VERSITA

Journal of Official Statistics, Vol. 30, No. 1, 2014, pp. 23–43, http://dx.doi.org/10.2478/jos-2014-0002

Dropout Rates and Response Times of an Occupation Search Tree in a Web Survey

Kea Tijdens[1]

Occupation is key in socioeconomic research. As in other survey modes, most web surveys use an open-ended question for occupation, though the absence of interviewers elicits unidentifiable or aggregated responses. Unlike other modes, web surveys can use a search tree with an occupation database. They are hardly ever used, but this may change due to technical advancements. This article evaluates a three-step search tree with 1,700 occupational titles, used in the 2010 multilingual *WageIndicator* web survey for UK, Belgium and Netherlands (22,990 observations). Dropout rates are high; in Step 1 due to unemployed respondents judging the question not to be adequate, and in Step 3 due to search tree item length. Median response times are substantial due to search tree item length, dropout in the next step and invalid occupations ticked. Overall the validity of the occupation data is rather good, 1.7-7.5% of the respondents completing the search tree have ticked an invalid occupation.

Key words: Job title; CAWI; occupation database; ISCO; paradata; time stamps; respondent's interest; respondent's age and education; total survey dropout; validity.

1. Introduction

The increasing popularity of web surveys as a new mode of data collection has fundamentally challenged traditional survey methodology. This article focuses on one feature of web surveys, namely how web surveys can substitute the absent interviewer for the survey question concerning occupations. Occupation is a key variable in socioeconomic research, used in studies on labour force composition, social stratification, gender segregation, skill mismatch, and many others. In web surveys the question about occupation is judged risky, as is for example noted by Statistics Netherlands in an exploration of the use of web surveys for their Labour Force Survey (Van der Laan and Van Nunspeet 2009). The authors' worries relate to, among others, breaks in the time series in the measurement of occupations due to the use of different survey modes. They aim to make improvements before using a web survey for their Labour Force Survey. In September 2011, Eurostat organised a workshop on data collection for social surveys using multiple modes, focusing on the measurement of occupations in web surveys among

[1] University of Amsterdam, Amsterdam Institute for Advanced Labour Studies (AIAS), Postbus 94025 1090 GA, Amsterdam, The Netherlands. Email: K.G.Tijdens@uva.nl
Acknowledgments: This article builds on research work done for the EU-funded FP6 project EurOccupations (no 028987, 2006-2009, www.euroccupations.org) and for the *WageIndicator* web survey on work and wages (www.wageindicator.org). The author thanks the editor and three anonymous referees for their valuable comments on earlier versions of this article. The WageIndicator Foundation is gratefully acknowledged for providing access to their database and Maarten van Klaveren for language editing. The author would like to acknowledge the contribution of WEBDATANET [COST Action IS1004].

others. As in other survey modes, most web surveys use an Open-Ended Question (OEQ) for the occupation question. Yet several drawbacks are associated with this OEQ, as will be discussed in this article.

A unique feature of web surveys is that they allow for a closed survey question on occupation, using a search tree and an underlying database of occupations. Despite this, search trees are hardly used in web surveys, although recent techniques such as text string matching, single page filtering and Application Programming Interface (API) as well as an increasing use of multi-country surveys may favour the use of a closed survey question in web surveys over that of an OEQ. This stresses the need for a data quality assessment of occupation search trees in web surveys that is not available to date. This article investigates the dropout rate, the response time and the validity of the ticked occupation in a search tree in the continuous, worldwide *WageIndicator* web survey, using the World database of occupations (WISCO) designed by the author for use in this web survey. Section 2 reviews the ISCO international occupational classifications and the pros and cons of the measurement of occupations in web surveys (CAWI) and in the three other survey modes (PAPI, CATI, and CAPI). This section also details the WISCO search tree and database of occupations. Section 3 reviews explanations for dropout rates and response times, presents hypotheses and details the data used. The results of the analyses concerning the dropout rates during search tree completion, the response time and the validity of the occupation data are discussed in Section 4. The article ends with conclusions and discussion (Section 5).

2. Reviewing the Measurement of Occupations

2.1. The ISCO Occupational Classification

A number of industrialised countries have their own occupational classifications, such as the US, the UK, Germany, the Netherlands, and France. To facilitate cross-country comparisons, Eurostat requires the National Statistical Offices of the EU countries to deliver the occupation variable in their labour force data using the International Standard Classification of Occupations (ISCO). For more than half a century the ISCO has been issued by the International Labour Organisation (ILO), a United Nations organisation (Hunter 2009). ISCO provides a hierarchical classification system with four levels. The ISCO-08 update is increasingly being adopted worldwide. The European Union (2009) has adopted ISCO-08 as its occupational classification.

In ISCO-08 job titles with the same set of tasks and duties performed by one person are aggregated into 433 ISCO four-digit occupation units, which on the basis of similarities of tasks and duties are grouped into three- and two-digit groups. In turn, the latter are grouped into nine one-digit groups on the basis of four skill levels (Greenwood 2004). Although Eurostat has gone to great effort to encourage cross-country discussions about coding problems, an empirical underpinning of the similarity of occupation coding across countries is still lacking. The more disaggregated the hierarchical level, the larger the problem. Elias and McKnight (2001) identify several problems in multi-country datasets and call for the harmonisation of survey questions, the adoption of common coding procedures and a common understanding of the conceptual basis of ISCO, in particular its skill concept. They stress the need to undertake studies for validity testing of occupations measurement. Apart from the Eurostat discussion platform for National Statistical Offices, hardly any cross-country studies have investigated whether similar job titles are coded into the same ISCO-08 four-digit level.

2.2. *The Open Response Formats in PAPI, CATI, CAPI and CAWI*

Many socioeconomic surveys, such as Labour Force Surveys (LFS) and Censuses, include a question "What is your occupation?", "What kind of work do you do?" or similar, using either an open or a closed response format. Both formats can be used in all four survey modes, but the Open-Ended Question (OEQ) is most often used. Ganzeboom (2010, p. 7) advises using the open format, "because occupations are complicated". Compared with the variables education and industry, which are also mostly asked in an open response format, the measurement of occupations is problematic given that in many countries the stock of job titles may exceed 100,000 and that the occupational distribution has a very long tail, challenging the number of categories in a coding index or lookup database. For example, the state of Texas, USA, reported over 500,000 job titles in its job evaluation system (Tippins and Hilton 2010). In the OEQ respondents report their job titles as they like, implying that the data collector has to code the job titles according to a national or international occupational classification. CAPI and CATI allow for field and office coding, but PAPI and CAWI have to rely solely on office coding. (Semi-)automatic indexes can be used to assign occupational codes.

The response to the occupation OEQ varies largely. Respondents tend to report their job title in great detail, as they know it from their employment contract, a job evaluation scheme, or a common understanding in the workplace, but they may also report highly aggregated categories, such as 'clerical worker' or 'teacher', or unspecific categories, such as 'employee of department X' or 'senior supervisor'. In CAPI or CATI interviewers will prevent ambiguous, crude or overly detailed responses, but in PAPI and CAWI this is not the case. In CAWI the share of inadequate answers may be even larger than in PAPI, taking into account the habit of web visitors to key in whatever they like. Ganzeboom (2010) suggests coding crude titles in ISCO one- or two-digits, using trailing zeroes. He concludes that office coding can lead to substantial percentages of unidentifiable responses and to data at various levels of aggregation. This is confirmed in the World Values Survey, a predominantly postal survey using office coding for the occupation variable. Its 1999 data for Belgium, the Netherlands, and the UK, selecting only respondents with employment status employee or self-employed, reveals that for Belgium the occupation variable is coded only at ISCO88 two-digit and for the Netherlands and the UK also at three- and four-digit (two-digit: NLD 5%, GBR 8%; three-digit: NLD 22%, GBR 26%; four-digit: NLD 72%, GBR 59%; missing BEL 2%, NLD 1%, GBR 6%). Hence the measurement of various levels of aggregation is a much larger problem than the missing values. Note that the data of the unemployed, who are more likely not to be able to report an occupational title, have been excluded in these percentages. In the World Values Survey in Belgium the occupations of the unemployed are coded at two-digit, whereas for the Netherlands and the UK the question is not considered applicable for this group.

Against the backdrop of the wide variety of job titles as well as the occupational dynamics and the organisation specificity of job titles, it is not surprising that Elias (1997) concludes that office coding of occupations is an inexact process. Similarly, Eurostat (2009) states that inconsistencies are large for variables that require codification, such as occupations. In an analysis of the misclassification of occupation descriptions in the US Current Population Survey, Conrad and Couper (2008) find that the longer the occupation description, the less reliably it is coded. Thus a number of arguments call for an exploration of alternatives to the OEQ format.

2.3. *The Closed Response Formats in PAPI, CATI, CAPI and CAWI*

In a closed response format question, a tick list offers respondents a choice of occupational titles for self-identification. This method can be used in all four survey modes. However, in CATI the choice is limited to 5-7 categories that are inevitably highly aggregated. Otherwise the respondents will not remember all items. PAPI allows for a choice of at most 50 categories, because otherwise the printed questionnaire would exceed a reasonable length. CAPI allows for slightly more categories when using show cards. A limited set of choices may result in lower data quality, because it is difficult to assure consistency in how respondents fit their own job titles into the highly aggregated categories, introducing aggregation bias (De Vries and Ganzeboom 2008). This calls for a decomposition of the task, as has been proven to lead to better judgements (Armstrong et al. 1975).

CAWI allows for an almost unlimited choice of occupational titles. To navigate through a large look-up database, a search tree with two or three steps is needed. This so-called multipage filtering is a convenient way to collect data if a variable has too many possible values to be presented on a single page (Funke and Reips 2007). For quite some years now, job sites have used search trees to help web visitors to identify an occupation. In CAWI, an extended search tree is advantageous because aggregation bias and aggregation heterogeneity are prevented and unidentifiable; ambiguous or crude occupational titles are absent. In addition, search trees can easily be applied in multi-country and multi-language surveys, allowing for cross-country comparisons of highly disaggregated occupational data while ensuring comparable survey operations. However, a disadvantage of search trees is that they are cognitively demanding and time-consuming, as will be discussed later.

2.4. *The Web Survey's Occupation Question*

This article analyses the occupation data from the volunteer *WageIndicator* web survey on work and wages, designed by the author (Tijdens et al. 2010). The survey is posted on the national *WageIndicator* websites (www.wageindicator.org). These websites consist of job-related content, labour law and minimum wage information, and a free Salary Check presenting average wages for occupations based on the web survey data. The websites receive millions of visitors because of their collaboration with media groups with a strong internet presence. The first website and its web survey started in the Netherlands in 2001, expanded to other EU member states from 2004 onwards, included countries outside the EU and in other continents from 2006 onwards, and is operational today in 70 countries in five continents. In return for the free information provided, web visitors are invited to complete the web survey with a lottery prize incentive. The web survey takes approximately ten minutes to complete. Each web survey is in the national language(s) and adapted to the peculiarities of the country. In 2010, 417,137 web visitors started and 134,960 completed the survey, hence a dropout of 68%.

In 2010, the web survey has 22 pages. Page 1 of the *WageIndicator* web survey asks a question about employment status. The main options are employee, self-employed, and unemployed. Pages 2a and 2b ask a few questions of respondents with and without a job respectively. Page 3 asks about region. On pages 4-6, respondents self-identify their occupation by means of a three-step search tree allowing them to navigate through the WISCO multilingual database of occupations with more than 1,700 occupational titles (one page per step). The database details occupations with a greater precision than ISCO-08 four-digit by adding further digits. The closed response format is preferred over an OEQ with office coding. Apart from preventing aggregation bias and aggregation heterogeneity, an OEQ would have required a continuous and costly coding effort for the 70 countries given the large numbers of observations. The long-term experience with the web survey has revealed that respondents like to specify their occupational title, for example supervisor, senior, junior, trainee and similar. To satisfy these respondents, page 7 has a radio button question with these extensions and an OEQ where respondents are invited to add additional text about the occupational title ticked in the search tree. This text data is analysed in Subsection 4.2.

The WISCO database aims to facilitate respondents' easy but valid self-identification of their job title. To do so, the 433 units in the four-digit ISCO-08 classification are certainly too aggregated. A disaggregated list has to optimise between the demand to include as many occupational titles as possible to facilitate valid self-identification and the demand to be as brief as possible to reduce reading time. In WISCO, the aggregation level of occupations is defined as follows: "An occupation is a bundle of job titles, clustered in such a way that survey respondents in a valid way will recognize it as at their job title; an occupation identifies a set of tasks distinct from another occupation; an occupation should have at least a not-negligible number of jobholders and it should not have an extremely large share in the labour force" (Tijdens 2010, p. 16). Following this definition, broad occupational titles with large numbers of jobholders, such as clerk, teacher or nurse, are broken down into disaggregated occupational titles. Where needed, some occupational titles include a reference to industry or firm size, because the occupational coding does not use auxiliary variables. Similarly, handicraft workers have been distinguished from comparable manufacturing workers. For unskilled occupations, broad occupational titles have been preferred, because job holders may perform several jobs in a short period. From the next sections it can be concluded that the database of 1,700 unique occupational titles is sufficiently detailed for the vast majority of respondents in a multi-country survey.

To navigate through the database, WISCO has a three-step search tree based on a clustering of related occupations. The search tree's first step consists of 23 items, using a mixture of broad occupational groups and industry groups, such as 'Agriculture, nature, animals, environment' or 'Care, children, welfare, social work'. The second step specifies the ticked item in the first step and the third step presents the list of occupations related to the choice in the second step. Approximately one fourth of the occupations can be found through multiple search paths. Screenshots can be seen in Figure. 1, showing that in each step the list of occupations is sorted alphabetically. Due to technical constraints, the web survey uses a one page per step approach with back-and-forth buttons.

All occupational titles in the WISCO database are coded according to the four-digit ISCO-08 classification with follow-up numbers. In reverse, all ISCO-08 four-digit occupational units have at least one entry in the WISCO list of occupations. ISCO-08 has 27 residual ('not elsewhere classified') units, which are useful for office coding but problematic in the case of self-identification. This problem has been solved by rephrasing all 27 residual occupation units as 'Occupational unit X, all other' and sorting them at the bottom of the appropriate third step of the search tree, assuming that respondents have read all occupational titles in that particular step before deciding to tick the residual occupation.

For the multi-country WISCO database, translations by national labour market experts have been preferred over translations by professional translators. The wording of the occupational titles is kept brief, easy to understand, and hopefully unambiguous. Thus the singular is preferred over the plural and beekeeper over apiarist. No different male and female occupational titles have been used, apart from some countries where this was considered necessary. Synonymous titles are not included as these might confuse respondents. If national experts indicated that two distinct occupational titles were not considered distinct in their country, one occupation was removed from the country list. During the preparation of ISCO-08, the main discussions concerned the skill levels assumed with the ISCO one-digit codes (Elias and Birch 2006). In the WISCO country lists of occupations, this skill ambiguity is solved by adding skill requirements to the occupational titles, when known and applicable. For example in Germany, the 'Archivar/in, Diplom (FH)' has been distinguished from the 'Archivar/in, Diplom (Uni)' and the 'Archivar/in, Fachschule'. Skill requirements have been added when national experts

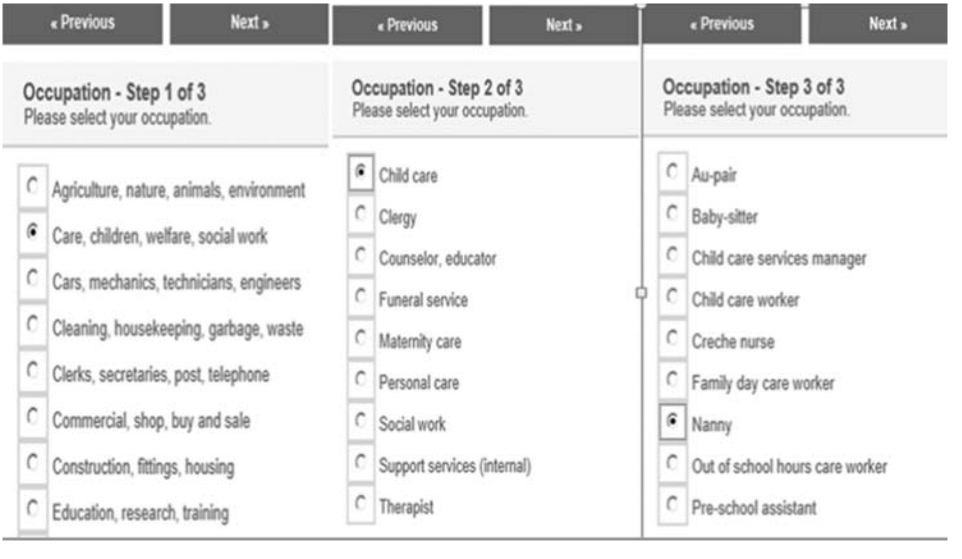

Fig. 1. Screenshots of the pages 4-6 in the occupation survey question in the web survey; note that this figure does not show the full list of 23 entries in Step 1 of 3. Source: *WageIndicator* Survey, UK

indicated a need for it. This turned out to be only relevant in countries where the educational system and the job market are firmly intertwined.

3. Dropout Rates and Response Time

3.1. Explanations for Dropout and Response Time

Given all the efforts to design a database of occupations and a search tree for respondents' self-identification in a web survey, it is certainly important to ask what the response times and dropout rates are, and which theories can explain these outcomes. In addition, how well does the search tree allow respondents to identify their job title as an occupational title from the list, according to the comments posted in an OEQ following the search tree? This section reviews the theoretical explanations and the related hypotheses.

High dropout rates are a major shortcoming of web surveys, threatening data quality. Many studies on dropout rates have been related to the use of progress indicators (e.g., Kaczmirek 2009; Callegaro et al. 2011), but some studies have detailed the impact of respondents' characteristics and survey characteristics on dropout. Dropout is a problem when it is systematic. This might be the case when survey questions are suboptimally formulated, the questionnaire is too lengthy, or other item and survey characteristics are poor (Reips 2002). The support for the interest hypothesis is in line with the findings of Heerwegh and Loosveldt (2006) that personalisation has a significant effect on the probability of starting the web survey and on the probability of reaching and submitting the final web survey page. Galesic (2006) finds in addition that the lower respondents experienced the overall survey burden, the lower the dropout risk. Pages that required more time to complete were followed by dropout more often. Using the German Longitudinal Election Study, Blumenstiel et al. (2010) find that dropout is a function of both respondents' characteristics and page characteristics. Dropout rates are higher for respondents with a lower level of education and in the case of open ended questions. In summary, the length of the questionnaire items, the respondents' level of education and interest in the topic of the questionnaire influence dropout.

Response time has been the subject of increased attention in the survey methodology literature over the last decade. Following the model for analysing survey response proposed by Tourangeau et al. (2000), Yan and Tourangeau (2008) explain response time in web surveys through question complexity and respondents' working memory capacity. They apply a cross-classification model for data from four web surveys in the USA with 27-61 questions. Concerning question complexity, the findings indicate that response times are longer when there are more clauses in a question, more words per clause, larger numbers of answer categories, and more factual and attitudinal questions compared to demographic questions. For respondents' working memory capacity, the authors conclude that the response time is longer for less educated respondents, for older respondents, and for respondents without previous web and survey experience. This is in line with Malhotra's (2008) finding that older respondents take significantly more time to complete a questionnaire. A recent body of knowledge focuses on the impact of question clarity on data quality, including response time. For example, investigating how easily and consistently respondents understand text features in survey questions, Lenzer et al. (2010)

show that the overall effect of seven text features on total response times is highly significant.

This leads us to explore three hypotheses:

Hypothesis 1: We expect that the dropout rates in the occupation search tree are affected by the length of the questionnaire items, operationalised as the number of characters to be read in previous steps of the search tree, and by the respondent's interest in the occupation question, operationalised as the relevance of the question for employed, self-employed and unemployed respondents.

Hypothesis 2: We expect that the response time in each step of the search tree is affected by the search tree item length, the respondent's valid self-identification, the respondent's dropout in the next step, and the respondent's interest, age and education.

Hypothesis 3: We expect that the total survey dropout after the search tree is affected by the response time in the search tree, the respondent's valid self-identification, and the respondent's interest, age and education.

3.2. Data

For the analyses, a new dataset has been compiled, derived from the 2010 second quarter *WageIndicator* web survey in the United Kingdom, Belgium (Dutch), Belgium (French) and the Netherlands. These were the most recent data available at the time of the study. The choice of the three countries was related to the author's language capacities, needed to investigate the respondent's valid self-identification. The new dataset is compiled as follows.

- The web survey contributes data about the ticked items in the 1st, 2nd and 3rd step of the occupation search tree, and the variables employment status, educational level, age, and search tree and total survey dropout.
- The web survey contributes the text that respondents have keyed into the open question following the search tree. The author has coded these responses and the results are shown below. From this data a variable called 'wrong match' is derived, indicating that respondents have keyed in an occupation in the open question other than that ticked in the search tree to identify the validity of the respondent's self-identification.
- The paradata contributes the time stamp for the start of the survey and three time stamps for completion of the 1st, 2nd and 3rd step of the search tree; note that the paradata measures the server-side time stamps, that in case of back-and-forth clicking only the latest time stamps are recorded and that the number of back-and-forth clicks is not recorded.
- The WISCO occupation database contributes the number of characters including blanks and commas in the most efficient search paths for each ticked item in the 2nd and 3rd step, assuming no further reading once respondents have identified their occupations; note that the number of characters read due to back-and-forth clicking is not included.

The total number of observations is 24,811 respondents at the start of the survey, of which 22,990 have completed the survey questions before the search tree and 18,824 have completed the search tree (Table 1). The large majority of respondents are based in

Table 1. Means of respondents' employment status and their education and age in four country/language combinations

	UK	Belgium (French)	Belgium (Dutch)	Netherlands	N
Employee Status					
Employee	0.90	0.88	0.89	0.83	22,990
Self-employed	0.06	0.05	0.04	0.06	22,990
Unemployed	0.04	0.07	0.07	0.11	22,990
Age	35.6	33.2	34.4	35.9	13,194
Education level					
Low education	0.14	0.17	0.12	0.10	11,449
Middle education	0.67	0.60	0.70	0.66	11,449
High education	0.19	0.23	0.18	0.24	11,449
N at entry search tree	1,611	1,515	2,278	17,586	22,990

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter.

the Netherlands, while smaller groups are from the UK and Belgium. Table 1 provides the descriptive statistics concerning the personal characteristics of respondents. Note that the survey question concerning employment status is asked preceding the search tree, and that age and education are asked in pages following the search tree. Table 1 shows that between 4 and 11% of the respondents are unemployed, mean age varies around 34 years, about one fifth is highly educated and one sixth has a low level of education.

4. Findings

4.1. Explaining Dropout Rates During Search Tree Completion

What explains the dropout rate in the occupation search tree? Table 2 shows that the dropout rates in the 1st step of the search tree across the four country/language

Table 2. Percentages dropout in the three steps of the occupation search tree and percentages employees, self-employed and unemployed, by country/language combination

	UK	Belgium (French)	Belgium (Dutch)	Netherlands
N at start survey	1,808	1,720	2,473	18,810
Dropout page 2	5.8%	7.3%	4.8%	4.6%
Dropout page 3	5.1%	4.6%	3.1%	1.9%
Dropout page 4 – occ Step 1	9.2%	10.5%	10.4%	14.0%
Dropout page 5 – occ Step 2	3.9%	2.4%	3.0%	2.3%
Dropout page 6 – occ Step 3	6.0%	3.0%	4.1%	4.2%
Dropout page 7 till end survey	38.1%	45.9%	37.2%	47.8%
Reached end survey	31.9%	26.2%	37.5%	25.2%
Total	100%	100%	100%	100%

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter (N=24,811 observations at start of survey).

combinations vary between 9 and 14% and in the 2nd and in the 3rd step between 2 and 6%. Hence, almost one in five respondents drop out during search tree completion and more than half of them do so in the 1st step. The table also indicates that the search tree causes approximately one third of total survey dropout. In Hypothesis 1 it is assumed that the dropout rate is dependent on the number of characters read in the most efficient search path and on respondents' interest in the occupation question. Table 3 shows that the number of characters read in the three steps ranges between a minimum of 62-72 and a maximum of 2,543-3,215 in the four combinations.

Binary logistic regression analysis is used to investigate dropout probabilities in each step of the search tree (Table 4). In Step 1 of the search tree, being employed or self-employed lowers the odds ratio of the dropout probability substantially with 88% and 90%, respectively, compared to the reference group of unemployed. In Step 2 and 3 no significant employment status effects are noticed. Hence the dropout of the unemployed respondents occurs in the 1st step of the search tree. By definition the number of characters read in the 1st step is not available and thus not investigated. In the 2nd step no effect of the number of characters read on the dropout is identified, but in the 3rd step a substantial effect is found. The number of characters in the 1st and 2nd step increases the odds ratio of the dropout probability with 0.1% and 0.2% respectively for each character read. So, for example, if the text string has 100 additional characters the dropout rate at Step 3 increases

Table 3. Descriptive statistics of the number of characters read in Step 1, Step 2 and Step 3 of the search tree, by country/language combination. IQR = Inter Quartile Range, SD = Standard Deviation.

	N	Min.	Max.	Median	IQR	Mean	SD
UK							
# characters read in Step 1	1,415	41	742	408	371	416.6	195.9
# characters read in Step 2	1,334	4	307	50	65	65.4	56.3
# characters read in Step 3	1,215	8	1760	133	195	201.9	235.8
# characters read in Step1+2+3	1,215	72	2543	644	343	676.8	316.5
Belgium (French)							
# characters read in Step 1	1,297	43	824	309	434	366.8	239.8
# characters read in Step 2	1,246	4	305	82	96	100.7	68.9
# characters read in Step 3	1,189	6	2378	154	238	241.8	260.6
# characters read in Step1+2+3	1,189	62	2705	622	471	708.4	350.9
Belgium (Dutch)							
# characters read in Step 1	1,968	46	826	300	435	355.0	241.6
# characters read in Step 2	1,883	6	283	79	94	89.1	61.4
# characters read in Step 3	1,768	6	2411	151	230	236.1	279.9
# characters read in Step1+2+3	1,768	67	3196	599	510	675.2	375.1
Netherlands							
# characters read in Step 1	14,846	46	839	313	500	379.0	258.8
# characters read in Step 2	14,363	6	283	73	102	88.6	65.4
# characters read in Step 3	13,564	6	2456	153	214	227.4	253.9
# characters read in Step1+2+3	13,564	63	3215	625	505	690.0	362.1

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter

Table 4. Effect of employment status and number of characters in the search tree on the probability of dropping out during search tree completion (0=no dropout, 1=dropout)

	Step 1 Odds ratio	Step 2 Odds ratio	Step 3 Odds ratio
# characters in Step 1 (41–839)		1.000	1.001***
# characters in Step 2 (4–307)			1.002***
Employee[1]	.123***	1.054	1.137
Self-employed[1]	.097***	.790	1.193
Country UK[2]	.991	1.345	1.524***
Country Belgium (French)[2]	1.065	.845	.724
Country Netherlands[2]	1.229*	.763	1.004
Constant	.792*	.032***	.030***
−2 Log likelihood	16805.52	5401.84	7771.6
N	22,990	19,524	18,824

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter
Reference categories: [1] Unemployed individuals; [2] Country Belgium (Dutch)
Significance levels: *** $p < .001$, ** $p < .005$; * $p < .010$

10 plus 20%. Country controls have been included, but Table 4 reveals that country hardly influences dropout, except for the UK in Step 3. In conclusion, these results confirm Hypothesis 1. The dropout rates in Step 1 of the search tree are influenced by the respondent's interest and in Step 3 they are affected by the search tree item length.

4.2. *Explaining Response Time During Search Tree Completion*

Hypothesis 2 asks whether the response time in each step of the search tree is related to the search tree item length or to the respondent's valid self-identification, dropout in the next step and respondent's characteristics. To test Hypothesis 2, the response times for each completed step in the search tree have been derived from the server-side time stamps. Unfortunately, no time stamps are available for the last question before the start of the search tree, hence no response time could be computed for Step 1. The response times are measured in rounded seconds with a minimum of one second. Because response times are skewed, the values have been normalised by taking their natural logs, following discussions by Fazio (1990). Extreme outliers have been deleted by removing the 0.1% values in the long upper tail of the distribution. Table 5 shows that for the four country/language combinations, the median response times are between 10 and 13 seconds for the 2nd step and between 13 and 16 seconds for the 3rd step.

To measure respondent's valid self-identification a 'wrong-match' indicator was developed, based on the OEQ on survey page 7 asking if respondents want to add additional information about the occupational title ticked in the search tree. In total, 4,020 respondents have keyed in relevant text in the OEQ (22.6% of the 17,782 who completed the 3rd step of the search tree). Relevant text is defined as text that includes at least two letters and is not a 'no' response to the question. Particularly in Belgium, this percentage is relatively high (29.6% for BE(French) and 50.4% for BE(Dutch)), whereas it is almost equal for the Netherlands and the United Kingdom (18.9% and 16.7% respectively). The

Table 5. Descriptive statistics of the response time in seconds for Step 2 and Step 3 in the search tree

	N	Minimum	Maximum	Median	(IQR)	Mean	(SD)
UK							
Response time Step 2	1,330	1	210	10	10	15.2	16.6
Response time Step 3	1,211	1	269	13	14	18.3	19.6
Belgium (French)							
Response time Step 2	1,242	1	204	13	11	17.4	18.2
Response time Step 3	1,179	1	206	16	16	20.5	19.8
Belgium (Dutch)							
Response time Step 2	1,887	1	187	11	10	16.7	18.2
Response time Step 3	1,762	1	235	14	14	19.6	21.9
Netherlands							
Response time Step 2	14,321	1	223	11	10	16.1	16.6
Response time Step 3	13,510	1	287	14	13	19.0	20.9

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter

author has compared the ticked occupational title and the answers in the text box, resulting in a classification in six categories (Table 6). The category ADDITIONAL includes either extended task descriptions or refers to composite jobs. An example is: ‘I am a secretary with HR tasks’. Most text items fall into this category, demonstrating that the occupational boundaries are not as distinct as the search tree and the occupational classification assume. This problem could be solved by facilitating a second choice in the search tree. An example of 50% MATCH is when the ticked title is ‘civil servant in a municipality’ and the text box states that the respondent has a clerical job. An example of IRRELEVANT is ‘I like my job but not my boss’. The category GENERAL is used particularly in Belgium, where respondents refer to the distinction between blue and white collar workers, which is relevant in this country. The category WRONG reveals that the text includes another occupation than the one ticked in the search tree, thus a wrong match between the search tree data and the text question. The WRONG responses are not equally distributed over the occupational titles in the search tree. The four titles with the most frequent WRONG answers are ‘Craft or related worker, all other’, ‘Paramedical practitioner, all other’, ‘Process controller, all other’, and ‘Sales representative’. Similar to the ‘not elsewhere classified’ occupations in office coding, in search trees in web surveys the category ‘all other’ fills easily. For these four occupations, the search paths in the occupation database need revision. In total 7.5% of OEQ respondents or 1.7% of respondents with a valid response on the search tree could not identify their occupational title.

OLS regression analysis has been applied to investigate the response time, measured in log seconds, in Step 2 and in Step 3 (Table 7). Model 1 estimates response time without education and age and Model 2 does so with education and age. Two models are used because the number of observations is higher for employment status (asked on page 1) than for education and age (page 10) due to dropout during survey completion. The results confirm Hypothesis 2. The response times in Steps 2 and 3 are indeed influenced by the search tree item length: response times are significantly longer when more characters have

Table 6. The categories and frequencies of responses to the OEQ question on occupation compared to the ticked occupation

Match category	Explanation	% of valid OEQ after search tree	% of valid response in search tree
PERFECT	Text and ticked occupational title are similar	3.6	0.81
ADDITIONAL	Text provides additional information to ticked occupational title	69.7	15.8
50% MATCH	Text indicates that ticked occupational title is not wrong, but the search tree has better alternatives	13.5	3.1
IRRELEVANT	Text is irrelevant given ticked occupational title	4.8	1.1
GENERAL	Text refers to an aggregated occupational title compared to ticked occupational title	0.9	0.2
WRONG	Text indicates that ticked occupational title is wrong	7.5	1.7
		100	22.6
		(N = 4,020)	(N = 17,782)

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter

to be read. For every additional character read in Step 2, the response time in Step 2 is 0.2% larger in both models. For every additional character read in Step 3, the response time in Step 3 is 0.1% larger in both models. This effect is hardly noticeable for the number of characters read in Step 1 affecting the response time in Step 2 and in Step 3, and it is not noticeable for the number of characters read in Step 2 affecting the response time in Step 3. The results also show that for the respondents who drop out in Step 3 the response time in Step 2 is 17% higher, which is in accordance to the findings on the dropout probabilities in the previous section. Finally the results show that the 'wrong-match' respondents need substantially more time in both Step 2 and Step 3, as their response time is 22% and 27% larger respectively (Model 1).

In contrast to expectation, Table 7 shows that the response time is not influenced by the respondent's interest in the occupation survey question: no significant difference between the employed, self-employed and unemployed is found in any of the four models. It makes sense that the unemployed are more likely to drop out in the 1st step, but if they do not, there are no obvious reasons for why they would need more response time. As expected, response times are significantly influenced by respondents' age and educational characteristics: the less educated need more time in Step 3, the highly educated need less time in Steps 2 and 3, and for every additional year of age respondents need 7% more time in Steps 2 and 3. The analyses are controlled for country, revealing that only respondents in Belgium(French) need more time to complete Step 3.

Table 7. Effect of respondent and survey characteristics on the log response time of Step 2 and Step 3 in the occupation search tree (unstandardised coefficients of OLS regressions, standard errors are in parentheses)

	Log response time Step 2		Log response time Step 3	
	Model 1	Model 2	Model 1	Model 2
(Constant)	2.411***	2.197***	2.448***	2.195***
	(−.028)	(−.041)	(−.03)	(−.042)
# characters in Step 1 (41–839)	.000***	.000***	.000	.000**
	(.000)	(.000)	(.000)	(.000)
# characters in Step 2 (4–307)	.002***	.002***	.000	.000
	(.000)	(.000)	(.000)	(.000)
# characters in Step 3 (6–2456)			.001***	.001***
			(.000)	(.000)
Dropout in Step 3	.165***	−.220		
	(−.023)	(−.478)		
Wrong match according to OEQ	.221***	.169***	.275***	.252***
	(−.039)	(−.047)	(−.041)	(−.048)
Employee[1]	−.022	−.020	−.030	−.004
	(−.021)	(−.027)	(−.022)	(−.027)
Self-employed[1]	.006	−.014	−.070	−.040
	(−.028)	(−.036)	(−.03)	(−.037)
Education low[2]		.052		.129***
		(−.022)		(−.022)
Education high[2]		−.125***		−.136***
		(−.016)		(−.016)
Age (10–80)		.007***		.007***
		(−.001)		(−.001)
Country UK[1]	−.053	−.049	−.013	−.010
	(−.024)	(−.031)	(−.026)	(−.032)

Table 7. Continued

	Log response time Step 2		Log response time Step 3	
	Model 1	Model 2	Model 1	Model 2
Country Belgium (French)[3]	.047	.062	.085**	.125***
	(−.025)	(−.032)	(−.027)	(−.033)
Country Netherlands[3]	−.007	.006	.015	.018
	(−.017)	(−.021)	(−.018)	(−.021)
Adj R Sq	0.049	0.07	0.108	0.133
N	18,717	10,696	17,644	10,692

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter
Reference categories: [1] Unemployed individuals; [2] Education middle; [3] Country Belgium (Dutch)
Significance levels: *** $p<.001$, ** $p<.005$; * $p<.010$

These results confirm most of Hypothesis 2. The response time increases with search tree item length, with next-step dropout, with invalid self-identification, with higher age and lower education, but it is not affected by employment status.

4.3. Explaining Survey Dropout from Search Tree Response Time

Six to seven in ten respondents do not complete the survey (Table 2). Hypothesis 3 assumes that the total survey dropout is influenced by the search tree response time and valid self-identification, as well as by the respondent's interest, age and education. Table 8 holds the results of a binary logistic regression analysis on the survey dropout for the respondents who have completed at least the search tree on page 6 (Model 1) and the education question on page 10 (Model 2).

Both models reveal that the time-consuming search tree does not influence total survey dropout. Obviously, once the search tree hurdle is taken, its response time does not affect total dropout. Model 2 reveals that being a 'wrong-match' respondent does not influence the survey dropout, but having keyed in relevant text in the OEQ after the search tree does decrease the odds ratio by 35%. Furthermore, Model 2 shows that the odds ratios for the dropout probability increase by 54% for the less and decrease by 13% for the highly educated compared to those with a middling educational level. Neither interest (employment status) nor age affect survey dropout. In both models the country dummies are significant, showing that the odds ratios increase for respondents from Belgium(French) and from the Netherlands compared to those from Belgium(Dutch). This shows the need for explanations beyond this article. In summary, Hypothesis 3 is not

Table 8. Effect of response time on the probability of dropping out at the end of the questionnaire (0=no dropout, 1=dropout) after search tree completion (Model 1) and after completion of the education question (Model 2)

	Model 1 Odds ratio	Model 2 Odds ratio
Response time Step 2 (log)	1.000	1.010
Response time Step 3 (log)	1.037	1.051
Wrong match according to OEQ (0,1)		1.101
Responded to OEQ (0,1)		.645***
Employee[2]	.909	.857
Self-employed[2]	1.203	1.258
Education low[3]		1.540***
Education high[3]		.866***
Age (10–80)		1.001
Country UK[1]	1.196	.911
Country Belgium (French)[1]	1.869***	1.489***
Country Netherlands[1]	1.821***	1.513***
Constant	1.042	.582***
−2 Log likelihood	22829.837	14345.539
N	17,610	10,676

Source: *WageIndicator* survey, Belgium, UK, Netherlands, 2010 second quarter
Reference categories: [1] Country Belgium (Dutch); [2] Unemployed individuals; [3] Education middle
Significance levels: *** $p<.001$, ** $p<.005$; * $p<.010$

confirmed with respect to the effects of the search tree response times, the valid self-identification, interest and age. The respondent's education and country do influence survey dropout.

5. Conclusions and Discussion

Occupation is a key variable in socioeconomic research. Most surveys employ an open-ended question with field or office coding, but problems are associated with this method. The response to the OEQ includes very detailed and very crude occupational titles, and hence the level of aggregation in the occupational classification may vary across respondents. Unidentifiable or ambiguous responses cannot be coded, and this problem is particularly associated with CAPI and CAWI survey modes. Coding is an inexact process within countries and particularly across countries, hampering cross-country analyses. Finally, coding efforts are costly, particularly in case of large-scale multi-country surveys. For these reasons the continuous 70-country *WageIndicator* web survey with large numbers of respondents does not apply an OEQ, but uses a closed format question for which a three-step search tree and a multilingual database with 1,700 occupational titles has been developed, assuming that respondents are able to self-classify their job title into these occupational titles. Occupation search trees are hardly ever used in web surveys and no information is available with respect to the performance of this survey tool. Search trees are assumed to be cognitively demanding and time-consuming. To evaluate the data quality of an occupation search tree, this article explores the dropout rates, the response times and the validity of the ticked occupation from the 2010 second quarter *WageIndicator* web survey in the United Kingdom, Belgium(Dutch), Belgium(French) and the Netherlands.

The first conclusion is that the dropout rates during the occupation search are high, that is, approximately 20%, which is about one third of total survey dropout. The study shows that in the 1st step of the search tree the dropout probability increases substantially for the unemployed respondents, who may judge the occupation question as not adequate for their situation and hence display lower interest in completing the survey. The high dropout rates in Step 1 may also reflect a cognitively demanding task for respondents, who are trying to fit their job titles into highly aggregated categories. The study also shows that the dropout rates in the search tree are influenced by search tree item length, because the number of characters in the 1st and 2nd step increases the odds ratio of dropout in Step 3 with 0.1% and 0.2% respectively for each character read.

The second conclusion is that the median response times are between 10 and 13 seconds for the 2nd step and between 13 and 16 seconds for the 3rd step of the search tree (no data is available for the 1st step). Response times are largest in Belgium(French) and smallest in the UK. The logistic analysis show that the response time, measured in log seconds, is affected by search tree item length, in Step 2 with 0.2% and in Step 3 with 0.1% for every character read in the respective step. Respondents who drop out in Step 3 need 17% more response time for Step 2 and respondents who ticked an invalid occupational title in the search tree need 22% more time in Step 2 and 27% in Step 3. In line with earlier research, the response times are higher for the less-educated and older respondents and lower for the highly educated.

The third conclusion is that the validity of the occupation data is rather good. For this purpose, an open-ended question after the search tree asking for additional information about the ticked occupation was compared with the ticked occupation. More than one fifth of the respondents who completed the search tree used this OEQ. Only 7.5% of these comments indicated that the respondents had not been able to self-identify their occupational title. If all respondents who were unable to identify their occupation had completed the OEQ, the percentage of invalid answers would have been 1.7. Thus the invalid answers are between 1.7 and 7.5% of the respondents completing the search tree. The OEQ reveals another problem. More than two thirds of the OEQ comments refer to additional tasks in the job, suggesting that the occupational boundaries are not as distinct as the search tree and the occupational classification assume. If generalised to all respondents who completed the search tree, approximately 15% of them would have a composite occupation with broader occupational boundaries than suggested in the occupational title in the search tree.

Taking into account its substantial dropout rates and response times, a 3-page search tree apparently is not an optimal response format for the occupation question in web surveys, though recent techniques may in part solve the problems described. First, single page filtering instead of a 3-page search tree most likely will reduce both dropout and response time. Second, the use of text string matching (TSM) may do so even more. In an experiment offering 48 possible values, Funke and Reips (2007) show that these dynamic lists are feasible and that the response time is lower compared to radio buttons. Similarly to search engines, TSM uses dynamic lists with either auto-completion or suggestions for self-identification of occupation, drawing from the WISCO database of occupations. In combination with a single page search tree, TSM may lead to better quality data. If extended with a 'suggest new entry' box, the number of occupational titles in the WISCO database could grow. If made accessible through an Application Programming Interface (API), the tool could offer the research community a sound instrument for the occupation question in web surveys. Increasing use of multi-country web surveys may favour the use of a closed instead of an open survey question. The problem of the composite occupations could be solved by allowing respondents to tick more than one occupation in the search tree.

There are several limitations to this study. The data from only a limited set of countries has been investigated; thus the findings cannot be generalised to all industrialised countries, particularly because some country effects were found. The data has drawbacks. For instance, the time stamps of the question before the search tree were not available and no information was provided about the respondents' back-and-forth clicking in the search tree. Furthermore, the study did not investigate the validity of the occupation variable through a multitrait-multimethod approach. Finally, the results are based on a volunteer web survey, and a detailed comparison of the 2009 Netherlands *WageIndicator* data with a representative reference web survey has demonstrated that there is obviously still a difficulty in quantifying the quality of a nonprobability survey (Steinmetz et al. 2014). Hence the research results presented here should be considered explorative rather than representative. However, given the increasing popularity of web surveys and the urgent need to collect high quality occupation data in these surveys, particularly in multi-country surveys, the study definitely improves insights into the do's and don'ts of the occupation question for web surveys.

6. References

Armstrong, J.S., Denniston Jr., W.B., and Gordon, M.M. (1975). The Use of the Decomposition Principle in Making Judgments. Organizational Behavior and Human Performance, 14, 257–263. DOI: http://www.dx.doi.org/10.1016/0030-5073(75)90028-8

Blumenstiel, J.E., Roßmann, J., and Steinbrecher, M. (2010). Breakoff in Web Surveys of the German Longitudinal Election Study (GLES). Paper presented at the General Online Research Conference (GOR) 2010. Available at: http://www.websm.org/db/12/13906/Bibliography/Breakoff_in_Web_Surveys_of_the_German_Longitudinal_Election_Study_GLES/ (accessed November 1, 2013).

Callegaro, M., Yang, Y., Villar, A. (2011) Should We Use the Progress Bar in Online Surveys? A Meta-Analysis of Experiments Manipulating Progress Indicators. Mannheim: Paper presented at the General Online Research Conference (GOR). Available at: http://conftool.gor.de/conftool11/index.php?page=browseSessions&presentations=hide&form_session=4 (accessed November 1, 2013).

Conrad, F.G. and Couper, M.P. (2008) Classifying Open Occupation Descriptions in the Current Population Survey. Ann Arbor, MI: Paper presented at the conference on Optimal Coding of Open-Ended Survey Data, University of Michigan.). Available at: http://www.electionstudies.org/conferences/2008Methods/ConradCouper.pdf (accessed November 1, 2013).

De Vries, J. and Ganzeboom, H.B.G. (2008). Hoe meet ik beroep? Open en gesloten vragen naar beroep toegepast in statusverwervingsonderzoek. Mens & Maatschappij, 83, 70–95.

Elias, P. (1997). Occupational Classification (ISCO-88). Concepts, Methods, Reliability, Validity and Cross-National Comparability. Paris: OECD Labour Market and Social Policy Occasional Papers, No. 20. DOI: http://www.dx.doi.org/10.1787/304441717388

Elias, P. and Birch, M. (2006). The Review of ISCO-88: A European Perspective. Warwick: University of Warwick, Working paper Institute for Employment Research.

Elias, P. and McKnight, A. (2001). Skill Measurement in Official Statistics: Recent Developments in the UK and the Rest of Europe. Oxford Economic Papers, 3, 508–540. DOI: http://www.dx.doi.org/10.1093/oep/53.3.508

European Union (2009). Commission Regulation (EC) No. 1022/ of 29 October amending Regulations (EC) No. 1738/2005, (EC) No. 698/2006 and (EC) No. 377/2008 as regards the International Standard Classification of Occupations (ISCO). Official Journal of the European Union, L 283/3, 30 October. Available at: http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2009:283:0003:0004:EN:PDF (accessed November 1, 2013).

Eurostat (2009). Task Force on the Quality of the Labour Force Survey. Final report. Luxembourg: Publications Office of the European Union. Available at: http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-RA-09-020/EN/KS-RA-09-020-EN.PDF (accessed November 1, 2013).

Fazio, R.H. (1990). A Practical Guide to the Use of Response Latency in Social Psychological Research. In Research methods in personality and social research, C. Hendrick and M.S. Clark (eds). Newbury: Sage.

Funke, F. and Reips, U.D. (2007). Dynamics Form: Online Surveys 2.0. Leipzig: Presentation at the General Online Research conference, 26-28 March 2007. Available at: http://frederikfunke.net/papers/pdf/Funke&Reips(2007)Slides_Dynamic_Forms.pdf (accessed November 1, 2013).

Galesic, M. (2006). Dropouts on the Web: Effects of Interest and Burden Experienced During an Online Survey. Journal of Official Statistics, 22, 313–328.

Ganzeboom, H.B.G. (2010). Occupation Coding using ISCO-08. Training session for PIAAC, Bologna, January 20th. Amsterdam: Free University Amsterdam. Available at: http://www.harryganzeboom.nl/Pdf/2010-Ganzeboom-ISCO08-PIAAC-Bologna-(presentation).pdf (accessed November 1, 2013).

Greenwood, A.M. (2004). Updating the International Standard Classification of Occupations, ISCO-08. Geneva: ILO Bureau of Statistics. Available at: http://millenniumindicators.un.org/unsd/class/intercop/training/escwa04/escwa04-9.PDF (accessed November 1, 2013).

Heerwegh, D. and Loosveldt, G. (2006). Survey Length Statements, Progress Indicators, and Survey Sponsor Logos. Journal of Official Statistics, 22, 191–210.

Hunter, D. (2009). ISCO-08 Draft definitions. Geneva: ILO. Available at: http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm (accessed November 1, 2013).

Kaczmirek, L. (2009). Human-Survey Interaction: Usability and Nonresponse in Online Surveys. Neue Schriften zur Online-Forschung, 6. Cologne: Halem.

Lenzner, T., Kaczmirek, L., and Lenzner, A. (2010). Cognitive Burden of Survey Questions and Response Times: A Psycholinguistic Experiment. Applied Cognitive Psychology, 24, 1003–1020. DOI: http://www.dx.doi.org/10.1002/acp.1602

Malhotra, N. (2008). Completion Time and Response Order Effects in Web Surveys. Public Opinion Quarterly, 72, 914–934. DOI: http://www.dx.doi.org/10.1093/poq/nfn050

Reips, U.-D. (2002). Standards for Internet-Based Experimenting. Experimental Psychology, 49, 243–256, DOI: http://www.dx.doi.org/10.1027/1618-3169.49.4.243

Steinmetz, S., Tijdens, K.G., Bianchi, A., and Biffignandi, S. (2014). Improving Web Survey Quality – Potentials and Constraints of Propensity Score Weighting. Online panel research: A Data Quality Perspective, ed. M. Callegaro, R.P. Baker, J. Bethlehem, A.S. Göritz, J.A. Krosnick, and P.J. Lavraskas. Chichester: Wiley (forthcoming).

Tippins, N.T., and Hilton, M.L. (Eds) (2010). A Database for a Changing Economy: Review of the Occupational Information Network (O*NET). Panel to Review the Occupational Information Network (O*NET). Washington (DC): The National Academies Press. Available at: http://www.nap.edu/catalog/12814.html (accessed November 1, 2013).

Tijdens, K.G., Van Zijl, S., Hughie-Williams, M., Van Klaveren, M., and Steinmetz, S. (2010). Codebook and Explanatory Note on the WageIndicator Dataset, a Worldwide, Continuous, Multilingual Web-Survey on Work and Wages with Paper Supplements. Amsterdam: University of Amsterdam, AIAS Working Paper 102. Available at:

http://www.uva-aias.net/uploaded_files/publications/WP102-Tijdens,vanZijl,Hughie-Williams,vKlaveren,Steinmetz.pdf (accessed November 1, 2013).
Tijdens, K.G. (2010). Measuring Occupations in Web-Surveys, the Database. Amsterdam: University of Amsterdam, AIAS Working Paper 86. Available at: http://www.uva-aias.net/uploaded_files/publications/WP86-Tijdens.pdf (accessed November 1, 2013).
Tourangeau, R., Rips, L.J., and Rasinski, K. (2000). The Psychology of Survey Response. Cambridge: Cambridge University Press.
Van der Laan, P., and Van Nunspeet, W. (2009). Modernising Household Surveys in the Netherlands: Design, Efficiency Gains and Perspectives. Paper prepared for the European Directors of Social Statistics Seminar "Re-engineering of Social Statistics: A Perspective", Luxembourg, 25 September 2009. The Hague/Heerlen: Statistics Netherlands, Discussion paper 09044. Available at: http://www.cbs.nl/NR/rdonlyres/0D30D23B-FE40-4570-B41A-E9B2CADF01DB/0/200944x10pub.pdf (accessed November 1, 2013).
Yan, T. and Tourangeau, R. (2008). Fast Times and Easy Questions: The Effects of Age, Experience and Question Complexity on Web Survey Response Times. Applied Cognitive Psychology, 22, 51–68. DOI: http://www.dx.doi.org/ 10.1002/acp.1331

Received March 2011
Revised October 2012
Accepted September 2013