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How Well Do the Pre-stated Intentions Predict Actual Visit Behaviors for Regional Attractions?*

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Abstract This article examines the extent to which survey respondents' stated intentions to visit regional attractions predict their actual visit behaviors. To evaluate this relationship empirically, the article constructs a unique dataset that tracks the same respondents for three consecutive years and records the change of intentions over time and their actual visit behaviors. The empirical results show that intentions strongly predict visiting behaviors even though intentions change significantly over time. Moreover, there are substantial differences in the factors that influence intentions and behaviors, suggesting that analyzing intentions data alone without behavior data may be misleading. The article presents further regression results that verify the robustness of our findings with various regional attractions such as amusement parks, beaches, and forests. The implications of these results are consistent with the article's main findings.

Keywords Demand forecasting, intention-behavior gap, logistic regression, predictability.

JEL Classification C23, D91, P25, L83, Z32.

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1. INTRODUCTION

Demand forecasting for regional attractions, including mega-events such as the Olympics and Expos, is crucial for their success and effective maintenance. Those attractions' existence may positively impact the regional people and economy (e.g., Firgo, 2021). However, in the absence of historical data for new regional attractions, a feasible, nearly unique method to estimate visitor volume is to conduct surveys and elicit visit intentions from potential visitors. In such cases, the surveyed intention data can offer valuable insights into the expected demand for new attractions. Since the seminal works of Fishbein and Ajzen (1977), and Fishbein (1979), intention data have received considerable attention in the literature (e.g., Ajzen, 1985, 1991; Alexander *et al.*, 2008; Armstrong *et al.*, 2000; Rogers, 1983; Triandis, 1979; Van Ittersum and Feinberg, 2010; Young *et al.*, 1998).

Despite the aforementioned, the predictability of intentions for future behaviors has been a long-standing and contentious issue in various fields such as economics, psychology, and regional science. Many studies have questioned the validity of their relationship (e.g., Fennis *et al.*, 2011; Morwitz, 1997). It is because intentions can potentially help predict future behavior, but a large discrepancy is also noticed between intentions and behavior. Manski (1990, 2004), who is often quoted, also suggested that "researchers should not expect too much from intentions data."

A major challenge among such debates is the temporal gap between intentions and behaviors, so-called the intention-behavior gap, which may systematically distort self-reported intentions (Sheeran and Orbell, 1998) and cause people to overestimate or underestimate their intentions (Alexander *et al.*, 2008; Koehler and Poon, 2006). The above-mentioned may inevitably affect the validity of the relationship between intentions and behavior (Sun and Morwitz, 2010; Van Ittersum *et al.*, 2007). Consequently, the predictive power of intentions remains an open question.

Thus, the relationship between intentions and actual behaviors has been studied by many researchers and various theories have been suggested, including the rational expectation hypothesis (Juster, 1966; Manski, 1990, 2004), the theory of attitude, and the theory of reasoned actions (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1977), the theory of planned behaviors (Ajzen, 1985, 1991; Lam and Hsu, 2006), the attitude-behavior theory (Triandis, 1979), the protection motivation theory (Rogers, 1983), and so on. These theories suggest that intentions are an important predictor of behaviors. There also exist other studies that do not indicate a clear relationship between intentions and behaviors (Bass, 2004;

Manski, 1990). Reasons that are often listed for a weak relationship are biased intention measures (Hsiao and Sun, 1998), time-varying intentions (Morrison, 1979), and the imperfect relationship between intention and behavior (Morwitz, 1997).

Among all disciplines, however, the regional science literature and related fields including economic geography and tourism also have a substantial amount of research on behavioral intentions. For example, studies cover topics such as the relationship between intention to visit and cuisine image (Aydin *et al.*, 2021), the relationship between photo taking and intention to revisit (Lee *et al.*, 2021), brand experience and online brand credibility on tourists' behavioral intentions (Jiménez-Barreto *et al.*, 2020), and the television drama and intention (Kim *et al.*, 2012). While these studies deal with intentions data, they fail to examine the direct relationship between intentions and actual behavior.

Accurately forecasting the demand for regional attractions is essential for regional development as well as for making policies (Goh and Law, 2011; Lim, 1997; Park *et al.*, 2017; Song and Li, 2008; Uysal and Crompton, 1985). In the related literature, nonetheless, there are a few studies that examine the relationships between intentions and behaviors (e.g., Lee *et al.*, 2014). A critical problem in analyzing the intention-behavior relationship is that reliable data are not easily available because it is costly and difficult to follow the same person after they state intentions until they act on those intentions.

In this sense, this study has a unique advantage distinct from previous studies. We have collected the data set of intentions and subsequent behaviors for the same respondents, and examined the predictability of intentions for behaviors. The resultant data set deals with the case of the 2012 Yeosu Expo, held between May 12 and August 12, 2012, at Yeosu City in South Korea. It is mainly constructed from the supplementary data set to the National Domestic Travel Survey published by the Ministry of Culture, Sports, and Tourism. The survey has been asking the same respondents about their intention to visit the Yeosu Expo for 3 years from 2009 to 2011. In the year 2012, right after the Expo, it asked the same respondents whether they visited the Expo or not. We combine the survey results with other information and make a unique data set for our study. The data set directly captures separable personal data for intentions and visits for 3 consecutive years, and, to the best of our knowledge, the use of such a data set is the first attempt in the related literature. In previous research, reversely, direct observations have been rarely made for intentions and behaviors (e.g., Hsiao *et al.*, 2002). As intentions data are collected long after they are initially formed, the memory of their intentions may be biased (Festinger, 1957). Thus, the directly observed data may help correctly estimate the relationship between intentions and actual behaviors (McKercher and Tse, 2012).

Using the dataset with intentions and behaviors exactly matched, we estimate the relationships between intentions and behaviors with various econometric models. The empirical results show that intentions strongly predict visiting behaviors and intentions become more positive and precise as the event date nears. Our results also reveal the importance of no-visit intentions and, hence, no-visit intentions have a strong predictive power for future behaviors. The predictability of socio-demographic variables for intentions and behaviors are evaluated. It turns out that socio-demographic variables have different effects on intentions and behaviors. This implies that there are fundamental gaps between intentions and behaviors and that the analysis of intentions data alone without behavior data may be misleading. Analysis of other regional attractions such as spa, beaches, and forests, show that our results are robust.

The paper proceeds as follows. Section 2 will illuminate our empirical strategy and data set. Section 3 presents our main results using the Expo 2012 at Yeosu, one of the specialized Expos. The interpretation and implication for the results are also given. Section 4 contains the robustness check of our findings, which uses alternative regional attractions such as amusement parks and festivals, and the last section concludes.

2. EMPIRICAL STRATEGY AND DATA

2.1. PREDICTABILITY INDEX

In this subsection, we suggest an index that represents the predictability of intentions to evaluate the information quality of intentions data. Table 1 shows the visit/intention matrix for visit behavior and intention. In this table, A, B, C, and D denote the number of visitors with intentions, the number of non-visitors with intentions, the number of visitors with no-visit intentions, and the number of non-visitors with no-visit intentions, respectively. Thus, ideal values are $A > 0$, $B = 0$, $C = 0$, and $D > 0$. A and D are correct signals and B and C are wrong ones. With this matrix, we can evaluate the performance of intentions to predict visit behaviors.

That is, when actual visit occurs, we want to know how well intentions predict it. For this purpose, we use the ratio $A/(A+C)$. This ratio indicates how many people had visit intentions when actual visit occurs, and this ratio attempts to measure the predictability of intentions for visit behaviors. Moreover, when we evaluate the predictability of intentions for actual visits, no-visit intentions

Intention/Visit	Visit	No Visit
Intention	A	B
No intention	C	D

Table 1: VISIT/ INTENTION MATRIX. A, B, C, and D denote the number of visitors with intentions, the number of non-visitors with intentions, the number of visitors with no-visit intentions, and the number of non-visitors with no-visit intentions, respectively.

are also important as well as the visit intentions. That is, if one states no intention to visit and actually does not visit the event, then their intention contains important information about the actual visit. Thus, to reflect the predictability of no-visit intentions, we use the ratio $D/(B+D)$ as well.

We combine the two ratios to construct the predictability index. If intentions have predictability, an index should provide higher values when visitors have visit intentions and non-visitors have no-visit intentions. Thus, the predictability index may be defined by the product of the two intention measures, that is,

$$PI = \frac{A}{A+C} \times \frac{D}{B+D}.$$

Here, PI is the predictability index, $A/(A+C)$ measures the visit intention of visitors, and $D/(B+D)$ measures the no-visit intention of non-visitors. Thus, higher values of both ratios mean better predictability of intentions. We have five levels in our intentions data. Level 3 may represent indecisiveness, which indicates part visit and part no-visit intentions. Thus, in practice, we exclude Level 3 from the calculation of the predictability index. Visit intentions include Levels 4 and 5, whereas no-visit intentions include Levels 1 and 2. The predictability index may be sensitive to the definition of categories. Hence we calculate the index for smaller sets of categories, that is, visit intentions include level 5 and no-visit intentions include level 1 only. We provide both results in the empirical section.

The motivation behind combining these ratios is as follows. The first is that the ratios are used in the signal approach to predict financial crises in international finance literature. There are four cases where there is a signal or no signal for a crisis, and a crisis occurs or does not occur. The model tries to find the predictors that correctly provide early warning signals for an upcoming crisis, minimizing the noise-to-signal ratio, $([B/(B+D)]/[A/(A+C)])$. See, for example, Kaminsky *et al.* (1998) and the references therein.

Another is that the predictability index can be easily combined with the logit model introduced in the next subsection. It may improve the interpretability of β, the regression coefficient of interest. In the regression, given the visit behaviors in the dependent variable, we evaluate whether or not intention variables predict visit behaviors efficiently. If we interpret the intentions as a dichotomous variable, the coefficient β of the intention variable in the logit model is related to the log odds ratio as follows.

$$\log\left(\frac{P(\text{visit}=1|\text{intention}=1)/P(\text{visit}=0|\text{intention}=1)}{P(\text{visit}=1|\text{intention}=0)/P(\text{visit}=0|\text{intention}=0)}\right)$$
$$=\log\left(\frac{A/(A+B)/B/(A+B)}{C/(C+D)/D/(C+D)}\right)=\log\left(\frac{A}{B}\cdot\frac{D}{C}\right)=\beta,$$

which is slightly different from the predictability index. Thus, the coefficient of intentions in the logit model and the predictability index both are closely related.

It is worth noting that the ratios $C/(A+C)$ and $B/(B+D)$ may be regarded as the probabilities of type I error and type II error, respectively. Subsequently, the predictability of visit intentions and no-visit intentions can be written as $(1-P[\text{type I error}])$ and $(1-P[\text{type II error}])$, respectively, and the predictability index becomes the product of these two values: $PI=(1-P[\text{type I error}])\times(1-P[\text{type II error}])$. Good predictors will result in smaller probabilities of type I and II errors and a higher predictability index.

2.2. ECONOMETRIC MODELS

In this subsection, we introduce our theoretical and econometric models. We assume that intentions are determined by attitude, subjective norms, and perceived behavior control (Ajzen, 1985, 1991) and that they are important predictors of actual behavior. We propose that socio-demographic variables affect both intentions and behaviors. Thus, behavior is determined by socio-demographic variables and intentions. Our model is depicted in Figure 1.

In Figure 1, the three factors are reflected in the stated intentions and are not observable. However, stated intentions, socio-demographic variables, and actual behaviors are observable in our data set. Our strategy is the use of socio-demographic variables to predict both intentions and behaviors.

More details of this model are found in Ajzen (1991) and the references therein. Attitude toward visiting destination is related to an expected outcome or to a cost resulting from the behavior. We come to favor behaviors that give us desirable consequences and we form unfavorable attitudes toward behaviors with

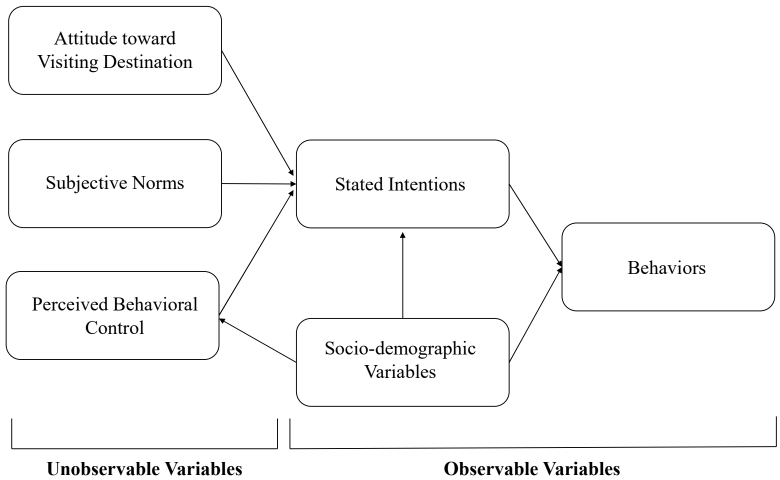


Figure 1: MODEL OF INTENTIONS AND ACTUAL BEHAVIORS. This model is slighly modified from the original model in Ajzen (1991). More specifically, socio-demographic variables are added and they affect both perceived behavioral control and behaviors.

undesirable consequences. Subjective norm is related to the extent to which significant others would agree or disagree with our behaviors. Perceived behavioral control refers to people's confidence in their ability to perform it. The confidence is related to resources and opportunities they possess. The more resources and opportunities people believe they have, the greater would be their perceived control over their behaviors. Previous studies found that these three factors failed to predict behaviors, and it was argued that three factors affected behaviors only indirectly by influencing intentions (Ajzen and Fishbein, 1980, Chap. 7). In Ajzen (1991), perceived behavioral control directly affects behavior. In this paper, however, we add another construct, socio-demographic variables and these variables affect both intentions and behaviors. By controlling the socio-demographic variables, perceived behavioral control does not directly affect behaviors. In this way, our paper tries to identify the important determinining factors of visit behaviors.

Good models must be able to predict the target variables well. Note that our target variable, visit behavior, is a binary response variable with 1 indicating that the respondent visited the site and 0 indicating that they did not visit the site. With this type of data set, a natural choice of an econometric model is the use of a logit model (e.g., Hsiao *et al.*, 2002; Lee *et al.*, 2014). We consider the following four models. We start with a simple model and expand it to a more general model.

Model 1

Following Fishbein and Ajzen (1977), we assume that behaviors are determined only by intentions, and intentions are determined by attitudes, subjective norms, and perceived behavioral control. Let I_i be the intention of respondent i, let y_i^* be the latent variable that indicates a respondent's unobservable behaviors, and let y_i be the respondent's actual behavior indicating visit=1 and no-visit=0. Intentions are functions of the unobserved factors z_i^*, i.e., $I_i = \mu + \delta z_i^* + v_i$. Observed intentions, I_i, are integer functions that have values ranging from 1 to 5 with 5 being the highest intention. Then,

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases},$$

where $y_i^* = \alpha + \beta I_i + u_i$. We assume that v_i and u_i denote the factors that are omitted in the model and they are uncorrelated with z_i^* and I_i. Now, the probability of $y_i = 1$ is found by the logit model:

$$P(y_i = 1|I_i) = F(\alpha + \beta I_i),$$

where $F(\cdot)$ is the logistic function. In this simple model, we propose that all the necessary information that determines actual behavior is reflected in the stated intention alone. If intentions do not have information for behaviors but socio-demographic variables do, then intention variables are still significant because of the covariance between intention variables and socio-demographic variables. If both intention variables and socio-demographic variables do not have information for behaviors, then intention variables will be insignificant.

Model 2

We estimate the effects of socio-demographic variables on visit behavior separately from intention variables. Let x_i be respondents' socio-demographic variables. Thus, the probability of $y_i = 1$ becomes:

$$P(y_i = 1|x_i) = F\left(\alpha + \gamma' x_i\right).$$

Here, x_i includes individual characteristics such as gender, age, education, house size, and so on. These variables will be introduced in the next section. This model implies that behaviors are determined by only socio-demographic variables. If socio-demographic variables affect intentions and the intention variable is not included in the equation even though it affects the visit behavior, socio-demographic variables in the equation can be found to be significant even if it has zero effect. This occurs because omitted variable bias is caused by the covariance between socio-demographic variables and intention variables. Figure 1 shows a uni-directional effect from socio-demographic variables to intention, and this uni-directional relationship can still produce non-zero covariance between them. Therefore, Model 3 or 4 should be used to examine whether socio-demographic variables have a direct effect on visits independent of intentions. Only if these variables prove to be insignificant in these models can we conclude that they do not influence visit while they do intentions.

Model 3

We include both stated intentions and socio-demographic variables and examine whether they have independent explanatory power. Next, the probability of $y_i = 1$ becomes:

$$P(y_i = 1|I_i, x_i) = F\left(\alpha + \beta I_i + \gamma' x_i\right).$$

This model implies that behaviors are determined by both intentions and socio-demographic variables. If behavior is only determined by socio-demographic variables, the coefficient of intention will not be significant. Otherwise, we may conclude that intentions have unique information independent of socio-demographic variables. If socio-demographic variables affect intention as shown in Figure 1 but do not affect visit behaviors, then they will be insignificant.

Model 4

The intention variable has an intrinsic ordering to the categories. If these categories are equally spaced, then the intention variable represents different 'degree' of intentions and we may regard it as a numerical variable. However, if there are different effects for each intentional level, we may have to estimate the effects of intention levels separately using dummy variables. Models 1 and 3 are based on the former assumption and Model 4 is based on the latter assumption.

In previous models, we denoted intentions by integer numbers ranging from 1 to 5. If we use the single-intention variable, we can estimate the average impact of the intention measures on behavior. Here we propose to measure the strength of each intention value by using four intention dummies. That is, let $D_{ij} = 1$ if $I_i = j$, $j = 2,3,4$ and 5. Subsequently, the model becomes

$$P(y_i = 1|I_i, x_i) = P(y_i = 1|D_{ij}, x_i) = F\left(\alpha + \sum_{j=2}^{5} \beta_j D_{ij} + \gamma' x_i\right).$$

The coefficients of intention dummies will tell us how each intention level affects actual behaviors.

We have four different models for estimating the determinants of behavior, which we can compare to find the best-fitting model. Note that Models 1 and 2 are nested in Model 3, but Model 3 is not nested in Model 4. Thus, we cannot apply the likelihood ratio (LR) test to find the best model because the LR test can be applied only to models with nesting relations. In this case, we can apply model selection criteria, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC):

$$AIC = 2k - 2\ln(L),$$
$$BID = k\ln(n) - 2\ln(L),$$

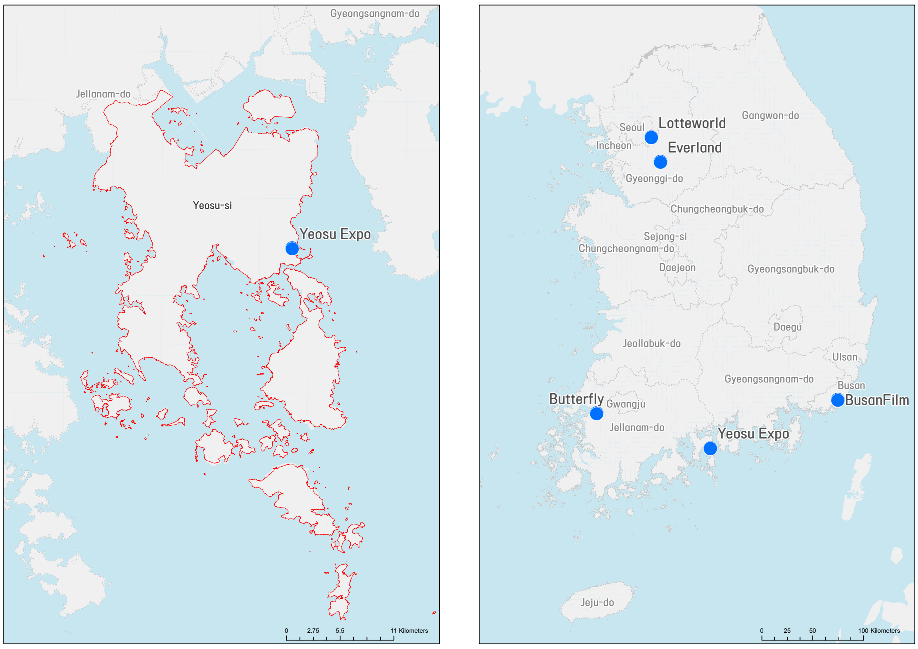
where k is the number of variables, n is the number of observations, and $\ln(L)$ is the value of the log likelihood. These model selection criteria are useful in comparing non-nested models such as ours.

Model 5

We also estimate the effects of socio-demographic variables on intentions as indicated in Figure 1. As intentions have five levels from 1 (lowest intentions) to 5 (highest intentions), we choose the ordered logit model to estimate the effects. The logit model handles binary choices (0 and 1) but the ordered logit model is appropriate in the current situation where dependent variables (intentions) are ordered integers. We compare the coefficients of the socio-demographic variables in Models 2–4 and Model 5 and examine how differently they affect intentions and behaviors.

2.3. DATA

Data on intentions and visit behaviors to the Yeosu Expo were collected for 3 consecutive years (see Figure 2 for the geographical location of Yeosu). They were obtained in January from 2010 to 2012 in the supplementary survey of



(a) Expo 2012 Yeosu (b) Regional Attractions

Figure 2: GEOGRAPHICAL MAP OF EXPO 2012 YEOSU AND OTHER REGIONAL ATTRACTIONS. This map shows the geographical location of 2012 Yeosu Expo and other regional attractions which are examined for robustness check.

the National Domestic Travel Survey by the Ministry of Culture, Sports, and Tourism. The population of our data set is from the Population and Housing Census by Statistics Korea conducted in 2005. The survey had been conducted for 5,401 individuals aged 15 and above for the entire nation by asking them about their travel records and conducting in-depth investigations.

The Expo 2012 Yeosu was held for the period between May 12 and August 12, 2012. Actual visit data are obtained by calling the same people who filed the survey right after the Expo was held, and asking them whether they visited the Expo or not. Intention is measured on a scale from 1 to 5, where 1 indicates 'Definitely Not Visit' and 5 indicates 'Definitely Visit.'

Most literature examine the behavioral intention itself, not the relationships between intentions and behaviors. For example, Lee *et al.* (2021) focus on the effect of allowing photo-taking on revisit intention. Other literature ask inten-

	Intentions		Visits	
Variables	Mean	SD	Mean	SD
Exhibition				
$Expo_{09}$	2.0704	1.1097		
$Expo_{10}$	2.0153	0.9787		
$Expo_{11}$	2.5360	1.0779	.0956	.2941
Sites				
Spa	2.9564	1.1475	.1238	.3294
Ski	2.1147	1.2307	.0331	.1790
Beach	2.5162	1.2276	.2224	.4159
Forest	2.6421	1.1901	.1258	.3316
Domestic	2.9895	1.1209	.7258	.4461
Outbound	1.9224	1.1399	.1000	.3000
Everland	2.1210	1.1612	.0337	.1805
Lotteworld	2.0470	1.1237	.0315	.1748
Butterfly	2.0932	1.0809	.0089	.0941
BusanFilm	1.8887	1.0405	.0117	.1076

Table 2: DESCRIPTIVE STATISTICS OF INTENTION AND VISIT DATA. The intentions data of Yeosu Expo were obtained for 3 consecutive years from 2009 to 2011, and actual visit data were obtained by calling the same people who filed the survey right after the Expo was held. The intentions data for ten other regional attractions were surveyed in 2009 and the actual visit data was collected in 2010.

tions after events occur (e.g., Lee *et al.* (2014)). In this case, the interviewees' memory may not be correctly reported. Our dataset is differentiated from previous literature in this regard. Thus, we ask intentions *before* the event occurs for 3 consecutive years and record their behaviors right after the event occurs for the same person. This data of *matched intention-behavior pair* is unique in the literature and may provide valuable insights on the relationships between intentions and behaviors.

In addition to the Yeosu Expo, we also consider ten other regional attractions for the purpose of robustness checks. They include spas, ski destinations, beaches, forests, domestic travel, outbound travel, the Everland, the Lotteworld, the Hampyung Butterfly Festival, and the Busan International Film Festival (see also Figure 2 for the geographical location of the above attractions). Outbound travel includes trips for tourism as well as for business, visiting relatives, short

Variables	Mean	SD	Min	Max
Retire	.1922	.3941	0	1
Male	.4719	.4993	0	1
Age	47.8853	17.1228	15	94
Edu	11.4993	4.2662	0	23
Unmarried	.1708	.3764	0	1
Married	.7320	.4430	0	1
Bereaved	.0774	.2672	0	1
Divorced	.0184	.1346	0	1
Disabled	.0728	.2598	0	1
Housesize	3.3541	1.2576	1	8
Saving	407.6751	364.8384	0	1,000
Debtsettle	119.3831	288.4671	0	1,000
Consumption	174.8225	264.8172	0	1,000
Leisure	182.2000	257.3701	0	1,000
Indinc	1,580.3650	2,530.888	0	100,000
Houseinc09	3,550.2810	2,717.473	0	50,120
Houseinc10	4,161.9710	3,646.908	0	105,000
Houseinc11	3,915.8010	2,741.256	0	30,000
Distance	280.7778	87.5231	126	456

Table 3: DESCRIPTIVE STATISTICS OF SOCIO-DEMOGRAPHIC VARIABLES. The units of Saving, Consumption, Leisure, Individual Income (Indinc), and Household Income (Houseinc) are 10,000 Korean Won, and those values are divided by 1,000 to have reasonable sizes of coefficients. The socio-demographic variables were collected in 2009.

education courses, hospitals, and so on. The intentions data for these sites were surveyed in January 2010 and the actual visit data was collected in January 2011. Table 2 summarizes the descriptive statistics of the intentions and behaviors.

Besides the intentions and visit behaviors data, we also use the socio-economic variables that were collected in the 2009 survey. Table 3 presents the descriptive statistics for the variables used in our analysis. Retire is a dummy variable with retired = 1. Male is a dummy variable with male = 1 and female = 0. Ages range from 15 to 94. Edu is the number of schooling year, which ranges from 0 to 23. Unmarried is a dummy variable with unmarried = 1, Married with married = 1, Bereaved with bereaved = 1, and Divorced with divorced = 1. Disabled is a dummy variable with disabled =1. Housesize is the number of household members. Saving, donation, consumption, leisure, and debt settle are respondents' propensities for saving, donation, expenditures on consumption goods, leisure, and debt settlement. We asked respondents how much money they would like to assign to each category if they were given 10 million Korean Won (KRW) so that the sum of the values becomes 10 million KRW. These values may represent the respondents' propensities toward each category. As the sum of the propensities is a fixed number, we have to drop one variable to avoid perfect collinearity in the regression. In the analysis, we omit donation because it has the smallest proportion among the categories. Indinc is the individual income. Houseinc09, Houseinc10, and Houseinc11 are the household incomes in 2009, 2010, and 2011, respectively. Propensities and individual and household incomes are divided by 1,000 to adjust scales. Distance is the distance in kilometers from the city hall of the respondents' hometown to the Yeosu Expo.

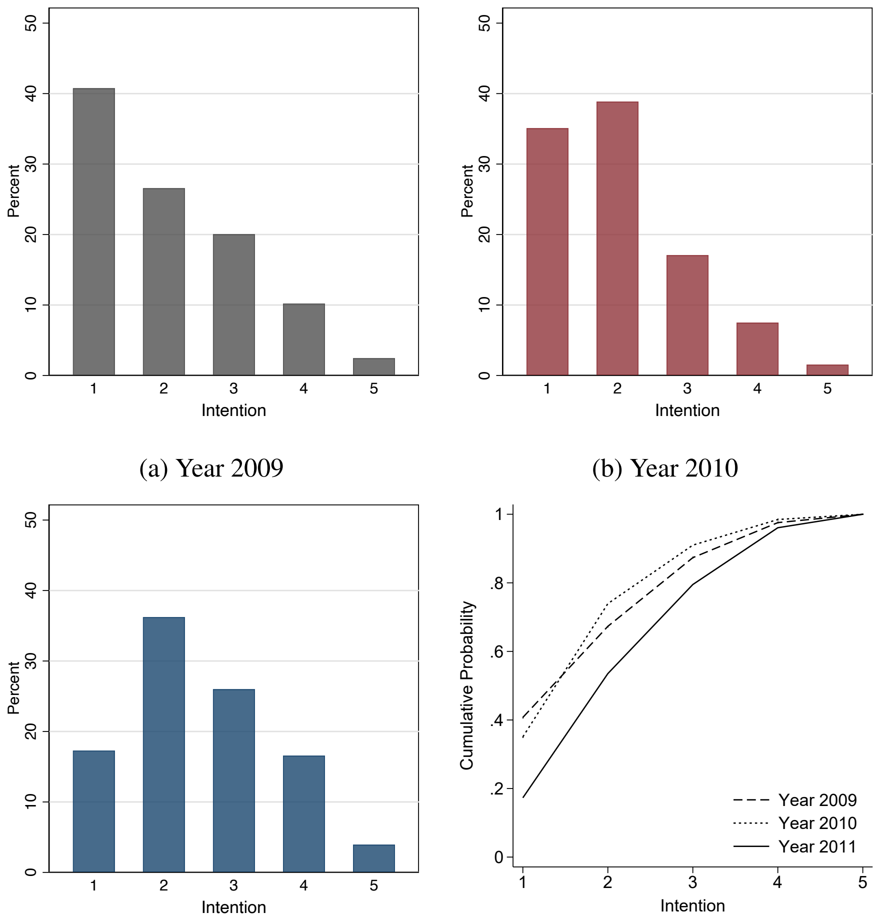
3. EMPIRICAL RESULTS

3.1. TEMPORAL CHANGE OF INTENTIONS

In this subsection, we examine the distribution of intentions and investigate how they change over time. As Figure 3 shows, the distribution of intentions changes over time. For instance, approximately 40 percent of the respondents in 2009 exposed no intention to visit. However, as time gets near the event in 2012, the peak frequency of intentions moves toward a higher score. This change in distribution may imply that people obtain more event-related information as the event nears. The year 2011's empirical c.d.f. also looks evidently distinguished from other years. Thus, Figure 3 may also imply that people tend to understate their visit intentions in the early period.

We more formally test the changes in distribution using various statistical tests. We consider the Kolmogorov–Smirnov (KS) test, the discrete KS test, and Pearson's Chi-square test. The null hypothesis of these tests is that compared distributions are equal. As our intention data has discrete values, the KS test is not appropriate because it is restricted to continuous distributions. Thus, we additionally consider the discrete version of the KS test (see Gawande *et al.* (2013) for the codes) and Pearson's Chi-square test because these tests are known to be applicable to discrete distributions.

Table 4 shows the results of the equality tests. The results show that the null hypothesis of equal distributions is strongly rejected for all comparison pairs. This means that the distribution of intentions changes over time and we need to determine which intention has the highest predictability for respondents' future



(a) Year 2009 (b) Year 2010

(c) Year 2011 (d) Empirical c.d.f.

Figure 3: HISTOGRAM OF INTENTIONS. Panel A, B, and C show the distribution of intentions in the years 2009, 2010 and 2011, respectively. Panel D shows the empirical cumulative distribution function.

behaviors. We will examine this issue in the following subsections. Data shows that only 16.8% of the respondents do not change their intentions over the 3 years. The other 83.2% of the respondents change their intentions at least once. Our results show that visit intentions change substantially over time.

Pair	KS	Discrete KS	Chi-squared
2009 vs. 2010	.0663	3.3235	181.9187
	(.0001)	(.0001)	(.0001)
2010 vs. 2011	.2041	10.2468	628.4010
	(.0001)	(.0001)	(.0001)
2009 vs. 2011	.2345	11.7730	684.5892
	(.0001)	(.0001)	(.0001)

Table 4: RESULTS OF EQUALITY TEST. The test statistic of each test is reported and p-values are in the parenthesis.

3.2. PREDICTABILITY INDEX OF INTENTIONS

Table 5 shows the results of the predictability index for the intentions data of the Yeosu Expo. Panel A shows the results of index for the larger sets of categories, that is, in Panel A, visit intentions include level 4 and 5 and no-visit intentions include level 1 and 2. Panel B shows the results of index for the smaller sets of categories, that is, in Panel B, visit intentions include level 5 and no-visit intentions include level 1 only.

In Panel A, the signals from visit intentions $(A/(A+C))$ slightly drop in 2010 but become very strong in 2011, where the ratio of visit intention is 0.6639. Conversely, no-visit intention goes up in 2010 but drops to 0.7652 in 2011. Overall, the ratio of no-visit intention $(D/(B+D))$ is higher than that of visit intention. This implies that the information from no-visit intentions should not be ignored in predicting actual behavior. The predictability index in 2009 is 0.3602, which drops slightly to 0.3276 in 2010 but increases to 0.5081 in 2011. In Panel B, the signals from visit intentions $(A/(A+C))$ monotonically increase from 0.2950 to 0.7442. No-visit intention shows similar pattern as in Panel A but the ratio of no-visit intention $(D/(B+D))$ is higher in Panel B than in Panel A. Overall, the predictability index monotonically increases from 0.2855 in 2009 to 0.6635 in 2011. Thus, if we extract stronger signals from the visit and no-visit intentions, we observe clearer pattern of monotonically increasing predictability index. In summary, the predictability index shows that the predictability of intentions becomes strong as the event approaches, and no-visit intentions have important information about behavior as visit intentions.

Another interesting aspect observed in Table 5 is that D_b does not change significantly over time compared to A_c. From the perspective of government policy implications, this suggests that while additional information about the Expo over

Year	Panel A					Panel B				
	A C	B D	A_c	D_b	PI	A C	B D	A_c	D_b	PI
2009	156 220	482 3,173	.4149	.8681	.3602	59 141	64 1,913	.2950	.9676	.2855
2010	131 235	323 3,492	.3579	.9153	.3276	45 102	32 1,666	.3061	.9812	.3004
2011	243 123	790 2,575	.6639	.7652	.5081	96 33	102 839	.7442	.8916	.6635

Table 5: VALUES OF PREDICTABILITY INDEX FOR YEOSU EXPO. A, B, C, and D denote the number of visitors with intentions, the number of non-visitors with intentions, the number of visitors with no-visit intentions, and the number of non-visitors with no-visit intentions, respectively. $PI = A_c \times D_b$, where $A_c = A/(A+C)$ and $D_b = D/(D+B)$. Panel A shows the results of index for the larger sets of categories, that is, visit intentions include level 4 and 5 and no-visit intentions include level 1 and 2. Panel B shows the results of index for the smaller sets of categories, that is, visit intentions include level 5 and no-visit intentions include level 1 only.

time does not influence those who initially have no intention to visit, it can affect those who are somewhat inclined, increasing their intention over time. In other words, when promoting events such as the Expo, it is more effective to focus on those who already have some level of intention. This finding will provide clearer guidance for event organizers and policymakers on how to effectively increase participation rates.

3.3. LOGISTIC REGRESSIONS

In this subsection, we run logistic regressions to find out which factors are important for the visit behaviors to the Yeosu Expo. Table 6 shows the estimation results.

The results are as follows. First, we examine whether intentions predict visit behavior. The null hypotheses of the models are that intention is not an important predictor of visit behavior. The results in Table 6 show that the intentions variables are, in most cases, highly significant. In Model 1, all three intention variables are significant at the 1% level. In particular, the pattern of the coefficients in Model 1 is similar to that of the predictability index in Panel B of Table 5. Thus, this shows that the result of the predictability index is comparable to that of the logistic regression model with only intention variables. In Model 3, with the socio-demographic variables included, the significances of the intention

Variables	(1)	(2)	(3)	(4)	Dummies	(4′)
Int_09	.1928***		.1656***		2.int_09	-.3393**
	(.0469)		(.0500)			(.1550)
Int_10	.2920***		.1416**		3.int_09	.0247
	(.0534)		(.0589)			(.1532)
Int_11	.5992***		.4755***		4.int_09	.2412
	(.0531)		(.0562)			(.1758)
Retire		-.2549*	-.0872	-.0880	5.int_09	.9777***
		(.1387)	(.1427)	(.1442)		(.2674)
Male		-.1305	-.1370	-.1737	2.int_10	-.1229
		(.1147)	(.1192)	(.1208)		(.1498)
Age		.0093*	.0127**	.0120*	3.int_10	.1102
		(.0056)	(.0058)	(.0058)		(.1702)
Edu		-.0359**	-.0375**	-.0380**	4.int_10	.1514
		(.0157)	(.0161)	(.0164)		(.2053)
Married		.2990	.0996	.0953	5.int_10	.9192***
		(.2193)	(.2248)	(.2289)		(.3365)
Bereaved		-.1285	-.2073	-.2167	2.int_11	.2450
		(.3106)	(.3195)	(.3226)		(.2159)
Divorced		-.3709	-.4187	-.4138	3.int_11	.6864***
		(.4787)	(.4959)	(.5090)		(.2187)
Disabled		-.1174	-.0419	-.0985	4.int_11	1.0061***
		(.1982)	(.2077)	(.2166)		(.2246)
Housesize		-.1626***	-.1182**	-.1082**	5.int_11	2.0779***
		(.0483)	(.0498)	(.0507)		(.2673)
Saving		-.0648	.0546	.0389		
		(.2173)	(.2266)	(.2285)		
Debtsettle		.2291	.4572*	.4485*		
		(.2500)	(.2609)	(.2634)		
Consumption		-.2083	-.1268	-.0828		
		(.2777)	(.2884)	(.2911)		
Leisure		.7849***	.5283**	.5907**		
		(.2536)	(.2657)	(.2694)		
Indinc		.0270	.0231	.0218		
		(.0184)	(.0197)	(.0185)		
Houseinc11		.0619***	.0409*	.0347		
		(.0195)	(.0209)	(.0213)		
Distance		-.0101***	-.0067***	-.0069***		
		(.0006)	(.0007)	(.0007)		
Constant	-5.0972***	.2149	-2.7974***	-1.3255**		
	(.1754)	(.4426)	(.5184)	(.5210)		
Observations	5,041	5,029	5,029	5,029		
Log Likelihood	-1394	-1385	-1301	-1276		

Table 6: MAIN ESTIMATION RESULTS. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively. The column (4′) reports estimates for intention dummies.

variables slightly decrease but they are still highly significant. In Model 4, in which intention dummies are used instead of intention variables, intention dummies are significant for Levels 2 and 5 in 2009, for Level 5 in 2010, and for Levels 3, 4, and 5 in 2011. Thus, here again, we have at least one significant intention dummy in each year. Therefore, as Hsiao *et al.* (2002) pointed out, these results mean that intentions are powerful predictors of future visit behavior.

Second, we examine whether the intentions of different years have different predictability. The results show that the intention variable in 2011 is the most statistically significant among the 3 years in Models 1 and 3 and this is also true for Model 4 in the last column. Thus, the importance of intentions data change over time, as shown in the previous section (Hsiao *et al.*, 2002; Salisbury and Feinberg, 2008; Van Ittersum, 2012).

Nonetheless, our results also show that intentions formed 3 years ago are still significant. Morrison (1979) also points out the change of intentions over time. Why do they change? We propose that information of the event may play an important role here. For example, we have sufficient information for beaches and forests, but we do not have much information about the 2012 Yeosu Expo. Thus, as time approaches the event, people get more information about the Expo and their intentions to visit will increase over time. That is, intentions to visit specific places will change as time passes because people get more information about them. On the contrary, people have enough information about general places such as beaches and forests and, hence, we expect that intentions to visit such general places will remain stable over time.

Third, Models 2–4 show that socio-demographic variables help to predict visit behavior. Among the considered socio-demographic variables, gender, marriage, disabled, saving, consumption, and individual income are not significant. On the contrary, retirement has a slightly negative coefficient when no intention variables are included in the regression. Also, age, debt settlement and leisure are positively related. Education, house size and distance to the Yeosu Expo have negative signs. Household income affects the visit behavior significantly, whereas individual income does not. These results show that socio-demographic variables are important predictors of visit behavior. Moreover, comparing the results in Models 1–4, the signs and significances of socio-demographic variables are similar whether or not intention variables are included. This implies that socio-demographic variables have independent explanatory power, which intentions data do not have.

Fourth, the estimated coefficient $\hat{\beta}$ is the effect of a variable on the log-odds of an outcome, not on the probability of the outcome. Thus, the coefficient does not have a useful economic interpretation. To better understand the coefficient, we provide the mariginal effects of the regressors. The marginal effect estimates the change of probability of an outcome with respect to a change of a regressor. Thus, the marginal effect is calculated by the derivative of the logit probability function with respect to explanatory variables. It is a nonlinear function of regressors and, hence, it depends on the values of all regressors. We fix the values of all the regressors at their sample means. For continuous variables such as the household income, a marginal effect estimates the change of probability with respect to a small change of a regressor. For dummy variables such as the married dummy, a marginal effect estimates the change of probability with respect to a change from 0 to 1 of a regressor. With the marginal effects we can compare the relative magnitudes of the effects of regressors on the probabilities of outcome.

In Table 7, the marginal effects are estimated at the means of explanatory variables. Comparing the results in Model 3, where the intention variable is used linearly, with those in Model 4, where it is divided into dummies, we see that as intention changes from 1 (Definitely Not Visit) to 5 (Definitely Visit), the average increase in visiting probability of the year 2011 in Model 3 is 0.0266*4=0.1064, whereas in Model 4, the increase of probability of intention level 5 is 0.1995. Furthermore, comparing the intention levels at 4 and 5 in Model 4, the visiting probability increases by 0.1995- 0.0587=0.1408. This indicates that the level of intention has a very nonlinear impact. From the perspective of policy implication, it shows that policy requires significantly boosting intention up to the highest level for higher visiting probability. This result is consistent with the differences between panel A and B in Table 5.

If we compare the marginal effects of intention variables with those of socio-demographic variables, the intention variable in 2011 is the second largest in Model 3 and the level 5 intention variable in 2011 is the largest in Model 4. For example, if a person shows level 5 intention in 2011, it will increase the probability of visit behavior by 19.95%. Moreover, the level 4 and level 5 intention dummies have larger effects than socio-demographic variables in Model 4. These results show that intention variables are the most important predictor for visit behaviors. Among the socio-demographic variables, Leisure has the largest values, Debtsettle is the second and Housesize is the third largest. In this way, we can evaluate the importance of the variables on the probability of visit behaviors.

Fifth, we compare four models to find the best-fitting model. As discussed above, we cannot apply the LR test and, therefore, will use AIC and BIC instead to find the best-fitting model. Table 6 shows that the value of the log likelihood of Model 4 is the largest. However, Model 4 has the largest number of variables

Variables	(1)	(2)	(3)	(4)	Dummies	(4′)
Int_09	.0125***		.0093***		2.int_09	-.0174**
	(.0030)		(.0028)			(.0078)
Int_10	.0190***		.0079**		3.int_09	.0015
	(.0035)		(.0033)			(.0092)
Int_11	.0389***		.0266***		4.int_09	.0159
	(.0033)		(.0031)			(.0122)
Retire		-.0148**	-.0048	-.0049	5.int_09	.0890***
		(.0075)	(.0076)	(.0079)		(.0328)
Male		-.0081	-.0076	-.0099	2.int_10	-.0067
		(.0071)	(.0066)	(.0069)		(.0082)
Age		.0006*	.0007**	.0007**	3.int_10	.0067
		(.0003)	(.0003)	(.0003)		(.0104)
Edu		-.0022**	-.0021**	-.0022**	4.int_10	.0093
		(.0010)	(.0009)	(.0009)		(.0130)
Married		.0175	.0055	.0054	5.int_10	.0794**
		(.0121)	(.0121)	(.0126)		(.0388)
Bereaved		-.0076	-.0108	-.0115	2.int_11	.0099
		(.0175)	(.0153)	(.0158)		(.0083)
Divorced		-.0197	-.0197	-.0207	3.int_11	.0343***
		(.0217)	(.0193)	(.0201)		(.0100)
Disabled		-.0070	-.0023	-.0054	4.int_11	.0587***
		(.0113)	(.0113)	(.0113)		(.0124)
Housesize		-.0101***	-.0066**	-.0062**	5.int_11	.1995***
		(.0030)	(.0028)	(.0029)		(.0345)
Saving		-.0040	.0031	.0022		
		(.0135)	(.0127)	(.0131)		
Debtsettle		.0142	.0256*	.0257*		
		(.0155)	(.0146)	(.0151)		
Consumption		-.0129	-.0071	-.0047		
		(.0172)	(.0161)	(.0167)		
Leisure		.0487***	.0296**	.0339**		
		(.0157)	(.0149)	(.0155)		
Indinc09		.0017	.0013	.0013		
		(.0011)	(.0011)	(.0011)		
Houseinc11		.0038***	.0023**	.0020		
		(.0012)	(.0012)	(.0012)		
Distance		-.0006***	-.0004***	-.0004***		
		(.0000)	(.0000)	(.0000)		
Observations	5,041	5,029	5,029	5,029		

Table 7: MARGINAL EFFECTS OF INDEPENDENT VARIABLES: EXPO. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively. The column (4′) reports estimates for intention dummies.

and gets the largest penalty value. Considering this, the values of AIC and BIC are as follows: Model 1 has AIC=2,796 and BIC = 2,822; Model 2 has AIC= 2,804 and BIC= 2,915; Model 3 has AIC=2,642 and BIC=2,772; and Model 4 has AIC=2,610 and BIC=2,799. Using AIC, Model 4 is the best and using BIC, Model 3 is the best. The two criteria attempt a balance between model fitting and model parsimony by imposing penalty terms on the large-sized models; BIC has a harsher penalty than AIC because ln(n) is usually >2.

Since we have a conflicting result between AIC and BIC, we ran another specification test, the link test. If a regression is properly specified, there should not be any other significant explanatory variable except by chance. The link test constructs two variables, $X\hat{\beta}$ and $(X\hat{\beta})^2$, and the model is reestimated with these two variables as regressors. If a model is correctly specified, $X\hat{\beta}$ should be significant but $(X\hat{\beta})^2$ should not be significant. We performed this test for Models 1-4, and the results show that $(X\hat{\beta})^2$ is significant at the 1% level for Models 1 and 3 and at the 5% level for Model 2. These results imply that Model 1-3 are not correctly specified. On the other hand, $(X\hat{\beta})^2$ is not significant for Model 4, which means that there is no specification error. Thus, we use the Model 4 in the following analysis of other regional attractions.

3.4. DETERMINANTS OF INTENTIONS

We apply Model 5 to investigate the determinants of intentions using socio-demographic variables. Table 8 shows the results of the ordered logit model. We have the same socio-demographic variables as in Table 6. However, the signs and significances are different from Table 6. For example, retirement is strongly negative in Table 8, whereas it is weakly negative in Table 6. Gender is negatively significant in Table 8, whereas it is not significant in Table 6. Age and debt settlement have different signs. Disabled is significantly negative in Table 8, whereas it is not in Table 6. Thus, the disabled negatively affects intentions but does not actually affect visit behaviors.

The results in Table 8 reveal important implications about the relationships among intentions, behaviors, and socio-demographic variables. Socio-demographic variables affect intentions and behaviors differently. Most literature examines the determinants of intentions, implicitly assuming that the determinants of intentions will have the same effect on behaviors. Our results show that this assumption may not be right and that an analysis of intentions alone is not enough. We need to examine the direct effects of explanatory variables on visit behaviors as well. Although the results show that intentions are important predictors of behaviors, gaps exist between them, and the results from the analysis of intentions

Variables	(1)	(2)	(3)
Retire	-.4036***	-.1252*	-.3462***
	(.0744)	(.0749)	(.0728)
Male	-.1108*	-.0947	-.1496**
	(.0591)	(.0616)	(.0583)
Age	-.0086***	-.0095***	-.0020
	(.0028)	(.0028)	(.0028)
Edu	.0273***	.0195**	.0072
	(.0086)	(.0085)	(.0085)
Married	.1625*	.4626***	.2744***
	(.0974)	(.1000)	(.0961)
Bereaved	.0075	.2471	-.1520
	(.1590)	(.1609)	(.1555)
Divorced	.3804*	.0825**	-.2445
	(.2136)	(.2193)	(.2080)
Disabled	-.2059*	-.3400***	-.4898***
	(.1092)	(.1125)	(.1096)
Housesize	-.0375	-.0500**	-.0864***
	(.0241)	(.0244)	(.0235)
Saving	.0290	-.2118*	-.3170***
	(.1255)	(.1238)	(.1197)
Debtsettle	-.0663	-.3032**	-.5768***
	(.1434)	(.1425)	(.1382)
Consumption	.1618	.0421	-.2285
	(.1468)	(.1461)	(.1421)
Leisure	.9667***	.7675***	.5405***
	(.1497)	(.1486)	(.1462)
Indinc	.0139	.0058	.0200*
	(.0115)	(.0148)	(.0118)
Distance	-.0047***	-.0071***	-.0060***
	(.0003)	(.0003)	(.0003)
Houseinc09	.0156		
	(.0112)		
Houseinc10		.0284***	
		(.0098)	
Houseinc11			.0681***
			(.0112)
Observations	5,029	5,029	5,029
Log Likelihood	-6621	-6159	-6948

Table 8: DETERMINANTS OF INTENTIONS. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively. Threshold parameters are omitted to save space.

data alone may be misleading.

Moreover, comparing the results of Table 6 and Table 8, we can categorize the socio-demographic variables into three groups: those affecting both intention and visits (Group1: Retire, Married, Divorced, Disabled, Saving, Indinc), those affecting only intention (Group2: Male), and those directly affecting visits independently even after controlling for intention (Group3: Age, Edu, Housesize, Debtsettle, Leisure, Houseinc, Distance). Groups 1 and 2 are sets of variables that represent the states of people when they are asked about intentions to visit a place. For example, people consider whethre they have good impressions about a place or whether they have enough time and money to visit a place. Thus, these variables affect intentions. Group 3 is a set of variables that people should take into practical consideration when turning their intentions into behaviors. For example, people consider whether they *can* visit a place with current household income or how much time and money they actually have to spend to visit a place with the number of household members. Thus, these variables have independent effects on visiting behavior separate from their effects on intention. Therefore, these results imply that intentions do not translate automatically into behaviors, and more careful analysis of the determinants of intentions and visit behaviors will provide valuable insights on designing tourism policies.

4. ROBUSTNESS CHECKS

In this subsection, we check whether intentions for other places are also significant determinants of visit behaviors. For other places, we consider 10 places; some are general places, such as ski destinations or beaches, and others are specific places, such as the Lotteworld or the Hampyung Butterfly Festival. For other places, we do not have 3 years of intentions data. Instead, we have data for both general places and specific places. Thus, by comparing them, we can evaluate whether intentions have similar predictability across different places.

Table 9 presents the predictability index for various places. Panel A and B show the results for larget sets of categories and smaller sets of categories as in Table 5, respectively. Specific places have low visit intentions and high no-visit intentions as in the case of the Yeosu Expo. On the contrary, general places have relatively high visit intentions and low no-visit intentions compared with specific places. Thus, overall predictability indices show similar values for specific and general places. Spas have the highest visit intention but have the lowest no-visit intention. Outbound travel has the lowest visit intention, and the Busan International Film Festival has the highest no-visit intention. Note that the

Year	Panel A A / C	B / D	A_c	D_b	PI	Panel B A / C	B / D	A_c	D_b	PI
Spa	370 106	1,496 1,653	.7773	.5249	.4080	95 33	245 634	.7422	.7213	.5353
Ski	78 53	832 3,308	.5954	.7990	.4758	27 19	186 2,206	.5870	.9222	.5413
Beach	488 328	773 2,203	.5980	.7403	.4427	120 151	126 1,264	.4428	.9094	.4027
Forest	295 137	1,047 2,108	.6829	.6681	.4563	76 52	173 1,098	.5938	.8639	.5129
Domestic	1,624 1013	250 671	.6159	.7286	.4487	311 336	30 248	.4807	.8921	.4288
Outbound	191 225	442 3,450	.4591	.8864	.4070	55 124	99 2,420	.3073	.9607	.2952
Everland	79 58	644 3,235	.5766	.8340	.4809	34 27	148 2,016	.5574	.9316	.5193
Lotteworld	65 55	552 3,373	.5417	.8594	.4655	16 20	137 2,126	.4444	.9395	.4175
Butterfly	19 18	626 3,352	.5135	.8426	.4327	5 5	75 1,921	.5000	.9624	.4812
BusanFilm	20 21	456 3,739	.4878	.8913	.4348	5 10	77 2,390	.3333	.9688	.3229

Table 9: PREDICTABILITY INDEX FOR OTHER REGIONAL ATTRACTIONS. A, B, C, and D denote the number of visitors with intentions, the number of non-visitors with intentions, the number of visitors with no-visit intentions, and the number of non-visitors with no-visit intentions, respectively. $PI = A_c \times D_b$, where $A_c = A/(A+C)$ and $D_b = D/(D+B)$. Panel A shows the results of index for the larger sets of categories, that is, visit intentions include level 4 and 5 and no-visit intentions include level 1 and 2. Panel B shows the results of index for the smaller sets of categories, that is, visit intentions include level 5 and no-visit intentions include level 1 only.

visit count of ski destinations is very small relative to other general places, and the number of visits to ski destinations is similar to those of specific places. This implies that ski destinations are less accessible tourist destinations compared with other general places. Overall, Panel A and B show similar results but Panel B has larger variations. That is, the predictability indices in Panel A varies from 0.4070 to 0.4809 but those in Panel B varies from 0.2952 to 0.5413. Thus, the results in Panel B show clearer information about the predictability of intentions than those in Panel A.

Table 10 presents the results of the regression analysis for other places. As the results show, intention variables have very significant predictability for actual visits. Level 3, 4, and 5 intentions are all significant at the 1% level and level 2 intentions are significant in most cases. The magnitudes of the coefficients are higher in higher intention levels. This implies that each intention level has different information regarding the visit behaviors. Thus, higher intention levels should get higher weights in predicting visit behaviors.

Other explanatory variables have the following results. Retire is not important in all cases. Thus, whether one has retired or not does not matter for travel. Male has negative effects on spa, domestic travel, and outbound travel. Age has an interesting result. For ski destinations, beaches, domestic travel, the Everland, the Lotteworld, and the Busan International Film Festival, and , age has a negative sign, but for outbound travel, age has a positive sign. This means that as people grow older, they prefer outbound travel. Education has a positive sign in most cases. Marriage is significantly positive in most cases except for the Busan International Film Festival. Disabled is not important in most cases except for the Lotteworld. Thus, disabled status is not an important determinant in travel. As we expected, house size has a negative sign for most sites. Savings, debt settlement, and consumption are negatively significant for domestic travel and the Hampyung Butterfly Festival. Leisure is significant only for spas. Individual income has positive signs, but household income has mixed signs. These results for various tourist destinations show that the same variables may have different impacts on the visit decision.

To better interpret the estimation results, Table 11 presents the marginal effects of the independent variabls. The results show that higher level intentions have higher marginal effects except the Lotteworld. For the Lotteworld, level 4 intention has the higher marginal effect. The marginal effects of the Busan Film festival are less sinificant. General places have higher marginal effects, except for ski destinations, than specific places as we proposed. As Table 9 shows, the visit behavior for ski destinations is very similar to those of specific places, and the marginal effects of ski destinations is comparable to those of specific places. Comparing the intention variables and other socio-demographic variables, intention variables have the highest marginal effects in most cases. For domestic travel and the Lotteworld, intention variables have the second largest marginal effects. Thus, intention variables are the most important predictor of visit behaviors in most cases. Among the socio-demographic variables, marital status variables have the largest marginal effects. Male, education, age, house size, and individual income come next. Marginal effects of socio-demographic variables are large for general places and they are small for specific places and ski destinations.

Variables	(1) Spa	(2) Ski	(3) Beach	(4) Forest	(5) Domestic	(6) Outbound	(7) Everland	(8) Lotteworld	(9) Butterfly	(10) BusanFilm
2.int_09	.2310	.7692***	.2333*	.4585**	.0865	.5522***	.2792	.8689***	1.2853**	.5211
	(.2181)	(.2976)	(.1230)	(.1843)	(.1094)	(.1422)	(.2732)	(.2898)	(.5307)	(.4430)
3.int_09	.6592***	1.0788***	.6373***	1.0545***	.3582***	.7977***	.2854	1.0615***	1.1435**	1.2201***
	(.2015)	(.3000)	(.1159)	(.1658)	(.1088)	(.1525)	(.2776)	(.2937)	(.5776)	(.4066)
4.int_09	1.2546***	1.4104***	1.1270***	1.4327***	1.1949***	1.7442***	1.1323***	1.9595***	2.3680***	1.7320***
	(.1939)	(.2921)	(.1183)	(.1659)	(.1206)	(.1464)	(.2689)	(.2926)	(.5318)	(.4322)
5.int_09	1.7604***	1.9175***	1.5682***	1.9551***	1.6924***	2.0889***	1.9314***	1.7961***	3.1095***	1.9250***
	(.2200)	(.3377)	(.1662)	(.2037)	(.2182)	(.2070)	(.3015)	(.3766)	(.6647)	(.5910)
Retire	.1640	.3558	-.0356	-.1341	.0531	-.1901	.1119	.0271	-.1198	.4927
	(.1233)	(.2637)	(.1095)	(.1286)	(.0956)	(.1449)	(.2452)	(.2681)	(.4166)	(.5310)
Male	-.3511***	.1233	-.0963	-.0978	-.1749**	-.2319**	-.1212	-.1624	.2721	-.2768
	(.1080)	(.1791)	(.0836)	(.0989)	(.0793)	(.1173)	(.1845)	(.1815)	(.3555)	(.2832)
Age	-.0048	-.0478**	-.0226**	.0064	-.0300**	.0210**	-.0677**	-.0626**	-.0056	-.0372**
	(.0048)	(.0102)	(.0040)	(.0047)	(.0037)	(.0053)	(.0105)	(.0104)	(.0164)	(.0173)
Edu	.0620***	.1312***	.0599***	.0615***	-.0207*	.0812***	.0696**	-.0221	.0267	.1083**
	(.0150)	(.0310)	(.0126)	(.0149)	(.0108)	(.0162)	(.0307)	(.0301)	(.0470)	(.0520)
Married	.5790***	.7610***	.8308***	.2518	1.4984***	-.1159	1.8910***	1.1359***	.3623	-1.0261**
	(.1773)	(.2698)	(.1309)	(.1657)	(.1300)	(.1868)	(.3098)	(.2916)	(.6072)	(.4454)
Bereaved	.8700***	1.7957***	.9261***	-.4425	1.3214***	-.5093	3.1906***	1.8537***	1.0703	
	(.2769)	(.6552)	(.2429)	(.3221)	(.1996)	(.3227)	(.5900)	(.6013)	(.8360)	
Divorced	.0004		-.0412	.1240	.6938***	-1.0282*				
	(.4349)		(.3556)	(.3623)	(.2543)	(.5579)				
Disabled	-.1553	.1369	-.3167*	-.0109	.0038	-.1064	.2677	.7516**	-.0593	-.1421
	(.2095)	(.4794)	(.1869)	(.2051)	(.1297)	(.2262)	(.4003)	(.3743)	(.5615)	(1.0404)
Housesize	-.0638	.0265	-.0762**	-.0479	-.1703***	-.1680***	-.0416	-.0793	.0393	.1149
	(.0421)	(.0810)	(.0346)	(.0424)	(.0300)	(.0489)	(.0815)	(.0822)	(.1393)	(.1281)
Saving	.3027	-.0846	-.2931	-.0241	-.3907**	-.1792	-.5179	-.4060	-1.1730**	1.3145
	(.2301)	(.4769)	(.1865)	(.2282)	(.1523)	(.2385)	(.4692)	(.4688)	(.5681)	(1.0582)
Debtsettle	.3219	-.0045	-.0458	.0809	-.4363**	-.3415	-.0893	.2938	-1.1961*	1.1977
	(.2532)	(.5101)	(.2022)	(.2505)	(.1772)	(.2880)	(.4819)	(.4811)	(.7193)	(1.1579)
Consumption	.0271	-.3854	-.2441	.1803	-.4525**	-.0752	-.3469	-.3898	-2.1867*	1.3377
	(.2709)	(.5305)	(.2105)	(.2567)	(.1809)	(.2767)	(.5154)	(.5226)	(.9155)	(1.1039)
Leisure	.4690*	-.3162	.1802	.2891	.1763	.3719	.0617	.0017	-.4280	.3092
	(.2585)	(.5338)	(.2101)	(.2543)	(.1996)	(.2593)	(.5053)	(.5154)	(.6340)	(1.1810)
indinc09	.0865***	.0197	.0316*	.0103	.1161***	.0733***	.0154	.0327*	.0013	.0397
	(.0231)	(.0180)	(.0181)	(.0155)	(.0254)	(.0246)	(.0206)	(.0188)	(.0665)	(.0287)
houseinc09	.0307*	.0508**	.0036	.0303*	-.0251*	.0197	.0398	.0197	-.2366**	-.2056***
	(.0165)	(.0246)	(.0146)	(.0158)	(.0142)	(.0175)	(.0254)	(.0278)	(.1002)	(.0794)
Observations	5,029	4,936	5,029	5,029	5,029	5,029	4,936	4,936	4,936	4,547
Log Likelihood	-1736	-632.3	-2411	-1765	-2651	-1435	-626.8	-614.9	-229.2	-259.9

Table 10: ESTIMATION RESULTS FOR OTHER REGIONAL ATTRACTIONS. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Variables	(1) Spa	(2) Ski	(3) Beach	(4) Forest	(5) Domestic	(6) Outbound	(7) Everland	(8) Lotteworld	(9) Butterfly	(10) BusanFilm
2.int_09	.0127	.0100**	.0279*	.0265**	.0199	.0329***	.0041	.0126***	.0053**	.0019
	(.0116)	(.0041)	(.0147)	(.0105)	(.0253)	(.0091)	(.0041)	(.0044)	(.0023)	(.0017)
3.int_09	.0441***	.0166***	.0879***	.0802***	.0789***	.0533***	.0042	.0171***	.0044*	.0066**
	(.0119)	(.0054)	(.0157)	(.0113)	(.0245)	(.0118)	(.0042)	(.0053)	(.0025)	(.0029)
4.int_09	.1098***	.0263***	.1813***	.1290***	.2186***	.1776***	.0260***	.0531***	.0194***	.0128**
	(.0131)	(.0069)	(.0187)	(.0136)	(.0238)	(.0201)	(.0078)	(.0114)	(.0061)	(.0053)
5.int_09	.1906***	.0482***	.2821***	.2185***	.2718***	.2435***	.0696***	.0442***	.0419**	.0161
	(.0249)	(.0141)	(.0347)	(.0288)	(.0278)	(.0382)	(.0187)	(.0156)	(.0211)	(.0099)
Retire	.0158	.0063	-.0055	-.0121	.0097	-.0126	.0020	.0005	-.0006	.0027
	(.0123)	(.0052)	(.0168)	(.0112)	(.0173)	(.0092)	(.0046)	(.0048)	(.0020)	(.0035)
Male	-.0323***	.0020	-.0150	-.0091	-.0322**	-.0161**	-.0021	-.0029	.0014	-.0013
	(.0099)	(.0029)	(.0130)	(.0092)	(.0146)	(.0081)	(.0032)	(.0032)	(.0019)	(.0014)
Age	-.0004	-.0008***	-.0035***	.0006	-.0055***	.0015***	-.0012***	-.0011***	-.0000	-.0002**
	(.0004)	(.0002)	(.0006)	(.0004)	(.0007)	(.0004)	(.0002)	(.0002)	(.0001)	(.0001)
Edu	.0057***	.0021***	.0093***	.0058***	-.0038*	.0057***	.0012**	-.0004	.0001	.0005**
	(.0014)	(.0005)	(.0020)	(.0014)	(.0020)	(.0011)	(.0005)	(.0005)	(.0002)	(.0002)
Married	.0484***	.0103***	.1149***	.0225	.3131***	-.0083	.0238***	.0160***	.0017	-.0068
	(.0133)	(.0032)	(.0159)	(.0141)	(.0286)	(.0137)	(.0035)	(.0035)	(.0026)	(.0045)
Bereaved	.1071**	.0651	.1778***	-.0357	.1753***	-.0298*	.2396**	.0760*	.0089	
	(.0431)	(.0440)	(.0544)	(.0221)	(.0176)	(.0156)	(.0976)	(.0454)	(.0106)	
Divorced	.0000		-.0063	.0121	.1054***	-.0480***				
	(.0402)		(.0541)	(.0372)	(.0308)	(.0161)				
Disabled	-.0136	.0023	-.0453*	-.0010	.0007	-.0072	.0052	.0184	-.0003	-.0006
	(.0174)	(.0086)	(.0244)	(.0190)	(.0238)	(.0146)	(.0087)	(.0122)	(.0027)	(.0043)
Housesize	-.0059	.0004	-.0119**	-.0045	-.0313***	-.0117***	-.0007	-.0014	.0002	.0005
	(.0039)	(.0013)	(.0054)	(.0040)	(.0055)	(.0034)	(.0014)	(.0015)	(.0007)	(.0006)
Saving	.0280	-.0013	-.0457	-.0022	-.0718**	-.0125	-.0090	-.0072	-.0059**	.0061
	(.0213)	(.0076)	(.0290)	(.0213)	(.0280)	(.0167)	(.0081)	(.0083)	(.0030)	(.0049)
Debtsettle	.0298	-.0001	-.0071	.0076	-.0801**	-.0239	-.0015	.0052	-.0061	.0056
	(.0234)	(.0081)	(.0315)	(.0234)	(.0325)	(.0201)	(.0083)	(.0085)	(.0037)	(.0053)
Consumption	.0025	-.0061	-.0380	.0168	-.0831**	-.0053	-.0060	-.0069	-.0111**	.0062
	(.0250)	(.0085)	(.0328)	(.0240)	(.0332)	(.0193)	(.0089)	(.0092)	(.0047)	(.0051)
Leisure	.0434*	-.0050	.0281	.0270	.0324	.0260	.0011	.0000	-.0022	.0014
	(.0239)	(.0085)	(.0328)	(.0237)	(.0367)	(.0181)	(.0088)	(.0091)	(.0032)	(.0055)
Indinc09	.0080***	.0003	.0049*	.0010	.0213***	.0051***	.0003	.0006*	.0000	.0002
	(.0021)	(.0003)	(.0028)	(.0014)	(.0046)	(.0017)	(.0004)	(.0003)	(.0003)	(.0001)
Houseinc09	.0028*	.0008**	.0006	.0028*	-.0046*	.0014	.0007	.0003	-.0012**	-.0010**
	(.0015)	(.0004)	(.0023)	(.0015)	(.0026)	(.0012)	(.0004)	(.0005)	(.0005)	(.0004)
Observations	5,029	4,936	5,029	5,029	5,029	5,029	4,936	4,936	4,936	4,547

Table 11: MARGINAL EFFECTS OF INDEPENDENT VARIABLES: OTHER REGIONAL ATTRACTIONS. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

Variables	(1) Spa	(2) Ski	(3) Beach	(4) Forest	(5) Domestic	(6) Outbound	(7) Everland	(8) Lotteworld	(9) Butterfly	(10) BusanFilm
Retire	-.2823***	-.2858***	-.3641***	-.1730**	.0132	-.2551***	-.1216	-.1648**	-.3410***	-.2488***
	(.0716)	(.0816)	(.0745)	(.0727)	(.0727)	(.0798)	(.0786)	(.0791)	(.0729)	(.0771)
Male	-.3680***	-.0704	-.1543***	-.2996***	-.3465***	-.2956***	-.1947***	-.1985***	-.1509***	-.1197**
	(.0579)	(.0619)	(.0589)	(.0581)	(.0609)	(.0638)	(.0605)	(.0608)	(.0583)	(.0606)
Age	-.0023	-.0383***	-.0457***	-.0133***	-.0281***	.0006	-.0506***	-.0481***	-.0100***	-.0182***
	(.0027)	(.0030)	(.0028)	(.0027)	(.0028)	(.0029)	(.0030)	(.0030)	(.0028)	(.0029)
Edu	.0272***	.1020***	.0653***	.0893***	.0498***	.0914***	.0560***	.0420***	.0115	.0413***
	(.0083)	(.0096)	(.0087)	(.0085)	(.0084)	(.0093)	(.0091)	(.0092)	(.0084)	(.0090)
Married	.6402***	-.1967**	.5425***	.6652***	.9428***	-.1367	.3857***	.1031	.3715***	-.1736*
	(.0956)	(.0989)	(.0969)	(.0955)	(.0983)	(.1005)	(.0981)	(.0984)	(.0969)	(.0990)
Bereaved	.5533***	.0627	.8178***	.5958***	.8182***	-.2458	.6909***	.3797**	.3366**	-.1333
	(.1517)	(.1776)	(.1601)	(.1555)	(.1556)	(.1702)	(.1697)	(.1702)	(.1566)	(.1655)
Divorced	.3637*	-.4601**	.2571	.6791***	.6396***	-.5188**	.2054	-.0273	.4642**	.2320
	(.2018)	(.2279)	(.2142)	(.2054)	(.2052)	(.2301)	(.2161)	(.2164)	(.2078)	(.2129)
Disabled	-.5725***	-.4233***	-.3785***	-.4089***	-.6600***	-.3378***	-.2192*	-.3843***	-.2378**	-.3126***
	(.1063)	(.1339)	(.1157)	(.1103)	(.1070)	(.1235)	(.1245)	(.1252)	(.1081)	(.1159)
Housesize	-.0521**	.0792***	.0574**	-.0428*	-.0733***	-.0467*	.0854***	.0739***	-.0460*	-.0090
	(.0231)	(.0255)	(.0239)	(.0234)	(.0234)	(.0253)	(.0248)	(.0249)	(.0238)	(.0250)
Saving	.0462	.6811***	.6321***	.2730**	.1458	-.0066	.4498***	.3655***	-.1440	-.0257
	(.1198)	(.1445)	(.1283)	(.1231)	(.1219)	(.1315)	(.1355)	(.1358)	(.1219)	(.1305)
Debtsettle	.1203	.4230***	.5208***	.2215	.0853	-.3518**	.3703**	.1901	-.2013	-.2114
	(.1377)	(.1597)	(.1444)	(.1402)	(.1397)	(.1518)	(.1516)	(.1520)	(.1396)	(.1488)
Consumption	.0727	.9223***	.6791***	.2211	-.0257	.0177	.4883***	.4487***	-.0325	.2542*
	(.1419)	(.1629)	(.1495)	(.1449)	(.1434)	(.1523)	(.1548)	(.1555)	(.1428)	(.1507)
Leisure	.9347***	1.0289***	1.2526***	1.0996***	1.5259***	1.0287***	.8802***	.7381***	.6784***	.8155***
	(.1467)	(.1670)	(.1528)	(.1488)	(.1503)	(.1545)	(.1591)	(.1600)	(.1455)	(.1532)
Indinc09	.0193*	.0049	.0111	.0182	.0912***	.0598***	.0056	.0023	.0189	.0166
	(.0116)	(.0115)	(.0112)	(.0118)	(.0167)	(.0157)	(.0110)	(.0109)	(.0116)	(.0116)
Houseinc09	.0158	.0464***	-.0034	.0219**	.0416***	.0972***	.0198*	.0147	-.0019	.0017
	(.0113)	(.0117)	(.0104)	(.0109)	(.0113)	(.0121)	(.0106)	(.0105)	(.0115)	(.0116)
Observations	5,029	5,029	5,029	5,029	5,029	5,029	5,029	5,029	5,029	5,029
Log Likelihood	-7393	-6196	-6899	-7271	-7007	-6146	-6354	-6203	-6753	-6121

Table 12: DETERMINANTS OF INTENTIONS FOR OTHER REGIONAL ATTRACTIONS. Standard errors are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

We present the results of the determinants of intentions for various tourist sites in Table 12. As we have seen in the case of the Expo, the results for intentions are slightly different in terms of signs and significance from those for visit behaviors. For example, retirement is strongly negative, and gender is more significantly negative in Table 12. Age, disabled, savings, debt settlement, and consumption have different signs or significance. Leisure is not significant in Table 9, whereas it is strongly positive in Table 12. Thus, we confirm our previous findings that socio-demographic variables affect intentions and visit behaviors differently.

5. CONCLUDING REMARKS

This paper has assessed the predictive power of stated intentions for actual visit behaviors. The findings contribute to the extant literature as follows. First of all, empirical results show that intentions data basically offer valuable information for forecasting future behavior beyond socio-demographic variables. Thus, survey data on intentions can be a helpful tool for predicting future behaviors.

The paper also finds that intentions become more positive and precise as the event date nears. At the same time, however, intentions formed three years before the event still have a sizable effect on future behaviors. We suspect that this temporal change is because respondents obtain more information about the destination as time passes and that it affects their intentions to visit the destination. To test this hypothesis, we would need data on how much information respondents are exposed to about the destination. It may need a longer and rich time series.

One of the other contributions of this paper is that it also revealed the importance of non-visiting intentions. It appears that no-visit intentions have a strong predictive power for future behaviors. Therefore, no-visit intentions should not be overlooked in survey design or empirical analyses. Also, the socio-demographic variables show nonnegligible predictability for future visit behaviors and considerably influence intentions. Socio-demographic variables, however, have different effects on intentions and behaviors. Most literature that examines the determinants of intentions implicitly assumes that the determinants will have the same effects on the behaviors. Our results show that this assumption may not hold sometimes. It implies that there are fundamental gaps between intentions and behaviors and that the analysis of intentions data alone without behavior data may be misleading.

Nevertheless, our results have some limitations. First, the socio-demographic control variables for regressions were surveyed in 2009, although the Yeosu Expo took place in 2012. Yet it is possible that the implication still has validity if the relationships between the destinations and the socio-demographic variables have temporal stability. Second, another limitation is that our data set contains three years of data for the intentions to visit Yeosu Expo but has no multi-year data for socio-demographic variables and intention variables for other places. If we had panel data, we might get interesting additional results to analyze how the estimation results differ when using yearly differences of variables like the fixed effect estimator. By examining whether intentions are primarily driven by time-invariant individual fixed effects (preferences) or by temporal changes in socio-demographic variables, we could identify significant time-varying factors beyond individual preferences. Such findings would have important policy implications for enhancing visitor intentions and, consequently, increasing future tourist numbers. Solving this issue and the generalizability of time-varying intentions both remain an open area for future research. Third, the predictability index is based on a univariate model and does not utilize other explanatory variables. We may extend this index to a multivariate model to find optimal predictors of behaviors as the noise-to-signal ratio is used to find optimal crisis predictors in the signalling approach (Kaminsky *et al.*, 1998). We do not pursue this idea here because it is beyond the scope of the current study.

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