STATISTICAL METHODS FOR REDUCING BIAS IN WEB SURVEYS

by

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Abstract

Web surveys have become popular recently because of their attractive advantages of data collection. However, in web surveys, bias may occur mainly due to limited coverage and self-selection. This paper reviews characteristics and problems of web surveys, and describes some adjustment weighting methods for reducing the bias. Propensity score adjustment is used for correcting selection bias due to non-probability sampling, and calibration adjustment is used for correction coverage bias. Those bias reduction methods will be explored by comparing face-to-face survey (reference survey) results with web survey results for the Social Survey produced by Statistics Korea. The methods studied include different variable selection methods for propensity score calculation and different propensity score weighting methods.

Keywords: Web survey; non-probability; self-selection; under-coverage; propensity score adjustment; calibration

To my beloved wife and two adorable daughters!

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Chapter 1

Introduction

1.1 Trends in Data Collection

Data collection methods for surveys have changed rapidly during the last few decades as technology has changed. Couper (2005) gives an overview of technology trends in survey data collection which is summarized below.

For many years surveys have been done using pencil and paper personal interviewing (PAPI) surveys or mail surveys. PAPI surveys are done with interviewers, whereas mail surveys are done as self-interviewing. As telephones became common in households, telephone surveys became popular for data collection. In addition, as computers have become popular, computer assisted interviewing has replaced all of these modes. Interviewers have been able to use computers instead of paper and pencil. Moreover, special software for telephone interviewing has enabled telephone surveys to be more convenient and accurate. Most recently web surveys have become popular. Web surveys are done via web browser in such a way that respondents answer questions by themselves. Web surveys have become more viable as Internet use has increased among residents of developed countries. The table below shows the high proportions of residents with Internet access ("Internet penetration") for a few developed countries, which supports the use of web surveys.

Countries	Norway	United Kingdom	South Korea	Canada	United States
Rate	94.80%	82.50%	81.10%	77.70%	77.30%

Source : International Telecommunication Union (Jan. 2011)

1.2 Pros and Cons of Web surveys

The advantages and disadvantages of web surveys are outlined briefly in Duffy *et al.* (2005) and Bethlehem (2010). The key advantages are low cost and speed. It takes little cost to distribute questionnaires and no cost in mailing, printing, and data entry. In addition, no interviewers are needed so interviewer effects can be avoided. Surveys can be launched and get data from respondents very quickly. This mode enables use of more visual, flexible and interactive technologies such as sound, pictures, animation and movies. Finally, web surveys can be done at respondents convenience, which means that people who could not have been reached by interviewers during the day can fill questionnaires whenever they like.

However, there are drawbacks to web surveys. The disadvantages focus mainly on sampling issues - under coverage and self-selection - which are dealt with in detail in later sections. However, other issues around mode effects, where online respondents may use scales differently from respondents in other modes, will not be dealt with in this paper.

1.3 Why web surveys?

Nowadays, it is more difficult to get information from people because of an increase in one-person households and dual-income households. Interviewers have difficulty in meeting those people during daylight hours. To illustrate, and because the data I explored in Chapter 5 originated from Korea, Tables 1.1 and 1.2 show the increasing trends of both one-person households and dual income households in Korea. In addition, growing concern for privacy is another primary problem that all surveys face.

Table 1.1: One-person household (%)

Year	1995	2000	2005	2010
Proportion	12.7	15.5	20.0	23.9

Source : Population and Housing Census in Statistics Korea

For the reasons given above, many national statistical agencies including Statistics Korea have begun utilizing web surveys in addition to other survey modes that use probability sampling methods. These are called “mixed mode” sampling surveys. However, even though

Table 1.2: Dual-income household (%)

Year	2007	2008	2009	2010
Proportion	33.2	34.5	36.4	37.3

Source : Household Income and Expenditure Survey in Statistics Korea

the web survey in mixed mode can help respondents to participate in the survey, agencies still suffer from a decrease in response rate, which may cause biases. Therefore, agencies are investigating alternatives to mixed mode surveys, such as volunteer panel web surveys. These types of web survey will be described further in Chapter 3.

One of the primary objectives of a sample survey is to estimate population characteristics. However, biases occur when the population quantities being estimated are not the same as true characteristics of population. In web surveys, biases occur mainly due to limited coverage and self-selection (Bethlehem, 2010). These issues are explored further in Chapter 3. Recently, statistical methods to reduce biases in web surveys have been studied. A possible solution may be weighting adjustment like post-stratification and propensity score weighting procedures. Propensity score weighting uses a popular tool from epidemiology, the propensity score, to compare attributes of web survey respondents to those from a traditional reference survey and apply subsequent adjustments to estimates.

In particular, Harris Interactive, a commercial polling agency, has developed a propensity score weighting technique to correct for attitudinal differences in data between web surveys and face-to-face surveys. Some researchers have evaluated the weighting procedures for web surveys by comparing them with other survey modes like face-to-face or RDD[1] surveys. However, their applications in research practice produce rather diverse results. Lee and Valliant (2009) showed that using propensity score adjustment and calibration adjustment together worked well in their simulation using 2003 Michigan Behavioral Risk Factor Surveillance System (BRFSS[2]) data. On the other hand, most other results do not seem to be so good. For example, Malhotra and Krosnick (2007) found that weighting adjustment could not eliminate the significant difference between both surveys. Huh and Cho (2009),

[1]Random Digital Dialing (RDD) is a method of telephone survey selecting subjects by generating telephone numbers at random

[2]Collaborative project of the Centers for Disease Control an Prevention (CDC) and U.S. states, Washington, D.C., and territories and is designed to measure behavioral risk factors in the adult population (18 years of age or older) living in households (Lee and Valliant, 2009)

whose research was supported by Statistics Korea, found similar results in the estimation for a volunteer panel web survey. According to the paper, the estimates of 79% of 106 variables showed bias reduction using inverse weights of propensity scores combined with rim weights for calibration, comparing to unadjusted estimates. However, only 35% of variables showed more than a 50% reduction in bias.

Nonetheless, I believe that it is worthwhile, even crucial, to investigate web survey estimation methods further in the future because web surveys are becoming the main data collection method for its advantages. Lee (2004) argues,

> "It becomes the methodologists' responsibility to devise ways to improve web survey statistical methods (e.g., sample selection and estimation) and measurement techniques (e.g., questionnaire design and interface usability)."

In this study, bias reduction methods for volunteer panel web surveys will be explored by comparing face-to-face survey results with web survey results for the Social Survey produced by Statistics Korea. The methods studied include different variable selection methods for propensity score calculation and different propensity score weighting methods.

1.4 Outline

The remainder of this study is comprised of the following five chapters. I will review basic sampling methods and sources of errors in surveys in Chapter 2. Chapter 3 will describe the web survey types and resulting sampling errors in detail. The core of this study is Chapter 4 and 5. In Chapter 4, I will offer several different approaches to selecting a propensity score model and discuss methods for using these scores. Propensity score adjustment and calibration adjustment will be discussed. Adjustment methods include inverse propensity scores as weights, subclassification (stratification). I will demonstrate these methods on real data sets originating from Statistics Korea and present results of the analyses in Chapter 5. Finally, evaluation from the results of the case study and some discussion will be given in Chapter 6.

Chapter 2

Review of sampling and errors in surveys

Surveys are conducted to collect information about characteristics of populations. A *census* can be done by surveying every unit in the population. However, a *sample survey* is more often used because of practical reasons like cost or other constraints. Many well-known sampling methodologies for conducting statistical inference on sample surveys have been developed, and many texts and papers have studied and used them. In this chapter, general sampling methods and sources of errors in surveys are described very briefly to make clear which sampling methods are possible and what kinds of errors can exist in general surveys. The next chapter deals with specific sampling methods and problems in statistical inference for web surveys.

2.1 Concept of sampling

Sampling is the selection of a subset of a larger population to survey. The two broad categories of sampling methods are *probability-based sampling* and *non-probability sampling* (Fricker, 2008) Probability methods are based on random selection in a variety of ways from the sample frame of the population. They support the use of statistical techniques for inferences about the population. In contrast, non-probability sampling is a process where some elements of the population have no chance of selection or where the probability of selection can't be accurately determined. The advantage of non-probability samples is that

they often need much less time and effort. However, the disadvantage is that they may give biased results because they are not selected randomly (Panacek and Thompson, 2007). Types of probability sampling include:

- Simple random sampling (SRS): a process in which each subject is selected randomly from the population with a known and equal probability of being chosen.
- Stratified random sampling: a process in which a population is divided into homogeneous subgroups and then random sampling is applied within each group.
- Systematic random sampling: a process in which selection of subjects is conducted systematically by selecting every n^{th} subject from an ordered sample frame. The starting point is selected randomly.
- Cluster sampling: a process in which total population is divided into smaller subgroups (or clusters) and sample is selected by choosing subgroups randomly.

Types of non-probability sampling include:

- Convenience sampling: a process in which a sample is selected from readily available and convenient subjects. For instance, in volunteer panel web surveys, the use of self-selection is a kind of convenience sampling.
- Snowball sampling: a process in which the initial subjects are selected in some convenient way and then new subjects are continually recruited based on some connection to existing subjects.
- Quota sampling: a process in which specified number of subjects for a specific subgroup are selected in convenient way.
- Purposive sampling: a process in which subjects are selected by the researchers specific judgment.

Many web surveys are conducted by non-probability sampling methods like convenience sampling. If a sample is not systematically representative of the population, the resulting estimates of population quantities may be biased. It is important to try to minimize bias in this case.

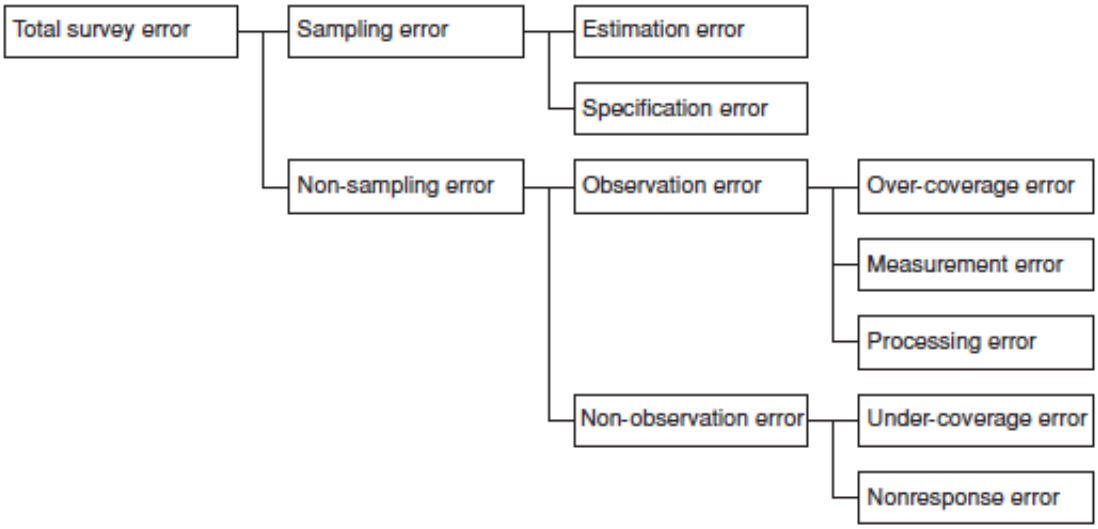


Figure 2.1: Taxonomy of survey errors, taken from Bethelehem (2010)

2.2 Sources of errors in surveys

The primary purpose of a survey is to estimate population characteristics. However, survey estimates are not exactly equal to their corresponding population quantities due to various errors. Bethlehem (2010) presents a taxonomy of survey errors like Figure 2.1 . Those errors are summarized below.

Total survey error is the difference between a survey-based estimate and the corresponding characteristic of the population. This can be categorized into sampling error and non-sampling error.

Sampling error occurs due to the fact that some parts of the population cannot be included in the sample. In other words, it happens that not every subject in the target population is in the survey. If the whole population can be observed, the sampling errors disappear. Sampling error can be split into estimation errors and specification errors.

Estimation error occurs because new samples result in different estimates. It is unavoidable, but can be quantified by applying probability theory. In the case of web surveys where samples are drawn by way of self-selection, estimation error occurs but cannot be quantified since selection probabilities are unknown.

Specification error is due to the difference between true selection probabilities and the

selection probabilities specified in the sampling design. There is no way to avoid specification error in the case of web surveys because selection probabilities are unknown as mentioned before. Therefore self-selection error is a kind of sampling error.

Non-sampling error occurs due to various causes such as data entry error, biased questionnaires, low response rate and so on. This can be categorized into observation error and non-observation error.

Observation error occurs when obtaining and recording answers. This can be categorized into over-coverage error, measurement error and processing error. An *over-coverage error* arises because of participation of people who are not in the target population or because of duplicated participations in the list of sampling units. *Measurement error* arises when survey response differs from the true value. It includes the case of respondents misunderstanding questions, not giving a true answer for sensitive questions, interviewers mistakes and so on. *Processing error* means data entry error. Certainly, any of these can occur in web surveys.

Non-observation error means errors caused by omission of intended measurements. This can be divided into under-coverage error and non-response error. *Under-coverage error* occurs when people in the target population cannot be in the sampling frame. This fact means these people cannot be contacted to participate in a survey. This error can be common and serious problem for web surveys because, for example, not all members of the population have Internet access or may find out about the survey. *Non-response error* is when selected people do not provide answers to the required questions. This is also common in web surveys because web surveys are done by self-interviewing. It is obvious that web surveys can suffer all kinds of errors. However, under-coverage error and sampling error (or self-selection error) may be the most serious problems in volunteer panel web surveys. This is described in more detail in the next chapter.

Chapter 3

Web surveys

Web survey mode has become popular for data collection. However, there are drawbacks to its use in terms of quality of sample estimates because of non-probability sampling and coverage problems. In this chapter, types of web surveys are described further according to their sampling methods and main potential problems as discussed in the last chapter. Volunteer panel web surveys, which are the focus of this paper are described in more detail than other kinds of web surveys.

3.1 Types of web surveys

"Internet surveys" and "web surveys" are often used interchangeably. However, strictly speaking, these are different concepts. Web surveys are done only on web browsers, whereas Internet surveys include both web surveys and surveys which are done by e-mail. Only web surveys are discussed in this paper. As described before, sampling methods can be categorized broadly into probability-based sampling and non-probability sampling. Types of web surveys can also be categorized based on both sampling methods. Table 3.1, which is a slightly adapted version of Couper (2000), shows the classification of types of web surveys based on availability of probability sampling. Couper (2000), Lee (2004) and Fricker (2008) describe characteristics of these kinds of web surveys, which are summarized below.

Web surveys using non-probability sampling methods include entertainment polls, unrestricted self-selected surveys and volunteer panel surveys.

At first, *entertainment polls* may not be considered a survey in the scientific sense, but

Table 3.1: Types of Web Surveys

Non-probability	Probability
1. Entertainment polls	4. Intercept surveys
2. Unrestricted self-selected surveys	5. List-based sample surveys
3. Volunteer panel surveys	6. Web option in mixed mode
	7. Pre-recruited panel surveys

they are very popular in many websites. As the name implies, they are mainly done for entertainment purposes. They consist of websites where any visitor can respond to posted surveys. There is no control over who responds. One example is question of the day polls like "CNN Quick vote" (www.cnn.com), which states, "This is not a scientific poll".

As with entertainment polls, *unrestricted self-selected surveys* are also open to the public for anyone to participate in; that is, there are no restrictions on participants. They may simply be posted on websites or may be prompted via banners. Generally, the distinction between this type of surveys and entertainment polls is that the latter usually makes few claims to generalizability, while the former does. Couper (2000) introduced some examples of this kind of web survey. One is National Geographic Societys "Survey 2000" which launched in the fall of 1988. An invitation to the survey was posted on its own website and the URL was published in its magazine. Over 50,000 respondents completed the survey. In their analysis of the survey results, they note that while the survey did not yield a random sample and the selection probabilities are unknown, they may yield representative social science data by estimating the selection probabilities by comparing the distributions of standard demographic variables to official government statistics and applying weighting, However, Couper (2000) points out that, in spite of the large sample size, the respondents of the surveys do not resemble the U.S. population on a number of key indicators due to self-selection error.

Another example is the web survey "to better understand the risks to adolescent girls online" which conducted by Berson *et al.* (2002). The survey was done by posting a link to their survey on Seventeen Magazine Online website. Over 10,000 responses were collected. Unlike the first example, the authors were careful to appropriately qualify their results:

> "The results highlighted in this paper are intended to explore the relevant issues and lay the groundwork for future research on youth in cyberspace. This is considered an exploratory study which introduces the issues and will need to be supplemented with ongoing research on specific characteristics of risk and prevention intervention. Furthermore, the generalizability of the study results to the larger population of adolescent girls needs to be considered. Due to anonymity of the respondents, one of the limitations of the research design is the possibility that the survey respondents did not represent the experience of all adolescent girls or that the responses were exaggerated or misrepresented."

The results of those kinds of surveys cannot be generalized to a larger population because researchers do not have any control over the participation mechanism (Lee, 2004). However, it does not mean that those surveys are useless. As Berson *et al.* (2002) illustrate, those kinds of surveys can be helpful in identifying relevant issues for future probability-based surveys. Furthermore, Fricker (2008) indicates that those kinds of surveys have an advantage in that they facilitate access to people who are difficult to reach because they are hard to identify or locate, or perhaps exist in such small numbers that probability-based sampling would be unlikely to reach them in sufficient numbers.

Volunteer panel web surveys are conducted based on panel lists which consist of people who decide to participate in continuing surveys via websites. Before surveys, basic demographic information is collected from those volunteers when they sign up for the registration. Then, based on the database of the potential respondents, researchers can select panel members for a particular survey using sampling procedures like quota sampling or probability sampling methods according to the volunteers' demographic information. In this regard, there is a distinction between this type of web survey and previous ones. However, it is notable that the initial panel is a self-selected sample of volunteers. This type of web survey has received much attention within web survey industry recently (Couper, 2000). The web survey data used for the analysis in this paper were collected using this type, which are described in detail in Chapter 5. A well-known example of this type is Harris Poll Online. Harris Interactive says on its website :

> "The Harris Poll Online Panel consists of individuals from throughout North America and Western Europe who have double opted-in and voluntarily agreed

> to participate in our various online research studies. Through our careful recruitment, management and incentivized panel members, we are confident that we have one of the highest quality panels anywhere in the world with sufficient capacity to provide our clients with the feedback they need to make sound and compelling business decisions. Top quality panels coupled with deep profiling of our members allows us to target and accurately survey certain low-incidence, hard-to-find subjects, rapidly survey large numbers of the general population, and conduct a broad range of studies across a wide array of industries and subject-matter sets."

For this kind of web survey, incentives are often offered to panels to encourage participating in the surveys. Harris Interactive also offers rewards to their panels. Their key approach to analysis for the survey is the use of propensity score adjustment for bias reduction, which is described in Chapter 4. In contrast to previous types of web surveys, probability-based web surveys begin with probability samples of various forms. Couper (2000) argues that there are essentially two approaches to achieve probability-based web samples because web access is not universal and no frame of web users exists. One is to restrict the population of interest so that the sample is restricted to the web users. The other is to use alternative methods such as RDD simultaneously in order to identify and reach a broader sample of the population. Probability-based web survey types include intercept surveys, web option in mixed mode, and pre-recruited panel surveys.

Intercept surveys are pop-up surveys placed on a specific website that generally use systematic sampling methods to invite every k^{th} visitor to the site to visit the survey website. The population in this case is defined as visitors to the site so that this sampling enables generalization the particular population. Internet Protocol (IP) addresses and cookies[1] can be used to restrict multiple submissions from the same computer user. These surveys seem to be very useful as customer-satisfaction surveys or site evaluations, but an important issue with this type of survey is nonresponse (Couper, 2000; Fricker, 2008). Low response rate may raise nonresponse bias and there may no way to assess it because those who complete the surveys may have different views compared to those who ignore the request.

Another type of probability-based web survey is *a list-based sample survey.* The approach

[1]Cookies are used for an origin website to send state information to a user's browser and for the browser to return the state information to the origin site.

of this type begins with a frame or list of those with web access. The population is restricted to the web users. Therefore, this type is typically used for intra-organizational surveys like student surveys, government organization surveys, and large corporation surveys. There is little chance of coverage problems in this type of survey. Couper (2000) calls this "list-based samples of high-coverage populations". E-mail is usually used to invite participation in the surveys. Simple random sampling is straightforward to implement and requires only contact information like e-mail addresses. To implement more complicated sampling methods such as a stratified sampling more auxiliary information is needed.

Third, *pre-recruited panel surveys* are similar to volunteer web panel surveys in the sense of that panels consist of individuals who have agreed to participate in surveys. The key difference is that the former uses probability sampling methods such as RDD for recruiting panels, while the latter does not. Researchers generally recruit panel members via telephone or postal mail rather than web or e-mail. After getting information from those panel members, sub-samples can be drawn by researchers' specification. If the population is restricted to the web users, then there is again little chance of coverage errors. In case the population includes people with no web access, equipment and web access are provided for corresponding panelists.

A final use of web surveys is as an alternative mode in mixed-mode surveys. Participants are selected by a probability sampling method and are given the option to complete the survey using one of several modes, such as web, telephone, mail, or face-to-face. The same survey is offered in each mode; the use of web mode represents a reduction in cost to the agency and in burden to the respondent. That is why many national statistical agencies (e.g. Canada, USA, Korea) have utilized this kind of web survey, as mentioned before. There is little chance of sampling errors or coverage errors in mixed-mode surveys. However, mode effects can be an issue in this case, but it is often assumed that they are ignorable. Lee (2004) argues that, strictly speaking, design-based statistical inferences can be drawn only under these last four probability-based web surveys.

This paper focuses on volunteer panel web surveys using non-probability sampling methods. As Lee (2004) suggests, it is not guaranteed that people who respond to a volunteer panel web survey are representative of the whole target population of the survey. This is because volunteer panel web survey respondents go through several filtering steps before

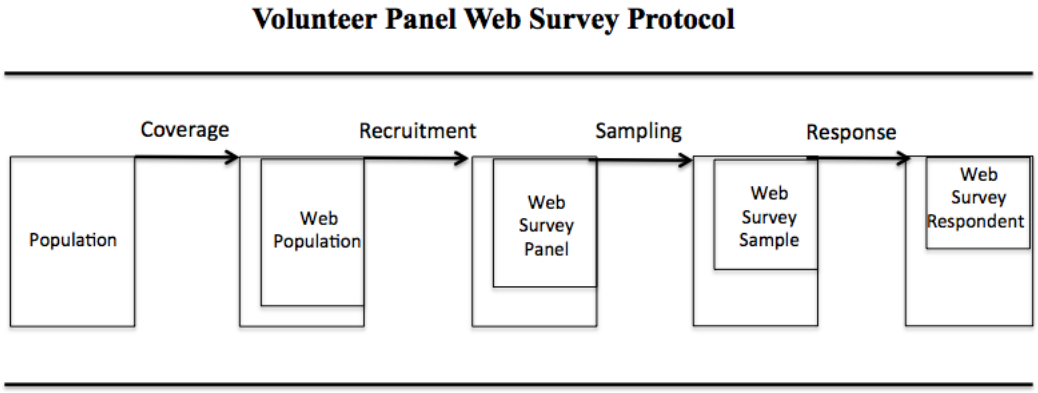


Figure 3.1: Volunteer Panel Web Survey Protocol, taken from Lee (2004)

supplying responses to a survey. This is depicted in Figure 3.1 from Lee (2004). It is certain that web surveys in general may suffer from all kinds of errors described in Chapter 2. In particular, web surveys that use convenience sampling are assumed to have higher likelihood of generating a biased sample (Fricker, 2008). The main potential is for coverage, self-selection and non-response errors (Bethlehem, 2010; Lee and Valliant, 2009; Fricker, 2008; Duffy *et al.*, 2005). These problems can occur in volunteer panel web surveys as well. Specifically, there is a gap between the whole population and the web population. This fact may cause coverage error. In addition, there are no known selection probabilities during the recruiting process from the web population. This fact may cause self-selection error, which was described in Chapter 2 as a kind of sampling error. Finally, there is the possibility of non-response error during the process of getting answers from respondents. These errors may combine to cause severe bias in any quantity that is estimated. Consequently, statistical inference for this kind of survey can be of doubtful quality. In the next section, main potential problems in web surveys are explored in detail.

3.2 Problems in web surveys

3.2.1 Coverage problems

Coverage error occurs when some part of the population cannot be included in the sample or there are duplicated participants in the list of sampling units. In that case, survey results

are likely to be biased. There are two kinds of coverage error that can occur in web surveys: under-coverage and over-coverage.

Under-coverage is more common because people who cannot access the Internet cannot participate in a web survey unless the target population includes only people with Internet. The possible bias is related not only to the numbers of people who have access to Internet, but also to the difference among them in age, gender, education and behavioral characteristics Steinmetz *et al.* (2009). As Bethlehem (2010) mentions, it is well known that young people and those with high levels of education more often have access to the Internet than elderly people and those with low levels of education. If some demographic[2] groups are under-represented, this may cause bias problems for inference.

It is worth noting that other modes like computer-assisted telephone survey suffer from this coverage problem when telephone directories are used as a sampling frame, because people without phones or who have unlisted numbers will be excluded from the survey. Surveys are not generally welcome on cell phones, so current technology changes may exacerbate this problem. Considering the rapid increase of Internet penetration rates in developed countries as shown in the Chapter 1, under-coverage problems with web surveys may decrease in the future.

Over-coverage for web surveys may occur when people participate in surveys multiple times because of incentives. This happens because it is common that people have multiple e-mail addresses. It is difficult to identify individual respondents in a web survey. Therefore, there is usually a possibility of over-coverage problem in web survey. However, it is often assumed that this problem is not too severe.

3.2.2 Selection problems in web surveys

Non-probability sampling methods, such as convenience sampling, are dominant in web surveys because of their ease and cost. As described before, this fact causes sampling errors including estimation and specification error. Horvitz and Thompson (1952) show that unbiased estimates can be computed only when a real probability sample is used, every unit in the population has a non-zero probability of selection, and all these probabilities are known to the researchers. In addition, the precision of estimates can be estimated under these conditions. However, self-selection surveys do not satisfy these conditions.

[2] age, sex, racial origin, education

It is also known that people who self-select into a survey differ from those who do not in terms of time availability, web skills or willingness to contribute to the project (Steinmetz *et al.*, 2009). In other words, the people who participate in volunteer web surveys may have specific characteristics. Consequently, their responses may differ substantially from those of people randomly chosen in the general population. Loosveldt and Sonck (2008) introduced some previous research to study this selectivity bias by comparing self-selection web surveys and telephone surveys or face-to-face surveys[3]. For example, Duffy *et al.* (2005) compared web volunteer panel surveys and face-to-face surveys that use probability sampling. They showed that web survey respondents were more socio-politically active than those responding to a face-to-face survey. Vehovar *et al.* (1999) found differences between web respondents and telephone survey respondents with frequent Internet access in four of the seven items concerning electronic trade largely due to different experience between two samples. Bandilla *et al.* (2003) also observed significant differences between responses of Internet users and those of mail survey respondents taken by self-interviewing, even after adjusting the sample of Internet users for basic socio-demographic characteristics.

Theoretically, there are no unbiased estimators in volunteer panel web survey using self-selection in sampling (Bethlehem, 2010). Therefore, strong structural assumptions must hold for valid inference (Lee, 2004). These assumptions will be dealt with in detail in Chapter 4.

3.2.3 Non-response problems

Non-response error occurs when people in a sample do not provide some required information. Non-response may be serious problem if answers are significantly different between respondents and non-respondents. The extent of non-response bias depends on both non-response rate and difference between respondents and non-respondents (Steinmetz *et al.*, 2009).

Non-response bias is not unique to web surveys. However, response rates in web surveys tend to be lower than other modes. Lozar *et al.* (2008) found that non-response rates of the

[3]An interviewer is physically present to ask the survey questions and to assist the respondent in answering them

web mode is on average 11% lower than those of other modes. Steinmetz *et al.* (2009) summarized the reasons for this: inefficiency of response-stimulating efforts (incentives, follow-up contacts), technical difficulties (slow, unreliable connections, low-end browsers), personal computer accessibility, and privacy and confidentiality concerns. For a non-probability web survey like a volunteer panel web survey, it is impossible to compute an exact non-response rate because selection probabilities are unknown.

Even though non-response bias can be a serious problem in web surveys, it is hard to detect the effect of it. In this paper, non-response will be assumed to be missing at random (MAR[4]). The imputation method for missing data that I applied to data sets is described briefly in Chapter 5.

[4]Missing data are partly caused by an auxiliary variable X. If there is a relationship between this variable X and the target variable Y, estimates for Y will be biased. But it can be corrected by a technique that uses the distribution of X in the sample.

Chapter 4

Methodology

As described above, bias can be caused by a variety of sources of errors. In order to reduce bias, the data can be adjusted to correct those errors. Weighting adjustments are techniques that attempt to improve the accuracy of survey estimates by using auxiliary information (Bethlehem, 2010). They are considered possible solutions to improve quality in web surveys. Weighting adjustment methods include post-stratification weighting, propensity score adjustment, and rim weighting adjustment (Lee, 2004; Bethlehem, 2010; Steinmetz *et al.*, 2009; Looseveldt and Sonck, 2008; Huh and Cho, 2009).

Post-stratification is a calibration estimation method to reduce the variance of the estimates and reduce bias due to non-coverage and non-response (Cervantes *et al.*, 2009). It is used to adjust for demographic differences between a sample and the population. Looseveldt and Sonck (2008) argue that the method does not solve the problem of selection bias since some response variables may be related to variables other than demographics. For example, attitudinal and behavioral differences can be observed even after applying post-stratification weighting adjustment using demographic variables. Post-stratification is described further in Section 4.1.

As an alternative, *propensity score adjustment* has been applied to volunteer panel web surveys. The technique is primarily used in the context of observational studies (e.g., Rosenbaum and Rubin (1983)). The idea is to make two samples comparable by weighting using all auxiliary variables that are thought to account for the differences. In context of web surveys, this technique aims to correct for differences between online people and offline people, which were caused by certain inclinations of people who participate in a volunteer panel web survey. In order to do that, a reference survey based on probability sampling is needed

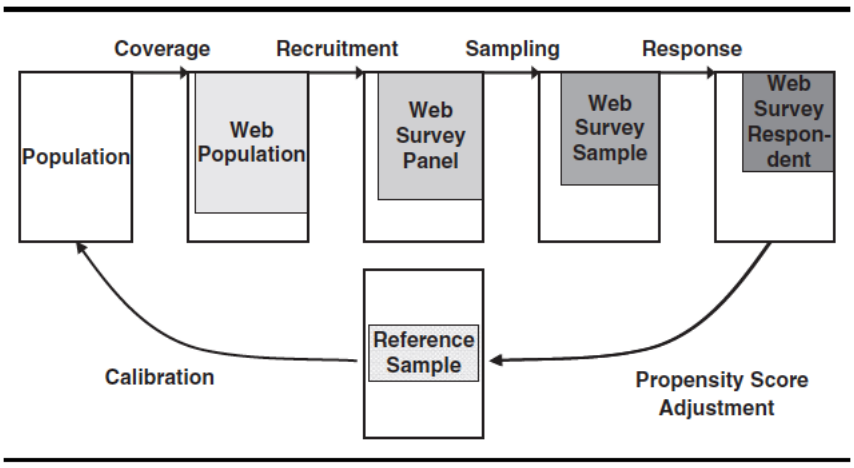


Figure 4.1: Proposed Adjustment Procedure for Volunteer Panel Web Surveys, taken from Lee (2004)

and is assumed to produce unbiased estimates (Bethlehem and Stoop, 2007). Propensity score adjustment using a reference survey is described further in Section 4.2.

Lee and Valliant (2009) suggest the combination of propensity score adjustment and calibration adjustment to reduce bias caused by nonrandomized sample selection and deficient coverage in volunteer panel web surveys. Figure 4.1 shows the proposed procedure for the surveys. Propensity score adjustment is used to make the web sample behave like the reference sample, calibration is used to make the reference sample represent the population. Calibration can be used to correct both non-response and coverage errors that are not controlled by the propensity score adjustment. Several calibration methods exist such as generalized regression estimators (GREG) and rim weighting. We use rim weighting which is described in detail in Section 4.3.

4.1 Post-stratification

It is important to have a representative sample of the population when conducting a survey. However, cases of not having such a sample often occur accidentally or intentionally. For example, the distribution of a certain characteristic such as age, education, race, or gender (so-called demographic variables) in a sample may differ from the distribution in the population. This gives rise to potential bias if responses are related to the demographic

variables, because statistical procedures will give greater weight to oversampled people. Post-stratification survey weighting corrects for this bias mathematically. The basic idea is to stratify the sample into a number of cells, based on characteristics of the population deemed important, and then to give more weight to respondents in under-represented groups and less weight to those in over-represented groups.

Steinmetz *et al.* (2009) suggest a formula for post-stratification weights in web surveys. The formula can be used for one or more demographic variables based on the cell proportions from contingency tables of those variables for both the sample and the target population. The weight w_i for an element i in stratum (i.e., cell) h is equal to

$$w_i = \frac{N_h/N}{n_h/n},$$

where N is the number of target population elements, N_h is the number of target population elements in stratum h, n is the sample size, and n_h is the sample size in stratum h. Identical weights are assigned to all elements in the same stratum. Note that this approach can be applied only when the population proportions in each stratum are available. Therefore, this approach is not applied in this study, because the population proportions were not available for many of the variables in my data.

4.2 Propensity Score Adjustment (PSA)

The original propensity score adjustment was suggested by Rosenbaum and Rubin (1983, 1984) for the purpose of the comparison of populations in the context of observational studies. For example, in observational studies where assignment of the study subjects to the two groups (e.g., treatment and control groups) is not random, the probability that a randomly selected subject with a given set of covariates would be in the treatment group rather than the control group is defined as that subject's "propensity" for treatment. Propensity scores are estimated for each subject, and then a treated case is matched to a control case or subclassified based on closeness of propensity score in order to estimate the difference in means for the two groups (Lee, 2004). Harris Interactive, a commercial polling company, is the first agency known to have applied this method in order to estimate population characteristics in the context of web surveys.

4.2.1 Reference surveys

In order to conduct propensity score adjustment in the context of web surveys, a reference survey is needed which represents the control group (Lee, 2004). It is assumed that the reference survey produces unbiased estimates (Bethlehem and Stoop, 2007). For instance, the reference survey may be conducted by using a traditional survey mode, such as RDD in Harris Interactive's case. A reference survey can be an existing survey or a smaller scale survey that collects data closely related to the web surveys. Variables which are included both the reference survey and the web survey can be used as covariates for predicting whether a randomly selected respondent participated in the web survey or the reference survey.

As described before, demographic variables can be used for correcting unrepresentativeness of web surveys with respect only to those variables. In order to further reduce self-selection bias in web surveys, some other variables to capture the differences between the online and offline populations are needed (Schonlau *et al.*, 2007). Questions designed for this purpose are diversely called webographic, attitudinal or lifestyle questions. Harris Interactive introduced webographic questions which consist of attitudinal questions, factual questions and privacy questions (Schonlau *et al.*, 2007). Table 4.1 shows all the questions used by Harris Interactive.

Lee (2004) uses attitudinal questions like self-rated social class, employment status, political party affiliation, having a religion, and opinion toward ethnic minorities as variables for propensity scoring. In this paper, the term "webographic variables" is used later for the above concepts.

4.2.2 Propensity score

A propensity score is simply the probability of a unit i $(i = 1, \ldots, n)$ being assigned to the treatment group $(z_i = 1)$ given a set of covariates $(\mathbf{x}_i)$ and is denoted as

$$e(\mathbf{x}_i) = Pr(z_i = 1|\mathbf{x}_i), \tag{4.1}$$

where it is assumed that z_i are independent given a set of covariates $(\mathbf{x}_i)$, and $e(\mathbf{x}_i)$ ranges from 0 to 1.

"Treatment" means being in a web survey in the web survey context. In other words, a propensity score is the conditional probability that a person will be in a web survey rather

Table 4.1: Webographic Questions by Harris Interactive

Attitudinal variables	Do you often feel alone? (yes/no) Are you eager to learn new things? (yes/no) Do you take chances? (yes/no)
Factual variables	In the last month have you traveled? (yes/no) In the last month have you participated in a team or individual sport? (yes/no) In the last month have you read a book? (yes/no)
Privacy Variables	Which of these practices, if any, do you consider to be a serious violation of privacy? Please check all that apply. 1. Thorough searches at airport checkpoints, based on visual profiles 2. The use of programs such as 'cookies' to track what an individual does on the Internet 3. Unsolicited phone calls for the purpose of selling products or services 4. Screening of employees for AIDS 5. Electronic storage of credit card numbers by Internet stores
Lifestyle variables	Do you know anyone who is gay, lesbian, bisexual, or transgender? Please check all that apply. 1. Yes, a family member 2. Yes, a close personal friend 3. Yes, a co-worker 4. Yes, a friend or acquaintance (not a co-worker) 5. Yes, another person not mentioned 6. No

than in a reference survey given a set of observed covariates (Steinmetz *et al.*, 2009). In addition, the propensity score is a *balancing score* which has the property that treatment assignment is conditionally independent of the covariates given the balancing score (Lee, 2004). This means respondents in both surveys with the same propensity score have the same distribution of $\mathbf{x}$ (Schonlau *et al.*, 2007). It can be expressed mathematically as

$$\mathbf{x} \perp z|b(\mathbf{x}),$$

where $b(\mathbf{x})$ is the balancing score.

Moreover, Lee (2004) also shows that in theory the adjustment based on a propensity score leads to an unbiased estimate of treatment effect, i.e., the difference between web and reference survey mean, as long as certain assumptions hold. The assumptions are described in the next subsection.

The aim of propensity score adjustment is to enable a form of post-stratification so that estimates of variables of interest for the web sample are similar to those for the reference sample within each group of approximately equal propensity scores. Modeling and some methods for the propensity score adjustment are described in detail in the Subsection 4.2.4 and 4.2.5.

4.2.3 Assumptions in propensity score adjustment

Lee (2004) outlines five assumptions in observational studies in order that propensity score adjustment should be valid for bias reduction and adapt these meanings to apply to web surveys. These are summarized below.

First, any propensity score should meet the 'strong ignorability assumption':

$$Y \perp z|e(\mathbf{x}) \qquad and \qquad 0 < Pr(z = 1|e(\mathbf{x})) < 1,$$

where Y is the response variable. In case of randomized treatment assignment, this assumption holds and adjustments based on the propensity scores produce the unbiased estimates. However, in case of nonrandomized treatment assignment, this is not necessary true. Therefore, this assumption is critical in web surveys using convenience sampling methods. Strong ignorability implies that there are no unobserved variables that explain selectivity into the web sample and that are also related to the question of interest Y (Schonlau *et al.*, 2007). In volunteer panel web surveys, strong ignorability could be violated if some important covariates in propensity score modeling are omitted or responses are related to covariates that

are not used.

The second assumption is no contamination among study units which means that a treatment assigned to one unit does not affect the outcome for any other unit. Third, any unit must be assigned to either treatment or control for any configuration of $\mathbf{x}$. Fourth, the observed covariates included in propensity score models represent the unobserved covariates, because balance is not necessarily achieved on unobserved covariates. If an important covariate, e.g., education, was omitted from the model and the web sample subjects and non-web sample subjects had different distributions of levels of education, then this assumption would be violated. The last assumption is that the assigned treatment does not affect covariates. None of them can be altered by a person's participation in one or the other survey.

4.2.4 Modeling propensity scores

There are several parametric models used for propensity score modeling. These include logistic regression, generalized linear models, generalized additive models and classification tree models. The most common one is logistic regression (Lee, 2004; Bethlehem, 2010; Schonlau *et al.*, 2007; Steinmetz *et al.*, 2009; Loosveldt and Sonck, 2008).

As described before, the propensity score is the probability of a unit being assigned to the treatment group given a set of covariates (Equation 4.1). In a logistic regression model, the propensity score is modeled as:

$$log\left[\frac{e(\mathbf{x})}{1-e(\mathbf{x})}\right] = \alpha + \beta'\mathbf{x}$$

Variable selection in propensity score modeling can be a critical issue because the covariates in the model affect performance of the propensity score adjustment. The covariates in the model should be related to not only treatment assignment but also response in order to satisfy the strong ignorability assumption (Rosenbaum and Rubin, 1984). Rosenbaum and Rubin (1984) recommend including all available covariates, even if they are not statistically significant, unless they are known to be unrelated to the outcomes.

In practice, however, variables have been often selected by using a stepwise variable selection algorithm to develop good predictive models for treatment assignment. One-step covariate selection based on theoretical and/or logical relevance has been adopted as another modeling method (Lee, 2004). However, Brookhart *et al.* (2006) have doubt about

effectiveness of this kind of variable selection method. They use a simulation study to show that variables that are unrelated to the treatment assignment but related to the response should always be included in a propensity model.

In many previous studies for evaluation of propensity score adjustment in web surveys, variable selection was conducted in such a way that models included all covariates, of which numbers range from 5 to 30 (e.g., Lee and Valliant, 2009; Bethlehem, 2010; Schonlau *et al.*, 2007; Steinmetz *et al.*, 2009; Loosveldt and Sonck, 2008). In fact, in most of these studies, the numbers of available variables in both web and web survey are within around 10. However, there is a limit on the number of covariates in models because those variables should be included in both web and reference surveys and it is difficult to recruit participants to complete very long surveys.

Lee and Valliant (2009) compare five different logistic models in order to separately examine effects of stratifying variables (age, gender, education, and race) and webographic variables. The base model (Model 2) includes all available 30 covariates. Models 1, 3, 4 and 5 use subsets of the covariates in Model 2. In order to test the role of significance testing, covariates roughly with p-value ≤ 0.2 are used in Model 3. In order to detect the marginal effect of stratifying variables used in their simulation, Model 1, 4 and 5 are constructed. Model 1 includes only the stratifying variables. Model 4 uses all variables *except* the stratifying variables. Model 5 includes significant covariates at the 0.2 level but excludes the stratifiers. The results of the study shows that Model 2 and 3 appear to produce reasonable bias reduction across all covariates. Huh and Cho (2009) use 9 or 7 covariates in their model out of 123 available covariates suggesting that some guidelines should be considered in selecting webographic variables, which include:

- Questions should be 'fundamental' so that the answers would not be changed easily. For example, people would not change their opinions regarding a 'fundamental' question asking about 'the necessity of unification of Korea', while the opinions regarding the 'necessity of the six-party talks[1]' can be changed easily by the political situations when the survey is taken.

- Questions should be easy to be answered in order to minimize measurement error

[1]The six-party talks aim to find a peaceful resolution to the security concerns as a result of the North Korean nuclear weapons program. There has been a series of meetings with six participating states: South Korea, North Korea, China, USA, Russia, Japan.

because hard ones have room for severe measurement errors.

- Questions should distinguish well between a web and a reference group participating in a survey.

This approach may be reasonable. However, there seems to be room for criticism that it can be subjective, because different people can select different questions as webographic variables if there are not enough studies of the questions.

For the best performance of propensity score adjustment, selecting covariates for each model corresponding to each response variable seems be important in order to meet the strong ignorability assumption. However, this approach seems to be impractical in web surveys, even impossible for large surveys. The number of available response variables and covariates in data sets used in this paper, which will be described in Chapter 5, is over 100. Constructing a separate propensity score model for each response variable, which may generate as many models as there are response variables in worst case, is not feasible. Therefore, it is important to select an acceptable number of webographic variables that work broadly with many responses for use in future surveys. As Lee (2004) mentions, there seem to be no clear-cut criteria for selecting variables for propensity score model building. It is hard to define what kind of questions could be used as webographic variables.

In this paper, some possible variable selection methods are explored, which include stepwise based on information criteria, and 'Least Absolute Shrinkage and Selection Operator' (LASSO) selection in a logistic regression model, and boosted tree models.

Stepwise techniques (including forward and backward selection) have been used as automated procedures (e.g., SAS PROC GLM or LOGISTIC) for regression analysis. They are summarized briefly below.

- Forward selection begins with null model and adds the most significant variable to the model one at a time until there are no variables that meet a stated criterion.

- Backward selection begins with full model and removes the least significant variable one at each step until there are no variables that meet a stated criterion

- Stepwise selection combines the elements of the previous two.

In particular, Shtatland *et al.* (2008) suggest the combination of stepwise logistic regression, information criteria, and best subset selection using SAS PROC LOGISTIC instead

of ordinary stepwise selection if the goal of modeling is prediction, when there is a large number of covariates and little theoretical guidance for choosing among them. The basic idea behind the information criteria is penalizing the likelihood for the model complexity. Akaike information criterion (AIC) and Schwarz's criterion (SIC[2]) are most popular. The general form is

$$IC(c) = -2logL(M) + c * K,$$

where $logL(M)$ is the maximized log likelihood for the fitted model, N is the sample size, K is the number of covariates, and c is a penalizing parameter. The AIC and SIC can be defined as information criteria with c=2 and $c = logN$ correspondingly. The first step for this approach is to use the stepwise selection method with significance level to enter and significance level to stay close to 1 (e.g., significance level to enter =0.99 and significance level to stay =0.995) in order to get a sequence of models starting with the null model and ending with the full model. Then, we can choose the model which has the smallest value of the information criteria.

Another technique of variable selection is LASSO selection. The LASSO parameter estimates are given by

$$\hat{\beta}^{lasso} = \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{n} (y_i - \sum_{j=1}^{p} x_{ij}\beta_j)^2$$

subject to

$$\sum_{j=1}^{p} |\beta_j| \leq s,$$

where n is sample size, y_i are values of the dependent variable, x_{ij} are the values of the predictor variables, and s is a shrinkage factor. The LASSO method can be used in SAS PROC GLMSELECT, which was originally developed in the context of linear models as fit by PROC GLM. However, it has been applied with binomial logistic as well (Roth, 2004).

Finally, classification tree modeling can be used. Classification tree is used for determining a set of split conditions that permit accurate classification of cases. Roe *et al.* (2005) indicate that classification trees are powerful, but unstable because a small change in the training data can produce a large change in the tree, so boosting can be a remedy. Boosting is based on the observation that finding many rough rules of thumb can be a lot easier than

[2]Also known as Bayseian information criterion (BIC) or Schwarz's Bayseian criterion (SBC), or Schwarz's criterion(SC)

finding a single, highly accurate prediction rule. Boosting can produce a very accurate prediction rule by combining rough rules via iterative algorithms (e.g., AdaBoost algorithm). Variables can be selected according to "relative influence" values (Elith *et al.*, 2008). The relative influence of each variable is scaled so that the sum adds to 100, with higher numbers indicating stronger influence on the response. A disadvantage of this approach is computational burden. In case of large numbers of categorical variables with many categories, the computations performed may require an unreasonable amount of effort and time. The theory of this method is not discussed in detail in this paper. The R package "gbm" (General Boosted Model) provides boosted classification tree modeling method.

Applications of those above three modeling methods are described and compared in Chapter 5. As described above, modeling for propensity score adjustment can be critical for its effectiveness. In addition, the number of covariates in the model can be important in terms of practice because few researchers would want to use those large complex models just for computing propensity scores.

4.2.5 Applyng methods for propensity score adjustment

D'Agostino (1998) introduces three propensity score adjustment methods: matching, subclassification (also called stratification) and regression adjustment. *Matching* is very popular in observational studies where there are a limited number of treated group members, and a larger number of control group members. Members of one sample are paired with members of the other sample according to their propensity scores. Then methods for estimating treatment differences using paired data are applied to the response variable. However, in the context of web surveys, pair matching has a limitation, because the response variable is typically measured only in the web surveys (Lee, 2004). The author also indicates that *regression adjustment* is not as widely applied as subclassification or matching because of poor performance. Therefore, the above two methods are not dealt with in this paper. Instead, using inverse propensity scores as weights is described as an alternative, along with subclassification. With both techniques, the propensity score is calculated the same way, but once it is estimated it is applied differently.

Inverse propensity scores as weights

This approach is the simplest method. Recall that a propensity score is the conditional probability that a person will be 'in a web survey' rather than 'in a reference survey' given a set of observed covariates, that is

$$e(\mathbf{x}_i) = Pr(z_i = 1|\mathbf{x}_i)$$

where z_i is an indicator variable for membership in the web survey, and $\mathbf{x}_i$ are covariates in the model.

After calculating the propensity scores, weights (w_i^{ps}) of web survey are formed as the inverse of the propensity scores (Steinmetz, 2009):

$$w_i^{ps} = \frac{1}{e(\mathbf{x}_i)}$$

Those weights can then be multiplied with base weights such as sampling weights (if applicable, e.g., in case that subjects of web survey are chosen from the pool of volunteers by probability-based sampling) for the final weights. Note that survey weights are not used in developing the propensity score model. Hahs-Vaughn and Onwuegbuzie (2006) state that this is not necessary because propensity scores are used only to form subclasses with similar background covariates, not to make inferences about the population-level propensity score model.

Subclassification (Stratification)

Subclassification is commonly used in observational studies to identify systematic differences between the treated and control groups. Harris Interactive and Lee and Valliant (2009) applied this approach to their web survey studies. Lee and Valliant (2009) describe the process of applying this approach, which is summarized below.

Denote the volunteer panel web survey sample as s^W with n^W units, each with a base weight of d_j^W, where j=1, ..., n^W, and the reference survey sample as s^R with n^R units, each with a base weight of d_k^R, where k=1, ..., n^R. Base weights can be sampling weights from larger panel in the web survey or population in the reference survey. We can set d_j^W and d_k^R as 1 if no base weights are already given in the both surveys. First, the two samples are combined into one, $s = (s^W \cup s^R)$, with $n = n^W + n^R$ units. After estimating each

propensity score from the combined sample ($e(\mathbf{x}_i) = Pr(i \in s^W|\mathbf{x}_i), i = 1, \ldots, n$), those units (s) are partitioned into C subclasses according to ordered values of $e(\mathbf{x}_i)$, where each subclass has about the same number of units. In the cth subclass in the merged data, denoted as s_c, there are $n_c = n_c^W + n_c^R$ units, where n_c^W is the number of units from the web survey data and n_c^R is the number of units from the reference survey. Total number of units in the combined data reamains the same :

$$\sum_{c=1}^{C}(n_c^W + n_c^R) = \sum_{c=1}^{C}(n_c) = n.$$

Then, compute the following adjustment factor that will be applied to all units in the cth subclass of the web survey data (s_c^W):

$$f_c = \frac{\sum_{k\in(s_c^R)} d_k^R / \sum_{k\in(s^R)} d_k^R}{\sum_{j\in(s_c^W)} d_j^W / \sum_{j\in(s^W)} d_j^W}, \tag{4.2}$$

where s_c^R and s_c^W are the sets of units in the reference sample and web sample, respectively, of the cth subclass. If the base weights in equation (4.2) are the inverses of selection probabilities, the adjustment is equivalent to

$$f_c \equiv \frac{\hat{N}_c^R/\hat{N}^R}{\hat{N}_c^W/\hat{N}^W},$$

where $\hat{N}_c^l = \sum_{k\in(s_c^l)} d_k^l$ is the estimated population count of units based on the reference or web survey ($l = R \; or \; W$) and $\hat{N}_l = \sum_C \hat{N}_c^l$. The propensity score adjusted (PSA) weights for unit j in s_c^W is

$$d_j^{W.PSA} = f_c d_j^W = \frac{\sum_{k\in(s_c^R)} d_k^R / \sum_{k\in(s^R)} d_k^R}{\sum_{j\in(s_c^W)} d_j^W / \sum_{j\in(s^W)} d_j^W} d_j^W.$$

If the base weights are equal for all units or are not available, an alternative adjustment factor can be used, which is

$$f_c \equiv \frac{n_c^R/n^R}{n_c^W/n^W}.$$

Finally, the estimator for the mean of a study variable, y, for the web survey sample is

$$\hat{\bar{y}}^{W.PSA} = \frac{\sum_c \sum_{j\in(s_c^W)} d_j^{W.PSA} y_j}{\sum_c \sum_{j\in(s_c^W)} d_j^{W.PSA}}.$$

It is notable that the reference sample is required to have only the covariate data, not necessarily the variables of interest. This is because the reference sample units are not used in in computing $\hat{\bar{y}}^{W.PSA}$ after adjustment weights are calculated. Finally, it is assumed that mode effects between web and reference survey can be disregarded.

It is possible to create numerous subclasses assuming that more homogeneous groups may be partitioned into each subclass. However, the possibility of no inclusion of either treated group or control group within subclasses increases as the number of subclasses increases. Since Cochran (1968) found that five subclasses are often sufficient to remove over 90 percent of the bias, many researchers use the quintiles of the estimated propensity score from the combined group to determine the cut-offs for the different subclass (D'Agostino, 1998).

Subclassification is popular because it has some advantages, which include (1) it is easier than matching, (2) the number of control group subjects need not be larger than that of the treated group, and (3) subclassification uses all subjects, whereas matching discards unmatched subjects (Lee, 2004).

4.3 Calibration (Rim weighting)

Propensity score adjustment makes response estimates in a web survey resemble those hypothetically taken in a probability-based reference survey. As discussed before, Lee and Valliant (2009) suggest a second stage adjustment to make the propensity-score-adjusted web survey sample resemble the target population. One such method of adjustment is called *rim weighting*.

Rim weighting was originally developed by Deming and Stephan (1940) in order to ensure that complete census data and samples taken from it gave consistent results. The method matches sample and population characteristics only with respect to the marginal distributions of selected covariates, while post-stratification needs the joint distributions of the covariates, which is often not available for the population. Rim weighting can be conducted by an iterative algorithm to alternately adjust weights according to each covariates' marginal distribution until convergence. There are many algorithms for doing this. The one below is developed by Little and Wu (1991).

Consider two discrete covariates, with I and J levels, respectively, and suppose that the sample frequencies are laid out in an $I \times J$ contingency table. Let n_{ij} be the cell count in ith row and jth column, $n =$ total counts, and let w_i and w_j be the target marginal proportions

of row i and column j in population, respectively.

1. Initialize the weights by setting each equal to $\hat{w}_{ij}^{(0)} = \frac{n_{ij}}{n}$.
2. Raking over rows : $\hat{w}_{ij}^{(1)} = w_i \times \frac{\hat{w}_{ij}^{(0)}}{\sum_i \hat{w}_i^{(0)}}$.
3. Raking over columns : $\hat{w}_{ij}^{(2)} = w_j \times \frac{\hat{w}_{ij}^{(1)}}{\sum_i \hat{w}_j^{(1)}}$.
4. Repeat step 2 and 3 until $\sum_j \hat{w}_{ij} = w_i$ and $\sum_i \hat{w}_{ij} = w_j$ for each i and j, i.e., convergence is achieved.

If the sample sizes in each cell are large enough, the raking estimator is approximately unbiased. However, a disadvantage of rim weighting is that the algorithm may be slow and even not converge if some of the cell estimates are zero. Huh and Cho (2009) indicate that rim weighting can be used in sampling methods such as systematic sampling from the weighted list. The sampling from the pool of all volunteers for the web survey in the case study for this paper was done by this method.

Chapter 5

Case Study

This chapter explores the performance of the proposed adjustment approaches for volunteer web panel surveys presented in Chapter 4. The purpose of the adjustment approaches is to reduce bias that may occur from the non-probability sampling and under-coverage errors. The web survey and reference survey data used in this study were provided by Statistics Korea. The effects of propensity score models, PSA methods and calibration adjustment are compared in order to examine the degree of bias reduction associated with each.

5.1 Data

In 2009 Statistics Korea conducted a web survey to evaluate statistical estimation methods like propensity score adjustment and rim weighting for volunteer panel web surveys. Some of the questions from the 2009 Social Survey (reference survey) were included in the web survey questionnaire. Huh and Cho (2009) performed an analysis of the results based on the data sets. The data sets are used in this paper as well, but methods are applied differently. The main differences are summarized in Table 5.1.

5.1.1 Reference survey data

The Social Survey consists of total 10 areas biennially. The 2009 survey included sections on Welfare, Culture & Leisure, Income & Consumption, Labor, and Social Participation. The 2010 survey included Family, Education, Health, Environment, and Safety. The 2009 survey, used in this study, sampled all persons aged 15 and over who normally reside in 17,000

Table 5.1: The main differences between Huh & Cho (2009) and this study

	Huh and Cho (2009)	This study
Model selection and evaluation	- Model selection and evaluation for all data - 9 or 7 variables in the model considering some guidelines (see the Subsection 4.2.4). - Imputation for those covariates in the model and complete data analysis without nonresponse variables.	- Data splitting : Training data for model selection and Test data for evaluation. - LASSO, Stepwise based on information criteria, Boosted tree. - Imputation for all covariates except over 50% nonresponse rate.
propensity score adjustment	- Inverse propensity scores as weights.	- Inverse propensity scores as weights and subclassification.

selected households during the survey period. A total of 37,049 respondents participated in the survey. This survey was conducted face-to-face. For estimation, post-stratification weights are calculated based on population characteristics by gender, age and area of residence. This survey plays the role of reference survey in this study, and the estimates of responses are assumed to be true values of the population for evaluation of bias in this survey.

5.1.2 Web survey data

Statistics Korea recruited volunteers for the web survey via advertisements placed on various web sites including its own. A total of 6,854 people participated in the invitation as households. Table 5.2 shows the relative proportion[1] of the volunteers vs. estimated population in terms of demographic variables : region[2], gender, age[3].

Table 5.2: Relative proportion of volunteers to estimated population

Major cities & Provinces	Seoul 1.20, Busan 1.12 Daegu 1.20, Incheon 0.99, Kwangju 0.94, Deajeon 1.68, Ulsan 1.14 Kyeonki 0.93, Kangwon 0.97, Chungbuk 0.84, Chungnam 0.64, Chenbuk 0.89, Chennam 0.62, Kyengbuk 0.76, Kyeonnam 0.79, Cheju 0.88
Urban & Rural	Urban 1.09, Rural 0.58
Gender	Male 0.89, Female 1.11
Age	Under 29 1.60, Thirties 1.75, Forties 0.73, Fifties 0.27, Over 60 0.06

There are some clear differences between the volunteers respondents and the general population. Relative proportions of age groups Fifties and Over 60 are only 27% and 6%, while that for Thirties is 175%. It means that young people participated in the web survey invitation more often than old people. In addition, people who reside in urban areas participated in the invitation with greater relative frequency than rural residents, as we can anticipate. Huh and Cho (2009) planned to adjust this unrepresentativeness to some extent in sampling from the volunteers. Weights were calculated by rim weighting method using the demographic variables above. They applied systematic sampling with non-equal

[1]The relative proportion in a given category is the proportion of the volunteers in that category divided by the proportion of the population in that category

[2]Region consist of 7 major cities and 9 provinces which are further divided into dongs (urban area) and eups & myeons (rural area)

[3]Age is grouped into five subgroups : under 29, 30-39, 40-49, 50-59, over 60

selection probabilities equal to the inverse of the weights. A total of 1,500 households were chosen as the sample, the size of which was related to the budget for incentives. Table 5.3 shows relative proportions of the sample to the estimated population. According to the Table 5.3, the relative proportions of the sample were improved compared to those of the all volunteers. For example, relative proportions of age groups of Fifties and Over 60 were improved to 107% and 29% from 27% and 6%, respectively. The relative proportion of rural area was improved to 85% from 58%. Huh and Cho (2009) state that the difference left after sampling happened because they prevented too much weighting of a small number of subjects by setting an upper limit on weights at five, and that it can be adjusted by further propensity score and rim weighting. In all, a total of 2,903 respondents, who reside in the 1,500 households, participated in the web survey. The number of overlapping covariates between the web survey and the reference survey is 123 (five covariates with over 50% of nonresponse rates were removed in this study). The overlapping covariates are described in the Appendix A.

Table 5.3: Relative proportion of web sample to estimated population

Major cities &Provinces	Seoul 1.03, Busan 0.97 Daegu 1.08, Incheon 1.13, Kwangju 0.90, Deajeon 1.13, Ulsan 1.14 Kyeonki 0.99, Kangwon 0.94, Chungbuk 0.97, Chungnam 0.85, Chenbuk 1.11, Chennam 0.95, Kyengbuk 0.85, Kyeonnam 0.95, Cheju 1.00
Urban & Rural	Urban 1.03, Rural 0.85
Gender	Male 0.95, Female 1.05
Age	Under 29 1.16, Thirties 1.16, Forties 1.16, Fifties 1.07, Over 60 0.29

5.1.3 Imputation and data splitting

In applying propensity score adjustment to web surveys, selection of covariates in the model is important. The covariates in the model cannot be allowed to have missing data because

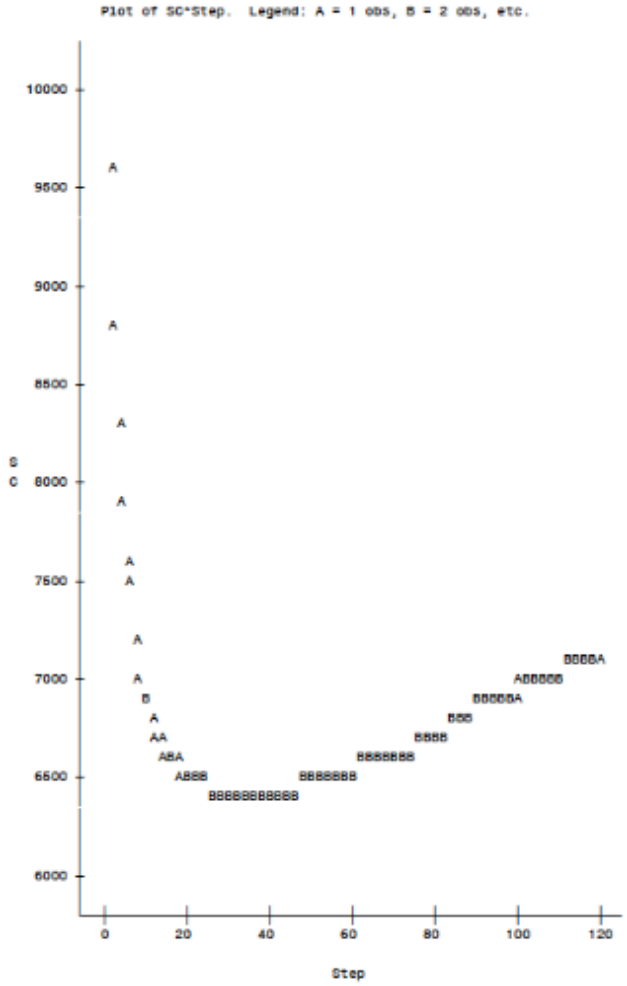
propensity scores must be able to be calculated even if there are non-responses. Therefore, imputation is needed before applying propensity score adjustment. In this study, hot deck imputation was used. The review of hot deck imputation in Andridge and Little (2010) is summarized below. Hot deck is a method to replace missing values for a non-respondent (a recipient) with observed values from a respondent (a donor) that is similar to the recipient with respect to characteristics observed on both. One hot deck method is a "hot deck within adjustment cells". This approach classifies the recipients and the donors into adjustment cells based on auxiliary variables, and then carries out imputation by randomly selecting a donor for each recipient within each cell. Hot deck assumes missing data are MAR. In this study, "hot deck within adjustment cells" is used by gender, age, region, and level of education as auxiliary variables. The SAS procedure 'HHdeck' is used for the method.

In addition, the reference data and the web data were split into two data sets: training data set and test data set. After generating random numbers according to a uniform (0,1) distribution for each observation, the data were divided at the point of 0.5, and then assigned to training and test data sets in order for the two data sets to have about same size. The training data set is used for model selection and the test data set is used for evaluation. The use of an independent test data set for evaluating models is useful for understanding their potential when used in future surveys.

5.2 Model Selection

As described in Subsection 4.2.4, three kinds of modeling methods are used based on the training data set, which consisted of 20,001 cases drawn from the full combined sample size of 39,952. The training data set consisted of 18,530 reference sample cases and 1,471 web sample cases. At first, in order to implement stepwise logistic regression method with information criteria, SAS PROC LOGISTIC was used by setting significance level to enter=0.99 and significance level to stay=0.995. The SIC was used instead of AIC in order to penalize more in terms of the number of covariates because the data in this paper have a lot of available covariates and sample size is big. The Figure 5.1 shows the SIC values at each step (step numbers mean the number of covariates in the stepwise model). Even though 28th step has smallest SIC value (6410.31), I chose the 22th step model (SIC value = 6479.338) as the Model 1, and the 17th step model (SIC value=6572.241) as Model 2 because too many covariates in the model is not practical for future surveys. The variables

Figure 5.1: Plot of SIC vs Step number in Stepwise logistic variable selection.



in these models are listed in Table 5.4.

The SAS PROC GLMSELECT was used for the LASSO model, and the model selected (Model 3) includes 12 covariates. This is also given in Table 5.4. For the boosted tree model, the R package "gbm" is used by setting iterations=10,000 because of limits on computer capacity. A total of 18 covariates that have over 0.5 relative influence were chosen out of total 35 covariates with relative influence > 0, and the model is set as Model 4 in Table 5.4. It should be noted ordinal categorical variables (e.g., frequency of reading newspapers (very often, often, sometimes, a little, no)) are treated as continuous variables in model selection.

Table 5.4: Covariates in the models

Covariate	M1	M2	M3	M4	Type[1]	Description
region1	x	x	x	x	16 cat	major city or province
news	x	x	x	x	5(cont)	how often read newspaper
i_news	x	x	x	x	5(cont)	how often read Internet newspaper
freetime	x	x	x	x	14 cat	how to spend free time during weekend
leisure	x	x	x	x	14 cat	type of leisure activities wanted to do
monnet	x	x	x	x	2 cat	social network in case of need of money
ordcommu	x	x	x	x	8 cat	participation in community activities
stecosp	x	x	x	x	2 cat	status of economic activity of spouse
ipspare	x	x	x		5(cont)	importance for quality of life (sparetime)
rel_hohead	x	x		x	10 cat	relationship to household head
age5	x	x			5 cat	age
marital	x	x			4 cat	marital status
freewhom	x	x			5 cat	with whom spend free time during weekend
satover	x	x			5(cont)	overall level of satisfaction
futuvol	x	x			3 cat	voluntary service in the future
workingh	x	x			cont	working hours
stemp	x	x			4 cat	employment status
tmanner	x			x	5(cont)	effect of traditional culture on a life (manner)
safety	x			x	5(cont)	safety of society
book	x				2 cat	reading books
magz	x				cont	book(magazine)
satcivils	x				5(cont)	levels of satisfaction with civil service
hchildvol			x	x	cont	voluntary service time (children,senior)
heduvol			x		cont	voluntary service time (education)
movie			x		cont	movie
b_life				x	cont	book (life)
b_other				x	cont	book (others)
perfo				x	cont	performance
dancing				x	cont	dancing
museum				x	cont	museum
odonate				x	cont	donation (others)

[1] # cat = number of categories for nominal variables; cont = continuous numerical variable.

5.3 Distributions of covariates in web survey and reference survey before weighting adjustment

Before applying weighting procedures to the survey data, some covariates are explored in order to investigate the difference between web survey respondents and reference survey respondents. Figure 5.2 shows distributions of four covariates in the models in web survey (WEB) and reference survey (REF). WEB respondents tend to read both actual and Internet newspapers more often REF respondents. The difference is larger for the Internet newspapers. REF people tend to consider 'spare time' more important than WEB people. The proportion of WEB people who consider it important (very + fairly) is 12%, while that in REF is 20%. For the age group covariate, the proportion of Under 29 is 33% in WEB and 22% in REF, while the proportion of Over 60 is 8% in WEB and 21% in REF. As discussed in Subsection 5.1.2, young people still tend to participate in web surveys with high relative frequency even though age was considered in choosing the pool of volunteer panelists. The Education level covariate (Figure 5.3) is explored even though it is not included in any of the four models because past work has shown a relationship with participating in the web survey. The proportion of people with postsecondary education (undergraduate + graduate) is 61% in WEB and 36% in REF, while that of 'under middle school' is 11% and 28% respectively. We can say that people with higher levels of education participated more often in the web survey, as we expect.

From the above results, we can see that there are considerable differences in many covariates between web survey respondents and reference survey respondents.

5.4 Weighting procedures

5.4.1 Propensity score adjustment

Once models were selected, the propensity scores were estimated by equation (4.1) for the test data set which consisted of 18,519 observations from the reference sample and 1,432 from the web sample. Figure 5.4 shows the distribution of propensity scores based on Model 1. As expected estimated probabilities of being in the web survey are generally low for reference survey respondents. However, web survey respondents are more poorly classified because

Figure 5.2: Distribution of 4 covariates in the models

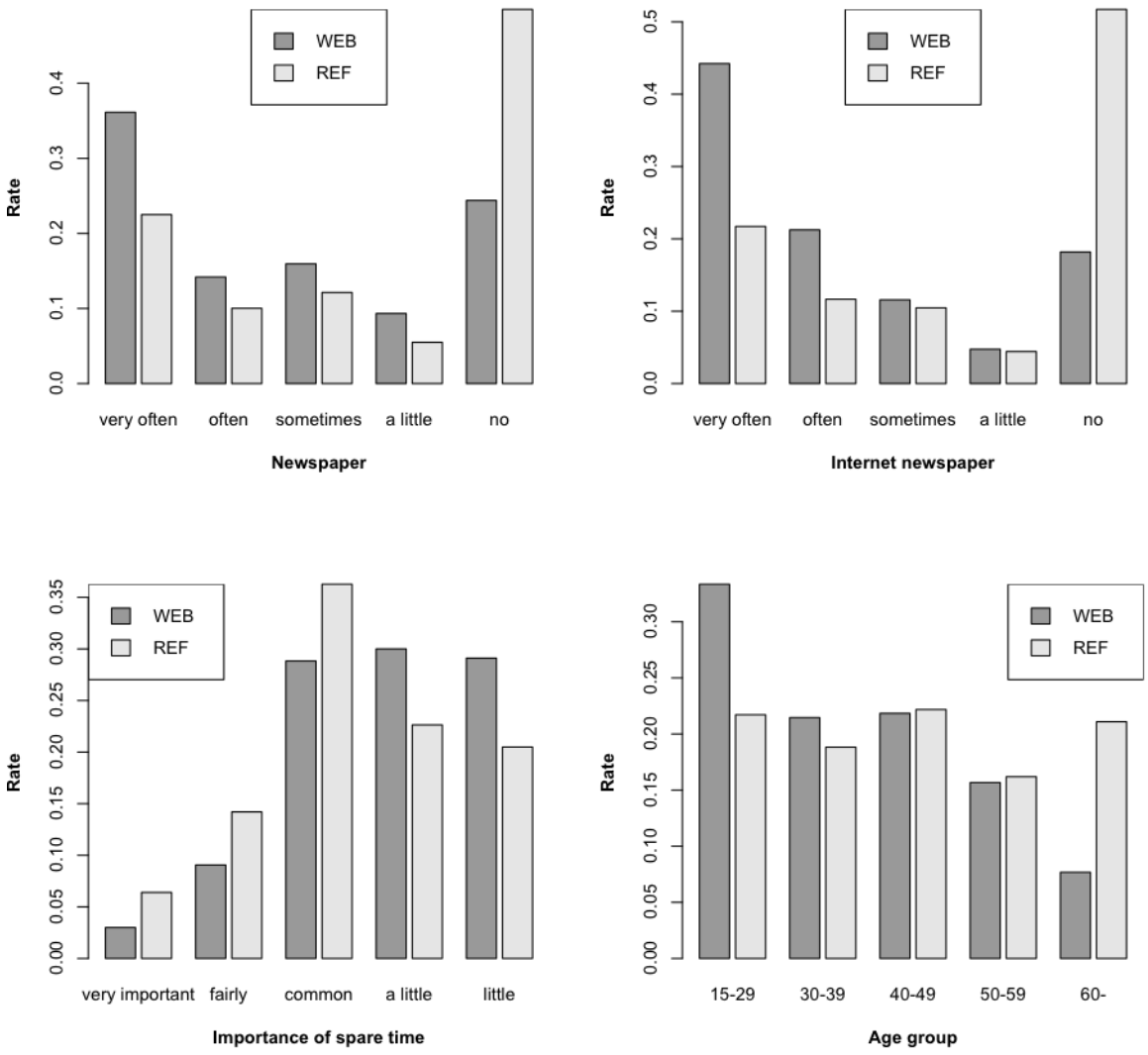


Figure 5.3: Distribution of education level

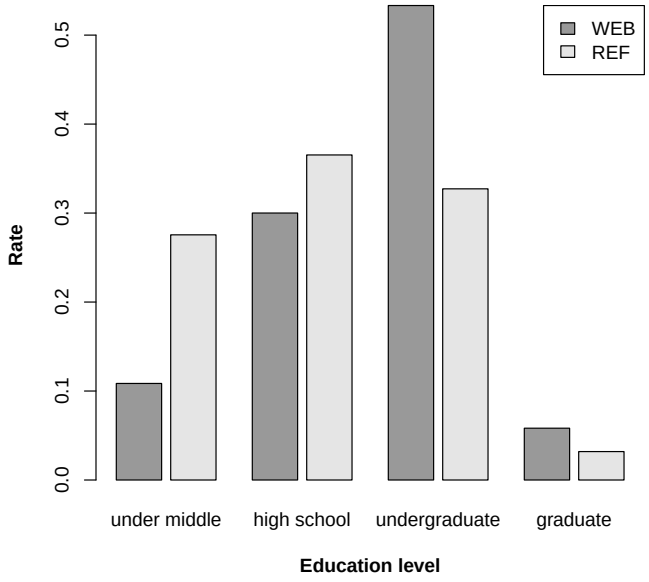
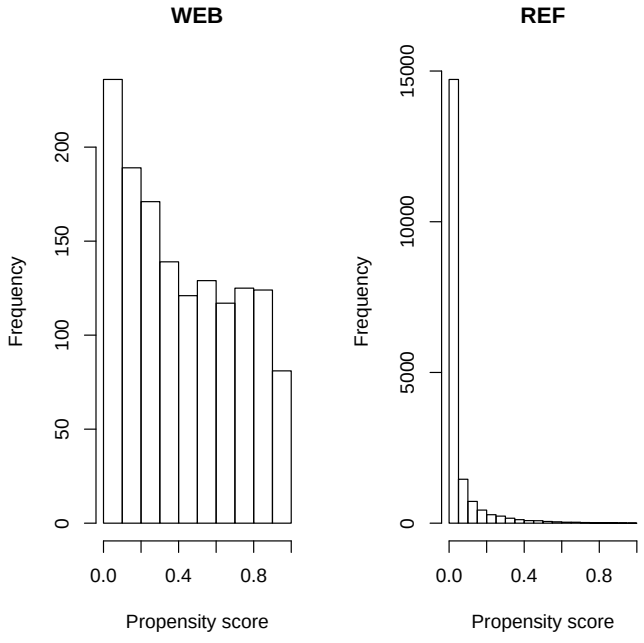


Figure 5.4: Distribution of propensity scores in Model 1



their proportion of the combined sample is small.

After calculating propensity scores, the PSA weights were calculated in each model by both inverse of propensity scores as weights and subclassification (using five subclasses) as discussed in Subsection 4.2.5. As base weights (or sampling weights), post-stratification weights[4] and rim weights[5] were used in the reference survey and the web survey respectively. The quantiles of PSA weights of all models are shown in the Table 5.5. Figure 5.5 and Figure 5.6 show the distribution of the PSA weights in Model 1. Here, the weights are scaled to match the sample size of web survey. In other words, the sum of the weights equals the total sample size of web survey in the test data set.

For all models, the distributions of inverse propensity score weights are severely right-skewed. For example, in Model 1, some subjects dominate the weights (minimum weight =0.0044, first quartile=0.0112, median=0.0203, third quartile=0.0512, and maximum= 757.2). The distribution of subclassification weights shows right-skewness, but it is less severe than the previous one (minimum weight=0.1081, first quartile=0.154, median=0.1965, third quartile=0.244, and maximum=168.5). In the inverse propensity score weights, if the probability of 'web people' is very small, the weight will be very large. Therefore, the weights may be affected substantially by propensity score models or properties of the data. In the subclassification, the effects can be reduced because the propensity scores are divided into groups so some smoothing of extremes occurs. In addition, Model 3 and Model 4 show slightly less skewed distributions than Model 1 and 2. Very large weights can be corrected by fixing a maximum value as in Huh and Cho (2009). This was not attempted in this paper.

[4]The post-stratification weights are calculated based on four demographic variables which include major city & province, urban & rural, gender, and age. They were obtained by Statistics Korea.

[5]The rim weights were used for sampling from the pool of all volunteers. Those were obtained by Huh and Cho.

Table 5.5: Summary of PSA weights

	PSA[1]	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Model 1	Inv.	0.00	0.01	0.02	1.00	0.05	757.20
	Sub.	0.11	0.15	0.20	1.00	0.24	168.50
Model 2	Inv.	0.00	0.01	0.01	1.00	0.03	798.60
	Sub.	0.11	0.16	0.20	1.00	0.26	195.10
Model 3	Inv.	0.02	0.07	0.12	1.00	0.32	678.50
	Sub.	0.12	0.18	0.23	1.00	0.41	231.50
Model 4	Inv.	0.02	0.07	0.15	1.00	0.35	681.40
	Sub.	0.12	0.17	0.22	1.00	0.40	205.80

[1] Inv. = inverse propensity scores as weights; Sub.=subclassification.

Figure 5.5: Distribution of PSA weights based on inverse propensity score weights in Model 1

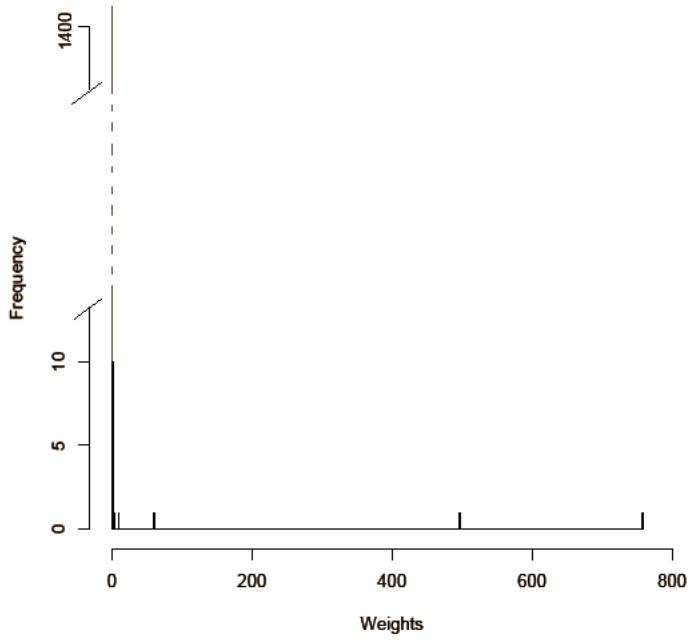
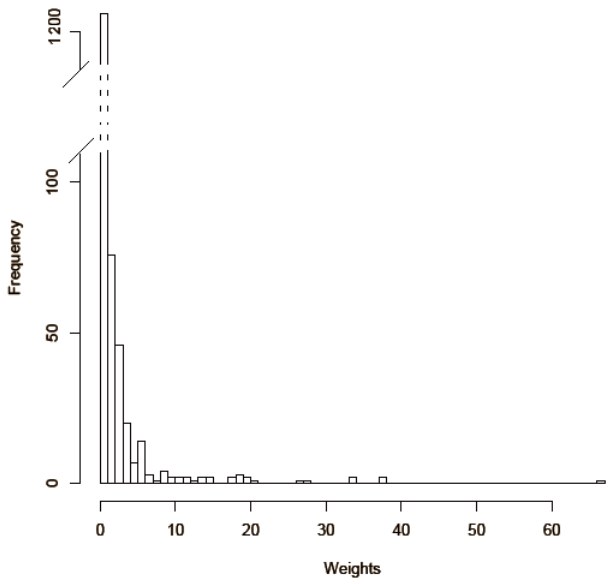


Figure 5.6: Distribution of PSA weights based on subclassification in Model 1



5.4.2 Calibration adjustment

Even though rim weights were already used for sampling in the web survey, propensity score adjustment might affect the distribution of demographic variables. Therefore, after calculating propensity score weights, rim weighting was applied again as a calibration adjustment as discussed in Section 4.3. The rim weights were calculated based on marginal distributions of four demographic variables: major city & province, urban vs. rural, gender, and age for the test data set. Table 5.6 shows the quantiles of final weights of all models after rim weighting, and Figure 5.7 and 5.8 shows the distribution of the final weights based on Model 1. Overall, the final weights are less positive skewed than propensity score weights, and the maximum values are smaller as well. Subclassification shows less skewed distributions than inverse weighting.

Table 5.6: Summary of final weights

	PSA	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Model 1	Inv.	0.00	0.14	0.28	1.00	0.59	172.40
	Sub.	0.06	0.22	0.33	1.00	0.59	66.38
Model 2	Inv.	0.00	0.13	0.27	1.00	0.63	194.50
	Sub.	0.08	0.25	0.35	1.00	0.56	64.45
Model 3	Inv.	0.02	0.17	0.29	1.00	0.73	60.08
	Sub.	0.06	0.23	0.40	1.00	0.60	45.94
Model 4	Inv.	0.01	0.16	0.30	1.00	0.69	67.09
	Sub.	0.06	0.21	0.30	1.00	0.58	59.96

Figure 5.7: Distribution of final weights based on inverse propensity scores as weights in Model 1

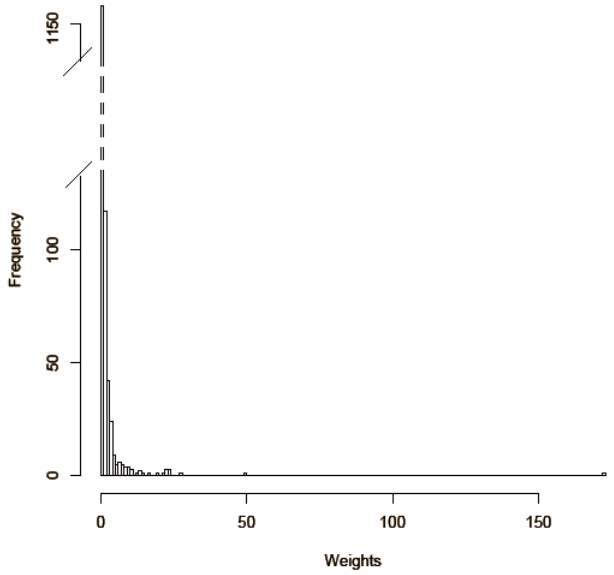
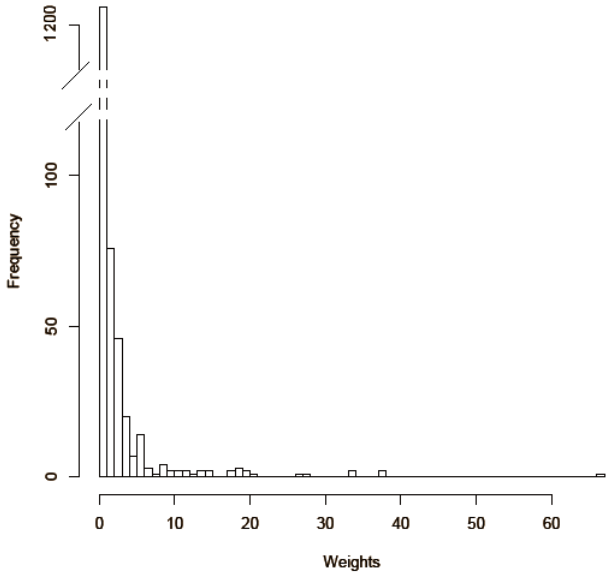


Figure 5.8: Distribution of final weights based on subclassification in Model 1



5.5 Assessment methods

As described above, four models for computing propensity scores were created and two methods for performing PSA were used. Finally, two calibration approaches—rim weighting or none—were applied to each combination of models and PSA methods. Thus, there are 16 different bias adjustment methods being compared.

First, in order to assess whether each stratum in the subclassification method consists of homogeneous groups, the balance of the propensity scores is checked. It is clear that good balancing for all variables is desirable. At least, we expect that the covariates in the models show balance. Fortunately or unfortunately, there are a lot of overlapping variables (size = 123) between the web survey and the reference survey in this study. It is hard to investigate all variables. Therefore, eight covariates which are included in all four models are explored in detail to investigate the effects on balancing due to the four models. The eight covariates are denoted as c1: major city or province ('region1'), c2: how often read newspaper ('news'), c3: how often read Internet newspaper ('i_news'), c4: how to spend free time during weekend ('freetime'), c5: type of leisure activities wanted to do ('leisure'), c6: social network in case of need of money ('monnet'), c7: participation in community

activities ('ordcommu'), c8: status of economic activity of spouse ('stecosp').

Furthermore, 12 variables, which are not included in the models, were chosen in order to check balance of responses (variables of interest). Those variables were chosen by three per each field from four fields of questions: culture & leisure, income & consumption, social participation, and quality of life. The 12 variables are denoted as y1: time of watching TV during weekday ('tv_wday'), y2: experience of traveling overseas ('otour'), y3: satisfaction with leisure activities ('satleisure'), y4: satisfaction with income ('satincome'), y5: expectation of future income ('expincome'), y6: satisfaction with consumption ('satins'), y7: social network in case of sick ('sicknet'), y8: social network in case of depression ('depnet'), y9: experience of donation ('donate'), y10: general health self-assessment ('health'), y11: degree of stress ('stress'), y12: how busy in daily life ('busy').

However, good balancing does not guarantee bias reduction in the response because survey weights and further adjustment are not considered yet. Thus, the main focus is on the performance of each procedure in terms of bias reduction. To assess this, we assume that estimates of reference survey are "true". Each of the 16 procedures will be assessed based on the 12 response variables above in terms of the percentage of bias reduction, as calculated as

$$p.bias(\hat{\theta}^{W.A}) = \left[\frac{|bias(\hat{\theta}^{W.U})| - |bias(\hat{\theta}^{W.A})|}{|bias(\hat{\theta}^{W.U})|}\right] \times 100,$$

where $\hat{\theta}^{W.U}$ is the unadjusted estimate and $\hat{\theta}^{W.A}$ is an adjusted estimate in the web survey.

5.6 Results of comparison

5.6.1 Balance check in subclassification method before applying sample weights and further adjustment

Balance checks were conducted by statistical tests (t-test for non-categorical covariates and χ^2 test for categorical covariates) in each subclassification stratum in order to decide whether differences between groups are significant. The tests were applied to data both before and after subclassification propensity adjustment. For those all 8 covariates, the web survey respondents and the reference survey respondents are significantly different before subclassification (p-values < 0.001). Figure 5.9 shows the p-values of each covariate in each stratum after adjustment. After adjustment, only one covariate (c1) based on Model

4 showed good balance at the significance level 0.05. In the first stratum, all covariates are balanced across models except c3 in Model 3 and c5 in Model 4. As order of stratum increases, more covariates show significant values. However, until $4th$ stratum, the imbalance is not so severe. Overall, there seems to be reasonable balance from first to fourth stratum. In stratum 5, all except one covariate in one model are unbalanced. That may be because most of the web respondents are gathered in the stratum 5 for all models. To illustrate, in Model 1, the sizes of web respondents in stratum 1 to 5 are 2, 4, 25, 163 and 1234 respectively. And, in Model 3, the sizes of web respondents in each stratum are 18, 45, 116, 203 and 1106. Web respondents (sample size=1,432) are a relatively small fraction of the REF respondents (sample size=18,519), i.e., the ratio is about 13 times. REF respondents dominate all of the strata. Because strata are constructed by equal numbers from the combined sample and web respondents generally do not have very low propensity socrese, it can be expected that large numbers of web respondents are grouped in the final stratum. For c7 covariate, in the first stratum, the χ^2 test of the covariate was not applicable due to small size. The differences among models seems much smaller than differences between strata.

Figure 5.10 shows the balance check results for response variables treated as covariates not in the model. This figure shows a similar trend to Figure 5.9. Model 3 appears to be more unbalanced in stratum 2 and stratum 4 for a few variables. However, overall, all models seem to be balanced until stratum 4. In stratum 5, unlike the covariates in Figure 5.9, four responses are balanced. The balance seems to be reasonable except final stratum.

5.6.2 Bias reduction

For each variable of interest, there is a REF estimate (assumed to be the population value), one unadjusted WEB estimate, and 16 estimates from the web sample based on different combinations of adjustment: (Propensity Score Model 1, 2, 3 and 4) $\times$ (Inverse weighting and Subclassification) $\times$ (No Calibration and Rim weighting). For variables which were measured on a Likert scale[6], mean scale values are used for the estimates. Table 5.7 and Table 5.8 show the results including percentage of bias reduction (*p.bias*). A large *p.bias*

[6]The Likert scale is often used to measure respondents' attitudes by asking the extent to which they agree or disagree with a particular question or statement. A typical scale might be "strongly agree, agree, neutral, disagree, strongly disagree" and this is often considered as ordinal data.

Figure 5.9: Balance check for covariates in the models

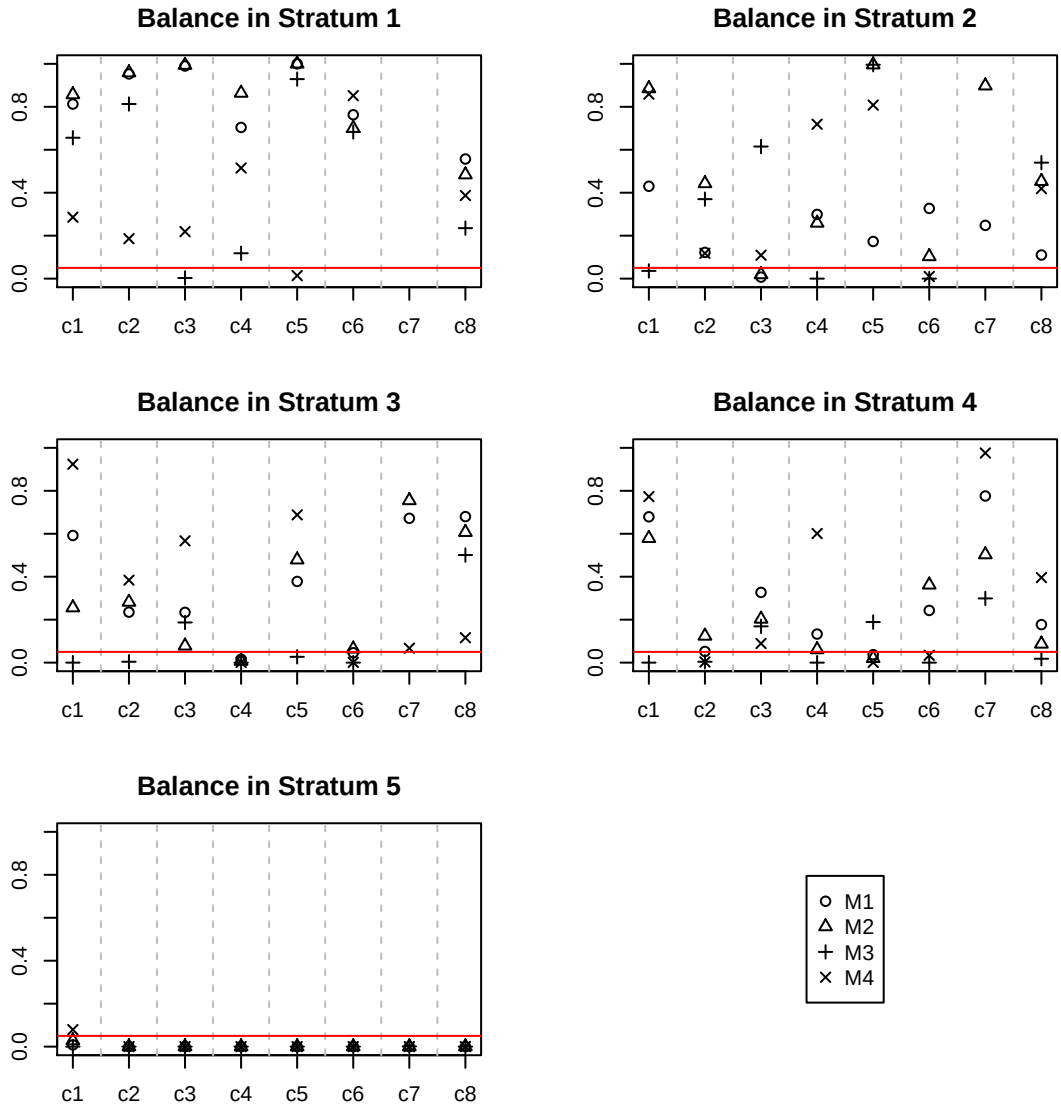
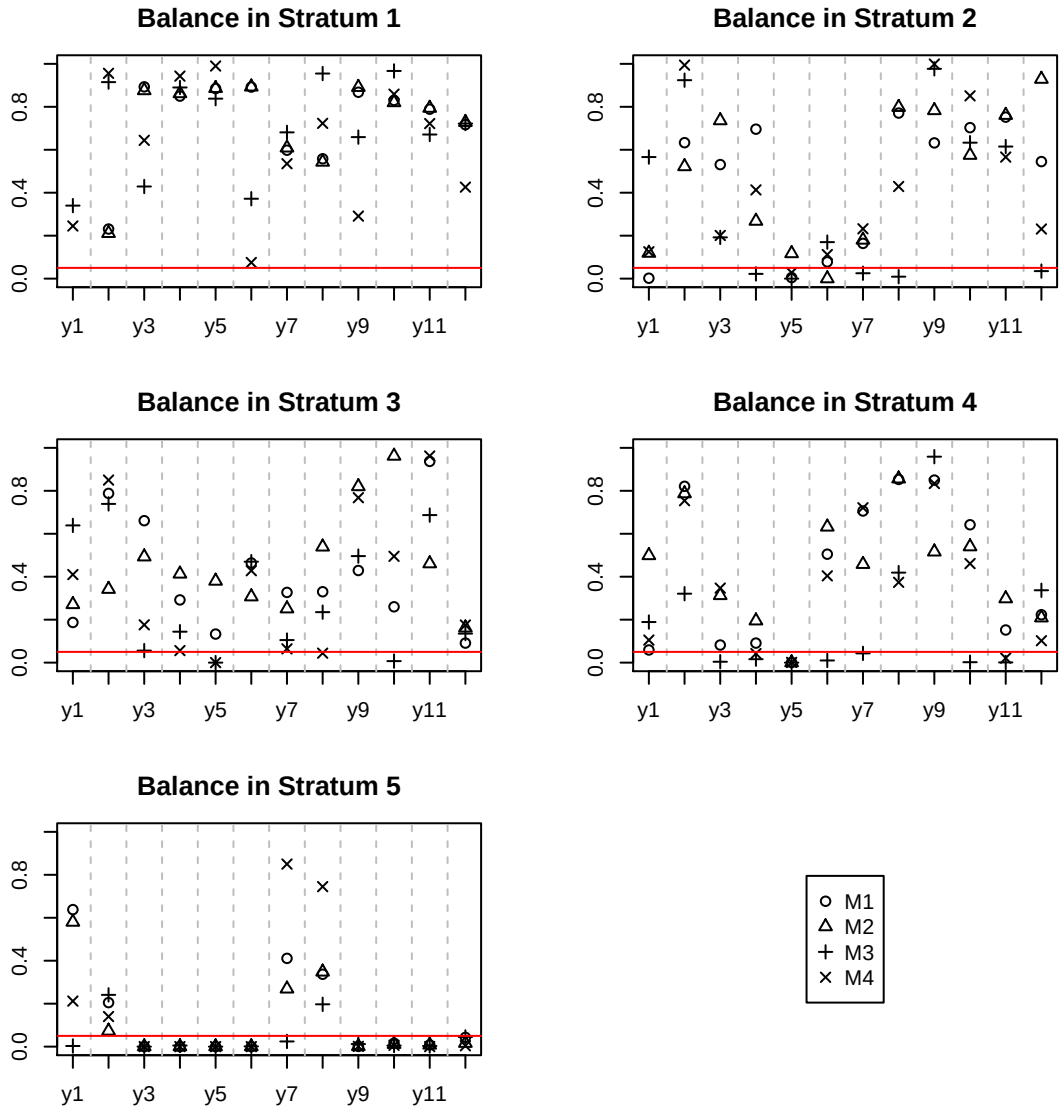


Figure 5.10: Balance check for variables of interest



means that the adjustment performed bias reduction to a greater degree because *p.bias* is a measure of bias in adjusted estimates relative to unadjusted estimates. A negative *p.bias* means that the bias gets worse after adjustment.

Each variable shows very different bias reduction rates according to each combination of adjustment. Figure 5.11 shows the results visually. To decide which combination accomplishes bias reduction best across all variables, ANOVA analysis was conducted. Tukey multiple comparisons of means were conducted as well. Table 5.9 shows the ANOVA table. All of factors are significant except three-way interaction and model:psa, which is marginal (p=0.08). For models, Model 3 (mean = -29%) and Model 4 (mean=-41%) are not significantly different. However Model 3 may perform slightly better than Model 4. Models 3 and 4 perform better than Model 1 (mean=-133%) and Model 2 (mean=-143%). For PSA methods, subclassification method (mean=-18%) performs better than inverse weighting (mean=-156%). For calibration factor, applying the calibration (mean=-4%) performs better than no adjustment (mean=-169%). Therefore, we can say tentatively that Model 3 with subclassification and calibration adjustment performs "best". The average value of percentage of bias reduction in this combination, the LASSO model with PSA and calibration adjustment, is 25%. Figure 5.12 shows the bias reduction rate of each variable in this combination. The ratio of bias reduction out of all variables (i.e., p.bias > 0) is 67% and the ratio of substantial bias reduction (i.e., p.bias > 50) is 42%. The worst case is observed in y3 variable, for which bias reduction is -97%.

	y1		y2		y3		y4		y5		y6	
	est.[1]	p.bias	est.[1]	p.bias	est.[1]	p.bias	est.[1]	p.bias	est.[1]	p.bias	est.[1]	p.bias
REF	2.89		0.13		3.13		2.27		1.89		3.34	
Unadjusted	2.36		0.15		2.98		2.22		1.60		3.26	
M1.Inv.n	2.60	46	0.01	-790	2.32	-453	2.65	-756	2.90	-239	2.69	-689
M2.Inv.n	2.58	42	0.01	-822	2.25	-501	2.61	-673	2.96	-257	2.65	-742
M3.Inv.n	2.77	78	0.06	-447	3.02	26	2.56	-549	2.24	-14	3.18	-96
M4.Inv.n	2.69	63	0.08	-319	2.95	-19	2.63	-700	2.26	-21	3.18	-101
M1.Sub.n	2.44	15	0.09	-217	2.95	-21	2.59	-619	2.14	19	3.19	-84
M2.Sub.n	2.50	27	0.08	-296	2.90	-56	2.60	-641	2.17	7	3.19	-87
M3.Sub.n	2.67	58	0.09	-206	2.99	6	2.28	83	1.79	66	3.25	-9
M4.Sub.n	2.49	25	0.13	53	2.89	-63	2.38	-146	1.80	71	3.32	69
M1.Inv.C	2.20	-30	0.12	-19	2.82	-108	2.33	-44	1.85	85	3.20	-76
M2.Inv.C	2.15	-39	0.11	-70	2.76	-150	2.30	35	1.88	94	3.16	-119
M3.Inv.C	2.47	21	0.12	36	2.98	-1	2.19	-70	1.56	-13	3.31	62
M4.Inv.C	2.39	7	0.14	22	2.86	-84	2.30	39	1.60	3	3.28	20
M1.Sub.C	2.29	-12	0.14	39	2.97	-6	2.33	-30	1.75	53	3.25	-19
M2.Sub.C	2.31	-9	0.12	32	2.95	-18	2.30	37	1.77	59	3.26	-0
M3.Sub.C	2.45	16	0.12	18	2.96	-15	2.18	-93	1.58	-4	3.31	57
M4.Sub.C	2.36	-1	0.16	-82	2.83	-101	2.28	63	1.61	5	3.33	89

[1] population value, unadjusted estimate of web sample, and estimates of web sample in each combination of adjustments.

Table 5.7: Percentage of bias reduction (p.bias) in 16 combination of adjustment (1)

	y7		y8		y9		y10		y11		y12	
	est.[1]	y1.b	est.[1]	y2.b	est.[1]	y3.b	est.[1]	y4.b	est.[1]	y5.b	est.[1]	y6.b
REF	0.77		0.82		0.32		2.79		2.52		2.61	
Unadjusted	0.81		0.85		0.35		2.61		2.28		2.50	
M1.Inv.n	0.98	-376	0.98	-387	0.38	-125	2.63	13	3.30	-233	1.76	-699
M2.Inv.n	0.99	-394	0.99	-410	0.40	-224	2.60	-2	3.35	-257	1.66	-796
M3.Inv.n	0.89	-164	0.91	-182	0.15	-601	2.86	60	2.71	20	2.36	-137
M4.Inv.n	0.89	-174	0.92	-186	0.15	-595	2.86	60	2.70	25	2.26	-226
M1.Sub.n	0.85	-79	0.87	-52	0.30	-0	2.70	50	2.70	22	2.37	-130
M2.Sub.n	0.85	-89	0.88	-79	0.31	37	2.70	54	2.69	27	2.48	-25
M3.Sub.n	0.83	-32	0.86	-14	0.25	-210	2.79	98	2.56	84	2.60	88
M4.Sub.n	0.84	-57	0.86	-18	0.27	-128	2.77	91	2.55	86	2.42	-81
M1.Inv.C	0.81	1	0.87	-47	0.39	-169	2.57	-17	2.59	70	2.21	-276
M2.Inv.C	0.80	19	0.87	-63	0.41	-251	2.53	-40	2.61	62	2.19	-292
M3.Inv.C	0.79	42	0.84	42	0.27	-97	2.76	86	2.45	72	2.61	100
M4.Inv.C	0.82	-10	0.84	31	0.27	-107	2.78	95	2.47	82	2.56	50
M1.Sub.C	0.81	-7	0.85	-8	0.33	62	2.65	22	2.51	95	2.33	-160
M2.Sub.C	0.80	18	0.85	-0	0.34	39	2.64	22	2.45	73	2.36	-135
M3.Sub.C	0.80	25	0.83	60	0.29	-9	2.73	70	2.46	77	2.61	97
M4.Sub.C	0.82	-26	0.84	35	0.29	-17	2.76	83	2.52	100	2.52	19

[1] population value, unadjusted estimate of web sample, and estimates of web sample in each combination of adjustments.

Table 5.8: Percentage of bias reduction (p.bias) in 16 combination of adjustment (2)

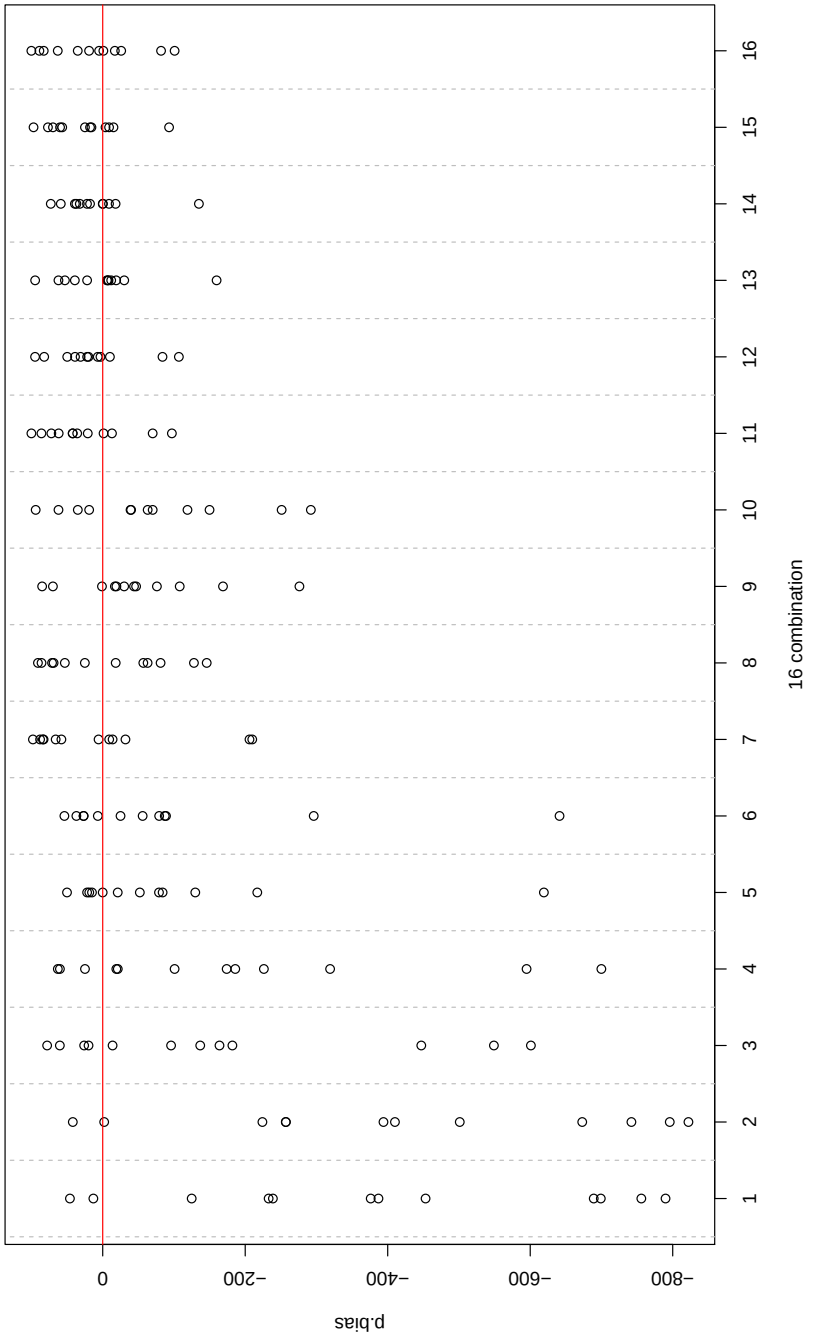


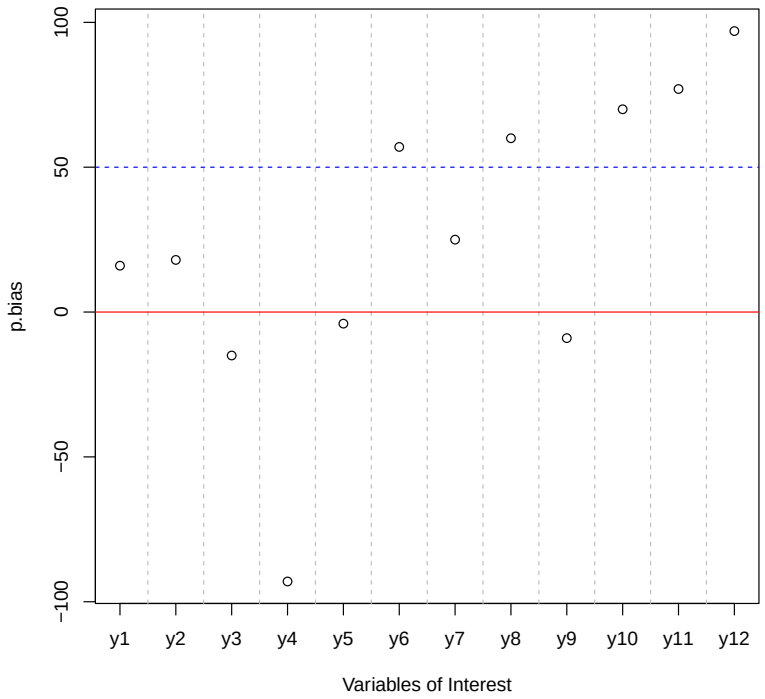
Figure 5.11: Percentage of bias reduction in 16 combination of adjustment

Table 5.9: ANOVA table for effects of model and adjustment

	Df	Sum Sq	Mean Sq	F value	Pr(>F)[1]	
var	11	1560639.14	141876.29	7.44	0.000	***
model	3	510577.60	170192.53	8.92	0.000	***
psa	1	914250.01	914250.01	47.92	0.000	***
cal	1	1303996.51	1303996.51	68.35	0.000	***
model:psa	3	131224.47	43741.49	2.29	0.080	.
model:cal	3	156369.64	52123.21	2.73	0.046	*
psa:cal	1	519896.26	519896.26	27.25	0.000	***
model:psa:cal	3	17740.31	5913.44	0.31	0.818	
Residuals	165	3147899.78	19078.18			

[1] Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Figure 5.12: Bias reduction rate in LASSO model with subclassification and rim weighting adjustments



Chapter 6

Discussion and Conclusion

This project explored the relative merits of different models, different propensity score adjustment methods and calibration adjustment for reducing bias in volunteer panel web survey. In Section 6.1, the evaluation of the results of this case study and some discussion are given. Section 6.2 concludes this project.

6.1 Discussion

The best case, the LASSO model with subclassification PSA and calibration adjustment, shows that bias reduction occurred in 67% variables out of total twelve variables. The proportion of over 50% bias reduction rate is 42% variables. The proportions seems to be reasonable compared to the result of Hur and Cho's research (79% and 35%, respectively). However, overall, a lot of negative bias reductions are observed specially in combinations where PSA was done without calibration. This fact implies PSA adjustments did not work well alone for my data set. It casts doubt on the PSA adjustment in this case study.

I believe that part of the immense failure of PSA using subclassification is the poor balance achieved in Stratum 5 (Figure 5.4). Table 6.1 shows how the combined sample was distributed in each stratum in Model 1 for the test data set. Partitioning the total sample into 5 groups creates 3 groups consisting of propensity scores in the 0-0.02 range. The last group covers the 0.08-1.0 range, which contains massively heterogeneous people. Assigning them a common adjustment is a poor idea. Meanwhile, the very tiny WEB sample sizes in the first group leads to a massive weight being applied to them. It may be corrected by setting maximum value of weights to 5 or something. However, it is speculative because

Table 6.1: Average propensity scores for each survey in 5 strata in Model 1

	WEB			REF		
Stratum	mean	range	size	mean	range	size
1	4.4e-5	[4.3e-5, 4.5e-5]	(2)	6.7e-5	[3.7e-8, 2.4e-4]	(3938)
2	0.002	[4.9e-4, 2.6e-3]	(4)	0.001	[2.4e-4, 2.8e-3]	(3986)
3	0.008	[0.003, 0.014]	(25)	0.007	[0.003, 0.014]	(3966)
4	0.05	[0.016, 0.078]	(163)	0.04	[0.015, 0.081]	(3827)
5	0.48	[0.082, 0.991]	(1238)	0.23	[0.081, 0.955]	(2752)

(#) is the sample size for each survey in each stratum

there is no guideline for the maximum value for all surveys. Even if a certain maximum value worked well for my data set, it would not guarantee that the value works for other survey data.

It would appear that a different subclassification algorithm needs to be employed. This would be a whole new piece of research, but perhaps someone at Statistics Korea will want to take it on. For example, it might be possible to find a formula for the variance of weights that depends on both the number of cases from each group within a stratum and the variability of propensity scores with the stratum.

Another possible solution to improvement of bias reduction may be a matching method. For my data, the proportion of sample size of the web survey vs. that of the reference survey is relatively small. Even though the web sample size (2,903) is large enough, the small proportion caused imbalance in subclassification method and eventually caused the creation of huge weights. A matching method can be performed well where there are a limited number of treated group members and a larger number of control group members. In order to use a matching method, it is necessary to select the web sample from reference survey respondents because the matching estimator for mean of a response works only when common sample weights are available. That means we should invite reference survey respondents to participate in web surveys. It seems to be worthwhile to try in future surveys.

Another reason for the poor result may be violation of some assumptions made during the analysis. The most important assumption in PSA adjustment is the 'strong ignorability assumption' which means responses in the web survey have a similar distribution to those in the reference survey given covariates. This assumption might be violated, resulting in poor

bias correction. Another assumption like MAR is hard to detect. It is also hard to detect whether mode effects between web survey and face-to-face survey can be discardable.

An interesting thing is that all three variables (y10, y11, and y12), which were chosen from 'quality of life' field of questions, show over 70% bias reduction rate in the "best" combination (Figure 5.12). This fact might imply that adjustment method applied in this study worked well for a certain field of questions.

Variable selection in the propensity score model is also a critical issue. In this study, LASSO and boosted tree models perform better than stepwise models. According to the covariates in the models, the results became significantly different. It is notable that many covariates in the model does not guarantee good performance, at least for the data used in this study. It is important to choose appropriate webographic variables. Expert knowledge, not a statistical approach, may be helpful in variable selection (Flom and Cassell, 2008). It is necessary to study webographic variables further.

Variance was not dealt with in this study, but it should be studied in future research in order to evaluate adjustment methods. While bias reduction is desirable, it does not mean a reduction of mean square error (MSE). In general, weighting adjustment increases variance. It may increase the MSE. According to Schonlau *et al.* (2007), bias dominates the MSE after adjustment in many cases. However, an increase of variance sometimes leads to an overall increase of the MSE.

6.2 Conclusion

Web surveys have become popular recently because of their attractive advantages in data collection discussed in Chapter 1. However, web surveys based on non-probability sampling cause problems such as selection errors, coverage errors and non-response errors. Many researchers have studied web surveys, especially volunteer web panel surveys, in order to correct the bias due to the above problems. So far, they have applied propensity score adjustment and calibration adjustment for web surveys. For PSA adjustment, inverse propensity scores and subclassification weighting methods were explored. For calibration adjustment, rim weighting was used for this case study.

Lee and Valliant (2009) show that these adjustments work well for the simulated data. However, study results of many other researchers do not seem to be so good. It may be because that, in the real world, assumptions made in applying adjustments are violated.

In particular, PSA adjustment may not work for large surveys because it is hard to meet 'strong ignorability assumption' for all responses.

Nonetheless, I definitely believe that researches of web surveys should keep going on because the advantages of web surveys are substantial. In terms of national statistical agencies, they suffer from getting information from people because of a growing concern for privacy. It is obvious that the problem will get worse in the future. A volunteer panel web survey may be a good alternative so long as the analysis is proper.

Appendix A

Description of covariates

All overlapping covariates are described here. The #cat means number of categories for nominal variables and cont means continuous numerical variable in type. The ordinal categorical variables are treated as continuous variables in model selection. The '-' in description field means sub question of above no '-' question.

Figure A.1: Description of all covariates (1)

Covariate	Type	Description	Coding
region1	16 cat	major city or province	1=Seoul, 2=Busan, 3= Daegu, 4= Incheon, 5= Kwangju, 6= Deajeon, 7= Ulsan , 8= Kyeonki, 9= Kangwon, 10= Chungbuk, 11= Chungnam 12= Chenbuk 13=Chennam, 14= kyengbuk, 15= Kyeonnam, 16=Jeju
region2	2 cat	urban or rural	1=urban, 2=rural
gender	2 cat	gender	1=male, 2=female
age5	5 cat	age group	1= under 29, 2=30-39, 3=40-49, 4=50-59, 5=over 60
educ4	4 cat	education level	1=under middle, 2=high, 3=undergraduate, 4=graduate
ty_living	5 cat	type of living quarter	1=house, 2=APT, 3=townhouse, 4=multiplex, 5=others
ty_occup	5 cat	type of occupancy	1=landlord, 2=big lump sum at the beginning without monthly rent fee 3=monthly rent with variable deposit, 4=monthly Rent without variable Deposit, 5=free
rel_hohead	10 cat	relationship to household head	1=head, 2=spouse, 3=single son/daughter, 4=married son/daughter, 5=grandchildren, 6=parent, 7=grandparent, 8=single sibling, 9=other relatives, 10=others
marital	4 cat	marital status	1=single, 2=married, 3=bereaved 4=divorced
news	5(cont)	how often read newspaper	1=nearly everyday, 2=three or four times a week, 3=one or two times a week, 4=one time every second week, 5=no
i_news	5(cont)	how often read internet newspaper	1=nearly everyday, 2=three or four times a week, 3=one or two times a week, 4=one time every second week, 5=no
tv	2 cat	watching TV	1=yes, 2=no
tv_wday	cont	- time during weekday	time in hours for one day
tv_sa	cont	- time during Saturday	time in hours
tv_su	cont	- time during Sunday/Holiday	time in hours

Figure A.2: Description of all covariates (2)

Covariate	Type	Description	Coding
book	2 cat	reading books	1=yes, 2=no
magz	cont	- magazine	number of volumes
b_educ	cont	- educational book	number of volumes
b_job	cont	- job	number of volumes
b_life	cont	- life	number of volumes
b_other	cont	- others	number of volumes
dtour	2 cat	domestic tour	1=yes, 2=no
d_night	cont	- number of night tour	number of night tour
d_m_night	cont	- mean of nights per each tour	mean of nights per each tour
d_day	cont	- number of day trip	number of day trip
otour	2 cat	experience of traveling overseas for 1 year	1=yes, 2=no
o_sight	cont	- number of sightseeing	number of sightseeing
o_family	cont	- number of family visiting	number of family visiting
o_busi	cont	- number of business	number of business
o_lang	cont	- number of language study	number of language study
o_life	2 cat	- in case no, experience of traveling overseas for whole life	1=yes, 2=no
recre	2 cat	use of recreational facilities	1=yes, 2=no
attract	cont	- # of tourist attraction	number of visiting
spa	cont	- # of spa	number of visiting
beach	cont	- # of beach	number of visiting
mount	cont	- # of mountain	number of visiting

Figure A.3: Description of all covariates (3)

Covariate	Type	Description	Coding
park	cont	- # of amusement park	number of visiting
cultevent	2 cat	visiting cultural facilities and sporting events or verves	1=yes, 2=no
concert	cont	- # of concert	number of visiting
perfo	cont	- # of performance	number of visiting
dancing	cont	- # of dancing	number of visiting
movie	cont	- # of movie	number of visiting
museum	cont	- # of museum	number of visiting
gallary	cont	- # of art gallery	number of visiting
sports	cont	- # of sports	number of visiting
freetime	14 cat	how to spend free time during weekend (1st)	1=TV or Video, 2=tour, 3=cultural facilities, 4=watching sporting event, 5=spots activity, 6=computer game or internet, 7=creational hobby, 8=learning, 9=volunteer activity, 10=religion activity, 11=housework, 12=rest, 13=social activity, 14=others
freewhom	5 cat	with whom spend free time during weekend	1=family, 2=friend, 3=club, 4=alone, 5=others
leisure	14 cat	type of leisure activities wanted to do(1st)	1=TV or Video, 2=tour, 3=cultural facilities, 4=watching sporting event, 5=spots activity, 6=computer game or internet, 7=creational hobby, 8=learning, 9=volunteer activity, 10=religion activity, 11=housework, 12=rest, 13=social activity, 14=others
satleisure	5(cont)	satisfaction with leisure activities	1=very satisfied, ... 5=very dissatisfied
leisuredis	9 cat	reasons for dissatisfaction with leisure activities	1=economic, 2=shortage of time, 3=inconvenience of transportation, 4=shortage of leisure facilities, 5=shortage of information or program, 6=no hobby, 7=health, 8=no persons to do together, 9=others

Figure A.4: Description of all covariates (4)

Covariate	Type	Description	Coding
		effect of traditional culture on life	
tcere	5(cont)	- the four ceremonial occasions of coming of age, wedding, funeral, and ancestral rites	1=very affected, ---, 5=very unaffected
tmanner	5(cont)	- manners	1=very affected, ---, 5=very unaffected
fgame	5(cont)	- folk game	1=very affected, ---, 5=very unaffected
tarts	5(cont)	- traditional arts	1=very affected, ---, 5=very unaffected
tfood	5(cont)	- traditional food	1=very affected, ---, 5=very unaffected
tcloth	5(cont)	- traditional cloth	1=very affected, ---, 5=very unaffected
thouse	5(cont)	- traditional house	1=very affected, ---, 5=very unaffected
tmarital	5(cont)	- traditional martial arts	1=very affected, ---, 5=very unaffected
income	2 cat	having income	1=yes, 2=no
satincome	5(cont)	- Level of satisfaction with income	1=very satisfied, ---, 5=very dissatisfied
expincome	5(cont)	- expectation of future income	1=very increase---5=very decrease
incomedist	5(cont)	opinion on income distribution	1=very fair,---, 5=very unfair
satcons	5(cont)	satisfaction with a daily life as a consumer	1=very satisfied, ---, 5=very dissatisfied
satover	5(cont)	overall level of satisfaction	1=very satisfied, ---, 5=very dissatisfied
sicknet	2 cat	social network in case of sick	1=yes, 2=no
nsicknet	Cont	- # of people to help	number of people to help
monnet	2 cat	social network in case of need of money	1=yes, 2=no
nmonnet	Cont	- # of people to help	number of people to help

Figure A.5: Description of all covariates (5)

Covariate	Type	Description	Coding
deprnet	2 cat	social network in case of depression	1=yes, 2=no
ndepnet	Cont	- # of people to help	number of people to help
donate	2 cat	donations	1=yes, 2=no
ddonate	Cont	- direct	number of donations
pdonate	Cont	- press	number of donations
sdodate	Cont	- social service	number of donations
rdonate	Cont	- religious group	number of donations
wdonate	Cont	- workplace	number of donations
odonate	Cont	- others	number of donations
commu	2 cat	participation in community activities	1=yes, 2=no
ordcommu	8 cat	- 1st order	1=friendly, 2=religion, 3=hobby & sports & leisure, 4=volunteer, 5=academic, 6=interest, 7=political, 8=others
volunt	2 cat	voluntary service	1=yes, 2=no
envvol	Cont	- envirionment, crime prevention (#)	number of participations
henvvol	Cont	- envirionment, crime prevention(time)	hours during each participation
govvol	Cont	- government event(#)	number of participations
hgovvol	Cont	- government event(time)	hours during each participation
eduvol	Cont	- education(#)	number of participations
heduvol	Cont	- education(time)	hours during each participation
childvol	Cont	- children,senior(#)	number of participations
hchildvol	Cont	- children,senior(time)	hours during each participation
disvol	Cont	- disaster(#)	number of participations

Figure A.6: Description of all covariates (6)

Covariate	Type	Description	Coding
hdisvol	Cont	- disaster(time)	hours during each participation
othvol	Cont	- others(#)	number of participations
hothvol	Cont	- others(time)	hours during each participation
futuvol	3 cat	voluntary service in the future	1=yes, 2=yes, but not now, 3=no
civils	2 cat	having civil service	1=yes, 2=no
satcivils	5(cont)	- levels of satisfaction with civil service	1=very satisfied, ---, 5=very dissatisfied
discivils	8 cat	- reasons for dissatisfaction with civil service(1st)	1=unkind, 2=long time, 3=difficult procedures, 4=unfair, 5=unskilled, 6=shortage of amenities, 7=bribe, 8=others
classaw	6 cat	class awareness	11=high-high, 12-high-low, 21=middle-high, 22=middle-low, 31=low-high, 32=low-low
clswg	5(cont)	class mobility within generation	1=very high, 2=somewhat high, 3=somewhat low, 4=very low, 5=don't know
clsng	5(cont)	class mobility future generation	1=very high, 2=somewhat high, 3=somewhat low, 4=very low, 5=don't know
health	5(cont)	general health	1=very good,---,5=very bad
stress	4(cont)	stress	1=very high, 2=high, 3=somewhat, 4=almost not
satres	5(cont)	Satisfacion with residential district	1=very satisfied, ---, 5=very dissatisfied
safety	5(cont)	safety of society	1=very safe,---, 5=very unsafe
crime	5(cont)	fear of crime	1=very much,---, 5=very little
satfam	5(cont)	satisfaction with family	1=very satisfied, ---, 5=very dissatisfied
contam	5(cont)	feeling of degree of contamination	1=very improved,---, 5=very worsen
suicide	2 cat	suicidal thinking	1=yes, 2=no
busy	5(cont)	life time - busy	1=always busy,---, 5=not at all

Figure A.7: Description of all covariates (7)

Covariate	Type	Description	Coding
		importance for quality of life	
ipincom	cont	- income/consumption	from 1 to 5 according to importance
iphealth	cont	- health	from 1 to 5 according to importance
iplabor	cont	- labour	from 1 to 5 according to importance
ipeduc	cont	- education	from 1 to 5 according to importance
ipresi	cont	- residence/transportation	from 1 to 5 according to importance
ipsaftey	cont	- safety	from 1 to 5 according to importance
ipfam	cont	- family	from 1 to 5 according to importance
ipenv	cont	- environement	from 1 to 5 according to importance
ipinteg	cont	- social integration	from 1 to 5 according to importance
ipspare	cont	- sparetime	from 1 to 5 according to importance
stecono	2 cat	status of economic activity	1=yes, 2=no
workingh	cont	- working hours	hours for a week
stemp	4 cat	- employment status	1=employee, 2=employer, 3=self-employment, 4=work without pay
stecosp	2 cat	status of economic activity of spouse	1=yes, 2=no
famincom	9(cont)	family income for a month	1=under 500$, 2='500$~1000$', 3='1000$~2000$', 4='2000$~3000$, 5='3000$~4000$', 6='4000$~5000$', 7='5000$~6000$', 8='6000$~7000$', 9=over 7000$

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