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by

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Abstract

This article investigates factors that influenced Japanese voters in the early 1996 in determining which political party to support. Proportional-odds model, a model which retains ordinal nature of political hues or ideologies of the Japanese political parties, is fitted to the data. Samples with answers "I do not know" to the questions are treated as missing. The EM algorithm enables us to incorporate the samples with missing-values. We found that determining which party to support is a purely political decision for Japanese voters based solely on their ideologies and attitude towards the current cabinet, not to be influenced by their geographical profiles nor economic situations. Missing-value problem can not be ignored in the sense that marginally significant or insignificant explanatory variables can easily turn otherwise when the same model is fitted only for the data with no missing-values.

Keywords: EM algorithm, Missing values, Political party, Proportional-odds model, Voters

1 Introduction

In the early 80's, Japanese voters were found to support a political party mainly because its ideology was consistent with their own. Watanuki, et al. [21] conducted two surveys called the Japan Election Study (JES for the rest of this article) directly after the Upper and the Lower House elections in 1983. They asked the voters to rate ideologies of all the major parties as well as of their own from conservative to liberal using five-point scale. Analyzing the Watanuki's data, Miyake [15] found that almost all the respondents supported a party whose score was the closest to their own.

There were evidences that economic factors, which were proven to be very effective in explaining voter behavior in the U.S. [16], may not be as strong a predictor of Japanese voter behavior. Economic factors herein include living standards and economy, both in the

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past and future. Inoguchi [5] tried to find factors to explain why the respondents voted for the governing party in the JES by discriminant analysis. Those factors included answers to questions such as whether Japanese economy and voters' living standards improved from a year before and would expect to do so a year later. He concluded that, unlike in the U.S. or the countries in the Western Europe, support for governing party in Japan was not so much influenced by economic factors.

These findings could be confounded by the realignment of the Japanese political parties and anemic recovery of the Japanese economy from recession, both in the ensuing years.

The realignment of political parties began when the Japan New Party was organized in May 1992. The breakup of the Liberal Democratic Party (LDP), launching of the Shinsei (Renewal) Party and Sakigake (Harbinger) Party, merger of several parties, principally the Japan Democratic Socialist Party, Clean Government Party, Japan New Party, and the Shinsei Party, to conservative-leaning New Frontier Party (NFP), followed. The Socialist Party (SP), which had been a leading minority party since the two conservative parties merged to form the LDP in 1955, changed some of its policies on defense and taxation so that its policies could be more closely aligned with those of the LDP after it became a minority partner in the coalition government. Eventually, it changed its name to the Social Democratic Party of Japan (SDPJ). Furthermore, the Democratic Party was recently formed by the members of the Sakigake, NFP, and SDPJ to represent city-voters. Only the Japan Communist Party (JCP) did not change.

This realignment is thought to have had influences on the voters. First, party loyalty is weakening. Kabashima and Yamada [8] found, in the four panel surveys from July 1993 to February 1995, that voters were changing their party much like "one might change television channels." See also Kabashima and Yamada [9].

Second, the voters' ideologies has become more moderate. For example, the "Jiji Monthly Survey" conducted by Kabashima [6] revealed that the distribution of their ideologies became more sharpened at the center in July 1996 than July 1994.

While realignment of political parties was taking place in political arena, Japanese economy had been experiencing anemic recovery from two and a half years of recession which ended in the last quarter of 1993 [2]. Many Japanese became disenchanted with the govern-

ment because its economic policies were not working. Such feelings of voters could presumably have some influence on supporting governing parties. In other words, it is conceivable that economic factor could have influenced party support, which would directly contradict findings of the preceding research [5].

We felt, therefore, investigation with the latest available data is warranted. We chose the latest available data from Kabashima's "Jiji Monthly Survey" for six consecutive months starting February 1996 because there had been no serious scandal in the Japanese political circle during the period. Past experiences have taught us that such scandal significantly reduce the support of the governing party. See, for example, Miyake [15]. Presumably voter's preference of political party would be rather stable during the period.

Voter behavior researches typically analyzed answers to questions such as "Are you economically better off now than a year ago?" or "Which party do you usually support?" Naturally, some of the respondents answered "I do not know," possibly indicating unwillingness to answer the question but more likely suggesting lack of knowledge or interest on their part.

The preceding researches considered such an ambiguous answer as a missing-value but managed to ignore them. For instance, Miyake [15] used only the samples in which variables of interest were present when, for instance, making cross tabulations or calculating correlation coefficients—we call this as available-case analysis after Little and Rubin [11]. All the articles in Watanuki, et al. [21], except one by Inoguchi [5], analyzed the data similarly. Inoguchi did not provide any information on how he treated a missing-value. The other studies on the Japanese voter behavior, e.g. Richardson [17], replaced missing-values with the average of recorded values—mean imputation according to Little and Rubin [11].

Their results, however, need to be scrutinized because the methods employed in these studies could imply presence of possible statistical issues. Available-case analysis could increase the standard errors in the estimation: First, it discards the information in cases even only one of the two variables of interest is missing. Second, the resulting sample-sizes might be different between the tables depending on the pattern of the missing-values [11].

More seriously, both available-case analysis and mean imputation could yield biased results unless cases without a single missing-value are a random subsample of the original

observations [11]. Even then, the variances and covariances of the variables under mean imputation were shown to be underestimated. See, for example, Little and Rubin [11].

In summary, the purpose of this article is to find factors that influenced Japanese voters in determining which political party to support during a relatively tranquil period with careful attention paid to missing-value problem. Ambiguous answers, "I do not know," were included here and assumed to be "Missing At Random" [11, 18] which implied that missingness can depend only on the observed answer, not on the unobserved one. We applied the likelihood-based EM algorithm for proportional-odds model to the data.

In section 2, the detailed explanation of the data is given. The method is described generally in section 3 and in greater detail in appendix 3. The result is given in section4. Finally profile of the voters whose answers included missing-values is discussed in detail in section 5.

2 Data

In the "Jiji Monthly Survey (JMS for the rest of this article)" supervised by Kabashima, two thousand eligible voters were selected monthly by multi-stage cluster sampling. Among them, about fourteen hundreds were interviewed in person.

The relevant questions in the JMS included the following:

Ideology:	Please rate your ideology from liberal to conservative using ten-point scale.
Politically-Satisfied:	How satisfied are you with the present situation in politics?
City-Size:	How large is your city?
Support-Cabinet:	Do you support the cabinet headed by the Prime Minister Ryutaro Hashimoto?
Economy:	Do you think Japanese economy has improved or deteriorated compared with month before?
Support-Party:	Which political party do you support?

We shall try to explain an answer to the question, "Support-Party" by answers to the remaining five questions. The second question intends to ask how satisfied voters are with the policies of the administration. Since political satisfaction is known not influenced by voters' ideologies but by political situation [6], answers to the questions are considered somewhat distinct from the voter's ideology. So as answers to the fourth question because the SDPJ and Sakigake which were considered more liberal than the LDP were joining the current coalition government. We think, therefore, that answers to the first five questions can be simultaneously used as explanatory variables.

The answers were coded as follows:

Ideology:	1 for "most liberal," 10 for "most conservative," 11 for "I do not know."
Politically-Satisfied:	1 for "greatly satisfied," 2 for "somewhat satisfied," 3 for "somewhat dissatisfied." 4 for "terribly dissatisfied," 5 for "neither satisfied nor dissatisfied," 6 for "I do not know."
City-Size:	1 for "thirteen big cities,"† 2 for "other cities,"‡ 3 for "towns or villages"
Support-Cabinet:	1 for "I do," 2 for "I do not support the cabinet headed by the Prime Minister Hashimoto.," 3 for "I do not know."
Economy:	1 for "Japanese economy has greatly improved.," 2 for "Japanese economy has somewhat improved.," 3 for "Japanese economy has not changed.," 4 for "Japanese economy has somewhat deteriorated.," 5 for "Japanese economy has terribly deteriorated.," 6 for "I do not know."
Support-Party:	1 for "LDP," 2 for "SDPJ," 3 for "JCP," 4 for "Sakigake," 5 for "NFP," 6 for "other party," 7 for "no political party at all," 8 for "I do not know."

In our analysis, we only include samples with answers 1 to 5 to the last question. This is mostly because we were only interested in people who had a political party to support, but

† "Thirteen big cities" are Tokyo, Yokohama, Osaka, Nagoya, Sapporo, Kobe, Kyoto, Fukuoka, Kawasaki, Hiroshima, Kita Kyushu, Sendai, and Chiba in decreasing order of population.

‡ In Japan, to be incorporated as a "city," it must have population of at least fifty thousands.

also because there were only less than seven people who chose answer 6 in every monthly data.

It is generally believed that major political parties can be ordered with respect to its ideology or political hue. Kabashima, et al. [7], in a separate study, asked voters to rate the parties according to their perceived ideology from liberal to conservative using ten-point scale. The result was summarized in table 1. Following the order in this table, we re-coded

Table 1: The average scores

Name of Party	LDP	NFP	Sakigake	SDPJ	JCP
Average	7.61	6.27	5.84	5.54	3.63

"Support-Party": 1 for the JCP, 2 for the SDPJ, 3 for the Sakigake, 4 for the NFP, and 5 for the LDP.

The table 2 illustrates the aforementioned missing-value problem for the six-month data. In the first row was the sample size, the second the number of sample without a single missing-value, the third the percentage of the latter relative to the former.

Table 2: The number of sample.

Month	February	March	April	May	June	July
Sample-size	523	510	554	564	545	548
# of sample with no missing-value	431	414	450	456	443	460
% of no missing-value	82.4	81.2	81.2	80.9	81.3	83.9

Throughout the six months, only about 81-84% of the sample did not have a single missing value. Ignoring the remaining 16-19% of the data could conceivably cause bias in the analysis.

3 Method

Since the response variable can be ordered according to ideology, we employed the following model using cumulative probabilities, $\gamma_{ik} \equiv \Pr\{Y \leq k|\boldsymbol{x}_i\}$:

$$\text{logit}(\gamma_{ik}) = \theta_k - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3} - \beta_4 x_{i4} - \beta_5 x_{i5} \quad (1)$$

$$, i = 1, \ldots, C, \text{and } k = 1, \ldots, 4,$$

where response random variable Y takes five possible values representing an answer to "Support-Party," $\boldsymbol{x}_i \equiv (x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5})$ indicates the value of the ith pattern of explanatory variable vector, $(x_{i,\text{Ideology}}, x_{i,\text{PoliticallySatisfied}}, x_{i,\text{CitySize}}, x_{i,\text{SupportCabinet}}, x_{i,\text{Economy}})$, and C is the number of possible patterns. The cumulative probability, γ_{ik}, denotes up to and including the kth category, conditional on the ith pattern of explanatory variable vector.

The model in equation (1) is known as proportional-odds model because the odds ratio of the event $Y \leq k$ at $\boldsymbol{x} = \boldsymbol{x}_i$ and $\boldsymbol{x} = \boldsymbol{x}_j$, $\frac{\gamma_{ik}/(1-\gamma_{ik})}{\gamma_{jk}/(1-\gamma_{jk})}$, depends only on the difference between $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$, and is independent of the choice of category k. With our data, the odds $\gamma_{ik}/(1-\gamma_{ik})$ represents the ratio of voters with profile $\boldsymbol{x}_i$ who support up to and including kth party against those who do not. The odds ratio, $\frac{\gamma_{ik}/(1-\gamma_{ik})}{\gamma_{jk}/(1-\gamma_{jk})}$, therefore, represents to what extent the odds of supporting up to and including kth party changes for voters with profile $\boldsymbol{x}_j$ relative to those with profile $\boldsymbol{x}_i$. Proportional-odds model guarantees that this ratio changes equally for any political party in the ideological spectrum. See, for example, McCullagh [13] and McCullagh and Nelder [14].

We employed the model partly because our response variable, "Support-Party," is ordered, and as suggested in McCullagh [13], proportional-odds model using cumulative probability retains ordinal nature of the response variable. We used the model also because it excludes the possibility that, for example, different voter profiles influence more on the odds of supporting a conservative-leaning party than on that of supporting a liberal-leaning party. The model was studied by, for instance, Snell [20] and Simon [19] as cumulative logit model. The term "proportional-odds model" was originated from McCullagh [13]. See McCullagh [13] and McCullagh and Nelder [14] for further discussion on the model.

We estimate parameters $\boldsymbol{\beta}^* \equiv (\theta_1, \ldots, \theta_4, \beta_1, \ldots, \beta_5)'$ in model (1) with partially missing explanatory variables using the EM algorithm, where $'$ on the right-hand shoulder denotes transposition of the vector or matrix. Answers "I do not know" to the explanatory variables were treated as missing. Answers "I do not know" to the response, "Support-Party," were excluded because voting behavior of those who did not have any political party to support is beyond the scope of this article. Occurrences of missing-values are assumed to be "Missing At Random" [11, 18] (MAR for short).

We manufacture an example to explain what MAR assumption implies with our data. Suppose that a male voter answered as follows:

Ideology:	9 (the second most conservative)
Politically-Satisfied:	3 (somewhat dissatisfied)
City-Size:	1 (thirteen big cities)
Support-Cabinet:	3 (I do not know)
Economy:	4 (Japanese economy has somewhat deteriorated.)
Support-Party:	1 (LDP)

He was somewhat dissatisfied with the present situation in politics, and also felt Japanese economy had somewhat deteriorated. The realization could have made him a little hesitant in supporting the current cabinet. On the other hand, he supported the LDP because of his ideological inclination. Since the party was a senior partner in the coalition cabinet, he could have felt to some degree obligated to support the current cabinet. The ambivalence could have forced him to answer "I do not know" to the question "Support-Cabinet." In other words, his "I do not know" answer could have depended on ideology, political satisfaction, economy, and support party, but not on his *a priori* attitude towards the current cabinet. MAR assumption allows this kind of dependence on the other variables.

In short, MAR assumes that probability of its occurrence can depend on observed variables, such as "Ideology," "Politically-Satisfied," "Economy," and "Support-Party" in the example, but not on the variable containing missing-values themselves, such as "Support-Cabinet" in the example. We felt the assumption a reasonable one. Rubin [18] showed that when the data is MAR, a likelihood-based inferences such as EM algorithm enables us to ignore the missing-data mechanism in estimating parameters β^* in equation (1).

A stronger assumption of "Missing Completely At Random" (MCAR for short)[11, 18], which additionally requires the variable containing missing-values be independent of any other variables and which makes available-case analysis valid, was not employed because not allowing the aforementioned dependence was unrealistic for our data. See in section 5.

Ibrahim [3] proposed EM algorithm for the class of generalized linear models with a single canonical (natural) parameter, in which incompleteness is due to partially missing categorical explanatory variables on some observations where the missing-data mechanism is MAR. We extend his result to a class of generalized linear models with multiple canonical parameters with the same missing covariate structure.

We suppose that explanatory variable vectors, $\boldsymbol{x}_i$, are random vectors which are mutually independent for each i and have multinomial distribution parameterized by $\boldsymbol{\rho} \equiv (\rho_1, \ldots, \rho_C)$. For the number of categories, C_τ, in each explanatory variable ($\tau = 1, \ldots, 5$), C is obtained as $C = \prod_{\tau=1}^{p} C_\tau$. The distribution of $\boldsymbol{x}_i$ is defined as follows:

$$\Pr\{\boldsymbol{x}_i = \text{the } r\text{th pattern}\} = \frac{1!}{u_1^i! \times \cdots \times u_C^i!} \prod_{r=1}^{C} {\rho_r}^{u_r^i} \tag{2}$$

where u_r^i is an observation of the following random variable, U_r^i:

$$U_r^i = \begin{cases} 1 & \text{if } \boldsymbol{x}_i \text{ is the } r\text{th pattern} \\ 0 & \text{otherwise.} \end{cases}$$

To obtain the maximum likelihood estimates of $\boldsymbol{\beta}^*$, the EM algorithm above simultaneously estimates all the C ρs as nuisance parameters where C is the number of possible patterns of explanatory vector. Appendix 3 provides the detailed explanation for EM algorithm for proportional-odds model.

Since the number of nuisance parameters ρs can run up to $10 \times 5 \times 3 \times 2 \times 5 = 1500$ as they are, we need to reduce either their number or the number of explanatory variables to a reasonable level so that our monthly data of about five hundred can handle them. We merged several neighboring categories in each of "Ideology," "Politically-Satisfied," and "Economy" to create trinomial variables. For details, see appendix 2.

We chose not to reduce the number of explanatory variables further because a variable which is considered as politically unimportant is not included in the explanatory variable vector to begin with. Although "Economy" was found insignificant in the preceding research [5], we opted to include it in our analysis because we wish to know if the same can be said with our data taken during the period of anemic economic recovery.

4 Results

We begin by fitting the model (1) using the EM algorithm incorporating missing-values. To evaluate the effect of missing-value problem, we performed available-case analysis as well. Monthly results for the analysis using the EM algorithm were in table 3, where $(x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5})$ indicates the value of the ith pattern of explanatory variable vector, $(x_{i,\text{Ideology}}, x_{i,\text{PoliticallySatisfied}}, x_{i,\text{CitySize}}, x_{i,\text{SupportCabinet}}, x_{i,\text{Economy}})$ as defined on page 6. Numbers in parentheses below each coefficients were large sample (asymptotic) t-values of the regression coefficients, respectively.

Table 3: Monthly results with missing-values included. "Satisfied" and "Cabinet" are abbreviations for "Politically-Satisfied" and "Support-Cabinet," respectively.

		Ideology	Satisfied	City-Size	Cabinet	Economy
February:						
	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.211x_{i1}$	$+0.013x_{i2}$	$+0.062x_{i3}$	$+1.125x_{i4}$	$+0.193x_{i5}$
		(-8.073)	(0.100)	(0.427)	(5.115)	(1.193)
March:						
	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.520x_{i1}$	$+0.228x_{i2}$	$+0.435x_{i3}$	$+1.248x_{i4}$	$+0.255x_{i5}$
		(-9.004)	(1.443)	(2.775)	(5.623)	(1.363)
April:						
	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.175x_{i1}$	$+0.187x_{i2}$	$+0.002x_{i3}$	$+1.171x_{i4}$	$+0.114x_{i5}$
		(-7.963)	(1.373)	(0.015)	(5.323)	(0.665)
May:						
	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.349x_{i1}$	$+0.179x_{i2}$	$-0.299x_{i3}$	$+1.206x_{i4}$	$+0.032x_{i5}$
		(-8.511)	(1.377)	(-2.079)	(5.865)	(0.203)
June:						
	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.480x_{i1}$	$+0.198x_{i2}$	$-0.074x_{i3}$	$+1.277x_{i4}$	$-0.074x_{i5}$
		(-8.766)	(1.513)	(-0.477)	(5.682)	(-0.421)
July:						
	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.323x_{i1}$	$+0.173x_{i2}$	$-0.320x_{i3}$	$+1.264x_{i4}$	$+0.242x_{i5}$
		(-7.749)	(1.300)	(-2.202)	(5.844)	(1.467)

We followed a often-used conservative convention for two-sided-5% t-test whereby explanatory variables with t-value more than two are deemed significant. We found: "Ideology" and "Support-Cabinet" were significant throughout. "City-Size" was significant only in three months, March, May, and July. The remaining two factors, "Politically-Satisfied" and "Economy," were not significant.

From the signs of the estimated regression coefficients of "Ideology" and "Support-

Cabinet," we observed that, in the early 1996, the voter

- whose ideology was more conservative, and
- who supported the current cabinet

were likely to support a conservative-leaning party rather than a liberal-leaning one.

That "Ideology" was significant could have two implications. First, ideology still substantially influences voters on which political party to support, despite the fact that ideological differences among voters have become less pronounced as stated in section 1. Second, voters were supporting a political party whose ideology was close to themselves. These findings are consistent with the result of Miyake [15].

"Politically-Satisfied" was not significant throughout. Therefore, voters' dissatisfaction with the current politics did not necessarily translate into support for opposition party. This could suggest the presence of voters' cynicism towards the politicians or the current political system in general. Another possibility is that political satisfaction might influence decisions on which party to support in a more indirect manner. For example, it is conceivable that it primarily influences decisions whether to support the current cabinet and the latter then influences decisions regarding the party support.

"City-Size" was significant only in three months. Its t-values, however, were between 2.1 and 2.8, much smaller in values than those of "Ideology" and "Support-Cabinet." In addition, signs of the coefficients for the three months were fluctuating: they were negative in March, and positive in May and July. Jointly, these facts imply that difference with respect to party support between rural and urban regions was weakening. It was found in Miyake [15] that support for the LDP was more firm in rural region, while, the liberal-leaning parties were more popular in urban area through 1980's. Our findings suggests this pattern was eroding.

Since "Support-Cabinet" was significant and its coefficient was negative, voters who affirmatively evaluated the performance of the current cabinet were inclined to support a conservative-leaning party. The most conservative party in our research was the LDP which was the senior partner of the coalition government, and policies of the government strongly reflected those of the LDP. Consequently, voters who were supporting the current cabinet

were likely to support the LDP.

Since "Economy" was insignificant throughout, voters were deciding which political party to support independent of Japanese economy, as was found in Inoguchi [5] for yearly data and also in Inoguchi [4]. This was contrary to findings in the U.S. [16]. As stated in section 1, Japanese economy had been experiencing anemic recovery [2]. If Japanese voters had thought that a political party had effective economic policies, they might have supported that party. Our results could imply that the Japanese voters were not presented with a clear-cut economic policy choice.

These results together led us to conclude that, in Japanese voters' mind, determining which party to support is a purely political decision, not to be influenced by their geographical profiles nor economic situations.

We compare the results with those obtained by available-case analysis to evaluate the extent of missing-value problem. Table 4 provides monthly results for the available-case analysis.

Table 4: Monthly results for analysis with missing-values excluded. "Satisfied" and "Cabinet" are abbreviations for "Politically-Satisfied" and "Support-Cabinet," respectively.

		Ideology	Satisfied	City-Size	Cabinet	Economy
February:	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.265x_{i1}$	$-0.073x_{i2}$	$+0.146x_{i3}$	$+1.396x_{i4}$	$+0.271x_{i5}$
		(-8.027)	(-0.545)	(0.924)	(5.955)	(1.565)
March:	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.704x_{i1}$	$+0.443x_{i2}$	$+0.394x_{i3}$	$+1.651x_{i4}$	$+0.062x_{i5}$
		(-8.971)	(2.306)	(2.273)	(6.730)	(0.296)
April:	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.294x_{i1}$	$+0.136x_{i2}$	$-0.137x_{i3}$	$+1.313x_{i4}$	$+0.013x_{i5}$
		(-8.149)	(0.940)	(-0.915)	(5.626)	(0.071)
May:	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.442x_{i1}$	$+0.093x_{i2}$	$-0.419x_{i3}$	$+1.392x_{i4}$	$+0.035x_{i5}$
		(-8.414)	(0.675)	(-2.714)	(6.334)	(0.211)
June:	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.521x_{i1}$	$+0.208x_{i2}$	$-0.072x_{i3}$	$+1.494x_{i4}$	$-0.234x_{i5}$
		(-8.549)	(1.480)	(-0.440)	(6.295)	(-1.273)
July:	$\text{logit}(\gamma_{ik}) = \theta_k$	$-1.481x_{i1}$	$+0.086x_{i2}$	$-0.245x_{i3}$	$+1.420x_{i4}$	$+0.168x_{i5}$.
		(-8.234)	(0.619)	(-1.564)	(6.213)	(0.959)

The estimated coefficients of "Ideology" and "Support-Cabinet" were bigger in available-

case analysis in absolute terms although the conclusions of t-test were the same and significant. This indicated that including missing-values into analysis somewhat weakened influence of the two variables on party support. It was due to the fact that support for the LDP was smaller and for the other parties larger with the missing-values included. The next section will elaborate this point.

The estimated coefficients of and relevant t-values for the remaining three variables in available-case analysis could be misleading. For example, "City-Size" in July, which was deemed significant, had to be dropped if we were to use available-case analysis. On the other hand, "Politically-Satisfied" in March, which needed to be taken out, must be included in available-case analysis.

Therefore, we must conclude that those samples without a single missing-value could not be safely considered as a random subsample of all the observations, and that missing-data mechanism of our data was not likely to be missing completely at random.

5 Discussions

Table 5 shows all the patterns of missing-values, which we call "missing-pattern" or "the pattern" hereafter, and their frequencies in our monthly data. The analysis in the preceding section indicated that voters who did not answer "I do not know" to any of the questions (voter group with missing-pattern 17) be probably not a random subsample of the original observations, and that they could have different profiles from those who answered "I do not know" to some of the questions (voter group with missing-pattern 16). In this section, we examine the difference between two voter groups with missing-patterns 16 and 17, through cross-tabulation and the corresponding χ^2-test.

The missing-pattern 14 was the most frequent. Between 42% (37/88×100) in July and 65% (58/92×100) in February of the voters with at least one missing-value answered "I do now know" only to the question regarding "Support-Cabinet." In other words, these voters were hesitant in answering only to whether they supported the current cabinet, while expressing their knowledge or opinions to all the remaining questions. We also investigate profiles of this voter group with missing-pattern 14 against that with missing pattern 17 using

Table 5: Patterns of missing-values (missing-pattern) in each month data and their frequencies. "Satisfied" for "Politically-satisfied," "Cabinet" for "Support-Cabinet," and "M" for occurrence of a missing-value. No missing-value was observed in "City-Size."

	Ideology	Satisfied	Cabinet	Economy	Feb.	Mar.	Apr.	May	June	July
1	M	M	M	M	0	0	0	2	0	0
2		M	M	M	0	0	0	0	0	0
3	M		M	M	1	1	0	2	0	1
4	M	M		M	2	0	0	0	0	1
5	M	M	M		0	1	0	0	0	2
6			M	M	2	1	3	3	1	3
7		M		M	0	0	1	3	1	0
8		M	M		1	0	2	2	0	2
9	M			M	1	2	2	3	5	4
10	M		M		4	2	6	4	5	3
11	M	M			3	1	2	0	2	0
12	M				12	20	18	16	14	15
13		M			2	7	3	0	3	1
14			M		58	54	51	55	52	37
15				M	6	7	16	18	19	19
16	At least one missing-value				92	96	104	108	102	88
17	No missing-value				431	414	450	456	443	460
	Total sample size				523	510	554	564	545	548

the same techniques. The differences in profiles of these voter groups were examined in terms of the corresponding differences in the response variable "Support-Party" for obvious reason and in the two explanatory variables, "Politically-Satisfied" and "City-Size," both of which were found in section 4 to be susceptible to the missing-value problem.

Percentages of voters supporting the LDP, NFP, Sakigake, SDPJ, and JCP with the patterns 14, 16, and 17 are shown in table 6. Percentages of voters supporting the LDP with the pattern 16 were on the average 4.9% lower than that of voters with the pattern 17. Among voters with the pattern 14, support for the LDP were 7.4% lower than those with the pattern 17. It appeared that voters with at least one missing-value, but particularly those with only "Support-Cabinet" missing, were less likely to support the LDP than voters without a single missing-value. The conclusion still holds with the median in place of the average.

On the other hand, percentages of voters supporting the NFP with the patterns 16

Table 6: Percentages of voters supporting the LDP, NFP, Sakigake, SDPJ, and JCP with the patterns 14, 16, and 17.

Party	Pattern	February	March	April	May	June	July	Average	Median
LDP	14	51.7	50.0	56.9	52.7	53.8	59.5	54.1	53.3
	16	52.2	47.9	60.6	55.6	60.8	62.5	56.6	58.1
	17	59.2	62.1	61.8	59.0	62.5	64.6	61.5	62.0
	Total sample	57.9	59.4	61.6	58.3	62.2	64.2	60.6	60.5
NFP	14	29.3	20.4	23.5	27.3	15.4	27.0	23.8	25.3
	16	29.3	19.8	20.2	28.0	14.7	19.3	21.8	20.0
	17	17.6	19.8	18.9	18.2	18.3	16.7	18.3	18.3
	Total sample	19.7	19.8	19.1	20.2	17.6	17.2	18.9	19.4
Sakigake	14	0	0	2.0	7.3	0	0	1.6	1.8
	16	1.1	0	1.0	3.7	1.0	0	1.1	1
	17	2.1	1.0	1.6	2.0	3.2	2.2	2.0	2.1
	Total sample	1.9	0.8	1.4	2.3	2.8	1.8	1.8	1.9
SDPJ	14	13.8	25.9	13.7	12.7	23.1	13.5	17.1	13.7
	16	12.0	27.1	13.5	10.2	16.7	17.0	16.1	15.1
	17	14.4	11.6	9.8	14.5	8.5	10.0	11.5	10.8
	Total sample	14.0	14.5	10.5	13.7	10.1	11.1	12.3	12.4
JCP	14	5.2	3.7	3.9	0	7.7	0	3.4	3.8
	16	5.4	5.2	4.8	1.9	6.9	1.1	4.2	5.0
	17	6.7	5.6	8.0	6.4	7.4	6.5	6.8	6.6
	Total sample	6.5	5.5	7.4	5.5	7.3	5.7	6.3	6.1

Table 7: χ^2 test statistic with degree of freedom 4 for testing whether the differences with respect to party support are significant between the pattern voter groups 16 and 17, and 14 and 17. $\chi^2(4)$ is 9.487 and 7.779 at 95% and 90% levels, respectively.

Patterns	February	March	April	May	June	July
14 and 17	5.563	9.391	2.443	11.456	12.119	5.839
16 and 17	6.835	16.460	2.559	10.480	7.489	9.330

and 14 were on the average 3.6% and 5.6% higher than that of voters with the pattern 17 respectively. Also percentages of voters supporting the SDPJ with the patterns 16 and 14 were on the average 4.6% and 5.7% higher than those of voters with the pattern 17 respectively. It seemed that voters with at least one missing-value, in particular those with a missing-value only in "Support-Cabinet," were more inclined to support the NFP and SDPJ than voters without a single missing-value. Again the tendency did not depend on the choice of representative statistic, be it average or median.

We examine whether the differences were statistically significant by χ^2-test at 95% level. Corresponding χ^2-test statistics are provided in table 7. The difference between the patterns 16 and 17 was significant in two months at 95% level. So was the differences between those with the patterns 14 and 17. It seems that these differences may not be negligible. In other words, voters who answered "I do not know" to any one of the questions (voter group with the pattern 16) or only to "Do you support the current cabinet?" (voter group with pattern the 14) may be less likely to support the LDP and more likely to support the NFP and SDPJ than the voters who did not answer "I do not know" to any of the questions (voter group with the pattern 17).

Table 8 provides us with percentages of voters with the patterns 14, 16, and 17 answering "Satisfied," "Neither," "Dissatisfied," and "I do not know" to the question "How satisfied are you with the current situation in politics?" Although we wished to compare voter group with the pattern 16 to that with 17 in terms of how satisfied they were with the current politics, it could not be done with the data presented table 8. This is because the former voter group itself included voters who answered "I do not know" to the very same question. To circumvent the difficulty, we create a new voter group with missing pattern 16*, which is a voter group with the patterns 1, 2, 4, 5, 7, 8, 11, and 13 removed from that of 16. New percentages with the voter group 16 replaced by the group 16* are presented in table 9.

Throughout the six months, percentages of voters answering "Satisfied" with the pattern 16* were on the average 8.4% lower than those with missing-pattern 17. Percentages of voters answering "Satisfied" with the pattern 14 were on the average 9.6% lower than those with the pattern 17. Voters with at least one missing-value, including those with only "Support-Cabinet" missing, were less inclined to answer "Satisfied" than voters without a single missing value.

Percentages of voters answering "Neither" with the pattern 16* were on the average 8.7% higher than those with the pattern 17. Among voters with pattern 14, answering "Neither" were on the average 5.0% higher than voters with pattern 17. It appeared that voters with at least one missing-value were more likely to answer "Neither" than those with no missing-value.

The average of percentages of voters answering "Dissatisfied" with the pattern 16* in

Table 8: Percentages of voters answering "Satisfied," "Neither," and "Dissatisfied" to the question "How satisfied are you with the current situation in politics?" with the patterns 14, 16, and 17.

Answer	Pattern	February	March	April	May	June	July	Average	Median
Satisfied	14	13.8	16.7	7.8	14.5	17.3	13.5	14.0	14.2
	16	10.0	13.5	10.6	17.6	20.6	12.5	14.1	13.0
	17	21.6	17.9	24.7	23.2	25.5	28.5	23.6	24.0
	Total sample	19.5	17.1	22.0	22.2	24.6	25.9	21.9	22.1
Neither	14	8.6	16.7	9.8	12.7	7.7	10.8	11.1	10.3
	16	13.0	15.6	12.5	14.8	8.8	17.0	13.6	13.9
	17	4.6	4.3	6.0	5.9	8.1	7.6	6.1	5.3
	Total sample	6.1	6.5	7.2	7.6	8.3	9.1	7.5	7.4
Dissatisfied	14	77.6	66.7	82.4	72.7	75.0	75.7	75.0	75.4
	16	68.5	61.6	69.2	61.1	65.0	63.6	64.8	64.3
	17	73.8	77.8	69.3	70.8	66.4	63.9	70.3	70.1
	Total sample	72.8	74.7	69.3	69.0	66.1	63.9	69.3	69.2
I do not know	16	8.7	9.4	7.7	6.5	5.9	6.8	7.5	7.3
	Total sample	1.5	1.8	1.4	1.2	1.1	1.1	1.4	1.3

Table 9: Percentages of voters answering "Satisfied," "Neither," and "Dissatisfied" to the question above with the pattern 16*.

Answer	Pattern	February	March	April	May	June	July	Average	Median
Satisfied	16*	10.7	14.9	11.5	18.8	21.9	13.4	15.2	14.2
Neither	16*	14.3	17.2	13.5	15.8	9.4	18.3	14.8	14.6
Dissatisfied	16*	75.0	67.8	75.0	65.3	68.8	68.3	70.3	68.6

Table 10: χ^2 test statistic with degree of freedom 4 for testing whether the differences with respect to party support are significant between the pattern voter groups 16* and 17, and 14 and 17. $\chi^2(3)$ is 7.825 and 6.251 at 95% and 90% levels, respectively.

Patterns	February	March	April	May	June	July
14 and 17	3.184	13.376	7.785	5.107	1.796	3.981
16* and 17	14.728	19.439	12.682	11.622	0.633	14.846

six months was the same as that with pattern 17, and percentages of voters answering "Dissatisfied" with the pattern 16* were only 1.5% lower in median than with pattern 17. On the other hand, percentages of voters answering so with the pattern 14 were on the average 4.7% and higher than those with the pattern 17. The voters with the pattern 16* were likely to answer "Dissatisfied" as much as those with the pattern 17. The voters with only "Support-Cabinet" missing were more likely to answer "Dissatisfied" than those with

Table 11: Percentages of voters answering "Thirteen big cities," "Other cities," and "Towns or villages" to the question "How large is your city?" with the patterns 14, 16, and 17.

Answer	Pattern	February	March	April	May	June	July	Average	Median
Thirteen big cities	14	10.3	16.7	13.7	23.6	15.4	13.5	15.5	14.6
	16	10.9	14.6	14.4	17.6	16.7	10.2	12.5	14.5
	17	19.3	21.0	23.4	17.8	17.6	18.9	19.7	19.1
	Total sample	17.8	19.8	21.8	17.7	17.4	17.5	18.7	17.8
Other cities	14	56.9	50.0	64.7	49.1	69.7	59.4	58.3	58.2
	16	56.5	51.0	61.5	58.3	63.7	56.8	58.0	57.6
	17	54.1	51.7	50.4	55.3	53.5	53.8	53.1	53.7
	Total sample	54.5	51.6	52.5	55.9	57.1	53.8	54.2	54.2
Towns or villages	14	32.8	33.3	21.6	27.2	15.4	27.0	26.2	27.1
	16	32.6	34.4	24.0	24.1	19.6	33.0	28.0	28.4
	17	26.7	27.3	26.0	27.0	26.9	27.8	27.0	27.0
	Total sample	27.7	28.6	25.6	26.4	25.5	28.6	27.1	27.5

Table 12: χ^2 test statistic with degree of freedom 3 for testing whether the differences with respect to the answers regarding the question "How large is your city?" are significant between the missing-pattern voter groups 16 and 17, and 14 and 17. $\chi^2(3)$ is 7.815 and 6.251 at 95% and 90% levels respectively.

Patterns	February	March	April	May	June	July
14 and 17	2.996	1.089	4.110	1.264	4.055	0.792
16 and 17	4.045	2.999	5.332	0.427	2.729	4.033

the pattern 17.

χ^2 test at 95% level was conducted to examine whether these differences were statistically significant. Corresponding statistics are presented in table 10. Consequently, the differences between the patters 16* and 17 were significant except for in June at 95%. The differences between the patterns 14 and 17 were only significant in March at 95%. It appeared that the difference between the patterns 16* and 17 was substantial. Therefore, voters who answered "I do not know" to some of the questions except "How satisfied are you with the current situation of politics?" (voter groups with the patterns 16* and 14) were less likely to be politically satisfied than those who did not answer "I do not know" to any of the questions (voter group with the pattern 17).

Table 11 presents percentages of voters with the patterns 14, 16, and 17 answering

"Thirteen big cities," "Other cities," and "Towns and villages" to the question "How large is your city?" Table 12 shows χ^2 statistics for testing whether answers to the question differed between voters with the patterns 16 and 17, and 14 and 17. χ^2 test statistics in table 12 showed that the differences were not significant throughout six months at not only 95% but 90%. There was no substantial differences between voters with the patterns 14 and 17, nor 16 and 17.

Since voter groups with the patterns 16 and 17 jointly constitute the whole sample, and since there is a strong indication that they have different profiles in terms of party support and political satisfaction as we have repeatedly observed in this section, the latter group can not be considered as the subsample of the combined whole sample. Statistically speaking, the missing completely at random assumption can not be employed and available-case analysis should not be performed for the data.

Politically, this implies that neutral sounding "I do not know" is sometimes uttered with disapproval of the current politics of Japan. Further researches are needed to examine in what frame of mind and with which emotion the answers "I do not know" were voiced

Appendix 1: Original Questions

Ideology:	What is your political position on a scale of 1 to 10? 1 represents a liberal position, 10 represents a conservative position.
Support-Cabinet:	Do you support the Hashimoto Cabinet?
Economy:	Has the general economic situation been changed since last month?

Appendix 2: The Transformed Data for Analysis

For analysis, the data was transformed to reduce the number of categories of each answer, as following:

Ideology:	1 (liberal) for from 1 to 4 of originally coded answer, 2 (moderate) for 5 and 6, 3 (conservative) for from 6 to 10, -9999 (I do not know) for 11

Politically-Satisfied:	1 (I am satisfied) for 1 and 2, 2 (I am neither satisfied nor dissatisfied) for 5, 3(I am dissatisfied) for 3 and 4, −9999 (I do not know) for 6
City-Size:	1 (thirteen big cities) for 1, 2 (other cities) for 2, 3 (towns or Villages) for 3
Support-Cabinet:	1 (I do support the cabinet) for 1, 2 (I do not support the cabinet) for 2, −9999 (I do not know) for 3
Economy:	1 (Japanese economy has improved) for 1 and 2, 2 (Japanese economy has neither improved nor deteriorated) for 3, 3 (Japanese economy has deteriorated) for 4 and 5, −9999 (I do not know) for 6
Support-Party:	1 (JCP) for 3, 2 (SDPJ) for 2, 3 (Sakigake) for 4, 4 (NFP) for 5. 5 (LDP) for 1, −9999 ("I do not support any party among the five" or "I do not know") for 6, 7 and 8

Appendix 3: The EM Algorithm for Proportional-Odds Model

Let z_{ik}, $k = 1, \ldots, 5$, be the number of respondents with the ith explanatory vector, $\boldsymbol{x}_i$, who answered to support up to and including the kth political party. Following McCullagh and Nelder [14], we assume that $(z_{i1}, z_{i2} - z_{i1}, \ldots, z_{i5} - z_{i4})$ conditional on $\boldsymbol{x}_i$ have multinomial distribution parameterized with $(\gamma_{i1}, \gamma_{i2} - \gamma_{i1}, \ldots, \gamma_{i5} - \gamma_{i4})$ where γ_{ik}, $k = 1, \ldots, 5$, are the cumulative probability up to and including kth category as defined on page 6.

Denote the total number of the respondents with the ith explanatory vector as $m_i \equiv z_{i5}$. We define matrix representation, $\mathbf{X}_i^*$, for the ith pattern explanatory vector, $\boldsymbol{x}_i$, as follows:

$$\mathbf{X}_i^* \equiv \begin{bmatrix} 1 & 0 & 0 & 0 & \boldsymbol{x}_i \\ 0 & 1 & 0 & 0 & \boldsymbol{x}_i \\ 0 & 0 & 1 & 0 & \boldsymbol{x}_i \\ 0 & 0 & 0 & 1 & \boldsymbol{x}_i \end{bmatrix}.$$

The number of the observed patterns of explanatory vectors is n^*.

From the assumption above on distribution of $z_i \equiv (z_{i1}, \ldots, z_{i5})'$, we can write log-likelihood of β^* given $z_i^* \mid \mathrm{X}_i^*$ as

$$l_{z_i|\mathrm{X}_i^*}(\beta^*) \equiv \sum_{k=1}^{5} (z_{ik} - z_{i,k-1}) \cdot \log(\gamma_{ik} - \gamma_{i,k-1}) \tag{3}$$

where $z_{i0} \equiv 0$ and $\gamma_{i0} \equiv 0$ for all i. From equation (2) on page 9, log-likelihood $l_{\boldsymbol{x}_i}(\rho)$ of ρ is written as follows:

$$l_{\boldsymbol{x}_i}(\rho) = \sum_{r=1}^{C} \left(u_r^i \log \rho_r + \log \frac{1!}{u_1^i! \times \cdots \times u_C^i!} \right) = \sum_{r=1}^{C} u_r^i \log \rho_r. \tag{4}$$

With equations (3) and (4), "complete-data log-likelihood," log-likelihood obtained by assuming that all the $\boldsymbol{x}_i$ are observed, of $\phi \equiv (\beta^*, \rho)$ is written as

$$\begin{aligned} l(\phi; \mathrm{X}^*, z) &= \sum_{i=1}^{n^*} \left(l_{z_i|\mathrm{X}_i^*}(\beta^*) + l_{\boldsymbol{x}_i}(\rho) \right) \\ &= \sum_{i=1}^{n^*} \sum_{k=1}^{5} (z_{ik} - z_{i,k-1}) \cdot \log(\gamma_{ik} - \gamma_{i,k-1}) + \sum_{i=1}^{n^*} \sum_{r=1}^{C} u_r^i \log \rho_r \end{aligned}$$

where $\mathrm{X}^* \equiv (\mathrm{X}_1^{*\prime}, \ldots, \mathrm{X}_{n^*}^{*\prime})'$, $z \equiv (z_1, \ldots, z_{n^*})$, and $z_i' \equiv (z_{i1}, \ldots, z_{i5})'$.

Denote $\boldsymbol{x}_i$ as $(\boldsymbol{x}_{\mathrm{obs},i}, \boldsymbol{x}_{\mathrm{mis},i})$ where $\boldsymbol{x}_{\mathrm{obs},i}$ and $\boldsymbol{x}_{\mathrm{mis},i}$ correspond to observed and missing part in $\boldsymbol{x}_i$, respectively. The expected complete-data log-likelihood given the observed values, z and $\boldsymbol{x}_{\mathrm{obs},i}$ for all i, is as follows:

$$E\left[l(\phi; \mathrm{X}^*, z) \,|\, \boldsymbol{x}_{\mathrm{obs},i}, i = 1, \ldots, n^*, z, \phi \right] = \sum_{i=1}^{n^*} \sum_{\boldsymbol{x}_{\mathrm{mis},i}} w_i \left(l_{z_i|\mathrm{X}_i^*}(\beta^*) + l_{\boldsymbol{x}_i}(\rho) \right).$$

The weight, $w_i \equiv \Pr(\boldsymbol{x}_{\mathrm{mis},i} | \boldsymbol{x}_{\mathrm{obs},i}, z_i, \phi)$ is calculated by Bayes' theorem as

$$w_i = \frac{\Pr(z_i | \boldsymbol{x}_i, \phi) \Pr(\boldsymbol{x}_i | \phi)}{\sum_{\boldsymbol{x}_{\mathrm{mis},i}} \Pr(z_i | \boldsymbol{x}_i, \phi) \Pr(\boldsymbol{x}_i | \phi)}.$$

We obtain the EM algorithm for proportional-odds model as follows:
At the s-th step with U_r^i defined on page 9,

E- Step

1. Calculate $E\left[\sum_{i=1}^{n^*} U_r^i \,\middle|\, \boldsymbol{x}_{\mathrm{obs},i}, i = 1, \ldots, n^*, z, \phi^{[s]} \right]$, for all $r = 1, \ldots, C$.
2. Calculate $w_i^{[s]}$ and $E\left[\sum_{i=1}^{n^*} l_{z_i|\mathrm{X}_i^*}(\beta^{*[s]}) \,\middle|\, \boldsymbol{x}_{\mathrm{obs},i}, i = 1, \ldots, n^*, z, \phi^{[s]} \right]$.

M- Step

1. Estimate $\rho^{[s+1]}$: For $r = 1, \ldots, C$, $\rho_r^{[s+1]} \equiv \frac{1}{n^*} E\left[\sum_{i=1}^{n^*} U_r^i \left| \boldsymbol{x}_{\text{obs},i}, i = 1, \ldots, n^*, \boldsymbol{z}, \boldsymbol{\phi}^{[s]} \right.\right]$.
2. Estimate $\boldsymbol{\beta}^{*[s+1]}$. For $\boldsymbol{\beta}^{*[s+1]}$, substitute $\boldsymbol{\beta}^*$ that maximizes the function obtained at the stage 2 in E-step.

As stated in Ibrahim [3], the stage 2 in M-step is equivalent to maximizing the complete-data log-likelihood with the explanatory vector with missing part replaced by a set of weighted "filled-in" explanatory vectors. For example, a explanatory variable $\boldsymbol{x}_i \equiv (1, 1, 1, \text{missing}, 0)$ was replaced by a set of explanatory variables, $w_{i0} \cdot (1, 1, 1, 0, 0)$ and $w_{i1} \cdot (1, 1, 1, 1, 0)$. To do so, we chose a descent method [10] similar to Fisher's scoring, not Newton-Raphson method as in Ibrahim [3]. Since it is difficult to obtain expected second-order derivative of complete-data log-likelihood of $\boldsymbol{\beta}^*$ with respect to $\boldsymbol{z}_i$, we use the following non-positive-definite matrix in place of the Hessian:

$$\begin{aligned}\sum_{i=1}^{n^*} \sum_{\boldsymbol{x}_{\text{mis},i}} w_i^{[s]} E\left[\frac{\partial^2 l_{\boldsymbol{z}_i|\mathbf{X}_i^*}(\boldsymbol{\beta}^*)}{\partial \boldsymbol{\beta}^* \partial \boldsymbol{\beta}^{*\prime}} \middle| \mathbf{X}_i^*\right] &= -\sum_{i=1}^{n^*} \sum_{\boldsymbol{x}_{\text{mis},i}} w_i^{[s]} E\left[\left(\frac{\partial l_{\boldsymbol{z}_i|\mathbf{X}_i^*}(\boldsymbol{\beta}^*)}{\partial \boldsymbol{\beta}^*}\right)\left(\frac{\partial l_{\boldsymbol{z}_i|\mathbf{X}_i^*}(\boldsymbol{\beta}^*)}{\partial \boldsymbol{\beta}^*}\right)' \middle| \mathbf{X}_i^*\right] \\ &= -\sum_{j=1}^{N} (\tilde{\mathbf{X}}_j^*)' \tilde{\mathbf{W}}_j^{[s]} \mathbf{M}_j \boldsymbol{\Delta}_j^{[s]} (\boldsymbol{\Gamma}_j^-)^{[s]} \boldsymbol{\Delta}_j^{[s]} \tilde{\mathbf{X}}_j^* \qquad (5)\end{aligned}$$

where $\tilde{\mathbf{W}}_j^{[s]} \equiv w_j^{[s]} \mathbf{I}$, $\tilde{\mathbf{X}}_j^*$, $j = 1, \ldots, N$, is a matrix representation of any explanatory vector with missing part replaced by a set of weighted "filled in" vectors, $\mathbf{M}_j \equiv m_j \mathbf{I}$, $\boldsymbol{\Delta}_j^{[s]}$ is a diagonal matrix, $\text{diag}(\frac{\partial \gamma_{j1}^{[s]}}{\partial \eta_{j1}^{[s]}}, \ldots, \frac{\partial \gamma_{j4}^{[s]}}{\partial \eta_{j4}^{[s]}})$, $\eta_{jk}^{[s]} \equiv \text{logit}(\gamma_{jk}^{[s]})$ for $k = 1, \ldots, 4$, $\boldsymbol{\Gamma}_j^{-[s]}$ is a generalized inverse matrix of a variance-covariance matrix of $\boldsymbol{z}_j$, N is the total number of the matrix $\tilde{\mathbf{X}}_j^*$, and $\mathbf{I}$ is a 4×4 identity matrix. The first-order derivative of the complete-data log-likelihood is written as

$$\frac{\partial l_{\boldsymbol{z}_j|\mathbf{X}_j^*}(\boldsymbol{\beta}^*)}{\partial \boldsymbol{\beta}^*} = \sum_{j=1}^{N} (\tilde{\mathbf{X}}_j^*)' \tilde{\mathbf{W}}_j^{[s]} \mathbf{M}_j \boldsymbol{\Delta}_j^{[s]} (\boldsymbol{\Gamma}_j^-)^{[s]} (\boldsymbol{z}_j - m_j \boldsymbol{\gamma}_j^{[s]}). \qquad (6)$$

From the equation (5) and (6), we can obtain an interim estimate based on the descent method for the stage 2 in M-step as following:

At the tth step,

$$\begin{aligned}\boldsymbol{\beta}^{*[s][t+1]} = \boldsymbol{\beta}^{*[s][t]} &+ \left(\sum_{j=1}^{N} (\tilde{\mathbf{X}}_j^*)' \tilde{\mathbf{W}}_j^{[s]} \mathbf{M}_j \boldsymbol{\Delta}_j^{[s][t]} (\boldsymbol{\Gamma}_j^-)^{[s][t]} \boldsymbol{\Delta}_j^{[s][t]} \tilde{\mathbf{X}}_j^*\right)^{-1} \times \\ &\left(\sum_{j=1}^{N} (\tilde{\mathbf{X}}_j^*)' \tilde{\mathbf{W}}_j^{[s]} \mathbf{M}_j \boldsymbol{\Delta}_j^{[s][t]} (\boldsymbol{\Gamma}_j^-)^{[s][t]} (\boldsymbol{z}_j - m_j \boldsymbol{\gamma}_j^{[s][t]})\right).\end{aligned}$$

This reduces to iteratively re-weighted least square estimate [14]:

$$\beta^{*[s][t+1]} = \left(\sum_{j=1}^{N}(\tilde{\mathrm{X}}_j^*)'\tilde{\mathrm{W}}_j^{[s]}\mathrm{M}_j\Delta_j^{[s][t]}(\Gamma_j^-)^{[s][t]}\Delta_j^{[s][t]}\tilde{\mathrm{X}}_j^*\right)^{-1} \times \left(\sum_{j=1}^{N}(\tilde{\mathrm{X}}_j^*)'\tilde{\mathrm{W}}_j^{[s]}\mathrm{M}_j\Delta_j^{[s][t]}(\Gamma_j^-)^{[s][t]}\Delta_j^{[s][t]}q_j^{[s][t]}\right) \tag{7}$$

where $q_j^{[s][t]} \equiv \tilde{\mathrm{X}}_j^*\beta^{*[s][t]} + \left(\Delta_j^{[s][t]}\right)^{-1}\left(z_j - m_j\gamma_j^{[s][t]}\right)$. If the iteratively re-weighted least square methods terminates at the t^*th step, substitute $\beta^{*[s][t^*]}$ for $\beta^{*[s+1]}$.

For a prescribed $\epsilon > 0$, the EM algorithm terminates if $\left|\beta^{*[s]} - \beta^{*[s-1]}\right| < \epsilon$.

The asymptotic variance-covariance matrix for the ML estimate of β^* is obtained by inverting an observed information matrix based on $\boldsymbol{x}_{\mathrm{obs},i}$ for all i. For the actual inversion, the following Louis's formula [12] can be applied:

$$\begin{aligned}\frac{\partial^2 l_{z,x_{\mathrm{mis}}|x_{\mathrm{obs}}}(\beta^*)}{\partial\beta^*\partial\beta^{*\prime}} &= E\left[\frac{\partial^2 l_{z|x}(\beta^*)}{\partial\beta^*\partial\beta^{*\prime}}\middle| x_{\mathrm{obs}}, z\right] - E\left[\left(\frac{\partial l_{z|x}(\beta^*)}{\partial\beta^*}\right)\left(\frac{\partial l_{z|x}(\beta^*)}{\partial\beta^*}\right)'\middle| x_{\mathrm{obs}}, z\right] \\ &\quad + E\left[\frac{\partial l_{z|x}(\beta^*)}{\partial\beta^*}\middle| x_{\mathrm{obs}}, z\right] E\left[\frac{\partial l_{z|x}(\beta^*)}{\partial\beta^*}\middle| x_{\mathrm{obs}}, z\right]'.\end{aligned}$$

We implemented the EM algorithm as a macro program of S-PLUS for Windows. The convergence criterion was set as $\epsilon = 10^{-5}$ because it would take more iteration and time of computation than shown below if the criterion had been set more strictly. The number of iterations until the EM algorithm terminates is summarized in table 13.

Table 13: The number of iterations

Month	February	March	April	May	June	July
Number of iteration	11	100	61	26	11	28

We note the three problems which arise when using our EM algorithm. The first is that it is possible to be forced to restrict the number of explanatory variables and to reduce the number of categories due to necessity of estimating γ_{ij}s along with βs. Second, our EM algorithm demands many extended memory when creating the matrix, $\tilde{\mathrm{X}}_i^*$ for all i, in the equation 7. The memory size required depends on the number of the samples with

missing-values and of possible patterns of explanatory variables. In our case, we used 48Mb memory after the try with 16Mb failed. Finally, convergence of the algorithm is very slow [1]. Although we used a computer with the 133MHz Pentium processor, it has taken at least four hours and maximum 4 days to obtain estimated regression coefficients and relevant t-values for one month data.

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