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Dynamic Panel Data Modelling of International Tourist Arrivals to Maldives

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Abstract

This paper aims to model international tourist arrivals to Maldives. Using panel data of annual tourist arrivals from 35 countries, various models were estimated for the time period 2001-2016. Four different econometric models which include, the pooled Ordinary Least Squares (OLS), the "within" fixed effect panel regression model, the Arellano-Bond Generalised Method of Moments (GMM) estimation technique, and the Blundell-Bond system GMM technique, were used to identify the main determinants of inbound tourism in Maldives. The results indicate the high fidelity of tourists visiting Maldives, as well as, the significance of income of the tourist generating country in determining the number of arrivals. In addition, results also illustrate, the importance of excluding mutually exclusive variables for exchange rates and prices in the empirical model.

Introduction

The tourism industry has been experiencing immense expansions across developed and developing nations. In particular, this industry has the potential, to contribute to significant growth and prosperity within developing countries, constrained by their size, remoteness or by their lack of natural resources (Riza and King, 2010). This contribution to economic growth comes through the tourism sectors effect on employment, exports, stimulation of infrastructure provision, generation of tax income, as well as by its means of promotion of world peace (Eilat and Einav, 2003).

The tourism industry of Maldives has been growing rapidly since its inception in 1972. This profound growth has resulted in the Maldivian economy being extremely reliant and dependent on the developments of the tourism sector. For instance, the increase in the number of tourist arrivals has been associated with an immense influx of foreign currency receipts. This is evident by the huge proportion of tourism revenue recorded in the exports of services in the balance of payments of Maldives[1]. Not only is the tourism sector responsible for the majority of the income received within the country, the sector accounts for a significant portion of the total employment in Maldives[2].

[1] Balance of payment numbers indicate that Export Revenue from travel component of services account for 83% of total export income.

[2] Per World Travel & Tourism Council's "Travel & Tourism – Economic Impact 2018, Maldives", travel and tourism directly accounted for 16.0% of total employment and indirectly accounted for 37.4% of total employment in Maldives: https://www.wttc.org/-/media/files/reports/economic-impact-research/countries-2018/maldives2018.pdf.

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While the importance of the tourism sector for the growth of the local economy is implicit, limited research has been conducted on analysing the dynamic relationship between tourism demand and its determinant in Maldives. Given the vulnerability of the economy to shocks to the tourism sector, understanding the determinants of demand of tourist arrivals, will provide vital information for policy makers, when formulating strategies to attract more tourists to Maldives. This research attempts to understand this tourism demand behaviour by using panel data econometrics for the period 2001-2016.

This paper is structured as follows. This brief introduction will be followed by a review of literature of tourism demand modelling. Section 3 will present an overview of arrivals to Maldives, while Section 4 outlines the methodology employed to model tourism demand in Maldives along with a description of the data used for this analysis. Next, Section 5 will present the results of this study which is then followed by the conclusion.

Literature Review

The importance of tourism sector has resulted in extensive empirical modelling of the demand for international tourism, as well as, its determinants. Song and Li (2008) identified, 121 such studies published only between 2000 and 2007. Given the literature on econometric modelling of tourism demand dates back to 1960s, an amalgam of techniques and models have been proposed within the academia to analyse tourism demand. These techniques span from time series models such as simple integrated autoregressive moving average (ARIMA) models and Generalised Autoregressive Conditional Heteroskedastic (GARCH) models, to panel data analysis using numerous combinations of input variables. More recently, techniques such as artificial neural network (ANN) methods have been applied to analyse tourism demand.

Most of the non-causal time series models used for tourism modelling is motivated by forecasting purposes (Naudé and Saayman, 2005). However, such time series models provide limited information to policy makers, as these models are not based on explaining the underlying theory behind the tourist's decision making process. Though seasonality in tourism demand can be incorporated into such time series models, there are large inconsistencies in the forecasting performance of these models (Song and Li, 2008).

Given the poor forecasting performances of simple time series models, econometric models shifted towards combining economic theory together with the time series aspects of tourism, to model tourism demand more effectively. Such models include, autoregressive distributed lag (ADL) models (e.g. Song, Wong and Chon, 2003), the error correction (EC) models (e.g. Kulendran and Wilson, 2000), and the vector autoregressive (VAR) models (e.g. Shan and Wilson, 2001). While models apart from VARs use exogenous explanatory variables in the model, VARs treat all variables as endogenous. Although, academic research of tourism demand using these models have generally produced better projections than simple time series models (Song and Li, 2008), they do not shed much light on the dynamics and economic theory behind the demand for tourism.

The panel data sets and analysis provides numerous advantages in the study of tourism demand. Given that these datasets consists of spatial (N) and temporal (T) dimensions, the datasets are associated with a large number of observations providing more degrees of freedom for computation (Seetaram, 2009, Song and Li, 2008). In addition to this, the panel analysis reduces the problems of multicollinearity and allows the modelling of intricate relationships into the tourism demand function. Despite the advantages of panel data analysis, the literature on applications of panel data on tourism demand have been limited. Examples of few such applications include, Naudé and Sayyman (2005), which used a panel data regression analysis to understand the determinants of tourist arrivals in Africa, and Seetaram (2009), which used a panel data cointegration approach to model international arrivals to Australia, with a particular focus on estimating the extent of fidelity within tourists; repeat visitations. In addition to these, Ibrahim (2011) used a dynamic panel model and identified the income, tourism price and trade value elasticities of tourism demand in Egypt, whilst, Dogru, Sirakaya-Turk and Crouch (2017) illustrated that using exchange rates and prices as mutually exclusive variables in panel data regressions generates misleading results in the analysis of tourism demand.

A majority of literature on international tourism demand utilises tourist arrivals as the main dependent variable (Song and Li, 2008), while a number of studies also used, level of expenditure by tourists, as a measure for demand for tourism (Seetaram, 2009). Several explanatory and exogenous variables have been considered in the analysis of tourism demand, and these include: income expressed in terms of gross domestic product (GDP), relative prices, exchange rates, and distance or transportation costs. In addition, econometric models of tourism demand also include dummy variables to account for crisis or extreme situations such as the financial crisis, and climate change events (Surugiu, Leitão and Surugiu, 2011). Furthermore, studies have also investigated dynamic relationships in the tourism demand function. As mentioned above, few studies (e.g. Seetaram, 2009 and Seetaram 2012) have focussed on unravelling the extent of loyalty of tourists to a particular destination by incorporating lag structures to tourism demand.

While the use of panel data helps to solve the issues related to multicollinearity, the inclusion of lagged dependent variables complicates the estimation procedures (Seetaram, 2009). It is often the case that variables are collinear with their lagged values resulting in a multicollinearity problem in the estimation of such panel data. As a result of the complexity involved in estimating dynamic panel data models, alternative techniques have been proposed to compute these dynamic tourism demand models. These alternative techniques include Arellano-Bond (AB) Generalised Method of moment (GMM) estimation technique (Arellano and Bond, 1991) used by Naudé and Saayman (2005), Garín-Muñoz (2006) and Khadaroo and Seetanah (2007), corrected least square dummy variable (CLSDV) estimation technique used by Seetaram (2009) and Seetaram (2012), and Blundell and Bond GMM estimation technique (Blundell and Bond, 1998, 2000) used by Leitão (2009). The aforementioned GMM techniques of Arellano-Bond and Blundell-Bond, controls for the endogeneity of explanatory variables, as well as, alleviates the problems arising from static panel data analysis, such as serial correlation, and heteroskedasticity. The use of CLSDV techniques is recommended for dynamic panel data sets which consists of a small time span, due to the biased and inconsistent estimates resulting from GMM approach applied to such datasets (Seetaram, 2009).

Overview of Arrivals to Maldives

Since the initial phase of tourism development in Maldives, the main marketing strategy of the tourism industry has been to advertise the tropical "sun, sea and sand" concept. This strategy has mainly attracted European tourists, and as such, the composition of tourist arrivals has been dominated by European markets. Till 2009, the number of tourist arrivals from Europe accounted for, approximately more than 70% of the total tourist arrivals to Maldives. The main European countries which have been dominating the market share of inbound tourism include: Italy, Germany and United Kingdom (Adam and Nizar, 2014).

Though the market share of tourist arrivals from European markets has declined during the past decade, the total tourist arrivals to Maldives has been rising steadily. The small deviations from this immense trend upwards are observed only during years in which a significant event occurred; following the destructive Indian Ocean Tsunami in 2004, and following the global financial crisis of 2008/2009. The impressive growth rates realised by the tourism sector since 2009, can be mainly attributed to the high contribution of tourists from China. As shown by the Figure 1, the percentage of arrivals from China accounts for more than 20% of the total arrivals since 2011, making China, the country with the most market share in inbound tourism of Maldives. Two potential reasons which accounted for this shift in composition towards Chinese market are; (a) the Chinese GDP per capita purchasing power parity (PPP in U.S. dollars) rose markedly by 308% from 1991 to 2007 (Seetaram, 2009), and (b) because Maldives received the Approved Destination Status (ADS) in 2003, which spurred travel to Maldives from China from 2003 onwards[3] (Adam and Nizar, 2014).

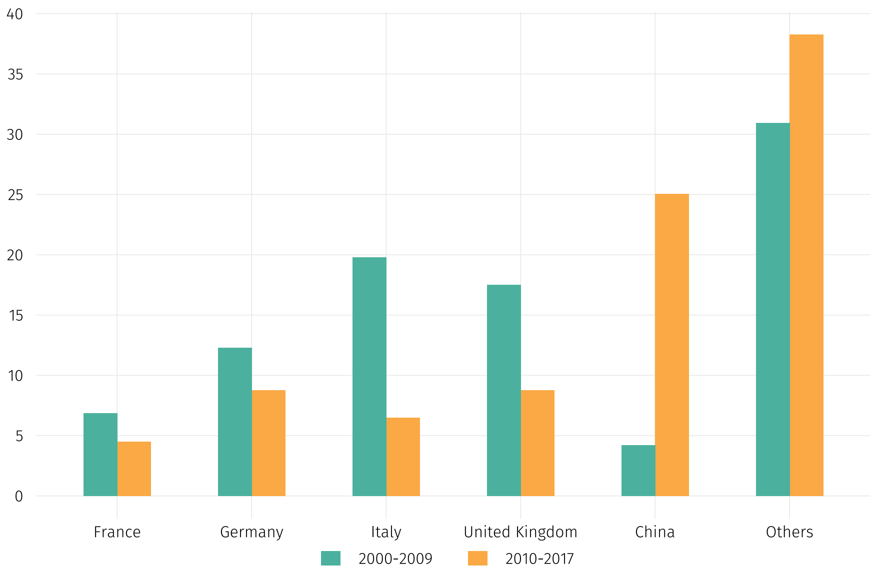
Figure 1: Tourist Arrivals and Percentage of Total Arrivals from China to Maldives, 2009 - 2017
(thousands of people, percent)

Source: Ministry of Tourism

[3] Despite the grant of ADS in 2003, the effect of ADS was realised with a lag possibly due to the unfamiliarity of Maldives within China (Adam and Nizar, 2014).

While the market composition has changed in the recent years the seasonality aspect of tourism is still extant in Maldives (Figure 2). Traditionally, significant differences were observed between the off-peak and peak seasons, as peak seasons coincide with the winter months in the Europe and include the Christmas and New Year Holiday periods. However, given the dominance of Chinese tourist arrivals in recent years, the seasonality trend has been softened considerably (Adam and Nizar, 2014).

Figure 2: Changes in Market Composition between 2000-2009 and 2010-2017
(percent)



Source: Ministry of Tourism

Methodology and Data Description

Based on the literature on inbound tourism demand, this study uses the following generic demand equation (Equation 1), to analyse the tourism demand function for Maldives. The subscript *t* denoted the time period (2001-2016), while the subscript *i* denotes the 35 countries analysed in this study.

$$y_{i,t} = \alpha\, y_{i,t-1} + x'_{i,t}\,\beta + \mu_i + \varepsilon_{i,t}$$

Although several dependent variables have been considered in the context of tourism demand analysis, this empirical research uses tourist arrivals from different countries as the dependent variable. While this remains the most commonly used dependent variable (Song and Li, 2008), alternatives such as expenditure and number of nights spent by tourists, disaggregated by country, is unavailable in Maldives.

In choosing a sample for the cross-sectional dimension of the panel data regression, countries are chosen based on the availability of required data, for the estimated time period (2001-2016). This curtails the analysis to a balanced panel regression, as it ignores the non-randomly missing data for excluded countries. The non-randomness could stem from the availability of flights to Maldives from the analysed country. However, given this study is the initial step in unravelling demand for tourism in Maldives, further studies can focus on understanding the exit and entry of countries into the sample; by estimating unbalanced panel regressions.

As mentioned above, in modelling the tourism demand function, the academia has focussed on a range of explanatory variables. This study considers analysing the tourism demand elasticities for the following independent variables: income, distance, population, relative prices, and exchange rates.

Income variable is proxied by the GDP per capita of the tourist generating country, and theory suggests income of tourist generating country to have a positive relationship with the number of arrivals from that country.

This study uses the variable population, to analyse the changes in the demand for tourism associated with population change; as it is likely that higher population origins dominate the tourist arrivals market. However, this variable could be highly collinear with income, leading to mulicollinearity issues (Leitão, 2009).

Tourism demand models incorporate some form of price or exchange rate measure to account for the differential prices experienced by tourists in visiting country compared to the home country. It is expected that if prices at home country are relatively expensive compared to the visiting country, it is more likely for the tourists to consider the visiting country as a favourable tourist destination. This change in relative prices may be due to deviations in the inflation, and/or, due to appreciation/depreciation of the home currency compared to that of the visiting country; which in this study is the Maldives. While some literature consider relative price level and exchange rates to be separate variables, few literature have also combined these measures to create a price level adjusted for exchange rate differential. One argument as mentioned above, is that separating the two measures generate ambiguous results.

The distance variable is used as a proxy to account for the transportation costs incurred by tourist. Theory indicates that, the higher the transportation expenses a tourist has to incur, the less likely the destination becomes appealing to that tourist. While transportation costs can be assumed to have a direct linkage with the distance between countries, the distance variable does not take into consideration the evolving dynamics of the transportation costs across the time horizon. A better indicator would be airfare data, nevertheless only few studies have obtained significant coefficient for travel costs proxied by air fare (Li, Song and Witt, 2005). Given the difficulty in obtaining historical data for airfare for the chosen sample, as well as the complications involved in computing airfare when considering the different classes of airfare, and the number of airlines in operations between the two countries, this study uses the simple measure of distance, to substitute for transportation costs between tourist generating country and Maldives.

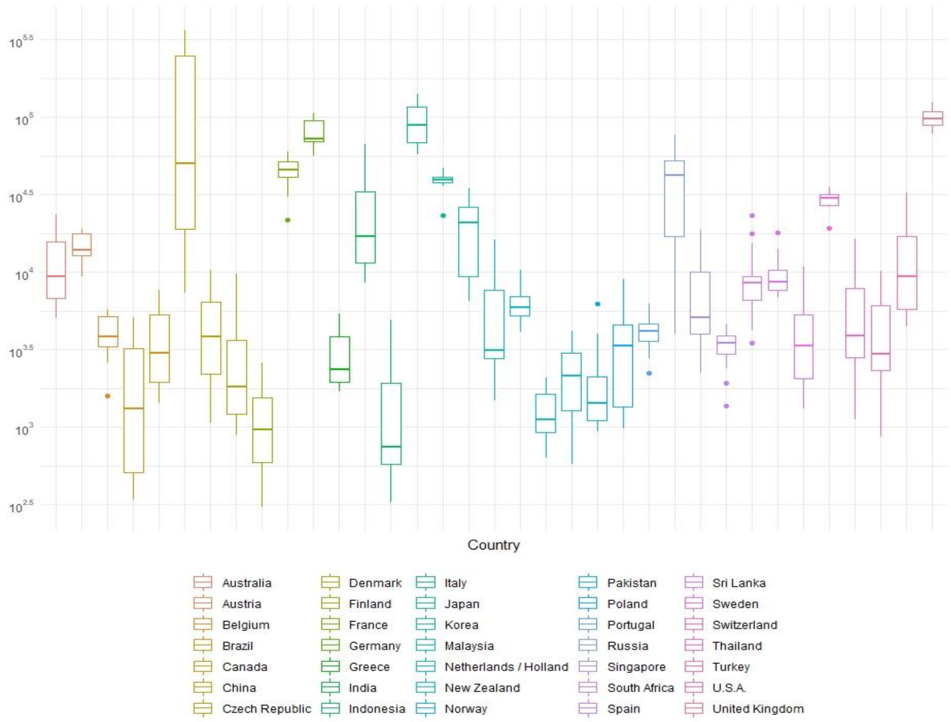
The following table (Table 1) provides the descriptive statistics for the dependent variable and the explanatory variables used in this study, along with the source from which the data was obtained.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev	Median	Min	Max	Skewness	Kurtosis	Source
Arrivals (No of people)	21,016.47	40,310.79	5,868.50	304.00	363,626.00	4.71	30.51	Ministry of Tourism, Maldives
Gross domestic product per capita, constant prices (Purchasing power parity; 2011 international dollar)	30,988.93	16,331.96	33,575.55	2,627.33	82,621.50	0.18	-0.27	World Economic Outlook (WEO) database
Consumer Price Index (2010=100)	96.05	17.53	97.75	31.80	162.20	-0.13	2.32	WEO database
Population (in Millions)	127.74	286.87	38.12	3.92	1,382.71	3.49	11.12	WEO database
Bilateral Nominal Exchange Rate (in MVR)	8.40	7.49	7.31	0.00	25.61	0.34	-1.36	WEO database
Distance (in Kilometres)	7,241.83	3,065.11	7,419.84	903.09	15,309.71	0.42	0.73	https://www.distancefromto.net/

In addition to this, the model specification above, introduces unobserved country-specific heterogeneity into the analysis. As demonstrated below (Figure 3), the tourist arrivals from different countries exhibit major differences across the sample. Hence, the fixed-effect model is analysed in this study; by including the country-specific and time invariant variable (μ_i) to account for this unobserved heterogeneity.

Figure 3: Degree of Hetreogeneity in tourist arrivals across countries, 2001-2016
(logarithm base 10)



Source: Ministry of Tourism

To understand the impact of repeat visitors to Maldives, the model encompasses the lag of the dependent variable ($y_{i,t-1}$)based on Seetaram (2009). This variable will show the extent to which the arrivals of a specific year depends on the arrivals of the previous year; fidelity or loyalty of tourists to a specific destination. Given the popularity of Maldives amongst European travellers, surveys conducted among the tourism industry indicate that the percentage of repeat visitors to Maldives to be high[4]. This study will formally investigate the importance of repeat visitors in determining the tourist arrivals to Maldives.

As this inclusion of lagged dependent variable allows for dynamics in the demand equation, using ordinary lease squares (OLS) estimation procedures generates inconsistent and biased estimates. Hence, to account for the endogeneity amongst the explanatory variables, a GMM approach has been used in this study. The first GMM approach uses the aforementioned AB GMM estimation technique which is most commonly employed in the literature. In this estimation technique, the bias of the coefficients is reduced by first differencing the equation and then by using lagged values of $y_{i,t}$ as instruments. However, according to Kiviet (1995), the AB estimator is not as efficient as the least squares dummy variable (LSDV) estimation technique. This is because, the lagged variables are poor instruments for first differenced variables, especially if the variables are close to a random work. Furthermore, the bias and inconsistency in estimates magnify, when the analysed sample time span is small (Kiviet, 1995). One augmentation to the AB GMM estimator is to use the Blundell-Bond GMM estimator or the system GMM (sys-GMM) estimator; by using lagged first differences of variables for one or two period as instruments for equations in levels (Blundell and Bond, 1998, 2000). By using additional restrictions (instruments) sys-GMM, obtains more efficient estimates compared to AB GMM estimates.

The first moment condition stated below is used in AB GMM estimation, while the sys-GMM uses both the moment conditions stated below.

$$\boldsymbol{E}\{\boldsymbol{y}_{\boldsymbol{i},\boldsymbol{t}-\boldsymbol{s}}(\Delta \boldsymbol{y}_{\boldsymbol{i},\boldsymbol{t}} - \boldsymbol{\alpha}\, \Delta \boldsymbol{y}_{\boldsymbol{i},\boldsymbol{t}-\boldsymbol{1}} - \Delta \boldsymbol{x}'_{\boldsymbol{i},\boldsymbol{t}}\, \boldsymbol{\beta})\} = \boldsymbol{0} \qquad \boldsymbol{for}\ \boldsymbol{t} = \boldsymbol{3}, \ldots, \boldsymbol{T}\ \boldsymbol{and}\ \boldsymbol{s} \geq \boldsymbol{2}$$

$$\boldsymbol{E}\{\Delta \boldsymbol{y}_{\boldsymbol{i},\boldsymbol{s}}(\boldsymbol{y}_{\boldsymbol{i},\boldsymbol{T}} - \boldsymbol{\alpha}\, \boldsymbol{y}_{\boldsymbol{i},\boldsymbol{T}-\boldsymbol{1}} - \boldsymbol{x}'_{\boldsymbol{i},\boldsymbol{T}}\, \boldsymbol{\beta} - \boldsymbol{\mu}_{\boldsymbol{i}})\} = \boldsymbol{0} \quad \boldsymbol{for}\ \boldsymbol{s} = \boldsymbol{2}, \ldots, \boldsymbol{T} - \boldsymbol{1}$$

As per the literature on tourism demand modelling, the econometric model used in this study is specified in double logarithmic form, in which the coefficients are demand elasticities except the coefficient of the dummy variables. Since this study considers the dynamic relationship in the tourism demand function, the long run elasticities also may be computed, by dividing the respective coefficient by the coefficient of the lagged dependent variable; assuming a long run steady-state equilibrium is extant.

The following tourism demand model has been estimated[5] using four different methodologies: pooled OLS estimation, "within" fixed effects estimation – accounts for the heterogeneity across countries by including dummies specific for each country, AB GMM estimation, and sys-GMM estimation.

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[4] As per the Maldives Visitor Survey conducted in February 2018, 22% of international visitors to Maldives in February 2018 were repeat visitors and the highest repeat visitors were from European countries.

[5] All the aforementioned estimations have been computed using R software.

$$
\begin{aligned}
Log\left(Arrivals_{i,t}\right) \\
&= \alpha + \beta_1 Log\left(Arrivals_{i,t-1}\right) + \beta_2 Log\left(GDP_{i,t}\right) + \beta_3 Log\left(Relative\ Price_{i,t}\right) \\
&+ \beta_4 Log\left(Exchange\ Rate_{i,t}\right) + \beta_5 Log\left(Population_{i,t}\right) + \beta_6 Log\left(Distance_{i,t}\right) \\
&+ \beta_7 Tsunami_{2004} + \beta_8 GFC_{2009} + \varepsilon_{i,t}
\end{aligned}
$$

where $Relative\ Price_{i,t}$ is defined as the ratio between the the CPI of Maldives and CPI of tourist generating country *i* in time *t*, $Tsunami_{2004}$ and GFC_{2009} are two dummy variables to account for the adverse impact of Indian Ocean Tsunami in December 2004, and the global financial crisis of 2008/2009 respectively. $Tsunami_{2004}$ is equal to one in the year 2005, and zero otherwise, while GFC_{2009} is equal to one in the year 2009, and zero otherwise. Exchange rate is defined as the bilateral nominal exchange rate between Maldivian currency (Maldivian rufiyaa) and the tourist generating country's domestic currency. $\varepsilon_{i,t}$ is assumed to be a normal, randomly distributed error term, which is identically distributed (IID) with $E(\varepsilon_{i,t})=0$ and $Var(\varepsilon_{i,t})=\sigma^2 \ngeq 0$. Based on theory and literature, we expect the coefficients to have the following signs; β_1, β_2, β_4, and β_5 to be positive, whilst, β_3, β_6, β_7, and β_8 to be negative.

Furthermore, estimation procedures also consider alternative specifications in which the relative prices and exchange rate measures are combined together; as literature on tourism modelling has illustrated that using exchange rates and prices as two different variables in panel data regressions could potentially produce ambiguous results (Dogru, Sirakaya-Turk and Crouch 2017).

Results

Table 2, presents the regressions results of the pooled OLS estimation, as well as the, "within" fixed effects panel estimation. As mentioned above, given the variables are in logarithmic form, the coefficients can be interpreted as demand elasticities.

The pooled OLS estimation results indicates the significance of explanatory variables apart from and in explaining the movements in tourist arrivals; all the significant variables are statistically significant at 1% level. For instance, a 1% increase in GDP per capita of the tourist generating country, is associated with a 0.87% increase the number of tourist arrivals to Maldives. In addition, 1% increase in the population and nominal bilateral exchange rate of tourist generating country corresponds to a 0.41% and 0.05% increase in tourist arrivals to Maldives respectively. Similarly, the results illustrate the significant impact of exchange rate on the demand for tourism. Apart from the significant coefficients, the signs of these coefficients are also consistent with the theory.

The pooled OLS estimation results indicates the significance of explanatory variables apart from $Relative\ Price_{i,t}$ and GFC_{2009} in explaining the movements in tourist arrivals; all the significant variables are statistically significant at 1% level. For instance, a 1% increase in GDP per capita of the tourist generating country, is associated with a 0.87% increase the number of tourist arrivals to Maldives. In addition, 1% increase in the population and nominal bilateral exchange rate of tourist generating country corresponds to a 0.41% and 0.05%

increase in tourist arrivals to Maldives respectively. Similarly, the results illustrate the significant impact of exchange rate on the demand for tourism. Apart from the significant coefficients, the signs of these coefficients are also consistent with the theory.

Table 2: Results from Pooled OLS, "Within" Fixed Effects Model Regressions

	Pooled OLS	"Within" Fixed Effects Model	Expected sign
α	-1.860*** (0.543)	-	
$Log(Arrivals_{i,t-1})$	0.648*** (0.024)	0.155*** (0.021)	(+)
$Log(GDP_{i,t})$	0.865*** (0.073)	2.331*** (0.140)	(+)
$Log(Relative\ Price_{i,t})$	0.120 (0.142)	0.285** (0.114)	(-)
$Log(Exchange\ Rate_{i,t})$	0.047*** (0.013)	0.366*** (0.099)	(+)
$Log(Population_{i,t})$	0.409*** (0.030)	2.453*** (0.369)	(+)
$Log(Distance_{i,t})$	-0.600*** (0.065)	-0.404 (0.469)	(-)
$Tsunami_{2004}$	-0.493*** (0.097)	-0.441*** (0.055)	(-)
GFC_{2009}	-0.086 (0.094)	-0.098* (0.053)	(-)
$Adj.\ R^2$	0.864	0.742	
$Observations$	559	559	
$F\ Statistic$	442.832***	205.698***	

Standard Errors are presented in the round brackets
Significance Levels: *** P < 0.01, ** P < 0.05, * P < 0.1

Despite the statistically significant output generated by the pooled OLS model, theory indicates the importance of using "within" fixed effects estimation when estimating with samples consisting of cross-sectional heterogeneity such as the one utilised in this study. Although the methodologies vary contrastingly, the panel regression results from the fixed effects estimation methodology – which accounts for the country-specific characteristics – support the findings of the pooled OLS model. All coefficients except the coefficient for $Distance_{i,t}$ (contrasting to the pooled OLS estimation) and GFC_{2009} is significant at the 1% level. The demand elasticities obtained illustrates the importance of income, exchange rate, and population in explaining the demand for inbound tourism to Maldives. In addition, the coefficients for dummy variables: $Tsunami_{2004}$ and GFC_{2009}, show the adverse impact of these events on tourist arrivals. Furthermore, almost all signs obtained in this analysis are as expected.

Both the pooled OLS estimation and the "within" fixed effects model, generates a coefficient with a positive sign for $Relative\ Price_{i,t}$. This implies any increase in inflation domestically or a deflation in the tourist generating country, would lead to an influx of tourist arrivals to Maldives, which is contradictory to the literature. This might be a result of biased or inconsistent coefficients of pooled OLS and fixed effects panel regression models when a lag term is introduced to the estimated model.

To address this inconsistencies, the AB GMM estimation and sys-GMM methodology has been utilised in this study. Table 3 present the results of these two approaches. Output from the one-step and the robust AB and sys-GMM has been reported for comparison purpose. The difference between the one-step and two-steps (robust) methodologies are in the computation of the covariance matrix; one-step uses a previously known weighting matrix while the two-steps estimator uses the residuals obtained from the one-step estimate to compute the weighting matrix (Croissant and Millo, 2008).

The Sargan tests the null hypothesis of the validity of instruments used (over-identification) and indicates that the instruments used in AB GMM estimation; lagged values for the differenced equation, and instruments used in sys-GMM; in addition to lagged values, the differenced lag values for equation in levels, are valid instruments. Autocorrelation test statistics in first and second order are displayed by the M1 and M2 statistics. The sys-GMM estimator is consistent if there is no second-order serial correlation (Leitão, 2009), and results indicate the presence of no serial correlation in the second-order for all models.

Analogous to the pooled OLS model and the fixed effects panel regression model, the AB GMM models and the sys-GMM models, produces almost all coefficients with the expected sign. Furthermore, these dynamic models also demonstrate the significance of fidelity amongst tourists visiting to Maldives – lagged dependent variable is significant at 1% significant level in all models. This is of particular interest as this confirms the beliefs among tourism industry; the percentage of repeater tourists is profound in Maldives.

Concentrating the analysis on the coefficients of other explanatory variables indicate, although the sign of $Relative\ Price_{i,t}$ are now in line with theory, the coefficient is still not significant. Moreover, the models illustrate the insignificant impact of exchange rate on tourism, contradicting the findings of the pooled OLS and fixed effects panel regression models. Furthermore, the impact of distance, on tourist arrivals to Maldives seem to be minimal except in the one-step sys-GMM model, contrasting to the results obtained in the pooled OLS. A positive increase in income and population has a significant positive impact on inbound tourism to Maldives in the one-step models, but this significance is absent in the robust models (the sign of the coefficient of income variable in the robust sys-GMM is also negative). Lastly, both the dummy variables: $Tsunami_{2004}$ and GFC_{2009}, are significant at 1% significance level in all the models, indicating the negative shock on tourism due to these events.

One potential issue with the aforementioned model specifications in the computations of AB GMM models and sys-GMM models, is the inclusion of $Exchange\ Rate_{i,t}$ and $Relative\ Price_{i,t}$ (in terms of CPI) as two separate variables. A study by Dogru, Sirakaya-Turk and Crouch (2017), illustrated that using these two variables as mutually exclusive variables produce equivocal results. This is because any differences in the inflation rate

Table 3: Results from Arellano-Bond GMM and Blundell-Bond GMM estimations

	Arellano-Bond (AB) GMM		Blundell-Bond GMM (sys-GMM)		Expected sign
	One-Step	Robust	One-Step	Robust	
$Log(Arrivals_{i,t-1})$	0.597*** (0.063)	0.608*** (0.085)	0.878*** (0.020)	0.831*** (0.080)	(+)
$Log(GDP_{i,t})$	0.875*** (0.289)	0.616 (0.535)	0.220*** (0.049)	-0.043 (0.507)	(+)
$Log(Relative\ Price_{i,t})$	-0.028 (0.130)	-0.102 (0.219)	-0.085 (0.074)	-0.197 (0.190)	(-)
$Log(Exchange\ Rate_{i,t})$	0.076 (0.079)	0.118 (0.118)	0.011 (0.010)	0.043 (0.076)	(+)
$Log(Population_{i,t})$	1.492** (0.615)	2.097 (1.695)	0.121*** (0.025)	1.593 (2.128)	(+)
$Log(Distance_{i,t})$	-0.244* (0.127)	0.076 (1.084)	-0.165*** (-0.050)	-0.414 (0.387)	(-)
$Tsunami_{2004}$	-0.559*** (0.049)	-0.535*** (0.058)	-0.608*** (0.051)	-0.610*** (0.061)	(-)
GFC_{2009}	-0.165*** (0.026)	-0.178*** (0.038)	-0.187*** (0.023)	-0.195*** (0.031)	(-)
$Sargan\ Test$	35.000 [1.000]	32.297 [1.000]	35.000 [1.000]	31.827 [1.000]	
$M1$	-3.461 [0.000]	-3.434 [0.000]	-3.831 [0.000]	-3.619 [0.000]	
$M2$	0.042 [0.966]	0.016 [0.987]	-0.678 [0.498]	-0.390 [0.697]	

Standard Errors are presented in the round brackets.
Significance Levels: *** P < 0.01, ** P < 0.05, * P < 0.1
P values are in square brackets.
Sargan test is a test of over-identifying restrictions, asymptotically distributed as χ^2 under the null of the instruments validity.
M1 and M2 are tests for first-order and second-order serial correlation in the first differenced residuals, asymptotically distributed as $\mathbf{N}(\mathbf{0}, \mathbf{1})$ under the null hypothesis of no serial correlation.

could be offset by the exchange rate and vice versa causing multicollinearity problems in the econometric model (Dogru, Sirakaya-Turk and Crouch, 2017). Hence, it is recommended to use prices standardised by exchange rates, as a single measure to proxy for relative price level. As such, this research uses the following variable to replace the relative price level and exchange rate variable in the dynamic panel regressions above. Table 4 presents the results of this analysis.

$$Price\ Level_{i,t} = Relative\ Price_{i,t} \times \left(\frac{1}{Exchange\ Rate_{i,t}}\right)$$

Table 4: Results from Augmented Arellano-Bond GMM and Blundell-Bond GMM estimations (One step and Robust)

	Arellano-Bond GMM		Blundell-Bond GMM		Expected sign
	One-Step	Robust	One-Step	Robust	
$Log(Arrivals_{i,t-1})$	0.602*** (0.062)	0.612*** (0.083)	0.868*** (0.021)	0.835*** (0.077)	(+)
$Log(GDP_{i,t})$	0.888*** (0.271)	0.659 (0.499)	0.203*** (0.054)	0.086 (0.455)	(+)
$Log(Price\ Level_{i,t})$	-0.061 (0.076)	-0.106 (0.111)	-0.022* (0.014)	-0.056 (0.078)	(-)
$Log(Population_{i,t})$	1.493*** (0.560)	1.933 (1.330)	0.143*** (0.029)	0.887 (1.719)	(+)
$Log(Distance_{i,t})$	-0.275* (0.144)	0.094 (0.945)	-0.147** (0.060)	-0.283 (0.323)	(-)
$Tsunami_{2004}$	-0.563*** (0.046)	-0.536*** (0.056)	-0.600*** (0.049)	-0.599*** (0.060)	(-)
GFC_{2009}	-0.167*** (0.025)	-0.176*** (0.034)	-0.183*** (0.024)	-0.188*** (0.030)	(-)
$Sargan\ Test$	35.000 [1.000]	32.330 [1.000]	35.000 [1.000]	32.522 [1.000]	
$M1$	-3.449 [0.001]	-3.449 [0.000]	-3.720 [0.000]	-3.700 [0.000]	
$M2$	0.066 [0.947]	-0.003 [0.998]	-0.675 [0.499]	-0.556 [0.578]	

Standard Errors are presented in the round brackets.
***/**/* - statistically significant at the 1%, 5%, and 10% levels.
P values are in square brackets.
Sargan test is a test of over-identifying restrictions, asymptotically distributed as χ^2 under the null of the instruments validity.
M1 and M2 are tests for first-order and second-order serial correlation in the first differenced residuals, asymptotically distributed as $N(0, 1)$ under the null hypothesis of no serial correlation.

Similar to the GMM models which used the mutually exclusive variables for prices and exchange rates, the GMM models with an augmented measure for relative prices, pass the diagnostic tests. The Sargan test and the serial correlations tests illustrate the validity of the instruments, as well as the presence of no serial correlation in the second-order respectively.

The one-step AB GMM model and the one-step sys-GMM model produces coefficients which are highly significant, outperforming the previously discussed models. In particular the one-step sys-GMM model produces coefficients which are significant at 1% significance level for all coefficients except for the combined price measure and distance variable which are significant at 10% level and 5% significant level respectively. The one-step sys-GMM approach suggests that a 1% increase in income, is associated with a 0.20% increase in tourist arrivals to Maldives, while distance which proxies for travel expenses has a significant negative impact on inbound tourism. The results also indicate the role of population as a substantial determinant of tourism.

Although, moving towards the robust GMM models, decrease the significance of the coefficients, the signs of these coefficients do not change (except for coefficient of distance in AB model) and are as intuited by the literature and theory. One stark result is the significance of lagged dependent variable in all the augmented estimation techniques; the importance of repeater tourists for the tourism industry in Maldives. In addition, akin to the previous GMM models, the augmented models also present significant coefficients for the dummy variables: $Tsunami_{2004}$ and GFC_{2009}.

Conclusion

This study analyses the inbound tourism demand in Maldives, by employing various econometric models. As theory indicates, the Blundell-Bond system GMM model (sys-GMM) outperforms the Arellano-Bond (AB) GMM model, the "within" fixed effects panel regression model and the pooled OLS model, due to the shortcomings in the latter models. The pooled OLS model cannot be used for samples that exhibit large cross-sectional heterogeneity, while both the pooled OLS model and the fixed effects panel regression model are not immune to multicollinearity issues. Furthermore, AB GMM model may yield inconsistent and biased parameter estimates in small samples.

In general, the results of these methodologies indicate the high degree of habit persistence amongst the tourists visiting Maldives; tourists are more likely to be repeat visitors to Maldives. Given this high fidelity, the tourism should prioritise customer satisfaction, to encourage tourists to visit Maldives multiple times. In addition to this, variables such as income, and population are significant determinants of number of tourist arrivals. Although distance between countries have been used as a simple yet weak proxy for travel expenses incurred by tourists, analysis illustrates the negative impact of distance on tourism demand for Maldives. Apart from this, the significant events which occurred during the investigated sample period (2001-2016), such as the Tsunami in 2004 and the global financial crisis in 2008/2009, have had a substantial negative impact on the number of tourist arrivals.

While initial analysis of this paper concentrated on untangling the impact of relative prices incurred by tourists and the impact of changes in bilateral exchange rates separately, the results implied the presence of multicollinearity in such model, as these two explanatory variables lacked significance in the regression results. To account for this collinear behaviour of relative prices and exchange rates, the two measures were combined, and the GMM models were recomputed. Despite the results of the augmented models indicating, the rise in relative prices in Maldives, will dissuade tourists from visiting to Maldives, the significance of this effect is negligible. This maybe because the computations of prices in this study involve the usage of CPI, which does not reflect the prices normally incurred by tourists. In particular, given the tourism sector in Maldives is dominated by the resort industry - who typically set their prices distinct to the prices charged for locals - CPI will be a misleading measure of the relative prices experienced by tourists (Riza and King, 2010). Future studies could potentially seek a solution to this issue; by computing a measure for relative prices that reflect the prices charged for tourists in Maldives[6].

[6] Riza and King (2010) construct a variable called PDL, by collecting price data on accommodation and meal prices from resorts.

Potential limitations of this research include the use of arrivals as a dependent variable, and the lack of control variables to account for the marketing efforts of the tourism industry. Average duration of stay or expenditure of tourists by nations possibly will be better demand indicators. However, in the absence of such data, total arrivals from each country can be viewed as an appropriate alternative. As few studies in the tourism demand literature have incorporated marketing effort variables, such as expenditure on marketing by the government in certain destinations, future work can study the impact of marketing on the tourism demand dynamics using such variables.

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