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# New Evidence of Dynamic Links between Tourism and Economic Growth based on Mixed-frequency Granger Causality Tests

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**Abstract**

The relationship between tourism and economic growth has created a large body of literature investigating the hypotheses of tourism-led economic growth (TLEGH) and economic-driven tourism growth (EDTGH). In this paper, we use mixed-frequency Granger causality tests to investigate the relationship between the two types of growth in Hong Kong from 1974 to 2016. Our analysis reveals the following empirical regularities. First, the hidden short-run causality of TLEGH is detected, and EDTGH is proved in the short run and also in the long run when Granger causality tests are performed in a mixed-frequency framework. Second, mixed-frequency Granger tests demonstrate more power in testing the TLEGH and EDTGH via the rejection frequencies (bootstrap p-value). Finally, rolling Granger causality tests reveal an unstable relationship between tourism and economic growth in both magnitude and direction, and the relationship is highly economic- and tourism-event-dependent.

***Keywords***: Tourism-led growth, econometric model, mixed-frequency time series, Granger causality tests

## 1. Introduction

Tourism has been one of the fastest-growing economic activities over the past six decades. It has grown virtually uninterrupted over time despite occasional shocks, demonstrating the strength and resilience of the sector. Tourism has thus become a key driver of socioeconomic progress through the creation of jobs and enterprises, export revenues, and infrastructure development (Parrilla, Font, and Nadal 2007). According to the latest statistical data from the World Tourism Organization (UNWTO), international tourist arrivals are now 47 times higher than they were 60 years ago, growing from 25 million in 1950 to 1.18 billion in 2015, with related revenue reaching US$1.26 trillion in 2015, a 630-fold increase over the US$2 billion recorded in 1950 (UNWTO 2016).

The expansion of tourism is generally seen to have a positive relationship with economic growth as it generates jobs, tourism-related investment and consumption, foreign exchange earnings, and tax revenues, although they may also negatively affect the economy due to the crowding out effect. Tourism affects a host country's economy in three ways (Khan, Seng, and Cheong 1990; Bilen, Yilanci, and Eryuzlu 2017; Meng and Siriwardana 2016). First, it makes a direct contribution: the initial injection of tourist spending creates direct revenues for airlines, travel agents, hotels, shops, restaurants, and other tourist facilities. Second, it has an indirect effect: the additional revenue to businesses and firms supplying necessary inputs generated by the recipients of direct tourist expenditures. Finally, the beneficiaries of these direct and indirect effects spend their increased income on consumption or investment goods, which in turn generates successive rounds of purchases by the supplying sectors and further induced consumption. This is referred to as the total contribution. According to the latest annual report of the World Travel and Tourism Council (WTTC), the tourism sector directly contributed US$2.22 trillion and ultimately contributed US$7.17 trillion to global GDP (3.0% and 9.8% respectively), and directly supported more than 107 million jobs (3.6% of total employment) in 2015 (WTTC 2016b). The tourism sector is also very important to the Hong Kong economy. In 2015 the combined direct GDP contribution of travel and tourism was HK$194.0 billion (8.0% of total GDP), providing over 328,000 jobs (8.8% of total employment), and the total contribution was HK$469.9 billion (19.5% of GDP), accounting for 17.7% of total employment (WTTC 2016a).

Tourism has long been and remains the essential bedrock of Hong Kong's economy. In general, tourist expenditure can be viewed as both the export of host country goods and services and as expenditure by nonresidents. Thus, travel expenditure records can be captured in national accounts relating to private consumption expenditure by nonresidents and in balance of payment accounts (Heng and Low 1990; Lee and Chang 2008; Castro-Nuño, Molina-Toucedo, and Pablo-Romero 2013; Meng and Siriwardana 2016). Employment levels, public sector revenue, and balance of payments all benefit from tourism receipts, and tourism also generates a healthy flow of foreign currency (Archer 1995; Seetanah 2011; Tribe 2015).

Over the years, Hong Kong has managed to expand inbound tourism even though it offers relatively few natural attractions. Business travelers generally account for a relatively small proportion of total visitor arrivals, and more than 80% of visitors are tourists, transit passengers, or visitors to friends and relatives from mainland China. Thus, local tourism policy and local people's attitudes toward mainland China are likely to influence total visitor arrivals. Recently, Hong Kong's high-cost structure, declining competitiveness, and perceived decline in value for money have led to a fall in visitor numbers and a reduction in real tourism receipts. Jin (2011) suggests that the local tourism sector needs to improve its service-related technology (including management and marketing skills) to attract more overseas tourists. Such improvements would lower transportation costs and increase efficiency in the service sector.

As various sectors in an economy are usually interrelated, changes in tourism expenditure tend to have a magnified effect on the economy. The magnitude of the total effect depends on the strength of the links between various sectors or industries such as tourism, domestic suppliers, and the import sector (Khan, Seng, and Cheong 1990). From the theoretical perspective, international tourism is regarded as a non-standard type of export because it involves a source of receipts and consumption in situ (Brida, Cortes-Jimenez, and Pulina 2016). Hence, there has been a proliferation of empirical studies testing the tourism-led economic growth hypothesis (TLEGH), which is analogous to the export-led growth hypothesis, in addition to analyses of the possible temporal relationship between tourism and economic growth, which is considered a key research area in the field of tourism economics (Song et al. 2012). Empirical tests of the TLEGH, the economic-driven tourism growth hypothesis (EDTGH), and the bidirectional relationship between tourism and economic growth have commonly involved the Granger causality test (Granger 1969) or its extension, particularly since the study by Balaguer and Cantavella-Jordá (2002). There are several comprehensive surveys of the relationship between tourism and economic growth (Castro-Nuño, Molina-Toucedo, and Pablo-Romero 2013; Pablo-Romero and Molina 2013; Brida, Cortes-Jimenez, and Pulina 2016). However, the results of recent studies concerning the direction of causality between tourism and economic growth appear to be sensitive to the countries analyzed, the sample period and the methodology adopted (Balcilar et al. 2014). Some empirical studies of various countries and regions support the TLEGH (Katircioglu 2009; Balaguer and Cantavella-Jordá 2002), some support the EDTGH (Lee 2008; Tang and Jang 2009; Payne and Mervar 2010; Oh 2005), and some support both (Lee and Chang 2008; Kim, Chen, and Jang 2006; Dritsakis 2012). One empirical study even proposes that there is no causal relationship between tourism and economic growth (Ozturk and Acaravci 2009).

Time-series data on tourism and economic growth in Hong Kong and elsewhere can be sampled at different frequencies (e.g., monthly tourism demand or quarterly GDP), whereas traditional time-series causality tests are designed for single-frequency data. Temporal aggregations are generally used to change high-frequency variables into the lowest common frequency. However, temporal aggregation can introduce spurious effects when testing for Granger causality, as a number of papers have noted (Zellner and Montmarquette 1971; Amemiya and Roland 1972; Granger 1980; Granger 1988). Zellner and Montmarquette (1971) suggest that policy decisions based on results marred by temporal aggregation effects often produce poor results. Temporal aggregation can lead to poorer estimation and prediction precision, lower test power, inability to make short-run forecasts, and reduced likelihood of discovering new hypotheses about short-run behavior. Breitung and Swanson (2002) examine the impact of temporal aggregation on Granger causal relations in vector autoregressions (VARs) and find that the causality issue is muddled once the data are aggregated. Hence, if data were observed at intervals in which the dynamics were not working properly, no causality would be observed. How then can we exploit all available data whatever their sampling frequencies? One approach to resolving the problem of evaluating the mixed-frequency relationship between tourism and economic growth is to use mixed-frequency Granger causality tests (MFGCT), which Ghysels, Hill, and Motegi (2016) develop and prove to have a higher degree of local asymptotic power and more power in finite samples relative to conventional tests.

Studies have addressed the causal relationship between tourism and economic growth, but the findings have been mixed. In addition, a small number of studies have explored the temporal aggregation problem in the Granger causality tests. However, to the best of our knowledge, no studies to date (including those in Hong Kong) have examined the temporal aggregation problem in the relationship between tourism and economic growth in a mixed-data frequency framework.

The major aim of this study is to empirically test the short- and long-run causal relationship between tourism and economic growth under a mixed-frequency framework. The second objective is to investigate whether the MFGCT of TLEGH and EDTGH hold for Hong Kong over time. The final objective is to compare the mixed- and low-frequency Granger causality test results when applied to the TLEG hypothesis.

The present study contributes to the literature in at least three ways. First, it is the first study to analyze the temporal causal relationship between tourism and economic growth under a mixed-frequency framework. Second, it examines the short- and long-run causal relationship between tourism and economic growth in the Hong Kong context. Third, the stability of Granger causality tests has been questioned due to the time-varying nature of the TLEG hypothesis. We address this issue using rolling mixed- and low-frequency Granger causality tests under a time-varying framework.

This study assesses the temporal Granger causality between tourism and economic growth in Hong Kong using monthly tourism arrival data from January 1973 to January 2016 and quarterly GDP data from 1973:Q1 to 2016:Q1. To avoid the spuriously hidden or generated causality problem, a bivariate mixed-frequency-VAR (MF-VAR) model is used to determine the temporal causal relationship between tourism and economic growth in Hong Kong. We then apply the modified Wald causality approach together with the bootstrap simulation approach to verify the direction of causality. In addition, we examine the stability of the TLEGH and EDTGH by incorporating the rolling regression technique. Our empirical results are thus robust and reliable for policymaking purposes.

The remainder of the paper is organized as follows. Section 2 discusses the econometric methods adopted. Section 3 presents the empirical results, and Section 4 offers concluding remarks.

## 2. Methodology and data description

### 2.1 Mixed-frequency VAR model and Granger causality test

This study adopts the MF-VAR model proposed by **Ghysels (2016)** to examine the relationship between monthly visitor arrivals (VA) and quarterly GDP. The MF-VAR model is an observation-driven model that directly relates to standard VAR model settings, and is suitable for exploiting Granger causality tests. We begin our empirical framework by specifying the following MF-VAR(*p*) model.

$$\underbrace{\begin{bmatrix} \mathbf{VA}(\tau,1) \\ \vdots \\ \mathbf{VA}(\tau,m) \\ \mathbf{GDP}(\tau) \end{bmatrix}}_{\mathbf{X}(\tau)} = \sum_{k=1}^{p} \underbrace{\begin{bmatrix} A_{HH,k} & a_{HL,k} \\ a_{LH,k} & a_{LL,k} \end{bmatrix}}_{\mathbf{A}_K} \underbrace{\begin{bmatrix} \mathbf{VA}(\tau-k,1) \\ \vdots \\ \mathbf{VA}(\tau-k,m) \\ \mathbf{GDP}(\tau-k) \end{bmatrix}}_{\mathbf{X}(\tau-k)} + \boldsymbol{\varepsilon}(\tau), \tag{1}$$

where $VA(\tau,1)$ denotes the first month of Hong Kong inbound VA in quarter $\tau$, $VA(\tau,m)$ is the last month of VA in quarter $\tau$, $m=3$ for the mixed frequency of monthly and quarterly data, and $GDP(\tau)$ denotes real GDP in quarter $\tau$. In each low-frequency quarterly period $\tau$, we sequentially observe monthly data $VA(\tau,1)$, $VA(\tau,2)$, and $VA(\tau,3)$. Rather than working on aggregate monthly data, we stack all of the monthly observations in each quarterly period $\tau$ to obtain $\mathbf{X}(\tau)=[\mathbf{VA}(\tau,1)', \mathbf{VA}(\tau,\ 2)', \mathbf{VA}(\tau,\ m)', \mathbf{GDP}(\tau)']'$. The MF-VAR(*p*) model can then be written as

$$\mathbf{X}(\tau) = \sum_{k=1}^{p} \mathbf{A}_k \mathbf{X}(\tau-k) + \boldsymbol{\varepsilon}(\tau)\,. \tag{2}$$

To investigate the long-run Granger causality between tourism and economic growth, we iterate (2) over the desired test horizon *h*, and the result is the following MF-VAR(*p*, *h*) model:

$$\mathbf{X}(\tau+h) = \sum_{k=1}^{p} \mathbf{A}_k^{(h)} \mathbf{X}(\tau+1-k) + \boldsymbol{\xi}^{(h)}(\tau)\,, \tag{3}$$

where $\mathbf{A}_k^{(1)} = \mathbf{A}_k$ , $\mathbf{A}_k^{(i)} = \mathbf{A}_{k+i-1} + \sum_{l=1}^{i-1} \mathbf{A}_{i-l}\mathbf{A}_k^{(l)}$ ( $i \geq 2$ ), $\boldsymbol{\xi}^{(h)}(\tau_L) = \sum_{k=0}^{h-1} \boldsymbol{\psi}_k \boldsymbol{\varepsilon}(\tau_L - k)$ , and, by convention, $\mathbf{A}_k^{(1)} = \mathbf{0}_{k\times k}$ whenever $k > p$ .

MFGCT exploit Wald statistics based on the coefficients of MF-VAR(*p*, *h*), $\mathbf{B}(h) = [\mathbf{A}_1^{(h)},...,\mathbf{A}_p^{(h)}]'$ . Here, we test two types of non-causality from one single variable to another. For example, **VA** does not Granger-cause **GDP** given a mixed-frequency information set equal to $a_{LH,1} = a_{LH,2} = \cdots = a_{LH,p} = 0_{1\times m}$ , whereas **GDP** does not Granger-cause **VA** given a mixed-frequency information set equal to $a_{HL,1} = a_{HL,2} = \cdots = a_{HL,p} = 0_{m\times 1}$ . Hence, the null hypothesis of interest is a linear restriction:

$$H_0(h) : \mathbf{R}\text{vec}[\mathbf{B}(h)] = \mathbf{r} , \tag{4}$$

where $\mathbf{R}$ is a $q \times pK^2$ selection matrix of full row rank *q*. The complete details of the construction of $\mathbf{R}$ can be found in Ghysels, Hill, and Motegi (2016). $\mathbf{r}$ is a restricted vector, and zeros are always chosen when performing Granger causality tests. Thus, the null hypothesis of MFGCT can be tested via the following Wald statistic:

$$W_{T_L^*}[H_0(h)] \equiv T_L^* \left(\mathbf{R}vec[\hat{\mathbf{B}}(h)] - \mathbf{r}\right)' \times \left(\mathbf{R}\hat{\boldsymbol{\Sigma}}_p(h)\mathbf{R}'\right) \times \left(\mathbf{R}vec[\hat{\mathbf{B}}(h)] - \mathbf{r}\right), \tag{5}$$

where $T_L^* = T_L - h + 1$ is the effective sample size of the MF-VAR(*p*, *h*) model, $\hat{\mathbf{B}}(h)$ is the least squares estimator of the MF-VAR(*p*, *h*) model, $\hat{\boldsymbol{\Sigma}}_p(h)$ is the positive-definite covariance with the assumptions proposed by Ghysels, Hill, and Motegi (2016), and $W_{T_L^*}[H_0(h)] \xrightarrow{d} \chi_q^2$ under $H_0(h)$.

Finally, we use the parametric bootstrap method (Dufour, Pelletier, and Renault 2006) to compute the resulting *p*-value of (5), which is defined as

$$\hat{p}_N\left(W_{T_L^*}[H_0(h)]\right) = \frac{1}{N+1}\left(1 + \sum_{i=1}^{N} I\left(W_i[H_0(h)] \geq W_{T_L^*}[H_0(h)]\right)\right). \tag{6}$$

The null hypothesis is rejected at level α if $\hat{p}_N\left(W_{T_L^*}[H_0(h)]\right) \leq \alpha$ . In this study, we bootstrap the *p*-value with $N = 999$ replications (Gonçalves and Kilian 2004).

**2.2 Data**

We use 100× annual log-differences of monthly Hong Kong VA from January 1973 to March 2016 and quarterly real GDP from 1973:Q1 to 2016:Q1 for the MF-VAR modeling and to perform MFGCT. The value of real output is derived from quarterly real GDP data deflated by the price level in 2010, which were downloaded from the Hong Kong SAR Government's Census and Statistics Department website. VA in Hong Kong are used as a proxy for inbound tourism, and are taken from the Hong Kong Tourism Board's annual statistical reviews.

Figure 1 plots the two series and shows a fairly strong correlation between VAg and GDPg in Hong Kong, with the former considerably more volatile than the latter. We can also see from the figure that VA in Hong Kong are sensitive to political and economic shocks and one-off events (Jin 2011) and that economic growth also suffers from such shocks. For example, the number of tourist arrivals in Hong Kong decreased noticeably after the June 1989 Tiananmen Square protests in Beijing, and GDP growth also declined at the same time. A more serious drop can be seen after the handover of sovereignty from the United Kingdom to China in July 1997, and that drop was further magnified and prolonged by the Asian financial crisis (1997–1998), with the influence of economic growth lasting longer than that of VA growth. Another severe decline occurred during the SARS epidemic (winter 2002–spring 2003), and the meager number of arrivals in May 2003 set a record in the Hong Kong tourism history. However, the decline in real GDP growth rate was not as deep as that in tourism growth. The latest significant decrease in VA occurred during the international financial crisis of 2008–2009. The effect on economic growth was much more significant than the effect on tourism growth, but they followed the same trend.

————————— **Figure 1 about here** —————————

Table 1 presents the sample statistics, including sample standard deviations of 16.245% for VAg and 4.709% for GDPg. As VAg and GDPg have positive sample means of 9% and 5.11%, respectively, we demean each series and fit the MF-VAR model without a constant term. The sample kurtosis is 26.873 for VAg and 3.536 for GDPg. The J-B statistic suggests that VAg follows a non-normal distribution, whereas GDPg does not. Ghysels, Hill, and Motegi (2016) note that the asymptotic theory of MFGCT is free of the normality assumption.

————————— **Table 1 about here** —————————

## 3. Empirical Results

Several studies investigate the relationship between tourism and economic growth in Hong Kong (Jin 2011; Kwong 1997; Khan, Seng, and Cheong 1990). However, to the best of our knowledge, the TLEGH and EDTGH have not been formally tested in the Hong Kong context, although Jin (2011) uses a five-variable VAR model to show that tourism exerts a positive short-run effect on Hong Kong's economic growth.

The first task when modeling MF-VAR is to choose a suitable lag order. Ghysels, Hill, and Motegi (2016) choose lag 1 for a tri-variable MF-VAR model, and argue that including redundant lags would have a large adverse effect on power (particularly for a longer prediction horizon *h*). We use five information criteria to select the optimal lag order. The results presented in Table 2 show that the optimal lag order varies with differing maximum lag orders, except that the Schwarz information criterion (SC) always chooses lag 1, and the Hannan-Quinn information criterion (HQ) and corrected Akaike information criterion (AICc) (Hurvich and Tsai 1989) choose lag 1 when the maximum lags are under four and lag 4 otherwise.

**—————————— Table 2 about here ——————————**

### 3.1 Mixed-frequency versus low-frequency Granger causality in the short and long run

To investigate the influence of lag order and horizon (Dufour, Pelletier, and Renault 2006); (Dufour and Taamouti 2010) on the MFGCT, we choose $p \in \{1, 2, 3, 4\}$ and $h \in \{1, 2, 3, 4, 8, 12, 20\}$ to model the MF-VAR model and test the mixed-frequency Granger causality between tourism and economic growth in Hong Kong. For comparison purposes, we also fit an unrestricted low-frequency VAR (LF-VAR) model with the same lag orders and horizons as those in the MF-VAR model. The Granger causality test results for both the MF-VAR and LF-VAR models are reported in Table 3.

—————————— **Table 3 about here** ——————————

Table 3 reports the Wald statistic values and the bootstrapped p-values for the mixed- and low-frequency Granger causality tests at each lag order $p \in \{1, 2, 3, 4\}$ and each quarterly horizon $h \in \{1, 2, 3, 4, 8, 12, 20\}$. We consider whether rejection occurs at the 5% and 10% levels, and find that the results of the two sets of tests suggest rather different conclusions. The MFGCT results in Panel A of Table 2, for instance, reveal a bi-directional causality in the short run, and only the is EDTGH supported in the long run, regardless of whether the 5% or 10% level is used. The low-frequency Granger causality test (LFGCT) results in Panel B show only unidirectional causality running from economic growth to tourism in the short run, and no Granger causality between the two in the long run, regardless of whether the 5% or 10% level is used. Note that the significant causality of the TLEGH is found using the low-frequency approach only if the 10% level is used in the LF-VAR(4,1) model.

Our results suggest that the MFGCT produces more intuitive results, with the LFGCT too coarse to capture short-run TLEG and long-run EDTG. The difference between the MFGCT and LFGCT is probably caused by temporal aggregation based on the results in Panels A and B of Table 2. The use of a mixed-frequency methodology has considerable influence on the empirical study of the Granger causality between tourism and economic growth.

### 3.2 Time-varying Granger causality tests

The Granger causality analysis reported thus far is carried out on the full sample with the assumption that the relationship between tourism and economic growth is stable over the sample period. However, there is a lack of consensus on that relationship on both theoretical and empirical grounds (Antonakakis, Dragouni, and Filis 2015). Several studies investigate the stability of the link between tourism and economic growth (Antonakakis, Dragouni, and Filis 2015; Arslanturk, Balcilar, and Ozdemir 2011; Balcilar et al. 2014; Lean and Tang 2010; Tang, Lai, and Ozturk 2015; Tang and Tan 2013; Wu et al. 2016) and report different results, although all mention that the reasons for an unstable link are related to changes in economic and tourism conditions.

We set a rolling window size of 40 quarters for both the MFGCT and LFGCT to extend our study to subsample causality analysis because Hong Kong VA are known to be sensitive to political and economic shocks (Jin 2011). In our time-varying causality analysis of the link between tourism and economic growth, we use the MF-VAR(1,1) and LF-VAR(1,1) models to compare the stability of that link. The *p*-values for all rolling Granger causality tests for $H_0 : \mathrm{VA}g \nrightarrow \mathrm{GDP}g$ and $H_0 : \mathrm{GDP}g \nrightarrow \mathrm{VA}g$ ($\nrightarrow$ means "does not Granger cause") are given in Figures 2 and 3, respectively. Note that the *p*-values at time *t* in both figures are calculated by the most recent 40-quarter subsample because the rolling window size is 40 quarters. For example, the first *p*-value at 1983:Q4 is obtained using the subsample from 1974:Q1 to 1983:Q4. The last p-value of the Wald statistic at 2016:Q1 is then calculated using the subsample from 2007:Q2 to 2016:Q1.

——————— **Figure 2 is about here** ———————

Table 3 shows that neither the MF-VAR(1,1) nor LF-VAR(1,1) model support unidirectional causality running from tourist arrivals to economic growth for the full sample. However, Figure 2 shows that the rolling Granger causality test results for $H_0: \mathrm{VA}g \nrightarrow \mathrm{GDP}g$ are valid and persistent over certain subsamples, particularly the period around the handover (1996–2003) and the post-international financial crisis period (2008–2013). Furthermore, the MF-VAR(1,1) model significantly rejects the null hypothesis for 1984:Q1 to 1985:Q1 and 1985:Q4 to 1987:Q4, whereas the LF-VAR(1,1) model does not. The rejection frequencies at different significance levels for the 130 rolling Granger causality tests are shown in Table 4. The results show that the MF-VAR(1,1) model has more power than the LF-VAR(1,1) model in testing Granger causality at the 5% and 10% significance levels, whereas the reverse is true at the 1% significance level.

However, significant causality in the direction of VA to economic growth in the subsamples not only implies the positive effect of TLEG, but also points to the adverse effect that a decline in tourism growth can have. Hence, TLEG is not the best way to express the unidirectional causality running from tourism arrivals to economic growth. Examining the contribution of tourism to temporal forecasts of economic growth would be a better way to consider the relationship in the subsamples.

**———————— Figure 2 and Table 4 about here ————————**

Figure 3 presents the rolling Granger causality test results for $H_0: \mathrm{VA}g \nrightarrow \mathrm{GDP}g$. The null hypothesis of EDTGH is rejected from 1989:Q4 to 1996:Q1 for both MFGCT and LFGCT, whereas the LF-VAR(1,1) model significantly rejects the null hypothesis from 2009:Q1 to 2013:Q4 and the LF-VAR (1,1) model does not. Moreover, the rejection frequencies at different significance levels for the 130 rolling Granger causality tests of

EDTGH show that the LF-VAR(1,1) model has more power than the MF-VAR(1,1) model in testing Granger causality at the 1%, 5%, and 10% significance levels. Taken together, the results in Figure 3 and Table 4 indicate that the LF-VAR(1,1) model is more powerful than the MF-VAR(1,1) model in testing the unidirectional causality running from economic growth to tourism arrivals at 1%, 5%, and 10% significance levels. These results differ from the conclusion in Ghysels, Hill, and Motegi (2016) that the results of MFGCT are more powerful.

—————————— **Figure 3 about here** ——————————

**4. Conclusion**

In this paper we report the results of a study investigating the link between the growth in VA and the real GDP growth rate in Hong Kong using MFGCT. Temporal aggregation in Granger causality tests is an important yet often overlooked problem that can generate spurious and hidden effects. We demonstrate that MFGCT can address this limitation and exploit all available data whatever their sampling frequency. These tests also have a higher degree of local asymptotic power than current single-frequency tests.

The empirical results of MFGCT show that the tests support bidirectional causality between tourism and economic growth in the short run, whereas the EDTGH is supported in long-run causality tests carried out in a mixed-frequency framework. The short-run bidirectional causality result is consistent with the conventional view that economic growth may be caused by an increase in tourism-related investment and employment in the short run, but also that international tourism demand may be enhanced by the expansion of economic growth as a result of increased consumer income levels. At the same time, the confirmation of the long-run EDTGH suggests that changes in technology and long-run investment in the economy have a significant causal influence on tourism development. These findings are important for policymakers: they indicate that more resources should be allocated to the tourism industry because it has both short- and long-run effects on economic growth.

The LFGCT results suggest only unidirectional causality running from economic growth to tourism in the short run at the 5% significance level, and no Granger causality between them in the long run. The different results produced by the MFGCT and LFGCT are probably caused by temporal aggregation. In addition, the latter is too coarse to capture short-run TLEG and long-run EDTG. One implication of the results is that the temporal aggregation effect should not be ignored in future research. For instance, studies could include very high frequency data in the model to discover very short-run relationships between tourism and economic growth.

As both sample size and sample period are known to affect the reliability of Granger causality tests, we also carry out rolling mixed- and low-frequency Granger causality tests to further investigate the stability of the tourism-economic growth link in various subsamples, leading to three conclusions. First, the relationship between VA and economic growth in Hong Kong is not stable over time. Second, the total rejection frequencies at different significance levels for the 130 rolling Granger causality tests show that the MFGCT is more powerful than the LFGCT in testing Granger causality at the 5% and 10% significance levels, although the reverse is true at the 1% significance level. Third, LFGCT are more powerful than MFGCT when testing the unidirectional causality running from economic growth to tourism arrivals, a conclusion that differs from that of Ghysels, Hill, and Motegi (2016). The time-varying relationship between tourism and economic growth suggests that strategic planning and policymaking in the tourism sector needs to be flexible and consider the changing character of the tourism-economic growth relationship. Policymakers should therefore closely monitor and forecast tourism demand and economic growth in Hong Kong, as the causal relationship between the two varies over time. For instance, policymakers could reduce the volatility of tourism demand with timely planning of human and capital resources in the tourism sector, which would counter the effect of the business cycle in the economy.

The use of a mixed-frequency methodology has considerable implications for empirical studies of the Granger causality between tourism and economic growth. In this study, we focus only on Hong Kong when we test the causal relationships between tourism and economic growth, as tourism is one of the four pillar industries in Hong Kong and has played an important role in the economy. This focus on one particular economy raises the issue of generalizability. The authors intend to extend the study into other regions/countries with a view to generalizing their research findings.

In the context of both the TLEGH and EDTGH, Granger causality indicates not only a positive link between tourism and economic growth, but also the adverse effects of one on the other. Thus, the best way to express the causality between tourist arrivals and economic growth is to state that tourism (economic growth) contributes to temporal forecasts of economic growth (tourism).

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**Table 1**

*Descriptive Statistics.*

| Variable | Obs | Mean | Std. dev. | Max. | Min. | Skewness | Kurtosis | J-B (Probability) |
|---|---|---|---|---|---|---|---|---|
| VAg | 507 | 9.000 | 16.245 | 137.770 | -113.724 | -0.090 | 26.873 | 12040.53 (0.000)*** |
| GDPg | 169 | 5.110 | 4.709 | 18.649 | -8.631 | -0.026 | 3.536 | 2.04 (0.360) |

*Notes*: VAg and GDPg denote 100× annual log-difference of monthly Hong Kong inbound visitor arrivals and quarterly Hong Kong real GDP, respectively. The sample period is January 1973 to March 2016 for monthly data and 1973:Q1 to 2016:Q1 for quarterly data.

**Table 2**

*Optimal VAR Lag Order Selected by Different Criteria.*

| Max Lag | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LR | 1 | 2 | 3 | 4 | 5 | 5 | 5 | 8 | 8 | 8 | 11 | 11 |
| FPE | 1 | 1 | 3 | 4 | 5 | 5 | 5 | 8 | 8 | 8 | 8 | 8 |
| AIC | 1 | 1 | 3 | 4 | 5 | 5 | 5 | 8 | 9 | 9 | 9 | 9 |
| SC | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| HQ | 1 | 1 | 1 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |
| AICc | 1 | 1 | 1 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 |

*Notes*: LR: sequentially modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion; AICc: corrected Akaike information criterion (Hurvich and Tsai 1989).

**Table 3**

*Results of Granger Causality Tests for TLGH and EDTH in Hong Kong.*

| $p$ | $H_0$ | $H$ 1 | 2 | 3 | 4 | 8 | 12 | 20 |
|---|---|---|---|---|---|---|---|---|
| Panel A. Mixed-frequency Model | | | | | | | | |
| 1 | EDTGH | 3.640 (0.325) | 4.988 (0.186) | 5.103 (0.187) | 15.358 (0.010)*** | 5.469 (0.210) | 5.297 (0.251) | 6.433 (0.404) |
| | TLEGH | 4.544 (0.397) | 6.630 (0.209) | 3.745 (0.482) | 2.266 (0.693) | 1.988 (0.767) | 2.032 (0.729) | 4.006 (0.728) |
| 2 | EDTGH | 13.552 (0.331) | 14.975 (0.053)* | 16.969 (0.115) | 24.260 (0.010)*** | 17.507 (0.048)** | 23.638 (0.045)** | 43.108 (0.107) |
| | TLEGH | 22.014 (0.121) | 7.777 (0.458) | 6.003 (0.604) | 4.878 (0.791) | 6.662 (0.688) | 10.434 (0.396) | 4.160 (0.971) |
| 3 | EDTGH | 23.324 (0.046)** | 39.912 (0.024)** | 22.7921 (0.026)** | 34.397 (0.006)*** | 18.709 (0.177) | 54.508 (0.011)** | 39.428 (0.428) |
| | TLEGH | 32.119 (0.041)** | 8.572 (0.907) | 9.620 (0.627) | 10.846 (0.567) | 9.218 (0.756) | 17.231 (0.360) | 9.164 (0.974) |
| 4 | EDTGH | 102.577 (0.021)** | 45.049 (0.027)** | 42.533 (0.003)*** | 55.966 (0.006)*** | 24.8558 (0.376) | 64.426 (0.061)* | 75.063 (0.5075) |
| | TLEGH | 83.006 (0.061)* | 15.166 (0.787) | 9.855 (0.790) | 15.191 (0.696) | 16.704 (0.668) | 21.422 (0.692) | 23.751 (0.927) |
| Panel B. Low-frequency Model | | | | | | | | |
| 1 | EDTGH | 3.216 (0.045)** | 0.627 (0.498) | 0.139 (0.746) | 1.471 (0.295) | 0.369 (0.634) | 3.175 (0.126) | 2.450 (0.274) |
| | TLEGH | 0.104 (0.815) | 0.592 (0.557) | 0.098 (0.839) | 0.102 (0.819) | 1.635 (0.355) | 2.049 (0.265) | 1.327 (0.526) |
| 2 | EDTGH | 7.034 (0.021)** | 6.310 (0.040)** | 2.349 (0.567) | 5.535 (0.104) | 0.945 (0.739) | 4.541 (0.193) | 3.680 (0.456) |
| | TLEGH | 3.950 (0.385) | 0.806 (0.761) | 0.127 (0.972) | 0.650 (0.801) | 5.029 (0.222) | 2.182 (0.469) | 1.806 (0.739) |
| 3 | EDTGH | 8.568 (0.024)** | 10.032 (0.032)** | 13.543 (0.314) | 6.075 (0.237) | 1.650 (0.772) | 8.077 (0.139) | 4.662 (0.639) |
| | TLEGH | 10.021 (0.167) | 0.470 (0.966) | 0.823 (0.969) | 10.567 (0.118) | 7.123 (0.201) | 3.153 (0.482) | 2.003 (0.872) |
| 4 | EDTGH | 8.071 (0.121) | 11.591 (0.052)* | 3.054 (0.661) | 5.474 (0.396) | 4.306 (0.568) | 8.048 (0.320) | 6.787 (0.686) |
| | TLEGH | 21.614 (0.089)* | 3.153 (0.695) | 0.973 (0.926) | 8.528 (0.207) | 9.330 (0.209) | 3.159 (0.712) | 1.946 (0.956) |

*Notes*: The mixed frequency approach uses monthly visitor arrivals and quarterly GDP. The low-frequency approach uses all quarterly series. (We use the average of three months of visitor arrivals to denote the quarterly visitor arrivals.) The sample period covers January 1973 to March 2016, which has 519 months (173 quarters, 44 years). All variables are mean-centered and annual log-differenced. We follow the method in Ghysels, Hill, and Motegi (2016) and use bootstrapped p-values with $N$ = 999 replications (Gonçalves and Kilian 2004). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 4**

*Rejection Frequencies at Different Significant Levels for 130 Rolling Granger Causality Tests.*

| Hypothesis | Model | Significance level | | |
|---|---|---|---|---|
| | | 1% | 5% | 10% |
| $H_0: \text{VA}g \nrightarrow \text{GDP}g$ | MF-VAR(1,1) | 0.169 | 0.415 | 0.538 |
| | LF-VAR(1,1) | 0.331 | 0.400 | 0.415 |
| $H_0: \text{GDP}g \nrightarrow \text{VA}g$ | MF-VAR(1,1) | 0.138 | 0.192 | 0.300 |
| | LF-VAR(1,1) | 0.185 | 0.354 | 0.400 |

**Figure 1**

*Mixed-frequency Time Series of Visitor Arrivals and Real GDP in Hong Kong.*

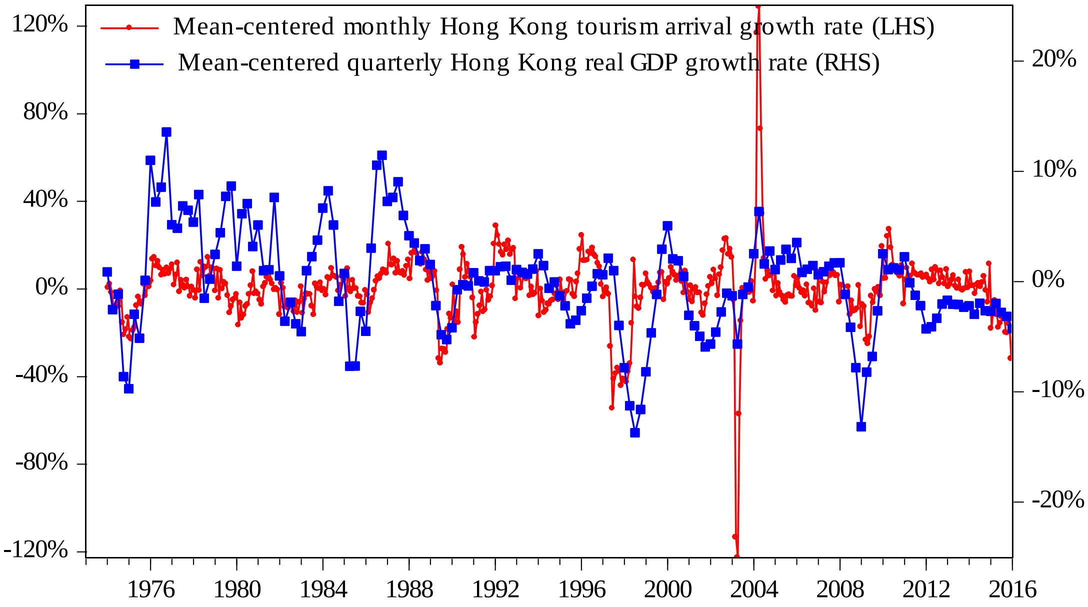

**Figure 2**

*P-values of Rolling Mixed-frequency Granger Causality Test for TLEGH.*

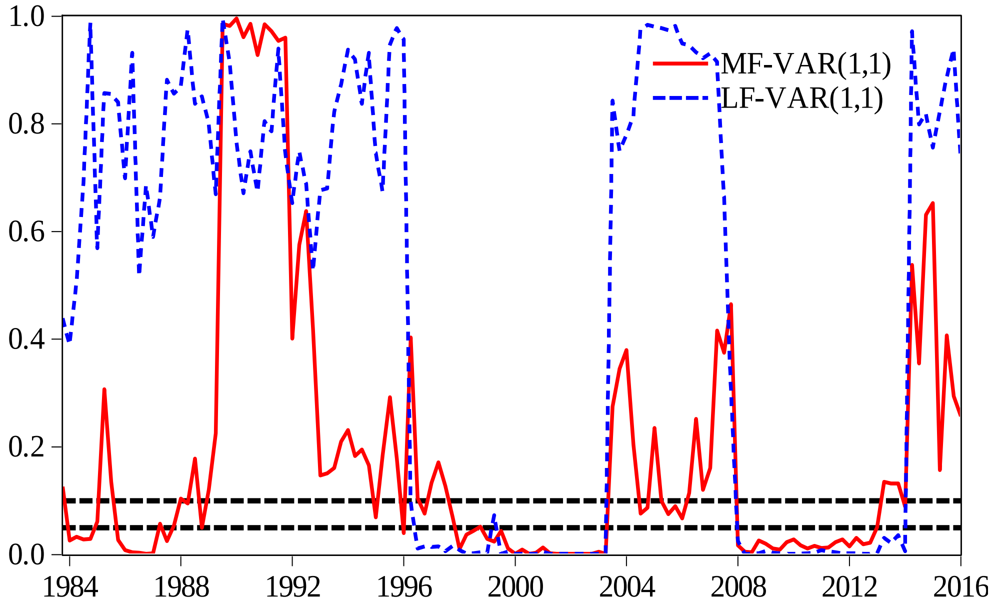

**Figure 3**

*Rolling Mixed-frequency Granger Causality Test Rejection Frequency for EDTGH.*