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Survey Nonresponse, Attrition and Unemployment Duration

Marjo Pyy-Martikainen* Leif Nordberg†

Abstract

We study the effectiveness of re-weighting methods in correcting for bias due to nonresponse and attrition in the analysis of unemployment duration. We use the Finnish subset of European Community Household Panel (ECHP) data complemented by a longitudinal register data. Data on unemployment spells as well as covariates are taken from the register. This information is available both for respondents and non-respondents. The survey data is used only to obtain the result of the interview and information about the sample design. Separate analyses are conducted based on the full information sample and its subsets restricted by nonresponse and attrition. The observed information set of unemployment spells corresponds to the data normally available for a survey data analyst. The third set consists of unemployment spells by total respondents. Estimates based on the full information set serve as benchmarks to which estimates from the other sets are compared. In the first phase of the study, weights available in ECHP User Data Base (UDB) are used. In the second phase, we use inverse probability of censoring (IPC) adjusted weights specifically created for the analysis of unemployment duration. The observed information estimates are closer to benchmark values than total respondents estimates. However, the weighting strategies used in the observed information set of spells improve estimates only slightly. In the subgroup of men, using the total respondents set of unemployment spells and UDB weights from the last wave produce badly biased results. The IPC adjustment to weights is not helpful in correcting for bias.

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1 Introduction

During recent years, dynamic individual-level analyses have gained popularity among social scientists. For example, event history analysis deals with individuals' transitions between a set of states and with the timing of these transitions. It is usually of interest to study the effect of certain covariates on the timing of the transitions.

In response to the need of data sets suitable for dynamic analyses, panel surveys have been launched in many countries. The European Community Household Panel (ECHP) was conducted during 1994-2001 in 15 EU member states. The Finnish ECHP started two years later resulting in 6 panel waves during 1996-2001. The ECHP was centrally designed and coordinated by Eurostat. It covers a wide range of topics concerning living conditions, the core topics being income and employment.

Survey data sets have always some degree of nonresponse. In panel surveys, nonresponse may occur not only at the initial wave but also at each of the subsequent waves of the panel. The resulting response patterns can be classified into four groups (Kalton and Brick 2000): total respondents, who provide data on every wave; attrition nonrespondents, who drop out of the panel at some wave after the first and remain out of the panel for all subsequent waves; temporary drop-outs, who return to the panel after missing one or more waves; and total nonrespondents, who provide data for none of the waves. Nonresponse not only reduces the sample size available for analysis but may also lead to biased estimates. Bias occurs if nonresponse is nonignorable i.e. it is related to the process under study even after controlling for covariates.

In an earlier study by Pyy-Martikainen and Rendtel (2006), it was shown that nonresponse in the Finnish subset of ECHP (Fi ECHP) data is nonignorable with respect to analysis of unemployment duration. This means that the nonresponse mechanism is related to the length of unobserved duration of unemployment spells even after conditioning on covariates and observed duration of spells. The analysis made use of a register panel data combined at person-level to Fi ECHP survey data. Data on unemployment spells as well as covariates were taken from the register data. These data are available both for respondents and nonrespondents. The survey data were used only to obtain the result of the interview. The existence of bias, taken as evidence of nonignorable nonresponse, was evaluated by comparing estimates based on different sets of unemployment spells. The full information set has no restrictions by nonresponse or attrition. The partial information set is obtained by excluding spells unobserved by total nonresponse. The observed information set of spells is obtained from partial information set by excluding spells unobserved by attrition.

Weights are frequently used in survey analysis to correct for nonresponse. Weights are also used to compensate for unequal selection probabilities and for non-coverage. For descriptive inference i.e. inference about known functions of the finite population values, the use of weights is widely accepted (Pfeffermann 1993). However, for analytic inference about model parameters, there is no consensus on whether weights should be included in the analysis or not (see e.g. Pfeffermann 1993, Little 1991).

There are two approaches to the analytic inference of survey data. In the *model-based* approach, it is assumed that the finite population data values $y_1, \ldots, y_N$ are generated by a model $f(y;\theta)$ often called a superpopulation model. The parameter of interest is the superpopulation parameter θ. The superpopulation parameter θ is estimated for example by maximum likelihood. The probability distribution induced by the sampling design is ignored in the estimation procedure; the sample is held fixed. The only source of random variation in the estimate of θ is due to the model. In a pure model-based approach, survey weights play no role in the analysis.

A *design-based* approach to the inference about θ is to specify a finite population parameter θ_U that would be obtained from the model estimation procedure if all data values in the finite population U were available instead of having a sample only. An estimate of θ_U is then obtained using sample data values and survey weights. In the design-based approach, the only source of random variation in the estimate is due to sampling. The finite population data values are treated as fixed.

In this paper, we take the design-based approach to the analysis of unemployment duration. We study whether weighting methods help to correct for bias due to nonresponse and attrition. If weights include information not included as covariates and if this information is related both to nonresponse and to the duration of unemployment, then weights may help to reduce bias.

In the first phase, we use weights included in ECHP Users' DataBase (UDB). ECHP UDB is a user-friendly version of ECHP data created by Eurostat. ECHP UDB includes a multitude of survey weights to be used in all analyses based on ECHP data. These weights were constructed centrally at Eurostat using the same weighting procedure for each ECHP country. It is questionable whether these all-purpose all-country weights are helpful in reducing bias in the analysis of unemployment duration. This is assessed by comparing nonresponse-weighted estimates to full information estimates i.e. to the estimates that would be obtained without nonresponse and attrition.

In the second phase, we try constructing alternative weights aiming to be better suited for the analysis of unemployment duration. These weights are used to produce new estimates and the estimates are again compared to full information estimates.

2 Data

2.1 Finnish subset of the ECHP

Target population

The target population consists of members of private households permanently resident in Finland. Persons living permanently abroad, as well as persons without a permanent place of residence and persons living in institutions do not belong to target population.

Sample design

The sample and data collection were joined with the Income Distribution Statistics (IDS). The IDS has a two-year rotating panel design. The ECHP sample consisted of the households belonging to the new part of the sample i.e. households participating in the survey for the first time in 1996. The IDS sample is a two-phase stratified network sample. The population information system of the Population Register Centre was used as a frame. The frame population consisted of persons permanently living in Finland aged 15 and above. A master sample was drawn by systematic selection from the frame ordered according to domicile code. Dwelling units were constructed by adding to the master sample all the persons sharing the same domicile code as the persons originally drawn into the master sample (so called target persons). Before the drawing of the final sample, persons living permanently in institutions and other overcoverage were excluded. The final sample was drawn using stratification according to target person's socio-economic group and aggregate taxable income; farmers, entrepreneurs and high-income wage earners having the largest sampling fractions.

Pattern	w1	w2	w3	w4	w5	Frequency	Percent
Total respondents	0	0	0	0	0	4364	37.5
Attrition at wave 5	0	0	0	0	1	1486	12.8
Attrition at wave 4	0	0	0	1	1	469	4.0
Attrition at wave 3	0	0	1	1	1	680	5.8
Attrition at wave 2	0	1	1	1	1	575	4.9
Total nonrespondents	1	1	1	1	1	3146	27.0
Temporary drop-outs						921	7.9
All						11641	100.0

Table 1: Distribution of missingness patterns of the 11641 sample persons.

2.2 Construction of unemployment spell data

Our analysis was based on the unemployment spells from the 11641 sample persons aged 16 or over at the beginning of 1996. Sample persons are defined in the ECHP as all members of the initial sample of households.

The ECHP contains information on unemployment spells on a monthly level for the year preceding the interview. However, to get identical information for both respondents and nonrespondents, data on unemployment spells was taken from the register of job seekers compiled by the Ministry of Labour. The background variables used in the analysis were also taken from administrative registers. By using register-based spells and covariates, we get identical information for both respondents and nonrespondents. The survey data were used only to obtain information of the occurrence and timing of nonresponse. The first five waves of the Fi ECHP survey data covering the years 1996-2000 were used in the analysis. The survey and register data were linked at person level by personal identification numbers.

Table 1 shows the distribution of missingness patterns of the 11641 sample persons. Value 0 refers to observed data and value 1 to missing data. Of all sample persons, 37.5% responded in each of the 5 interviews. This group of total respondents also includes the small group of persons who exited the survey population during waves 2 to 5. Exits from the survey population occurred because of death, moving abroad or into an institution. Attriters constituted 27.6% of sample persons. Slightly fewer, 27.0% of sample persons did not respond in any of the survey waves. Most of these total nonrespondents were wave 1 nonrespondents that were not forwarded to wave 2. For the follow-up rules implemented in the Finnish ECHP, see Pyy-Martikainen et al. (2004). In the following, we will use the terms total nonrespondent and nonrespondent to indicate the same group.

# spells	Frequency	Percent
0	7790	72.7
1	695	6.5
2	602	5.6
3	457	4.3
4	326	3.0
5	233	2.2
6-10	460	4.3
11 or more	157	1.5
All	10720	100.0

Table 2: Distribution of number of spells among the 10720 sample persons having a regular response pattern.

Temporary drop-outs are persons who do not participate in one wave but re-enter the panel the next wave. Temporary drop-out can occur in any of waves 1 to 4. Of all sample persons, 7.9% dropped temporarily out of the panel. For simplicity, they were excluded from the analysis. After this exclusion we were left with 10720 sample persons.

Spells by sample persons beginning during 1 January 1995 and 31 December 1999 were chosen for the analysis. This corresponds to the period of observation that would have been available had one taken information on unemployment spells from the ECHP survey data. Spells lasting one or two days were excluded from the analysis as they were not considered as "true" unemployment spells but just registrations into the records of the employment office for some legislative reason. This way we got 10734 spells from 2930 persons. Of all spells, 47.6% ended because of getting employed.

Table 2 shows how the spells are distributed among the 10720 sample persons having a regular response pattern. The majority of the sample persons had no unemployment spells at all during the 5-year period. Among those having one spell or more, the mean number of spells was 3.7.

3 A taxonomy of unemployment spells

For each person who generates one or more spells the participation behavior in the survey is known. It is assumed that unemployment spells are observed until the time of last interview or until the end of the observation period, whichever comes first. This creates a number of different cases:

a Spells that end before the last interview (or before 31.12.1999, whichever comes first) are regarded as *fully observed*.

b Spells ongoing at the time of the last interview which is followed by attrition are regarded as *right censored by attrition* at the time of last interview.

c Spells that start after the last interview which is followed by attrition are *not observed by attrition*.

d Spells by persons without any interviews are *not observed by total nonresponse*.

e Spells that continue at 31.12.1999, unless they are unobserved by attrition or by total nonresponse or censored by attrition, are *right-censored by end of follow-up period*. This category includes also spells that start before the last interview which is followed by exit from survey population.

Table 3 shows the distribution of taxonomy of unemployment spells. At the level of unemployment spells, the most important pattern of nonresponse was total nonresponse: 28.2 % of all spells were not observed for this reason. 11.3 % of spells were not observed by attrition whereas only 2.4 % of spells were right-censored for the same reason. The small percentage of spells right-censored by attrition is a consequence of the high frequency of spells with short duration. Apparently the chance of a spell to be censored increases with its length.

Taxonomy	Frequency	Percent
a Fully observed	5959	55.5
b Censored by attrition	253	2.4
c Not observed by attrition	1216	11.3
d Not observed by total nonresponse	3022	28.2
e Censored by end of follow-up	284	2.7
All	10734	100.0

Table 3: Distribution of taxonomy of unemployment spells

The boxplots in Figure 1 show the distribution of spell length according to the type of spell. For spells right-censored by the end of the follow-up, the duration is recorded only until the censoring time. These spells are therefore excluded from the figure. For spells right-censored by attrition, the whole duration is used. The median of right-censored spells is far above the median of other spells. The median of fully observed spells, 49 days, is close to the median of spells unobserved by attrition, which is 41 days.

Spells unobserved by total nonresponse have a somewhat higher median: 67 days. All spell distributions are heavily skewed towards long durations.

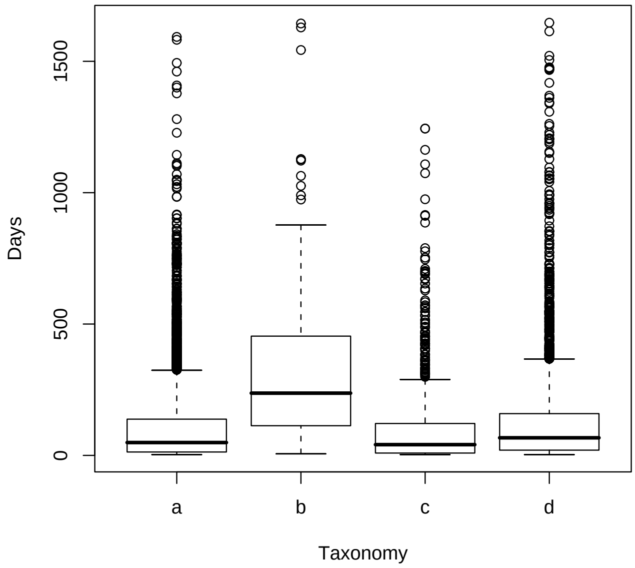

Figure 1: Boxplots of spell length by type of spell.

For analysis purposes, the unemployment spells were grouped into three different sets:

> The *full information* set of spells uses the entire register information without restrictions by nonresponse or attrition.
>
> The *observed information* set of spells is obtained from the full information set of spells by excluding spells unobserved by total nonresponse and attrition and the remaining length of the spells censored by attrition.
>
> Spells by *total respondents*, a subset of observed information spells, belong to persons who have responded in each of the five survey waves.

Estimates from the full information set serve as benchmarks to which estimates from the other two sets are compared. The observed information set of spells corresponds to the set of spells normally available for a survey analyst. A longitudinal analysis comprising n waves is sometimes restricted to persons who have responded in each of the n waves i.e. by discarding attriters. This corresponds to the third set of spells, spells by total respondents. There were 10734 spells in the full information set, 6496 spells in the observed information set and 4066 spells by total responders.

4 Survival analysis in a design-based setting

4.1 Kaplan-Meier estimator

The Kaplan-Meier estimator (Kaplan & Meier 1958) is a nonparametric estimator of the survival function $S(t) = P(T \geq t)$, where T is the event time. Williams (1995) developed an estimator that is appropriate when survival data is obtained from a complex survey. Let $t_i, i = 1, \ldots, n$ be the observed event and censoring times in the sample of size n. In our application, an event is defined as getting employed. Spells ending for other reasons such as retirement, as well as spells ending because of end of follow-up or because of attrition are treated as censored. Let $t_{(1)}, \ldots, t_{(h)}, \ldots, t_{(r)}$ be the ordered event times. The weighted number of observations undergoing an event at $t_{(h)}$ is $D_{(h)} = \sum_{i=1}^{n} I(t_i = t_{(h)})\delta_i w_i$, where w_i is the weight attached to observation i and δ_i is an event indicator that gets value 1 if observation i undergoes an event at time t and 0 otherwise. The weighted number of observations with event or censoring times exceeding $t_{(h)}$ is $N_{(h)} = \sum_{i=1}^{n} I(t_{(h)} \leq t_i)w_i$. The weighted Kaplan-Meier estimator of survival function is defined as

$$\hat{S}(t) = \prod_{h=1}^{r} \left(1 - \frac{D_{(h)}}{N_{(h)}}\right)^{I(t_{(h)} \leq t)}. \quad (1)$$

Variance estimation

4.2 Cox proportional hazards model

Models for event history data are usually constructed by defining the way covariates affect the hazard function. The value of hazard function at time t describes the conditional probability of the event of interest given survival until t. In the Cox proportional hazards model (Cox 1972) the hazard function is specified as a product of two terms:

$$\lambda(t \mid x) = \lambda_0(t)\exp(x\beta), \tag{2}$$

where $\lambda_0(t)$ is a baseline hazard function that depends only on the event time t and $\exp(x\beta)$ defines the way covariates affect the hazard function. One reason for the popularity of the Cox proportional hazards model is the fact that the model parameters β can be estimated without assuming any parametric distribution for the event time variable T. Binder (1992) developed a modification of Cox proportional hazards model that is suitable for survival data obtained from a complex survey.

The model is estimated by maximising a partial likelihood function. For a population of N unemployment spells, the partial likelihood function is defined as

$$PL = \prod_{i=1}^{N} \left[\frac{\lambda(t_i \mid x_i)}{\sum_{j=1}^{N} I(t_i \le t_j)\lambda(t_i \mid x_j)} \right]^{\delta_i}, \tag{3}$$

where t_i is the length of i^{th} spell and δ_i is an event indicator that gets value 1 if spell i is ended by employment and 0 otherwise. $I(t \le t_j)$ indicates whether spell j is still going on at time t. The sum $\sum_{j=1}^{N} I(t \le t_j)$ defines the size of the risk set, i.e. the number of spells still going on at time t. We define time as the time since the start of an unemployment spell; if a person has multiple spells, the "clock" is set to zero at the beginning of each spell. Note that the part of the hazard function that depends on event time only is common to each observation and cancels from the expression. The partial likelihood function can thus be expressed as

$$PL = \prod_{i=1}^{N} \left[\frac{\exp(x_i B)}{\sum_{j=1}^{N} I(t_i \le t_j)\exp(x_j B)} \right]^{\delta_i}, \tag{4}$$

where B is the vector of population regression coefficients. B is determined as the solution to the score equations:

$$\frac{\partial \log PL}{\partial B} = \sum_{i=1}^{N} \delta_i \left[x_i - \frac{\sum_{j=1}^{N} I(t_i \le t_j) x_j \exp(x_j B)}{\sum_{j=1}^{N} I(t_i \le t_j)\exp(x_j B)} \right] = 0. \tag{5}$$

To estimate the population regression coefficient B from a sample of n observations, Binder (1992) proposed the following estimating equations:

$$\sum_{i=1}^{n} w_i \delta_i \left[x_i - \frac{\sum_{j=1}^{n} w_j I(t_i \leq t_j) x_j \exp(x_j \hat{B})}{\sum_{j=1}^{n} w_j I(t_i \leq t_j) \exp(x_j \hat{B})} \right] = 0, \tag{6}$$

where $w_j, j = 1, \ldots, n$ are the weights attached to the sample observations.

Variance estimation

5 Weights used to correct for nonresponse and attrition

Nonresponse in sample surveys is usually handled by weighting methods i.e. by discarding the nonresponding units and and assigning weights to the responding units that attempt to compensate for possible bias entailed by restriction to the respondent sample (Little 1992). If weights include information not included in the analysis and if this information is related both to nonresponse and to the duration of unemployment, then weights may help to reduce bias.

5.1 Weights in ECHP UDB

For the first wave, weights were calculated at Statistics Finland. For the subsequent waves, the common weighting procedure developed at Eurostat was applied.

5.1.1 Weights for the initial wave

Design weights

The design weight of a household is calculated as the inverse of the inclusion probability of the household. The inclusion probability of household k is calculated as

$$\pi_k = \frac{m_k n_1}{M} \times \frac{n_{2,h}}{n_{1,h}}, \tag{7}$$

where m_k is the number of persons aged 15 or more in dwelling unit k; n_1 is the number of dwelling units in the master sample; M is the number of people aged 15 or more in the frame population; $n_{2,h}$ is the number of dwelling units in stratum h in the master sample. The design weights are calculated for each household selected in the sample. The design weight of a household member equals the design weight of his/her household.

Calibrated weights

In calibration, auxiliary information is used to improve the precision of estimates. Calibration modifies weights so that the sample sum of the weighted auxiliary variables equals the population total for that variable, while retaining the weights as close as possible to the original weights. If the auxiliary information is correlated both with the probability of nonresponse and with the study variable, then calibration may also help to reduce nonresponse bias.

Calibrated weights are calculated for interviewed households. The provisional weight a_k of household k used as input in the calibration is

$$a_k = \frac{1}{\pi_k(s_{r,h}/n_{2,h})}, \tag{8}$$

where $s_{r,h}$ is the number of respondent households in stratum h in the sample. The construction of weights is thus a three-stage procedure involving the calculation of design weights, the calculation of stratum-specific nonresponse-adjustment weights and the calculation of adjustment factors (g-weights) due to calibration. The sample of interviewed households was to have the same distribution as the population of households for the following variables: age (5-year categories) and sex, dwelling unit size, region of residence, income liable to state taxation. After calibration, weights were scaled so that the average weight of interviewed households is one. In the first wave, all household members get the weight of his/her household.

5.1.2 Weights for the subsequent waves

The common algorithm to construct weights in the ECHP includes correction for attrition, calibration and scaling. The algorithm is explained in various documents by Eurostat (Eurostat 2000b, Eurostat 2002b, Eurostat 2002c). In the following, we give a summary of the weighting algorithm.

The weighting algorithm provides 3 types of weights: base weights to be used in longitudinal analyses and personal weights and household weights to be used in cross-sectional analyses. Base weights are defined for sample persons only and they represent the basis for adjusting weights from one wave to the next. Personal weights and household weights are derived from base weights. Personal weights allow the inclusion of non-sample persons into cross-sectional analyses. As our analysis is based on sample persons, we describe the construction of base weights only.

The first step in the analysis is to estimate probabilities of being resident i.e. being a member of an interviewed household and of response:

- $P1$ probability for an individual being resident in current wave t given he/she was resident in previous wave
- $P2$ probability for an individual for having been resident in previous wave given he/she is resident in current wave
- $P3$ probability for an individual being interviewed in current wave given he/she is eligible for interview

Logistic regression is used to estimate these probabilities. Explanatory variables are selected from the following variables collected at the previous year's interview: region, household status (whether a split-off household), number of arrivals or departures from the household, main source of income, number of economically active persons in the household, household size, tenure status, sex, age and equivalised income. The base weights from the previous year are then multiplied by the ratio of $P1$ and $P2$ to obtain provisional weights. For sample person i the provisional weight a_i is

$$a_i = w_i \times \frac{P1}{P2}, \tag{9}$$

where w_i is the base weight from previous wave. The provisional weight a_k of each household is calculated as the average of provisional weights of sample persons in that household:

$$a_k = \frac{\sum_{i=1}^{n_k} a_i}{n_k}, \tag{10}$$

where n_k is the number of sample persons in household k. These provisional household weights are then calibrated using household size, region and cross-classification of age and sex as auxiliary information. In order to calculate weights of interviewed sample persons the calibrated household weight was assigned to each interviewed sample person and divided by the probability of being interviewed, if eligible (P3). The weights were scaled so that the average weight of interviewed sample persons is one.

5.2 Alternative weights

Our alternative weighting strategy consists of calculating inverse probability of censoring (IPC) adjusted weights of Robins (1993) that aim to correct for dependent censoring. Loosely speaking, censoring is dependent if it is related to the process under study. In our application, it may very well be that censoring due to attrition is dependent. This would be the case if individuals with low employment probability droppped out of the study more probably than others. Sometimes it can be assumed that the censoring and event times are independent, given a set of covariates. These covariates may then be used to construct IPC adjusted weights. The IPC weighted estimates can then correct for bias due to dependent censoring attributable to these covariates. The IPC adjusted weights of observation i are defined as follows:

$$w_i(t)^{-1} = \pi_k \times G(t \mid x_i), \text{ where} \tag{11}$$

π_k is the inclusion probability of the household related to observation i. $G(t \mid x_i)$ is the conditional probability of having remained uncensored by attrition until time t, given covariates and defined for the observations in the sample:

$$G(t \mid x_i) = P(C \geq t \mid x_i, R_i = 1), \tag{12}$$

where C is the censoring time and R_i is a sample inclusion indicator that gets value 1 if observation i is in the sample and 0 otherwise. Note that for each observation i, only the shorter of the censoring and event times is observed: $t_i = min(T_i, C_i)$. $G(t \mid x_i)$ can be estimated on the basis of a Cox proportional hazards model with censoring by attrition as the event of interest and x_i as the covariates.

Note that the weights $w_i(t)$ are time-varying and they get a new value each time a censoring occurs in the sample. In case there are both events and censorings occurring at the same time, censorings are assumed to occur after events.

In order to be effective, the covariates used in the IPC adjustment should explain both the probability of censoring and of getting employed. Therefore, the covariates in the censoring model were chosen among those used to model the hazard of getting employed. Only covariate groups containing covariates significant at the 10 % level were retained in the censoring model. The models were estimated separately for women and men as the final analyses were also conducted in this manner. The variables in the censoring model for women were: proportion of unemployment time and year dummies indicating the starting year of the unemployment spell. The covariates included in the censoring model for men were, in addition to the above mentioned covariates: the statistical grouping of municipalities and area dummies. The variables are described in section 6.3.

6 Results

6.1 Estimation strategies

A longitudinal survey data set usually contains one or more weights for each survey wave. One has then to decide which wave weights to use in a longitudinal analysis. In an analysis involving waves 1 to t, it is sometimes recommended to use the wave t weight (see for example Kalton & Brick 2000, Eurostat 2003). However, this strategy involves the loss of unemployment spells by persons who have attrited from the panel during waves 2 and t. This strategy discards a part of available information and may increase the possible bias due to nonignorable attrition. Roberts and Kovacevic (2001) suggest the use of the first year weight or the weight from the year when the spell began. These weighting strategies enable to retain the spells by attriters in the analysis. However, first year weights are not able to correct for possible bias due to attrition.

We use all the 3 weighting strategies combined with two different sets of unemployment spells: observed information set of spells and total respondents set of spells. As wave t weights are not available for all spells in the observed information set, we have altogether 5 different estimation strategies involving different combinations of spell sets and weights. Our 6^{th} estimation strategy involves the use of IPC weights that we have specifically constructed for the analysis of unemployment duration. These weights aim to correct for right-censoring due to attrition and are therefore applicable in the observed information set of spells only.

We calculate also design-weighted estimates in the full information, observed information and total respondents sets of spells. The design-weighted full information estimates serve as benchmarks to which the other estimates are compared. The comparison of design-weighted observed information estimates to full information estimates show the effect of nonresponse and attrition. The design-weighted total respondents estimates show whether the discarding of spells by attriters results in additional bias. The comparison of the 6 estimation strategies with the design-weighted estimates shows how the weights aiming to correct for nonresponse and attrition are performing.

The estimation was performed by Sudaan software (Research Triangle Institute 2004). The sample design was approximated by Sudaan WR option. The estimation procedure is able to take into account unequal weighting, stratification, and clustering of spells into individuals. The clustering of individuals into households was ignored as a majority, 73 %, of individuals in the unemployment spell data lived in households without other unemployed. Sudaan estimates the variances by Taylor linearization using the between cluster within stratum variance estimator. The IPC weighted Kaplan-Meier estimates were calculated by R (R Development Core team 2005). The variance estimation methodology for IPC weighted Kaplan-Meier estimates in the longitudinal survey context is undeveloped (Lawless 2003). Therefore, no variance estimates are provided.

6.2 Kaplan-Meier estimates

The Kaplan-Meier estimates are shown in figures 2 to 5. Estimates of survival functions along with their standard errors at time points $t = 3, 100, 200, 300, \ldots$ are shown in Appendix A. The plots are truncated at 1000 days as there are very few events occurring after 1000 days. The estimates are calculated separately for women and men. Design weights are denoted by dweight, first year weights by weight1, weights from the starting year of the unemployment spell by weight2 and last year weights by weight3.

Figure 2 shows how the observed information estimates are performing in the subgroup of women. The bias due to nonresponse and attrition is quite small in this subgroup. First year weights and weights from the starting year of the unemployment spell produce almost identical estimates which are a little bit better than design-weighted estimates. The IPC correction has virtually no effect at all in the estimates. Therefore, the IPC weighted estimates are omitted from Figure 2 and only shown in Appendix A, Table A.

The use of total respondents only increases the bias in the subgroup of women (Figure 3). Weights from the starting year of the unemployment spell and last year weights "overcorrect" the estimates both at durations less than 300 days and exceeding 800 days.

In the subgroup of men the bias due to nonresponse and attrition is larger than in the subgroup of women (Figure 4). Nonresponse weighting has virtually no effect at all: both first year weights and weights from the starting year of the unemployment spell produce estimates almost identical to design-weighted estimates. Also in the subgroup of men, IPC weights produce estimates that are very close to to design-weighted estimates. The IPC weighted estimates are shown in Appendix A, Table A.

By comparing the design-weighted estimates in the subgroup of men we see that restricting the analysis to total respondents only does not cause any additional bias in the estimates (Table X in Appendix A). Figure 5 shows that first year weights do not have an effect in the estimates. Weights from the starting year of the unemployment spell shift estimates even somewhat further from the true values. Last year weights are performing disastrously at durations exceeding 300 days: the estimates of survival function are shifted further from the true values by 5 percentage points or more.

6.3 Estimates from Cox regression

Before discussing the estimation results, we briefly comment on the construction of the explanatory variables used in the model. The variables are spell-specific and they are usually measured at the end of the year preceding the start of the unemployment spell. Age is measured in years. Level of education divides individuals into three classes. Basic education corresponds to the completion of comprehensive school. Upper secondary education comprises matriculation examination and upper secondary vocational education. Higher education comprises, for example, vocational college education and university education. Proportion of unemployment time measures the share of a person's follow-up time (since 1 January 1995) spent in unemployment before the spell in question. The statistical grouping of municipalities divides municipalities into urban, semi-urban and rural ones by the proportion of the population living in urban settlements and by the population of the largest urban settlement. The area dummies are based on the NUTS3 classification of regions. Earnings-related unemployment benefit indicates

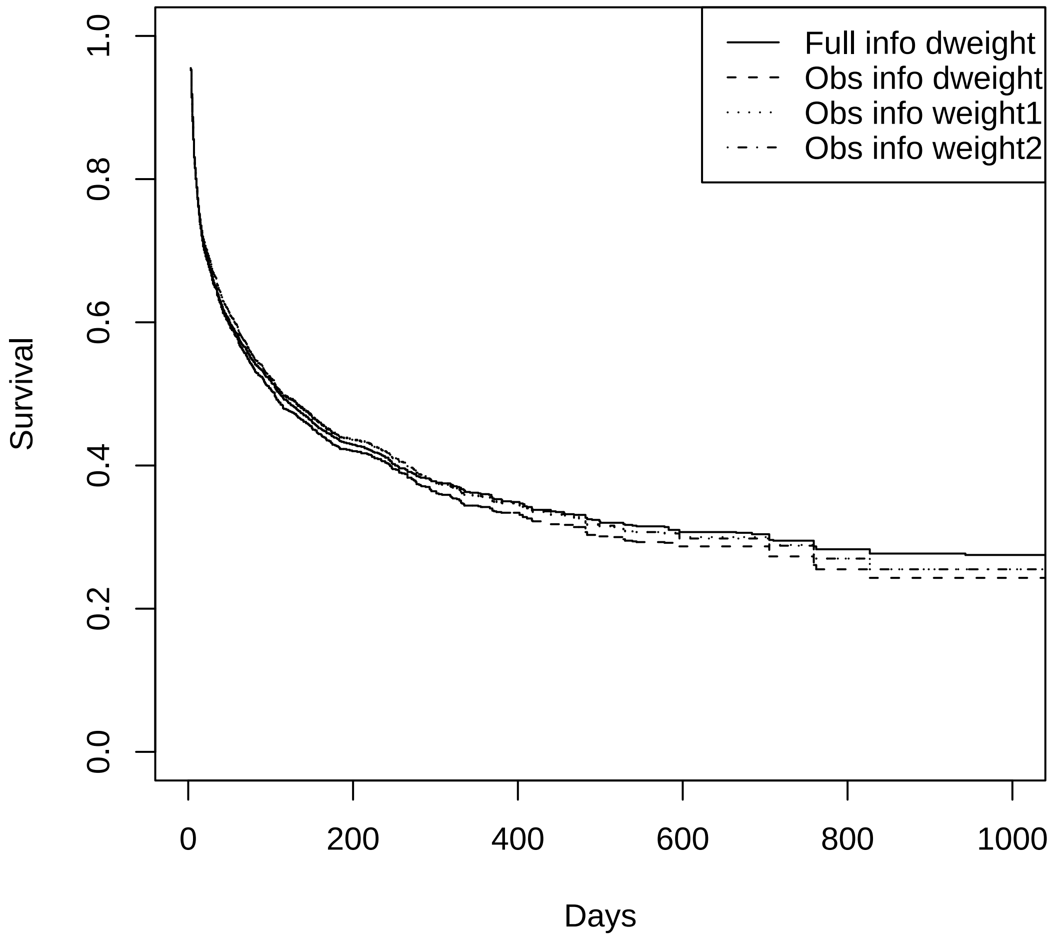

Figure 2: Kaplan-Meier estimates of survival function for women. Observed information set of unemployment spells. Design weights are denoted by dweight, first year weights by weight1 and weights from the starting year of the unemployment spell by weight2.

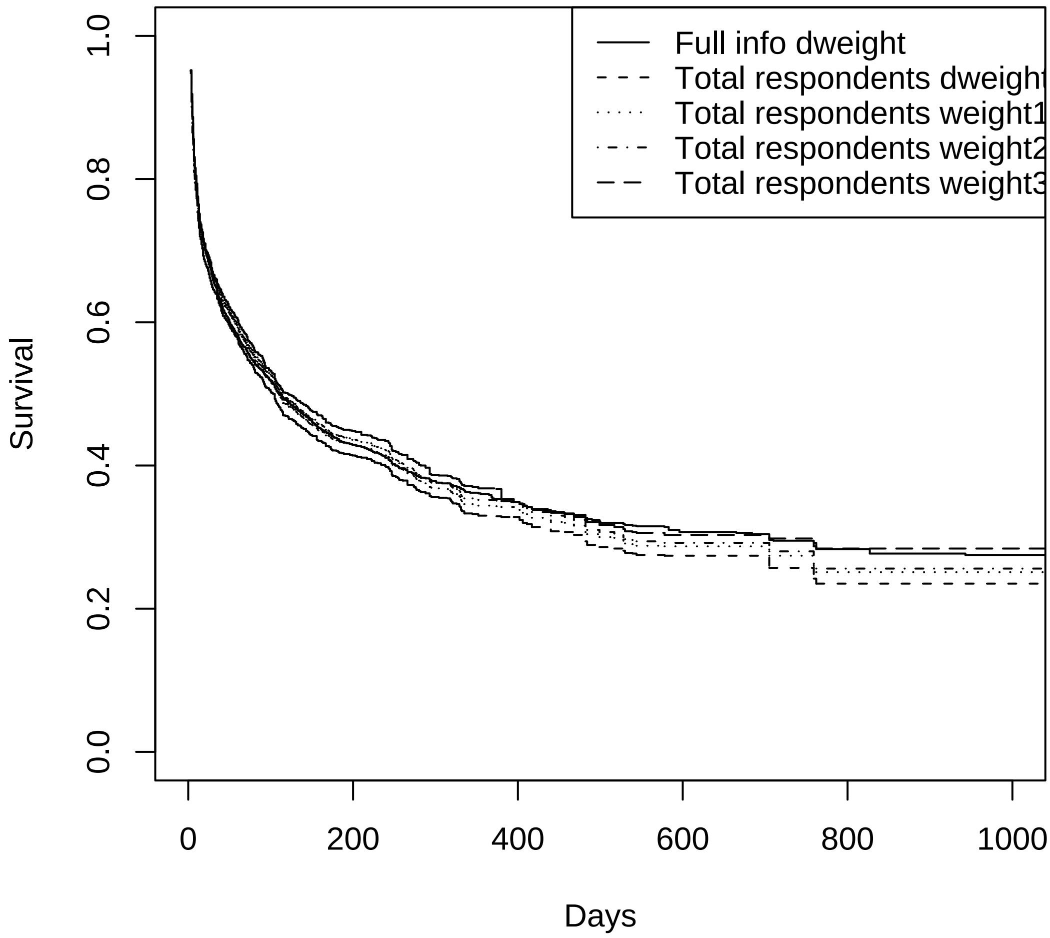

Figure 3: Kaplan-Meier estimates of survival function for women. Total respondents set of unemployment spells. Design weights are denoted by dweight, first year weights by weight1, weights from the starting year of the unemployment spell by weight2 and last year weights by weight3.

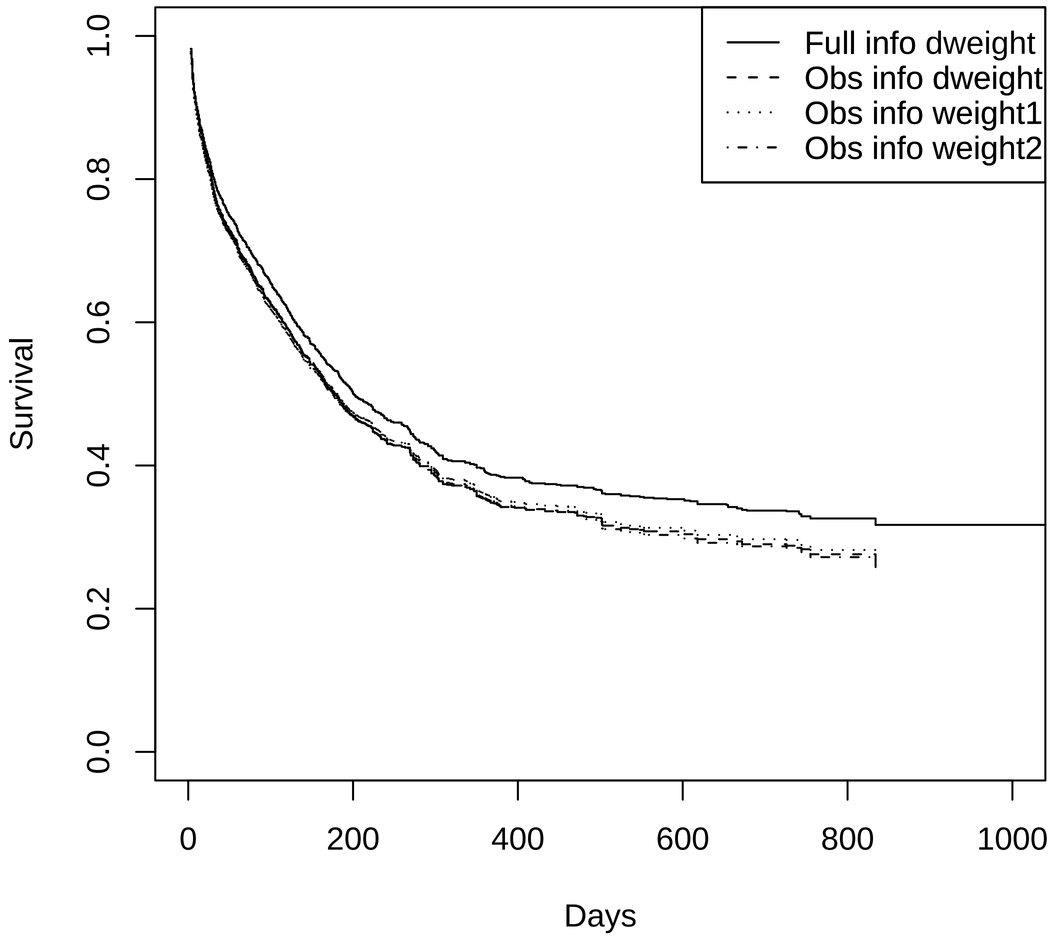

Figure 4: Kaplan-Meier estimates of survival function for men. Observed information set of unemployment spells. Design weights are denoted by dweight, first year weights by weight1 and weights from the starting year of the unemployment spell by weight2.

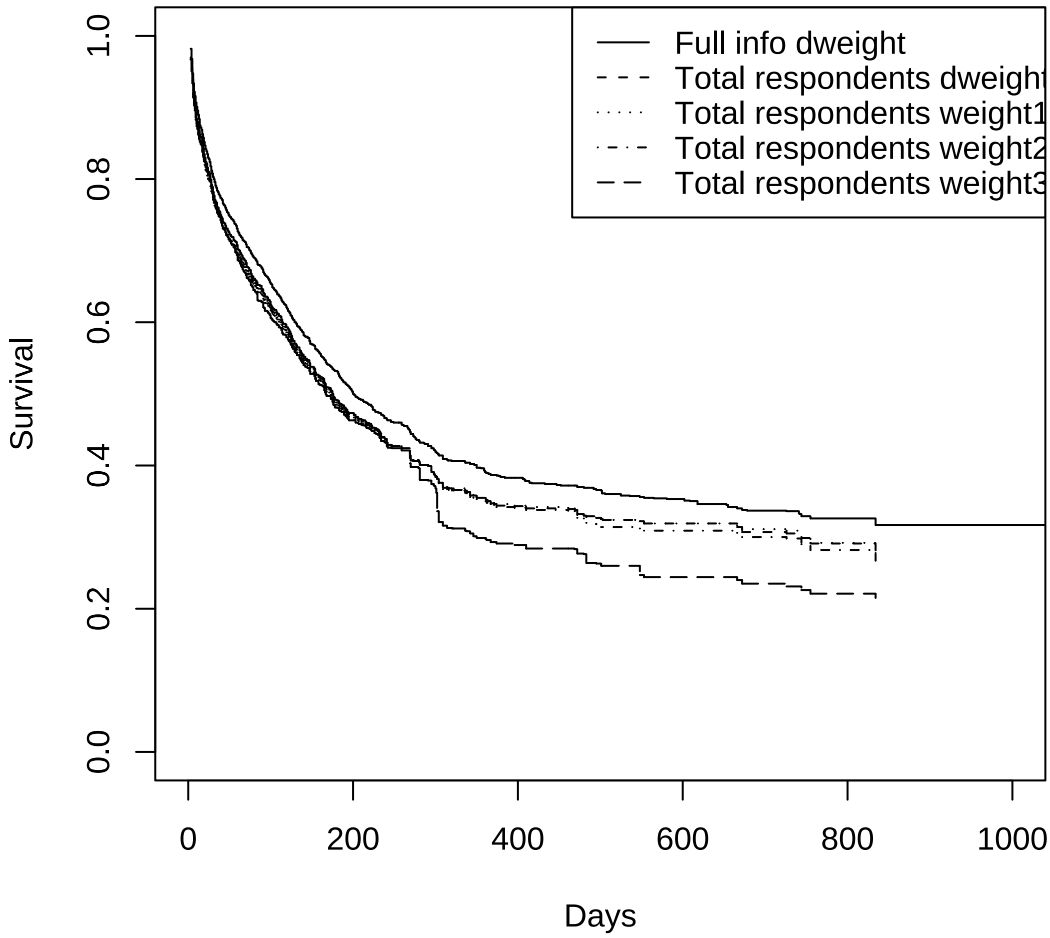

Figure 5: Kaplan-Meier estimates of survival function for men. Total respondents set of unemployment spells. Design weights are denoted by dweight, first year weights by weight1, weights from the starting year of the unemployment spell by weight2 and last year weights by weight3.

whether a person has received this kind of benefit at the starting year of the unemployment spell. Year dummies indicate the starting year of the unemployment spell. Continuous variables age and proportion of unemployment time are transformed to measure deviation from variable mean.

The estimation results from Cox regression models for women are shown in table 4 and for men in table 5. The Efron's (1977) approximation of partial likelihood was used to handle tied event times. The overall impression from the tables is that none of the weights used are very helpful in reducing bias. However, it is difficult to compare the models because of a multitude of regression coefficients. We therefore computed quadratic distances of estimated regression coefficient vectors by using the following formula:

$$d(x, y) = (x - y)^T S^{-1}(x - y), \tag{13}$$

where x is the vector of full information coefficient estimates, y is the vector of coefficient estimates from the model being evaluated and S^{-1} is the inverse of the estimated covariance matrix of y.

It is clear from Table 4 that the observed information estimates are superior to total respondents estimates. First year weights bring the estimates somewhat closer to full information estimates whereas weights from the starting year of the unemployment spell increase the distance between full information estimates and observed information estimates. Using total respondents only increases the bias in the model estimates. Weighting improves estimates slightly. The three weights perform equally well in terms of distance of model estimates from full information estimates.

Also in the subgroup of men the observed information estimates are superior to total respondents estimates. Both first year weights and weights from the starting year of the unemployment spell bring estimates closer to full information estimates, the latter performing slightly better. All weights are performing badly in the total respondents set of spells. The weights aiming to correct for nonresponse and attrition shift estimates further from full information values. Last year weights are again performing disastrously.

7 Discussion

In this paper, we studied the effectiveness of re-weighting methods in correcting for bias due to nonresponse and attrition in the analysis of unemploy-

	Full information	Observed information			Total responders			
	dweight	dweight	weight1	weight2	dweight	weight1	weight2	weight3
Variable	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*
Age	**0.081** (0.040)	**0.111** (0.055)	*0.090* (0.051)	**0.105** (0.051)	0.082 (0.060)	0.070 (0.056)	0.087 (0.057)	0.089 (0.057)
Age squared	**-0.001** (0.001)	**-0.002**(0.001)	*-0.001* (0.001)	**-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Upper sec. educ.	0.058 (0.170)	0.058 (0.217)	0.118 (0.223)	0.117 (0.213)	0.118 (0.245)	0.145 (0.265)	0.139 (0.264)	0.320 (0.267)
Higher education	**0.512** (0.207)	**0.632** (0.247)	**0.652** (0.246)	**0.645** (0.238)	**0.719** (0.248)	**0.697** (0.256)	**0.674** (0.260)	**0.614** (0.271)
Prop. of ue time	**0.009** (0.003)	**0.011** (0.003)	**0.011** (0.003)	**0.011** (0.003)	**0.014** (0.004)	**0.015** (0.004)	**0.014** (0.004)	**0.012** (0.004)
S-U municipality	0.187 (0.197)	0.236 (0.245)	0.128 (0.244)	0.100 (0.234)	0.308 (0.278)	0.183 (0.295)	0.185 (0.282)	-0.021 (0.255)
Rural municipality	0.015 (0.141)	-0.048 (0.191)	-0.003 (0.195)	-0.005 (0.193)	-0.018 (0.220)	0.026 (0.226)	0.035 (0.229)	-0.148 (0.238)
Southern Finland	0.183 (0.276)	0.176 (0.387)	0.139 (0.403)	0.157 (0.400)	-0.091 (0.456)	-0.155 (0.460)	-0.150 (0.460)	-0.160 (0.443)
Eastern Finland	0.035 (0.327)	0.071 (0.456)	-0.067 (0.443)	-0.084 (0.426)	0.089 (0.519)	-0.073 (0.514)	-0.113 (0.499)	0.007 (0.467)
Mid-Finland	0.057 (0.272)	0.071 (0.388)	0.063 (0.401)	0.069 (0.395)	-0.180 (0.474)	-0.202 (0.477)	-0.208 (0.472)	-0.137 (0.461)
Northern Finland	0.289 (0.284)	0.342 (0.391)	0.350 (0.402)	0.319 (0.403)	0.014 (0.449)	0.060 (0.448)	-0.024 (0.448)	-0.085 (0.438)
ER ue benefit	**0.505** (0.144)	*0.330* (0.170)	*0.313*(0.170)	*0.297* (0.165)	**0.427** (0.212)	*0.394* (0.210)	*0.375* (0.208)	**0.395** (0.182)
Year 1996	0.017 (0.101)	0.003 (0.116)	0.020 (0.116)	0.015 (0.115)	-0.157 (0.143)	-0.171 (0.136)	-0.158 (0.136)	-0.201 (0.156)
Year 1997	0.023 (0.118)	0.048 (0.122)	0.043 (0.124)	0.028 (0.125)	-0.091 (0.149)	-0.107 (0.146)	-0.117 (0.146)	-0.271 (0.182)
Year 1998	**0.352** (0.160)	*0.306* (0.175)	0.287 (0.193)	0.265 (0.189)	0.025 (0.223)	-0.012 (0.237)	-0.024 (0.234)	-0.086 (0.224)
Year 1999	**0.371** (0.169)	0.272 (0.186)	0.264 (0.202)	0.235 (0.199)	-0.000 (0.242)	-0.048 (0.248)	-0.098 (0.241)	-0.111 (0.232)
Dist. from Full info estimates		4.226	3.639	4.521	10.496	9.658	9.207	9.396
# (spells)	5953		3695			2303		
# (events)	2991		1888			1196		

Estimates significant at 5 % (10 %)level are displayed in **boldface** (*italic*).

Table 4: Design-based estimates of Cox regression model: women

	Full information	Observed information			Total responders			
	dweight	dweight	weight1	weight2	dweight	weight1	weight2	weight3
Variable	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*	$\hat{\beta}$ *s.e.*
Age	**0.072** (0.035)	**0.090** (0.032)	**0.094** (0.032)	**0.079** (0.033)	**0.128** (0.042)	**0.140** (0.042)	**0.125** (0.044)	**0.086** (0.041)
Age squared	**-0.001** (0.001)	**-0.001**(0.000)	**-0.001** (0.000)	**-0.002** (0.000)	**-0.002** (0.001)	**-0.002** (0.001)	**-0.002** (0.001)	*-0.001* (0.001)
Upper sec. educ.	-0.040 (0.146)	-0.070 (0.175)	-0.098 (0.205)	-0.098 (0.196)	-0.277 (0.243)	-0.354 (0.267)	-0.326 (0.254)	-0.205 (0.207)
Higher education	**0.435** (0.202)	*0.420* (0.237)	0.427 (0.264)	*0.436* (0.251)	0.264 (0.314)	0.214 (0.337)	0.249 (0.315)	0.345 (0.262)
Prop. of ue time	0.001 (0.002)	**0.005** (0.003)	**0.005** (0.003)	*0.005* (0.003)	**0.007** (0.003)	**0.007** (0.003)	**0.007** (0.003)	**0.009** (0.003)
S-U municipality	0.256 (0.162)	0.182 (0.223)	0.247 (0.251)	0.253 (0.248)	0.167 (0.244)	0.262 (0.247)	0.264 (0.246)	0.276 (0.236)
Rural municipality	**0.410** (0.162)	0.010 (0.147)	0.121 (0.159)	0.129 (0.152)	0.041 (0.201)	0.093 (0.208)	0.088 (0.208)	-0.073 (0.176)
Southern Finland	**0.446** (0.148)	*0.317* (0.169)	0.287 (0.180)	0.276 (0.172)	0.132 (0.219)	0.063 (0.230)	0.072 (0.221)	0.095 (0.204)
Eastern Finland	*0.312* (0.167)	*0.346* (0.186)	*0.342* (0.201)	*0.343* (0.194)	0.080 (0.258)	0.055 (0.271)	0.037 (0.265)	-0.004 (0.249)
Mid-Finland	0.307 (0.190)	*0.412* (0.248)	0.386 (0.273)	0.295 (0.268)	0.433 (0.308)	0.355 (0.337)	0.264 (0.334)	0.043 (0.267)
Northern Finland	**0.563** (0.236)	**0.712** (0.291)	**0.757** (0.331)	**0.758** (0.300)	**0.923** (0.337)	**0.941** (0.353)	**0.955** (0.324)	**0.975** (0.263)
ER ue benefit	0.158 (0.148)	0.112 (0.195)	0.091 (0.225)	0.134 (0.222)	0.068 (0.254)	0.027 (0.269)	0.060 (0.266)	0.026 (0.228)
Year 1996	0.078 (0.115)	0.060 (0.130)	0.026 (0.137)	0.032 (0.138)	-0.019 (0.156)	-0.036 (0.165)	-0.041 (0.168)	-0.064 (0.143)
Year 1997	0.073 (0.180)	-0.125 (0.214)	-0.172 (0.243)	-0.144 (0.240)	-0.321 (0.276)	-0.359 (0.294)	-0.335 (0.283)	-0.332 (0.232)
Year 1998	0.197 (0.191)	0.156 (0.206)	0.110 (0.234)	0.111 (0.230)	-0.488 (0.242)	-0.077 (0.259)	-0.114 (0.254)	-0.178 (0.235)
Year 1999	0.224 (0.247)	-0.024 (0.261)	-0.062 (0.299)	-0.006 (0.288)	-0.269 (0.334)	-0.310 (0.358)	-0.339 (0.336)	-0.397 (0.302)
Dist. from Full info estimates		14.281	13.644	12.699	22.886	23.527	23.959	32.537
# (spells)	4781	3376			1763			
# (events)	2120	1621			809			

Estimates significant at 5 % (10 %)level are displayed in **boldface** (*italic*).

Table 5: Design-based estimates of Cox regression model: men

ment duration. We used the Finnish subset of ECHP data complemented by a longitudinal register data. The register data provides us with information on unemployment spells as well as covariates both for respondents and nonrespondents. The survey data was used only to obtain the result of the interview and information about the design of the sample.

The analyses were conducted separately for three different data sets. The full information set of unemployment spells uses the entire register information without restrictions by nonresponse or attrition. The observed information set of unemployment spells corresponds to the set of spells normally available for a survey data analyst in the presence of nonresponse and attrition. A longitudinal analysis comprising of waves 1 to t is sometimes restricted to persons who have responded in each wave i.e. by discarding attriters. Unemployment spells by these total respondents constitute the third data set. Estimates from the full information set serve as benchmarks to which estimates from the other two sets were compared.

In the first phase of the study, weights available in the ECHP UDB were used to produce design-based Kaplan-Meier estimates and estimates from the Cox proportional hazards model. The analyses were conducted separately for men and women. In the second phase, we used inverse probability of censoring (IPC) adjusted weights that were specifically created for the analysis of unemployment duration.

According to the estimation results, the bias due to nonresponse and attrition is larger in the subgroup of men than in the subgroup of women. Also, the observed information estimates are closer to full information estimates than estimates based on total respondents. Among observed information estimates, estimates calculated by using first year UDB weights and estimates calculated by using UDB weights from the starting year of the unemployment spell are close to each other. However, neither of the weighting strategies is able to remove bias: at best, they produce estimates that are slightly better than design-weighted estimates. In the subgroup of men, using total respondents set of unemployment spells and weights from the last wave produce badly biased results. This result is remarkable as this is the estimation strategy recommended in ECHP UDB manual (Eurostat 2003). Our results stress the importance of using all the information available in the sample. The IPC weighted Kaplan-Meier estimates were almost identical to design-weighted estimates. The calculation of IPC weighted estimates of Cox proportional hazards model is in progress so the results are not reported here.

According to the study by Pyy-Martikainen and Rendtel (2006), nonresponse at the initial wave biases estimates more than attrition. Hence, it is not so surprising that weights from the starting year of the unemployment spell are not doing better than weights from the initial wave. It is the nonresponse at the initial wave that needs to be corrected in order to achieve unbiased estimates. The uneffectiveness of IPC weighting points to the same direction and confirms our earlier results on effects of censoring (Pyy-Martikainen & Rendtel 2003).

Our results stress the importance of minimising nonresponse at the start of the panel. However, some extent of nonresponse and attrition is inevitable. One should then put all the efforts to the careful construction of initial wave weights, as these weights form the basis of constructing weights for all the subsequent waves.

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A Kaplan-Meier estimates of survival function

	Full information	Observed information				Total respondents			
	dweight	dweight	weight1	weight2	IPC weight	dweight	weight1	weight2	weight3
t	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$
3	0.952 (0.007)	0.953 (0.010)	0.955 (0.010)	0.955 (0.010)	0.953	0.948 (0.014)	0.950 (0.015)	0.951 (0.015)	0.952 (0.014)
100	0.518 (0.026)	0.506 (0.034)	0.522 (0.032)	0.523 (0.032)	0.505	0.503 (0.044)	0.520 (0.042)	0.527 (0.041)	0.532 (0.039)
200	0.429 (0.023)	0.420 (0.031)	0.436 (0.030)	0.436 (0.029)	0.420	0.414 (0.039)	0.429 (0.038)	0.436 (0.037)	0.448 (0.037)
300	0.378 (0.021)	0.364 (0.028)	0.378 (0.027)	0.378 (0.026)	0.364	0.356 (0.035)	0.369 (0.034)	0.376 (0.036)	0.387 (0.034)
400	0.349 (0.021)	0.334 (0.027)	0.347 (0.026)	0.348 (0.026)	0.334	0.328 (0.034)	0.342 (0.033)	0.349 (0.033)	0.349 (0.033)
500	0.320 (0.021)	0.301 (0.027)	0.315 (0.026)	0.316 (0.026)	0.302	0.286 (0.034)	0.300 (0.033)	0.307 (0.032)	0.317 (0.032)
600	0.307 (0.022)	0.287 (0.027)	0.300 (0.026)	0.298 (0.026)	0.287	0.274 (0.033)	0.287 (0.032)	0.292 (0.032)	0.303 (0.032)
700	0.304 (0.022)	0.287 (0.027)	0.300 (0.026)	0.298 (0.026)	0.287	0.274 (0.033)	0.287 (0.032)	0.292 (0.032)	0.303 (0.032)
800	0.283 (0.023)	0.255 (0.028)	0.270 (0.028)	0.270 (0.028)	0.253	0.235 (0.034)	0.251 (0.033)	0.256 (0.034)	0.284 (0.033)
900	0.277 (0.023)	0.243 (0.029)	0.255 (0.030)	0.255 (0.029)	0.240	0.235 (0.034)	0.251 (0.033)	0.256 (0.034)	0.284 (0.033)
1000	0.275 (0.023)	0.243 (0.029)	0.255 (0.030)	0.255 (0.029)	0.240	0.235 (0.034)	0.251 (0.033)	0.256 (0.034)	0.284 (0.033)
1100	0.275 (0.023)	0.243 (0.029)	0.255 (0.030)	0.255 (0.029)	0.240	0.235 (0.034)	0.251 (0.033)	0.256 (0.034)	0.284 (0.033)
1200	0.275 (0.023)	0.243 (0.029)	0.255 (0.030)	0.255 (0.029)	0.240	0.235 (0.034)	0.251 (0.033)	0.256 (0.034)	0.284 (0.033)
1300	0.246 (0.030)	0.210 (0.042)	0.211 (0.048)	0.211 (0.048)	0.208	0.199 (0.047)	0.202 (0.054)	0.206 (0.055)	0.214 (0.065)
1400	0.235 (0.031)								

Table 6: Design-based estimates of survival function: women

	Full information	Observed information				Total respondents			
	dweight	dweight	weight1	weight2	IPC weight	dweight	weight1	weight2	weight3
t	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	$\hat{S(t)}$ *s.e.*	
3	0.982 (0.006)	0.978 (0.009)	0.975 (0.011)	0.976 (0.011)	0.978	0.970 (0.014)	0.967 (0.017)	0.967 (0.166)	0.968(0.015)
100	0.654 (0.019)	0.625 (0.024)	0.624 (0.028)	0.618 (0.027)	0.625	0.624 (0.034)	0.620 (0.040)	0.617 (0.039)	0.606(0.039)
200	0.500 (0.019)	0.469 (0.025)	0.474 (0.027)	0.468 (0.027)	0.468	0.473 (0.033)	0.471 (0.037)	0.468 (0.036)	0.463(0.038)
300	0.419 (0.019)	0.385 (0.024)	0.394 (0.026)	0.390 (0.026)	0.383	0.384 (0.031)	0.386 (0.034)	0.386 (0.034)	0.368(0.032)
400	0.383 (0.019)	0.341 (0.024)	0.349 (0.026)	0.343 (0.026)	0.339	0.343 (0.031)	0.344 (0.034)	0.341 (0.033)	0.289(0.036)
500	0.366 (0.019)	0.327 (0.024)	0.333 (0.026)	0.324 (0.025)	0.325	0.327 (0.031)	0.327 (0.033)	0.318 (0.033)	0.263(0.035)
600	0.353 (0.019)	0.308 (0.024)	0.313 (0.026)	0.303 (0.026)	0.306	0.319 (0.031)	0.319 (0.033)	0.309 (0.033)	0.244(0.038)
700	0.337 (0.020)	0.290 (0.025)	0.297 (0.027)	0.287 (0.027)	0.287	0.307 (0.031)	0.311 (0.033)	0.300 (0.033)	0.235(0.037)
800	0.326 (0.021)	0.276 (0.026)	0.282 (0.028)	0.272 (0.027)	0.275	0.291 (0.032)	0.292 (0.034)	0.282 (0.034)	0.221(0.036)
900	0.317 (0.022)	0.260 (0.029)	0.268 (0.030)	0.258 (0.029)	0.259	0.272 (0.034)	0.276 (0.036)	0.267 (0.035)	0.208(0.036)
1000	0.317 (0.022)								
1100	0.314 (0.022)								
1200									
1300									
1400									

Table 7: Design-based estimates of survival function: men