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Applying an Intelligent Method to Estimate Air Passenger Demand: Theory and Computerized Implementation

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Abstract

Air travel demand estimation is vital for airlines and government authorities to make reasonable decisions. However, when estimating the demand, air passenger volume has been frequently employed as an instrumental variable, although there exists a big deviation between them. This inappropriate practice will lead to misleading conclusions and seriously perverse decisions. This paper, based on the partial adjustment theory, proposes a new method to distinguish and estimate air travel demand from air passenger volume. A multi-dimensional variable selection method is originally proposed and a new estimation method is advanced to solve the problem of endogeneity and serial correlation. The proposed model is finally applied to estimate and analyze the aggregate air travel demand in China, the results show that air travel demand in China is enjoying a big potential. The model may also be applied to study road, rail and ocean transportation demand.

Keywords*: air travel demand estimation, air travel volume, partial adjustment theory*

1. Introduction

Air passenger transportation has become increasingly important to the national and global economy and its development involves huge capital investments. Moreover, air transportation services are perishable. Once an aircraft takes off, the empty seats are considered as sunk costs to the airline.[1] Therefore the analysis of air travel demand is crucial for enhancing profitability of airlines and is the indispensable base of airline planning and development policy making by the aviation authority.

Many analytical methods of interest have been proposed, among which time-series based models are frequently used. [2] and [3] used ARIMA model and intervention model to estimate the impact of the September 11 terrorist attacks on air transport passenger demand in Spanish and US, respectively. [4] employed SARIMA and other techniques to replicate monthly inbound air travel arrivals to Taiwan. [5] took advantage of Holt-Winters model and SARIMA model to forecast airline passenger numbers for the Lisbon metropolitan area. [6] applied a SARIMA model following Box-Jenkins methodology to forecast daily air passenger demand to Antalya International Airport.[1]

Majorities of time series methods are based on univariate models and ignore a few significant economic variables, therefore they perform unsatisfactorily in a long horizon, especially in a volatile economic environment. Consequently, multivariate models involving macroeconomic variables have absorbed much attention. [7] constructed an intertemporal travel choice model to investigate dynamic international tourism travel demand. In their model, two factors, individual's ability to travel and the external environmental factor, were included in the utility function. [8] proposed a cross nested logit model to investigate air passengers' choice behavior. Nine factors were considered in the model, including departure airport, airline, aircraft type, arrival time, number of connections, airport to airport travel time, on-time performance, parking cost and attributes

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of rail service. For more examples of multivariate models, see [9], [10], [11], [12], [13], [14], [15]. Other Models can also be found in prior studies, such as gravity model (e.g., [16], [17]), time varying parameter model (e.g., [18], [19]), system dynamics model (e.g., [20]) and elasticity model (e.g., [21]).

To our best knowledge, no paper has been focused on addressing the difference between air travel observations and air travel demand. Almost all of the prior studies confuse air passenger volume with air travel demand. However, air passenger volume may deviate from air travel demand, owing to some reasons like transaction costs and irrational consumption, which would mislead the relevant authorities and investors to make wrong decisions. For example, investors would confront a big loss due to an overoptimistic investment decision misled by the irrational consumption during a specific period that is often not representative. To avoid this risk, decisions should be based on the analysis of demand rather than the volume, which necessitates this paper.

The remainder of this paper is organized as follows: Section 2 investigates the relationship between demand and volume. Section 3 proposes a multidimensional method to select explanatory variables of air travel demand, based on which, a multivariate model for estimating air travel demand is constructed. Section 4 proposes a new estimation method to solve the problems of endogeneity and serial correlation in the model. Section 5 applies the proposed method to study the aggregate air travel demand in China and summarizes the insights from the results. Section 6 concludes this paper.

2. Relationship between Volume and Demand

According to the economic theory, demand during a particular period refers to the quantities of a product or service that purchasers are willing and able to buy at various prices with all other factors being held constant. Demand for one particular goods or service during period t is influenced by its own price (p_t), prices of related goods (pr_t), personal disposable income (pdi_t), consumers' expectation of the future (cef_t), population (pop_t), *etc*. The mathematical expression of demand can be written as

$$D_t = D(p_t, pr_t, pdi_t, cef_t, pop_t)$$

Supply during a specific period t is the amount of some product or service that producers are willing and able to offer at various prices with all other factors being held constant. Supply of one particular goods or service during period t is influenced by its own price (p_t), cost (c_t), the number of suppliers (ns_t), suppliers' expectations of the future (sef_t), government's policies and regulations (gpr_t), *etc*. The mathematical expression of supply can be written as

$$S_t = S(p_t, c_t, ns_t, sef_t, gpr_t)$$

In an efficient market, the equilibrium is codetermined by demand and supply, and the mathematical expression can be written as

$$\begin{cases} D_t^* = D(p_t^*, pr_t, pdi_t, cef_t, pop_t) \\ S_t^* = S(p_t^*, c_t, ns_t, sef_t, gpr_t) \\ D_t^* = S_t^* \end{cases} \tag{1}$$

where p_t^* is the equilibrium price and D_t^* is the demand of interest.

Note that volume does not always keep in accordance with D_t^* owing to market transaction costs and some other complex factors, such as irrational consumption, bandwagon effect, positive or negative news on the goods, *etc*. The volume during period t can be computed as

$$V_t = D_t^* + f(trans_t, oth_t) \tag{2}$$

where V_t is the volume, D_t^* is defined by Equation 1, $trans_t$ is the transaction cost, oth_t denotes other factors, during period t, and $f(\cdot)$ is the function of $trans_t$ and oth_t.

Let $D_t^T = f(trans_t, oth_t)$, and Equation 2 can be rewritten as

$$V_t = D_t^* + D_t^T$$

Obviously, air passenger volume, frequently mistaken as air travel demand in most of the prior studies, is actually the sum of demand (D_t^*) and an additional term (D_t^T). It is obvious that a deviation will occur if $D_t^T \neq 0$.

3. Explanatory Variable Selection and Model Construction

3.1. Multidimensional Explanatory Variable Selection Method

It is widely accepted that selecting suitable explanatory variables is one of the key factors to a successful causal model. However, up to now, variable selection is highly dependent on individual's experience and lack of guidelines. To solve this problem, a multi-dimensional method for variable selection is proposed in this section.

Four dimensions should be considered concerning explanatory variable selection, *i.e.*, the aggregation level, dependent variable's historical information, macroeconomic background and social-cultural traditions.

The aggregation level means the level at which the dependent variable is investigated, such as the airport-pair level, itinerary level, specific airport level and total industry level. We need to make sure that the aggregate levels of the dependent and independent variables are matched.

Dependent variable's historical information denotes development characteristics of the dependent variable, such as the historical development trend, seasonality and significant events, *etc*.

The macroeconomic background denotes the economic situation heavily affecting the dependent variable. The background can be reflected by several key economic indicators, such as GDP and disposable income per capita, and some unexpected important events, such as the U.S. subprime crisis and Japan's earthquake and tsunami.

The social-cultural traditions mean the social system and culture imposing large influence on the dependent variable. For example, China's particular reimbursement system makes Chinese people on business trips less sensitive to air fare than people in other countries. Chinese traditional holidays also lead to particular periodicity of Chinese air travel demand, different from that in other countries.

From the above analysis, the explanatory variable selection method can be briefly described as follows:

Step 1. Obtain as many explanatory variables as possible by referring to prior studies.

Step 2. Compare characteristics of the dependent variable in this investigation with the priors in terms of the above four dimensions. If deviation appears in some dimension, the corresponding explanatory variables should be updated.

For example, taking into account substitution effects of rail transportation on the air mode, the rail fare is indeed an important explanatory variable for air travel demand, (e.g., [20]), but it cannot directly be included in the model when analyzing Chinese air passenger demand, because the price of train ticket is relatively stable owing to the regulation by the Chinese Government and thus provides little useful information to reflect the competition between the rail and air mode.

Step 3. Search new explanatory variables for the dependent variable. For example, if significant seasonality is found in the historic data of the dependent variable, dummy variables capturing its influence should be added to the demand model. Some Chinese traditional festivals and several events significantly impacting air travel demand should also be taken into consideration.

Step 4. Explanatory variables obtained in Step 2 and Step 3 are accepted as finally selected variables.

3.2. Finally Selected Explanatory Variables

Following the selection method described in Section 3.1, this paper collects from prior studies explanatory factors, which are divided into four categories. Considering that this investigation addresses air travel demand on the aggregate level, only macro variables in Table 1, together with several China-specific ones, are finally selected. Details are explained as follows:

(1) Industrial added value denoted by x_1. Income is able to capture travelers' purchasing power and economic activities that generate air travel demand. GDP (per capita) is usually taken as a proxy of income (e.g., [10], [14], [16], [20], [22]). In this paper, the industrial added value of China published monthly is employed instead of GDP issued quarterly to collect more abundant data.

(2) China's foreign trade denoted by x_2. Trade is used to capture the extent of economic interaction and is expected to positively affect air travel demand ([23]), and this kind of relationship is often significant between more developed and less developed economies ([24]). China's foreign trade is an index of economic communication activity between China and other countries. China's air travel demand is expected to increase when China's foreign trade volume goes up, and vice versa.

(3) Jet fuel price denoted by x_3. According to economic theories, price plays a major role in demand. The full price afforded by an air passenger comprises the air fare and the access cost. Since the air fare is the dominate component and the access cost difficult to compute, the former is frequently included in a model and the latter omitted (e.g., [10], [14], [20], [22], [23], [25]). Considering that the air fare is endogenous and its volatility is mainly attributable to fluctuation of the jet fuel price, this paper takes the jet fuel price as a proxy of the air fare.

(4) Three Holidays including the Spring Festival, Chinese National Festival and summer vacation, denoted by x_4, x_5 and x_6, respectively. The former two are both one-week-long holidays and the summer vacation lasts from July to September. In Chinese National Festival and summer holidays, a lot of Chinese people will travel for relaxation, while in the Spring Festival, they return home to gather with their families. Therefore, air travel demand is expected to change significantly during the three holidays. Consequently, three dummy variables denoting the Spring Festival, Chinese National Day and summer holiday are included in our model.

(5) Rail competition. Rail transport is expected to become a stronger rival to air transport owing to its lower fares, stronger resistibility to adverse weather. Although the rail fare is suited for capturing the competition effect (e.g., [1]), the rail fare in China is too stable to provide enough useful information, owing to the Chinese governments control on it. Therefore, the rail competition effect is estimated by employing an expert system, instead of including a variable representative of the rail fare in the mathematic function of our model.

It is notable that the effects of rail competition will become tiny when the traveling distance is long enough, given that people traveling domestically can conveniently switch between air and rail travel modes, but most of them have no choice but to take a plane when they travel to or from abroad. This proposition has been further confirmed by the latest statistics of Chinese government which reveals that vast majority of air passengers tend to travel more than 800 kilometers. Therefore, this paper divides air passengers into the domestic and international, and respectively constructs models for these two groups.

(6) Impacts from two types of irregular events, e.g., foreign irregular event effect denoted by x_7 and native irregular event effect denoted by x_8. x_7 captures negative

effects of the US subprime crisis and European debit crisis on the international air travel demand.

Benefiting from the continuingly increasing disposable income per capita, China's domestic air travel demand has been booming in recent years and successfully resisted, to some degree, the negative impacts of the above two crisis. However, China's domestic passenger traffic confronted some native disturbances in 2008, such as the winter storms in the south of China, Wenchuan massive earthquake and air traffic control during the 2008 Olympic Games. Consequently a dummy variable x8 is adopted to capture the combined effect of these disturbances.

3.3. Model Specification

Given the selected explanatory variables in Section 3.2, models of domestic and international air travel demand can be constructed. The equation of international air travel demand is written as

$$\mathrm{int}_t^* = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + \alpha_3 x_{3t} + \alpha_4 x_{4t} + \alpha_5 x_{5t} + \alpha_6 x_{6t} + \alpha_7 x_{7t}, \tag{3}$$

where int_t^* is international air travel demand in period t. The equation of domestic air travel demand is expressed as

$$dom_t^* = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + \beta_5 x_{5t} + \beta_6 x_{6t} + \beta_8 x_{8t}, \tag{4}$$

where dom_t^* is domestic air travel demand in period t.

Because neither int_t^* nor dom_t^* is observable, Equation 3 and Equation 4 cannot directly be estimated. Considering that the government tends to adjust the economy through economic stabilization policies, this paper adopts the partial adjustment theory that is widely used to forecast demand, such as money demand ([26], [27]), agriculture supply ([28]) and electricity demand ([29], [30]). [31] argues that the standard partial adjustment model has quite satisfactory performance at high aggregate level. The standard adjustment model is written as

$$y_t - y_{t-1} = \delta\left(y_t^* - y_{t-1}\right). \tag{5}$$

y_t^* is the desired demand (e.g., int_t^* or dom_t^* in this paper), δ is a constant to be estimated and y_t is the actual output in period t (e.g., int_t^* or dom_t in this paper). Equation 5 assumes that the actual output adjustment is composed of a constant fraction of the difference between the desired output and the previous period's actual output.

Respectively replace y_t^*, y_t and y_{t-1} by int_t^*, int_t and int_{t-1}, and we can get

$$\mathrm{int}_t^* = \delta\,\mathrm{int}_t + (1-\delta)\,\mathrm{int}_{t-1}, \tag{6}$$

where int_t^* is defined by Equation 3. Substitution of int_t^* in Equation 6 and solving for int_t gives the dynamic equation, presented by Equation 7

$$\mathrm{int}_t = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + \alpha_3 x_{3t} + \alpha_4 x_{4t} + \alpha_5 x_{5t} + \alpha_6 x_{6t} + \alpha_7 x_{7t} + (1-\delta)\,\mathrm{int}_{t-1}. \tag{7}$$

In the same way, the dynamic equation of domestic air travel demand can be expresses as

$$dom_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + \beta_5 x_{5t} + \alpha_6 x_{6t} + \beta_8 \beta_{8t} + (1-\delta)\,dom_{t-1}. \tag{8}$$

Since all of the variables in Equation 7 and Equation 8 are observable, the two equations can be estimated.

4. Estimation Method

4.1. Function Transformation

To estimate Equation 7, three methods including OLS (Ordinary Least Squares), fixed effects and GMM (Generalized Method of Moments) are frequently applied in prior studies, e.g., [32], [33], [34] and [35]. However, preconditions of the above methods are not met in this study, owing to the following three problems.

The first one is that the lagged dependent variable (*i.e.*, int_{t-1}) appears on the right side in the mathematic expression of our model, see Equation 7, which brings endogeneity. The second one lies in the fact that residuals tend to be serially related, owing to inertia of the economy resulted from some factors such as the delayed effect of monetary and fiscal policies, traveling habit of passengers and Cobweb Phenomenon. The third one is attributed to the difficulty of searching reasonable instrumental variables for y_{t-1}, which makes GMM impractical in this investigation. To address the above problems, this section proposes a new estimation method.

Without loss of generality, we assume the inequality constraint of $0 < 1-\delta < 1$, and rewrite Equation 6 as

$$\text{int}_t = \lim_{T\to+\infty} \delta \sum_{i=0}^{T} (1-\delta)^i \text{int}_{t-i}^* + \lim_{T\to+\infty} (1-\delta)^{T+1} \sum_{i=0}^{T} \text{int}_{t-(T+1)} . \tag{9}$$

It is reasonable to assume that the capacity of air passenger transportation market has an upper limit, which means $\{\text{int}_t^* \le c,\ t = 1,2,...\}$ where c is a constant. There definitely exists a big enough integer p, where the value of $\sum_{i=p+1}^{+\infty} (1-\delta)^i \text{int}_{t-i}$ is so little that it can be ignored. Therefore Equation 9 can be transformed to

$$\text{int}_t \approx \delta \sum_{i=0}^{p} (1-\delta)^t \text{int}_{t-i}^* . \tag{10}$$

Substituting Equation 3 into Equation 10 generates

$$\begin{aligned} \text{int}_t &\approx \sum_{i=0}^{p} \delta(1-\delta)^i (\alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t} + \alpha_3 x_{3t} + \alpha_4 x_{4t} + \alpha_5 x_{5t} + \alpha_6 x_{6t} + \alpha_7 x_{7t}) \\ &= \alpha_0 \delta \sum_{i=0}^{p} (1-\delta)^i + \alpha_1 \delta \sum_{i=0}^{p} (1-\delta)^i x_{1t-i} + \cdots + \alpha_7 \delta \sum_{i=0}^{p} (1-\delta)^i x_{7t-i} \end{aligned} . \tag{11}$$

By defining $\lambda = 1-\delta$ and adding a stochastic term v_t independent of explanatory variables in Equation 11, we can get

$$\text{int}_t = \alpha_0 (1-\lambda) \sum_{i=0}^{p} \lambda^i + \alpha_1 (1-\lambda) \sum_{i=0}^{p} \lambda^i x_{1t-i} + \ldots + \alpha_7 (1-\lambda) \sum_{i=0}^{p} \lambda^i x_{7t-i} . \tag{12}$$

v_t is assumed to follow a mean zero and covariance stationary process, formulated as

$$v_t \sim N(0, \sigma_v).$$

Define

$$b_j = \alpha_j (1-\lambda),\quad j = 0,..., 7 ; \tag{13}$$

$$\{z_{0t}, z_{1t}, \ldots, z_{7t}\} = \left\{ \sum_{i=0}^{p} \lambda^i, \sum_{i=0}^{p} \lambda^i x_{1t-i}, \ldots, \sum_{i=0}^{p} \lambda^i x_{7t-i} \right\}, \tag{14}$$

and then Equation 12 can be transformed to

$$\text{int}_i = b_0 z_{0t} + b_1 z_{1t} + \cdots + b_7 z_{7t} + v_t . \tag{15}$$

4.2. Steps of the Estimation

We first estimate Equation 15 and then compute parameters α_i (i = 0, 1,...,7) in Equation 3 by Equation 13. Equation 15 can be estimated by the following steps:

Step 1. Define the range of λ as $0 < \lambda_l < \lambda < \lambda_u < 1$, then the step length is set to be len, the initial value of λ to be λ_0 and j to b 0.

Step 2. If $\lambda \in (\lambda_l, \lambda_u)$, compute z_i (i=0, …,7) in light of Equation 14. Otherwise, the algorithm stops.

Step 3. Use OLS to estimate Equation 15 and compute the residual e_t. Then employ Box-Jenkins methodology to estimate $\varphi(L)$, subject to the condition of $\varphi(L)e_t = \eta_t$ where η_t is white noise. Denote the estimate of $\varphi(L)$ by $\hat{\varphi}(L)$.

Step 4. Transform Equation 15

$$\text{int}_i = b_0\hat{\varphi}(L)\, z_{0t} + b_1\hat{\varphi}(L)\, z_{1t} + \cdots + b_7\hat{\varphi}(L)\, z_{7t} + \hat{\varphi}(L)\, v_t \tag{16}$$

Let $\tilde{\text{int}}_t = \hat{\varphi}(L)\,\text{int}_t$, $\tilde{z}_{it} = \hat{\varphi}(L) z_{it}$ (i=0, 1,⋯ , 7.) and $\tilde{v}_t = \hat{\varphi}(L) v_t$, and then we can obtain

$$\tilde{\text{int}}_t = \tilde{z}_{0t} + b_1\tilde{z}_{1t} + \cdots + b_7\tilde{z}_{7t} + \tilde{v}_t \tag{17}$$

Step 5. Use OLS to estimate parameters in Equation 16, denoted by B_j, and record the goodness-of-fit value R_j^2.

Step 6. Update $j = j+1$ and $\lambda_j = \lambda_{j-1} + len$. If $\lambda_j \in (\lambda_l, \lambda_u)$, go back to Step 2.

Step 7. Select $\left\{ B_k \,\middle|\, R_k^2 = \max_j \left(R_j^2\right) \right\}$ as the final estimate of parameters in Equation 15.

Step 8. Given B_k and λ_k, compute the parameters in Equation 3 in light of Equation 13.

4.3. Detailed discussion on the estimation

(1) Theorem 1. With a large sample, B_k is unbiased, consistent and efficient.

Proof. Obviously, values of the parameters in $\tilde{\varphi}(L)$ obtained in Step 3 are consistent estimates of those in $\varphi(L)$, therefore the following Equation is established

$$\tilde{v}(t) = \tilde{\varphi}(L) v_t \xrightarrow{p} \eta_t \tag{18}$$

Because η_t is white noise, we can obtain

$$\text{cov}\left(\tilde{v}_i, \tilde{v}_j\right) = 0,\ i \neq j \tag{19}$$

Because $\tilde{v}_t$ is independent of explanatory variables, we can get

$$\text{cov}\left(\tilde{z}_{it}, \tilde{v}_t\right) = 0, \quad i = 0,1,\ldots,7 \tag{20}$$

According to Equation 14, (z_{it} $(i = 0,\ldots, 7)$ is nonrandom, which means

$$E\left(\text{int}_t \middle| Z_t\right) = b_0\tilde{z}_{0t} + b_1\tilde{z}_{1t} + \ldots + b_7\tilde{z}_{7t} \tag{21}$$

where $Z_t = [\tilde{z}_{0t}, \tilde{z}_{1t}, \ldots, \tilde{z}_{7t}]$.

With Equations 17, 18, 19 and 20, OLS estimates for parameters in Equation 16 are unbiased, consistent and efficient. Considering that Equation 16 is a linear transformation of Equation 15, the theorem is established.

(2) Determination of p. Given a predefined p, in light of Equations 9 and 10, the ignored error can be expressed as

$$\delta \sum_{i=p+1}^{+\infty} (1-\delta)^i\, \text{int}_{t-i}^* = (1-\lambda)\sum_{i=p+1}^{+\infty} \lambda^i\, \text{int}_{t-i}^* \le (1-\lambda)\xi \sum_{i=p+1}^{+\infty} \lambda^i = \lambda^{p+1}\xi$$

ξ is the upper limit of int_t^*, $t = p+1$. To control the omitted error, we can set $\lambda(p+1)$ to a small enough number σ and solve p from the following equation

$$p = \left\lceil \ln\left(\frac{\sigma}{\xi}\right) \Big/ \lambda - 1 \right\rceil$$

where $\lceil x \rceil$ denotes the smallest integer larger than x.

With the above mentioned estimation method, Equations 3 can be estimated, and Equation 4 can also be estimated in the same way.

5. Empirical Study

5.1. Data Description and Preparation

The Monthly data used in this study is collected from the CEIC Macroeconomic Database, including volumes of international and domestic air passengers in China, China's industrial added value (IAV), China's foreign trade, producer price index (PPI) and RMB-dollar exchange. The domestic air passengers are composed of people traveling in Mainland China, including Hong Kong and Taiwan. China's foreign trade is defined as the sum of import and export of China. The Brent crude price is used as a proxy of the jet fuel price.

The growth rate of IAV is deflated by PPI in order to eliminate the effect of inflation. The growth rates of China's foreign trade and Brent crude price are adjusted by the RMB-dollar exchange rate. X-12 seasonal adjustment algorithm is applied to eliminate effects of seasonality.

5.2. Empirical Results

5.2.1. Analysis of parameter estimates: Use the method described in Section 4, we obtain parameter estimates for international air travel demand (see Table 2) and domestic air travel demand (see Table 3).

Table 2. Estimated Results of the International Air Travel Demand Response

Dependent variables[a]	Estimated parameters[a]	Dependent variables[b]	Estimated parameters[b]
$\tilde{z}_{1t}$	0.290** (0.144)	x_1	0.874** (0.434)
$\tilde{z}_{2t}$	0.313*** (0.133)	x_2	0.943*** (0.401)
$\tilde{z}_{3t}$	−0.166** (0.064)	x_3	−0.349** (0.193)
$\tilde{z}_{6t}$	0.119** (0.053)	x_6	0.158** (0.160)
$\tilde{z}_{7t}$	−0.183* (0.101)	x_7	−0.551* (0.160)

Note: $\lambda = 0.668$, $R^2 = 0.972$; ** means $p < 0.05$ and *** means $p < 0.01$; [a] refers to Equation 16, and [b] Equation 3; Data in the brackets are standard errors

Table 3. Estimated Equations of Domestic Air Travel Demand Response

Dependent variables[a]	Estimated parameters[a]	Dependent variables[b]	Estimated parameters[b]
$\tilde{z}_{1t}$	0.138** (0.066)	x_1	0.425** (0.203)
$\tilde{z}_{2t}$	0.142*** (0.052)	x_2	0.437*** (0.160)
$\tilde{z}_{3t}$	−0.042** (0.02)	x_3	−0.130** (0.073)
$\tilde{z}_{4t}$	−0.083*** (0.028)	x_6	−0.255** (0.086)

Table 3. (Continued) Estimated Equations of Domestic Air Travel Demand Response

$\tilde{z}_{4t}$	−0.083*** (0.028)	x_6	−0.255** (0.086)
$\tilde{z}_{5t}$	0.108** (0.021)	x_6	0.332** (0.065)
$\tilde{z}_{6t}$	0.269** (0.025)	x_6	0.419** (0.120)
$\tilde{z}_{8t}$	−0.136* (0.039)	x_7	−0.551* (0.160)

Note: $\lambda = 0.675$, $R^2 = 0.975$; ** means $p < 0.05$ and *** means $p < 0.01$; [a] refers to Equation 16, and [b] Equation 3; Data in the brackets are standard errors

We can draw from the Tables 2 and 3 the following conclusions:

(1) The adjustment speed ($\delta = 1 - \lambda$) of international and domestic air travel demand is respectively 0.332 and 0.325, which means, with regard to both kinds of demand, the actual adjustment accounts for about one third of the difference between demand in period t and the observed volume in period t-1.

(2) The jet fuel price (x_3) and the economic crisis (x_7) have significantly negative effects on both international and domestic air travel demand, while China's foreign trade (x_2) and industrial added value (x_1) have significantly positive effects on them.

(3) The international air travel demand in summer vacation (x_6) increases significantly, but it shows no significant change in the Spring Festival (x_4) or in the National Day (x_5). One possible reason is that summer vacation are long enough for students and their relatives or friends to travel abroad by air, but the other two are short to some extent for outbound tourism.

(4) Consistent with our expectation, the National Day (x_5) and summer vacation (x_6) have significant positive effects on domestic air travel demand. However, the Spring Festival (x_4) surprisingly has negative effect. One reasonable explanation is that although quantities of people to return home will raise the air travel demand in the one-week-long Spring Festival, business and tourism travel demand will decrease sharply over the whole month and this negative effect exceeds the positive effect of the Spring Festival.

(5) The US sub-prime crisis and European debit crisis (x_7) heavily damage the international air travel demand but have trivial influence on the domestic; Chines

domestic factors (x_8) impose significant effects on the domestic air travel demand but not on the international.

5.2.2. The Growth Potential of the Air Travel Demand: To evaluate the growth potential of the air travel demand, we construct a new index r_t, *i.e.*, the ratio of the observation to the air travel demand. With Equation 6 and some algebraic operations, we can get

$$r_t = \frac{\text{int}_t}{\text{int}_t^*} = \frac{\delta}{1 + (\delta - 1)\sigma_t}$$

and

$$\sigma_t = \frac{y_{t-1}}{y_t}$$

Where y_{t-1} is the passenger volume in period $t-1$, δ (*i.e.*, the adjustment speed) is estimated from the demand equation, and y_t (the passenger volume at period t) is the combination of the estimated value of demand and judgment by a panel of experts on the rail competition effect.

It is notable that r_t is of high consultative value for decision making. $r_t < 1$ means that the air passenger volume is less than the potential demand and correspondingly the air travel demand is reasonably expected to continue growing. $r_t > 1$ means the number of air passengers has exceeded the potential demand, which warns people that the present economy is not on its own track. The reason may be that the air passenger transport industry is overloaded or that the overall economic situation is degrading, and thus the growth of the industry is not sustainable.

We respectively compute r_t for China's international and domestic air travel demand in recent 5 years. The results are listed in Table 4.

Table 4. The Spectrum of r_t from 2008 to 2014

Year	International	Domestic
2014	82.6%	84.0%
2013	80.5%	83.2%
2012	84.4%	85.2%
2011	85.2%	84.9%
2010	71.1%	78.8%
2009	106.1%	72.8%
2008	121.8%	91.1%

From Table 4, we can make the following conclusion:

(1) r_t for the international air travel demand was larger than 1 in 2008 and 2009, which indicates that the economy slowed down in the two years and could not sustain the high growth speed of international air passenger transport. This line of reasoning is confirmed by the fact that China's international air travel demand indeed degraded sharply in 2008 and 2009 owing to the US subprime crisis.

(2) The domestic air travel demand was smaller than 1 in 2008 and 2009, though very close to 1 in 2008. It means that although domestic air travel demand in China suffered a lot from the US subprime crisis, it succeeded to keep growing in the crisis and quickly get back to its normal track.

(3) From 2010 up to now, China's air travel demand has boomed and it still has a great growth potential in the future, considering that the observed number of air passengers

(international, domestic and aggregate) only account for about 85% of the corresponding demand in 2014.

6. Conclusion

This paper addresses the difference between air travel demand and the air passenger volume. The relationship between the demand and volume is discussed, and then a multidimensional variable selection method is proposed. In order to obtain more accurate estimates, we divide air passengers into the international and domestic and respectively construct models for these two groups. A new estimation method based on partial adjustment theory is advanced to solve the problem of endogeneity and serial correlation. To evaluate the growth potential of air travel demand, a new indicator r_t is proposed.

The proposed method is applied to study China's aggregate air travel demand. The results show that, in terms of the international air travel demand, China's industrial added value, China's foreign trade and Chinese summer vacation present significant positive effects, while the jet fuel price, the US subprime crisis and European debit crisis show negative influence. With regard to the domestic air travel demand, China's industrial added value, China's foreign trade, Chinese summer vacation and the National Day significantly promote the domestic demand, while the jet fuel price and some China's domestic negative factors (e.g., the winter snow storms in southern China, Wenchuan massive earthquake and the air traffic control during the 2008 Olympic Games) do harm to it. One interesting finding is that Chinese Spring Festival impose negative influence on domestic air travel demand, reverse to many people's expectation.

The spectrum of r_t suggests that China has a great growth potential of air passenger transportation. Actually, despite of a slowing-down economic growth speed, China is still the top dynamic economy in the world. Besides, it has set up some promising development plans. For example, China's "One Belt One Road" initiative will lead to much more communication and cooperation between China and her partners, which is expected to generate more air travel demand.

However, a panel of 12 experts, of whom, 1/3 are econometric modelling experts from Center for Forecasting Science Chinese Academy of Sciences, 1/3 from the leading airlines in China, and the remainder from China's major airports, have warned the in-coming competition launched by China's booming high speed rail service for passengers, especially in terms of short distance transportation of less than 800 kilometers.

With the above analysis, the Chinese Government has to expand the air transport network and raise individual airport's capacity to meet the demand in the future. Meanwhile, close attention should be paid to avoiding excessive construction in a specific local region. Moreover, the selection between two alternatives, *i.e.*, constructing the high speed railway or airports, should be carefully weighed, given that high speed railways would deliver a fierce competition to airports in a variety of resources like investments and passengers at the distance less than 800 kilometers.

It is worth to note that the proposed method is not limited to the analysis of air travel demand, but can be applied to investigating road, rail and ocean transportation demand.

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Appendix

Table 1. Collection of Eexplanatory Factors from Prior Studies

Category	Casual factors	Reference
Social economic factors	Population	Uddin, *et al*. (1985); Hendry & Krolzig (2001); Bailey, *et al*. (1985); Suryani, *et al*. (2010); Wei & Hansen (2005); Fernandes & Pacheco (2010).
	Income	Fildes, *et al*. (2011); Wei & Hansen (2006); Bailey, *et al*. (1985); Kopsch (2012); Chi & Baek (2012); Fernandes & Pacheco (2010).
	GDP	Fildes, *et al*. (2011); Wei & Hansen (2006); Bailey, *et al*. (1985); Kopsch (2012); Chi & Baek (2012); Fernandes & Pacheco (2010).
	Purchasing power	Wei & Hansen (2006); Fildes, *et al*. (2011); Bailey, et al. (1985); Kopsch (2012); Chi & Baek (2012); Fernandes & Pacheco (2010).
	World trade	Fildes, *et al*. (2011).
	Price of fuel	Carson, *et al*. (2011); Hsiao & Hansen (2011).
Facility variables	Aircraft size	Hsiao & Hansen (2011); Jorge-Calderon (1997).
	Spokes property	Bailey, *et al*. (1985); Hansen (1990); Wei & Hansen (2006); Hsiao & Hansen (2011).
	Hub airport property	Bailey, *et al*. (1985); Hansen (1990); Wei & Hansen (2006); Hsiao & Hansen (2011).
Service variables	Flight frequency	Bailey, *et al*. (1985); Hansen (1990); Wei & Hansen (2006); Jorge-Calderon (1997); Hsiao & Hansen (2011); Hsu, *et al*. (2013).
	On-time rate	Hsiao & Hansen (2011); Hess, *et al*. (2013); Bailey, *et al*. (1985).
	Average travel time	Bailey, *et al*. (1985); Hsiao & Hansen (2011); Wei & Hansen (2005); Hess, *et al*. (2013); Grosche, *et al*. (2007).
	Competing airline quantity	Murel, *et al*. (2011); Bailey, *et al*. (1985); Hess, *et al*. (2013); Grosche, *et al*. (2007)
Mode competition variables	Rail mode	Kopsch (2012); Wei & Hansen (2006); Hess, *et al*. (2013).
	Road mode	Kopsch (2012); Wei & Hansen (2006); Hess, *et al*. (2013).
	Air fare	Fildes, *et al*. (2011); Murel, *et al*. (2011); Alekseev & Seixas (2009); Bailey, *et al*. (1985); Grosche, *et al*. (2007); Wei & Hansen (2006); Kopsch (2012); Chi & Baek (2012).
	Geographical distance	Bailey, *et al*. (1985); Grosche, *et al*. (2007); Hsiao & Hansen (2011).

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