	0.0547	0.0342	0.0399	-0.1854	0.0489
Cent	-0.3625	0.0677	0.2969	0.0471	0.0470	0.0587
Nor	-0.6390	0.1021	0.4764	0.0568	-0.0192	0.0763
Rur	-0.8846	0.0713	0.3071	0.0540	-0.2716	0.0650
Dens	-0.4199	0.0507	0.3098	0.0478	0.0537	0.0518

Table 9: Model A. Binomial model of prevalence. Partial derivatives of probabilities, evaluated at sample mean and α_i = 0. Based on 1000 bootstrap replications. Non-smoke is basis alternative. LLLL-model. No. of obs. = 25,180				
	Non-smoke		**Smoke**	
	Coeff.	**St.err.**	**Coeff.**	**St.err.**
Const	-2.9799	0.4383	2.9799	0.4383
Texp	-0.1716	0.0355	0.1716	0.0355
P_tob	0.1053	0.1552	-0.1053	0.1552
Dem1	0.1082	0.0164	-0.1082	0.0164
Dem2	-0.2361	0.0215	0.2361	0.0215
Dem3	-0.3543	0.0286	0.3543	0.0286
Dem4	-0.2613	0.0405	0.2613	0.0405
Age	0.4875	0.0605	-0.4875	0.0605
Cohort	0.2056	0.0558	-0.2056	0.0558
Gend	0.2006	0.0353	-0.2006	0.0353
Inac	-0.2137	0.0362	0.2137	0.0362
West	0.1507	0.0353	-0.1507	0.0353
Cent	-0.0690	0.0368	0.0690	0.0368
Nor	-0.1337	0.0444	0.1337	0.0444
Rur	0.1152	0.0427	-0.1152	0.0427
Dens	-0.0064	0.0359	0.0064	0.0359

Table 10: Model B. Binomial model of composition. Partial derivatives of probabilities, evaluated at sample mean and α_i = 0. Based on 1000 bootstrap replications. Hand rolled is basis alternative. LLLL-model. No. of obs. = 8,136				
	Hand rolled		**Manufactured**	
	Coeff.	**St.err.**	**Coeff.**	**St.err.**
Const	-0.0289	0.2311	0.0289	0.2311
Texp	-0.1301	0.0413	0.1301	0.0413
P_rel	0.2745	0.1567	-0.2745	0.1567
Dem1	0.0132	0.0058	-0.0132	0.0058
Dem2	0.0155	0.0062	-0.0155	0.0062
Dem3	0.0370	0.0121	-0.0370	0.0121
Dem4	0.0108	0.0090	-0.0108	0.0090
Age	-0.0200	0.0115	0.0200	0.0115
Cohort	-0.0320	0.0139	0.0320	0.0139
Gend	-0.0624	0.0200	0.0624	0.0200
Inac	0.0301	0.0114	-0.0301	0.0114
West	0.0595	0.0205	-0.0595	0.0205
Cent	0.0598	0.0207	-0.0598	0.0207
Nor	0.1011	0.0327	-0.1011	0.0327
Rur	0.1088	0.0356	-0.1088	0.0356
Dens	0.0753	0.0241	-0.0753	0.0241

Table 11: Model C. Multinomial Logit. Partial derivatives of probabilities, evaluated at sample mean and $\alpha_i = 0$. Based on 1000 bootstrap replications. Non-smoke is basis alternative. LLLL-model. No. of obs. = 25,180

	Non-smoke		Manuf. cig		Hand roll. cig		Both types	
	Coeff.	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
Const	-2.5684	0.4241	0.1998	0.1085	1.4932	0.2347	0.8755	0.1334
Texp	-0.1325	0.0358	0.1159	0.0094	-0.0912	0.0208	0.1078	0.0114
P_man	-0.4493	0.4823	-0.0492	0.1246	0.5222	0.2666	-0.0237	0.1576
P_hand	0.4904	0.4063	0.0048	0.1044	-0.4873	0.2225	-0.0080	0.1337
Dem1	0.1049	0.0160	-0.0320	0.0041	-0.0343	0.0086	-0.0386	0.0050
Dem2	-0.2388	0.0213	0.0326	0.0054	0.1206	0.0114	0.0856	0.0066
Dem3	-0.3663	0.0295	0.0439	0.0070	0.2044	0.0160	0.1180	0.0090
Dem4	-0.2698	0.0413	0.0477	0.0105	0.1375	0.0223	0.0846	0.0132
Age	0.4858	0.0568	-0.0669	0.0144	-0.2508	0.0317	-0.1681	0.0178
Cohort	0.1976	0.0520	-0.0014	0.0133	-0.1276	0.0291	-0.0686	0.0163
Gend	0.2127	0.0363	-0.0073	0.0087	-0.1723	0.0202	-0.0331	0.0117
Inac	-0.2106	0.0384	0.0226	0.0099	0.1239	0.0206	0.0641	0.0121
West	0.1498	0.0352	-0.0720	0.0087	-0.0261	0.0189	-0.0517	0.0111
Cent	-0.0700	0.0378	-0.0304	0.0098	0.0897	0.0202	0.0106	0.0121
Nor	-0.1234	0.0465	-0.0482	0.0130	0.1555	0.0250	0.0161	0.0154
Rur	0.1169	0.0429	-0.1035	0.0110	0.0438	0.0233	-0.0573	0.0138
Dens	-0.0255	0.0363	-0.0456	0.0090	0.0722	0.0200	-0.0011	0.0112

Table 12: Model C, $\sigma_\alpha = 0$. Multinomial Logit. Partial derivatives of probabilities, evaluated at sample mean. No panel structure imposed. No. of obs. = 25,180

	Non-smoke		Manuf. cig. only		Hand rolled cig. only		Both types of cig.	
	Coeff.	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
Const	-0.4162	0.1142	-0.2661	0.0658	0.3871	0.0971	0.2952	0.0717
Texp	-0.0112	0.0104	0.0838	0.0051	-0.1441	0.0095	0.0715	0.0058
P_man	-0.1785	0.1452	-0.1111	0.0795	0.3835	0.1285	-0.0938	0.0920
P_hand	0.1965	0.1198	0.0687	0.0631	-0.3344	0.1094	0.0692	0.0753
Dem1	0.0299	0.0040	-0.0156	0.0023	0.0027	0.0034	-0.0170	0.0025
Dem2	-0.0674	0.0050	-0.0029	0.0029	0.0304	0.0041	0.0399	0.0028
Dem3	-0.1060	0.0063	-0.0101	0.0036	0.0694	0.0052	0.0467	0.0039
Dem4	-0.0651	0.0098	0.0087	0.0061	0.0298	0.0080	0.0267	0.0070
Age	0.1224	0.0152	0.0112	0.0089	-0.0638	0.0128	-0.0698	0.0096
Cohort	0.0466	0.0146	0.0313	0.0085	-0.0483	0.0123	-0.0295	0.0092
Gend	0.0665	0.0092	0.0307	0.0048	-0.1131	0.0083	0.0159	0.0059
Inac	-0.0700	0.0098	-0.0087	0.0058	0.0517	0.0082	0.0271	0.0065
West	0.0353	0.0080	-0.0436	0.0048	0.0236	0.0068	-0.0153	0.0052
Cent	-0.0209	0.0098	-0.0408	0.0059	0.0607	0.0080	0.0010	0.0062
Nor	-0.0240	0.0126	-0.0694	0.0089	0.1016	0.0096	-0.0082	0.0081
Rur	0.0280	0.0107	-0.0845	0.0061	0.0846	0.0092	-0.0281	0.0069
Dens	-0.0199	0.0090	-0.0464	0.0044	0.0642	0.0081	0.0021	0.0055

Table 13 A: Model C, $\sigma_\alpha = 0$. Multinomial Logit for separate years. Derivative of probabilities with respect to Age. No panel structure imposed. Evaluated at year-specific sample mean. No constant term included									
		Non-smoke		Manuf. cig. only		Hand rolled cig. only		Both types of cig.	
Year	**No. obs.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
1975	1076	0.0571	0.0141	0.0010	0.0062	-0.0087	0.0133	-0.0494	0.0095
1976	1100	0.0391	0.0131	0.0037	0.0064	-0.0100	0.0125	-0.0329	0.0089
1977	941	0.0739	0.0153	-0.0104	0.0083	-0.0374	0.0134	-0.0261	0.0102
1978	923	0.1008	0.0155	-0.0197	0.0076	-0.0391	0.0129	-0.0420	0.0094
1979	1418	0.0934	0.0126	-0.0166	0.0059	-0.0254	0.0112	-0.0514	0.0080
1980	1102	0.0492	0.0135	-0.0090	0.0068	-0.0024	0.0118	-0.0378	0.0090
1981	1502	0.0749	0.0117	-0.0185	0.0054	-0.0271	0.0103	-0.0292	0.0078
1982	1434	0.0869	0.0123	-0.0079	0.0055	-0.0419	0.0110	-0.0371	0.0074
1983	1438	0.0795	0.0121	-0.0151	0.0058	-0.0360	0.0109	-0.0285	0.0068
1984	1470	0.0809	0.0125	-0.0185	0.0064	-0.0228	0.0110	-0.0396	0.0078
1985	1500	0.0810	0.0128	-0.0133	0.0071	-0.0067	0.0112	-0.0610	0.0083
1986	1426	0.0809	0.0126	-0.0157	0.0079	-0.0164	0.0106	-0.0488	0.0083
1987	1183	0.0862	0.0140	-0.0320	0.0088	-0.0235	0.0109	-0.0307	0.0101
1988	1367	0.0710	0.0130	-0.0134	0.0082	-0.0122	0.0105	-0.0454	0.0085
1989	1133	0.1113	0.0154	-0.0424	0.0101	-0.0130	0.0118	-0.0560	0.0101
1990	1154	0.0938	0.0137	-0.0241	0.0090	-0.0183	0.0107	-0.0514	0.0087
1991	1216	0.1064	0.0140	-0.0285	0.0091	-0.0365	0.0102	-0.0415	0.0092
1992	1306	0.1091	0.0142	-0.0320	0.0096	-0.0226	0.0096	-0.0545	0.0094
1993	1216	0.0839	0.0158	-0.0300	0.0112	-0.0056	0.0118	-0.0482	0.0108
1994	1275	0.1133	0.0150	-0.0404	0.0101	-0.0123	0.0102	-0.0606	0.0095

Table 13 B: Model C, $\sigma_\alpha = 0$. Multinomial Logit for separate years. Derivative of probabilities with respect to Cohort. No panel structure imposed. Evaluated at year-specific sample mean. No constant term included									
		Non-smoke		Manuf. cig. only		Hand rolled cig. only		Both types of cig.	
Year	**No. obs.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
1975	1076	0.0032	0.0107	-0.0056	0.0043	0.0019	0.0099	0.0006	0.0063
1976	1100	0.0170	0.0102	-0.0099	0.0043	0.0001	0.0097	-0.0072	0.0059
1977	941	-0.0073	0.0109	-0.0008	0.0052	0.0156	0.0095	-0.0076	0.0064
1978	923	0.0026	0.0110	0.0049	0.0054	0.0048	0.0093	-0.0124	0.0065
1979	1418	-0.0134	0.0086	0.0036	0.0039	0.0090	0.0076	0.0008	0.0050
1980	1102	-0.0043	0.0095	-0.0035	0.0043	0.0011	0.0081	0.0066	0.0056
1981	1502	0.0099	0.0078	-0.0016	0.0035	-0.0009	0.0070	-0.0073	0.0046
1982	1434	0.0082	0.0084	0.0042	0.0033	-0.0094	0.0076	-0.0030	0.0044
1983	1438	0.0123	0.0083	0.0001	0.0036	-0.0077	0.0076	-0.0047	0.0041
1984	1470	0.0112	0.0077	0.0012	0.0034	-0.0104	0.0069	-0.0020	0.0039
1985	1500	0.0122	0.0080	-0.0034	0.0040	-0.0008	0.0070	-0.0080	0.0047
1986	1426	0.0197	0.0081	-0.0032	0.0047	-0.0135	0.0070	-0.0030	0.0047
1987	1183	0.0210	0.0086	0.0093	0.0049	-0.0148	0.0070	-0.0156	0.0056
1988	1367	0.0239	0.0080	0.0001	0.0045	-0.0133	0.0066	-0.0107	0.0048
1989	1133	-0.0015	0.0091	0.0146	0.0056	-0.0136	0.0072	0.0005	0.0052
1990	1154	0.0163	0.0085	0.0006	0.0050	-0.0111	0.0071	-0.0058	0.0048
1991	1216	0.0180	0.0078	0.0038	0.0048	-0.0100	0.0060	-0.0118	0.0048
1992	1306	0.0117	0.0079	0.0055	0.0051	-0.0143	0.0059	-0.0029	0.0051
1993	1216	0.0278	0.0085	-0.0016	0.0056	-0.0238	0.0069	-0.0024	0.0055
1994	1275	0.0089	0.0084	0.0109	0.0053	-0.0239	0.0063	0.0041	0.0053

Table 13 C: Model C, $\sigma_{\alpha} = 0$. Multinomial Logit for separate years. Derivative of probabilities with respect to Gender. No panel structure imposed. Evaluated at year-specific sample mean. No constant term included

		Non-smoke		Manuf. cig. only		Hand rolled cig. only		Both types of cig.	
Year	**No. obs.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
1975	1076	0.1927	0.0495	-0.0104	0.0217	-0.2181	0.0509	0.0359	0.0347
1976	1100	0.1224	0.0499	-0.0082	0.0234	-0.1408	0.0507	0.0266	0.0354
1977	941	0.1155	0.0558	0.0329	0.0282	-0.1024	0.0517	-0.0460	0.0409
1978	923	0.0264	0.0522	0.0148	0.0252	-0.0342	0.0453	-0.0070	0.0363
1979	1418	0.1231	0.0430	0.0166	0.0193	-0.1738	0.0404	0.0341	0.0278
1980	1102	0.2648	0.0490	0.0584	0.0219	-0.3012	0.0465	-0.0220	0.0328
1981	1502	0.0475	0.0400	0.0462	0.0169	-0.1449	0.0381	0.0513	0.0251
1982	1434	0.1598	0.0426	-0.0021	0.0175	-0.1276	0.0400	-0.0301	0.0261
1983	1438	0.0454	0.0412	0.0270	0.0178	-0.0675	0.0388	-0.0049	0.0236
1984	1470	0.0566	0.0401	0.0045	0.0191	-0.1057	0.0376	0.0446	0.0215
1985	1500	0.1173	0.0393	0.0452	0.0196	-0.1908	0.0367	0.0283	0.0242
1986	1426	0.0762	0.0387	0.0434	0.0230	-0.1448	0.0351	0.0252	0.0233
1987	1183	0.0150	0.0417	0.0236	0.0242	-0.0419	0.0344	0.0033	0.0281
1988	1367	0.1060	0.0389	0.0280	0.0225	-0.1483	0.0346	0.0144	0.0245
1989	1133	0.1076	0.0425	0.0398	0.0261	-0.1065	0.0344	-0.0409	0.0271
1990	1154	0.0541	0.0388	0.0122	0.0237	-0.0639	0.0326	-0.0025	0.0229
1991	1216	-0.0490	0.0365	0.0791	0.0218	-0.0586	0.0284	0.0285	0.0220
1992	1306	-0.0141	0.0356	0.0393	0.0234	-0.0588	0.0275	0.0336	0.0227
1993	1216	-0.0547	0.0387	0.0700	0.0245	-0.0437	0.0318	0.0284	0.0252
1994	1275	-0.0396	0.0361	0.0013	0.0232	0.0156	0.0262	0.0227	0.0224

Table 13 D: Model C, $\sigma_{\alpha} = 0$. Multinomial Logit for separate years. Derivative of probabilities with respect to Inactivity. No panel structure imposed. Evaluated at year-specific sample mean. No constant term included

		Non-smoke		Manuf. cig. only		Hand rolled cig. only		Both types of cig.	
Year	**No. obs.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**	**Coeff.**	**St.err.**
1975	1076	-0.0537	0.0461	-0.0125	0.0202	0.0338	0.0433	0.0323	0.0329
1976	1100	0.0398	0.0446	0.0078	0.0219	0.0099	0.0429	-0.0575	0.0336
1977	941	-0.0906	0.0510	0.0020	0.0280	0.0516	0.0443	0.0369	0.0340
1978	923	-0.0034	0.0523	0.0111	0.0266	0.0245	0.0446	-0.0323	0.0371
1979	1418	-0.0526	0.0433	-0.0045	0.0211	0.0728	0.0377	-0.0157	0.0308
1980	1102	-0.0327	0.0499	-0.0149	0.0256	0.0279	0.0427	0.0197	0.0341
1981	1502	-0.0159	0.0421	-0.0475	0.0210	0.0889	0.0374	-0.0255	0.0293
1982	1434	-0.1354	0.0424	-0.0482	0.0199	0.1740	0.0372	0.0097	0.0251
1983	1438	-0.0061	0.0409	-0.0082	0.0198	0.0065	0.0378	0.0078	0.0244
1984	1470	-0.1114	0.0401	-0.0088	0.0208	0.0828	0.0346	0.0374	0.0232
1985	1500	-0.1234	0.0400	-0.0108	0.0222	0.0742	0.0341	0.0600	0.0244
1986	1426	-0.0966	0.0450	0.0053	0.0289	0.0198	0.0373	0.0714	0.0284
1987	1183	-0.0002	0.0460	0.0169	0.0288	-0.0059	0.0363	-0.0108	0.0340
1988	1367	-0.0615	0.0442	-0.0247	0.0291	0.0379	0.0351	0.0483	0.0283
1989	1133	-0.1756	0.0511	0.0520	0.0327	0.0690	0.0374	0.0545	0.0315
1990	1154	-0.0775	0.0444	0.0011	0.0286	-0.0086	0.0359	0.0849	0.0252
1991	1216	-0.1272	0.0454	0.0081	0.0287	0.0610	0.0321	0.0581	0.0266
1992	1306	-0.1392	0.0438	0.0066	0.0304	0.1109	0.0285	0.0218	0.0284
1993	1216	-0.1003	0.0433	0.0009	0.0303	0.0355	0.0324	0.0639	0.0276
1994	1275	-0.0553	0.0432	-0.0283	0.0305	0.0542	0.0290	0.0294	0.0274

Appendix:
ML estimation of multinomial logit model with random heterogeneity

In this appendix, we explain the ML estimation procedure for the multinomial model. We model the household's decisions as qualitative choices by means of a multinomial logit model with J mutually exclusive alternatives, indexed by $j = 0, 1, \ldots, J$.

Let the households be indexed by i and the observation periods by t, N is the index set of households observed at least once, $i \in N$, and T_i is the set of periods during which household i is observed, $t \in T_i$. Let

$$y_{jit} = \begin{cases} 1 & \text{if household } i \text{ in year } t \text{ chooses alternative } j, \\ 0 & \text{otherwise,} \end{cases} \qquad i \in N,\ t \in T_i,\ j = 0, 1, \ldots, J, \tag{A.1}$$

and

$$p_{jit} = P(y_{jit} = 1), \quad i \in N,\ t \in T_i,\ j = 0, 1, \ldots, J. \tag{A.2}$$

Using the multinomial logit parametrization, we have [cf. (3)]

$$p_{jit} = \frac{\exp(v_{jit})}{\sum_{k=0}^{J} \exp(v_{kit})}, \tag{A.3}$$

where

$$v_{jit} = \begin{cases} \sum_{a=1}^{A} x_{ait}\beta_{ja} + \sigma_j \mu_{ji} = x_{it}\beta_j + \sigma_j \mu_{ji}, & j = 1, \ldots, J, \\ 0, & j = 0 \end{cases} \tag{A.4}$$

$x_{it} = (x_{1it}, \ldots, x_{Ait})$, $\beta_j = (\beta_{j1}, \ldots, \beta_{jA})'$, α_{ji} is the random effect related to alternative j $(j = 1, \ldots, J)$ for household i, with standard deviation σ_j, and $\mu_{ji} = \alpha_{ji}/\sigma_j$. Here and in the following $\sum_j$ means $\sum_{j=0}^{J}$. We let β_{ja} denote the coefficient of the a'th regressor in alternative j. By this formulation, we assume (i) that all coefficients are the same for all households in all periods, (ii) that the set of regressors is the same for all alternatives, and (iii) that the random effect μ_{ji} is specific to household i and alternative j $(j = 1, \ldots, J)$.

Assuming that all observations are independent across households, conditionally on the x_{it}'s, the likelihood function of the y_{jit}'s, conditionally on the x_{it}'s, can be written as

$$\ln(\mathcal{L}) = \sum_i \ln\left(\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \phi(\mu_{1i}, \ldots, \mu_{Ji}) L_i d\mu_{1i} \cdots d\mu_{Ji}\right) = \sum_i \ln(K_i), \tag{A.5}$$

where $\phi(\cdot)$ is the joint density function of $\mu_{1i}, \ldots, \mu_{Ji}$,

$$L_i = \prod_t \prod_j p_{jit}^{y_{jit}}, \tag{A.6}$$

and

$$K_i = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} \phi(\mu_{1i}, \ldots, \mu_{Ji}) L_i d\mu_{1i} \cdots d\mu_{Ji}. \tag{A.7}$$

Note that p_{jit} and L_i are functions of the integration variables μ_{ji}. The function L_i can be interpreted as the part of the likelihood function that would relate to household i in the case where the μ_{ji}'s were considered as fixed (or conditionally on these variables).

In order to avoid having to evaluate multiple integrals numerically, we assume, for simplicity, that the latent household specific effect is the same for alternatives $1, \ldots, J$, *i.e.*,

$$\alpha_{ji} = \alpha_i, \quad \mu_{ji} = \mu_i, \quad \sigma_j = \sigma, \qquad j = 1, \ldots, J. \tag{A.8}$$

Then (A.5) and (A.7) can be simplified to

$$\ln(\mathcal{L}) = \sum_i \ln\left(\int_{-\infty}^{\infty} \phi(\mu_i) L_i d\mu_i\right) = \sum_i \ln(K_i) \tag{A.9}$$

and

$$K_i = \int_{-\infty}^{\infty} \phi(\mu_i) L_i d\mu_i. \tag{A.10}$$

Let $\eta \in \{\beta_1, \ldots, \beta_J, \sigma\}$ be a typical parameter in the likelihood function. From (A.9) and (A.10) it follows that

$$\frac{\partial \ln(\mathcal{L})}{\partial \eta} = \sum_i \frac{1}{K_i} \frac{\partial K_i}{\partial \eta}, \tag{A.11}$$

where

$$\frac{\partial K_i}{\partial \eta} = \int_{-\infty}^{\infty} \phi(\mu_i) \frac{\partial L_i}{\partial \eta} d\mu_i. \tag{A.12}$$

Differentiating (A.6) yields

$$\frac{\partial L_i}{\partial p_{jit}} = \frac{L_i}{p_{jit}} y_{jit}, \tag{A.13}$$

and hence, using the chain rule,

$$\frac{\partial L_i}{\partial \eta} = \sum_t \sum_j \frac{\partial L_i}{\partial p_{jit}} \frac{\partial p_{jit}}{\partial \eta} = L_i \sum_t \sum_j \frac{y_{jit}}{p_{jit}} \frac{\partial p_{jit}}{\partial \eta}. \tag{A.14}$$

We obtain an expression for $(\partial p_{jit})/(\partial \eta)$ as follows: From (A.3) we obtain

$$\frac{\partial \ln(p_{jit})}{\partial v_{kit}} = \begin{cases} 1 - p_{jit}, & j = k, \\ -p_{kit}, & j \neq k, \end{cases} \qquad \begin{array}{c} j = 0, 1, \ldots, J, \\ k = 1, \ldots, J, \end{array}$$

and hence

$$\frac{\partial p_{jit}}{\partial v_{kit}} = p_{jit}(\delta_{jk} - p_{kit}), \tag{A.15}$$

where $\delta_{jk} = 1$ for $j = k$, and 0 otherwise. We therefore have

$$(A.16)\quad \frac{\partial p_{jit}}{\partial \eta} = \sum_k \frac{\partial p_{jit}}{\partial v_{kit}} \frac{\partial v_{kit}}{\partial \eta} = \sum_k p_{jit}(\delta_{jk} - p_{kit}) \frac{\partial v_{kit}}{\partial \eta} = p_{jit} \left(\frac{\partial v_{jit}}{\partial \eta} - \sum_k p_{kit} \frac{\partial v_{kit}}{\partial \eta} \right).$$

Inserting (A.16) into (A.14), we get

$$(A.17)\quad \begin{aligned} \frac{\partial L_i}{\partial \eta} &= L_i \sum_t \sum_j y_{jit} \left(\frac{\partial v_{jit}}{\partial \eta} - \sum_k p_{kit} \frac{\partial v_{kit}}{\partial \eta} \right) \\ &= L_i \sum_t \left(\sum_j y_{jit} \frac{\partial v_{jit}}{\partial \eta} - \sum_k p_{kit} \frac{\partial v_{kit}}{\partial \eta} \right), \end{aligned}$$

because $\sum_{j=0}^{J} y_{jit} = 1$. Inserting next (A.12) and (A.17) into (A.11) we obtain

$$(A.18)\quad \frac{\partial \ln(\mathcal{L})}{\partial \eta} = \sum_i \frac{1}{K_i} \int_{-\infty}^{\infty} \phi(\mu_i) L_i \sum_t \left(\sum_j y_{jit} \frac{\partial v_{jit}}{\partial \eta} - \sum_k p_{kit} \frac{\partial v_{kit}}{\partial \eta} \right) d\mu_i.$$

Since

$$(A.19)\quad \frac{\partial v_{kit}}{\partial \beta_{ja}} = \begin{cases} \delta_{kj} x_{ait}, & k \neq 0, \\ 0 & k = 0, \end{cases}$$

$$(A.20)\quad \frac{\partial v_{kit}}{\partial \sigma} = \begin{cases} \mu_i, & k \neq 0, \\ 0, & k = 0, \end{cases} \qquad a = 1, \ldots, A;\; j = 1, \ldots, J;\; k = 0, 1, \ldots, J,$$

we find from (A.18) that the *first-order derivatives* of the log-likelihood function are

$$(A.21)\quad \frac{\partial \ln(\mathcal{L})}{\partial \beta_{ja}} = \sum_i \frac{1}{K_i} \int_{-\infty}^{\infty} \phi(\mu_i) L_i \sum_t (y_{jit} - p_{jit}) x_{ait} d\mu_i, \qquad \begin{array}{l} j = 1, \ldots, J, \\ a = 1, \ldots, A, \end{array}$$

$$(A.22)\quad \begin{aligned} \frac{\partial \ln(\mathcal{L})}{\partial \sigma} &= \sum_i \frac{1}{K_i} \int_{-\infty}^{\infty} \phi(\mu_i) L_i \mu_i \sum_t \left(\sum_{j=1}^{J} y_{jit} - \sum_{k=1}^{J} p_{kit} \right) d\mu_i \\ &= -\sum_i \frac{1}{K_i} \int_{-\infty}^{\infty} \phi(\mu_i) L_i \mu_i \sum_t (y_{0it} - p_{0it}) d\mu_i, \end{aligned}$$

because $y_{0it} = 1 - \sum_{j=1}^{J} y_{jit}$ and $p_{0it} = 1 - \sum_{k=1}^{J} p_{kit}$. The first-order conditions,

$$(A.23)\quad \frac{\partial \ln(\mathcal{L})}{\partial \beta_{ja}} = \frac{\partial \ln(\mathcal{L})}{\partial \sigma} = 0, \qquad j = 1, \ldots, J;\; a = 1, \ldots, A,$$

give $JA + 1$ equations which define the ML estimators of β_{ja} and σ.

We next turn to the *second-order derivatives* of the log-likelihood function. We write (A.21) and (A.22) as

$$(A.24)\quad \frac{\partial \ln(\mathcal{L})}{\partial \beta_{ja}} = \sum_i \frac{1}{K_i} H_{jai}, \qquad \begin{array}{l} j = 1, \ldots, J, \\ a = 1, \ldots, A, \end{array}$$

$$(A.25)\quad \frac{\partial \ln(\mathcal{L})}{\partial \sigma} = -\sum_i \frac{1}{K_i} G_i,$$

where

$$(\text{A.26})\qquad H_{jai} = \int_{-\infty}^{\infty} \phi(\mu_i) L_i z_{jai} d\mu_i, \qquad \begin{array}{c} j = 1,\ldots,J, \\ a = 1,\ldots,A, \end{array}$$

$$(\text{A.27})\qquad G_i = \int_{-\infty}^{\infty} \phi(\mu_i) L_i z_{0i} d\mu_i,$$

and

$$(\text{A.28})\qquad z_{jai} = \sum_t (y_{jit} - p_{jit}) x_{ait}, \qquad \begin{array}{c} j = 1,\ldots,J, \\ a = 1,\ldots,A, \end{array}$$

$$(\text{A.29})\qquad z_{0i} = \mu_i \sum_t (y_{0it} - p_{0it}).$$

Let $\lambda \in \{\beta_1, \ldots, \beta_J, \sigma\}$ be a typical parameter in the likelihood function. From (A.24) – (A.27) it follows that

$$(\text{A.30})\qquad \frac{\partial^2 \ln(\mathcal{L})}{\partial \beta_{ja} \partial \lambda} = \sum_i \frac{1}{K_i^2} \left(K_i \frac{\partial H_{jai}}{\partial \lambda} - H_{jai} \frac{\partial K_i}{\partial \lambda} \right),$$

$$(\text{A.31})\qquad \frac{\partial^2 \ln(\mathcal{L})}{\partial \sigma \partial \lambda} = - \sum_i \frac{1}{K_i^2} \left(K_i \frac{\partial G_i}{\partial \lambda} - G_i \frac{\partial K_i}{\partial \lambda} \right),$$

where

$$(\text{A.32})\qquad \frac{\partial H_{jai}}{\partial \lambda} = \int_{-\infty}^{\infty} \phi(\mu_i) \left[\frac{\partial L_i}{\partial \lambda} z_{jai} + L_i \frac{\partial z_{jai}}{\partial \lambda} \right] d\mu_i, \qquad \begin{array}{c} j = 1,\ldots,J, \\ a = 1,\ldots,A, \end{array}$$

$$(\text{A.33})\qquad \frac{\partial G_i}{\partial \lambda} = \int_{-\infty}^{\infty} \phi(\mu_i) \left[\frac{\partial L_i}{\partial \lambda} z_{0i} + L_i \frac{\partial z_{0i}}{\partial \lambda} \right] d\mu_i.$$

Inserting (A.14), with η replaced by λ, and

$$(\text{A.34})\qquad \frac{\partial z_{jai}}{\partial \lambda} = - \sum_t \left(\frac{\partial p_{jit}}{\partial \lambda} \right) x_{ait},$$

$$(\text{A.35})\qquad \frac{\partial z_{0i}}{\partial \lambda} = - \sum_t \left(\frac{\partial p_{0it}}{\partial \lambda} \right) \mu_i,$$

which follow from (A.28) and (A.29), in (A.32) and (A.33) we obtain

$$(\text{A.36})\qquad \frac{\partial H_{jai}}{\partial \lambda} = \int_{-\infty}^{\infty} \phi(\mu_i) L_i \left[\left(\sum_s \sum_k \frac{y_{kis}}{p_{kis}} \frac{\partial p_{kis}}{\partial \lambda} \right) z_{jai} - \sum_t \frac{\partial p_{jit}}{\partial \lambda} x_{ait} \right] d\mu_i,$$

$$(\text{A.37})\qquad \frac{\partial G_i}{\partial \lambda} = \int_{-\infty}^{\infty} \phi(\mu_i) L_i \left[\left(\sum_s \sum_k \frac{y_{kis}}{p_{kis}} \frac{\partial p_{kis}}{\partial \lambda} \right) z_{0i} - \sum_t \frac{\partial p_{0it}}{\partial \lambda} \mu_i \right] d\mu_i.$$

From (A.12) and (A.14) with η replaced by λ, we obtain

$$(\text{A.38})\qquad \frac{\partial K_i}{\partial \lambda} = \int_{-\infty}^{\infty} \phi(\mu_i) L_i \left[\sum_t \sum_k \frac{y_{kit}}{p_{kit}} \frac{\partial p_{kit}}{\partial \lambda} \right] d\mu_i.$$

Now, (A.16), (A.19), and (A.20) imply

$$\text{(A.39)}\qquad \begin{aligned} \frac{\partial p_{kit}}{\partial \beta_{rb}} &= p_{kit}(\delta_{kr} - p_{rit})x_{bit}, \\ \frac{\partial p_{0it}}{\partial \beta_{rb}} &= p_{0it}(0 - p_{rit}x_{bit}) = -\, p_{0it}p_{rit}x_{bit}, \end{aligned}$$

$$\text{(A.40)}\qquad \begin{aligned} \frac{\partial p_{kit}}{\partial \sigma} &= p_{kit}(\mu_i - \textstyle\sum_{r=1}^{J} p_{rit}\mu_i) = p_{kit}p_{0it}\mu_i, \\ \frac{\partial p_{0it}}{\partial \sigma} &= p_{0it}(0 - \textstyle\sum_{r=1}^{J} p_{rit}\mu_i) = -\, p_{0it}(1 - p_{0it})\mu_i, \end{aligned} \qquad \begin{aligned} k &= 1, \ldots, J, \\ r &= 1, \ldots, J, \\ b &= 1, \ldots, A, \end{aligned}$$

and hence

$$\text{(A.41)}\qquad \sum_s \sum_k \frac{y_{kis}}{p_{kis}} \frac{\partial p_{kis}}{\partial \beta_{rb}} = \sum_s \sum_k y_{kis}(\delta_{kr} - p_{rit})x_{bit} = z_{rbi}, \qquad \begin{aligned} r &= 1, \ldots, J, \\ b &= 1, \ldots, A, \end{aligned}$$

$$\text{(A.42)}\qquad \sum_s \sum_k \frac{y_{kis}}{p_{kis}} \frac{\partial p_{kis}}{\partial \sigma} = -\, \sum_s \sum_k y_{kis}(\delta_{kr} - p_{0it})\mu_i = -\, z_{0i}.$$

Inserting (A.39) – (A.42) in (A.36) – (A.38), we get

$$\text{(A.43)}\, \frac{\partial H_{jai}}{\partial \beta_{rb}} = \int_{-\infty}^{\infty} \phi(\mu_i)L_i \left[z_{jai}z_{rbi} - \sum_t p_{jit}(\delta_{jr} - p_{rit})x_{ait}x_{bit} \right] d\mu_i, \qquad \begin{aligned} j, r &= 1, \ldots, J, \\ a, b &= 1, \ldots, A, \end{aligned}$$

$$\text{(A.44)}\, \frac{\partial G_i}{\partial \beta_{rb}} = \int_{-\infty}^{\infty} \phi(\mu_i)L_i \left[z_{rbi}z_{0i} + \sum_t p_{0it}p_{rit}x_{bit}\mu_i \right] d\mu_i, \qquad \begin{aligned} r &= 1, \ldots, J, \\ b &= 1, \ldots, A, \end{aligned}$$

$$\text{(A.45)}\, \frac{\partial K_i}{\partial \beta_{rb}} = \int_{-\infty}^{\infty} \phi(\mu_i)L_i z_{rbi} d\mu_i = H_{rbi}, \qquad \begin{aligned} r &= 1, \ldots, J, \\ b &= 1, \ldots, A, \end{aligned}$$

$$\text{(A.46)}\, \frac{\partial H_{jai}}{\partial \sigma} = \int_{-\infty}^{\infty} \phi(\mu_i)L_i \left[-\, z_{0i}z_{jai} - \sum_t p_{jit}p_{0it}\mu_i x_{ait} \right] d\mu_i, \qquad \begin{aligned} j &= 1, \ldots, J, \\ a &= 1, \ldots, A, \end{aligned}$$

$$\text{(A.47)}\, \frac{\partial G_i}{\partial \sigma} = \int_{-\infty}^{\infty} \phi(\mu_i)L_i \left[-\, z_{0i}^2 + \sum_t p_{0it}(1 - p_{0it})\mu_i \right] d\mu_i,$$

$$\text{(A.48)}\, \frac{\partial K_i}{\partial \sigma} = \int_{-\infty}^{\infty} \phi(\mu_i)L_i z_{0i} d\mu_i = -\, G_i.$$

By finally inserting (A.43) – (A.48) in (A.30) and (A.31), we obtain the following expressions for the second derivatives of the log-likelihood function

$$\text{(A.49)}\quad \begin{aligned} \frac{\partial^2 \ln(\mathcal{L})}{\partial \beta_{ja} \partial \beta_{rb}} \quad = \quad & \sum_i \frac{1}{K_i^2} \Bigg(K_i \int_{-\infty}^{\infty} \phi(\mu_i)L_i \\ & \quad \times \left[z_{jai}z_{rbi} - \sum_t p_{jit}(\delta_{jr} - p_{rit})x_{ait}x_{bit} \right] d\mu_i - H_{jai}H_{rbi} \Bigg), \end{aligned}$$

$$\text{(A.50)}\quad \begin{aligned} \frac{\partial^2 \ln(\mathcal{L})}{\partial \sigma^2} \quad = \quad & -\, \sum_i \frac{1}{K_i^2} \Bigg(K_i \int_{-\infty}^{\infty} \phi(\mu_i)L_i \\ & \quad \times \left[-\, z_{0i}^2 + \sum_t p_{0it}(1 - p_{0it})\mu_i \right] d\mu_i + G_i^2 \Bigg), \end{aligned}$$

$$
\begin{aligned}
\text{(A.51)}\quad \frac{\partial^2 \ln(\mathcal{L})}{\partial\sigma\partial\beta_{rb}} &= -\sum_i \frac{1}{K_i^2}\Bigg(K_i \int_{-\infty}^{\infty} \phi(\mu_i) L_i \\
&\quad \times \left[z_{0i} z_{rbi} + \sum_t p_{0it} p_{rit} x_{bit} \mu_i\right] d\mu_i - G_i H_{rbi}\Bigg), \\
\text{(A.52)}\quad \frac{\partial^2 \ln(\mathcal{L})}{\partial\beta_{ja}\partial\sigma} &= \sum_i \frac{1}{K_i^2}\Bigg(K_i \int_{-\infty}^{\infty} \phi(\mu_i) L_i \\
&\quad \times \left[- z_{0i} z_{jai} - \sum_t p_{jit} p_{0it} x_{ait} \mu_i\right] d\mu_i + H_{jai} G_i\Bigg).
\end{aligned}
$$

We note that $(\partial^2 \ln(\mathcal{L})/(\partial\beta_{ja}\partial\sigma) = (\partial^2 \ln(\mathcal{L})/(\partial\sigma\partial\beta_{ja})$, which is in accordance with Young's theorem.

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