MSR

Working Papers **03-2021**

May 2021

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Publisher and Distributor

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 ISSN: 2748-3916

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Adriel Ong[1,2]

Abstract

In light of increasing domestic travel demand, policymakers in local government units need to adjust to the growth in visitors. The Department of Tourism outlines a national tourism of strategy of increased investment to address deficiencies in infrastructure and lodging. In order to adapt the national policy to local needs, local government units need access to context surrounding visitors. Under the Additive Random Utility framework, we propose a multinomial logit model of provincial destination choice, with sampled alternatives, using data from the 2005 Household Survey on Domestic Visitors to provide needed context behind a domestic traveler's decision to go to a province. Using 8 predictors such as sex, age, marital status, and the like, we intend to capture each predictor's effects on the likelihood of choosing provinces with similar characteristics as well as each predictor's individual significance on the national level.

JEL Classification: L83, R11, R15, Z32, Z38

Introduction

Background of the Study

Domestic related travel expenditures reached PhP 2,644.8 billion in 2017. This amount composes 22.8 percent of household final consumption expenditure for that year (Bersales, 2018). All these helped the tourism sector to contribute 12.2 percent to the economy. 56 million residents travelled within the country in 2015, helping employment within tourism characteristic industries to reach 5.3 million jobs. These industries compose 13.1 percent of total employment in the country. While domestic travel has been a boon to the economy, its growth left policymakers unable to adjust in time. For example, the island of Boracay was closed for two months because of environmental damage that a growing number of travelers caused. The government also to do the same for other well-visited tourist sites. Tourism secretary Wanda Teo considers Baguio as needing rehabilitation. This excludes other sites with potential to attract visitors, and consequently degradation. While Boracay was closed, sites such as Pagudpud, Samal, and Siargao took a large share of arrivals. New sites, with San Vicente in Palawan recently opening an airport, also need attention. The Department of Tourism's website outlines its national tourism policy, highlighting an investment-driven strategy to address

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infrastructure inadequacies, limited lodging, and the like. This national policy could be further modified to suit local government units' needs after conducting an analysis of what factors influence domestic travelers' choice of provincial destination.

Objectives

We intend to identify which predictors from a set of 11 significantly affect a domestic traveller's decision of province to travel to. We do so by implementing a multinomial logit model with sampling of alternatives. Specifically, we aim to:

- estimate the effect of each predictor on the log-odds ratio of choosing a province;
- determine the marginal effect of each predictor on the probability of choosing a province;
- estimate the same for the decision to travel and the regional groupings of provinces; and
- determine each predictor's significance in influencing domestic travellers' decisions.

To determine each predictor's significance, we conduct an individual test of significance on estimated coefficients. The null and alternative hypotheses are as follows:

$$H_0: \beta_k = 0$$
$$H_1: \beta_k \neq 0$$

for the kth predictor.

Significance of the Study

Conducting an empirical analysis of factors that affect the decision of province to travel to will benefit policymakers. Local government units may improve adaptations of the national tourism policy to their needs as context exists with regards to what kind of people visit their province and for what reason. The national government may also improve decision making in matters related to tourism, travel, and movement of peoples because of access to this information. Additionally, we use sampling of alternatives to circumvent the large number of destination choices. Policymakers and other interested parties may use this method to feasibly analyze similar situations.

Scope and Limitations

This study is only valid at the national level, as the National Statistics Office deemed the original data source. As such, this study's results may vary slightly from reality at different local levels. This study also only deals with domestic Filipinos, as the original data source does. As such, overseas Filipinos and foreign residents are excluded. Finally, we limit our age bracket to those 15 years old and above, as not only does the original data source do the same, but 15 years old is the youngest Philippine working age, allowing for some measure of independent travel.

Review of Related Literature

With travel being an essential part of human activity, several methods have been employed to model travel behavior. Destination choice models became popular recently for their accuracy (Clifton et al, 2016). Existing literature provide varying specifications based on their circumstances.

Baltas (2007) gives an overview on commonly used models. He remarks on the theory-driven nature of discrete choice analysis, deeming it as an effective method to model qualitative choice behavior in areas such as travel and tourism research. He discusses the basic random utility model and its bearing on discrete choice analysis. he notes that this approach allows researchers to analyze the structure of demand at an individual level. The multinomial logit model, he notes, springs from the random utility model under the Independence of Irrelevant Alternatives (IIA) assumption. In our case, we sample our alternatives instead of using them outright because of dimensionality issues.

Brau and Cao (2006) perform their estimations with various lodging destinations as alternatives. They focus on tourists visiting Sardinia, an Italian island. They use alternative specific regressors such as proximity to attractions, natural environmental state, and availability of recreational services. The authors see these factors as enhancing the demand for destination choice. Although they have individual data at hand, they choose to use only destination attributes in their model. While they specify their model as a multinomial logit model, their use of alternative specific regressors points to them using a conditional logit model with an erroneous description. Their results show how congested tourist attraction affect the local environment. They note policy implications from their results, namely how learning the determinants of traveling behavior can help prepare for spikes in visits. In our case, we treat the type of lodging as a regressor for the sampled provincial destination choices. Like the authors, we also use alternative invariant regressors.

Garin Muñoz and Moral (2012) determine the factors that affect Spanish tourists' outbound destination choice. Using data collected by the Institute of Tourism Studies in 2009, authors performed a multinomial logit regression on the data.They include individual socio-demographic attributes as well as travel characteristics as regressors in their model. Their results show that France attracts the most tourists from all individual classifications. Car owners are more likely to visit France, Portugal, and Andorra, while airbound tourists are more likely to visit Italy. The authors did not use destination characteristics as regressors, which they admit as a failing. We remedy this limitation by using destination characteristics as our sample of alternatives.

Seddighi and Theocharous (2002) develop a model of tourism destination choice. They rationalize their study by appealing to the fast growth of the tourism sector in various parts of the world. Using data from a survey conducted in Cyprus, the authors applied a conditional logit model for analysis. The model's regressors include service quality, advertising, and political instability, among others. The authors conclude that including destination attributes in modelling allows a better look into travel behavior.

Because of our dataset's nature, several alternatives exist in the choice set. Dimensionality remains a possibility to overcome. One solution lies in alternative sampling (McFadden, 1978). McFadden proposes that ‘representative' alternatives be chosen from each alternative ‘class'. He uses this method in context of residential location, with indices for communities and housing units within.

Route choice models may also fall under alternative sampling (Frejinger et al., 2009). After defining their multinomial logit model, they explain their use of importance sampling. Here, they select attractive alternatives, those with higher probability of being chosen, over unattractive ones. They note that obtaining such samples must come from a large dataset. To do so, they use an algorithm to determine which choices to consider. One may note that in practice, they disregard some alternatives. In our case, to account for all provinces, our sampling of alternatives method uses common destination specific attributes as regressors.

Another work using a ‘labeling approach’ falls closer to our intentions with sampling of alternatives (Ben-Akiva et al., 1984). They list three hypotheses previous research used to explain route choice behavior, namely knowledge about alternative routes, route choice decision processes, and route attributes with drivers' preferences. They mention, however, that using these criteria alone is not feasible because of potentially large choice sets. They propose a labeling approach where they assign descriptive labels to different paths. Here, one may make a model with choice set generation, consisting of assigning labels to routes with similar characteristics, and choosing a choice from that set. In our case, we closely resemble the third hypothesis by accounting for traveler's preferences.

Still important to consider are tourist motivations for traveling to a destination. These may somewhat factor into their satisfaction (Albayrak and Caber, 2018). The authors list 13 possible motivations for a rafting activity, with respondents scoring them from 1 to 5. They regress these scores to a satisfaction score, its estimation method not stated but which we believe to be OLS. Intellectual, social, and mastery motivations all contributed positively to satisfaction, while stimulus avoidance negatively affected it. Intellectual motivation effects were not significant. These findings somewhat relate to our trip purpose variable, although overlap exists between the latter's elements. Study/training, for example, may be counted as both an intellectual and mastery motivation.

Student travel takes upon differences and commonalities between countries (Marques et al., 2018). The authors employ a leisure motivation scale to analyze a sample of 3431 observations from different countries. They use cluster analysis on seven clusters grouped by certain characteristics. These had varying preference distribution, with the first cluster, grouped based on preferring memorable experiences, responding positively to adventurous, countryside, and functional pursuits. Although their method is novel, we forego cluster analysis in our case because it fails to determine predictor effects significance.

Although price may affect tourist motivations, we find no previous literature tackling so. With these past findings at hand, we proceed to our theoretical framework.

Theoretical Framework

Our model takes advantage of the Additive Random Utility Model (ARUM) framework. In making choices, Louviere, Hensher, and Swait specify the following assumptions (2000):

- Individuals maximize their utility.
- Each individual's utility has a systematic component, V_{iq} and a stochastic component, ε_{iq}.

In notation,

$$U_{iq} = V_{iq} + \varepsilon_{iq}$$

for the utility U of the ith individual and the qth alternative. While V is systematic, attribute levels may vary between individuals, giving need for the q subscript.

Since an individual i maximizes his utility, he will choose an alternative q if

$$U_{iq} > U_{ip}, \forall\, p \neq q$$

We can then infer that

$$V_{iq} + \varepsilon_{iq} > V_{ip} + \varepsilon_{ip}$$

Rearranging the terms,

$$V_{iq} - V_{ip} > \varepsilon_{ip} - \varepsilon_{iq}$$

Since we cannot observe $V_{iq} - V_{ip}$, we instead estimate probabilities

$$P(Y_i = q) = P[\max(U_{iq})] = P(V_{iq} - V_{ip} > \varepsilon_{ip} - \varepsilon_{iq})$$

We also make an additional assumption to suit our needs:

- The ratio of non-zero probabilities of a choice is unaffected by the presence of additonal alternatives.

also known as *Independence from Irrelevant Alternatives* (IIA). This assumption implies that no correlation exists between each alternative's error.

Using our first assumption of utility maximization, we know that observed domestic travelers will choose the province that gives them the highest utility. Our 11 predictors form the deterministic component of utility. Each predictor contributes to the utility received based on its magnitude.

The different predictor's contributions sum up into a deterministic component. One may explain further differences as part of an unobserved random component. An Additive Random utility model may take a different values for each individual depending on their choice and predictor values. Complicating this, however, is our use of alternative aggregation. We follow a method stated elsewhere (Ben-Akiva et al., 1985).

We use the provincial choice set as one of elemental alternatives. Each element has qualities that lends itself to a grouping scheme. Each group becomes an aggregate alternative, with the number of elements unobserved. With our elemental alternative choice set C, we partition it into nonoverlapping subsets:

$$C_i \subset C, i = c, \ldots, J$$

wJ being the number of aggregate alternatives in the universal choice set D. Let P_n be the probability of a the nth individual choosing elemental alternative $p \in P$. He has an equal probability of choosing the aggregate alternative holding his elemental choice. The individual's probability of choosing $i \in D$ is:

$$C_n = \sum_{c \in C} P_n(c), i = c, \ldots, J$$

Using these, we now define random utilities of aggregate alternatives:

$$U_{iq} \max_{c \in C} = V_{iq} + \varepsilon_{iq}, i = c, \ldots, J$$

The authors note that if IIA holds for the elemental alternative set, it will also hold for the aggregate set.

It can be shown (Quinet et al., 2004) that one may derive from an Additive Random Utility Model the following:

$$P(y = q | y = q \text{ } or \text{ } p) = \frac{(\exp(x^T \beta_q + w_i^T \gamma_j))}{\sum_{p=1}{}^{P} \exp(x^T \beta_p + w_i^T \gamma_j)}$$

with $x^T\beta_q w^T{}_i + \gamma_j$ being the parameterized ARUM for a mixed-logit model, x^T being a vector of alternative specific predictors, w_i being a vector of individual specific predictors, and β_q, γ_j being parameters, interpreted as log-odds ratios in this case. This model uses the logistic link function extended for a multinomial case. One may estimate this model with simple Maximum Likelihood Estimation.

Methodology

Afterwards, we need to test whether the model is correctly specified. Our test, the Likelihood Ratio test, has these hypotheses:

H_0: The reduced model is true

H_1: The current model is true

For any regressor being constrained in regression. We also need to test whether IIA holds. We use the Hausman-McFadden test with these hypotheses:

H_0: The difference in coefficients is not systematic

H_1: The difference in coefficients is systematic

Our data comes from the 2005 Household Survey on Domestic Visitors (HSDV) conducted by what was then the National Statistics Office. The 2005 HSDV was the first conducted out of five as of writing. Communications with the Philippine Statistics Authority on the Freedom of Information website reveal that later editions are still under review for release. According to the official press release, the 2005 HSDV presents the profile, characteristics, and travel patterns of domestic Filipinos throughout the country. The NSO's rationale was to help policymakers, local government units, and private firms develop and prepare tourism programs. The 2005 HSDV used the 2003 Master Sample sampling design for household surveys. The Master Sample used the Philippines' 17 regions as its sampling domain, with provinces ignored because of their high number. The 2000 Census's Enumeration Area Reference File was used as a sampling frame. Out of this frame were formed primary sampling units which held a barangay or barangays with at least 500 households. With the country's 17 regions as primary strata, groupings such as provinces, highly urbanized cities, and independent component cities were used for further stratification. These substrata were further stratified using the proportion of strong houses in an area, intensity of agricultural activity, and per capita income. Overall, the multi-stage sampling design had a sample of 51000 households, with 12,500 being deemed sufficient by the NSO to determine domestic travel patterns.

The 2005 HSDV used two questionnaires. Form 1 tackled household members and characteristics. Form 2 was distributed to individual household members aged 15 and above. It asked about details of the last domestic trip (ie. place, length, decision maker, travel mode, purpose), factors that influenced the trip (ie. source of information), what attractions were visited, and others. The National Capital region was taken as a whole when listed as a destination. Data processing took 10 months using tabulation into the Census and Survey Processing (CSPro) software from America. Out of the 11414 households surveyed, 95.5 percent or 10896 responded. 30325 individuals filled out Form 2 out of an eligible 34041. The NSO considered the 2005 HSDV eligible only at a national level since it used a quarter of the 2003 Master Sample total samples. As skims of the data show, null values persist in most observations. To remedy this, we use multiple imputation.

To circumvent our large choice set, we use the labeling approach mentioned above (Ben-Akiva, Bergmann, Daly, and Ramaswamy, 1984). We use Human Development Index as a classification:

Human Development Index

- Very high
- High
- Medium
- Low

We use the following predictors for provincial destination choice as recorded in the 2005 HSDV:

Individual-specific predictors:

- Sex
  - Male
  - Female
- Age (Continuous)
- Marital Status
  - Single
  - Married
  - Divorced/Separated
  - Unknown
- No. of nights in Destination (Continuous)
- Traveling Companion
  - Alone
  - Family

  - Associate
  - Others
- How many transport modes used
- Purpose of trip
  - Pleasure
  - Personal
  - Conference
  - Medical
  - Profession
  - Study/training
  - Other

Alternative-specific predictors (2005 values):

- Precipitation
- Air temperature
- Population density
- Poverty threshold

As one may see, we use both individual-specific and alternative-specific attributes. The latter helps resolve any spatial bias from the elemental alternative set. We forego cluster analysis for its descriptive nature and its lack of determining significance in predictor effects.

As stated before, we use a mixed-logit model to capture predictors' effects on the probability of choosing a destination for travel to. While the 2005 HSDV recorded whether an individual traveled or not, we do not include this data as it is irrelevant to the study. The large choice set influenced us to perform sampling of alternatives. Seddighi and Theocharous's (2002) inclusion of destination attributes influenced their inclusions in our study, which Garinn Muñoz and Moral cite as their limitation. Additionally, our alternative aggregation scheme comes from Ben-Akiva et al, which uses characteristic labels for each group.

Results and Discussion

In light of our using multiple imputation, slight multicollinearity persists and we omit standard errors from our results, located in the appendix for convenience. Additionally, failures in imputation for some variables cause their removal from the estimation. We start our discussion with provinces classified by Human Development Index.

We obtained a Pseudo-R^2 of 0.524 and a $p > |\chi^2|$ of 0.000, indicating a relatively good fit and collective significance. The base variable is Medium HDI. We start with High HDI. These provinces are Bataan, Bulacan, Cavite, Ilocos Norte, Laguna, and Pampanga. Personal and professional purposes in travel increased the probability relative to traveling for pleasure. Professional purposes would obviously favor high HDI provinces, especially since Bataan and Pampanga have special economic zones. That personal purposes also increase probability may indicate that people in these provinces have family members from others. Medical and Other purposes, however decrease probability. Healthcare in these provinces may be either too expensive to draw patients and medical tourists or relatively inferior to places like Very High HDI provinces, which had a positive coefficient. Relative to traveling alone, being with a teacher or student decreases probability of traveling to a High HDI province. Most academic events take place in Very High HDI provinces, as supported by the results below. High HDI provinces may not have equally interesting events, at least compared to Medium HDI provinces. Additionally, although insignificant, traveling for study or training purposes decreases probability too. Relative to working for a family business, working for a private establishment decreases the probability of travel to a High HDI province. Heavy hours in these enterprises may preclude travel. Relative to the mean, a higher number of transport modes used increases probability. Accounting the results for Low and Very High provinces, this result may show that the subject provinces have relatively undeveloped transport systems, or that travelers have no access to personal vehicles. High HDI provinces with higher population densities relative to the mean decrease probability of travel. So do those with a higher poverty threshold. As seen below, these two factors increase the probability of travel in Very High HDI provinces. Qualitative factors, such as lack of attractions or interest, may explain this. Higher air temperatures and number of nights spent increase probability, relative to their means. The former may show that good weather encourages travel, especially with the insignificant precipitation having a negative marginal effect.]The latter may show that travelers attracted by these provinces tend to stay longer. With that, we move to Low HDI provinces.

There are too many Low 2005 HDI provinces to list. Interesting about them is how professional and personal purposes also increase probability, relative to Medium HDI provinces. When taken with the results for High and Very High HDI provinces, one may guess that travelers from Metro Manila either have business outside of it or are employees returning to loved ones in other provinces. Conference purposes also increase probability. We are not aware whether 2005 saw major conferences occurring in these provinces. That aside, traveling with an associate or others decreases probability. Being single decreases it too, relative to being married. Being male increases it, relative to female. In 2005, there were more employed males than females (Philippine Statistics Authority, 2005), possibly meaning that many workers traveled homewards before the data collection. Working for a private firm and being self-employed decreased probability relative to family businesses, as did higher traveler ages, relative to the mean. Just like High HDI provinces, a higher number of transport modes used increased probability. Higher population densities and poverty thresholds also decrease probability relative to means. Finally, higher air temperatures increase probability relative to the mean, similar to High HDI provinces.

While travelers to High and Low HDI provinces may have different reasons in traveling, one may see that they share many results. Expounding on these are the ones for Very High HDI Provinces, consisting of the four Metro Manila districts, Rizal, and Benguet. Medical purposes increase probability, probably because of better healthcare facilities. Personal and professional purposes decrease probability, while Other purposes increase it. Traveling with family or a teacher/student increase probability relative to alone, as do being separated or single relative to being married, working for a private establishment relative to family business, and a higher traveler age relative to the mean. A higher number of transportation modes used decreases probability, possibly because of relatively more developed transportation and access to personal vehicles. A higher population density, poverty threshold, and precipitation increase the probability while a higher air temperature decrease it, all relative to the mean.

These results seem odd until one knows that Metro Manila districts constitute most of the Very High HDI provincial destinations. Similarities between Low and High HDI provinces may be taken to show that differences in a predictor's effect lie in whether a destination is in Metro Manila or not. General policy conclusions based on these results should now account for differences between provincial and Manila predictors. Also worth noting is how these results are accurate to 2005 only. Newer data, still publicly unavailable, may provide updated insights.

One may note that two arguably important factors, source of information and lodging are not present. These were originally included, but were dropped because of lack of data and errors in imputation. We argue that having the original data set lack these factors points to the respondents not caring about them. In other words, these factors did not influence their choice of destination considering they failed to either remember them or jot them down.

Evidence from abroad sheds further light on these results. Massidda and Etzo (2012) conducted a system GMM regression on determinants of domestic tourist arrivals in Italy. Instead of using destinations as we did, they used tourist origins to produce sub-samples. Southern Italian tourists factored in destination road quality and pollution significantly, contrasting with their insignificance for Northerners. The authors connect these results to Southern Italy's poor road infrastructure, heavy car usage, and high pollution levels.

Additionally, increases in Southern GDP caused a larger increase in travel than for Northerners. The authors note that this result with literature suggesting that the elasticity of tourism with respect to income decreases as the latter increases. With the above findings, one can apply the same principles to our results.

Lastly, we present results from specification and IIA violations tests in Table 4. Both registered a p-value of 0.00, suggesting a rejection of both null hypotheses, except in the case of Very High HDI provinces, constraining which causes the regression not to converge and the Hausman Test to give asymptotic errors.

Concluding Remarks

In dividing provinces based on Human Development Index, a divide occurs between Very High HDI provinces and others. Metro Manila destinations comprising most of the former may account for such. Regardless, concrete policy implications follow. Non-Very High HDI provinces would do well to play up their receipt of professionals. Providing better business opportunities would draw their crowd. More facilities and amenities would also benefit those returning for family or other personal reasons. Developing transportation infrastructure should become a priority to allow greater convenience to visitors. That conferences may have become common in Low HDI provinces is an optimistic sign. Additionally, these provinces should work on improving their standing with regards to the predictors with negative marginal effects. Some of these have no ready explanations, showing that qualitative factors such as attractions play large roles in drawing visitors. A lack of interest in lodging and sources of information may point to a need for innovation in these factors on the part of local government units.

This study used data from 2005. As of writing, many things have changed since then. The most important asset future research needs is the latest dataset regarding traveler choice. This set should have more complete data on lodging and sources of information to see if these matters have improved. Additionally, new ways of grouping provinces should be explored to provide new insights regarding provincial characteristics and traveler choice.

References

Albayrak, T. and Caber, M. (2018). Examining the relationship between tourist motivation and satisfaction by two competing methods. Tourism Management, 69:201–213.

Baltas, G. (2007). Econometric models for discrete choice analysis of travel andtourism demand. Journal of Travel & Tourism Marketing, 21(4):25–40.

Ben-Akiva, M., Bergman, M., Daly, A. J., and Ramaswamy, R. (1984). Modeling inter-urban route choice behaviour. In Proceedings of the 9th international symposium on transportation and traffic theory, pages 299–330. VNU Science Press: Utrecht, The Netherlands.

Ben-Akiva, M. E., Lerman, S. R., and Lerman, S. R. (1985). Discrete choice analysis: theory and application to travel demand, volume 9. MIT press.

Bersales, L. G. (2018). Contribution of tourism to the economy is 12.2 percent in 2017.

Brau, R. and Cao, D. (2006). Uncovering the macrostructure of tourists' preferences. a choice experiment analysis of tourism demand to sardinia.

Clifton, K. J., Singleton, P. A., Muhs, C. D., and Schneider, R. J. (2016). Development of destination choice models for pedestrian travel. Transportation Research Part A: Policy and Practice, 94:255–265.

Frejinger, E., Bierlaire, M., and Ben-Akiva, M. (2009). Sampling of alternatives for route choice modeling. Transportation Research Part B: Methodological, 43(10):984–994.

Garin Muñoz, T. and Moral, M. J. (2012). Outbound tourism holiday behavior of Spanish residents: choice of destination.

Goodman, S., Ben Yishay, A., Lv, Z., and Runfola, D. (2019). Geoquery: Integrating hpc systems and public web-based geospatial data tools. Computers & Geosciences, 122:103–112.

Marques, C., Mohsin, A., and Lengler, J. (2018). A multinational comparative study highlighting students' travel motivations and touristic trends. Journal of Destination Marketing & Management, 10:87–100.

Massidda, C. and Etzo, I. (2012). The determinants of italian domestic tourism: A panel data analysis. Tourism Management, 33(3):603–610.

McFadden, D. (1978). Modeling the choice of residential location. Transportation Research Record, (673).

Philippine Statistics Authority (2005). 2005 philippine labor force survey.

Quinet, E., Vickerman, R., et al. (2004). Principles of transport economics. Books.

Seddighi, H. R. and Theocharous, A. L. (2002). A model of tourism destination choice: a theoretical and empirical analysis. Tourism management, 23(5):475–487.

Likelihood Ratio Specification and IIA Violations Tests

Test	High	Low	Very high
LR Test	0	0	0
Hausman Test	0	0	N/A

High HDI Relative to Medium

Variable	z	p > |z|	95 percent Confidence Interval	Marginal Effect	
Conference (relative to Pleasure)	-0.3245537	0.373	-1.038751	0.3896436	-0.0052441
Medical	-0.8756337	0.001	-1.398677	-0.35259	-0.0024536
Others	-0.5850009	0	-0.8416019	-0.3283999	-0.0013361
Personal	-0.2956224	0.002	-0.4842355	-0.1070093	0.0011844
Profession	-0.9537611	0	-1.280016	-0.6275063	0.0060574
Study/training	-0.2661638	0.443	-0.946499	0.4141713	-0.0019889
Associate (Relative to Alone)	0.1515242	0.152	-0.0556227	0.358671	-0.0014277
Family	-0.0060348	0.951	-0.1980194	0.1859497	-0.0054425
Other	-0.1777305	0.53	-0.7328551	0.3773941	-0.0046399
Teacher/student	1.571076	0.04	0.0703446	3.071807	-0.0048776
Separate (Relative to Married)	0.4375005	0.166	-0.1808669	1.055868	-0.0071295
Single	-0.000501	0.996	-0.2233209	0.2223189	-0.0037595
Widowed	-0.3163723	0.126	-0.7214456	0.088701	-0.0041492
Male (Relative to Female)	-0.0960282	0.239	-0.2558245	0.0637682	-0.0017164
Government (Relative to Family business)	-0.0655376	0.684	-0.3812443	0.2501691	-0.0008223
Private establishment	0.4223325	0	0.2005693	0.6440957	-0.0001937
Self-employed	0.129765	0.516	-0.2615155	0.5210455	-0.0011997
Private household	0.123488	0.304	-0.1118524	0.3588284	0.0028611
Age	0.0054159	0.122	-0.0014414	0.0122731	-0.0000752
Modes	-0.5210153	0	-0.6483656	-0.393665	0.000139
Population density	0.0033932	0	0.0031859	0.0036005	-0.0000167
Threshold	0.0005314	0	0.0004058	0.0006569	-0.0000111
Precipitation	-0.0001014	0.927	-0.0022826	0.0020797	-0.0002243
Air temperature	0.1684238	0	0.0757875	0.26106	0.0117961
Nights	0.0090331	0.029	0.0009017	0.0171644	0.0000456
Constant	-14.6851	0	-17.74352	-11.62669	N/A

Low HDI Relative to Medium					
Variable	z	p > |z|	95 percent Confidence Interval	Marginal Effect	
Conference (relative to Pleasure)	0.6517653	0.001	0.256642	1.046889	0.000000135
Medical	0.0226648	0.873	-0.2543984	0.299728	0.000000447
Others	0.0778429	0.397	-0.1021319	0.2578176	0.000000357
Personal	0.4113332	0	0.2777829	0.5448836	0.000000667
Profession	0.2585168	0.008	0.0665568	0.4504767	0.00000231
Study/training	0.3318983	0.169	-0.1415725	0.805369	0.000000239
Associate (Relative to Alone)	-0.2118708	0.002	-0.3454635	-0.0782781	-0.000000572
Family	-0.1831324	0.002	-0.2995086	-0.0667561	-0.00000076
Other	-0.4228703	0.04	-0.8272984	-0.0184422	-0.000000738
Teacher/student	0.7527767	0.26	-0.5574497	2.063003	-0.00000109
Separate (Relative to Married)	-0.1684851	0.503	-0.6609847	0.3240146	-0.000000988
Single	-0.3097611	0	-0.4547386	-0.1647836	-0.000000629
Widowed	0.0909454	0.466	-0.1535791	0.3354699	-8.12E-09
Male (Relative to Female)	0.1053545	0.045	0.0022081	0.2085009	3.89E-08
Government (Relative to Family business)	-0.102357	0.273	-0.2853014	0.0805873	-0.00000014
Private establishment	-0.1964717	0.006	-0.3377559	-0.0551874	-0.000000572
Self-employed	-0.3240173	0.019	-0.5941914	-0.0538433	-0.000000535
Private household	0.1019854	0.147	-0.0358822	0.239853	0.000000315
Age	-0.0135394	0	-0.0179209	-0.0091579	-2.63E-08
Modes	-0.3344042	0	-0.4130753	-0.255733	0.000000202
Population density	0.0009706	0	0.0007864	0.0011549	-4.04E-09
Threshold	-0.0004772	0	-0.0005344	-0.0004201	-2.08E-09
Precipitation	0.014507	0	0.013566	0.0154481	-6.72E-09
Air temperature	-0.0532451	0	-0.0801064	-0.0263838	0.000000905
Nights	0.0030265	0.259	-0.0022254	0.0082784	-1.7E-09
Constant	5.000123	0	3.995493	6.004754	N/A

Very High HDI Relative to Medium					
Variable	z	p > |z|	95 percent Confidence Interval	Marginal Effect	
Conference (relative to Pleasure)	0.4280818	0.359	-0.4866641	1.342828	0.005244
Medical	-0.5904187	0.127	-1.349456	0.1686184	0.0024532
Others	-0.4396554	0.033	-0.8445184	-0.0347924	0.0013357
Personal	-0.4091543	0.01	-0.7204429	-0.0978657	-0.0011851
Profession	-1.434899	0	-2.005285	-0.8645125	-0.0060597
Study/training	-0.0414711	0.93	-0.9678648	0.8849226	0.0019886
Associate (Relative to Alone)	0.2658719	0.134	-0.0821439	0.6138877	0.0014282
Family	0.5220133	0.001	0.2012896	0.8427371	0.0054433
Other	0.2531027	0.557	-0.5922305	1.098436	0.0046407
Teacher/student	2.029739	0.041	0.0795492	3.979929	0.0048787
Separate (Relative to Married)	1.317288	0.005	0.4074676	2.227108	0.0071305
Single	0.3699799	0.048	0.003006	0.7369538	0.0037601
Widowed	0.1014994	0.743	-0.5051314	0.7081301	0.0041492
Male (Relative to Female)	0.0685541	0.612	-0.1959866	0.3330948	0.0017164
Government (Relative to Family business)	0.0213625	0.925	-0.4251894	0.4679144	0.0008225
Private establishment	0.4421497	0.013	0.0935337	0.7907657	0.0001943
Self-employed	0.2591773	0.442	-0.4015134	0.9198681	0.0012003
Private household	-0.1316743	0.5	-0.5141382	0.2507896	-0.0028614
Age	0.0126204	0.027	0.0014042	0.0238366	0.0000752
Modes	-0.5343396	0	-0.7596744	-0.3090047	-0.0001393
Population density	0.0049933	0	0.0046978	0.0052887	0.0000167
Threshold	0.0015934	0	0.0013427	0.001844	0.0000111
Precipitation	0.021389	0	0.01804	0.0247379	0.0002243
Air temperature	-0.96199	0	-1.026211	-0.8977689	-0.011797
Nights	0.0046673	0.523	-0.009666	0.0190007	-0.0000456
Constant	-8.828966	0	-11.90968	-5.748256	N/A