

## MEASURING AND TESTING THE INTERVIEW MODE EFFECT IN MIXED MODE SURVEYS

Furio Camillo

*Dipartimento di Scienze Statistiche, Università di Bologna, Via delle Belle Arti 41, 40126, Bologna, Italia*

Ida D'Attoma

*Dipartimento di Scienze Statistiche, Università di Bologna, Via delle Belle Arti 41, 40126, Bologna, Italia*

### 1. INTRODUCTION

This work stems from the consideration that different interview modes might cause differences in answers. Considering the case of the mixed use of the computer assisted telephone interviewing (CATI) and computer assisted web interviewing (CAWI) modes the following research question will be explored: Do different treatments (CATI and CAWI) generate different outcomes (answers to the question of interest)? To answer to such a question the influence of self-selection on the observed answers must be considered, being quite often the assignment to different interview modes (the treatment) not random.

On many fields, the problem of selection bias is mainly faced by referring to the propensity score (PS) approach proposed by (Rosenbaum and Rubin, 1983). The authors scrutinized such a problem by modelling the selection process given a set of pre-treatment covariates as a way of reducing bias in the estimation of the treatment effect. They demonstrated that, having in hand several pre-treatment information which characterizes the units under analysis, it is possible to create groups of units having similar pre-treatment characteristics. These groups are, therefore, theoretically independent from the kind of undergone treatment. Within these groups it becomes possible to compare the target variable among those who have undergone the treatment and those who have not. Actually, the PS method is widely used also in the survey field. Lee (2006), for example, suggested the use of the PS adjustment as an approach of adjustment for volunteer panel web survey data. Another work which investigates PS as a method for dealing with selection bias in web surveys is that of (Schonlau *et al.*, 2006) who proposed to construct weights based on the PS to correct for selectivity. Despite PS is widely applied to correct for selection bias it suffers from some drawbacks: the main of which is that it is prone to model dependence (i.e. see King and Zeng, 2006 ; Ho *et al.*, 2007). To control for selection bias this paper proposes for the first time in survey literature the use of the multivariate approach introduced in Camillo and D'Attoma (2010) applied in Peck *et al.* (2010) and extended in D'Attoma and Camillo (2011).

Such multivariate approach has three main features. The first feature - the measure of global imbalance (GI)- is a single measure of imbalance in data, mainly based on the concept of inertia as a measure of association among categorical covariates and the assignment-to-treatment indicator variable. The second feature -the multivariate test of imbalance- allows to test GI and represents an improvement over the variable-by-variable tests. The last feature - the use of cluster analysis enhances the possibility of finding local spaces in which balance holds according to the GI measure

and its related test; within balanced groups data gathered with different data collection techniques are homogeneous and the mode effect estimates are ascribable to the type of technique being used. This paper applies the multivariate approach to AlmaLaurea survey data on second level graduates' employment condition one year from graduation conducted in 2008<sup>1</sup> as an example of potential application. Such data are used for two main reasons. First, because data are related to a large-scale survey that includes a data collection process well controlled in each phase. Hence, other sources of non-sampling errors besides that due to the two data collection methods (i.e. CAWI/CATI) are a priori minimized. Second, because we can compare the multivariate approach to the approach that AlmaLaurea used to adopt in their surveys a complex system to monitor data quality that includes also the measure of the mixed modes effect. In this way we can ascertain if the new method is equally or more effective than the traditional propensity score method in reducing selection bias. The remainder of this paper is organized as follows: section 2 briefly presents the AlmaLaurea survey on graduates' condition. Section 3 introduces the multivariate approach and the PS subclassification. Section 4 presents AlmaLaurea PS subclassification results and the multivariate approach ones. Finally, section 5 discusses and concludes.

## 2. MIXED USE OF CAWI AND CATI METHODS: THE ALMALAUREA CASE

Data are increasingly collected with a combination of different survey modes. Such tendency is widely documented in literature (Dillman *et al.*, 1996; Bethlehem, 2010; Kreuter *et al.*, 2008; De Leeuw, 2005; Borkan, 2004; Vannieuwenhuyze *et al.*, 2010; Mora, 2011). Mixed mode surveys combine the use of different data collection procedures (i.e. telephone, mail, web, face-to-face interview) in a single survey project. In some instances, a mixed mode survey may provide an opportunity for respondents to choose or switch methods that may increase the participation rate. Some methods are significantly less costly than others. Furthermore, in large-scale surveys, some methods like mail questionnaires (Wright, 2005) may also allow to save time in conducting the survey. If on one hand, the use of the mixed mode gives some advantages, on the other hand, it may introduce a big disadvantage that is different modes potentially provide different answers. Many articles document the increased use of mixed modes and propose methods to minimize the problem of distortion in answers (i.e. Jansen, 2006; Woltman *et al.*, 1980; Schonlau *et al.*, 2006; Schonlau *et al.*, 2002; Vannieuwenhuyze *et al.*, 2010). Applications of mixed modes are also increased. Here, the case of AlmaLaurea survey on second level graduates' employment condition one year from graduation, that is part of the more comprehensive survey conducted in 2008, is presented. As reported in Camillo *et al.* (2011) and Cammelli *et al.* (2011), the survey makes possible to analyze the most recent labour market trends through an examination of the career opportunities available for the Italian graduates of the universities taking part in the AlmaLaurea consortium<sup>2</sup> during the 5 years after graduation. All graduates are contacted 1,3, and 5 years after graduation. In 2008, more than 287,000 graduates were examined. The survey also involved all first and second level graduates from the class of 2007 (about 140,000). The huge number of graduates involved has determined the necessity to use survey methods that allow the reduction of costs and duration. These objectives have been achieved through the introduction of two survey methods:

<sup>1</sup> For more details about the survey look at [http://www2.almalaurea.it/cgi-  
php/universita/statistiche/framescheda.php?anno=2008&corstipo=LS&ateneo=tutti&facolta=tu  
tti&gruppo=tutti&pa=tutti&classe=tutti&postcorso=tutti&annolau=1&disaggregazione=tutti&L  
ANG=en&CONFIG=occupazione](http://www2.almalaurea.it/cgi-<br/>php/universita/statistiche/framescheda.php?anno=2008&corstipo=LS&ateneo=tutti&facolta=tu<br/>tti&gruppo=tutti&pa=tutti&classe=tutti&postcorso=tutti&annolau=1&disaggregazione=tutti&L<br/>ANG=en&CONFIG=occupazione)

<sup>2</sup> Further information on AlmaLaurea Consortium and survey methods can be found at: [www.almalaurea.it](http://www.almalaurea.it)

CAWI and CATI. The graduates having a mailbox (85% of the cohort) have been emailed with two email reminders. Afterwards, all graduates who had not answered to the online questionnaire (and, obviously, graduates not having a mailbox) have been contacted by phone.

More precisely, given the survey's cohort, self-selected respondents voluntarily participate to CAWI. Afterwards, the non-respondents are followed by CATI. The use of CATI, for some aspects, overcomes the CAWI under-coverage problem (Bethlehem 2010), namely only respondents with internet access can complete the questionnaire form. The CAWI self-selection problem remains, that is individuals select themselves for the survey. Based on the belief that any interview mode affects the probabilities of including respondents in a sample (Schonlau *et al.*, 2006), and also their answers, the AlmaLaurea aim was to determine if the observed differences in the answers were determined by self-selection (e.g. those who are inclined to answer to CAWI interviews are the same who have specific characteristics in terms of auxiliary information) or just by the different data collection method. If on one hand, the presence or absence of interviewers is an important determinant for the quality of the information collected, on the other hand, because of the cultural level of the cohort involved in the interview, the contribution given by the interviewers may be limited: in some instances it may even be counterproductive, since they may influence the answers of the graduates. For such reasons, it has become important to determine if there are significant differences among the answers given by those who filled in the online questionnaire and those who gave their answers during the telephone interview (interview mode effect). This need has also been confirmed by the fact that these two groups of graduates turned out to be different in some preliminary analysis; for example, as it will be showed in the section 4, in terms of their studies and area of residence and all other examined characteristics with the exception of gender (self-selection effect). The survey enabled the AlmaLaurea consortium to collect the main information related to academic and work experiences made after graduation (table 1): employment condition at the time of interview, characteristics of the job, time-to-entry into the labour market.

TABLE 1  
Collected data

Pre-treatment (X)	Treatment (T)	Post-treatment (Y)
Information on career		Employment
Information on the family		Contract Type
Information on the social class	CAWI	Skills
Geodemographics information	CATI	Importance of qualification
Expectations on the future after graduation		Seeking employment
		Earning

Such information is integrated by the huge quantity of pre-survey data on sociodemographics characteristics of graduates, pre-university studies, academic studies (e.g. degree course, graduation mark) and further experiences made during studies (e.g. foreign languages and IT skills, internships, study experiences made abroad and work experiences). The pre-survey information is mainly based on detailed administrative data from Universities archives and on a preliminary survey conducted close to the end of the university experience. In order to understand if a mode effect was present, AlmaLaurea firstly performed a PS subclassification and then, in case of bias, in its public reports adopted the adjustment method proposed by Lee (2006).

### 3. METHODOLOGY

This section begins by briefly introducing the propensity score subclassification method adopted by AlmaLaurea and then to the proposed multivariate approach and its notation.

#### 3.1. Propensity Score subclassification

In Rubin's potential outcome approach (Rosenbaum and Rubin, 1983), the aim of the resulting propensity score is to balance non-equivalent groups on observed pre-treatment covariates in order to reduce bias in causal effect estimation. Rubin demonstrated that, having in hand pre-treatment information that characterizes units under analysis, it is possible to create groups of units with similar pre-treatment characteristics. These groups are, therefore, theoretically independent from the treatment. Within these groups, the target variable is compared among those who have undergone the treatment and those who have not. Let's consider a population of  $n$  units and denote  $T$  the assignment-to-treatment indicator vector  $T = (0/1)$ . More formally, in Rubin's perspective, each unit  $i$  has two potential outcomes, the potential control outcome  $Y_i(0)$  under the control condition  $T_i(0)$  and the potential treatment outcome  $Y_i(1)$  under treatment condition . After treatment, only one of the two potential outcomes is observed, the outcome corresponding to the treatment condition of the  $i$  unit  $Y_{i,obs} = T_i Y_i(1) + (1 - T_i) Y_i(0)$ , with  $Y_{i,obs}$  as the observed outcome for the  $i$  unit. As it is not possible to observe both potential outcomes (missing data problem), the causal effect for each unit, defined as  $\tau_i = Y_i(1) - Y_i(0)$  could not be determined. Thus, at the group level, only the expected treatment outcomes for the treated,  $E(Y_i(1)|T_i = 1)$  and the expected control outcomes for the untreated,  $E(Y_i(0)|T_i = 0)$  can be observed. Therefore, the simple difference in observed groups means defined as in equation (1)

$$\hat{\tau} = \frac{1}{N_{T_1}} \sum_{i \in T_1} Y_{i,obs} - \frac{1}{N_{T_0}} \sum_{i \in T_0} Y_{i,obs} \quad (1)$$

is a biased estimator for the average treatment effect. In equation (1)  $T_1$  indexes the set for the treated units  $T_0$ , the set for the control units,  $N_{T_1}$  is the number of treated and  $N_{T_0}$  the number of control units. The Propensity Score is a very popular technique that overcomes the missing data problem. In particular, with the PS defined as the conditional probability of treatment exposure given the observed covariates  $X$  that is  $e(X) = \Pr(T = 1|X)$ , units under different treatment conditions are comparable if their probabilities to get assigned to one treatment given the observed covariates are the same. Once obtained the estimated propensity score, PS subclassification can be used to find groups of treated-comparison units with similar characteristics. In particular, the estimated PS is used for subclassifying all units into  $Q$  homogeneous strata being demonstrated that treated-comparison cases within each balanced stratum are homogeneous on both the PS and the observed traits.

### 3.2. The Multivariate Approach to measure the interview mode effect

The multivariate approach, as the PS subclassification, helps to measure the interview mode effect controlling for selection bias. The key aspect underlying the proposed method, involves measuring and testing global imbalance under non-experimental conditions. In the following of the present section a brief description of the GI measure and its related test is provided. The GI measure (D'Attoma and Camillo, 2011) is computed as in equation (2):

$$GI = \frac{1}{Q} \sum_{t=1}^T \sum_{j=1}^{J_Q} \frac{b_{jt}^2}{k_{.t}k_{.j}} \quad (2)$$

In equation  $Q$  denotes the number of pre-treatment covariates,  $T$  denotes the number of treatment levels,  $J_Q$  denotes the set of all categories of  $Q$ ,  $b_{jt}$  is the number of units with category  $j \in J_Q$  in the treatment group  $t \in T$ ,  $k_{.t}$  is the group size  $t \in T$ , and  $k_{.j}$  is the number of units with category  $j \in J_Q$ . The GI measure<sup>3</sup> is the result of using Conditional Multiple Correspondence Analysis (MCA) (Escofier, 1988) to quantify the between-groups inertia<sup>4</sup>. In fact, when dependence among categorical pre-treatment covariates ( $X$ ) and  $T$  is outside the control of researchers, displaying the relationship among them on a factorial space represents a first step for discovering the hidden relationship. But, in the presence of dependence among  $X$  and  $T$ , any descriptive factorial analysis may exhibit this link. Commonly, the problem of the factorial decomposition of the variance related to the juxtaposition of the  $X$  matrix and  $T$  is faced within the MCA framework. With reference to MCA, the structure of the data matrix eigenvectors and eigenvalues decomposition process, could be strongly influenced by the presence of an external conditioning variable (i.e.  $T$ ). Hence, a conditional analysis is used in order to isolate the part of the variability of the  $X$ -space due to  $T$ . With reference to the Huygens' inertia decomposition of total inertia ( $I_T$ ) as within-groups ( $I_W$ ) and between-groups ( $I_B$ ), Conditional MCA consists in the factorial decomposition of the within-group inertia. The key result of using Conditional MCA is represented by the quantified between groups inertia that represents the measure of global imbalance in data. Then, to determine the significance of the detected imbalance, an hypothesis test is performed. The null hypothesis of no dependence among  $X$  and  $T$  is specified as in equation (3):

$$H_0 : I_W = I_T \quad (3)$$

On the basis of the asymptotic distribution function of  $I_B$  (Estadella *et al.*, 2005) expressed as in (4):

<sup>3</sup> For a more comprehensive treatment of the development of GI and its related test see Camillo and D'Attoma (2010) and D'Attoma and Camillo (2011).

<sup>4</sup> The term inertia is used by analogy with the definition in applied mathematics of moment of inertia which stands for the integral of mass times the squared distance to the centroid (Greenacre, 1984).

$$I_B \approx \frac{\chi_{(T-1)(J-1),\alpha}^2}{nQ} \quad (4)$$

the interval of plausible values for GI is defined as in equation (5):

$$GI \in \left( 0, \frac{\chi_{(T-1)(J-1),\alpha}^2}{nQ} \right) \quad (5)$$

with  $n$  as the sample size,  $Q$  as the number of pre-treatment covariates and  $\chi_{(T-1)(J-1)}^2$  as the chi-square value with  $(T-1)(J-1)$  degrees of freedom. If the measured  $GI$  is outside the interval, then the null hypothesis is rejected and data are deemed unbalanced. Then, a three step strategy for estimating the effect of the interview mode on answers in an unbiased way is provided.

1. Measuring imbalance via the  $GI$  measure and testing the extent to which it is significant.  
In other words: are differences between CATI and CAWI groups such that a simple comparison of their answers may be biased by self selection? Such differences are measured in terms of between-group inertia, which represents the global measure of imbalance in the data. The advantage of this  $GI$  measure stems from the consideration that the most common variable-by-variable imbalance measures, such as differences in means or in proportions between treatment groups, might fail in detecting imbalance since they do not take into account any interactions among variables. Then, within data that demonstrate the presence of imbalance, proceed to the second analytic step.
2. Executing a cluster analysis (CA) that identifies homogeneous groups on the basis of the continuous multiple correspondence analysis (MCA) coordinates. Using MCA coordinates before clustering exploits the advantage of working with continuous variables (MCA coordinates) rather than categorical covariates (original variables), that need to be treated with unusual metrics.
3. Assessing the balance within step 2's resulting clusters, computing local effects within balanced groups and pruning observations in unbalanced clusters. The interview mode effects are estimated within each balanced cluster, being sure that they are unbiased from self-selection given the observed covariates.

## 4. EMPIRICAL RESULTS

### 4.1. Propensity Score subclassification AlmaLaurea results

AlmaLaurea adopted a PS subclassification method to understand if an interview mode effect was present. Here, for the sake of simplicity, only results concerning 26997 2nd level graduates interviewed in 2008 one year on from graduation are reported. Of these, 15749 (58:3%) have been contacted via CAWI method and the remaining ones via CATI method. In order to estimate the

PS, a logit model was specified<sup>5</sup> by AlmaLaurea analysts, where the interview mode indicator variable is expressed as function of the observed pre-treatment covariates<sup>6</sup>.

TABLE 1  
Variable-by-variable balance checking: pre-treatment covariates vs interview mode

Pre-treatment covariates	Chi-Square Value	Prob	Balance
Internet surfing skills	2236.83	<.0001	No
Willingness to accept mobility	2169.69	<.0001	No
Attended class on a regular basis	2277.03	<.0001	No
Intended to pursue postgraduate studies	2274.02	<.0001	No
Command of spoken English	2067.13	<.0001	No
Command of written English	2172.37	<.0001	No
Not yet graduated	2210.40	<.0001	No
Did the student study abroad?	2288.79	<.0001	No
Social class	2099.60	<.0001	No
Pure-hybrid graduates	2275.39	<.0001	No
Regular attendance during studies	185.94	<.0001	No
Educational qualifications of parents	2179.71	<.0001	No
Gender	0.0072	0.9323	Yes
Degree-course group	598.86	<.0001	No
Geographical area of the University	172.72	<.0001	No
Geographical area of residence	112.99	<.0001	No
Age at graduation (in class)	451.02	<.0001	No
Graduation Mark (in class)	57.02	<.0001	No

Thereafter, a subclassification on the estimated PS was performed. This was first done sorting units by the estimated PS and partitioning units in a predefined number of strata, where each stratum had approximately the same number of units. AlmaLaurea analysts have first divided the estimated range of propensity score in 5 strata<sup>7</sup>. Afterwards, being the common support<sup>8</sup> not satisfied in one of them, they divided the range of the estimated PS in 4 strata. One of these resulted unbalanced (table 3) and units within it were discarded.

<sup>5</sup> The logit of the estimated PS,  $\log\left[\frac{e(X)}{1-e(X)} = \alpha + \beta^T f(X)\right]$ , also called linear propensity score, is

more frequently used than PS itself since the logit is typically more linearly related to the outcome of interest than the PS (Steiner and Cook, 2011)

<sup>6</sup> More details on the estimated logistic regression model can be found in Camillo *et al.* (2011), pp. 5-9.

<sup>7</sup> Based on Cochran (1968) results one may expect a 90% bias reduction for each of the 18 covariates when a subclassification at the quintile of the distribution of the propensity score is performed.

<sup>8</sup> The region of common support is defined as those values of  $e(X)$  that have a positive density within the  $T = 1$  and  $T = 0$  observations.

TABLE 2  
Balance within Propensity Score Strata

Stratum	CAWI	CATI	Total	Balance
1	1248	5501	6749	No
2	2810	3939	6749	Yes
3	3372	3378	6750	Yes
4	3818	2931	6749	Yes
Total	11248	15749	26997	

Within each balanced stratum, the effect of the interview mode on the outcome was estimated by calculating the difference, for each target variable, between the observed and the expected distribution in case of absolute independence (i.e. independence between type of interview and target variable) (Camillo *et al.*, 2011). Obtained results will be presented in subsection 4.3.

#### 4.2. Multivariate approach results

On the 26997 2nd level graduates the multivariate approach is also applied to measure the influence of the interview mode on their answers. Due to the possible presence of self-selection the ultimate intent is to find balanced groups of respondents, whose pre-treatment characteristics (i.e., career, family, social class, geodemographics information, expectations on the future after graduation) are free of any dependence from the kind of undergone treatment (CAWI/CATI). In order to find balanced groups, the 18 categorical pre-treatment covariates used by AlmaLaurea (table 2) are considered. Two of the 18 covariates considered are previously discretized (age and graduation mark). From table 2 it emerges that dependence among interview mode status and baseline covariates exists, since across all traits the chi-square, with the exception of gender, results always significant. Therefore, assessing if the interview mode causes an effect on answers requires to disentangle the effect of the interview mode from the influence of the respondents characteristics. The expected result is that such differences in characteristics might explain differences in answers that are distinct from the contribution of the interview mode, although the expected direction of the bias is not obvious. With this as context, we begin by implementing the three step analysis by computing the GI measure for this data set. As reported in table 4 the resulting value of GI , 0.0531, can be interpreted as demonstrating the presence of imbalance in data.

TABLE 3  
Global balance checking

N	N(T=1)	N(T=0)	GI	Interval	Balance
26997	15749	11248	0.0531	(0;1.28E-08)	No

In fact, the GI measure falls in the critical region, thereby demanding adjustment in order to estimate the presence of an interview mode effect that is not biased by self-selection. The second step in the proposed analytic process is to use CA to identify homogeneous groups on the basis of the MCA coordinates. CA is carried out on the SAS system employing Ward's algorithm on the MCA coordinates<sup>9</sup> where the proximity between two groups is taken to be the square of the

<sup>9</sup> The MCA coordinates were obtained using as input the 18 categorical pre-treatment covariates (table 2)



Euclidean distance between them. Different cluster solutions are examined with the aim of identifying which one achieves balance in an acceptable number of clusters. We move from a 2-cluster partition to a 34-cluster partition. Finally, the 28-cluster solution is retained because it provides balance within a suitable number of clusters with fewer pruned observations (around 19%), compared to larger cluster solutions. With the 28-cluster solution, balance within each group is tested, again using the computation of the GI and considering whether it falls in the critical region, as described in the prior step<sup>10</sup>. Five of the clusters (table 5) result in having unbalanced characteristics by the GI measure. In total these five clusters represent about 19 percent of the observations (5264 units) being excluded from the third analytic step.

TABLE 4  
Balance by clusters

Cluster	N	N(T=1)	N(T=0)	GI	Interval	Balance
1	1736	883	853	0.0029	(0; 0.003)	Yes
2	1236	784	452	0.004	(0;0.0044)	Yes
3	1499	735	764	0.0045	(0;0.0039)	No
4	1059	538	521	0.0056	(0;0.0054)	No
5	1122	634	488	0.0036	(0;0.0051)	Yes
6	1708	891	817	0.00319	(0;0.0032)	Yes
7	751	365	386	0.0056	(0;0.0072)	Yes
8	1392	687	705	0.0034	(0;0.0039)	Yes
9	829	444	385	0.0051	(0;0.0069)	Yes
10	930	471	459	0.005	(0;0.0066)	Yes
11	582	314	268	0.010	(0;0.010)	Yes
12	550	315	235	0.009	(0;0.011)	Yes
13	112	74	38	0.0312	(0;0.05)	Yes
14	321	211	110	0.0155	(0;0.018)	Yes
15	1043	518	525	0.0052	(0;0.0056)	Yes
16	1327	655	672	0.0039	(0;0.0045)	Yes
17	575	333	242	0.0130	(0;0.0112)	No
18	693	345	348	0.0061	(0;0.0086)	Yes
19	761	420	341	0.0065	(0;0.0081)	Yes
20	792	495	297	0.0054	(0;0.0077)	Yes
21	245	157	88	0.0171	(0;0.0246)	Yes
22	768	404	364	0.0063	(0;0.0079)	Yes
23	154	106	48	0.0028	(0;0.041)	Yes
24	497	311	186	0.0135	(0;0.0117)	No
25	865	420	445	0.0041	(0;0.0066)	Yes
26	677	351	326	0.0059	(0;0.0078)	Yes
27	1634	822	812	0.0046	(0;0.0036)	No
28	3139	3066	73	0.0126	(0;0.0182)	Yes

During the final stage of the procedure, the effect of the interview mode on each outcome variable is estimated. Being all outcomes categorical, for each balanced group the observed frequency of each answer is compared to the corresponding expected frequency under the hypothesis of independence between the answer and the interview mode.

<sup>10</sup> The procedure to check and test balance is completely automatic, see Camillo and D'Attoma (2012).

### 4.3. Comparison of results

Within AlmaLaurea PS strata and our balanced clusters, it is possible to evaluate discrepancies existing in responses given by graduates interviewed with different modes. Such discrepancies are calculated taking the difference, for each target variable, between the observed and theoretical frequencies under the hypothesis of independence between interview mode and the target variable. Both methods (PS subclassification and multivariate approach) provided very similar results (table 6). The resulting effects of interview mode on the response rates to the specific categories of each outcome variable were generally found to be lower than two percentage points in terms of deviation. Such a result confirms that the two data collection mode did not generate high differences in terms of responses. There were only two exceptions to this finding: the first case refers to the contract type question and the second to the question seeking employment. For the sake of simplicity, only results concerning the aggregate effect of the interview mode on contract type<sup>11</sup> are reported. The aggregate observed frequencies are obtained as the sum of the observed frequencies within clusters (or strata). Differences between observed and expected frequencies have to be interpreted as an aggregate measure of the mode effect. As reported in table 6 the effects of interview mode on the answers are equal or greater than two percentage points<sup>12</sup>.

---

<sup>11</sup> The Contract Type variable applies only to a subset of the 26997 2nd level graduates, because not all second-level graduates are in work. For percentages of graduates by employment status refer to Camillo *et al.* (2011).

<sup>12</sup> The differences greater than  $\pm 2$  percentage points are considered high because they are greater than the percentage commonly accepted as sampling error in the design of survey data.

TABLE 5  
Differences between observed and expected frequencies of responses to the question "contract type"

Outcome	Observed Distribution (column rates)	Ps Approach		Multivariate Approach	
		Differences (%) CAWI	Differences (%) CATI	Differences (%) CAWI	Differences (%) CATI
Permanent employment	28.8	-0.543	0.462	-0.776	0.477
Work/training	7.1	1.598	-1.358	1.505	-0.925
Apprenticeship	9.1	0.329	-0.279	0.204	-0.126
Temporary work	2.6	0.235	-0.199	0.320	-0.196
Project work	17.0	1.083	-0.921	1.399	-0.860
Occasional collaboration	3.5	-0.140	0.119	-0.098	0.060
Socially useful work	0.1	0.064	-0.055	0.080	-0.049
Intermittent work	0.5	0.063	-0.053	0.096	-0.059
Job sharing	0.0	0.027	-0.023	0.031	-0.019
Auxiliary temporary work	0.3	0.181	-0.154	0.192	-0.118
Other fixed-term contract	20.2	-3.102	2.638	-3.136	1.927
Self-employed	5.5	-1.056	0.898	-1.038	0.638
Working without any contract	3.6	0.272	-0.231	0.237	-0.146
Provision of services	1.4	0.842	-0.716	0.817	-0.502
Professional Integration Plan	0.2	0.071	-0.060	0.068	-0.042
Joint partnership	0.2	0.052	-0.044	0.067	-0.041
Non response	0.2	0.026	-0.022	0.032	-0.020

As reported in table 6, CATI and CAWI operate in opposite directions: where CAWI underestimates the expected frequencies, the CATI overestimates them and viceversa. Those differences could be attributable to the fact that the question about the type of contract could be perceived in different ways. In fact, CATI involves an oral and long list of categories; whereas, CAWI allows respondents to analyze and compare each category in the due time. Furthermore, using the word other to list the fixed term contract (table 6) might generate a wrong perception. Especially with the CATI method it might be intended as a residual category. In sum, both methods support the conclusion that answers to the question "contract type" are affected by the interview mode. For such reason it is justifiable that AlmaLaurea in its public report adopted the

adjustment proposed by Lee (2006).

## 5. DISCUSSION AND CONCLUSIONS

The main aim of this work has been to apply the multivariate method to measure the interview mode effect controlling for selection bias and compare its result to the results generated by PS subclassification. Such an approach allows to understand if observed differences in the answers are attributable to self selection or just to the interview mode without specifying any model. We worked through the use of the multivariate approach with an application to AlmaLaurea 2008 survey on 2nd level graduates' condition one year from graduation that adopted a mixed data collection strategy. In conducting such survey AlmaLaurea has to deal with the strong growth in the reference population. Consequently, the need to reduce survey costs and duration has led to the introduction of a mixed data collection strategy (CATI and CAWI). The adoption of such mixed strategy has been undoubtedly facilitated by the increasing availability of email addresses. However, on one hand the mixed strategy led to a reduction of data collection costs; on the other hand, the use of the two data collection modes required a method to control for two sources of bias in answers: the self-selection effect and the mode effect. In this work two alternative methods to measure the interview mode effect controlling for self-selection were discussed and compared: the multivariate approach (Camillo and D'Attoma, 2010) and the PS subclassification applied by AlmaLaurea, and both led to similar results. The multivariate method was applied in order to avoid the PS model dependence problem and consists in a cluster-based procedure to find balanced groups whose pre-treatment characteristics are free of any dependence from the kind of the undergone treatment according to the GI measure and its related test. Therefore, within these groups of respondents any observed difference in the study outcome (e.g. the occupational status) among treatment groups could be attributed to the interview mode. We report two main findings corresponding to the research question we posed initially. First, for what concerns the contract type target variable, respondents self-select in one of the two interview modes. Second, the interview mode affects answers all the other characteristics of respondents being equal. The innovative aspect of the control system implemented by AlmaLaurea is that it allows to disentangle the mode effect from self selection effect and thus, to understand if estimates have to be adjusted. In this way bias is reduced, or eliminated, also when a mixed data collection mode is adopted.

Looking only to final results does not allow to confirm the superiority of the multivariate approach with respect to the propensity score approach. But, we can support its methodological superiority with some issues that we highlight in the rest of the present section.

For what concerns the methodological issue, we address that the multivariate approach overcomes the PS model dependence problem and facilitates the control of selection bias being completely model free. Especially when working with huge databases, as in the AlmaLaurea case, the use of the multivariate approach avoids problems that occur when models do not fit data.

As discussed in a previous work (Peck *et al.*, 2012), we believe that the approach has a promise. The cluster-based approach is an improvement over conventional propensity score methods, which require subjective judgment in several areas: the specification of model used to estimate the propensity scores, the choice of covariates and interaction terms or higher order terms to be included in the model, and the matching strategy, which can take many forms. As reported in Steiner and Cook (2011), "the strong ignorability assumption might be violated if the propensity score model is not correctly specified, even if all covariates for establishing strong ignorability are observed". Regarding the many possible matching strategies, common practice is to use five bins (Cochran, 1968), but if balance is not achieved, then dividing the propensity score into more bins

still may not produce any greater balance. In contrast, our strategy groups each observation in the treatment group with those in the comparison group whose observed characteristics are similar according to a predefined distance measure. In turn, estimated mode effects are not biased in a systematic way. Such a conclusion is enhanced by the observation that the GI measure is a global measure of comparability between groups, objective because it is based on the concept of observed variance in the data, among observed baseline covariates (considered simultaneously) and the mode indicator. It is also enhanced by use of the multivariate imbalance test that allows determining the imbalance's significance, thereby overcoming standard variable-by-variable test of balance that do not consider interaction among variables. Furthermore, cluster analysis makes it possible to use all available information independently from the number of variables and their nature, categorical or continuous. Propensity score subclassification solves in part this problem at the cost of incrementing subjective choices (i.e. propensity score estimation method, model specification). In addition, in the AlmaLaurea case here presented, the cluster-based multivariate approach discards less units (around 19%) than PS subclassification (around 25%). Finally, but not less important, another strength of the cluster-based method is that it captures heterogeneity in the effects, which cannot be done by matching or PS adjustment. Average treatment effects often obscure the changing effects within heterogeneous populations, the cluster-based approach capitalizes on this heterogeneity and allows for impact estimates within subgroups that might otherwise fail to be easily recognized.

#### REFERENCES

- R. E. BARLOW, D. J. BARTHOLOMEW, J. M. BREMNER, H. BRUNK (1972). *Statistical Inference Under Order Restrictions*. John Wiley & Sons, New York.
- J. BETHLEHEM (2010). *Selection in Web Surveys*. *International Statistical Review*, 78(2), pp. 161–188.
- J.M. BORKAN (2004). *Mixed Methods Studies: A Foundation for Primary Care Research*. *Annals of Family Medicine*, 2(1), pp. 4-6.
- F. CAMILLO, V. CONTI, S. GHISELLI (2011). *Integration of different data collection techniques using the propensity score*. AlmaLaurea Working Papers n 4.
- F. CAMILLO, I. D'ATTOMA (2010). *A New Data Mining Approach to Estimate Causal Effects of Policy Interventions*. *Expert Systems with Applications*, 37(2010), pp. 171-181.
- F. CAMILLO, I. D'ATTOMA (2012). *%GI: A SAS Macro for Measuring and Testing Global Imbalance of Covariates within Subgroups*. *Journal of Statistical Software*, 51, Code Snippet 1, pp. 1-19.
- A. CAMELLI, G. ANTONELLI, F. CAMILLO, A. DI FRANZIA, S. GHISELLI, M. SGARZI (2011). *Graduates' employment and employability after the "Bologna Process" reform. Evidence from the Italian experience and methodological issues*. AlmaLaurea Working Papers.
- W.G. COCHRAN (1968). *The Effectiveness of Adjustment by Subclassification in Removing Bias in Observational Studies*. *Biometrics*, 24, pp. 205–213.
- I. D'ATTOMA, F. CAMILLO (2011). *A Multivariate Strategy to measure and test global imbalance in*

- observational studies*. Expert Systems with Applications, 38, pp. 3451-3460.
- E. D. DE LEEUW (2005). *To mix or not to mix data collection modes in surveys*. Journal of Official Statistics, 21, pp. 233-255.
- D.A. DILLMAN, R.L. SANGSTER, J.TARNAI, T. H. ROCKWOOD (1996). *Understanding Differences in People's Answers to Telephone and Mail Surveys*. New Direction for Evaluation. 70, pp. 45-61.
- B. ESCOFIER (1988). Analyse des correspondances multiples conditionnelle. In: E. Diday (Ed.), Data Analysis and Informatics. North Holland, Amsterdam: Elsevier Science, pp. 333-342.
- J.D. ESTADELLA, T. ALUJA, S. THIÒ-HENESTROSA (2005). *Distribution of the inter and intra inertia in conditional MCA*. Computational Statistics. 20(3), pp. 449-463.
- M.J. GREENACRE (1984). *Theory and Applications of Correspondence Analysis*. London: Academic Press.
- D.E. HO, K. IMAI, G. KING, E. A. STUART (2007). *Matching as nonparametric pre-processing for reducing model dependence in parametric causal inference*. Political Analysis, 15, pp. 199-236.
- B. JANSSEN (2006). Web data collection in a mixed mode approach: an experiment. Proceedings of Q2006. European Conference on Quality in Survey Statistics.
- G. KING, L. ZENG (2006). *The Dangers of Extreme Counterfactual*. Political Analysis, 14, pp. 131-159.
- F. KREUTER, S. PRESSER, R.TOURANGEAU (2008). *Social desirability bias in CATI, IVR, and Web Surveys. The effects mode and question sensitivity*. Public Opinion Quarterly, 72(5), pp. 847-865.
- S. LEE (2006). *Propensity Score Adjustment as a Weighting Scheme for Volunteer Panel Web Survey*. Journal of Official Statistics. 22(2), pp. 329-349.
- M. MORA (2011). *Understanding the pros and cons of mixed-mode research*. Quirk's Marketing Research Review, 50 .
- L.R. PECK, F. CAMILLO, I. D'ATTOMA (2010). *A Promising New Approach to Eliminating Selection Bias*. The Canadian Journal of Program Evaluation, 24(2), pp. 31-56.
- L.R. PECK, I. D'ATTOMA, F. CAMILLO, C. GUO (2012). *A new strategy for Eliminating Selection Bias in Non-Experimental Evaluations: The Case of Welfare Use's Impact on Charitable Giving*. Policy Studies Journal, 40(4), pp. 601-625.
- P.R. ROSENBAUM, D.B. RUBIN (1983). *The Central Role of Propensity Score in Observational Studies for Causal Effects*. Biometrika. 70, pp. 41-55.
- M. SCHONLAU, R. D. FRICKER, M. N. ELLIOT (2002). *Conducting research survey via email and the web*. Rand Corporation.
- M. SCHONLAU, A. VAN SOEST, A. KAPTEYN, M. P. COUPER (2006). *Selection Bias in Web Surveys*

*and the Use of Propensity Score.* Rand Corporation.

- J. VANNIEUWENHUYZE, G. LOOSVELDT, G. MOLENBERGHS (2010). *A Method for Evaluating Mode Effects in Mixed-Mode Surveys.* Public Opinion Quarterly. 74(5), pp. 1027–1045.
- P.M. STEINER, D. COOK (2011). Matching and Propensity Scores. In Little, T.D. (Ed.), *The Oxford Handbook of Quantitative Methods*, Oxford: Oxford University Press.
- H. F. WOLTMAN, A. G. TURNER, J. M. BUSERY (1980). *A comparison of three Mixed-Mode Interviewing Procedures in the National Crime Survey.* Journal of the American Statistical Association, 75(371), pp. 534–543.
- K. B. WRIGHT (2005). *Researching Internet-Based Populations: Advantages and Disadvantages of Online Survey Research, Online Questionnaire authoring software packages, and web survey services.* Journal Of Computer-Mediated Communication, 10(3).

#### SUMMARY

##### *Measuring and testing the interview mode effect in mixed mode surveys*

Many studies are showing an increased tendency to use more than one data collection mode for a particular survey. However, mixed data collection modes may influence responses given by interviewees and require researchers to verify if differences in responses, when present, are ascribable to the type of data collection mode. Often, random assignment is not feasible and requires researchers to solve an additional and not negligible problem, namely to verify if differences in responses are ascribable to the self selection or to the type of data collection mode being used. The aim of the present paper is to measure the mode effect on the answers using a new data driven multivariate approach, that allows to disentangle the interview mode effect on answers from the effect of self selection. We will work through the use of the new multivariate method with AlmaLaurea case concerning the evaluation of two different data collection methods: the CAWI (Computer Assisted Web Interviewing) and the CATI (Computer Assisted Telephone Interviewing). As with any new statistical method, the success of this method depends on its efficacy in relation to that of the existing methods. Therefore, results of the multivariate approach will be compared to the Propensity Score method that AlmaLaurea usually applies to identify the presence of an interview mode effect. Both methods produce similar results.

Key words: self-selection; global imbalance; mixed interview mode; mode effects