Domestic tourism demand of urban and rural residents in China: Does relative income matter?

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A R T I C L E   I N F O

Article history:
Received 2 May 2012
Accepted 23 February 2013

Keywords:
Domestic tourism demand
China
Multilevel model
Relative income

A B S T R A C T

The aim of this research is to investigate the domestic tourism demand of urban and rural residents in China. Based on the data from the National Household Tourism Survey, we specify Chinese domestic tourism demand as a function of absolute income, relative income, domestic tourism price, and substitute price. As a major contribution of this study, relative income is measured using the distance between individual income and average income over a city/province. Based on the estimation results from multilevel models, this paper highlights the effect of relative income on domestic tourism demand in some sub-regions of China. Furthermore, regional differences between residents in different sub-regions and different patterns of determinants between urban and rural residents are identified and discussed.

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1. Introduction

The tourism industry boomed in China following the “reform and opening up” policy instituted in 1978. The initial incentives for tourism development were based on political and economic considerations, and inbound tourism was given priority in China and treated as the backbone of the tourism industry for a substantial period. Therefore, little attention had been focused on the development of domestic tourism. However, over the past decade, rapid economic growth has contributed to the improvement of living conditions and real growth in the income of Chinese citizens, thereby promoting domestic travel. According to the statistics from China National Tourism Administration, domestic tourist arrivals in China increased from 240 million in 1985 to 1610 million in 2007. During the same period, domestic tourism receipts increased from 8 billion RMB to 777 billion RMB, with an average annual growth rate of 23.12% (CNTA, 2008). In 1999, the Golden Weeks—long public holidays encompassing Labour Day, National Day, and the Spring Festival—were introduced in China to stimulate domestic travel. These long public holidays strongly spurred the growth of China’s domestic tourism because they provided additional leisure time for travelling to both short-distance and long-distance destinations. In 2007, 417 million domestic tourists travelled during the three Golden Weeks, and the overall tourism receipts added up to 182 billion RMB, accounting for 23.37% of the total domestic tourism receipts in that year (CNTA, 2008).

Together with the rapid growth of Chinese domestic tourism, an increasing demand exists for tourism literature in this field for policy and marketing suggestions. Using a sociological approach, Wang (2004) proposed a theoretical model to understand the factors that contribute to tourism consumption, including social stratification, policy change, and the marketisation of the economy. Another paper by Wu, Zhu, and Xu (2000) identified three major factors that promote domestic tourism in China: income growth, leisure increase, and structural adjustment of the national economy. Using spatial analysis tools, Yang and Wong (2013) found that a high disposable income level and a strong propensity to travel among residents might contribute to the prosperity of certain domestic tourism hotspots. Among a handful of studies that estimate demand for domestic tourism in China, certain determinants have been identified empirically, including income (Cai, Hu, & Feng, 2001; Cai & Knutson, 1998; Gu & Liu, 2004; Wang, 2010), infrastructure (Wang, 2010), leisure time (Cai & Knutson, 1998), and the effect of special economic zones (Cai et al., 2001). However, these studies have overlooked the effects of price on domestic tourism demand and have not considered the dichotomy of domestic tourism demand between urban and rural residents.

In past tourism demand research, personal disposable income (which represents the absolute income of each individual) was used as the dominant measure of the income effect (Lim, 1997). However, tourism demand research has not taken relative income
into account. Although certain studies have advocated the inclusion of relative income in tourism demand modelling (Sauran, 1978), to the best of our knowledge, no empirical study has yet adopted this approach. Relative income, or personal income with respect to a certain benchmark, tends to affect domestic tourism demand because implicit income comparison affects individual economic decision-making (Cole, Mailath, & Postlewaite, 1992; Cole, Mailath, & Postlewaite, 1995). Moreover, relative income can be treated as a proxy for the socio-economic status of each individual (Coleman, 1960). As documented by many previous articles, socio-economic status/class influences people’s attitudes towards tourism, tourism behaviour, and expenditures on tourism activities (Moeran, 1983; Mok & Defranco, 2000; Song, Peter, & Liu, 2000). Therefore, it is reasonable to assume that relative income should be an important determinant of domestic tourism demand.

This paper contributes to the current body of tourism demand literature in three major ways. First, although a few studies have attempted to consider the relative income effect on tourism, this paper represents one of the first attempts to quantify this effect using an empirical model. By including this variable, we expect to capture the influence of implicit income comparison on tourism demand in the sense that tourism demand also depends on the gap between the individual’s actual income and selected benchmarks. Because tourism demand research has been criticised for lacking the inclusion of non-economic factors, our research represents an important attempt in investigating this sociological/psychological variable within tourism demand analysis. Second, this study applies a multilevel model to analyse tourism demand under a rigorous tourism demand analysis framework, and the model both captures the hierarchical structure of our dataset and allows for slope heterogeneity over different areas. The results from the models discussed in this paper could aid both the governmental and private tourism sectors in understanding the domestic tourism demand of Chinese residents, and provide insights into resource allocation to satisfy residents’ tourism demand. Third, because the urban—rural dichotomy induces different tourism demands for urban and rural residents (Gu & Liu, 2004), by comparing the results from models of urban and rural residents, practitioners could be able to carry out more specific tourism planning and marketing strategies aimed towards distinct segments of domestic tourists.

The rest of this paper is organised as follows. Section 2 discusses the research hypotheses adopted in this study to investigate domestic tourism demand in China. Section 3 describes the data sources and models used in this study, and Section 4 presents and explains the estimation results. Finally, Section 5 presents several conclusions and implications based on the findings of this study.

2. Research hypotheses

After reviewing the previous literature on domestic tourism demand analysis, tourism marketing in China, and sociological analysis of tourism consumption, we propose several research hypotheses regarding the Chinese domestic tourism demand model.

An analysis and understanding of tourism demand is necessary for increasing our knowledge of the relative importance of diverse economic determinants (Cooper, 2003). Guided by the traditional demand theory, domestic tourism demand can be specified as a function of disposable income, tourism price, and substitute price (Allen, Yap, & Shareef, 2009; Hamal, 1996; Seddighi & Shearing, 1997). Income has been identified as a crucial determinant of domestic tourism demand, which is consistent with the fact that domestic tourism is a “normal” commodity. Wang (2010) established a VAR model to analyse Chinese domestic tourist arrivals and found income to be an important factor. Cai and Knutson (1998) modelled Chinese domestic personal trips and reported that GDP was a significant factor. Furthermore, Cai et al. (2001) used a cross-sectional sample of thirty-five cities to study domestic tourism demand in China, and the income elasticity was estimated to be 0.30. Another empirical paper by Gu and Liu (2004) investigated the relationship between domestic tourism demand and household income and found that income was the major determinant of Chinese domestic tourism demand. According to the studies from previous studies, the first hypothesis is proposed as follows:

Hypothesis 1. Personal absolute income has a positive influence on domestic tourism demand in China.

From a further review of domestic tourism demand studies, considerable variations have been observed in the estimated income elasticities across various countries. Although certain studies have confirmed the positive effect of income on domestic tourism demand (Garín-Muñoz, 2009; Roget & Rodríguez González, 2006; Seddighi & Shearing, 1997; Taylor & Ortiz, 2009), other studies have reported contradictory evidence. Salman, Shukur, and von Bergmann-Winberg (2007) investigated the domestic tourism demand function of Swedish tourists and suggested that real income was not of great significance. In a study on Australian domestic tourism demand, Athanasopoulos and Hyndman (2008) found that income growth was negatively correlated; the authors concluded that as income increases, a greater number of citizens are likely to travel abroad instead of domestically. This negative impact of income on Australian tourism demand was also confirmed by Allen et al. (2009) through co-integration analysis; this group suggested that the coefficient of income levels could be negative in the long run. Taken together, these findings suggest the heterogeneity of the absolute income effect, which varies across different research areas. To test this heterogeneity, we propose the following hypothesis in addition to Hypothesis 1:

Hypothesis 1a. The effect of absolute income varies across different cities/provinces in China.

As stated by the traditional demand theory, the own price of domestic tourism is expected to exert a negative effect on domestic tourism demand, whereas the substitute price has a positive effect (Song & Li, 2008). According to the domestic tourism literature, domestic tourism prices have been measured in different ways. Certain studies have applied a single measurement, i.e., the overall consumer price index (CPI) (Salman et al., 2007), the relative CPI or other price indices relative to an origin (Garín-Muñoz, 2009; Quayson & Var, 1982; Seddighi & Shearing, 1997), and the price index for domestic holiday travel and accommodation (Athanasopoulos & Hyndman, 2008; Hamal, 1996), whereas others have applied more than one price variable to capture the price effects of different components on domestic tourism (Allen et al., 2009; Roget & Rodríguez González, 2006). To measure the substitute price, most studies have specified the price index of outbound tourism (Allen et al., 2009; Hamal, 1996). However, among studies on Chinese domestic tourism demand, no known research has incorporated any price measure into empirical models. To fill this research gap, we propose two hypotheses with respect to the effects of price factors on Chinese domestic tourism demand:

Hypothesis 2. The domestic tourism price has a negative influence on domestic tourism demand in China.

Hypothesis 3. The substitute price for domestic tourism has a positive influence on domestic tourism demand in China.

Apart from the absolute income of individual residents, relative income also tends to influence tourism demand, an observation that has been overlooked in the previous literature. Relative income refers to personal income relative to a benchmark, i.e., the average income in a society/country (Alpizar, Carlsson, & Johansson-
Stenman, 2005; Clark, Frijters, & Shields, 2008), and it reflects an individual’s perceived income relative to others’ income. By incorporating relative wealth into the utility function, several authors have argued that people evaluate the relative standing of their own income when making economic decisions (Cole et al., 1992, 1995), and other people’s income influences individuals’ utility via an implicit income comparison. To the best of our knowledge, nearly all tourism demand research has overlooked the effect of relative income and has employed only absolute income in empirical studies. Several social and economic theories can be further extended to explain how relative income influences domestic tourism demand, such as the theories of conspicuous consumption and individual well-being/happiness.

Conspicuous consumption is a type of consumption designed to signal the social position and wealth status of an individual (Veblen, 1899; Rege, 2008) argued that the major incentive to signal wealth is to gain preferential treatment via social contacts with high relative wealth. With this in mind, tourism can communicate socio-economic status because it could be associated with higher personal income and additional leisure time (Guo, Kim, & Timothy, 2007; Todd, 2001). People often make their tourism consumption visible to others via pictures, souvenirs, and verbal descriptions. To symbolise socio-economic status through tourism, tourists often purchase luxury products and services (Park, Reisinger, & Noh, 2010) to consume fancy local foods (Kim, Eves, & Scarles, 2009). Many empirical studies have highlighted the influence of socio-economic status on tourism, such as outbound travel behaviour (Moeran, 1983), the vacation decision process (van Raaij & Francken, 1984), the tourism experience (Prentice, Witt, & Hamer, 1998), and cultural tourism participation (Kim, Cheng, & O’Leary, 2007). Moreover, the influence of socio-economic status on conspicuous tourism consumption might be more significant in China. As indicated by Mok and Defranco (2000), in Chinese culture, the symbolic value of goods and services is of great importance, and people value status symbols as being necessary to their daily lives.

A large body of literature has highlighted the positive association between individual well-being/happiness and relative income (Clark et al., 2008; Cummins, 2000; Ferrer-i-Carbonell, 2005). People with a relatively high standing in the income hierarchy are more likely to report greater well-being/happiness (Easterlin, 2001). It has also been suggested that people with a higher level of well-being/happiness are more likely to participate in various tourism activities. Gilbert and Abdullah (2004) found that people in a holiday-taking group exhibited a higher sense of well-being before a holiday than those in a corresponding non-holiday-taking group. Therefore, people who possess a positive attitude towards life are more likely to participate in domestic tourism, which is a type of activity that can enhance people’s sense of happiness and achievement. Following this logic, we argue that relative income can influence tourism demand indirectly through its effect on individual well-being/happiness.

Therefore, we propose the following hypothesis with respect to the relationship between relative income and domestic tourism demand:

### Hypothesis 4

Relative income has a positive influence on domestic tourism demand in China.

As reported in many empirical studies, income comparisons are not symmetric (Clark & Senik, 2010; Ferrer-i-Carbonell, 2005; McBride, 2001), suggesting that the relative income effect varies across different income groups. In the context of domestic tourism demand, the impact of relative income is quite likely to depend on the absolute income of each individual. For those residents with high absolute incomes, relative income tends to play a more important role in determining domestic tourism demand to signal their wealth status. We propose the following hypothesis to incorporate this concern:

### Hypothesis 4a

The effect of relative income varies across residents in different income groups.

With China’s vast land area, great regional differences are also observed across different sub-regions in terms of physical, cultural, and economic conditions. Therefore, regional heterogeneity in terms of tourism demand could be significant across different sub-regions of China. A study by Yang and Wong (2012) highlighted significant regional differences in tourist flow models for the eastern, central, and western parts of China. To accommodate this heterogeneity, the authors developed separate models for each sub-region. We propose the following hypothesis with respect to the regional differences in the Chinese domestic tourism demand model:

### Hypothesis 5

Significant differences exist among the domestic tourism demand models across different sub-regions of China.

The hukou system refers to the residency registration system used by the Chinese government to minimise rural-to-urban migration. Based on their hukou types, Chinese citizens are divided into urban and rural categories, which are two apparently heterogeneous groups in terms of social welfare and economic opportunities. Due to the existence of the hukou system and the rural-urban dichotomy in terms of social and economic conditions, urban and rural residents display different consumption patterns (Yusuf, Brooks, & Zhao, 2008) as well as price and brand perceptions (Sun & Wu, 2004). Therefore, the domestic tourism demand functions of urban and rural residents might be different to predict (Wang, 2004), and we propose the following hypothesis:

### Hypothesis 6

Substantial urban—rural differences exist in domestic tourism demand in China.

3. Model specification and data description

The multilevel model (also known as the hierarchical linear model, the mixed effect model, and the contextual effects model) is specifically designed for the analysis of hierarchical data, and it allows for the disentanglement of factors among different levels with reliable statistical results. A simple two-level multilevel model can be specified as follows:

$$y_{ijt} = \alpha + \sum_{m=1}^{p} \beta_{jm}^m x_{ijmt}^m + \sum_{n=1}^{q} \beta_{jn}^m z_{ijnt}^m + r_{ijt} \tag{1}$$

$$\beta_{jm}^m = \beta_{jm}^* + \eta_{jm} \tag{2}$$

where $i$ indicates the level-1 unit (i.e., an individual resident), $j$ indicates the level-2 unit to which the level-1 unit belongs, and $t$ indicates time. Equation (1) is the individual level equation, whereas Equation (2) is the slope equation that explains the slope heterogeneity across the level-2 units. In Equation (1), $y$ is the dependent variable of individual $i$ nested in the level-2 unit $j$ at time $t$, $\alpha$ is a constant, $x$ is a set of $p$ explanatory variables on level-1, $z$ is a set of $q$ explanatory variables on level-2, $r$ is the random effect of the level-2 unit $j$ used to capture unobserved characteristics of the unit, and $\epsilon_{ijt}$ is the usual error term. As indicated in Equation (1), the coefficients of the level-1 explanatory variables $\beta_{jm}^m$ are allowed to vary across different level-2 units. In Equation (2), we define these coefficients as a mean slope $\beta_{jm}^m$ plus a random effect $\eta_{jm}$ that contributes to the variation of the coefficient over different level-2 units. In practice, we allow only a subset of the coefficients $\beta_{jm}^m$ to vary. For those fixed coefficients, we assume that the variance of error term $\eta_{jm}$ is zero.
Two issues should be considered for this seemingly panel structure in Equations (1) and (2). First, a set of time dummy variables should be included to capture the fixed time effects, which account for the temporal changes that are the same for all level-1 and level-2 units. Second, because we specify a random effect for each level-2 unit, this implies that the unobservable level-2 characteristics are not correlated with level-2 explanatory variables, \( z_{jt} \). However, this strong assumption is likely to be violated in practice, and a widely used solution is to reformulate \( r_j \) by Mundlak’s (1978) formula (Baltagi, 2005), which is specified as

\[
y_j = \sum_{n=1}^{q} \lambda_n z_{jn} + \mu_j
\]

In Equation (3), the level-2 random effect \( r_j \) is decomposed into two parts. The first part captures the correlation with level-2 explanatory variables \( z_{jn} \) by including a linear combination of the average over time, which is specified as \( \lambda_n z_{jn} \). In the second part of Equation (3), \( \mu_j \) captures the pure random effect, which is uncorrelated with other explanatory variables. The coefficients are used specifically to correct for possible correlations, and no practical meaning commonly exists for these coefficients. By including fixed time effects (D\(_t\)) and substituting Equation (3) into Equation (1), the model becomes

\[
y_{ijkt} = \alpha + \beta_j y_{ijkt} + \sum_{n=1}^{q} \delta_n z_{jn} + \lambda_n \mu_j + D_t + \mu_j + e_{ijkt}
\]

We apply the multilevel model to analyse domestic tourism demand in China, covering a sample of urban residents in thirty-five major cities from 1996 to 2007 and rural residents in thirty provinces from 2000 to 2007. As such, we are able to identify two sources of random variation in our domestic tourism demand model: within- and between-city/province variation. To construct the multilevel model of domestic tourism demand, we conceptualise two levels, which are the resident individuals (level-1) nested within the cities/provinces in which they live (level-2). Our domestic tourism demand data are taken from the National Household Tourism Survey, obtained from the Chinese Domestic Tourist Survey Yearbook (1997–2008). This dataset is aggregated by income groups in different sample cities/provinces. To disaggregate this data, we weight each income group by the corresponding number of observations. Therefore, the only level-1 information we can obtain is the income group to which each resident belongs, and the income variable is available over intervals instead of on a continuous scale. In previous Chinese tourism demand studies, tourism demand data were aggregated by administrative units, and this imposes the restriction of full homogeneity of each individual within the unit in terms of economic status. If we ignore individual heterogeneity, we run the risk of incurring an ecological or aggregation fallacy (Robinson, 1950), which suggests that the results from group-level studies might not be valid when transferred to the individual level. Therefore, to draw a more reliable conclusion, it is important to take personal income information into consideration in domestic tourism demand analysis.

A set of explanatory variables in different levels is explained in Table 1. The dependent variable in the model is lnD, which is the annual domestic tourism expenditure per person (in log). For the level-1 explanatory variables, since personal income data are banded into seven categories, a set of dummy variables, inc(2) to inc(7), are used to capture income effects, leaving inc(1) as a reference. Moreover, the variable RI is introduced to capture the relative income effect, which is defined as the log of personal income minus the log of the average income of the city/province. Therefore, we assume that domestic tourism demand depends on the distance between an individual’s own income and the average income of the city/province. We calculate the personal income in terms of the mid-point of each income group and assign a value of half of the upper bound for the lowest income group and 1.5 times the lower bound for the highest income group. The data for the average income of each city/province were obtained from the China Statistical Yearbook (1997–2008).

With respect to other explanatory variables, lnP is the tourism price index (in log) and lnPS is the substitute price index for tourism (in log). We treat lnP and lnPS as level-2 variables by assuming that residents in the same city/province in the same year face the same price and substitution price for domestic tourism. The tourism price index is constructed following the origin-destination matrix weighted method developed by Lanza, Temple, and Urga (2003). The tourism price index \( P \) of level-2 unit \( j \) at time \( t \) is specified as

\[
P_{jt} = \sum_k \frac{T_{jk}}{\sum_k T_{jk}} \frac{P_{kt}}{\bar{P}_{kt}}
\]

where \( T_{jk} \) is the number of tourist arrivals from origin \( j \) to destination \( k \) at time \( t \), the sum \( \sum_k T_{jk} \) is the total number of tourist

<table>
<thead>
<tr>
<th>Continuous variable</th>
<th>Urban resident model</th>
<th>Rural resident model</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnD</td>
<td>Mean</td>
<td>Std. dev.</td>
</tr>
<tr>
<td>Annual domestic tourism expenditure per person (in log)</td>
<td>6.463</td>
<td>0.591</td>
</tr>
<tr>
<td>lnP</td>
<td>4.626</td>
<td>0.039</td>
</tr>
<tr>
<td>lnPS</td>
<td>4.632</td>
<td>0.088</td>
</tr>
<tr>
<td>RI</td>
<td>0.939</td>
<td>0.627</td>
</tr>
<tr>
<td>The distance between personal income (in log) and the average city/province income (in log)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>inc(1)</td>
<td>~499</td>
<td>3.12</td>
</tr>
<tr>
<td>inc(2)</td>
<td>500–999</td>
<td>11.42</td>
</tr>
<tr>
<td>inc(3)</td>
<td>1000–1999</td>
<td>31.42</td>
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<tr>
<td>inc(4)</td>
<td>2000–2999</td>
<td>22.62</td>
</tr>
<tr>
<td>inc(5)</td>
<td>3000–3999</td>
<td>13.83</td>
</tr>
<tr>
<td>inc(6)</td>
<td>4000–4999</td>
<td>7.73</td>
</tr>
<tr>
<td>inc(7)</td>
<td>5000~</td>
<td>9.85</td>
</tr>
<tr>
<td>Categorical variable</td>
<td>Monthly income (in RMB Yuan)</td>
<td>Percent</td>
</tr>
<tr>
<td>inc(1)</td>
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<td>inc(7)</td>
<td>5000~</td>
<td>9.85</td>
</tr>
<tr>
<td>Number of observations</td>
<td>Urban resident model</td>
<td>Rural resident model</td>
</tr>
<tr>
<td>Level-1 unit</td>
<td>138,797</td>
<td>40,840</td>
</tr>
<tr>
<td>Level-2 unit</td>
<td>35</td>
<td>30</td>
</tr>
</tbody>
</table>
arrivals from origin $j$ at time $t$, and $\hat{P}_{jt}$ is a measure of the price index in destination $k$ at time $t$. We use CPI (2000 = 100) as the price index measurement for urban residents and use the price index of tourism (2000 = 100) for rural residents because we cannot obtain the price index of tourism from 1996 to 1999 for urban residents, and the preliminary results suggest that CPI and the price index of tourism are highly correlated. In terms of the substitute price, we cannot specify outbound tourism as a substitute good for domestic tourism in the demand function (Allen et al., 2009; Hamal, 1996) due to visa restrictions and the relatively low GDP per capita for Chinese residents in general. Instead, we use the local price index of cultural activities and entertainment (2000 = 100) by assuming that local cultural activities and entertainment are a substitute good for domestic tourism. City/province level price data were obtained from the China Price Statistical Yearbook (1997–2008), and tourist arrival data were obtained from the China Domestic Tourist Survey Yearbook (1997–2008).

As indicated in Equation (4), we also include a set of year dummy variables to capture the fixed time effects, such as the impact of the SARS outbreak in 2003. Moreover, following Mundlak’s formula (Equations (3) and (4)), we include three time-invariant explanatory variables to alleviate the possible endogeneity problem of the level-2 random effect, which include the average city/province income ($\text{inc}(1)$), the average tourism price index (in log), and the average substitute price index for tourism (in log) of the city/province over the study period.

There are several noticeable advantages of applying multilevel models in this study. First, the multilevel model takes full advantage of the hierarchical structure of our dataset to avoid the ecological fallacy induced by ignoring level-1 information. Second, we can use the local price index of cultural activities and entertainment (2000 = 100) by assuming that local cultural activities and entertainment are a substitute good for domestic tourism. City/province level price data were obtained from the China Price Statistical Yearbook (1997–2008), and tourist arrival data were obtained from the China Domestic Tourist Survey Yearbook (1997–2008). As indicated in Equation (4), we also include a set of year dummy variables to capture the fixed time effects, such as the impact of the SARS outbreak in 2003. Moreover, following Mundlak’s formula (Equations (3) and (4)), we include three time-invariant explanatory variables to alleviate the possible endogeneity problem of the level-2 random effect, which include the average city/province income ($\text{inc}(1)$), the average tourism price index (in log), and the average substitute price index for tourism (in log) of the city/province over the study period.

There are several noticeable advantages of applying multilevel models in this study. First, the multilevel model takes full advantage of the hierarchical structure of our dataset to avoid the ecological fallacy induced by ignoring level-1 information. Second, and more importantly, the multilevel model accounts for the heterogeneity across different levels and specifies the random effects that occur over particular levels. Equation (4) incorporates the random effect $\mu_j$ of each city/province $j$, which is used to capture the unobserved city/province specific factors that influence tourism demand but have not been incorporated in our model, such as location relative to major tourist attractions and travelling cultures. In the slope equation (Equation (2)), a set of $\eta_{it}$ values can also be used to capture the variation of slopes across different cities/provinces (level-2 units).

A large number of models could be estimated to consider all possible random effects and interaction terms. However, because we are particularly interested in various income effects on Chinese domestic tourism demand, only the models relevant to our research goals are estimated. A three-step sequential modelling strategy is adopted to successively introduce complexity. The first model uses Equations (2) and (4) and only captures the absolute income effect, excluding the explanatory variable $R_l$; this model is labelled the “baseline model”. In the second model, in addition to the baseline model, $R_l$ is introduced to capture the relative income effect over cities/provinces. In the specified model, a positive estimated coefficient of $R_l$ indicates the expected relative income effect. For example, imagine that there are two residents with the same personal income in two different level-2 units (different cities/provinces). The one living in the unit with a lower average income exhibits a higher relative income, which contributes to a higher level of domestic tourism demand given the same tourism price and substitute price. In the third model, we test the asymmetry of the relative income effect in different income groups (Hypothesis 4a). To this end, the explanatory variable $R_l$ is replaced by seven interaction terms, i.e., $\text{inc}(1)^*R_l$ to $\text{inc}(7)^*R_l$, to estimate the specific relative income effect of each income group.

Several estimation issues should be noted. We use the full maximum likelihood estimation (FMLE) with expectation–maximisation (EM) iterations to estimate the specified multilevel model. The FMLE generates robust estimates with a large sample size, and the estimates are asymptotically efficient and consistent (Hox, 2010). Because Equations (2) and (4) include several random components, we assume that these components are independent from each other and follow normal distributions with a zero mean and finite variance. Therefore, their co-variances are set to zero to avoid the burdensome co-variance structure in computation. Furthermore, although the random effect cannot be directly estimated during the maximum likelihood estimation, we can obtain the estimate from best linear unbiased predictions (BLUPs) (Bates & Pinheiro, 1998). Finally, we compute the robust standard error of each coefficient from the clustered variance calculated from level-2 (city/province level) in the multilevel models.

The descriptive statistics for the variables specified are presented in Table 1. The sample consists of 138,797 urban residents and 40,840 rural residents in China. A proportion of 54.04% of urban residents fall into income groups 3 and 4, with a monthly income between 1000 and 2999 RMB Yuan during the study period. Among the rural residents, the sample is relatively evenly distributed across different income groups. The mean values of $R_l$ are 0.939 and –0.064 for urban and rural residents, respectively, suggesting that in the sample, a larger number of urban residents have a personal income that is higher than the average income of the city. The average values of $\text{lnP}$ and $\text{lnPS}$ are 4.626 and 4.632 for urban residents, respectively, and 4.589 and 4.627 for rural residents, respectively.

4. Results

4.1. Demand model for urban residents

Table 2 presents the estimation results of domestic tourism demand models for urban residents. The first three models in the table, Urban-All-1, Urban-All-2, and Urban-All-3, include all 138,797 observations across thirty-five cities. In the Urban-All-1 model, which is the baseline model, only the absolute income effect is considered. The estimated coefficients of $\text{inc}(2)$ to $\text{inc}(7)$ are positive, statistically significant, and in ascending order, suggesting a positive and significant absolute income effect on the domestic tourism demand of Chinese urban residents. $\text{lnPS}$ is estimated to be positive and significant, whereas $\text{lnP}$ is insignificant. In the Urban-All-2 model incorporating the relative income effect, $R_l$ is estimated to be insignificant albeit positive. Moreover, in the Urban-All-3 model, after including a set of interaction terms to capture the asymmetry of the relative income effect, these interaction terms of $R_l$ are still not significant. Therefore, based on nationwide data, the influence of relative income on domestic tourism demand of urban residents is limited and insignificant.

Table 2 also presents the estimation results of various random effects, which are the estimated variances of random effects. In the multilevel model, a common way to test the significance of random effects is the Likelihood Ratio (LR) test (Rabe-Hesketh & Skrondal, 2008). As suggested by the results of LR tests in Table 2, all random effects are estimated to be statistically significant in the first three models, highlighting the substantial heterogeneity across cities. From the estimated variance of each random effect, one can compare the degree of the heterogeneity. For example, the estimated variances of the random effects for high-income residents, like $\text{VAR(inc(6))}$ and $\text{VAR(inc(7))}$, are larger than their counterparts of low-income residents, suggesting a more intense cross-city heterogeneity in absolute income effects for high-income residents. Furthermore, we can predict this random effect and unveil the absolute income effect for each city. Fig. 1 illustrates the average predicted random effect of absolute income through BLUPs. Each circle represents each sampled city, and its size reflects the
Notes: * indicates significance at 0.05, ** indicates significance at 0.01. Robust standard errors are in parentheses. The estimates of year dummies and lnPS in Equation (4) are not presented. VAR() indicates the estimated variance of random effects, and LR test refers to the Likelihood Ratio test for random effects based on the non-robust standard error model.

**Table 2**

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>lninc(2)</td>
<td>0.407*** (0.066)</td>
<td>0.402 (0.337)</td>
<td>0.503 (0.361)</td>
<td>-0.0420 (0.252)</td>
<td>0.069** (0.351)</td>
<td>0.792 (0.533)</td>
<td>1.062* (0.548)</td>
</tr>
<tr>
<td>lninc(3)</td>
<td>0.696*** (0.062)</td>
<td>0.687 (0.518)</td>
<td>0.832 (0.541)</td>
<td>0.0316 (0.322)</td>
<td>0.841* (0.438)</td>
<td>1.284 (0.872)</td>
<td>1.653* (0.870)</td>
</tr>
<tr>
<td>lninc(4)</td>
<td>0.908*** (0.069)</td>
<td>0.898 (0.661)</td>
<td>0.903 (0.670)</td>
<td>0.102 (0.400)</td>
<td>0.804* (0.481)</td>
<td>1.580 (1.120)</td>
<td>2.116* (1.082)</td>
</tr>
<tr>
<td>lninc(5)</td>
<td>1.040*** (0.070)</td>
<td>1.027 (0.755)</td>
<td>0.911 (0.782)</td>
<td>0.144 (0.443)</td>
<td>0.610 (0.543)</td>
<td>1.762 (1.271)</td>
<td>2.408* (1.239)</td>
</tr>
<tr>
<td>lninc(6)</td>
<td>1.154*** (0.083)</td>
<td>1.140 (0.832)</td>
<td>1.358 (0.834)</td>
<td>0.144 (0.493)</td>
<td>0.696 (0.585)</td>
<td>1.929 (1.398)</td>
<td>2.723*** (1.365)</td>
</tr>
<tr>
<td>lninc(7)</td>
<td>1.276*** (0.095)</td>
<td>1.260 (0.968)</td>
<td>1.805 (1.115)</td>
<td>0.174 (0.572)</td>
<td>1.117* (0.614)</td>
<td>2.181 (1.563)</td>
<td>2.989* (1.636)</td>
</tr>
<tr>
<td>lnP</td>
<td>0.428 (1.586)</td>
<td>0.435 (1.585)</td>
<td>0.622 (1.626)</td>
<td>-1.228 (2.727)</td>
<td>-1.298 (2.805)</td>
<td>2.718 (1.980)</td>
<td>2.922 (1.950)</td>
</tr>
<tr>
<td>lnPS</td>
<td>1.252*** (0.395)</td>
<td>1.253*** (0.397)</td>
<td>1.294*** (0.391)</td>
<td>1.607** (0.434)</td>
<td>1.683** (0.425)</td>
<td>0.548* (0.237)</td>
<td>0.558 (0.954)</td>
</tr>
<tr>
<td>RI</td>
<td>0.00472 (0.275)</td>
<td>0.309** (0.149)</td>
<td>0.309** (0.149)</td>
<td>-0.281 (0.478)</td>
<td>-0.478 (0.455)</td>
<td>-0.308 (0.269)</td>
<td>-0.308 (0.269)</td>
</tr>
</tbody>
</table>

Random effects

<table>
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<tbody>
<tr>
<td>VAR(city)</td>
<td>0.151</td>
<td>0.151</td>
<td>0.149</td>
<td>0.067</td>
<td>0.074</td>
<td>0.058</td>
<td>0.141</td>
</tr>
<tr>
<td>VAR inc(2)</td>
<td>0.129</td>
<td>0.129</td>
<td>0.115</td>
<td>0.207</td>
<td>0.182</td>
<td>0.045</td>
<td>0.054</td>
</tr>
<tr>
<td>VAR inc(3)</td>
<td>0.116</td>
<td>0.116</td>
<td>0.111</td>
<td>0.158</td>
<td>0.165</td>
<td>0.032</td>
<td>0.085</td>
</tr>
<tr>
<td>VAR inc(4)</td>
<td>0.142</td>
<td>0.142</td>
<td>0.128</td>
<td>0.181</td>
<td>0.182</td>
<td>0.071</td>
<td>0.086</td>
</tr>
<tr>
<td>VAR inc(5)</td>
<td>0.140</td>
<td>0.141</td>
<td>0.126</td>
<td>0.167</td>
<td>0.168</td>
<td>0.112</td>
<td>0.094</td>
</tr>
<tr>
<td>VAR inc(6)</td>
<td>0.201</td>
<td>0.201</td>
<td>0.191</td>
<td>0.207</td>
<td>0.191</td>
<td>0.107</td>
<td>0.216</td>
</tr>
<tr>
<td>VAR inc(7)</td>
<td>0.254</td>
<td>0.254</td>
<td>0.245</td>
<td>0.250</td>
<td>0.248</td>
<td>0.221</td>
<td>0.264</td>
</tr>
<tr>
<td>LR test</td>
<td>93588.785***</td>
<td>93573.895***</td>
<td>91473.917***</td>
<td>35718.087***</td>
<td>3592.482***</td>
<td>6760.732***</td>
<td>21727.755***</td>
</tr>
<tr>
<td>Obs.</td>
<td>138,797 (35)</td>
<td>138,797 (35)</td>
<td>138,797 (35)</td>
<td>57,086 (35)</td>
<td>78,295 (16)</td>
<td>19,495 (8)</td>
<td>41,007 (11)</td>
</tr>
<tr>
<td>AIC</td>
<td>128040.4</td>
<td>112613.7</td>
<td>111098.3</td>
<td>30944.0</td>
<td>41839.9</td>
<td>14777.1</td>
<td>44122.4</td>
</tr>
<tr>
<td>BIC</td>
<td>128163.8</td>
<td>128006.0</td>
<td>113443.3</td>
<td>31158.9</td>
<td>41978.9</td>
<td>14832.2</td>
<td>44208.7</td>
</tr>
</tbody>
</table>

magnitude of this average effect. As shown in the map, one noticeable finding is that in some of the most developed cities, like those in the Yangtze River Delta and the Pearl River Delta, this average effect is moderate, suggesting a modest absolute income effect on urban residents' domestic tourism demand in the developed area.

To compare the absolute income effect for each geographic sub-region, we use the same specification as the Urban-All-1 model to estimate the dataset of each sub-region. A common approach to regionalisation China is to divide it into eastern, central, and western regions (Yang & Wong, 2012). Due to space limitations, we do not present the detailed estimation results in this work. Instead, to compare the estimates intuitively, **Fig. 2** shows the estimated coefficient of inc(2) to inc(7) for the different sub-regions and illustrates that the absolute income effect is always greatest for the western urban residents and smallest for the eastern urban residents. This result suggests that in the least developed areas, i.e., the west of China, absolute income plays a more important role in determining the level of domestic tourism demand.

In the last four columns of **Table 2**, we estimate the models including the relative income effect with the sample in different sub-regions. From the Urban-East-2, Urban-Centre-2, and Urban-West-2 models, we find that between the two price variables, only lnPS is statistically significant for the east and centre and is estimated to be positive. RI is estimated to be significant and positive for urban residents in eastern cities. The positive coefficient suggests that a higher relative income is associated with a higher level of domestic tourism demand for urban residents in the east of China. This result supports **Hypothesis 4** and highlights the importance of implicit income comparison in determining domestic tourism demand. Not only absolute income but also relative income is likely to influence individual tourism demand. To further investigate the magnitude of this relative income effect for different income groups, we developed the Urban-East-3 model, which includes a set of interaction terms between the income dummies and relative income. This model shows that inc(4)*RI, inc(5)*RI, and inc(6)*RI are estimated to be positive and significant. This result highlights the significant relative income effect for middle- and high-income residents (monthly income between 2000 and 4999 RMB Yuan) and is also consistent with the findings reported by McBride (2001) in that the relative income effects are smaller at low-income levels. To test the heterogeneity of the relative income effect over different income groups (**Hypothesis 4a**), we use the Wald test to validate the equality of seven interaction terms. The test statistic is 29.47 with six degrees of freedom, thus rejecting the null hypothesis of homogeneity at the 0.01 significance level.

**4.2. Demand model for rural residents**

In this section, we use the same methods to examine the domestic tourism demand of rural residents. **Table 3** presents the estimation results of models for Chinese rural residents across thirty provinces from 2000 to 2007. The Rural-All-1 model is the baseline model that incorporates nationwide data. Variables inc(2) to inc(7) are estimated to be positive, significant, and in ascending order, emphasising the positive effect of absolute income on the domestic tourism demand of Chinese rural residents. Neither lnP nor lnPS are statistically significant, although their signs are consistent with the traditional demand theory. The estimated substitute elasticity is 0.533 in the Rural-All-1 model and is lower than the estimate in the Urban-All-1 model, which is 1.252. This result suggests that the substitution effect of local cultural activities and entertainment for domestic tourism is stronger for urban residents. The Rural-All-2 and Rural-All-3 models incorporate symmetric and asymmetric relative income effects, respectively.
insignificant in these two models. Similar to the results of various urban models, the nationwide data do not support the significant relative income effect on the domestic tourism demand of Chinese rural residents.

With respect to the slope heterogeneity in the Urban-All-2 model, LR tests suggest that all random effects are statistically significant. This result indicates that the absolute income effects on rural residents’ domestic tourism demand are also heterogeneous across different provinces. The larger estimated variances for the high-income groups highlight the more intense cross-province heterogeneity in absolute income effects. We can predict the random effects of each province using BLUPs. Fig. 3 shows the average predicted random effects of the income dummy variables, which are calculated in the same way as those shown in Fig. 1. This average effect is found to be strongest in some eastern provinces, such as Fujian and Shandong.

To compare the absolute income effect from the eastern, central, and western sub-samples, Fig. 4 presents the results of baseline models for different sub-regions, which are similar to those presented in Fig. 2. The absolute income effects in the east are always greater than those in the centre. However, for the west, we observe that the absolute income effects are greater than those of other regions for low-income groups and smaller for high-income groups.

In the last four models presented in Table 3, we compare the estimation results for different sub-regions when the relative income effect is considered. In the Rural-West-2 model, $\ln P$ is estimated to be significant, suggesting that the own price effect is significant for western rural residents in China. Moreover, the significant and positive estimated coefficient of $R$ in the Rural-Centre-2 model highlights the significant relative income effect for rural residents in central provinces. By incorporating a set of interaction terms to capture the possible asymmetry of this relative income effect, the Rural-Centre-3 model indicates that the relative income effect is greater for middle-income rural residents in central provinces. A Wald test statistic of 158.23 with six degrees of freedom rejects the null hypothesis of the homogeneous relative income effect across different income groups in central provinces.

4.3. Summary of results

After obtaining the estimation results of the multilevel models, we summarise the conclusions obtained for the research hypotheses proposed in Section 2. We cannot reject Hypothesis 1 and identify significant and dominant absolute income effects on
domestic tourism demand for both urban and rural residents. This result is consistent with the findings reported by Cai et al. (2001), Gu and Liu (2004), and Wang (2010). Therefore, it is projected that, together with China’s economic growth and the concomitant increase in household income expected in the future, Chinese domestic tourism demand will continue to increase. Moreover, the cross-city/province heterogeneity of this absolute income effect was identified, and Hypothesis 1a was accepted. We found that this

Table 3

<table>
<thead>
<tr>
<th>Variable</th>
<th>Rural-All-1</th>
<th>Rural-All-2</th>
<th>Rural-All-3</th>
<th>Rural-East-2</th>
<th>Rural-Centre-2</th>
<th>Rural-Centre-3</th>
<th>Rural-West-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>inc(2)</td>
<td>0.260***</td>
<td>0.398 (0.586)</td>
<td>0.614 (0.594)</td>
<td>1.244 (0.946)</td>
<td>-1.714** (0.702)</td>
<td>-0.884 (0.866)</td>
<td>-0.118 (0.912)</td>
</tr>
<tr>
<td>inc(3)</td>
<td>0.309***</td>
<td>0.488 (0.756)</td>
<td>0.701 (0.760)</td>
<td>1.525 (1.249)</td>
<td>-2.331** (0.916)</td>
<td>-1.567 (1.002)</td>
<td>-0.0955 (1.189)</td>
</tr>
<tr>
<td>inc(4)</td>
<td>0.338***</td>
<td>0.549 (0.904)</td>
<td>0.783 (0.895)</td>
<td>1.757 (1.466)</td>
<td>-2.785** (1.084)</td>
<td>-1.986* (1.139)</td>
<td>-0.129 (1.415)</td>
</tr>
<tr>
<td>inc(5)</td>
<td>0.443***</td>
<td>0.692 (1.068)</td>
<td>0.910 (1.052)</td>
<td>2.285 (1.760)</td>
<td>-3.189*** (1.307)</td>
<td>-2.448* (1.345)</td>
<td>-0.300 (1.630)</td>
</tr>
<tr>
<td>inc(6)</td>
<td>0.564***</td>
<td>0.855 (1.247)</td>
<td>1.158 (1.204)</td>
<td>2.678 (2.052)</td>
<td>-3.654** (1.476)</td>
<td>-2.596* (1.517)</td>
<td>-0.267 (1.966)</td>
</tr>
<tr>
<td>inc(7)</td>
<td>0.798***</td>
<td>1.171 (1.604)</td>
<td>1.320 (1.553)</td>
<td>3.631 (2.644)</td>
<td>-4.835** (1.962)</td>
<td>-3.927** (1.866)</td>
<td>-0.233 (2.477)</td>
</tr>
<tr>
<td>lnP</td>
<td>-0.307 (0.391)</td>
<td>-0.328 (0.389)</td>
<td>-0.335 (0.381)</td>
<td>0.526 (1.099)</td>
<td>0.762 (1.308)</td>
<td>0.636 (1.285)</td>
<td>-0.473** (0.188)</td>
</tr>
<tr>
<td>R1R2</td>
<td>0.553 (0.628)</td>
<td>0.518 (0.597)</td>
<td>0.559 (0.636)</td>
<td>0.218 (0.809)</td>
<td>-2.685** (1.316)</td>
<td>-2.509* (1.338)</td>
<td>1.662 (1.504)</td>
</tr>
<tr>
<td>lnP*R1</td>
<td>-0.163 (0.690)</td>
<td>-1.130 (1.137)</td>
<td>-1.130 (1.137)</td>
<td>2.324** (0.838)</td>
<td>1.665* (0.878)</td>
<td>2.442*** (0.799)</td>
<td>1.262 (0.605)</td>
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<tr>
<td>lnP*R2</td>
<td>-0.200 (0.701)</td>
<td>-0.244 (0.666)</td>
<td>-0.244 (0.666)</td>
<td>2.172** (0.888)</td>
<td>2.706*** (0.938)</td>
<td>2.729*** (0.804)</td>
<td>1.512* (0.867)</td>
</tr>
<tr>
<td>lnP*R3</td>
<td>-0.176 (0.710)</td>
<td>0.00741 (0.624)</td>
<td>0.00741 (0.624)</td>
<td>1.512* (0.867)</td>
<td>2.178*** (0.786)</td>
<td>2.178*** (0.786)</td>
<td>0.461 (14.403)</td>
</tr>
<tr>
<td>constant</td>
<td>-6.779 (9.122)</td>
<td>-6.562 (9.946)</td>
<td>-5.664 (9.883)</td>
<td>3.903 (11.758)</td>
<td>-1.883 (20.181)</td>
<td>0.461 (18.403)</td>
<td>-0.194 (34.335)</td>
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</table>

Notes: * indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01. Robust standard errors are in parentheses. The estimates of year dummies and l’s in Equation (4) are not presented. VAR(.) indicates the estimated variance of random effects, and LR test refers to the Likelihood Ratio test for random effects based on the non-robust standard error model.

Fig. 3. Estimated random effects of rural residents’ income for provinces.
effect is stronger in certain cities/provinces than in others. More importantly, this heterogeneity was discovered to be more intense for high-income groups. With respect to price effects, because $\ln P$ was estimated to be insignificant in most models, the results did not support Hypothesis 2, which predicts a negative own price effect on domestic tourism demand. However, the significant and positive coefficient of $\ln P$ in the urban models supports Hypotheses 3, which predicts a positive substitute price effect. With respect to the relative income effect, Hypothesis 4 is not supported by nationwide data; however, we did find evidence to support this hypothesis with sub-regional data. For instance, the relative income effect was found to be significant for eastern urban residents and central rural residents, suggesting that the richer an individual is compared with others within the same city/province, the higher the level of domestic tourism demand that individual will display. Moreover, in those sub-regions exhibited a significant relative income effect, we found that this effect varies across different income groups, which supports Hypothesis 4a. The results showed that the relative income effect is less intense for low-income residents. Finally, we identified substantial differences across residents in different sub-regions and between urban and rural residents, and Hypotheses 5 and 6 are thus corroborated. For instance, the results suggested that absolute income plays a more important role in determining domestic tourism demand for eastern urban residents than in determining that in other sub-regions, and the substitute price effect is more substantial for urban residents than rural ones.

5. Conclusion

This study applied multilevel models to investigate the domestic tourism demand of urban and rural residents in China. The data from the National Household Tourism Survey covered urban residents in thirty-five major cities from 1996 to 2007 and rural residents in thirty provinces from 2000 to 2007. Absolute personal income was found to be the dominant factor that influenced Chinese domestic tourism demand for both urban and rural residents. According to the results of the multilevel models, this absolute income effect varies across different cities/provinces, showing significant heterogeneity. Moreover, this paper breaks new ground by estimating the effect of relative income on domestic tourism demand and highlights the significant relative income effect on tourism demand in certain sub-regions of China. For those sub-regions with significant relative income effects, we found that this effect is asymmetric and is smaller for low-income groups. Based on these findings, several insights are provided in terms of government policy and marketing strategy. First, when designing marketing plans to target potential tourists, relative income should be another important factor to consider apart from absolute income because in certain areas, it also determines the level of domestic tourism demand. Second, different marketing strategies should be proposed for residents in different areas as well as residents in urban and rural areas. For example, urban residents in the east are more concerned with relative income, and western urban residents are more sensitive to absolute income. Third, depending on the fixed price, tourism products and services should be designed with additional status signalling to satisfy the needs of certain residents because domestic tourism is a type of conspicuous consumption for such residents.

Certain limitations of this research should be noted. We could not obtain the micro-data for individual residents, and the data actually consist of the weighted data of each income group nested in each sample city/province. Therefore, the socio-demographic information of each individual cannot be obtained. Moreover, our model is static and does not incorporate dynamic factors. No additional information on short-term and long-term effects can be obtained. Because previous research has indicated that seasonality is significant in domestic tourism demand (Deng & Athanasopoulos, 2011), future research should apply quarterly data to model the demand in place of the annual data used in this work. Finally, although our paper presents evidence of the relative income effect on domestic tourism demand, it is of interest to define more accurate reference groups of income comparison rather than using the average income of cities/provinces.

Acknowledgement

This research was financially supported by National Natural Science Foundation of China (No. 41001070). The preliminary version of this paper was presented at 2012 TTRA International Annual Conference. We are grateful for the helpful comments of Prof. Robertico Croes and two anonymous referees.

References


