

Instrumental Variable Estimation of Tourism Demand: Comparing Level versus Change-rate Models

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Tourism demand is highly sensitive to economic fluctuations. If variables are subject to such time-specific effects, lagged variables in dynamic models can cause the OLS estimation to be biased. This study estimates tourism demand with controlling for time-specific effects using instrumental variables. The empirical results show that the models of change rate variables produce more significant and reliable estimates than the ones of level variables. It is because the level variables are nonstationary and also because the instrumental variables constructed by the level variables are not exogenous and cannot solve the endogeneity problem caused by the time specific effects.

Field of Research: Econometrics

1. Introduction

Tourism demand is highly sensitive to economic fluctuations, in particular during global economic crisis. If variables are subject to such time-specific effects, their lagged variables can bias estimation of dynamic models; dynamic relations are a key component in causality tests and are also included in modeling tourism demand. Since the time-specific effects are not observable and cannot be separated from observed variables, we need to employ appropriate estimation methods to control for them. Treating the lagged time-specific effects as measurement errors in explanatory variables, this study uses instrumental variables from the literature on measurement errors.

In modeling tourism demand many studies in the literature use change-rate variables to account for nonstationarity in time-series. Estimation could be negatively affected if nonstationary level-variables are included in a model. After we examine whether the level variables are nonstationary, we evaluate the level-variable models versus the change-rate models.

This study reports that the models of change-rate variables produce more significant and reliable results than the ones of level variables because the level-variables are nonstationary. Another reason for the poor level-variable results is that the instrumental variables constructed by the level variables are not exogenous and cannot solve the endogeneity problem caused by the lagged time specific effects. The empirical results also show that the generalized method of moments (GMM) estimation produces more

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Min

significant estimates for tourism demand than the two-stage-least-squares method (2SLS). It is because there are several outlying observations. The 2SLS method assumes homoscedastic disturbances and thus applies equal weights to all observations. In contrast, the GMM accounts for heteroscedasticity and can reduce the effects of those outlying observations.

The following section formulates a model for tourism demand and explains an instrumental variable estimation which can correct a possible bias in the Granger-causality test. Section 3 reports the estimation results for annual and quarterly data. Conclusions are presented in section 4.

2. Models and Methodology

2.1 Dynamic Models and Time-Specific Effects

The Granger-causality is defined as a relationship between a variable and the lagged values of other variables. Thus, the causality test uses an autoregressive model which is a reduced-form equation of structural equations. There are many studies in the tourism literature which test the causality between tourism demand and economic growth. Nowak et.al. (2007) analyze time series data for Spain, Bonham et al. (2009) for Hawaii, Dritsakis (2004) for Greece, Katircioglu (2009) for Turkey, Mishra et al. (2011) for India, among others. These studies report empirical results supporting the tourism-led economic growth hypothesis for each selected country.

To estimate the tourism demand, this study employs a dynamic model with focusing on a causality from economic growth to tourism demand. For such case of two variables, an autoregressive model of order one is expressed as¹

$$\% \Delta ARR_t^* = \alpha + \beta_1 \% \Delta GDP_{t-1}^* + \beta_2 \% \Delta ARR_{t-1}^* + u_t \quad (1)$$

where $\% \Delta ARR_t^*$, a measure of tourism demand, is the (percentage) change rate of foreign tourist arrivals during time period t , and $\% \Delta GDP_t^*$ is the (percentage) GDP change rate and is used as a measure of economic growth. A null hypothesis of $\beta_1 = 0$ implies that the economic growth ($\% \Delta GDP^*$) does not Granger-cause the tourism demand ($\% \Delta ARR^*$). The OLS method is often used for estimating the autoregressive models, but the OLS estimators become biased if any of the lagged variables on the right-hand side are correlated with the disturbances, called the endogeneity problem.

Every time period the economy experiences unexpected changes and almost all economic variables are influenced by the changes. The effects on economic variables of the changes in each period, called time-specific effects, are merged into the variables $\% \Delta ARR^*$ and $\% \Delta GDP^*$ in Eq.(1). A problem arises in estimating Eq.(1) since neither these time-specific effects nor the underlying variables $\% \Delta ARR^*$ and $\% \Delta GDP^*$ are

Min

observed. Letting δ_t^A and δ_t^G denote the time-specific effects for $\% \Delta ARR_t^*$ and $\% \Delta GDP_t^*$, respectively, we can observe only the sum of the latent variables and their corresponding time-specific effects.

$$\begin{aligned}\% \Delta ARR_t &= \% \Delta ARR_t^* + \delta_t^A \\ \% \Delta GDP_t &= \% \Delta GDP_t^* + \delta_t^G\end{aligned}\quad (2)$$

As changes in each period are unexpected, their time-specific effects are independent between periods. Therefore, they are not associated with any dynamic relationship. Instead, the dynamic relationship holds only for the latent variables. Since $\% \Delta ARR_t^*$ and $\% \Delta GDP_t^*$ are not observable, however, we need to transform Eq.(1) into equations expressed in observable variables. Substituting Eq.(2) for $\% \Delta ARR^*$ and $\% \Delta GDP^*$ in Eq.(1), we obtain

$$\% \Delta ARR_t = \alpha + \beta_1 \% \Delta GDP_{t-1} + \beta_2 \% \Delta ARR_{t-1} + \theta_t + u_t \quad (3)$$

where $\theta_t = \delta_t^A - \beta_1 \delta_{t-1}^G - \beta_2 \delta_{t-1}^A$; this is a function of current and lagged time-specific effects. Notice that the lagged time-specific effects are included not only in θ_t but also in $\% \Delta ARR_{t-1}^*$ and $\% \Delta GDP_{t-1}^*$. Thus, ignoring θ_t (or δ_{t-1}^G and δ_{t-1}^A) biases the OLS estimators due to the endogeneity. This resulting bias belongs to the problem of measurement errors in explanatory variables. This indicates that lagged time-specific effects need to be controlled for in the estimation of the dynamic model.

If there are multiple observations in each time period, the time-specific effects can be controlled for by the within-period transformation. However, this approach cannot be applied to the single time series in this study. Alternatively, we employ an instrumental variable (IV) estimation method.

2.2 Instrumental Variable Estimation

Dagenais and Dagenais (1997) propose an instrumental variable estimator for linear regression models with errors in explanatory variables. This estimator uses instrumental variables obtained from sample moments of order two and three. The moments are constructed by the endogenous explanatory variables which contain measurement errors but do not require any extraneous information. Such IVs are contemporaneous with the endogenous explanatory.

Consider the following regression model for time-series observations from period 1 to T .

$$Y = \alpha + X\beta + u_t \quad (4)$$

where X is a $T \times K$ matrix of explanatory variables measured with error. Since X^* is not observable, we use observable variables X which include measurement errors V .

Min

$$Y = \alpha 1_T + X\beta + (u - V\beta) = \alpha 1_T + X\beta + \eta \quad (5)$$

where $X = X^* + V$. The higher moment estimator for (α, β') is derived using the following instrumental variables.

$$\begin{aligned} Z &= (1_T, z_1, \dots, z_7), \\ z_1 &= x * x, \quad z_2 = x * y, \quad z_3 = y * y, \\ z_4 &= x * x * x - 3x[E(x'x/T) * I_K], \\ z_5 &= x * x * y - 2x[E(x'y/T) * I_K] - y\{1_K[E(x'x/T) * I_K]\}, \\ z_6 &= x * y * y - x[E(y'y/T) * I_K] - 2y[E(y'x/T)], \\ z_7 &= y * y * y - 3y[E(y'y/T)] \end{aligned} \quad (6)$$

where the symbol $*$ designates the Hadamard element-by-element matrix multiplication operator and (x, y) corresponds to (X, Y) in a mean deviation form. As Z is orthogonal to η as proven in Dagenais and Dagenais (1997), we use Z as instrument variables in the next section. These IVs are contemporaneous with the endogenous variables. Using simulated data, Min (2012) shows that these IVs correct a bias in a Granger-causality test.

When there are exogenous explanatory variables, Lewbel (1997) develops IVs which are higher moments of the endogenous variables and functions of the exogenous variables. These IVs are also contemporaneous with the endogenous variables. In addition, Griliches and Hausman (1986) suggest use of appropriately lagged values of the relevant variables as instruments, assuming that the measurement errors are serially uncorrelated.

2.3 A Model for Tourism Demand

Tourism demand is obviously influenced by many other factors, not just by lagged values of the variables included in the Granger-causality test. They include the cost of travel, the cost of living of tourists in the destination country relative to the origin countries, the cost of travel to the competing destinations, the economic condition in the origin and destination countries, tourism infrastructure and political stability, etc (Garin-Munoz, 2006; Naude and Saayman, 2005; Song et al., 2003, among others).

In this application we focus on the cost of travel among many possible factors. An extended model for tourism demand is

$$\% \Delta ARR_t = \alpha + \beta_1 \% \Delta GDP_{t-1} + \beta_2 \% \Delta ARR_{t-1} + \beta_3 \% \Delta CPI_t + \beta_4 \% \Delta OIL_t + \eta_t \quad (7)$$

where $\% \Delta CPI_t$ is the % change rate of consumer price index (CPI) in the destination country during period t , and $\% \Delta OIL_t$ is the % change rate of the crude oil price during period t . Since these added factors are measured in period t , they are not correlated with the lagged time-specific effects which cause a bias in the causality test. Thus, these can be treated as exogenous variables.²

3. Data and Estimation Results

3.1 Data

The models in this study are estimated using annual and quarterly data about the Hong Kong tourism. The data period is from the first quarter of 1985 until the fourth quarter of 2009. The arrival data are collected from Visitor Arrival Statistics (published monthly) via <http://partnetnet.hktb.com/>; these are used as a measure of tourism demand for Hong Kong. The data on Hong Kong GDP and CPI are collected from the IMF database and the data on the crude oil price are from Energy Information Administration.

Table 1: ADF Test of Non-Stationarity for the Level Variables

Variable	ADF statistic	p -value
Annual data		
$\log ARR$	-0.78	0.89
$\log GDP$	-1.45	0.83
$\log CPI$	-4.74	0.43
$\log OIL$	-1.61	0.81
Quarterly data		
$\log ARR$	-2.07	0.77
$\log GDP$	-3.17	0.63
$\log CPI$	-2.40	0.73
$\log OIL$	-6.74	0.28

The null hypothesis of the Augmented Dickey-Fuller (ADF) test is that the variable concerned is non-stationary. This ADF test uses an autoregressive order of 1 for the annual data and 4 for the quarterly data.

3.2 Change-Rate versus Level Variables

We first examine the stationarity of the variables. If a regression model includes nonstationary variables, its estimation results could be wrong. In Table 1 the augmented Dickey-Fuller (ADF) test shows that all of the four level variables are nonstationary as the null of nonstationarity is not rejected with large p -values. Figure 1 also confirms the nonstationarity with growing trends. In contrast, as shown in Figure 2, the first-differenced variables of $\log ARR$ and $\log GDP$ become stationary. In addition, the change rates are free from quarterly effects in the quarterly data as the change rates are calculated over the same quarter of the previous year. Therefore, our main models for the causality test and tourism demand use the first-differences of logarithmic values, i.e., change-rates.³

Min

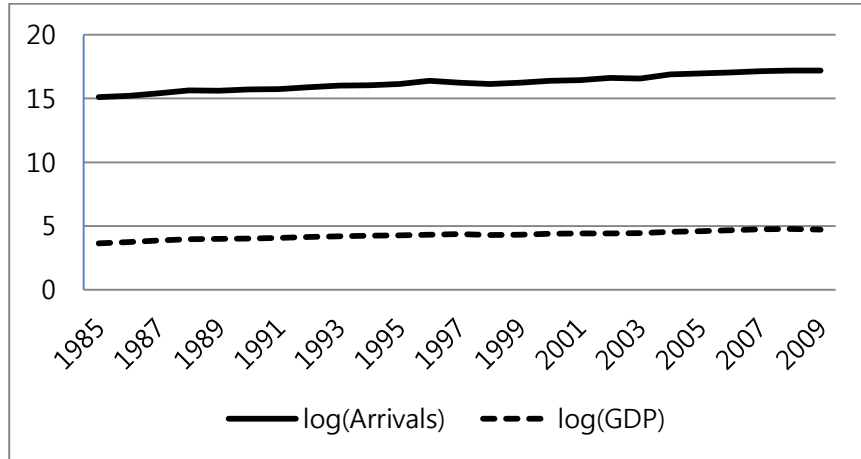


Figure 1 Plots of Level Variables (annual data)

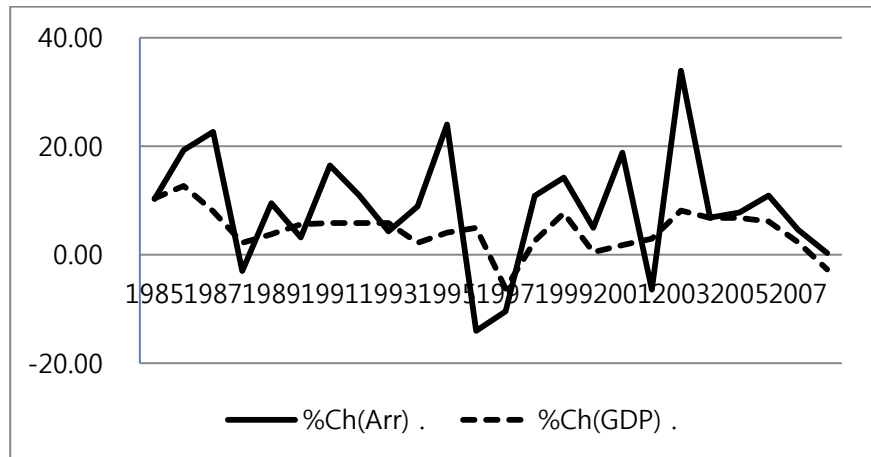


Figure 2: Plots of Change-rate Variables (annual data)

The nonstationarity is an asymptotic issue and thus causes an estimation problem for infinitely long time series. However, the data periods are 25 for the annual data (1985~2009) and 100 for the quarterly data (1985.I~2009.IV). Given these finite-sized time series the estimation in this study might not have the nonstationarity problem of spurious results. One advantage of using level variables is that level variables can keep the variations in them while change-rate variables lose much of the variations because they are calculated as differences between two consecutive periods. If so, the level-variable models can be estimated more precisely with smaller standard errors. For comparison purpose this study also uses the level variables for testing the causality and estimating tourism demand.

3.3 Estimation Results: Annual Data

For the annual data we have selected the lag order of one after applying a sequential test; we start with a sufficiently large lag (e.g., 5) and test down to the right lag order until we reject a null hypothesis that the coefficients on the last lag are jointly zero. For a

Min

robustness check of the selected lag order, we have also applied the Portmanteau test to examine whether the residuals are autocorrelated; this test supports the selected lag order by concluding that the residuals are not autocorrelated.

Table 2 shows the estimation results for the models without and with exogenous variables, $\% \Delta CPI_t$ and $\% \Delta OIL_t$. For the endogenous lagged variables $\% \Delta GDP_{t-1}$ and $\% \Delta ARR_{t-1}$, their higher moments suggested by Dagenais and Dagenais (1997) are used as instruments. According to Griliches and Hausman (1986), their lag-two variables ($\% \Delta GDP_{t-2}$ and $\% \Delta ARR_{t-2}$) can also be used as IVs. However, since the change rate variables are weakly autocorrelated, the relevance of such lag-two IVs is too weak to produce reliable estimates. In contrast, the higher moments are contemporaneous with the endogenous explanatory variables and are therefore more relevant as IVs.

For both models the GMM estimates have smaller standard errors than the OLS and 2SLS ones. It is because there are several outlying observations, particularly on the change rate of tourist arrivals ($\% \Delta ARR_t$); Figure 2 shows such observations during years 1988, 1996, 1997, 2003 and 2004. The OLS and 2SLS methods assume homoscedastic disturbances and thus apply equal weights to all observations. In contrast, the GMM accounts for heteroscedasticity and can reduce the effects of those outlying observations. As a result, the Granger causality from $\% \Delta GDP$ to $\% \Delta ARR$ is significant only by the GMM estimation.

Table 3 shows the estimation results for the models of the level variables. The standard errors of the coefficient estimates are smaller for the level-variable GMM than for the change-rate variable GMM in Table 2. It is because the level variables can keep the variations in them while the change-rate variables lose much of the within variations because change rates are calculated as differences between two consecutive periods. However, the higher-moment IVs of the level variables ($\log GDP_{t-1}$ and $\log ARR_{t-1}$) have a problem in their exogeneity. The over-identifying restrictions test rejects the null hypothesis that the higher-moment IVs are exogenous; the p -values are 0.094 and 0.017. Therefore, the estimates for the level variables are inconsistent.

Min

Table 2: Estimation Results Using Change-rate Variables of Annual Data

$$\% \Delta ARR_t = \alpha_0 + \alpha_1 \% \Delta GDP_{t-1} + \alpha_2 \% \Delta ARR_{t-1} + \alpha_3 \% \Delta CPI_t + \alpha_4 \% \Delta OIL_t + u_t$$

Instrumental Variables	Higher moments of all lagged variables (% ΔGDP_{t-1} , % ΔARR_{t-1})			Higher moments of all lagged variables and Exogenous (% ΔCPI_t , % ΔOIL_t) ^{a)}		
	OLS	2SLS	GMM	OLS	2SLS	GMM
Coefficient for						
% ΔGDP_{t-1}	-0.028 (0.590)	0.375 (0.679)	1.037*** (0.300)	0.335 (0.809)	2.007 (1.184)	4.480*** (0.987)
% ΔARR_{t-1}	0.527* (0.287)	0.510 (0.296)	0.524*** (0.125)	0.310 (0.349)	0.160 (0.353)	-0.210 (0.307)
% ΔCPI_t				-0.053 (0.359)	-0.644 (0.446)	-1.863*** (0.357)
% ΔOIL_t				0.104 (0.155)	-0.059 (0.162)	-0.417*** (0.140)
Granger causality test ^{b)}						
p-value	0.962	0.588	0.003	0.685	0.111	0.0004
Exogeneity test ^{c)}						
p-value		0.147	0.398		0.797	0.985

a) It is assumed that % ΔCPI_t and % ΔOIL_t are exogenous and do not need any instrumental variables.

b) This Granger-causality from % ΔGDP to % ΔARR tests the null of $H_0 : \alpha_1 = 0$.

c) This is to test whether the IVs are exogenous (i.e., orthogonal to the structural disturbances) and called an over-identifying restrictions test when the number of IVs exceeds the number of endogenous regressors. As the null hypothesis here is that all IVs are exogenous, large p-values cannot reject the null.

The symbols of ***, ** and * attached to the coefficient estimates indicate that its coefficient is significantly different from zero at the 1%, 5% and 10% levels, respectively.

Min

Table 3: Estimation Results Using Level Variables of Annual Data

$$\log ARR_t = \beta_0 + \beta_1 \log GDP_{t-1} + \beta_2 \log ARR_{t-1} + \beta_3 \log CPI_t + \beta_4 \log OIL_t + u_t$$

Instrumental Variables	Higher moments of all lagged variables (% ΔGDP_{t-1} , % ΔARR_{t-1})			Higher moments of all lagged variables and Exogenous % ΔCPI_t , % ΔOIL_t		
	OLS	2SLS	GMM	OLS	2SLS	GMM
Coefficient for						
$\log GDP_{t-1}$	0.440 (0.545)	0.085 (0.697)	-0.557 (0.327)	1.144 (0.716)	0.601 (0.950)	1.514*** (0.286)
$\log ARR_{t-1}$	0.755** (0.271)	0.928*** (0.346)	1.218*** (0.155)	0.190 (0.315)	0.395 (0.390)	-0.148 (0.166)
$\log CPI_t$				0.075 (0.258)	0.202 (0.336)	0.110 (0.102)
$\log OIL_t$				0.240** (0.108)	0.256* (0.130)	0.444*** (0.056)
Granger causality test ^{a)}						
p-value	0.429	0.904	0.103	0.127	0.535	<0.0001
Exogeneity test ^{b)}						
p-value		0.116	0.150		0.094	0.017

a) This Granger-causality from $\log GDP$ to $\log ARR$ tests the null of $H_0 : \beta_1 = 0$.

c) This is to test whether the IVs are exogenous (i.e., orthogonal to the structural disturbances) and called an over-identifying restrictions test when the number of IVs exceeds the number of endogenous regressors. As the null hypothesis here is that all IVs are exogenous, large p -values cannot reject the null. The symbols of ***, ** and * attached to the coefficient estimates indicate that its coefficient is significantly different from zero at the 1%, 5% and 10% levels, respectively.

3.4 Estimation Results: Quarterly Data

For the quarterly data the lag order of four has been selected by a sequential test. The lag order of four is expected to account for the quarterly seasonal effects. The Portmanteau test confirms that the residuals from the lag order of four are not autocorrelated.

Min

Table 4: Estimation Results Using Change-rate Variables of Quarterly Data

$$\% \Delta ARR_t = \alpha_0 + \alpha_1 \% \Delta GDP_{t-1} + \alpha_2 \% \Delta GDP_{t-2} + \alpha_3 \% \Delta GDP_{t-3} + \alpha_4 \% \Delta GDP_{t-4} + \beta_1 \% \Delta ARR_{t-1} + \beta_2 \% \Delta ARR_{t-2} + \beta_3 \% \Delta ARR_{t-3} + \beta_4 \% \Delta ARR_{t-4} + \delta_{CPI} \% \Delta CPI_t + \delta_{OIL} \% \Delta OIL_t + u_t$$

Instrumental Variables	Higher moments of all lagged variables (% ΔGDP_{t-S} , % ΔARR_{t-S})			Higher moments of all lagged variables and Exogenous % ΔCPI_t , % ΔOIL_t		
	OLS	2SLS	GMM	OLS	2SLS	GMM
Coefficient for % ΔGDP_{t-1}	2.239** (0.996)	2.427** (1.023)	1.083*** (0.146)	1.849* (1.052)	2.049* (1.092)	1.108*** (0.152)
% ΔGDP_{t-2}	-0.905 (1.447)	-0.757 (1.467)	-0.632*** (0.203)	-0.793 (1.444)	-0.631 (1.468)	-0.652*** (0.210)
% ΔGDP_{t-3}	-1.274 (1.461)	-1.505 (1.468)	0.245 (0.257)	-1.270 (1.459)	-1.482 (1.472)	0.229 (0.239)
% ΔGDP_{t-4}	1.384 (0.946)	1.379 (0.945)	-0.115 (0.143)	1.832* (0.983)	1.787* (0.984)	-0.168 (0.133)
% ΔARR_{t-1}	0.160 (0.111)	0.135 (0.112)	0.556*** (0.038)	0.158 (0.110)	0.134 (0.112)	0.589*** (0.043)
% ΔARR_{t-2}	0.073 (0.115)	0.055 (0.116)	-0.019* (0.010)	0.058 (0.115)	0.040 (0.116)	-0.019* (0.010)
% ΔARR_{t-3}	0.055 (0.120)	0.050 (0.120)	-0.054*** (0.012)	0.041 (0.120)	0.037 (0.121)	-0.052*** (0.011)
% ΔARR_{t-4}	-0.513*** (0.111)	-0.540*** (0.112)	-0.172*** (0.035)	-0.534*** (0.111)	-0.557*** (0.113)	-0.153*** (0.040)
% ΔCPI_t				-0.338 (0.389)	-0.341 (0.388)	0.050 (0.080)
% ΔOIL_t				0.084 (0.067)	0.073 (0.068)	-0.008 (0.010)
Granger causality test ^{b)} ρ -value	0.076	0.045	<0.0001	0.096	0.076	<0.0001

a) This Granger-causality from % ΔGDP to % ΔARR tests the null of $H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$.

The symbols of ***, ** and * attached to the coefficient estimates indicate that its coefficient is significantly different from zero at the 1%, 5% and 10% levels, respectively.

Min

Table 5: Estimation Results Using Level Variables of Quarterly Data

$$\log ARR_t = \alpha_0 + \alpha_1 \log GDP_{t-1} + \alpha_2 \log GDP_{t-2} + \alpha_3 \log GDP_{t-3} + \alpha_4 \log GDP_{t-4} + \beta_1 \log ARR_{t-1} + \beta_2 \log ARR_{t-2} + \beta_3 \log ARR_{t-3} + \beta_4 \log ARR_{t-4} + \delta_{CPI} \log CPI_t + \delta_{OIL} \log OIL_t + (\text{quarter dummies}) + u_t$$

Instrumental Variables	Higher moments of all lagged variables (% ΔGDP_{t-S} , % ΔARR_{t-S})			Higher moments of all lagged variables and Exogenous $\log CPI_t$, $\log OIL_t$		
	OLS	2SLS	GMM	OLS	2SLS	GMM
Coefficient for $\log GDP_{t-1}$	1.973** (0.909)	2.802** (1.346)	0.734*** (0.247)	1.785* (0.923)	2.317** (1.164)	-1.038** (0.447)
$\log GDP_{t-2}$	-2.116 (1.286)	-3.318* (1.951)	-0.153 (0.347)	-1.848 (1.260)	-2.945* (1.681)	-0.928 (0.564)
$\log GDP_{t-3}$	1.840 (1.268)	2.981 (1.972)	0.194 (0.441)	1.757 (1.239)	2.732* (1.632)	1.517*** (0.522)
$\log GDP_{t-4}$	-0.848 (0.762)	-1.528 (1.196)	-0.783*** (0.244)	-0.259 (0.780)	-0.682 (1.001)	-0.852** (0.329)
$\log ARR_{t-1}$	0.266** (0.128)	0.224 (0.170)	0.713*** (0.048)	0.185 (0.129)	0.155 (0.150)	0.869*** (0.064)
$\log ARR_{t-2}$	0.212 (0.130)	0.229 (0.171)	-0.027 (0.019)	0.138 (0.130)	0.159 (0.151)	0.516*** (0.064)
$\log ARR_{t-3}$	-0.031 (0.128)	-0.053 (0.168)	-0.024 (0.022)	-0.098 (0.128)	-0.122 (0.147)	-0.136*** (0.029)
$\log ARR_{t-4}$	0.116 (0.099)	0.138 (0.158)	0.373*** (0.043)	0.034 (0.124)	0.042 (0.145)	0.195*** (0.052)
$\log CPI_t$				-0.118 (0.168)	-0.071 (0.214)	0.254*** (0.063)
$\log OIL_t$				0.093 (0.073)	0.111 (0.087)	0.042 (0.030)
Granger causality test ^{a)} p-value	0.104	0.192	<0.0001	0.047	0.091	<0.0001

Note: The quarter dummy variables are included for all models, but their coefficient estimates are not reported in this table. The symbols of ***, ** and * attached to the coefficient estimates indicate that its coefficient is significantly different from zero at the 1%, 5% and 10% levels, respectively.

a) This Granger-causality from $\log GDP$ to $\log ARR$ tests the null of $H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$.

Similarly to the annual data, Tables 4 and 5 show that the GMM produces more significant estimates with smaller standard errors than the OLS and 2SLS. Therefore, the GMM supports the causality from GDP to ARR more significantly.

Min

The standard errors are bigger for the level-variable models than the change-rate models. This is because the level variables are highly autocorrelated (i.e., nonstationary) and the variance of the disturbance grows as the time period increases. This growing variance will inflate the standard errors, more for the quarterly data as there are four times as many time periods. This inflating effect has overridden the decreasing effect by more variations contained in the level variables than in the change-rate variables.

4. Summary and Conclusions

This study estimates tourism demand with controlling for time-specific effects. If variables are subject to time-specific effects, their lagged variables can bias dynamic relations in testing a causality and estimating tourism demand. Since the time-specific effects are not observable and cannot be separated from observed variables, they have to be accounted for by appropriate estimation methods. Treating the lagged time-specific effects as measurement errors in explanatory variables, this study uses instrumental variables.

The empirical results support use of the change rate variables because the level variables in this study are nonstationary and their results are affected by the nonstationarity. In addition, the instrumental variables constructed by the level variables are not exogenous and cannot solve the endogeneity problem caused by the lagged time specific effects.

The discussion in this study will be useful for testing causality of economic variables and for estimating dynamic relations, particularly when the variables involved are sensitive to time-specific effects. In addition, regarding a search for instrumental variables, Lewbel (1997) develops an alternative set of instrumental variables using higher moments of endogenous variables and functions of exogenous variables. Use of these instrumental variables is planned for future work.

Endnotes

¹ If the order of autoregressive models is not large enough, the disturbances will be autocorrelated, leading to inconsistent estimates. In this study we test for autocorrelation of the disturbances as a way of supporting the chosen lag order.

² When we treat $\% \Delta CPI_t$ and $\% \Delta OIL_t$ as endogenous variables and use IVs of their higher moments, the estimation results are qualitatively unchanged and are not reported in the following tables.

³ The quarterly variables show the same results about the nonstationarity test and their first-differences are thus used for the main models.

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Min

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