Nowcasting the GDP in Taiwan and the Real-Time Tourism Data

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Abstract

In this paper, we examined the relationship between tourism and GDP in Taiwan. The GDP in Taiwan is nowcasted with the real-time tourism data in Google Trends database. We used the high-frequency internet-searching tourism data to predict the low-frequency GDP data, for the real-time data with rich information could enhance prediction accuracy. Applying the Principal Components Analysis (PCA), we used the internet-searching tourism keywords in Google Trends database to construct the diffusion indices. Following the classification of the tourism keywords in Matsumoto et al. (2013), we classified those keywords into five groups and twenty-nine classifications. We focused on the reciprocal reactions between those diffusion indices with GDP to conclude which component has higher influence on GDP in Taiwan. Our empirical results indicated that the keywords in "Recreational areas, Grand tour, and Travel-related" group have significant effects on various concepts of national income in Taiwan via nowcasting. Among the components of those diffusion indices, "Amusement park, Hot spring, Farm, Working holiday, and Travel insurance" are important variables with higher weights in common.

Key words: Nowcasting, the Principal Components Analysis (PCA), Internet-searching Keywords, GDP, Tourism

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1. Introduction

Tourism industries play an important role in Taiwan's economy. The Taiwan Tourism Bureau (MOTC) proposed two major axes in new tourism strategies, Tourism 2020, which focused on exploiting markets and revitalizing tourism. The tourism statistics in Taiwan Tourism Bureau (MOTC) demonstrates that the number of domestic-travel visitors amounts to 150 million times, showing that traveling has already been part of daily life for people. In Taiwan, the domestic major recreational activities are "Nature appreciation activities, Other leisure activities, and Gourmet events," which accounts for 65.7%, 54.6%, 48.5%, respectively.

Since the outbreak of COVID-19, the accommodation industry, transport industry, and travel agency in Taiwan have suffered from huge adverse effects. People reduced their overseas tourism, and the local tours were in turn promoted. Taiwan government put forward several subsidy programs, which appealed people to participate the local tours. In July 2020, Taiwan Tourism Bureau (MOTC) proposed "Feeling-Safe Travel Subsidy" to stimulate traveling consumption. Over four million citizens had participated in this project by mid-August 2020, and the anticipated tourism receipts reached more than seven times. During 2020, the local tours were marketable until May 2021.

Preparing for traveling in advance, people are used to looking up travel-related keywords online, such as searching information of travel agency, travel insurance, or route planning with popular attractions. From the statistical data of Google Trends database, domestic-travel related keywords account for 74% of the internet-searching tourism keywords in Taiwan. The popular and wide range of traveling attractions cover "Zoo, Amusement Park, Places of interest, Hot spring, Night market, Farm, Historic sites, and Cultural old street." Besides, "Backpacker, Free travel, and Working holiday" are also such a big hit on the internet-searching traveling attractions.

In this paper, we focused on exploring the preferred tourism internet-searching tourism keywords, which stimulate tourists to expand their consumption in tours and further to increase the national income in Taiwan. It is anticipated to figure out which information has prominent effect on GDP in Taiwan. Following the important internet-searching tourism keywords in literatures, we have collected numerous real-time high frequency data from Google Trends database to proceed the empirical tests. Recently, big data issue has received lots of attention, and the high-frequency internet-searching keywords are applied to nowcast low-frequency dependent variables in literatures, for well forecasting economic data and providing multiple decision-making suggestions. In this paper, with numerous real-time data in Google Trends database, we adopted high-frequency tourism data to nowcast low-frequency GDP in Taiwan. The main purposes lie in using abundant real-time information to enhance predictability for GDP in Taiwan.

We used the Principal Components Analysis (PCA) to extract diffusion indices from internet-searching tourism keywords in Google Trends database. Following the classifications in Matsumoto et al. (2013), we classified the internet-searching tourism keywords into five main groups and twenty-nine classifications to construct the diffusion indices. Verifying the predictability of those diffusion indices for GDP in Taiwan, we explored which tourism classification has higher impact on GDP in Taiwan. For robust check, we used both quarterly and monthly tourism data to nowcast annual GDP data in Taiwan. And we treated GDP, GNI and NI as dependent variables separately in three different models for robust check, owing to the fact that various concepts of national income could explain the facts of economic activities.

In this paper, we focused on the impact of internet-searching tourism data on GDP. There is currently a lack of literature focusing on nowcasting GDP in Taiwan via real-time tourism keywords . We look forward to well explaining the correlation between tourism keywords with GDP in Taiwan and the abundant high-frequency information.

2. Literature

Recently, big data issue has been in the spotlight in numerous literatures, and high-frequency internet-searching keywords have been applied to nowcast low-frequency dependent variables for well forecasting economic and providing multiple decision-making suggestions. Since Klein and Park (1994), the high-frequency statistical data have been applied to nowcast the low-frequency data for reducing the predictability difficulties. Then, GDP has been nowcasted with dynamic models and other related techniques in literatures to make researchers to extract useful information (Evans, 2005; Barhoumi et al, 2010; Marcellino et al., 2003; Bolivin and Ng, 2005; Bragoli and Fosten, 2016; Chernis and Sekkel, 2017; Chikamatsu et al., 2018; Kabundi et al., 2016; Luciani et al., 2018).

Following Giannone et al. (2005), many literatures used lots of data to nowcast GDP in different countries. Yiu and Chow (2011) used sixteen categories of variables to nowcast GDP in China to conclude that interest rate could be predicted effectively. Using the Kalman Filter in State-Space model, Lahiri and Monokroussos (2013) used the bridge equation and the dynamic factor model to nowcast GDP with diffusion indices, and put stress on its marginal effectiveness and real-time characteristics. Banbura (2011) mixed twenty-four categories of data to construct forecasting model to predict GDP, and those data frequencies were daily, weekly, monthly, and quarterly, respectively. Since the mixed-frequency data in the same model would result in dimension disasters and imprecise estimates, they applied Kalman filter to reduce the uncertainties. The results showed that the mixed-frequency data indeed improved the forecast accuracy for GDP. Mazzi and Montana (2009) used simultaneous indicators to build model and offered real-time information of economic activities in their paper, which aimed at nowcasting the GDP growth rate.

As supplementary tool, Notinietal (2012) used monthly data of energy demand, steel production, cement, vehicles, industrial production, and sales to forecast GDP. They used Kalman filter to assess three-month summation data to be 1 quarterly data for acquiring new quarterly data in advance. Their research figured out that in-sample forecasting results were better than central bank's estimating data. Liebermann (2012) used the bridge equation and dynamic factor model to forecast quarterly GDP data in Ireland, and they used fourteen monthly variables in domestic and external economies. Luciani and Ricci (2013) used the Bayesian Dynamic Factor Model (BDFM) to apply monthly data including "PMI, Unemployment Rate, Industrial Production, Employee, Retail Sales, New Orders, Import and Export, and Consumer Confidence Index" in nowcasting the annual GDP growth of Norway. Their research showed that the forecasting performance was equal to the survey of Bloomberg

Research. In addition, their nowcasting annual GDP data results were better than the forecast of Bank of Norway, and the results had significant smaller MSE and implied that Bayesian Dynamic Factor Model (BDFM) could effectively forecast via newer information. Summing up the research results in Notini et al. (2012), Liebermann (2012), and Luciani and Ricci (2013), the high-frequency monthly macroeconomic indicators could improve the low-frequency quarterly forecasting.

Some nowcasting literatures had focused on employment rate and stock issue, which were as follows. Nikolaos Askitas and Klaus F. Zimmermann (2009) used the real-time data on internet to forecast economic behavior, and they found the strong correlation between Germany internet-searching keywords and unemployment rates. The internet-searching data could be applied to forecast economic behavior with their abundant information, which showed the forecasting method with higher explanatory power. D'Amuri, F., and Marcucci, J. (2010) searched for job-related data in Google Insight for Search database, and transformed those weekly data into monthly ones, and then arranged those data into quarterly data as leading indicator for forecasting US employment rates. They concluded that the increasing searching times of job might reflect the growing unemployment rate. Their result represents that the forecasting effects of internet-searching keywords model are better than the traditional forecasting model for unemployment rate. Takeda and Wakao (2014) explored the relationship between stock names of Japan Nippon index and stock market behavior. They showed the insignificant positive relationship between searching times and stock prices, and the significant relationship between searching times and stock market trading volume. They pointed out the increasing searching times might expand stock market trading volume, but the expanded stock market trading volume cannot represent the stock price being rising.

Some nowcasting literatures, which focused on tourism issues, are as follows. Matsumoto et al. (2013) examined the influence of internet-searching tourism data on Japan's service consumption around the "Japan's 311 Earthquake." Choi and Varian (2012) explored the tourism issues with internet-searching keywords and compared with the traditional model to conclude which model has higher explanatory power.

Some nowcasting literatures focused on nowcasting service consumption with internet-searching data, such as Vosen and Schmidt (2011, 2012) and Kholodilin, et. Al. (2010). They all found that new style indicators have higher predicting accuracy than traditional ones.

In this paper, the advantages of real-time data are elaborated, and the low-frequency GDP data in Taiwan is nowcasted with high-frequency tourism data. We look forward to the more precise prediction of GDP in Taiwan.

We therefore concluded five main categories of internet-searching tourism data, namely Transport, Rest, Recreational areas, Grand tour, and Travel-related groups. The descriptions are as follows.

(1) **Transport.** The transport-related tourism keywords cover six classifications, sequentially "Cruise, Bus, Train, Car rental, Taxi, and Airplane." When traveling in one single county, "Bus, Car rental and Taxi" are highly used. When traveling across counties, "Train" is the best choice. "Airplane" covers both external travel line and domestic travel line; "Cruise" is making a round-the-ocean passenger liner.

(2) Rest. Rest includes "Hotel, Accommodation, and Resort." In Taiwan, there are nearly 100 "Hotels" which offer tourists commercial facilities to take a break. "Accommodation" is necessary for tourism, and also the main keywords. “Resort” includes recreation area, combining hotel, restaurant, amusement park, and indoor and outdoor leisure and recreation facilities, focusing on designated travel and offering tourists large scale and hotel facilities.

(3) **Recreational areas.** In this paper, we divided recreational areas into seven classifications, which are “Amusement Park, Zoo, Traveling attractions, Places of interest, Hot spring, Night market, and Farm,” Respectively.

(4) **Grand tour.** We divided grand tour into three classifications, which are “Backpacker, Free travel and Working holiday.”

(5) **Travel-related.** We divided Travel-related affairs into ten classifications, including “Guidebook, Travel insurance, Subsidy, Travel agency, Travel, Guide, Souvenir, Luggage, Visitor center, and Package tour.”

3. Empirical model

In this paper, we nowcasted low-frequency annual GDP in Taiwan with high-frequency quarterly and monthly internet-searching tourism keywords data. The empirical steps are as follows.

STEP 1: Transforming high-frequency data into low-frequency data

In this paper, we referred to the approach of Klein and Park (1994) to rearrange high-frequency data through ARIMA model. Then, following Giannone et al. (2008), we transformed the quarterly and monthly internet-searching tourism keywords data into the annual data. The transformation procedure is as follows.

The information set is composed of n variables, $\Omega_{v_j} = \left\{X_{it|v_j}; t = 1, \ldots . T_{iv_j}; i = 1, \ldots, n\right\}$. Among them, $X_{it|v_j}$ is the individual time series data. i represents n variables. t represents the data frequency, which is quarterly from the first observation to the last one (T_{iv_j}).

At first, we nowcasted annual GDP data with quarterly data. Assume $\mathrm{y} = \text{the last quarter of each year}$. There are four quarters each year, and it could be represented as $\mathrm{y} = 4\mathrm{k}, \mathrm{k} = 1,2, \ldots.$, and k is the observed year. The quarterly data (j) is announced four times each year, and there are four data collections, sequentially the 1st to the 4th quarter. They are represented as $\Omega_{v_j},\ v = 4k - l,\ l = 0, .., 3$

According to the information collection, the estimated GDP forecast is the nowcasting estimation. $\mathrm{y}_{4\mathrm{k}}$ is the estimated GDP in Taiwan, which is evaluated based on quarterly data information.

$$\mathrm{y}_{4k|v_j} = E\left[y_{4k}|\Omega_{v_j}\right],\ v = 4k - l;\ l = 0, .., 3, \tag{1}$$

Equation (1) is the bridge equation, nowcasting annual GDP in Taiwan with quarterly data. As aforementioned, we have four quarterly data each year to nowcast four current year data, which are treated as four methods. The four methods are separately Q1 to Q4, sequentially the 1st quarter to the 4th quarter of each year chosen as the quarterly data.

Then, we nowcasted annual GDP data with monthly data. Assume $\mathrm{y} = \text{the last month of each year}$. There are twelve months each year, and it could be represented as $\mathrm{y} = 12\mathrm{k},\ \mathrm{k} = 1,2, \ldots,$ and k is the observed year. The monthly data (m) will be announced twelve times each year, then there will be twelve data collections, sequentially the 1st month to the 12th month. They are represented as Ω_{v_m}, $v = 12k - \mathrm{q}$; $q = 0, \ldots, 11$

According to the information collection, the estimated GDP forecast is the nowcasting estimation. $\mathrm{y}_{12\mathrm{k}}$ is the estimated GDP in Taiwan, evaluated based on monthly data information.

$$\mathrm{y}_{12k|v_m} = E\left[y_{12k}|\Omega_{v_m}\right],\ v = 12k - \mathrm{q};\ q = 0, \ldots, 11, \tag{2}$$

Equation (2) is the bridge equation, nowcasting annual GDP in Taiwan with monthly data. As aforementioned, we have twelve-month data each year to nowcast twelve current year data, which are treated as twelve methods. The twelve methods are separately M1 to M12, which is the 1st month to the 12th month of each year chosen as the monthly data.

STEP 2: Index construct reduction---construct diffusion index

Diffusion indices are Principal Components Analysis (PCA) in statistics, which conclude several groups of series to have strongest correlation with variables. Then the series estimated by X are called diffusion indices or common factors. The methods are as follows.

Assume X is the $\mathrm{T} \times \mathrm{N}$ matrix composed of N time series variables, and T is the number of samples. Assume F is a $\mathrm{T} \times \mathrm{k}$ matrix, representing k diffusion indices estimated by X, and the relationship between X and F is as follows.

$$\mathrm{X} = \mathrm{F}\beta + \varepsilon \tag{3}$$

β represents the $\mathrm{k} \times \mathrm{N}$ coefficients matrix, which results from regressing X by the estimated F, or called as the factor loading matrix. ε is the vector of residuals, independent and identical distribution with white noise.

In other words, the distribution of each ε satisfying with $\mathrm{E}(\varepsilon) = 0$ and $\mathrm{V}[\mathrm{vec}(\varepsilon)] = \Omega$, Ω is the symmetric positive-definite matrix of positive diagonal term, with mutually independent ε in different periods. Equation (3) describes the linear relationship between X and F, and its regression error terms satisfying the basic assumption of residuals, as the basis of forecasting single series with diffusion indices in the future. To ensure the asymptotic distribution, all the time series in the X vector should be series without unit roots.

F and β are all the estimated variables in Equation (3), which could not be identified in one estimation method. We have to use the two-step method to estimate F and β, which is to estimate F in the first step, and the best parameter estimator $\hat{\beta}$ will be estimated in the second step. As mentioned above, the estimation in the first step, F could be treated as a set of k diffusion factor series having the strongest correlation with X vector. That is the vector satisfying this condition, which is the solution of minimizing the objective function as follows.

$$\min_F \sum_{i=1}^{N} (X_i - F\beta_i)'\,(X_i - F\beta_i) \tag{4}$$

X_i and β_i are separately the ith element in X and the ith element in β vector. For solving F and β, we assumed temporarily F is known in equation (3), and then the least square estimator β could be represented as $\widehat{\beta_\iota} = (F'F)^{-1}(F'X_i)$. Treating $\widehat{\beta_\iota}$ as β_i of equation (4), we could then rewrite the objective function as

$$\min_F \sum_{i=1}^{N} X'[I - F(F'F)^{-1}F']X_i,$$

or further

$$\min_F \{trace[X'X - X'F(F'F)^{-1}F'X]\} \tag{5}$$

Trace (·) represents the function of dimensional elements summation in square matrix. Because X'X comes from the sample series, not the estimated parameter, the solution to equation (4) would be the same with which in the equation (6).

$$\max_{F}\{trace[X'F(F'F)^{-1}F'X]\} \quad (6)$$

Stock and Watson (1998a, 1998b) adopted the proof in Connor and Korajczyk (1986, 1993), and concluded that the solution to F in equation (6) was the eigenvector corresponded by the maximizing k eigenvectors. In this way, the matrix $\hat{F}$ is composed of k eigenvectors in $T \times 1$, which was the estimated diffusion indices. Taking the estimated $\hat{F}$ into equation (3), the least square estimator of factor loading matrix β was derived as follows.

$$\hat{\beta}_{OLS} = (F'F)^{-1}(F'X) \quad (7)$$

In this paper, we estimated several Taiwan tourism diffusion indices. The procedure is as follows. At first, all the time series data were examined with Augmented Dickey-Fuller unit root tests, identifying these variables satisfying transformation without unit root. If the original series should be differenced to be stationary, the log difference will be adopted to build matrix X. The maximized k eigenvalues of XX' and its corresponding eigenvector would be estimated by programming-calculation, which were the estimated diffusion indices.

In this paper, we applied the tourism-related variables to construct the tourism diffusion indices, which is the "internet-searching tourism data indices." The n diffusion indices extracted from the tourism-related variables are the common factors of GDP in Taiwan. According to Stock and Watson (1998a,1998b, 2002a, 2002b), the n diffusion indices extracted from the tourism related variables, which are named separately DF1 to DFn, are the possible common factors for GDP in Taiwan.

We want to explore the prediction performance of those tourism-related diffusion indices. Through decomposing the weights of diffusion indices, we could find out which variable have much more impact on GDP in Taiwan and conclude which tourism common factor has prominent impact on GDP in Taiwan via the prediction performance.

STEP 3: Constructing the bridge equation

We set up the bridge equation related to diffusion indices with GDP in Taiwan, and then added up the ARMA terms to solve the serial correlation problem in error terms to raise up the explanatory power. Following Giannone et al. (2008) and Giannone et al. (2010), we used the Kalman filter and nowcasted GDP in Taiwan through the bridge equation and the dynamic factor model.

At first, there are many variables in the information sets, which might have the curse of dimensionality and imprecise estimates. Hence, the Principal Components Analysis (PCA) was applied to estimate the common factors, which are

$$x_{i,t|v_j} = \mu_i + \lambda_{i1}f_{1,t} + .. + \lambda_{i,r}f_{r,t} + \xi_{i,t|v_j}, i = 1, \ldots, n$$

μ_i is the intercept, and $\chi_{it} \equiv \lambda_{i1}f_{1k} + \cdots + \lambda_{ir}f_{rk}$ are the common factors. Represented by matrix forms, $x_{t|v_j} = \mu + \Lambda F_t + \xi_{t|v_j}$. Among them, $x_t = (x_{1t|v_j}, \ldots, x_{nt|v_j})'$, $\xi_{t|v_j} = (\xi_{1t|v_j}, \ldots, \xi_{nt|v_j})'$, $F_t = (f_{1t}, \ldots, f_{rt})'$, Λ is a $n \times r$ factor loading matrix.

$$\hat{y}_{4k|v_j} = \alpha + \beta'\hat{F}_{4K|v_j}, \ \hat{F}_{4K|v_j} = E[F_{4k}|\Omega_{v_j}] \ \text{for} \ v = 4k - l; \ l = 0, .., 3, \quad (8)$$

$$F_t = AF_{t-1} + Bu_t, \quad u_t \sim WN(0, I_q) \tag{9}$$

B is the $r \times q$ matrix of full rank; A is the $r \times r$ matrix with eigenvalues larger than 1; u_t is the white noise of common factors.

Equation (8)[3] is the bridge equation. $\hat{y}_{4k|v_j}$ is the estimated GDP in Taiwan, which is the linear relationship between GDP nowcasting estimates with the common factors. Giannone et al. (2008) assumed the common factor dynamics satisfies the VAR form, which is equation (9). They used the Kalman filter to estimate the common factors in two steps and brought them into equation (8) to get the nowcasting estimates. The two-step procedures are as follows.

STEP1: Use the Principal Components Analysis (PCA) to find the common factors, and then regress the common factors and dependent variables to get the estimated parameter in the state-space model.

STEP2: Use the Kalman filter to re-estimate the common factors and dependent variable.

Bai (2003), Bai and Ng (2002), Forni et al. (2005) and Stock and Watson (2002a) had already found the diffusion indices which were estimated from observable variables, and they were consistent with the unobservable common factors estimated from the aforementioned two-step procedures. That is why we adopted the way of estimating diffusion indices in Stock and Watson (2002a), which was proxied as the common factor for nowcasting GDP.

STEP 4: VAR model for diffusion indices

The estimated diffusion indices represent the k sequences having the strongest correlation with the original series components of **X**. In this paper, we followed the approach in previous section to estimate the diffusion indices for four individual quarters and twelve individual months. Although the diffusion indices estimation is a purely statistical approach without economical granger causality background, we could further explore the relationship between GDP patterns with different diffusion indices and understand the implications of nowcasting annual GDP in Taiwan via diffusion indices.

Using diffusion indices to construct the VAR model to predict the future periods of objective variables, we concluded that X_{it} is the observation of the ith economic variable in t period, N is the number of economic variables, and γ is the estimating parameter originated from maximizing the DF_t variations. Under the limitation of variable standardization, satisfying with $\sum_{i=1}^{N}\gamma^2 = 1$, $DF_t = \gamma_1 x_{1t} + \gamma_2 x_{2t} + \ldots.. + \gamma_N x_{Nt}$ is called the first Principal Component, which is DF_t.

In this step, we used the VAR model to measure the relationship between the diffusion indices and objective

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[3] If the estimated GDP in Taiwan is monthly data, then equation (8) will be rewritten to be as follows, $\hat{y}_{12k|v_m} = \alpha + \beta'\hat{F}_{12K|v_m}$, $\hat{F}_{12K|v_m} = E[F_{12k}|\Omega_{v_m}]$ for $v = 12k - q;\ q = 0, \ldots, 11,$

variables, representing the VAR (p) model as AR (1) form,

$$Z_t = AZ_{t-1} + \varepsilon_t \tag{10}$$

Let $\begin{pmatrix} x_t \\ y_t \end{pmatrix} \in R^2$, and assume $(x_t y_t)'$ to be the VAR (p) form. Hence, $E_t(Z_{t+j}) = A^j Z_t$ and

$$E_t(y_{t+j}) = [010 \cdots 0] A^j Z_t = e_2' A^j Z_t \text{, among them, } e_2 = \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}}_{2p\times 1}.$$

In addition, $x_t = [010 \cdots 0] Z_t = e_2' Z_t$. Combining the terms before, we can conclude,

$$e_2' Z_t = x_t = \sum_{j=1}^{\infty} \beta^j E_t(y_{t+j}) = \sum_{j=1}^{\infty} \beta^j e_2' A^j Z_t \tag{11}$$

Arranging them, we get $e_2' Z_t = e_2' (\sum_{j=1}^{\infty} \beta^j A^j) Z_t$.

And $e_1' = e_2' \beta A (I - \beta A)^{-1}$, that is $e_1'(I - \beta A) = e_2' \beta A$. The hypothesis testing for coefficient matrix A in VAR (p) could use the Wald test,

$$x_t = \Phi_{11} x_{t-1} + \Phi_{12} y_{t-1} + \varepsilon_{xt}$$

$$y_t = \Phi_{21} x_{t-1} + \Phi_{22} y_{t-1} + \varepsilon_{yt} \tag{12}$$

Then,

$$\underbrace{\begin{bmatrix} x_t \\ y_t \end{bmatrix}}_{Z_t} = \underbrace{\begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix}}_{Z_{t-1}} + \underbrace{\begin{bmatrix} \varepsilon_{xt} \\ \varepsilon_{yt} \end{bmatrix}}_{\varepsilon_t}$$

Therefore, $\underbrace{e_1'(I - \beta A)}_{1\times 2} = [1 \quad 0](I - \beta A) = [1 - \beta\Phi_{11} \quad -\beta\Phi_{12}]$

$$\underbrace{e_2' \beta A}_{1\times 2} = [0 \quad 1] \beta A = [\beta\Phi_{21} \quad \beta\Phi_{22}]$$

And the null hypothesis is,

$$\begin{cases} 1-\beta\Phi_{11} = \beta\Phi_{21} \\ -\beta\Phi_{12} = \beta\Phi_{22} \end{cases}, \text{ or } \begin{cases} \Phi_{11}+\Phi_{21} = \dfrac{1}{\beta} \\ \Phi_{12}+\Phi_{22} = 0 \end{cases}$$

If the null hypothesis is rejected, then the model is failed.

We aimed at understanding the correlation between the diffusion indices of four individual quarterly data and annual GDP data in Taiwan, and the interrelationship between the diffusion indices of twelve individual monthly with annual GDP data in Taiwan. We used the VAR model to examine the individual diffusion index of four individual quarters and twelve individual months to verify their lead, lag or feedback relationship. The model is as follows.

$$y_t = \alpha_1 + \beta_1 y_{t-1} + \beta_2 DF1_{t-1} + \beta_3 DF2_{t-1} + \beta_4 DF3_{t-1} + \varepsilon_{yt}$$

$$DF1_t = \alpha_2 + \beta_5 y_{t-1} + \beta_6 DF1_{t-1} + \beta_7 DF2_{t-1} + \beta_8 DF3_{t-1} + \varepsilon_{DF1t}$$

$$DF2_t = \alpha_3 + \beta_9 y_{t-1} + \beta_{10} DF1_{t-1} + \beta_{11} DF2_{t-1} + \beta_{12} DF3_{t-1} + \varepsilon_{DF2t}$$

$$DF3_t = \alpha_4 + \beta_{13} y_{t-1} + \beta_{14} DF1_{t-1} + \beta_{15} DF2_{t-1} + \beta_{16} DF3_{t-1} + \varepsilon_{DF3t}$$

$$\begin{bmatrix} y_t \\ DF1_t \\ DF2_t \\ DF3_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} + \begin{bmatrix} \beta_1 & \beta_2 & \beta_3 & \beta_4 \\ \beta_5 & \beta_6 & \beta_7 & \beta_8 \\ \beta_9 & \beta_{10} & \beta_{11} & \beta_{12} \\ \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ DF1_{t-1} \\ DF2_{t-1} \\ DF3_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{DF1t} \\ \varepsilon_{DF2t} \\ \varepsilon_{DF3t} \end{bmatrix} \tag{13}$$

y_t is the annulled data of GDP in Taiwan, $DF1_t$,$DF2_t$,$DF3_t$are the individual diffusion indices for four quarters, and the individual diffusion index for twelve months.

4. Data and Empirical results

a. Data description

In this paper, we used the high-frequency internet-searching tourism keywords data to nowcast the low-frequency annual Taiwan GDP data. The data descriptions and sources are listed in Table 1. Owing to the fact that the data in Google Trends database starts from January 2004, the data in this paper covers from 2004 to 2020. For robust check, we adopted both quarterly and monthly internet-searching tourism keywords data from Google Trends database. There are various concepts of national income including GDP, GNI, and NI, which explain the facts of economic activities. In this paper, we focused on the impact of internet-searching tourism keywords data on GDP. And for robust check, we compared three kinds of national income, namely GDP, GNI, and NI[4], which

[4] (1) GDP (Gross domestic product) is the standard measure of the value added created through the production of goods and services in a country during a certain period. (2) GNI (Gross National Income) is the total amount of money earned by a nation's people and businesses. It is used to measure and track a nation's wealth from year to year. The number includes the nation's gross domestic product plus the income it receives from overseas sources. The formula is "GNI=GDP+ Income from citizens and businesses earned abroad - Income remitted by foreigners living in the country back to their home countries." (3) NI (National Income) means the value of goods and services produced by a country during a financial year. Thus, it is the net result of all economic activities of any country during a period of one year and is valued in terms of money. The formula is

are sourced from “Directorate General of Budget, Accounting and Statistics, Executive Yuan, Taiwan.”

b. Empirical results

Part1 The factor loading of components in diffusion indices

At first, we examined the significant diffusion indices, in which those components with highest weights are treated as the prominent important tourism keywords. Those results are sequentially showed in Table 2 to 3[5,6]. Table 2 showed the results with quarterly data. Among those statistically significant diffusion indices in Table 2, the higher-weight components are separately “Car rental, Amusement Park, Attraction, Places of interest, Hot spring, Farm, Working holiday, Travel insurance, Travel agency, Luggage, and Visitor center.” Those are eleven important tourism-related keywords, representing the keywords in “Transport, Recreational areas, Grand tour, and Travel-related” groups have prominent effects on GDP in Taiwan. Those results are sequentially shown in Table 2-Part A to Part C.

Table 3 showed the results with monthly data. Among the statistically significant diffusion indices in Table 3 , the higher-weight components are separately “Amusement Park, Hot spring, Farm, Working holiday, and Travel insurance.” Those are five important tourism-related keywords, representing the keywords in “Recreational areas, Grand tour, and Travel-related” groups have prominent effects on GDP in Taiwan. Those results are sequentially shown in Table 3-Part A to Part C.

The possible explanations of those components having higher weights are as follows. “Amusement Park” has higher weight, pointing out that tourists who search the tourism-related information on internet are interested in several Amusement Parks in Taiwan. “Hot spring” has higher weight, owing to the recent popular combination of hotel and hot spring resources in the same industry in Taiwan. “Farm” has higher weight, for the Taiwan leisure farms have been gradually transformed into leisure industry configuration to meet customer’s requirements. “Travel insurance” has higher weight, for preventing emergencies and reducing the adverse effect of tourists. “Luggage” has higher weight, for the internet information of tips for storing luggage, the rules of check-in luggage, and carry-on luggage all enhance the internet-searching motivation. “Visitor center” has higher weight for its merchandise, food supply, and information enquiry. “Cruises” has higher weight, for the recent popular taking a cruise to nearby countries. “Working holiday” has higher weight, for the trending of working overseas on holiday and overseas internship.

Part2 VAR model

(1) The results with quarterly data

Table 4 shows the results of VAR model with quarterly data. We extracted three diffusion indices, in which

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“NI＝GNI－depreciation－Net indirect tax.”

[5] Before we estimated the tourism diffusion indices, all the time series data were examined with Augmented Dickey-Fuller unit root tests, identifying these variables satisfying transformation without unit root. If the original series should be differenced to be stationary, the log difference will be adopted.

[6] In this paper, the log difference is adopted for all original data, including three kinds of national income and the tourism internet-searching keywords data. The empirical results of Augmented Dickey-Fuller unit root tests show that all data are stationary without unit root.

these components covered quarterly internet-searching tourism keywords. At first, the low-frequency annual data were nowcasted by high-frequency quarterly data, and then those diffusion indices were adopted to proceed VAR tests with GDP, GNI, NI separately. Those results are sequentially shown in Table 4-Part A to Part C.

Table 4-Part A is the results of treating GDP as the dependent variable. The lagged DF2 and lagged DF3 constructed by the 4th quarter data (Q4) have significant predictability for GDP. Also, the lagged GDP has significant predictability for both DF2 constructed by the 1st quarter data (Q1) and DF1 constructed by the 3rd quarter data (Q3).

Although GDP has no granger causality reciprocal reaction with diffusion indices constructed by quarterly data, the lagged information of those diffusion indices significantly affects GDP in the next period, representing the tourism information could enhance the motivation of consuming in Taiwan and further push up the GDP in Taiwan. Among the components of those diffusion indices, the higher-weight variables are separately "Amusement Park, Hot spring, Farm, Travel insurance, Luggage and Visitor center." In other words, among those tourism-related keywords in this VAR model, the "Recreational areas, and Travel-related" groups have prominent predictability.

Table 4-Part B is the results of treating GNI as the dependent variable. The lagged diffusion indices have no significant predictability for GNI. The lagged GNI has significant predictability for DF2 constructed by the 1st quarter data (Q1), and for DF1, DF2, DF3 constructed by the 3rd quarter data (Q3), and for DF3 constructed by the 4th quarter data (Q4).

However, GNI has no granger causality reciprocal reaction with diffusion indices constructed by quarterly data, and those diffusion indices were constructed by tourism keywords, in which its lagged information indeed has no effect on GNI in the next period.

Table 4-Part C is the results of treating NI as the dependent variable. The lagged DF2 and lagged DF3 constructed by the 4th quarter data (Q4) have significant predictability for NI. Also, the lagged NI has significant predictability for DF2 constructed by the 1st quarter data (Q1), and for DF1, DF2, DF3 constructed by the 3rd quarter data (Q3).

Although NI has no granger causality reciprocal reaction with diffusion indices constructed by quarterly data, the lagged information of those diffusion indices significantly affects NI in the next period, representing that interesting tourism information could enhance the motivation of consuming in Taiwan and further push up the NI in Taiwan. Among the components of those diffusion indices, higher-weight variables are separately "Car rental, Places of interest, Hot spring, Working holiday, Travel agency, and Visitor center." In other words, among the tourism-related keywords in the VAR model, the "Transport, Recreational areas, Grand tour, and Travel-related" groups have prominent explanatory power.

In conclusion, from the results of the VAR models in Table 4-Part A to Part C[7,8], both GDP and NI are

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7 In Table 4, we found whether the dependent variables are GDP, GNI, or NI, the det (SSE), AIC, BIC, and HQ are almost the same. That is to say, there is not much difference among the explanatory power of those three models.

8 We choose VAR model to lag 1 period to be VAR (1), based on the AIC and SC criteria.

robustly affected by the keywords of "Transport, Recreational areas, Grand tour, and Travel-related" groups, and their higher-weight components are separately "Car rental, Amusement Park, Attraction, Places of interest, Hot spring, Farm, Working holiday, Travel insurance, Travel agency, Luggage, and Visitor center." Whether for GDP or NI, among the quarterly internet-searching keywords, the "Car rental, Amusement Park, Attraction, Places of interest, Hot spring, Farm, Working holiday, Travel insurance, Travel agency, Luggage, and Visitor center" are important keywords having prominent effects on National Income in Taiwan.

(2) The results with monthly data

Table 5 to 7 are the results of the VAR model with monthly data. We extracted three diffusion indices, which were composed of several monthly tourism keywords. Adopting those diffusion indices to sequentially proceed the VAR test with GDP, GNI, and NI, we concluded the reciprocal reactions between diffusion indices with GDP in Taiwan. Those results are listed in Table 5 to 7.

Table 5 and Table 6 are the sequential results of treating GDP and GNI as the dependent variables. In Table 5 and Table 6, the results are the same, which are those tourism-related diffusion indices having the prominent effect on both GDP and GNI. Those results are summarized as follows.

The lagged DF1 and lagged DF2 constructed by the 4th month data (M4), the lagged DF2 and lagged DF3 constructed by the 10th month data (M10), the lagged DF3 constructed by the 11th month data (M11), and the lagged DF2 and lagged DF3 constructed by the 12th month data (M12) all have significant predictability for GDP and GNI. Also, the lagged DF2 constructed by the 8th month data(M8) have significant predictability for GDP.

Also, the lagged GDP and GNI have significant predictability for DF1 and DF2 constructed by the 1st month data (M1), for DF1 and DF2 constructed by the 3rd month data (M3), for DF1 and DF3 constructed by the 4th month data (M4), for DF3 constructed by the 6th month data (M6), for DF1 constructed by the 7th month data (M7), for DF2 constructed by the 9th month data (M9), for DF2 and DF3 constructed by the 10th month data(M10), and for DF2 constructed by the 12th month data (M12).

We concluded that GDP and GNI have granger causality reciprocal reactions with those lagged diffusion indices constructed by the 4th month data (M4), the 10th month data (M10), and the 12th month data (M12). And those lagged diffusion indices constructed by the tourism keywords in the 4th month (M4), the 10th month (M10), the 12th month (M12), and their information indeed significantly affect GDP and GNI in the next period.

This represents that the interesting tourism information could enhance the motivation of consuming in Taiwan and further push up GDP and GNI in Taiwan. Among the components of those diffusion indices, the higher-weight variables are "Amusement Park, Hot spring, Farm, Working holiday, and Travel insurance." In other words, among those tourism-related keywords in the VAR model, the "Recreational areas, Grand tour and Travel-related" groups have prominent predictability.

Table 7 is the results of treating NI as the dependent variable. The lagged DF1 and DF2 constructed by the 1st month data (M1), the lagged DF1 and DF3 constructed by the 4th month data (M4), the lagged DF3 constructed by the 6th month data (M6), the lagged DF1 constructed by the 7th month data (M7), the lagged DF2 constructed by the 9th month data (M9), the lagged DF2 and DF3 constructed by the 10th month data (M10) , and the lagged DF1 constructed by the 12th month data (M12) all have significant predictability for NI.

We concluded that NI has granger causality reciprocal reactions with those lagged diffusion indices constructed by the 4th month data (M4), the 6th month data (M6), and the 10th month data (M10). And those lagged diffusion indices constructed by the tourism keywords in the 4th month (M4), the 6th month (M6), the 10th month (M10) and their information indeed significantly affect NI in the next period. This represents that interesting tourism information could enhance the motivation of consuming in Taiwan and further push up the NI in Taiwan. Among the components of those diffusion indices, the higher-weight variables are "Amusement park, Hot spring, Farm, Working holiday, Travel insurance and Luggage." In other words, among those tourism-related keywords in the VAR model, the "Recreational areas, Grand tour and Travel-related" groups have prominent predictability.

Comparing the results in Table 6 to 7[9,10], in which the low-frequency yearly data are nowcasted by the high-frequency monthly data, the GDP, GNI, and NI are all robustly affected by the internet-searching tourism keywords in "Recreational areas, Grand tour and Travel-related" groups. Among them, the higher-weight internet-searching tourism keywords are separately "Amusement park, Hot spring, Farm, Working holiday, and Travel insurance."

From those empirical results in Table 4 to 7, we concluded that the robust results are in common for both quarterly data and monthly data. For various concepts of national income, we found that the internet-searching tourism keywords in "Recreational areas, Grand tour and Travel-related" groups could significantly explain the facts of economic activities. That is to say, people care about the tourism information of "Recreational areas, Grand tour and Travel-related" groups most, which also further affects the national income in Taiwan.

5. Conclusions

In this paper, we examined the effects of tourism on GDP in Taiwan via nowcasting the low-frequency annual GDP with the high-frequency monthly and quarterly internet-searching tourism keywords. Using the Principal Components Analysis (PCA), we extracted the diffusion indices from internet-searching tourism keywords, which are classified into five groups and twenty-nine classifications. We aimed at the reciprocal reactions between those diffusion indices and GDP in Taiwan.

With regards to the results of nowcasting annual data of GDP and NI with quarterly data, the keywords in "Transport, Recreational areas, Grand tour, and Travel-related" groups have significant effects. Among those keywords, "Car rental, Amusement Park, Attraction, Places of interest, Hot spring, Farm, Working holiday, Travel insurance, Travel agency, Luggage, and Visitor center" have highest weight. With regards to the results of nowcasting annual data of GDP, GNI and NI with monthly data, the keywords in "Recreational areas, Grand tour, and Travel-related" groups have significant effects. Among those keywords, "Amusement Park, Hot spring, Farm, Working holiday, and Travel insurance" have highest weight.

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[9] In Table 7 to 9, we found whether the dependent variables are GDP, GNI, or NI, the det (SSE), AIC, BIC, and HQ are almost the same. That is to say, there is no much difference among the explanatory power of those three models.

[10] We choose VAR model to lag 1 period to be VAR (1), based on the AIC and SC criteria.

We concluded that the internet-searching tourism keywords in “Recreational areas, Grand tour, and Travel-related” groups have significant predictability for various concepts of national income in Taiwan. Further, for both quarterly data and monthly data, the “Amusement park, Hot spring, Farm, Working holiday, and Travel insurance” are important internet-searching tourism keywords having significant effects on various concepts of national income in Taiwan.

To sum up, we found that the real-time information of internet-searching tourism keywords indeed significantly explained the correlation between tourism and GDP in Taiwan. Also, through the abundant high-frequency information, our robust empirical results pointed out the important impact of tourism activities on economic in Taiwan. It could be treated as important suggestions for the authority to enhance the tourists’ motivation of consuming in tours and further increase the national income in Taiwan.

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Table1 Data description and classifications

Variables	Groups	Classifications	Source	Period	Frequency
Dependent variables	National Income	GDP, GNI, NI	Directorate General of Budget, Accounting and Statistics, Executive Yuan, Taiwan	2004~2020	Annual
Real-time Tourism-related variables	Transport	Cruises	Google Trends database	2004M1~2020M12 2004Q1~2020Q4	Monthly, Quarterly
		Bus			
		Rail			
		Car rental			
		Taxi			
		Airplane			
	Rest	Hotel			
		Accommodations			
		Resort			
	Recreational areas	Amusement Park			
		Zoo			
		Attraction			
		Places of interest			
		Hot spring			
		Night market			
		Farm			
	Grand tour	Backpacker			
		Free travel			
		Working holiday			
	Travel-related	Guidebook			
		Travel insurance			
		Subsidy			
		Travel agency			
		Travel			
		Guide			
		Souvenir			
		Luggage			
		Visitor center			
		Package tour			

Table 2 The factor loadings of diffusion indices-quarterly data

Dependent variables	Part A		Part B	PartC	
	GDP		GNI	NI	
Quarterly data	Q4			Q4	
Diffusion index	DF2	DF3		DF2	DF3
Components of Diffusion index(keywords)	**Ranking of components (by weight)**				
Cruises					
Bus					
Rail					
Car rental (1)_				**1**	
Taxi					
Airplane					
Hotel					
Accommodations					
Resort					
Amusement Park (1)	**3**				
Zoo					
Attraction (1)				**1**	
Places of interest (1)					**1**
Hot spring (1)	**2**				
Night market					
Farm (1)		**2**			
Backpacker					
Free travel					
Working holiday (1)					**3**
Guidebook					
Travel insurance (1)		**1**			
Subsidy					
Travel agency (1)					**2**
Travel					
Guide					
Souvenir					
Luggage (1)	**1**				
Visitor center (2)		**2**		**3**	
Package tour					
First r eigenvalues of the correlation matrix:	4.81	3.62		5.48	3.56
Variability explained	0.73			0.67	

Source: The authors. (1). In the first column, the number in the parentheses after those components of diffusion index represents how many times that the keyword has ever been the top 3 components in each diffusion index. (2). In table 2, we choose those diffusion indices having significant effects on dependent variables in VAR tests in Table 4. And there's only those diffusion indices constructed by the 4th quarter data have significant effects on GDP and NI. (3). Based on the ranking of components, we conclude the higher-weight variables in bold italics, which are "Car rental, Amusement Park, Attraction, Places of interest, Hot spring, Farm, Working holiday, Travel insurance, Travel agency, Luggage, and Visitor center."

Table 3 The factor loadings of diffusion indices-monthly data

Dependent variables	**Part A**					**Part B**								**Part C**								
	GDP					**GNI**								**NI**								
Monthly data	**M4**		**M8**	**M10**		**M4**		**M8**	**M10**		**M11**	**M12**		**M3**	**M4**		**M6**	**M8**	**M9**	**M10**	**M12**	
Diffusion index	**DF1**	**DF2**	**DF2**	**DF2**	**DF3**	**DF1**	**DF2**	**DF2**	**DF3**	**DF3**	**DF3**	**DF2**	**DF3**	**DF1**	**DF1**	**DF2**	**DF3**	**DF2**	**DF3**	**DF2**	**DF2**	**DF3**
Components of Diffusion index(keywords)	**Ranking of components (by weight)**																					
Cruises (3)		**1**					**1**									**1**						
Bus																						
Rail (1)														**1**								
Car rental (3)	**3**					**3**									**3**							
Taxi																						
Airplane (1)										**3**												
Hotel (1)														**3**								
Accommodations (3)				**1**					**1**											**1**		
Resort																						
Amusement Park (6)		**3**					**3**					**2**				**3**	**1**				**2**	
Zoo (3)		**3**					**3**									**3**						
Attraction																						
Places of interest (2)													**1**									**1**
Hot spring (5)			**2**					**1**			**2**							**2**	**2**			
Night market																						
Farm (5)		**2**			**2**		**2**			**2**						**2**						
Backpacker (3)				**3**				**3**												**2**		
Free travel																						
Working holiday (7)			**1**	**1**					**3**				**3**					**1**		**1**		**3**
Guidebook(3)									**1**				**1**									**1**
Travel insurance (6)			**3**		**1**			**2**		**1**								**3**	**3**			
Subsidy																						
Travel agency (4)	**3**					**3**					**3**				**3**							
Travel (3)	**1**					**1**									**1**							
Guide (3)	**2**					**2**									**2**							
Souvenir (4)											**1**	**1**					**2**				**1**	
Luggage (4)												**3**		**2**					**1**		**3**	
Visitor center (1)																	**3**					
Package tour																						
First r eigenvalues of the correlation matrix:	9.74	4.79	4.78	5.45	4.32	9.74	4.79	4.78	5.45	4.32	4.20	4.52	4.21	8.32	9.74	4.79	4.13	4.78	2.90	5.45	4.52	4.21
Variability explained	0.64		0.65	0.68		0.64		0.65	0.68		0.65	0.63		0.61	0.64		0.69	0.65	0.60	0.68	0.63	

Source: The authors. (1). In the first column, the number in the parentheses after those components of diffusion index represents how many times that the keyword has ever been the top 3 components in each diffusion index. (2). In table 3, we choose those diffusion indices which have significant effects on dependent variables in VAR tests in Table 5 to Table 7. (3). Based on the ranking of components, we conclude the higher-weight variables in bold italics, which are "Amusement Park, Hot spring, Farm, Working holiday, and Travel insurance."

Table 4 VAR results (Quarterly data)

Model 1, $y_t = \alpha_1 + \beta_1 y_{t-1} + \beta_2 DF1_{t-1} + \beta_3 DF2_{t-1} + \beta_4 DF3_{t-1} + \varepsilon_{yt}$

Model 2, $DF1_t = \alpha_2 + \beta_5 y_{t-1} + \beta_6 DF1_{t-1} + \beta_7 DF2_{t-1} + \beta_8 DF3_{t-1} + \varepsilon_{DF1t}$

Model 3, $DF2_t = \alpha_3 + \beta_9 y_{t-1} + \beta_{10} DF1_{t-1} + \beta_{11} DF2_{t-1} + \beta_{12} DF3_{t-1} + \varepsilon_{DF2t}$

Model 4, $DF3_t = \alpha_4 + \beta_{13} y_{t-1} + \beta_{14} DF1_{t-1} + \beta_{15} DF2_{t-1} + \beta_{16} DF3_{t-1} + \varepsilon_{DF3t}$

Dependent variables		Part A				Part B				Part C			
		GDP				GNI				NI			
Model	Coefficients	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
1	α_1	2.10 (3.00)	-1.00 (2.90)	-0.50 (2.29)	-0.18 (2.29)	2.10 (3.00)	-1.00 (2.90)	-0.50 (2.29)	0.99 (1.27)	3.68 (3.68)	-1.90 (3.91)	1.35 (3.02)	0.58 (2.47)
	β_1	0.99† (0.18)	0.82† (0.23)	1.08† (0.23)	0.42† (0.17)	0.99† (0.18)	0.82† (0.23)	1.08† (0.23)	0.96† (0.09)	1.10† (0.21)	0.76† (0.34)	1.02† (0.27)	0.33* (0.20)
	β_2	5.32 (12.93)	-12.46 (16.23)	-2.32 (9.39)	-20.20 (11.64)	5.32 (12.93)	-12.46 (16.23)	-2.32 (9.39)	-0.51 (5.43)	15.28 (15.68)	-17.86 (22.86)	3.21 (12.70)	-19.46 (12.91)
	β_3	0.29 (2.04)	0.36 (2.42)	2.14 (2.91)	***5.61† (1.93)***	0.29 (2.04)	0.36 (2.42)	2.14 (2.91)	-0.45 (1.08)	1.19 (2.54)	0.30 (3.63)	1.14 (3.57)	***6.97† (2.22)***
	β_4	-0.37 (2.17)	1.6 1(1.39)	-1.71 (1.49)	***-1.67* (0.86)***	-0.37 (2.17)	1.61 (1.39)	-1.71 (1.49)	-0.40 (0.40)	-0.49 (2.66)	1.51 (1.99)	-0.22 (1.76)	***-3.02† (0.90)***
2	α_2	-0.18† (0.07)	-0.06 (0.05)	-0.03 (0.04)	-0.05 (0.03)	-0.18† (0.07)	-0.06 (0.05)	-0.03 (0.04)	-0.12 (0.08)	-0.18† (0.07)	-0.07 (0.05)	-0.04 (0.04)	-0.05 (0.03)
	β_5	-0.002 (0.004)	-0.002 (0.004)	**-0.01† (0.004)**	0.001 (0.003)	-0.002 (0.004)	-0.002 (0.004)	**-0.01† (0.004)**	-0.01 (0.01)	-0.002 (0.004)	-0.004 (0.004)	**-0.01† (0.003)**	0.0004 (0.003)
	β_6	0.22 (0.30)	0.72† (0.26)	0.63† (0.16)	0.83† (0.17)	0.22 (0.30)	0.72† (0.26)	0.63† (0.16)	0.29 (0.36)	0.22 (0.29)	0.60† (0.26)	0.63† (0.15)	0.81† (0.18)
	β_7	-0.01 (0.05)	0.06 (0.04)	-0.13† (0.05)	0.004 (0.03)	-0.01 (0.05)	0.06 (0.04)	-0.13† (0.05)	0.07 (0.07)	-0.01 (0.05)	0.08* (0.04)	-0.13† (0.04)	0.01 (0.03)
	β_8	0.08 (0.05)	-0.02 (0.02)	-0.05* (0.02)	0.09† (0.01)	0.08 (0.05)	-0.02 (0.02)	-0.05* (0.02)	-0.01 (0.03)	0.08 (0.05)	-0.01 (0.02)	-0.06† (0.02)	0.09† (0.01)
3	α_3	0.32 (0.23)	-0.15 (0.30)	0.41 (0.25)	-0.29 (0.26)	0.32 (0.23)	-0.15 (0.30)	0.41 (0.25)	-1.07† (0.29)	0.34 (0.22)	-0.13 (0.30)	0.38 (0.24)	-0.33 (0.28)
	β_9	**-0.08† (0.01)**	0.03 (0.02)	-0.05* (0.03)	0.03 (0.02)	**-0.08† (0.01)**	0.03 (0.02)	**-0.05* (0.03)**	0.003 (0.02)	**-0.08† (0.01)**	0.04 (0.03)	**-0.04*** (0.02)**	0.02 (0.02)
	β_{10}	-1.06 (1.01)	0.27 (1.67)	0.30 (1.05)	-0.45 (1.31)	-1.06 (1.01)	0.27 (1.67)	0.30 (1.05)	-4.21† (1.25)	-0.93 (0.92)	0.47 (1.78)	0.25 (1.00)	-0.97 (1.47)
	β_{11}	-0.05 (0.16)	0.46* (0.25)	0.22 (0.32)	0.55† (0.22)	-0.05 (0.16)	0.46* (0.25)	0.22 (0.32)	0.39 (0.25)	-0.08 (0.15)	0.40 (0.28)	0.24 (0.28)	0.64† (0.25)
	β_{12}	0.02 (0.17)	0.23 (0.14)	-0.06 (0.17)	-0.05 (0.10)	0.02 (0.17)	0.23 (0.14)	-0.06 (0.17)	0.002 (0.09)	-0.002 (0.16)	0.19 (0.16)	-0.11 (0.14)	-0.08 (0.10)
4	α_4	0.66 (0.47)	-0.11 (0.46)	-1.07† (0.48)	1.05 (0.70)	0.66 (0.47)	-0.11 (0.46)	-1.07† (0.48)	-0.50 (0.63)	0.67 (0.47)	-0.19 (0.46)	-0.97† (0.48)	1.16 (0.73)
	β_{13}	-0.0003 (0.03)	-0.02 (0.04)	0.09* (0.05)	-0.04 (0.05)	-0.0003 (0.03)	-0.02 (0.04)	**0.09* (0.05)**	**0.09* (0.04)**	-0.01 (0.03)	-0.03 (0.04)	0.07 (0.04)	-0.01 (0.06)
	β_{14}	2.72 (2.03)	-0.96 (2.57)	-1.76 (1.99)	3.13 (3.58)	2.72 (2.03)	-0.96 (2.57)	-1.76 (1.99)	0.23 (2.69)	2.59 (2.01)	-1.74 (2.69)	-1.91 (2.02)	4.35 (3.82)
	β_{15}	-0.39 (0.32)	0.49 (0.38)	1.22* (0.62)	0.93 (0.59)	-0.39 (0.32)	0.49 (0.38)	1.22** (0.62)	-1.16† (0.53)	-0.44 (0.32)	0.63 (0.43)	1.03* (0.57)	0.70 (0.66)
	β_{16}	0.05 (0.34)	-0.35 (0.22)	-0.58* (0.32)	-0.29 (0.26)	0.05 (0.34)	-0.35 (0.22)	-0.58* (0.32)	-0.45†(0.20)	0.01 (0.34)	-0.29 (0.23)	-0.43 (0.28)	-0.26 (0.27)
	det(SSE)	0.00000002	0.00000001	0.000000003	0.000000001	0.00000002	0.00000001	0.000000003	0.000000003;	0.00000002	0.00000001	0.00000001	0.000000003
	AIC	-16.03	-17.03	-17.73	-18.5	-16.03	-17.03	-17.73	-17.42	-15.88	-16.80	-17.13	-17.75
	BIC	-15.24	-16.25	-16.95	-17.7	-15.24	-16.25	-16.95	-16.67	-15.09	-16.02	-16.35	-16.98
	HQ	-15.95	-16.95	-17.66	-18.4	-15.95	-16.95	-17.66	-17.43	-15.80	-16.72	-17.06	-17.71

Source: The authors. Robust t statistics in brackets. * significant at 10%; ** significant at 5%; † significant at 1%.

Table 5 VAR results (Monthly data)

Model 1, $y_t = \alpha_1 + \beta_1 y_{t-1} + \beta_2 DF1_{t-1} + \beta_3 DF2_{t-1} + \beta_4 DF3_{t-1} + \varepsilon_{yt}$

Model 2, $DF1_t = \alpha_2 + \beta_5 y_{t-1} + \beta_6 DF1_{t-1} + \beta_7 DF2_{t-1} + \beta_8 DF3_{t-1} + \varepsilon_{DF1t}$

Model 3, $DF2_t = \alpha_3 + \beta_9 y_{t-1} + \beta_{10} DF1_{t-1} + \beta_{11} DF2_{t-1} + \beta_{12} DF3_{t-1} + \varepsilon_{DF2t}$

Model 4, $DF3_t = \alpha_4 + \beta_{13} y_{t-1} + \beta_{14} DF1_{t-1} + \beta_{15} DF2_{t-1} + \beta_{16} DF3_{t-1} + \varepsilon_{DF3t}$

Dependent variables		GDP											
Model	Coefficients	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
1	α_1	6.69 (4.74)	5.83* (3.13)	2.80 (1.94)	5.71† (1.87)	2.72 (2.53)	2.03 (2.36)	4.33* (2.63)	-2.31 (3.40)	-0.74 (2.41)	4.36* (2.51)	-1.42 (2.76)	2.67 (2.77)
	β_1	0.89† (0.17)	1.21† (0.27)	1.05† (0.15)	0.84† (0.12)	1.01† (0.15)	0.91† (0.21)	0.83† (0.22)	1.01† (0.17)	0.94† (0.19)	0.60† (0.19)	0.81† (0.12)	0.61† (0.17)
	β_2	20.77 (18.63)	27.46 (19.28)	10.19 (10.16)	***15.47† (7.49)***	8.48 (13.26)	2.56 (14.66)	9.34 (12.26)	-12.01 (16.99)	-7.71 (12.90)	2.28 (11.97)	-13.65 (13.48)	-3.59 (12.86)
	β_3	3.80 (3.60)	-0.32 (1.78)	-0.03 (1.66)	***-3.79† (1.55)***	0.19 (1.38)	0.75 (1.72)	2.67 (2.28)	***3.02* (1.76)***	-1.03 (2.10)	***5.71† (2.27)***	0.20 (1.21)	***3.61† (1.81)***
	β_4	1.76 (1.80)	-1.57 (2.12)	-0.62 (1.46)	1.78 (1.33)	0.03 (1.43)	1.24 (1.14)	1.59 (2.00)	0.47 (1.50)	-1.41 (1.17)	***2.03* (1.06)***	***1.81* (1.04)***	***-2.73** (1.37)***
2	α_2	-0.11 (0.10	-0.19† (0.07)	-0.11 (0.08)	-0.08 (0.06)	-0.09 (0.06)	-0.11* (0.07)	-0.14 (0.07)	-0.29† (0.07)	-0.05 (0.06)	-0.13 (0.09)	-0.07 (0.07)	-0.07* (0.04)
	β_5	-0.01† (0.004)	-0.003 (0.01)	-0.01* (0.01)	-0.01† (0.003)	-0.002 (0.004)	-0.004 (0.01)	-0.01* (0.01)	-0.01 (0.004)	-0.004 (0.005)	0.0003 (0.01)	-0.003 (0.003)	-0.003 (0.002)
	β_6	0.27 (0.41)	0.13 (0.41)	0.20 (0.40)	0.29 (0.22)	0.55* (0.32)	0.44 (0.41)	0.15 (0.32)	-0.33 (0.37)	0.66** (0.34)	0.49 (0.45)	0.63* (0.34)	0.62† (0.18)
	β_7	0.07 (0.08)	0.03 (0.04)	-0.09 (0.07)	-0.14† (0.05)	0.04 (0.03)	0.04 (0.05)	0.01 (0.06)	0.03 (0.04)	0.05 (0.05)	-0.05 (0.08)	0.02 (0.03)	0.06† (0.03)
	β_8	0.03 (0.04)	0.01 (0.04)	-0.01 (0.06)	0.04 (0.04)	0.01 (0.03)	0.01 (0.03)	0.05 (0.05)	0.06* (0.03)	0.004 (0.03)	0.05 (0.04)	-0.03 (0.03)	0.06† (0.02)
3	α_3	-0.33 (0.49)	1.09† (0.44)	0.61† (0.22)	0.85† (0.32)	0.91† (0.38)	-0.35 (0.35)	-0.16 (0.60)	1.01 (0.64)	-0.53 (0.37)	-0.69† (0.22)	-0.68* (0.40)	0.06 (0.56)
	β_9	0.06† (0.02)	-0.03 (0.04)	-0.04† (0.02)	-0.02 (0.02)	0.03 (0.02)	0.001 (0.03)	0.06 (0.05)	-0.01 (0.03)	0.06† (0.03)	0.06† (0.02)	0.02 (0.02)	0.06* (0.03)
	β_{10}	0.39 (1.92)	3.56 (2.69)	1.32 (1.16)	2.95† (1.29)	4.45† (1.99)	-1.45 (2.21)	1.09 (2.78)	3.83 (3.21)	-0.35 (1.99)	-1.16 (1.04)	-2.11 (1.94)	1.83 (2.62)
	β_{11}	0.08 (0.37)	-0.34 (0.25)	0.08 (0.19)	-0.32 (0.27)	0.20 (0.21)	0.74† (0.26)	-0.13 (0.52)	-0.03 (0.33)	-0.09 (0.32)	-0.11 (0.20)	0.45† (0.17)	0.10 (0.37)
	β_{12}	0.04 (0.19)	0.32 (0.30)	-0.36† (0.17)	-0.03 (0.23)	0.60† (0.21)	0.12 (0.17)	-0.14 (0.45)	0.02 (0.28)	-0.01 (0.18)	-0.04 (0.09)	-0.04 (0.15)	-0.25 (0.28)
4	α_4	-0.58 (1.20)	0.16 (0.44)	0.58 (0.46)	0.08 (0.40)	-0.73 (0.46)	0.42 (0.45)	-0.26 (0.52)	-0.18 (0.63)	0.57 (0.66)	0.92 (0.61)	-1.37* (0.75)	1.09* (0.62)
	β_{13}	0.01 (0.04)	0.06 (0.04)	0.01 (0.04)	0.07† (0.02)	0.002 (0.03)	0.09† (0.04)	-0.02 (0.04)	0.01 (0.03)	0.04 (0.05)	0.11† (0.05)	-0.04 (0.03)	-0.06 (0.04)
	β_{14}	-2.17 (4.71)	2.40 (2.72)	2.42 (2.39)	2.48 (1.59)	-2.89 (2.40)	4.65* (2.79)	-1.78 (2.41)	-0.30 (3.15)	3.51 (3.56)	6.91† (2.90)	-6.57* (3.64)	2.74 (2.89)
	β_{15}	-0.47 (0.91)	-0.13 (0.25)	-0.67* (0.39)	0.02 (0.33)	0.15 (0.25)	-0.32 (0.33)	0.59 (0.45)	-0.19 (0.33)	-0.23 (0.58)	-0.36 (0.55)	-0.76† (0.33)	0.61 (0.41)
	β_{16}	0.10 (0.46)	0.32 (0.30)	0.01 (0.34)	0.10 (0.28)	0.27 (0.26)	-0.57† (0.22)	0.30 (0.39)	0.23 (0.28)	0.09 (0.32)	-0.06 (0.26)	-0.24 (0.28)	-0.59* (0.31)
	det(SSE)	0.00000004	0.00000002	0.0000001	0.00000004	0.00000004	0.00000005	0.0000001	0.00000003	0.0000002	0.00000001	0.00000003	0.00000001
	AIC	-15.18	-15.66	-14.07	-15.13	-15.05	-14.96	-14.18	-15.40	-13.83	-16.58	-15.30	-16.19
	BIC	-14.40	-14.88	-13.28	-14.35	-14.27	-14.17	-13.39	-14.62	-13.04	-15.81	-14.52	-15.42
	HQ	-15.11	-15.58	-13.99	-15.05	-14.97	-14.88	-14.10	-15.32	-13.75	-16.54	-15.26	-16.15

Source: The authors. Robust t statistics in brackets. * significant at 10%; ** significant at 5%; † significant at 1%.

Table 6 VAR results (Monthly data)

Dependent variables		GNI											
Model	Coefficients	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
1	α_1	6.69 (4.74)	5.83* (3.13)	2.80 (1.94)	5.71† (1.87)	2.72 (2.53)	2.08 (2.36)	4.33* (2.63)	-2.31 (3.40)	-0.74 (2.41)	4.36* (2.51)	-1.42 (2.76)	2.67 (2.77)
	β_1	0.89† (0.17)	1.21† (0.27)	1.05† (0.15)	0.84† (0.12)	1.01† (0.15)	0.84† (0.20)	0.83† (0.22)	1.01† (0.17)	0.94† (0.19)	0.60† (0.19)	0.81† (0.12)	0.61*** (0.17)
	β_2	20.77 (18.63)	27.46 (19.28)	10.19 (10.16)	***15.47†*** ***(7.49)***	8.48 (13.26)	1.05 (13.26)	9.34 (12.26)	-12.01 (16.99)	-7.71 (12.90)	2.28 (11.97)	-13.65 (13.48)	-3.59 (12.86)
	β_3	3.80 (3.60)	-0.32 (1.78)	-0.03 (1.66)	***-3.79†*** ***(1.55)***	0.19 (1.38)	1.69 (1.64)	2.67 (2.28)	***3.02**** ***(1.76)***	-1.03 (2.10)	***5.71†*** ***(2.27)***	0.20 (1.21)	***3.61†*** ***(1.81)***
	β_4	1.76 (1.80)	-1.57 (2.12)	-0.62 (1.46)	1.78 (1.33)	0.03 (1.43)	0.32 (1.34)	1.59 (2.00)	0.47 (1.50)	-1.41 (1.17)	***2.03**** ***(1.06)***	***1.81**** ***(1.04)***	***-2.73**** ***(1.37)***
2	α_2	-0.11 (0.10)	-0.19† (0.07)	-0.11 (0.08)	-0.08 (0.06)	-0.09 (0.06)	-0.11* (0.06)	-0.14† (0.07)	-0.29† (0.07)	-0.05 (0.06)	-0.13 (0.09)	-0.07 (0.07)	-0.07* (0.04)
	β_5	-0.01† (0.004)	-0.003 (0.01)	-0.01* (0.01)	-0.01† (0.003)	-0.002 (0.004)	-0.004 (0.01)	-0.01* (0.01)	-0.01 (0.004)	-0.004 (0.005)	0.0003 (0.01)	-0.003 (0.003)	-0.003 (0.002)
	β_6	0.27 (0.41)	0.13 (0.41)	0.20 (0.40)	0.29 (0.22)	0.55* (0.32)	0.50 (0.35)	0.15 (0.32)	-0.33 (0.37)	0.66** (0.34)	0.49 (0.45)	0.63* (0.34)	0.62† (0.18)
	β_7	0.07 (0.08)	0.03 (0.04)	-0.09 (0.07)	-0.14† (0.05)	0.04 (0.03)	-0.001 (0.04)	0.01 (0.06)	0.03 (0.04)	0.05 (0.05)	-0.05 (0.08)	0.02 (0.03)	0.06† (0.03)
	β_8	-0.03 (0.04)	0.01 (0.04)	-0.01 (0.06)	0.04 (0.04)	0.01 (0.03)	0.05 (0.04)	0.05 (0.05)	0.06* (0.03)	0.004 (0.03)	0.05 (0.04)	-0.03 (0.03)	0.06† (0.02)
3	α_3	-0.33 (0.49)	1.09† (0.44)	0.61† (0.22)	0.85† (0.32)	0.91† (0.38)	-0.40 (0.26)	-0.16 (0.60)	1.01 (0.64)	-0.53 (0.37)	-0.69† (0.22)	-0.68* (0.40)	0.06 (0.56)
	β_9	0.06*** (0.02)	-0.03 (0.04)	-0.04† (0.02)	-0.02 (0.02)	0.03 (0.02)	0.03 (0.02)	0.06 (0.05)	-0.01 (0.03)	0.06† (0.03)	0.06† (0.03)	0.02 (0.02)	0.06* (0.03)
	β_{10}	0.39 (1.92)	3.56 (2.69)	1.32 (1.16)	2.95† (1.29)	4.45† (1.99)	-0.82 (1.48)	1.09 (2.78)	3.83 (3.21)	-0.35 (1.99)	-1.16 (1.04)	-2.11 (1.94)	1.83 (2.62)
	β_{11}	0.08 (0.37)	-0.34 (0.25)	0.08 (0.19)	-0.32 (0.27)	0.20 (0.21)	0.61† (0.18)	-0.13 (0.52)	-0.03 (0.33)	-0.09 (0.32)	-0.11 (0.20)	0.45† (0.17)	0.10 (0.37)
	β_{12}	0.04 (0.19)	0.32 (0.30)	-0.36† (0.17)	-0.03 (0.23)	0.60† (0.21)	-0.30† (0.15)	-0.14 (0.45)	0.02 (0.28)	-0.01 (0.18)	-0.04 (0.09)	-0.04 (0.15)	-0.25 (0.28)
4	α_4	-0.58 (1.20)	0.16 (0.44)	0.58 (0.46)	0.08 (0.40)	-0.73 (0.46)	0.22 (0.46)	-0.26 (0.52)	-0.18 (0.63)	0.57 (0.66)	0.92 (0.61)	-1.37* (0.75)	1.09* (0.62)
	β_{13}	0.01 (0.04)	0.06 (0.04)	0.01 (0.04)	0.07† (0.02)	0.002 (0.03)	0.07* (0.04)	-0.02 (0.04)	0.01 (0.03)	0.04 (0.05)	0.11† (0.05)	-0.04 (0.03)	-0.06 (0.04)
	β_{14}	-2.17 (4.71)	2.40 (2.72)	2.42 (2.39)	2.48 (1.59)	-2.89 (2.40)	2.31 (2.58)	-1.78 (2.41)	-0.30 (3.15)	3.51 (3.56)	6.91† (2.90)	-6.57* (3.64)	2.74 (2.89)
	β_{15}	-0.47 (0.91)	-0.13 (0.25)	-0.67* (0.39)	0.02 (0.33)	0.15 (0.25)	0.26 (0.32)	0.59 (0.45)	-0.19 (0.33)	-0.23 (0.58)	-0.36 (0.55)	-0.76† (0.33)	0.61 (0.41)
	β_{16}	0.10 (0.46)	0.32 (0.30)	0.01 (0.34)	0.10 (0.28)	0.27 (0.26)	-0.27 (0.26)	0.30 (0.39)	0.23 (0.28)	0.09 (0.32)	-0.06 (0.26)	-0.24 (0.28)	-0.59** (0.31)
	det(SSE)	0.00000004	0.00000002	0.0000001	0.00000004	0.00000004	0.00000003	0.0000001	0.00000003	0.0000002	0.00000001	0.00000003	0.00000001
	AIC	-15.18	-15.66	-14.07	-15.13	-15.05	-15.19	-14.18	-15.40;	-13.83	-16.58	-15.30	-16.19
	BIC	-14.40	-14.88	-13.28	-14.35	-14.27	-14.41	-13.39	-14.62	-13.04	-15.81	-14.52	-15.42
	HQ	-15.11	-15.58	-13.99	-15.05	-14.97	-15.15	-14.10	-15.32	-13.75	-16.54	-15.26	-16.15

Source: The authors. Robust t statistics in brackets. * significant at 10%; ** significant at 5%; † significant at 1%.

Table 7 VAR results (Monthly data)

Dependent variables		NI											
Model	Coefficients	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
1	α_1	7.40 (6.37)	5.47 (3.73)	5.04† (1.92)	6.90† (1.95)	3.70 (3.26)	2.57 (2.92)	5.35 (3.39)	0.29 (4.43)	0.35 (2.99)	5.62 (3.73)	-1.70 (3.78)	4.26 (3.51)
	β_1	0.90† (0.21)	0.99† (0.28)	1.08† (0.18)	0.78† (0.11)	1.10† (0.21)	0.84† (0.26)	0.82† (0.29)	1.17† (0.21)	0.91† (0.22)	0.61† (0.25)	0.77† (0.17)	0.60† (0.19)
	β_2	24.33 (24.51)	18.93 (21.26)	18.58* (9.91)	18.22† (7.69)	15.38 (17.55)	2.67 (18.29)	13.47 (15.15)	3.61 (22.14)	-4.15 (15.96)	7.58 (17.51)	-15.89 (18.44)	2.40 (15.86)
	β_3	3.69 (4.90)	-2.10 (2.16)	1.79 (1.49)	-5.93† (1.55)	-1.29 (1.83)	1.69 (2.15)	2.27 (3.22)	4.11* (2.22)	-0.39 (2.41)	6.22† (3.10)	0.37 (1.62)	3.93* (2.33)
	β_4	1.78 (2.40)	0.08 (2.50)	-0.64 (1.56)	1.54 (1.42)	0.09 (1.83)	2.38* (1.33)	2.72 (2.61)	-0.19 (1.88)	-2.67* (1.38)	2.40 (1.52)	2.25 (1.39)	-4.08† (1.66)
2	α_2	-0.07 (0.10)	-0.20† (0.06)	-0.20† (0.07)	-0.08 (0.05)	-0.11* (0.06)	-0.11 (0.07)	-0.12* (0.07)	-0.29† (0.08)	-0.03 (0.07)	-0.13 (0.09)	-0.06 (0.07)	-0.08† (0.04)
	β_5	-0.01† (0.003)	-0.01 (0.004)	-0.01 (0.01)	-0.01† (0.003)	-0.004 (0.004)	-0.004 (0.01)	-0.01* (0.01)	-0.01 (0.004)	-0.0004 (0.005)	0.0005 (0.01)	-0.002 (0.003)	-0.004** (0.002)
	β_6	0.38 (0.37)	0.02 (0.32)	0.10 (0.36)	0.32* (0.19)	0.44 (0.32)	0.40 (0.43)	0.17 (0.30)	-0.33 (0.38)	0.84† (0.35)	0.49 (0.44)	0.73† (0.35)	0.59† (0.16)
	β_7	0.10 (0.07)	0.03 (0.03)	-0.05 (0.05)	-0.14† (0.04)	0.05 (0.03)	0.04 (0.05)	0.03 (0.06)	0.03 (0.04)	0.02 (0.05)	-0.06 (0.08)	0.02 (0.03)	0.07† (0.02)
	β_8	-0.02 (0.04)	0.03 (0.04)	-0.02 (0.06)	0.05 (0.04)	0.01 (0.03)	0.01 (0.03)	0.06 (0.05)	0.05* (0.03)	-0.01 (0.03)	0.05 (0.04)	-0.02 (0.03)	0.06† (0.02)
3	α_3	-0.51 (0.46)	1.08† (0.39)	-0.62 (0.43)	0.83† (0.33)	0.87† (0.40)	-0.38 (0.37)	-0.19 (0.62)	1.01 (0.66)	-0.51 (0.39)	-0.67† (0.25)	-0.77* (0.42)	0.01 (0.57)
	β_9	0.06† (0.02)	-0.03 (0.03)	0.02 (0.04)	-0.01 (0.02)	0.02 (0.03)	-0.002 (0.03)	0.04 (0.05)	-0.01 (0.03)	0.05* (0.03)	0.05† (0.02)	0.01 (0.02)	0.05 (0.03)
	β_{10}	-0.28 (1.75)	3.52 (2.21)	-2.20 (2.25)	3.09† (1.31)	4.10* (2.16)	-1.65 (2.34)	0.55 (2.77)	3.82 (3.29)	-0.55 (2.10)	-1.44 (1.16)	-2.67 (2.04)	1.43 (2.57)
	β_{11}	-0.07 (0.35)	-0.35 (0.22)	0.03 (0.34)	-0.26 (0.26)	0.20 (0.23)	0.76† (0.28)	-0.08 (0.59)	-0.02 (0.33)	0.01 (0.32)	0.01(0.21)	0.44*** (0.18)	0.10 (0.38)
	β_{12}	-0.01 (0.17)	0.34 (0.26)	-0.56 (0.35)	-0.07 (0.24)	0.59† (0.22)	0.12 (0.17)	-0.05 (0.48)	0.02 (0.28)	0.03 (0.18)	-0.08 (0.10)	-0.06 (0.15)	-0.31 (0.27)
4	α_4	-0.60 (1.23)	0.002 (0.41)	0.13 (0.39)	0.04 (0.38)	-0.69 (0.47)	0.35 (0.51)	-0.26 (0.53)	-0.13 (0.64)	0.77 (0.63)	0.93 (0.67)	-1.41* (0.75)	1.13* (0.62)
	β_{13}	0.01 (0.04)	0.04 (0.03)	-0.05 (0.04)	0.07† (0.02)	0.01 (0.03)	0.08* (0.04)	-0.01 (0.05)	0.01 (0.03)	0.07 (0.05)	0.08* (0.04)	-0.04 (0.03)	-0.05 (0.03)
	β_{14}	-2.24 (4.72)	1.10 (2.36)	-0.80 (2.04)	2.29 (1.50)	-2.62 (2.52)	3.92 (3.22)	-1.45 (2.36)	-0.05 (3.21)	5.23 (3.39)	6.06* (3.15)	-6.77* (3.68)	3.09 (2.82)
	β_{15}	-0.48 (0.94)	-0.21 (0.24)	0.32 (0.31)	-0.004 (0.30)	0.13 (0.26)	-0.26 (0.38)	0.52 (0.50)	-0.17 (0.32)	-0.47 (0.51)	-0.07 (0.56)	-0.75† (0.32)	0.62 (0.41)
	β_{16}	0.09 (0.46)	0.44 (0.28)	0.26 (0.32)	0.03 (0.28)	0.26 (0.26)	-0.52† (0.23)	0.22 (0.41)	0.22 (0.27)	0.03 (0.29)	-0.15 (0.27)	-0.24 (0.28)	-0.53* (0.29)
	det(SSE)	0.0000001	0.00000003	0.00000	0.00000004	0.0000001	0.0000001	0.0000001	0.00000004	0.0000002	0.00000003;	0.0000001	0.00000002
	AIC	-14.91	-15.34	-11.16	-15.08	-14.88	-14.63	-14.05	-15.20	-13.78	-15.41	-14.36	-15.99
	BIC	-14.12	-14.55	-10.40	-14.30	-14.09	-13.85	-13.26	-14.42	-12.99	-14.64	-13.59	-15.22
	HQ	-14.83	-15.26	-11.16	-15.00	-14.80	-14.56	-13.97	-15.12	-13.70	-15.37	-14.32	-15.95

Source: The authors. Robust t statistics in brackets. * significant at 10%; ** significant at 5%; † significant at 1%.