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# Modeling and Forecasting Monthly Tourism Arrivals to Aruba Since COVID-19 Pandemic

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**Modeling and Forecasting Monthly Tourism Arrivals to Aruba Since COVID-19 Pandemic**
**Prepared by Olga G. Bespalova**

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**ABSTRACT:** This paper improves short-term forecasting models of monthly tourism arrivals by estimating and evaluating a time-series model with exogenous regressors (ARIMA-X) using a case of Aruba, a small open tourism-dependent economy. Given importance of the US market for Aruba, it investigates informational value of Google Searches originating in the USA, flight capacity utilization on the US air-carriers, and per capita demand of the US consumers, given the volatility index in stock markets (VIX). It yields several insights. First, flight capacity is the best variable to account for the travel restrictions during the pandemic. Second, US real personal consumption expenditure becomes a more significant predictor than income as the former better captured impact of the COVID-19 restrictions on the consumers' behavior, while income boosted by the pandemic fiscal support was not fully directed to spending. Third, intercept correction improves the model in the estimation period. Finally, the pandemic changed econometric relationships between the tourism arrivals and their main determinants, and accuracy of the forecast models. Going forward, the analysts should re-estimate the models. Out-of-sample forecasts with 5 percent confidence intervals are produced for 18 months ahead.

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WORKING PAPERS

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# Contents

# Glossary

| | |
|---|---|
| ADF test | Augmented Dickey–Fuller test |
| AIC | Akaike Information Criteria |
| ARIMA | Auto Regressive Integrated Moving Average |
| ARIMAX | ARIMA model with exogenous variables |
| ARMA | Auto Regressive Moving Average |
| ATA | Aruba Tourism Authority |
| BEA | Bureau of Economic Analysis |
| BTS | Bureau of Transportation Statistics |
| CBA | Central Bank of Aruba |
| COVID-19 | Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) |
| DFGLS | The modified Dickey–Fuller t test for a unit root in a time series |
| EPU | Economic Policy Uncertainty |
| GDP | Gross Domestic Product |
| GT | Google Trends |
| IC | Intercept Correction |
| MAE | Mean Absolute Error |
| NSA | Not Seasonally Adjusted |
| REER | Real Effective Exchange Rate |
| RGDP | Real Gross Domestic Product |
| RMSE | Root Mean Squared Error |
| RPCE | Real Personal Consumption Expenditures |
| SA | Seasonally Adjusted |
| US | United States |
| Theil U | Theil Inequality Coefficient |
| WHO | World Health Organization |
| WTO | World Tourism Organization |

# Executive Summary

**The Covid-19 pandemic triggered containment measures and disrupted businesses worldwide, severely affecting the economy in many countries, particularly in tourism destinations.** Aruba became no exception. To protect its citizens, in early March of 2020, the Government of Aruba introduced various safety measures and closed its borders for inbound travelers for almost three months. In June 2020, Aruba began to welcome tourists back, and the number of arrivals has been slowly recovering. In 2020 and 2021, country received about 34 and 72 percent of the 2019 tourist inflows, respectively.

**Accurate predictions of tourism inflows, used by Aruban policymakers to project Real Gross Domestic Product (RGDP)[1], became even more critical than before the pandemic.** The COVID-19 pandemic affected consumers' behavior, caused flight cancellation and movement restrictions and reduced flights' capacity. Thus, it becomes necessary to include these factors in the model to foresee future tourist inflows more accurately. To forecast tourism since the pandemic accurately, I need to find variables containing information about the drastic decline of tourism during the COVID-19 pandemic and tourism recovery in the post-pandemic world, which would be available in the past, present, and future.

**This paper improves the modeling and forecasting of tourism arrivals since the pandemic, highlighting that a structural change affected relative importance of some regressors over time.** It tests the ARIMA model (with monthly dummies) over three samples. Given that visitors from the USA constitute over 80 percent of all tourists, the model focuses on the explanatory variables related to the US markets. The original estimation sample uses 2004m1-2019m12, while the models' forecasting properties checked over 2020m1-2022m6. Then, the model is re-estimated, expanding the sample to include 2020 and 2021 respectively, yielding several insights. First, the Real Personal Consumption Expenditure (RPCE) became a more significant predictor than Real Personal Income (RPI) as the former was affected by the mobility restrictions while the latter was contaminated by the pandemic fiscal support not directed to spending. Second, Google Trends for All-Inclusive Hotels in Aruba (GT) and flight capacity utilization (CAP, also called the load factor) are always significant and strong predictors of tourism arrivals of regardless of the sample or model specification. Third, inclusion of the VIX improves the model before the intercept correction but loses significance once the model incorporates the binary indicator for covid-19 pandemic. Intercept correction helps to normalize residuals in the full sample. Fourth, the estimates are not sensitive to the use of the alternative to VIX risk measures, which include two variants of the US Economic Policy Uncertainty Index and the US unemployment rate. Finally, REER is dropped from the baseline specification because being weakly significant in the estimation sample it does not improve the forecasting properties of the model.

**The paper produces the out-of-sample forecasts of tourism arrivals to Aruba 18 months ahead.** It suggests that Aruba will invite on average 92.8 thousand tourist arrivals per month, with 78.9 and 106.6 thousand tourists indicating the lower and upper bounds of the 5 percent confidence level around the point forecast.

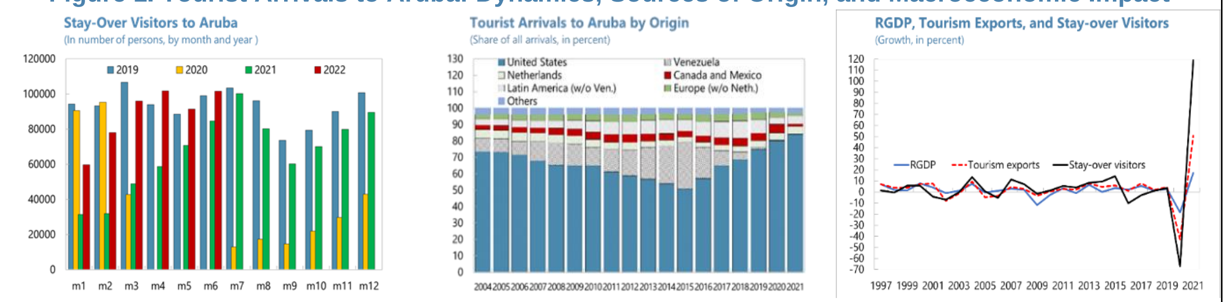
[1] In the macroeconomic forecasting model of Aruba ("MARUBA"), the number of tourism inflows is one of the most critical inputs.

# I. Introduction

**Tourism is the main economic pillar for many Caribbean countries.** The industry grew for decades, as many Caribbean islands recognized its benefits, such as improved infrastructure, higher local government revenue that allows enhancing community facilities and services, and spillovers into other economic sectors. Before the pandemic, in 2019, the number of international visitors globally had reached almost 1.5 billion (+4 percent YoY) [UNWTO, 2020]; Caribbean countries received 32 million of these tourists (+4.4 percent YoY), who generated about US$42 billion in gross expenditures (+6.4 percent YoY).

**Aruba is one of the most tourism-dependent Caribbean country.** It began developing the tourism industry in 1947 with the foundation of the Aruba Tourism Commission. Since then, and especially after the refinery's closure in 1985, Aruba pursued tourism as its main engine for economic growth and positioned itself as the most affluent destination in the region. In 2019, Aruba welcomed more than 1.1 million tourists – ten times its total population (compared to just about 200,000 in 1985). Most tourists to Aruba come from the USA; over 2015-2021, their share increased from 2/3 to more than 4/5. Europe, Latin America, and other regions take up almost equal parts of the non-US visitors (see the text-chart).

**Figure 1. Tourist Arrivals to Aruba: Dynamics, Sources of Origin, and Macroeconomic Impact**




Source: National Authorities and authors' calculations.

**During its onset in 2020, the COVID-19 pandemic had severely affected global economy, especially services and tourism sectors.** The social distancing measures and borders' closures had heavily hit the tourism-dependent small islands, which are vulnerable to external shocks, facing low export diversification and high external debt. In 2020, tourism arrivals to Aruba dropped by about 2/3 of the 2019 level (slightly better than a loss of 3/4 of tourism to the Caribbean region overall), triggering a shrinkage of real economy by 18.6 percent. Still, even in 2020, tourism directly created 44 percent of Aruban GDP and 36 percent of its jobs (López A.M. 2021a, 2021b), contributing about 4/5 of export revenues and providing a crucial source of the foreign exchange supply. The authorities' introduction of the "Aruba Health & Happiness Code" and a mobile app "Aruba Health" helped revive tourism once the borders re-opened in July 2020. In 2021, stay-over arrivals more than doubled, reaching 72 percent of 2019 level. In 2022, tourism recovery continued, and in April-June arrivals already exceeded the 2019 levels in the same months.

**Accurate projections of tourism arrivals are essential for the country's economic outlook.** The number of stay-over visitors highly correlates with the tourism exports and total output in Aruba (see the right panel of Figure 1 above). According to Stinge A.G. and A. V. Steeg (2010), one dollar of tourism receipts in Aruba generated a direct income of 68 cents and a total income of 95 cents (after accounting for indirect effects). Thus, estimates of the future tourism arrivals are crucial for the macroeconomic models to project real GDP.

**The main goal of this paper is to contribute to the modeling and forecasting of monthly tourism arrivals to Aruba in the post-pandemic world, focusing on the role of Google Trends and flight capacity data.** It poses several research questions: 1) What is the best model to explain and predict tourism arrivals to Aruba, and what are its explanatory variables? 2) What variables help to improve the forecast accuracy, compared to a pure time-series model, and what are their contributions to forecast improvement? 3) Has the pandemic changed econometric relationships between the tourism arrivals and their main determinants, and accuracy of the forecast models? 4) How to account for the structural shift in tourism since the pandemic and reduce forecast error? The onset of the COVID-19 pandemic had affected the tourism industry through the cancellation of flights, border closures, and changes in consumers' behavior. Thus, the forecasting models using a traditional set of regressors could overestimate future arrivals. The main challenge to this research is to find variables with a pre-pandemic history (and, ideally, easy to assume in the forecast period) which would reflect information about the structural and behavioral changes occurred in the tourism industry since COVID-19. It is addressed by exploring the value of the Google Trends, flight capacity utilization data, changes in financial risk and global uncertainty, and intercept correction. The paper also resolves practical questions, related to the choice of the most relevant Google Trends series, their extension, and making assumptions about the main explanatory variables, considering their release schedule and publication gaps.

**I address the challenges of forecasting tourism during the COVID-19 pandemics using several novel approaches.** The onset of the COVID-19 pandemic had affected the tourism industry through the cancellation of flights, border closures, and changes in consumers' behavior. Thus, the forecasting models using a traditional set of regressors without accounting for the pandemic conditions would likely overestimate the number of future arrivals. The main challenge is to find variables with a pre-pandemic history that would reflect information about the changes in the availability and capacity of flights and the tourism trends, which, ideally, should be easy to assume in the forecast period. In this paper, I utilize several novel approaches. First, I use the Google search frequency data (see section II and Annex I for details). Second, I calculate the flight capacity for the US carriers with the destination in Aruba. Third, I control for the market volatility using the CBOE volatility index (VIX), to capture the pandemic situation and related uncertainty. Fourth, I include the intercept correction. Finally, I test how the model properties change with expansion of the estimation sample from the pre-pandemic (2004-2019) to those including 2020 and 2021 respectively, and compare the forecasts accuracy in the training and test samples. Empirical results provide important insights regarding modeling and forecasting tourism arrivals since the pandemic.

**I organize the remainder of this paper as follows.** Section II reviews the literature. The data, their sources, and transformations, are featured in section III. Section IV summarizes the models and methodology of their estimation. and emphasizes the forecast assumptions. Section V highlights the main empirical results related to the estimated models, discusses their in-sample forecasting properties, and provides the out-of-sample forecasts for 18 months ahead. Section VI concludes.

# II. Literature Review

**This work relies on several strands of literature. First, there is a vast body of research on modeling and forecasting tourism arrivals, using different econometric techniques.** Among the plethora of publications on this subject[2], many authors supported the autoregressive integrated moving average (ARIMA) type of models, first proposed in Box and Jenkins (1976); Stellwagen E. & L. Tashman (2013) provide an excellent tutorial to their method. Goh and Law (2003) found that multivariate ARIMA (ARIMAX) is one of the most accurate among eight types of time-series models projecting tourism arrivals to Hong Kong. Preez & Witt (2003) demonstrated advantage of simple ARIMA over univariate and multivariate state space modelling for forecasting tourism arrivals to Seychelles. Athanasopoulos et al (2011) concluded that pure ARIMA was among the most accurate models, and even out-performed models with explanatory variables (although recognizing that the latter could be due to the models' misspecifications). Kim et al. (2011) emphasized that in tourism forecasting, point predictions should be complemented with the confidence intervals, which can enable the authorities and tourism promotion agencies to plan with higher flexibility; they evaluated several time-series models for tourism forecasting, and found that SARIMA produced accurate point forecasts and narrow prediction intervals. Gunter and Önder (2015) concluded that the univariate models of ARMA (1,1) were the most accurate in forecasting tourism arrivals to Paris from the USA and the United Kingdom. Claveria and Torra (2014) favored ARIMA models for predicting tourism demand in Catalonia.

**The second stream of papers looks at the demand factors for Caribbean destinations.** Laframboise et al. (2014) found that price and income factors in source markets determined tourism arrivals and revenue, pointing out that tourism price and income elasticities had declined since 2008. Culiuc (2014) showed that the tourism flows depend both on the GDP of a source country and Real Effective Exchange Rate (REER) in a destination country; however, arrivals to the small island economies depended less on the REER and more on the availability of direct flights. Acevedo et al. (2016) demonstrated the significance of the US air carriers' data for the Caribbean destinations.

**Third, a growing body of research explores the benefits of using the Google Trends data (GT) to model and forecast economic indicators, including tourism arrivals.** Economists began using the GT shortly after their first release to the public. For example, Choi and Varian (2009a, 2009b, 2012) applied them to nowcast initial unemployment claims, auto sales, and vacation destinations. Jun, Yoo, and Choi (2018) provided a comprehensive review of the research applying Google and other big data. Narita and Yin (2018) show that the GT help to project several economic indicators, including economic activity, prices, unemployment, tourism arrivals, and stock prices. Pan, Wu, and Song (2012) and Rivera (2016) applied the GT to predict the hotels' demand. Several papers have already used the GT to explain tourism arrivals to Caribbean destinations and demonstrated their benefit in forecasting (i.e., Jackman and Naitram, 2015; Bangwayo-Skeete and Skeete, 2015; Siliverstovs and Wochner, 2018; Cevik, 2020). However, not all the authors confirmed benefits to

[2] Alternative techniques included support vector regressions (Jackman and Naitram, 2015), mixed data sampling (Bangwayo-Skeete and Skeete, 2015), structural vector autoregressions (Acevedo et al., 2016), Bayesian model averaging (Siliverstovs and Wochner, 2018). Song and Li (2008) review the pre-2008 literature on tourism' modeling and forecasting.

forecast accuracy from their inclusion. For example, Jackman and Naitram (2015) found that the GT were helpful to project tourism flow to Barbados from the United Kingdom and Canada, but not from the USA.

**Finally, there are studies of tourism to Aruba, which either focus on its role in the economy in general, or on the importance of the all-inclusive tourism segment.** Ridderstaat, Croes, and Nijkamp (2014) showed the dual causality between Aruban tourism and economic growth, accurately documenting their long-run and short-run relationships. Stinge and Steeg (2010) estimated Aruba's average tourism income multiplier with the input-output tables. Vanegas and Croes (2003) documented positive distributional effects from tourism. Croes and Vanegas (2003) found that tourist arrivals to Aruba were highly elastic to the source countries' income (confirming that Aruban tourism is a luxury product) but were less sensitive to relative prices and exchange rates. Other studies focused on the role of all-inclusive tourism in the Aruban economy and its progress towards Sustainable Development Goals (see CBA, 2016; Peterson, DiPietro, and Harrill, 2020).

# III. Data: Sample, Sources, and Their Properties

**The number of tourist arrivals to Aruba serves as a dependent variable in the estimated models and as a subject to the forecast in the test sample, with a forecast horizon up to 3 months ahead**. I collect the data on the number of visitors (in thousands of persons) from the CBA's monthly tables[3], cross-checked with the Aruba Tourism Authority (ATA). To note, Aruba tourism market is geared towards wealthy visitors, has high level of time-shares and all-inclusive hotels. Although Aruba is outside the hurricane zone, it still has less visitors in May-June and September-November, with the lowest number of arrivals in September; there is a well-defined seasonality in the data, which should be accounted for in the model (see section IV). Important, historical tourism arrivals to Aruba have not increased linearly due to several external shocks, including the GFC, the onset of the Venezuela crisis, and lately, the COVID-19 pandemic.

**The sample includes 222 monthly observations, from January 2004 to June 2022.** The original estimation sample includes 192 monthly observations from the pre-pandemic period (2004m1-2019m12), testing forecasts through 2022m6. Then, I expand the sample to include 2020 and 2021. The test set includes the COVID-19 pandemic (declared by the World Health Organization (WHO) on March 11, 2020), which triggered mobility restrictions worldwide. On March 15, 2020, Aruba announced a lockdown on all inbound travel starting at midnight of March 16 lasting till June 10, when the country started gradual reopening of its borders. As of December 1, 2020, Aruba lifted all initial travel restrictions. However, new variants and local outbreaks in various countries have led to the partial reinstatement of the travel bans, both by Aruba and its counterparts[4].

**This paper focuses on the explanatory variables relevant for the USA because it is the primary source of tourism inflows to Aruba[5]:**

[3] See Table 10 "Tourism" in Monthly Tables at https://www.cbaruba.org/monthly-tables

[4] For example, Aruba set temporary entry bans for the residents of Brazil, India, and South Africa, when these countries experienced severe outbreaks. It also became a subject to the flights' ban from Canada during the periods of high local COVID-19 contagion.

[5] In 2020-2021, the USA accounted for more than 4/5 of all tourists to Aruba (up from about 2/3 before the pandemic

- St. Louis Fed provides seasonally adjusted monthly series for real personal income (RPI) and real personal consumption expenditures (RPCE), in trillions of chained 2012 USD[6]. It also publishes monthly population estimates[7] (in thousands of persons), helpful to calculate *per capita RPI* and *RPCE (in thousands of 2012 chained USD)*. To note, in 2020-21, the US government provided several fiscal stimuli, which boosted RPI but did not increase consumer spending in the same period as the COVID-19 measures restricting mobility and activities in the USA and world-wide limited ways how people could spend these incomes. See section V for a further discussion on using the RPI vs. RPCE per capita in econometric and forecasting models.

- The US carriers' data from the US BTS[8] help to obtain the *flights' capacity utilization ratio (CAP)*, found by dividing the total number of air passengers by the count of all available seats, expressed in percent, from 0 to 100. This measure offers several benefits: 1) showing a ratio of airlift demand to its supply, it captures well the short-run changes, useful for the short-term forecast horizons in this research (h=0-3 months ahead)[9]; ii) it is easier to assume for different forecasting scenarios than the number of flights, seats, or passengers, as the latter depend on the same factors as the tourism arrivals.

- The *monthly Google Trends (GT)[10] for the searches for "Aruba all-inclusive hotels"* performed from the USA. Graphical analysis indicated that its dynamics were the closest among available GT data in the US tourist arrivals to Aruba[11].

- The *Chicago Board Options Exchange Volatility Index (VIX)*[12] – based on the monthly maximums - is tested as a proxy for financial risks and uncertainty, which is assumed to capture the wealth effect and have impact on the decisions of the wealthy consumers. In the robustness analysis, I test two versions of the *US Economic Policy Uncertainty (EPU) index – EPU1* (based on three components: policy uncertainty in news, tax codes expiration, and forecast disagreement) and *EPU2 (*purely based on daily news[13], and the change in the US unemployment rate (UR).

**Timing of data releases is important for econometric model building and forecasting.** The US income, expenditure, population estimates are all published with a lag of about 2 months. Publication lag for monthly tourism arrivals is about 3 months, although an estimate of total number of stay-over-visitors may appear earlier in local press. Google Trends and VIX are available almost in real time – with a few days delay, although if one would want to have a full month of data to get a monthly aggregate, the lag would be up to one month. US airlift data are available only with a delay of 6-7 months[14].

[6] See https://fred.stlouisfed.org/series/RPI and https://fred.stlouisfed.org/series/RPCE96, respectively.

[7] See https://fred.stlouisfed.org/series/POPTHM

[8] We retrieve the form "T-100 International Segment (All Carriers)" from https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=FJE; identify a unique flight combining airline, airport of origin, and aircraft type; and aggregate these data by month and destination.

[9] The long-run changes in CAP due to a sudden change in either demand or a supply of an airlift could affect results only around the structural breaks.

[10] See Annex 1 for clarifications about GT data.

[11] We also considered queries for "Aruba Flights", "Aruba Hotels", and "Aruba Beach".

[12] Using averages of the highest daily readings (see https://www.cboe.com/tradable_products/vix/vix_historical_data/) over a month

[13] See https://www.policyuncertainty.com/us_monthly.html

[14] For example, as of August 4, 2022; data on the US income, expenditure, population estimates, and Aruba tourism arrivals were available for up to June 2022; REER – for May 2022; GT and VIX were known till the end of July 2022, and the latest airlift data were for January 2022.

**One should check the data stationarity to ensure that the time-series estimates are meaningful and useful in forecasting.** A well-defined time-series model requires stationary dependent variable and regressors and normally distributed error terms. I employ the Augmented Dickey–Fuller (ADF) and Modified Dickey-Fuller (DFGLS) unit-root tests to examine stationarity[15] in the data. Stationarity tests revealed that tourist arrivals (ARR), flight capacity utilization ratio (CAP), GT, and VIX data do not contain a unit root, and therefore do not need a transformation. However, the unit root could not be rejected for the US RPI (RPCE) per capita, and US unemployment rate. Thus, these variables are transformed and enter regression models as their first differences (which become stationary). The risk and uncertainty variables (VIX, EPU1, EPU2) are stationary both in levels, but are differenced due to the assumption that a change in the risk and uncertainty affects consumers' decisions about future vacations; their differences remain stationary.

**Table 1. Summary Statistics and Data Properties (2004m1 – 2019m12)**

| Variable[16] | N | Mean | St.d. | Min | Max | ADF[17] | DFGLS[18] |
|---|---|---|---|---|---|---|---|
| Total Tourist Arrivals to Aruba (ARR) | 192 | 77.12 | 15.63 | 48.00 | 118.47 | -4.49*** | -2.48* |
| Flight capacity utilization ratio (CAP) | 192 | 80.99 | 6.25 | 58.89 | 92.46 | -5.39*** | -1.73** |
| GT "all-inclusive hotels in Aruba" (GT) | 192 | 26.91 | 10.15 | 2.44 | 62.88 | -8.30*** | -6.69*** |
| US. Real pers. income per capita (RPIcap) | 192 | 44.83 | 3.02 | 40.01 | 51.02 | -0.24 | 2.03 |
| - First difference (D1.RPIcap) | 191 | 0.057 | 0.32 | -2.31 | 1.78 | -15.88*** | -11.39*** |
| Real pers cons. per capita (RPCEcap) | 192 | 35.87 | 1.84 | 32.85 | 40.05 | 1.10 | 4.70 |
| - First difference (D1.RPCEcap) | 191 | 0.037 | 0.11 | -0.386 | 0.280 | -15.41*** | -9.17*** |
| Chicago Board Options Exchange Volatility Index (VIX) | 192 | 23.50 | 11.61 | 12.44 | 89.53 | -4.92*** | -4.09*** |
| - First difference (D1.VIX) | 191 | -.004 | 7.84 | -24.08 | 41.13 | -16.17*** | -11.20*** |
| US EPU1 | 192 | 117.71 | 37.4 | 57.2 | 245.1 | -4.70*** | -3.40*** |
| - First difference (D1.EPU1) | 191 | 0.25 | 24.28 | -94.13 | 91.87 | -17.50*** | -13.01*** |
| US EPU2 | 192 | 125.6 | 49.4 | 44.8 | 284.1 | -6.23*** | -4.17*** |
| - First difference (D1.EPU2) | 191 | 0.54 | 41.05 | -160.50 | 157.01 | -17.84*** | -13.28*** |
| US unemployment rate (UR) | 192 | 6.07 | 1.93 | 3.5 | 10 | 0.09 | -0.31 |
| - First difference (D1.UR) | 191 | -0.01 | 0.17 | -0.50 | 0.50 | -11.21*** | -5.59*** |

# IV. Methodology, Models, and Assumptions

## Methodology

**This paper employs the time-series models of ARIMA class.** In general, the ARIMA (p, d, q) family of models, where p, d, and q stand for the numbers of non-seasonal lags, non-seasonal difference terms, and non-seasonal moving average terms (see equation #1 below). None of models in this paper include the non-seasonal difference terms (d=0), therefore simplifying ARIMA to ARMA. Three classes of ARMA models are

[15] Both tests use the null hypothesis that the variable contains a unit root, with the alternative hypothesis that a stationary process generated the variable.

[16] All variables are in original form (non-seasonally adjusted), except for the US income, published only in seasonally adjusted form.

[17] Augmented Dickey–Fuller (ADF) test is performed in Stata using a command "***dfuller***" (no trend). Critical values are -3.480, -2.884, and -2.574 for 1, 5, and 10 percent significance levels (denoted with ***, *, ** respectively).

[18] Dickey–Fuller GLS (DFGLS) test is performed in Stata using a command "***dfgls***" (no trend). Critical values are -2.588, -2.035, -1.720 for 1, 5, and 10 percent significance levels (denoted with ***, *, ** respectively).

considered: with (p=1, q=1), (p=2, q=1), (p=2, q=2) number of autoregressive and moving average terms respectively. Equation [1] below present pure time-series ARMA without additional regressors. On the left-hand side, $y_t$ denotes a dependent variable (tourism arrivals). The right-hand side includes a constant term $\mu$, $p$ lags of the dependent variable $y_{t-i:}:(y_{t-1}..y_{t-p})$, $q$ moving average terms $e_{t-q}$, and an error term $e_t$.

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, e_{t-j} + e_t \qquad [1]$$

**Multivariate ARIMA (ARIMAX) allows the inclusion of exogenous variables in the model.** Pure time-series models are not sufficient to explain the tourist arrivals. The ARIMAX specification (see equation #2) augments the univariate ARIMA presented in specification #1 with relevant explanatory variables $X_{l,t-n}$, where $n$ indicates the number of lags (if any).

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, e_{t-j} + \sum_{l=1}^{s} \delta_l \, X_{l,t-n} + e_t \qquad [2]$$

**Monthly tourism arrivals need to be adjusted for seasonal variations.** There are two main ways to deal with the seasonality: (i) prior seasonal adjustment or differencing of inputs (required for the specifications #1 and 2 above); (ii) use of the seasonal terms directly in the model. Gaw and Law (2001) note that the seasonal adjustment of inputs may lead to informational loss, and seasonal dummies can be beneficial when the seasonality is deterministic. Therefore, this paper adopts an alternative way to account for the seasonal factors, using the untransformed data with binary monthly indicators, taking the value of one in a given month and zero otherwise. To avoid multicollinearity, model uses 11 binary indicators $D_k$ (k=1...11), dropping September. I expect coefficients for all monthly dummies to have positive signs because tourist arrivals to Aruba reach their lowest interannual levels in September. Models in equations [3] and [4] below augment pure ARIMA in [1] and ARIMAX in [2] with seasonal dummies $D_k$: $(D_1 \ldots D_{11})$.

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, e_{t-j} + \sum_{k=1}^{11} \beta_k \, D_k + e_t \qquad [3]$$

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, e_{t-j} + \sum_{k=1}^{11} \beta_k \, D_k + \sum_{l=1}^{s} \delta_l \, X_{l,t-n} + e_t \qquad [4]$$

**Finally, one can incorporate an intercept correction by including a dummy variable for the pandemic periods.** Impact of the structural downward shift in tourism arrivals can be captured by a binary indicator $I_{covid}$ taking a value of 1 starting 2020m4-2023m12 (implicitly assuming that in 2024 tourism will return to pre-pandemic trend and will no longer require a correction[19]). Model in equation 5 augments a full ARIMA-X with a vector of exogenous variables $X_l$ in equation [4] with an intercept correction term $\mu_{cov} I_{covid}$.

$$y_t = \mu + \mu_{IC} IC + \sum_{i=1}^{p} \gamma_i \, y_{t-i} + \sum_{j=1}^{q} \theta_j \, e_{t-j} + \sum_{k=1}^{11} \beta_k \, D_k + \sum_{l=1}^{s} \delta_l \, X_{l,t-n} + e_t \qquad [5]$$

**Past research on modeling and forecasting of tourist arrivals suggests relevant explanatory variables on both demand and supply sides.** Following Cevik (2020), I include the US income and GT as the main non-autoregressive predictors for tourism arrivals. Similar to Acevedo et al. (2016), I employ the flight statistics from the US carriers, with a novel introduction and application of the flights' capacity variable (see section IV for

[19] Analysts applying this methodology in future should re-evaluate this assumption.

details). Also, instead of taking these regressors simultaneously, I use their lags. To choose the number of lags, I consider the time-series properties of the data and make assumptions on the decision-making process of a typical consumer about their upcoming vacation.

**This paper assumes that consumers start planning their future vacations about three months in advance.** In period $(T-3)$, consumers decide on the budget for the upcoming vacation. In period $(T-2)$, they search for vacation packages and compare destinations. In period $T$, consumers can cancel the upcoming trip in reaction to the changes in risks and uncertainty. Assumed data-generating process affects the choice of regressors (and their lags) used in the quantitative models of tourism arrivals. Therefore, the US income or expenditure variables enter the models with a third lag (after being differenced to remove the unit root), google trends are lagged by two months. Change in volatility index VIX, which is available on the daily basis, enters the model without a lag. Change in the alternative measures of uncertainty – US economic policy indices (EPU1, EPU2) or unemployment rate – are taken with a one-month lag, given the data availability.

## Models Used

**Full model uses ARIMA-X (2, 0, 2) with four exogenous regressors.** A set of exogenous variables $X_t$ in the main model (see equation 6) includes: 1) third lag of the first difference in the US RPCE as a measure of demand ($d1RPCE_{t-3} = RPCE_{t-3} - RPCE_{t-4}$), 2) second lag of the GT ($GT_{t-2}$), 3) concurrent capacity utilization CAP ($CAP_t$), and 4) the first difference in the VIX as a measure of risk ($d1VIX_t = VIX_t - VIX_{t-1}$). In addition, the model in equation [7] includes an intercept correction dummy indicator ($IC$). All models include a constant term two AR terms ($y_{t-1}$ and $y_{t-2}$), two MA terms ($e_{t-1}$ and $e_{t-2}$), and 11 seasonal monthly dummies ($D_1 \dots D_{11}$). The models are estimated over three samples: (i) 2004m1-2019m12; (ii) 2004m1-2020m12; and (iii) 2004m1-2021m12.

$$y_t = \mu + \sum_{i=1}^{p=2} \gamma_i \, y_{t-i} + \sum_{j=1}^{q=2} \theta_j \, e_{t-j} + \sum_{k=1}^{11} \beta_k \, D_k + \delta_1 d1RPCE_{t-3} + \delta_2 GT_{t-2} + \delta_3 CAP_t + \delta_4 d1VIX_t + e_t \quad [6]$$

$$y_t = \mu + \mu_{IC} IC + \sum_{i=1}^{p=2} \gamma_i \, y_{t-i} + \sum_{j=1}^{q=2} \theta_j \, e_{t-j} + \sum_{k=1}^{11} \beta_k \, D_k + \delta_1 d1RPCE_{t-3} + \delta_2 GT_{t-2} + \delta_3 CAP_t + \delta_4 d1VIX_t + e_t \quad [7]$$

**Robustness of the main model is assessed through estimation alternative specifications.** First, I assess the full model above using per capita real personal income in place of the consumption spending. Second, I test alternative risk proxies, such as lagged (by one month) differences of the US EPU indices and unemployment rate instead of VIX (equations are not presented for brevity).

**To evaluate model properties this paper employs several criteria:**

- *Statistical and economic significance* of the estimated coefficients. Estimated regression coefficients measure a change in the mean of the dependent variable driven by a one-unit shift in the explanatory variable *ceteris paribus* (keeping other things equal). Economic significance requires coefficients' signs to concur with the a priori assumptions, and their size to be large enough to have a distinct impact on the dependent variable. Statistical significance of the coefficients is measured at 1, 5, and 10 percent level. To note, it is possible for a strong forecasting model to include variables without statistically significant coefficients.

- *Low standard deviation (SD), consistency and normality of residuals*. The Shapiro–Wilk (SWILK) normality test helps to examine residuals in the estimated models.

- *The minimum Akaike Information Criteria (AIC)* helps find the most likely parsimonious model. Algebraically, the AIC=−2LL + 2k, where LL and k stand for the model log-likelihood and the number of estimated parameters. Thus, including an additional variable into a model would increase its likelihood but penalize the AIC for the estimation of one more coefficient. To note, a decrease in AIC of more than 2 is considered a significant improvement of the model.

- *Strong forecasting performance of the model*, especially since the pandemic. To choose the most accurate forecast model, I compare forecast error measures, including the root-mean-square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the Theil Inequality Coefficient (U-Theil). The lower the MAE, RMSE, and U-Theil values, the higher the forecast accuracy of a given model[20]. To emphasize, values of a Theil U coefficient below one indicates that a forecasting model is better than a random guess (and its deviation from 1 can be interpreted as a percentage of improvement).

**Finally, I assess the role of each regressor for a model fit.** Their contributions to a decline in standard deviation and AIC indicate contributions to the model accuracy, and their shares in the decline of RMSE and Theil U demonstrate roles of these indicators in improving forecast accuracy. To calculate such contributions, I estimate auxiliary models, excluding exogenous regressors one by one, and then calculating a ratio of the improvement in the measure of interest from adding an exogenous variable over the total improvement in the same measure from the full model, when compared to a pure ARMA.

## Forecast Assumptions

**The forecasting process requires an analyst to make assumptions for the exogenous regressors in order to produce the out-of-sample forecasts.** The analysts using the models from this paper can project out-of-sample tourist arrivals for various scenarios based on the proprietary assumptions of their choice. This paper produces out-of-sample forecasts for 18 months ahead – 2022m7-2023m12, using the following assumptions. First, due to a delay in release of the US airlift data, one should assume the capacity utilization rate (which enters a model as a concurrent indicator). For 2022, CAP is kept at 70 percent (which is very close to the actual value in December 2021); once monthly values for 2022 become available (courtesy of the Aruba Tourism Authority) the assumed value is replaced by an actual observation, while for the rest of 2022 and 2023 the capacity utilization load factor is assumed at the average known for 2022. Second, Second, GT, and VIX (or EPU1/EPU2/UR in the sensitivity analysis) are all kept at the latest available level (assuming no change in the forecast period). Third, US income (expenditure) per capita are assumed to grow at the rate equal to the projected growth of real GDP in the USA (according to the latest publicly available "Wells Fargo - U.S. Economic Forecast" [21]) minus the expected rate of population growth for the USA (according to the US BLS[22]).

[20] Note: MAE and MAPE weight all errors equally, while the RMSE penalizes large outliers.

[21] Using a vintage from September 30, 2022, this research assumes that personal consumption in the USA (in constant prices) would grow by 0.6, 0.9, and 0.5 percent in 2022q3, 2022q4, and 2023q1, following by a decline of 1.3, 1.8, and 0.7 percent in 2023 q2-2023q4. See https://wellsfargo.bluematrix.com/docs/html/88d2eafa-3a64-4cca-b013-4093132d9c99.html

[22] According to Chart 1 at https://www.bls.gov/opub/mlr/2021/article/projections-overview-and-highlights-2020-30.htm, US population will grow.9 percent in 2022, 0.8 percent in 2023.

# V. Main Empirical Results

## Estimated Models and Their Fit

**Comparison of estimated coefficients for the baseline model with intercept correction over alternative ARIMA specifications and three samples provides several insights (see Table 2 above)**:

- Coefficient estimates are stable across three ARIMA specifications for all samples. ARIMA (202) yields the highest likelihood and lowest residuals in all samples. However, when sample includes 2021, the ARIMA (101) produces the lowest AIC; in other words, inclusion of the AR2 and MA2 terms improves the likelihood of the model less than it penalizes the AIC. On a related note, AR1, AR2, and MA1 terms lose their significance when sample includes 2020 and 2021, but MA2 term remains significant.
- The US real personal consumption expenditure (RPCE), flight capacity utilization (CAP), and Google search frequencies (GT) are statistically and economically significant in all models.[23]
- COVID-19 pandemic affected the marginal impact of the main exogenous variables, reducing total tourism arrivals to Aruba by an average of 43-44 thousand tourists in 2020, and by 38-39 thousand visitors over 2020-2021. Inclusion of a COVID-19 dummy leads to a lower marginal effect of the higher financial risks and certainty, as measured by VIX[24]. Before the pandemic, a 1-point increase in maximum monthly VIX would cost Aruba a loss of about 5-9 tourists per months. In the extended samples and after the intercept correction, the coefficient on VIX decreases to -2, and loses its statistical significance.
- Average marginal effect of the flight capacity utilization increased from 0.37 before the pandemic to 0.61 and 0.71 in 2020 and 2021 respectively: based on the full sample, one more percent in load factor would increase the tourism inflow to Aruba by about 710 persons.
- Google Trends also become a stronger indicator of the future tourism arrivals: an increase of internet search frequency by one percent corresponds to 130 additional visitors (based on the full sample).
- At the same time, per capita consumption spending in the USA gained significance over time. When pandemic months are included, additional 100 USD per capita real spending in the USA would generate about 125 more tourist arrivals to Aruba. To put in perspective, an increase of the average per capita spending (equal to 36.3 thousand chained 2012 USD in 2004m1-2021m12) by 1 percent (or 363 USD) would imply about 435-490 more monthly tourist arrivals to Aruba.
- Residuals increased from 4.0-4.1 before the pandemic to 4.2-2.25 and 4.50-4.54 with extension of the sample to 2020 and 20221, respectively. The COVID-19 pandemic introduced additional factors affecting the tourism arrivals which the model cannot capture directly: the number of COVID-19 cases in Aruba and source countries, changing consumer preferences and behavior, border closures and stricter travel requirements (including vaccination cards and tests). Thus, the model likelihood slightly declines with an extension of the sample. Still, the model is useful in forecasting future tourist arrivals.
- Residuals are normally distributed for any ARIMA specification in the full sample (including 2021). In a sample covering 2004- 2020, one could reject normality of residuals at 10 percent level for all specifications. In the pre-pandemic sample, normality of residuals could not be rejected for ARIMA 202; for ARIMA 101 and 201 classes, one could reject normality at 10 percent level.

[23] An earlier version of this paper considered inclusion of the REER as an exogenous variable. However, results show that having REER in the model did not increase the AIC and did not help in forecasting. This finding is consistent with the literature, given that Aruba maintains a fixed peg to the USD (see Laframboise et al., 2014; Culiuc, 2014; Acevedo et al., 2016).

[24] Results are robust when VIX is replaced by alternative risk measures, including two variants of the US Economic Policy Uncertainty index, and the US unemployment rate.

**Table 2. Tourist Arrivals to Aruba—Model w/RPCE, GT, CAP, VIX (with intercept correction)** [25] [26]

| Sample | 2004m1-2019m12 | | | 2004m1-2020m12 | | | 2004m1-2021m12 | | |
|---|---|---|---|---|---|---|---|---|---|
| ARIMA | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| L3.dRPCE | 1.72 | 1.66 | 0.85 | 1.33* | 1.27* | 1.25* | 1.35* | 1.26* | 1.20* |
| | (2.55) | (2.49) | (2.43) | (0.53) | (0.54) | (0.54) | (0.60) | (0.59) | (0.61) |
| CAP | 0.37*** | 0.37*** | 0.37*** | 0.60*** | 0.61*** | 0.61*** | 0.71*** | 0.71*** | 0.71*** |
| | (0.10) | (0.10) | (0.10) | (0.09) | (0.08) | (0.09) | (0.07) | (0.07) | (0.07) |
| L2.GT | 0.09** | 0.09** | 0.08* | 0.10** | 0.10** | 0.09** | 0.13** | 0.13** | 0.13** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) |
| D.vixmax | -0.05 | -0.05 | -0.09*** | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| IC | X | X | X | -43.19*** | -43.19*** | -42.61*** | -38.54*** | -38.75*** | -38.43*** |
| | X | X | X | (3.71) | (3.54) | (3.67) | (3.39) | (3.25) | (3.25) |
| Constant | 34.29** | 33.90** | 34.43** | 16.74 | 16.27 | 16.58 | 13.96 | 14.72 | 14.57 |
| | (10.98) | (11.36) | (11.12) | (9.20) | (9.42) | (9.28) | (12.20) | (13.33) | (12.98) |
| L1.ar | 0.98*** | 1.18*** | 0.13** | 0.97*** | 1.36*** | 0.51 | 0.98*** | 1.31*** | 0.59 |
| | (0.02) | (0.21) | (0.05) | (0.02 | (0.21) | (0.28) | (0.02) | (0.18) | (0.32) |
| L2.ar | X | -0.19 | 0.83*** | X | -0.38 | 0.46 | X | -0.32 | 0.39 |
| | X | (0.20) | (0.05) | X | (0.20) | (0.27) | X | (0.17) | (0.31) |
| L1.ma | -0.37*** | -0.54** | 0.57*** | -0.32** | -0.68*** | 0.19 | -0.23* | -0.55** | 0.19 |
| | (0.09 | (0.19) | (0.08) | (0.10) | (0.18) | (0.30) | (0.10) | (0.17) | (0.33) |
| L2.ma | X | X | -0.43*** | X | X | -0.30*** | X | X | -0.22** |
| | X | X | (0.08) | X | X | (0.08) | X | X | (0.07) |
| SD | 4.11*** | 4.10*** | 3.98*** | 4.25*** | 4.23*** | 4.20*** | 4.54*** | 4.52*** | 4.50*** |
| LL | -533.7 | -533.2 | -528.8 | -571.8 | -570.5 | -569.4 | -620.2 | -619.3 | -618.4 |
| AIC | 1105.4 | 1106.4 | 1097.7 | 1183.6 | 1183 | 1182.8 | 1280.4 | 1280.5 | 1280.8 |
| SWILK | 0.99** | 0.99** | 0.99 | 0.99** | 0.99** | 0.99** | 0.99 | 0.99 | 0.99 |

**Another important insight from this paper is that analysts using the RPI as a measure of the US demand should have switched to the models with the RPCE instead.** Table 3 compares a pure time series ARIMA with the two variants of a full model with the exogenous variables– one with the RPCE per capita, and another with the RPI per capita – all for ARIMA (202) specification, across three samples. While both models help to reduce the error terms and increase the model likelihood, it is more likely that before the pandemic the analysts were using the RPI as a demand measure – as it was economically and statistically significant in the pre-pandemic sample. However, when COVID-19 came to the USA, the US government distributed fiscal support to its citizens, boosting their income, but these money were not directed to spending due to the mobility restrictions, and could not be spend on the international travel due to the travel restrictions and pandemic fears. As a result, there appeared a disconnect between the US RPI and the demand for international vacations from the US consumers. At the same time, the RPCE became a better predictor of tourist arrivals. Notably, estimates for other variables are quite similar: across all specifications, flight capacity utilization rate and popularity of the destination in Google have positive and statistically significant marginal impact on tourism arrivals to Aruba. Results do not change in other specifications of ARIMA[27].

[25] Results correspond to the model in equation [6]. Estimates for the for monthly dummy variables are omitted for brevity. See Table A2-1 in Annex 2 for full results.

[26] Hereafter, numbers in the first line are regression coefficients, with numbers below in brackets showing the standard errors; superscripts *, **, *** denote the 5, 10, and 1 percent significance levels. H0 for the Shapiro-Wilk (SWILK) test is the normality of the regression residuals.

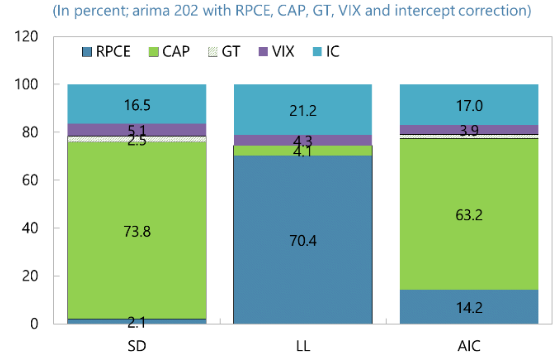
[27] Results in columns 2, 5, and 8 correspond to the model in equation [3]. Results in columns 3, 6, and 9 correspond to the full model with RPCE in equation [7]. Results in columns 4, 7, and 10 correspond to the full model with RPI in equation [8]. A motivated reader is invited to compare estimation results in Tables A2-1 and A5-1 in Annexes 2 and 5 for a detailed analysis.

**Table 3. Tourist Arrivals to Aruba—ARIMA 202—Models' Comparison**

| Sample | 2004m1-2019m12 | | | 2004m1-2020m12 | | | 2004m1-2021m12 | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | Pure | RPI | RPCE | Pure | RPI | RPCE | Pure | RPI | RPCE |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| L3.dRPCE | X | X | 0.85 | X | X | 1.25* | X | X | 1.20* |
| | X | X | (2.43) | X | X | (0.54) | X | X | (0.61) |
| L3.dRPI | X | 2.22*** | X | X | 0.03 | X | X | -0.17 | X |
| | X | (0.56) | X | X | (0.55) | X | X | (0.29) | X |
| CAP | X | 0.37*** | 0.37*** | X | 0.59*** | 0.61*** | X | 0.71*** | 0.71*** |
| | X | (0.10) | (0.10) | X | (0.09) | (0.09) | X | (0.07) | (0.07) |
| L2.GT | X | 0.09** | 0.08* | X | 0.09** | 0.09** | X | 0.12** | 0.13** |
| | X | (0.03) | (0.03) | X | (0.03) | (0.03) | X | (0.04) | (0.04) |
| D.vixmax | X | -0.06* | -0.09*** | X | -0.02 | -0.02 | X | -0.03 | -0.02 |
| | X | (0.02) | (0.02) | X | (0.03) | (0.03) | X | (0.03) | (0.03) |
| IC | X | X | X | X | -43.52*** | -42.61*** | X | -38.85*** | -38.43*** |
| | X | X | X | X | (3.99) | (3.67) | X | (3.40) | (3.25) |
| Constant | 64.92** | 34.67*** | 34.43** | 59.42 | 18.23 | 16.58 | 62.45*** | 15.3 | 14.57 |
| | (11.66) | (10.38) | (11.12) | (7.16) | (9.59) | (9.28) | (6.10) | (12.99) | (12.98) |
| L1.ar | 0.22* | 0.10* | 0.13** | 0.21 | 0.47 | 0.51 | 0.15 | 0.59 | 0.59 |
| | (0.10) | (0.05) | (0.05) | (0.13) | (0.39) | (0.28) | (0.10) | (0.42) | (0.32) |
| L2.ar | 0.76 | 0.86*** | 0.83*** | 0.69 | 0.49 | 0.46 | 0.71*** | 0.39 | 0.39 |
| | (0.10) | (0.05) | (0.05) | (0.12) | (0.37) | (0.27) | (0.08) | (0.42) | (0.31) |
| L1.ma | 0.40*** | 0.62*** | 0.57*** | 0.83*** | 0.24 | 0.19 | 0.94*** | 0.22 | 0.19 |
| | (0.11) | (0.09) | (0.08) | (0.15) | (0.39) | (0.30) | (0.17) | (0.43) | (0.33) |
| L2.ma | -0.45*** | -0.38*** | -0.43*** | -0.07 | -0.31** | -0.30*** | 0.03 | -0.24** | -0.22** |
| | (0.07) | (0.09) | (0.08) | (0.16) | (0.10) | (0.08) | (0.17) | (0.09) | (0.07) |
| SD | 4.33*** | 3.88*** | 3.98*** | 6.66*** | 4.25*** | 4.20*** | 6.88*** | 4.53*** | 4.50*** |
| LL | -555.3 | -524.2 | -528.8 | -677.7 | -571.6 | -569.4 | -709.3 | -620.1 | -618.4 |
| AIC | 1144.6 | 1088.4 | 1097.7 | 1389.4 | 1187.2 | 1182.8 | 1482.2 | 1284.2 | 1280.8 |
| SWILK | 0.98** | 0.99 | 0.99 | 0.78** | 0.99 | 0.99** | 0.82*** | 0.99 | 0.99 |

**Finally, the analysts may be interested to measure the relative importance of each explanatory variable to the improvement in the model**. Text-chart shows contribution of each regressor to the reduction in the regression residuals, increase in the likelihood, and decline in the AIC. Inclusion of the RPCE contributes more than 70 percent to the improvement in the model likelihood (LL) and boosts the model's informational value (AIC) by 14.2 percent, but only 2.1 percent to the residual reduction. Capacity utilization plays the largest role in decreasing error term and AIC, while its role in improving the likelihood is modest. An intercept correction during the COVID-19 pandemic is critical for the improvement in all measures: it contributes 16.5 percent to the error reduction, 2.2 percent to the higher likelihood, and 17 percent to the lower AIC. The role of VIX is moderate but almost equally important across all measures: it contributes 5.1 percent to the error reduction, 4.3 percent to an improvement in LL, and 3.9 percent to an improvement in AIC. Overall, without an IC term, four exogenous variables reduce the residuals by 29 percent, improve LL by 10 percent, and reduce the AIC by 11 percent (compared to a pure ARIMA). After the IC, a model fit is improved over pure ARIMA by 34, 13, and 14 percent (in terms of a reduction in the error terms, increase in the LL, and better AIC). See Table A2-2 in Annex 2 for detailed results, including for ARIMA 101 and 201 classes. Finally, Table A2-3 in Annex 2 presents results for a full model with RPCE, CAP, GT, VIX, and intercept correction, along with the auxiliary models (excluding

**Contributions of Each Regressor to the Model Fit**
(In percent; arima 202 with RPCE, CAP, GT, VIX and intercept correction)




Sources: Author's calculations

exogenous regressors one by one), for three classes of ARIMA, allowing for a thorough comparison of the model coefficients and fit.

## Forecast Accuracy in the Full, Training, and Test Samples

**Estimated models produce in-sample and out-of-sample projections for tourist arrivals to Aruba.** Table 4 compares RMSE of a pure ARIMA (col. 2), full model before the IC (col.6), full model with IC (col.7), and three auxiliary models (col. 3-5), all with RPCE. A model with RPCE, CAP, GT, and VIX reduces RMSE by about 60 percent in the test sample, with a gain around 31 and 29 percent in full and training samples respectively. Intercept correction term improves RMSE further in the training and full sample but reduces accuracy in the test sample. ARIMA (202) yields the lowest forecast errors and Theil's U coefficients for all the combinations of the estimation and evaluation samples.

**Table 4. Variables' Role in Reduction of the Forecast Error (est. sample: 2004m1 – 2021m12)**

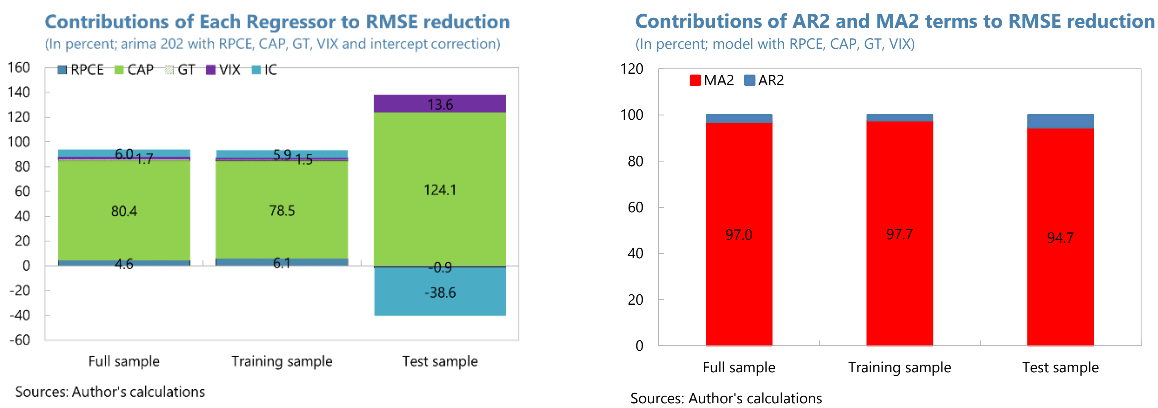
| Ex. Regr. (1) | None (2) | RPCE (3) | RPCE, CAP (4) | RPCE, CAP, GT (5) | RPCE, CAP, GT, VIX (6) | RPCE, CAP, GT, VIX, IC (7) | Change before IC (8)=(6)-(2) | Change after IC (9)=(7)-(6) |
|---|---|---|---|---|---|---|---|---|
| Full sample: 2004m1-2022m6 | | | | | | | | |
| ARIMA 101 | 7.36 | 7.24 | 5.27 | 5.16 | 5.11 | 4.71 | -2.25 | -0.40 |
| ARIMA 201 | 7.25 | 7.15 | 5.27 | 5.15 | 5.11 | 4.70 | -2.14 | -0.40 |
| ARIMA 202 | 7.24 | 7.14 | 5.17 | 5.08 | 4.99 | 4.69 | -2.26 | -0.30 |
| Training sample (same as estimation sample) | | | | | | | | |
| ARIMA 101 | 7.08 | 6.94 | 5.24 | 5.12 | 5.08 | 4.71 | -2.00 | -0.37 |
| ARIMA 201 | 6.98 | 6.86 | 5.24 | 5.12 | 5.08 | 4.70 | -1.90 | -0.38 |
| ARIMA 202 | 6.98 | 6.85 | 5.15 | 5.06 | 4.98 | 4.69 | -2.00 | -0.29 |
| Test sample | | | | | | | | |
| ARIMA 101 | 14.14 | 14.31 | 6.11 | 6.21 | 6.08 | 7.30 | -8.06 | 1.22 |
| ARIMA 201 | 13.78 | 13.94 | 6.10 | 6.17 | 6.04 | 7.21 | -7.75 | 1.17 |
| ARIMA 202 | 13.77 | 13.85 | 5.66 | 5.74 | 5.23 | 7.25 | -8.54 | 2.02 |

In general, including more observations in the estimation sample results in more accurate forecasts. The analysts should re-estimate a model including new data and revise forecasts once new observations become available. Comparison of the forecast performance of a model with the RPCE and a similar one with RPI suggests that the former was more accurate, while the latter became useless in the test sample – Theil's U coefficient reached exceeded 1. The real personal income per capita in the USA has less predictive power than the real personal consumption expenditure, though the latter did not have a statistically significant coefficient in the estimation sample. This observation can be explained by the extra income support during the COVID-19 pandemic boosted the RPI and precautionary savings but did not equally translate into the RPCE. See Table A5-2 in Annex 5 for details.

**Finally, it is important to measure the share of each exogenous regressor and model term in improving the forecast accuracy (as measured by the RMSE).** Intercept correction term helps to reduce the forecast error in the training and full samples but increases the RMSE in the full sample. This is explained by a binary nature of the IC dummy: it takes a value of 1 since March 2020, therefore assuming the same reduction in arrivals, while the tourism industry is on the gradual recovery path, therefore, one can expect a lower decline in tourism in 2022 than in 2020-21. The flight capacity utilization is a single most important factor, which reduces

RMSE by about 80 percent across all samples (and compensates for a worse RMSE from an IC term in the test sample. Adding GT helps only slightly in the full and training samples, but slightly worsens the accuracy in the test sample. VIX reduces RMSE by almost 14 percent in the test sample (being correlated with the uncertainty increased during the COVID pandemic). From the point of view of ARIMA specification, the MA2 term is the most important, as it contributes 95, 98, and 97 percent of the reduction in RMSE for the test, training, and full samples, respectively.

**Figure 2. Role of Regressors and Model Terms in the RMSE improvement**

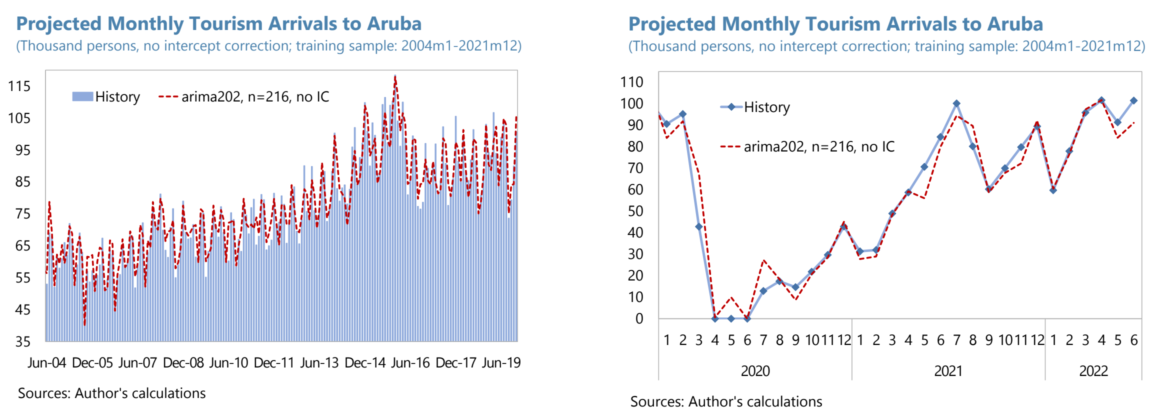



Source: Author's calculations. Charts are produced in Stata MP16.1.

**Forecasting properties of the estimated models can be checked over the training and test samples.** Values of tourist arrivals predicted in the corresponding training-sample are named as "backcasts", while values predicted for the test samples are called "in sample forecasts". Thus, I choose ARIMA 202 model with RPCE, CAP, GT, and VIX, without an intercept correction. Figure 3 below shows its in-sample performance.

**Figure 3. In-Sample Tourist Arrivals Projections**

**(Model with RPCE, GT, CAP, VIX, and no intercept correction)**




Source: Author's calculations. Charts are produced in Stata MP16.1.

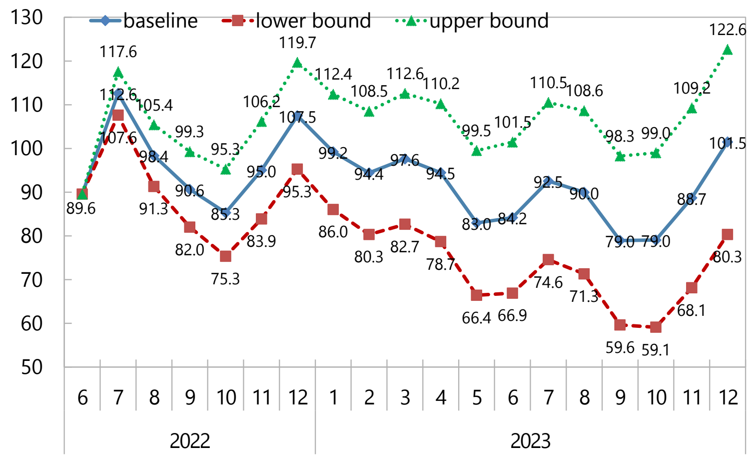
Figure A4-1 in Annex 4 depicts in-sample forecasts for the models with RPCE, CAP, GT, and VIX, with and without an intercept correction (IC), for three classes of ARIMA and three estimation samples. Adding an interception correction helps to improve the in-sample forecasts in the training sample, and slightly reduces the RMSE in the test sample. However, Theil's U is going up in the test sample. Without an intercept correction, ARIMA 202 is performs better than alternatives.

## Out-of-sample forecasts

**Chosen model produces out-of-sample forecasts for 2022m7-2023m12.** These observations have not yet realized at the time of writing this paper. The point forecasts indicate that over this period, Aruba will welcome on average 92.8 thousand tourist arrivals per month. Cumulatively, in the baseline scenario, Aruba is projected to receive 528.0 thousand tourists in 2022H2, 589.4 thousand in 2023H1, and 623.4 thousand vin 2023H2. Overall, it indicates a possibility of tourism growth of 5.3 percent in 2023. However, these forecasts are subject to the uncertainty. Thus, it is necessary to consider the confidence intervals around the point forecast[28]. I calculate the lower and upper bound around the point forecasts. Thus, the average monthly arrival over the 18 months ahead can reach a value between 78.9 and 106.6 thousand tourists, at the 5 percent confidence level.

**Out-of-sample Projections for Tourism Arrivals to Aruba**

(Thousand persons)




Sources: Author's calculations

## Robustness results

Models with RPI per capita in place of RPCE lose their significance once the estimation sample includes the periods in 2020-21, and model fit for the extended samples worsens (compare Tables A5-1 with A2-1). The alternative to VIX risk measures under consideration (US unemployment rate, US EPU1 or US EPU2) do not have significant impact on the tourism arrivals, deteriorating the model fit and their forecast properties. This is not surprising, as the typical visitors to Aruba have high-income, and are more likely to react to the volatility in financial markets than unemployment rate; and they seem to be disinterested in US EPU1 and 2 indices.

# VI. Conclusion

**Forecasting tourism arrivals during and after the COVID-19 pandemic have been challenging.** To forecast tourism since the pandemic accurately, I need to find a variable that would contain information about the drastic decline of tourism during the COVID pandemic and be readily available both in the past, present, and future. The most difficult task is to find a model which would quickly adjust and produce more accurate projections during the periods when tourism has nulled due to the borders' closures and movement restrictions (April-June 2020 in Aruba).

**This research highlights the benefits of using US RPCE per capita, Google Trends, flight capacity, and volatility index data to forecast tourist arrivals to Aruba since the pandemic.** The baseline model is ARIMA (2,0,2) with a full set of exogenous variables: it yields the best fit (as shown by higher likelihood and

[28] The upper and lower borders are obtained as a point forecast plus (minus) RMSE times the square root of forecast horizon.

lower AIC values) and yields lower forecast error for a full sample (compared to other sets of regressors for the same model class). Google Trends variable enhances the forecast accuracy over the pure ARIMA model by 11-13 percent. Flight capacity yields the highest marginal benefit for the forecasts' accuracy: it reduces the RMSE and Theil's U coefficient on average by 16.8 and 20.1 percent. Adding change in VIX marginally lowers the RMSE in all formulations, but it does not consistently improve other forecast accuracy measures. Still, it benefits the forecasts during the pandemic, which are 33 percent more accurate than the random guess. Inclusion of the RPCE contributes more than 70 percent to the improvement in the model likelihood (LL) and boosts the model's informational value (AIC) by 14.2 percent, but only 2.1 percent to the residual reduction. Capacity utilization plays the largest role in decreasing error term and AIC, while its role in improving the likelihood is modest.

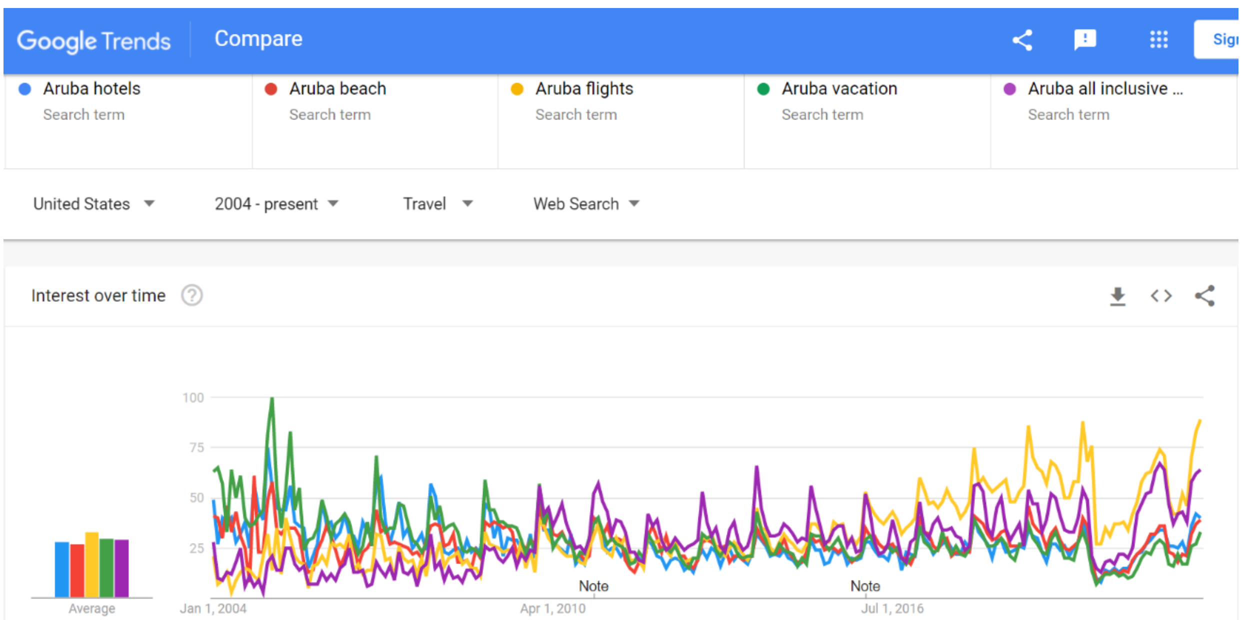
**The model is reevaluated over three samples**. Per capita consumption spending in the USA gained significance over time. When pandemic months are included, additional 100 USD per capita real spending in the USA would generate about 125 more tourist arrivals to Aruba. To put in perspective, an increase of the average per capita spending (equal to 36.3 thousand chained 2012 USD in 2004m1-2021m12) by 1 percent (or 363 USD) would imply about 435-490 more monthly tourist arrivals to Aruba. Residuals increased from 4.0-4.1 before the pandemic to 4.2-2.25 and 4.50-4.54 with extension of the sample to 2020 and 20221, respectively. The COVID-19 pandemic introduced additional factors affecting the tourism arrivals which the model cannot capture directly: the number of COVID-19 cases in Aruba and source countries, changing consumer preferences and behavior, border closures and stricter travel requirements (including vaccination cards and tests). Thus, the model likelihood slightly declines with an extension of the sample.

**COVID-19 pandemic affected the marginal impact of the main exogenous variables**. Inclusion of a COVID-19 dummy indicates that over 2020m3-2021m12, monthly tourism arrivals deceased by an average of 38-39 thousand visitors over 2020-2021. It also reduces a marginal effect of the VIX: before the pandemic, a 1-point increase in maximum monthly VIX would cost Aruba a loss of about 5-9 tourists per months. In the extended samples and after the intercept correction, the coefficient on VIX decreases to -2, and loses its statistical significance. Average marginal effect of the flight capacity utilization increased from 0.37 before the pandemic to 0.61 and 0.71 in 2020 and 2021 respectively: based on the full sample, one more percent in load factor would increase the tourism inflow to Aruba by about 710 persons. Google Trends also become a stronger indicator of the future tourism arrivals: an increase of internet search frequency by one percent corresponds to 130 additional visitors (based on the full sample). An intercept correction improves the model fit: it contributes 16.5 percent to the error reduction, 2.2 percent to the higher likelihood, and 17 percent to the lower AIC. The role of VIX is moderate but almost equally important across all measures: it contributes 5.1 percent to the error reduction, 4.3 percent to an improvement in LL, and 3.9 percent to an improvement in AIC. Overall, without an IC term, four exogenous variables reduce the residuals by 29 percent, improve LL by 10 percent, and reduce the AIC by 11 percent (compared to a pure ARIMA). After the IC, a model fit is improved over pure ARIMA by 34, 13, and 14 percent (in terms of a reduction in the error terms, increase in the LL, and better AIC).

**To forecast out-of-sample, I choose a model with RPCE, CAP, GT, and VIX.** It reduces RMSE by about 60 percent in the test sample, with a gain around 31 and 29 percent in full and training samples respectively. According to the baseline model. average monthly arrivals over the 18 months between 2022m7 and 2023m12 can reach 92.8 thousand tourists, with 78.9 and 106.6 as lower and upper bounds at the 5 percent confidence level.

# Annex 1. Notes on Google Trends Data

**Google Trends (GT) data require several clarifications**[29]. Google data are available at a monthly frequency, with the first observation in January 2004, from https://trends.google.com/trends/?geo=US. Important, Google does not report the raw number of queries. Instead, it provides an index measuring a relative popularity of a particular search in a specific region. Its value depends on two factors: (i) the share of the Google queries performed by the users in a particular region on the specific subject in the total number of searches in the same region; and (ii) the number of the search terms in the comparison. For a single query, the GT index is normalized to a range [0, 100], with a value of 100 in the period with the highest query share. For a query with several comparison items, the GT index for each term reflects its popularity relative to the most frequently searched term. Thus, when the GT data are downloaded simultaneously for several (at most five) terms, only one series may observe the index equals 100, with values for the other series being scaled down.




**Consider an example for GT search terms relevant for tourism in Aruba, presented in the chart above.** The series would have spiked at 100 in different periods if one looked at each term without comparators. When shown together, the index values are scaled to the query with the highest interest (in this example, "Aruba vacation"). In this example, on average, GT series for "Aruba hotels," "Aruba beaches," "Aruba flights," and "Aruba all-inclusive hotels" were scaled by a factor of 0.75, 0.61, 0.90, and 0.67, respectively.

**There are several more options to mention.** First, one can search for a term or a topic: search terms show matches for all terms in the query; topics group terms share the same concept in any language. This paper used only the search terms. Second, there are 25 distinct categories (including "Travel," used in this paper),

[29] Also, see "FAQ about Google Trends data" at https://support.google.com/trends/answer/4365533?hl=en for details.

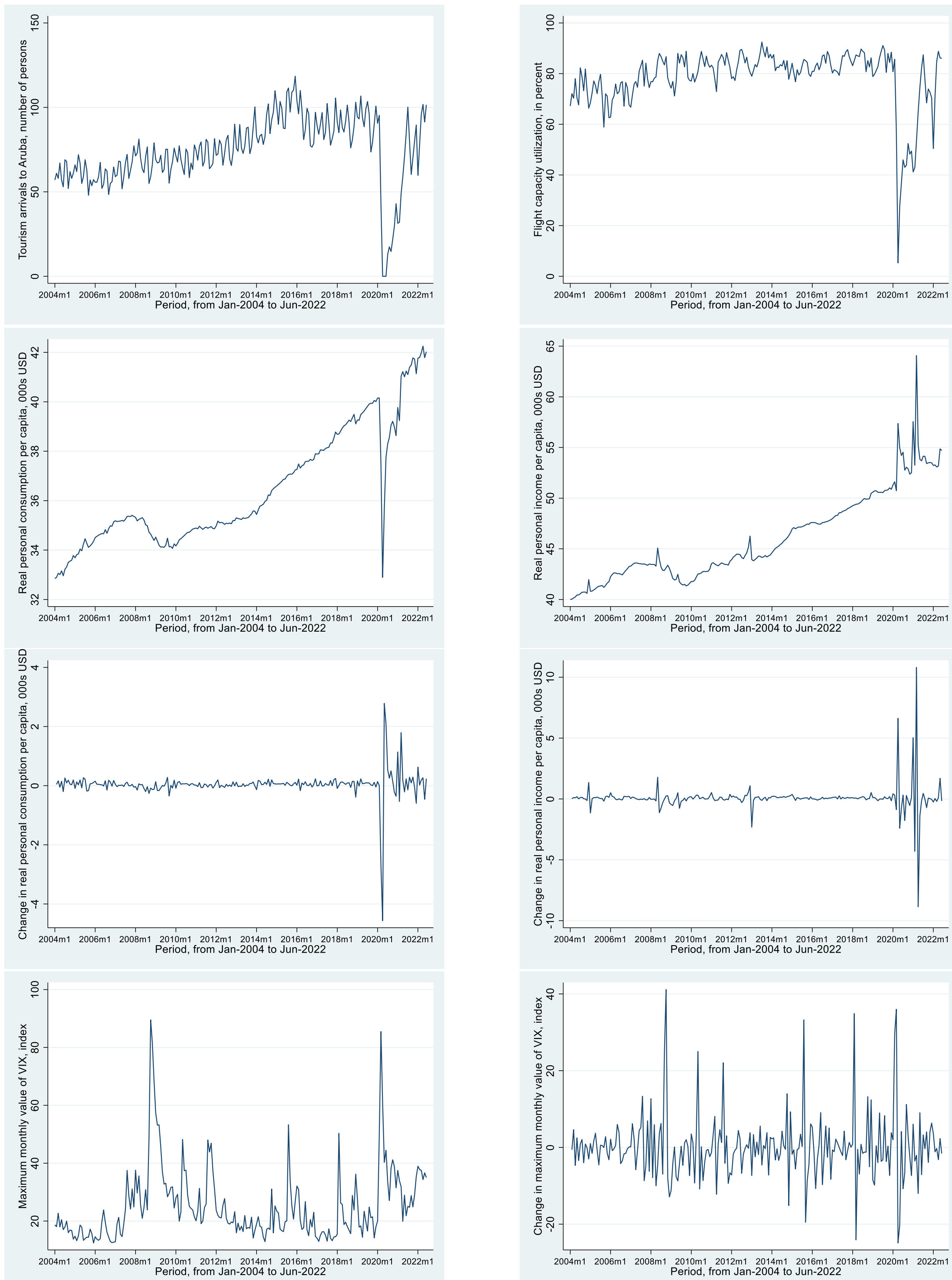
with the 26th option as “All” categories. Third, one can look at the Web Searches (used here), Image Searches, News Searches, Google Shopping, or YouTube Searches.

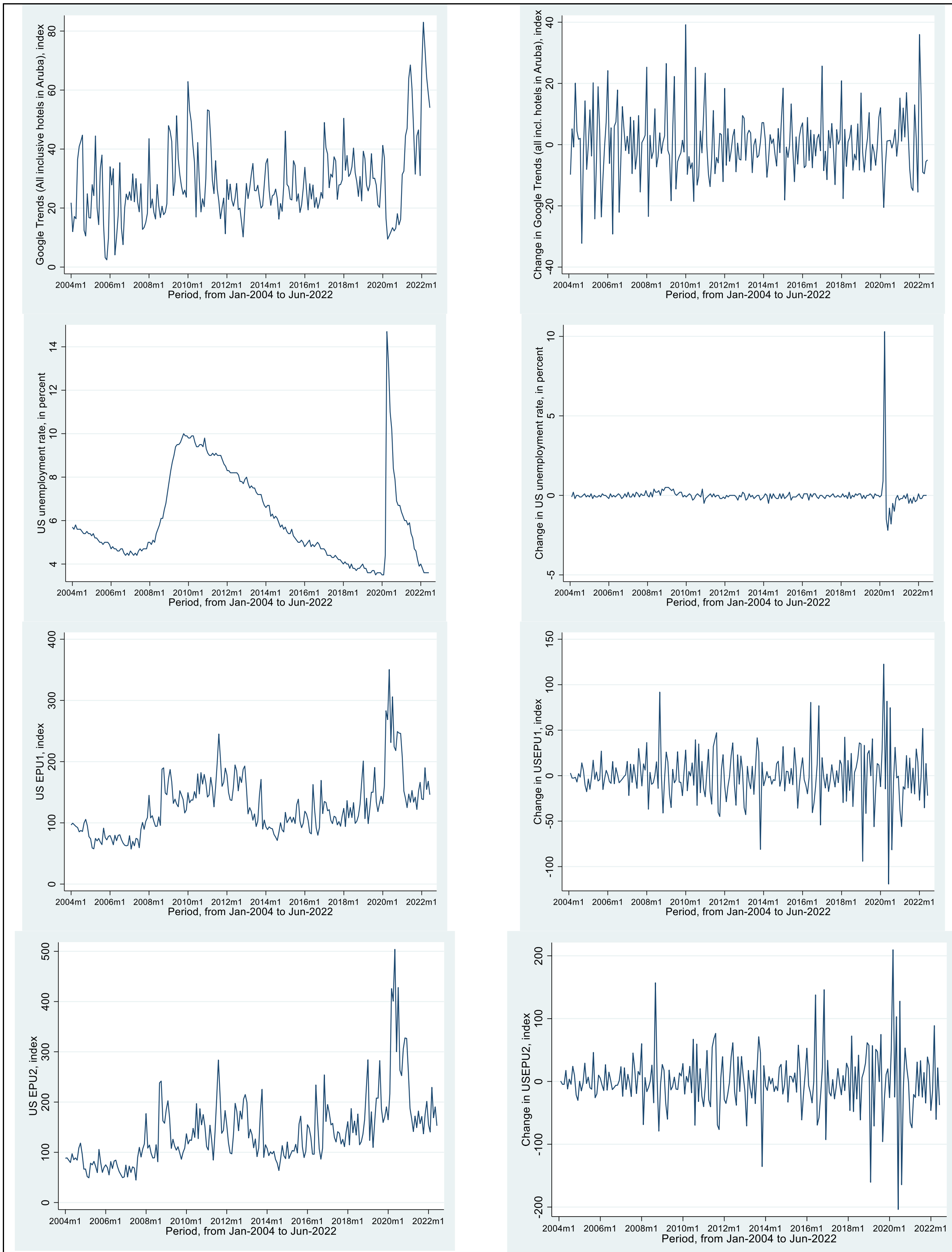
**This paper does not use real-time data.** Instead, it collects the historical Google Trends data, which start on January 1, 2004, and end 1.5 days before the search. The real-time data is available only for the last week. To perform real-time analysis, one would have to scrape data daily.

**The compilation of the GT data employs sampling techniques.** Two features of the GT series should be accounted for: (i) the series exclude searches made very few times, repeated by the same user over a short period, and queries with special characters; (ii) the values can differ from day to day and even within the day. Therefore, researchers often average the GT index, obtained during about four weeks. The GT data for this paper were first collected during 01/08/2021-02/06/2021, with monthly observations for 2004m1-2021m1; and were extended several times (in March 2022 and August 2022). Upon each extension, the monthly averages are recalculated to include new observations. This approach is also supported by Eichenauer et al., 2022.

# Annex 2. Panel Charts: Dynamics in Data

**Figure A2-1. Dynamics in Tourist Arrivals and Explanatory Variables**






Source: Author's calculations.

# Annex 3. Main Empirical Results

**Table 3-1. Tourist Arrivals to Aruba—Model w/RPCE, GT, CAP, VIX, IC and Monthly Dummies**

(Estimation Results Across Samples and Three ARIMA Classes) [30]

| Sample | 2004m1-2019m12 | | | 2004m1-2020m12 | | | 2004m1-2021m12 | | |
|---|---|---|---|---|---|---|---|---|---|
| ARIMA | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| i1 | 13.90*** | 13.88*** | 13.69*** | 14.79*** | 14.70*** | 14.63*** | 15.35*** | 15.33*** | 15.25*** |
| | (1.40) | (1.40) | (1.47) | (1.44) | (1.46) | (1.44) | (1.51) | (1.50) | (1.49) |
| i2 | 9.87*** | 9.84*** | 10.04*** | 10.62*** | 10.51*** | 10.52*** | 11.04*** | 11.01*** | 10.96*** |
| | (1.36) | (1.35) | (1.36) | (1.44) | (1.46) | (1.43) | (1.52) | (1.51) | (1.50) |
| i3 | 17.18*** | 17.21*** | 17.15*** | 17.87*** | 17.85*** | 17.89*** | 17.69*** | 17.65*** | 17.65*** |
| | (1.42) | (1.41) | (1.41) | (1.52) | (1.50) | (1.46) | (1.68) | (1.64) | (1.60) |
| i4 | 13.49*** | 13.52*** | 13.64*** | 13.43*** | 13.44*** | 13.43*** | 13.67*** | 13.69*** | 13.68*** |
| | (1.46) | (1.48) | (1.41) | (1.54) | (1.61) | (1.54) | (1.66) | (1.66) | (1.64) |
| i5 | 2.91* | 2.90* | 2.97* | 2.31 | 2.31 | 2.30 | 3.21* | 3.21* | 3.19* |
| | (1.29) | (1.32) | (1.34) | (1.40) | (1.47) | (1.43) | (1.55) | (1.59) | (1.58) |
| i6 | 5.52*** | 5.50*** | 5.64*** | 4.45** | 4.42** | 4.48*** | 5.23*** | 5.23*** | 5.25*** |
| | (1.23) | (1.26) | (1.23) | (1.36) | (1.43 | (1.34) | (1.41) | (1.44) | (1.40) |
| i7 | 16.20*** | 16.16*** | 16.15*** | 14.32*** | 14.24*** | 14.21*** | 14.77*** | 14.71*** | 14.68*** |
| | (1.25) | (1.29) | (1.32) | (1.33) | (1.39 | (1.40) | (1.32) | (1.34) | (1.37) |
| i8 | 15.17*** | 15.13*** | 15.40*** | 13.23*** | 13.19*** | 13.20*** | 12.95*** | 12.93*** | 12.92*** |
| | (0.93) | (0.92) | (0.88) | (1.13) | (1.10) | (1.10) | (1.03) | (1.00) | (0.99) |
| i10 | 3.85** | 3.81** | 4.12** | 2.58* | 2.53 | 2.53* | 2.33* | 2.29 | 2.27* |
| | (1.29) | (1.35) | (1.29) | (1.25) | (1.30) | (1.24) | (1.16) | (1.19) | (1.15) |
| i11 | 9.50*** | 9.47*** | 9.34*** | 9.83*** | 9.77*** | 9.70*** | 10.32*** | 10.32*** | 10.26*** |
| | (1.21) | (1.25) | (1.22) | (1.29) | (1.39) | (1.38) | (1.28) | (1.33) | (1.35 |
| i12 | 22.05*** | 22.03*** | 22.02*** | 22.67*** | 22.61*** | 22.54*** | 23.06*** | 23.05*** | 22.99*** |
| | (1.30) | (1.31) | (1.32) | (1.30) | (1.35) | (1.30) | (1.32) | (1.33) | (1.31) |
| L3.dRPCE | 1.72 | 1.66 | 0.85 | 1.33* | 1.27* | 1.25* | 1.35* | 1.26* | 1.20* |
| | (2.55) | (2.49 | (2.43) | (0.53) | (0.54) | (0.54) | (0.60) | (0.59) | (0.61) |
| CAP | 0.37*** | 0.37*** | 0.37*** | 0.60*** | 0.61*** | 0.61*** | 0.71*** | 0.71*** | 0.71*** |
| | (0.10) | (0.10) | (0.10) | (0.09) | (0.08) | (0.09) | (0.07) | (0.07) | (0.07) |
| L2.GT | 0.09** | 0.09** | 0.08* | 0.10** | 0.10** | 0.09** | 0.13** | 0.13** | 0.13** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) |
| D.vixmax | -0.05 | -0.05 | -0.09*** | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| IC | X | X | X | -43.19*** | -43.19*** | -42.61*** | -38.54*** | -38.75*** | -38.43*** |
| | X | X | X | (3.71) | (3.54) | (3.67) | (3.39) | (3.25) | (3.25) |
| Constant | 34.29** | 33.90** | 34.43** | 16.74 | 16.27 | 16.58 | 13.96 | 14.72 | 14.57 |
| | (10.98) | (11.36) | (11.12) | (9.20) | (9.42) | (9.28) | (12.20) | (13.33) | (12.98) |
| L1.ar | 0.98*** | 1.18*** | 0.13** | 0.97*** | 1.36*** | 0.51 | 0.98*** | 1.31*** | 0.59 |
| | (0.02) | (0.21) | (0.05) | (0.02 | (0.21) | (0.28) | (0.02) | (0.18) | (0.32) |
| L2.ar | X | -0.19 | 0.83*** | X | -0.38 | 0.46 | X | -0.32 | 0.39 |
| | X | (0.20) | (0.05) | X | (0.20) | (0.27) | X | (0.17) | (0.31) |
| L1.ma | -0.37*** | -0.54** | 0.57*** | -0.32** | -0.68*** | 0.19 | -0.23* | -0.55** | 0.19 |
| | (0.09 | (0.19) | (0.08) | (0.10) | (0.18) | (0.30) | (0.10) | (0.17) | (0.33) |
| L2.ma | X | X | -0.43*** | X | X | -0.30*** | X | X | -0.22** |
| | X | X | (0.08) | X | X | (0.08) | X | X | (0.07) |
| SD | 4.11*** | 4.10*** | 3.98*** | 4.25*** | 4.23*** | 4.20*** | 4.54*** | 4.52*** | 4.50*** |
| LL | -533.7 | -533.2 | -528.8 | -571.8 | -570.5 | -569.4 | -620.2 | -619.3 | -618.4 |
| AIC | 1105.4 | 1106.4 | 1097.7 | 1183.6 | 1183 | 1182.8 | 1280.4 | 1280.5 | 1280.8 |
| SWILK | 0.99** | 0.99** | 0.99 | 0.99** | 0.99** | 0.99** | 0.99 | 0.99 | 0.99 |

[30] Hereafter, numbers in the first line are regression coefficients, with numbers below in brackets showing the standard errors; superscripts *, **, *** denote the 5, 10, and 1 percent significance levels. H0 for the Shapiro-Wilk (SWILK) test is the normality of the regression residuals.

**Table A3-2. Tourist Arrivals to Aruba — Auxiliary Models w/RPCE (Sample: 2004m1-2021m12)**

| Ex. regr. | None | | | RPCE | | | RPCE & CAP | | |
|---|---|---|---|---|---|---|---|---|---|
| ARIMA | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| i1 | 12.70*** | 12.60*** | 12.60*** | 13.07*** | 12.90*** | 12.91*** | 15.22*** | 15.22*** | 15.10*** |
| | (2.55) | (2.36) | (2.40) | (2.61) | (2.39) | (2.48) | (1.75) | (1.74) | (1.77) |
| i2 | 10.38*** | 10.39*** | 10.38*** | 10.40*** | 10.40*** | 10.40*** | 10.83*** | 10.82*** | 10.79*** |
| | (2.76) | (2.59) | (2.62) | (2.86) | (2.65) | (2.74) | (1.66) | (1.66) | (1.63) |
| i3 | 15.73*** | 15.67*** | 15.67*** | 16.27*** | 16.13*** | 16.14*** | 17.98*** | 17.97*** | 17.90*** |
| | (3.23) | (3.17) | (3.18) | (3.30) | (3.28) | (3.29) | (1.94) | (1.94) | (1.89) |
| i4 | 11.17*** | 11.15*** | 11.15*** | 10.89** | 10.93*** | 10.93** | 13.78*** | 13.78*** | 13.81*** |
| | (3.28) | (3.24) | (3.27) | (3.39) | (3.30) | (3.39) | (1.76) | (1.76) | (1.73) |
| i5 | 2.62 | 2.57 | 2.58 | 2.41 | 2.34 | 2.32 | 2.38 | 2.38 | 2.3 |
| | (2.91) | (2.74) | (2.78) | (2.99) | (2.77) | (2.88) | (1.75) | (1.76) | (1.78) |
| i6 | 6.06* | 6.03* | 6.04* | 5.92* | 5.89* | 5.89* | 3.32* | 3.32* | 3.37* |
| | (2.43) | (2.42) | (2.46) | (2.50) | (2.42) | (2.52) | (1.65) | (1.65) | (1.66) |
| i7 | 18.14*** | 18.11*** | 18.12*** | 18.16*** | 18.03*** | 18.01*** | 12.43*** | 12.42*** | 12.17*** |
| | (1.94) | (1.96) | (1.98) | (2.04) | (2.02) | (2.07) | (1.76) | (1.77) | (1.77) |
| i8 | 15.97*** | 15.93*** | 15.93*** | 15.88*** | 15.91*** | 15.92*** | 11.42*** | 11.41*** | 11.35*** |
| | (0.94) | (1.03) | (1.03) | (0.98) | (1.01) | (1.03) | (1.38) | (1.38) | (1.41) |
| i10 | 5.59*** | 5.54*** | 5.54*** | 5.71*** | 5.71*** | 5.72*** | 0.58 | 0.57 | 0.47 |
| | (1.06) | (1.01) | (1.01) | (1.07) | (0.99) | (1.00) | (1.44) | (1.45) | (1.42) |
| i11 | 9.70*** | 9.74*** | 9.73*** | 9.93*** | 9.89*** | 9.89*** | 8.92*** | 8.92*** | 8.89*** |
| | (1.76) | (1.71) | (1.72) | (1.79 | (1.68) | (1.72) | (1.47) | (1.47) | (1.48) |
| i12 | 21.23*** | 21.16*** | 21.16*** | 21.58*** | 21.55*** | 21.57*** | 22.24*** | 22.24*** | 22.25*** |
| | (2.20) | (2.10) | (2.13) | (2.26 | (2.10) | (2.17) | (1.48) | (1.48) | (1.46) |
| L3.dRPCE | X | X | X | 0.49 | 0.12 | 0.10 | 1.55 | 1.53 | 1.25 |
| | X | X | X | (0.9 | (0.78) | (0.80) | (0.96) | (0.97) | (0.81) |
| CAP | X | X | X | X | X | X | 0.94*** | 0.95*** | 0.97*** |
| | X | X | X | X | X | X | (0.17) | (0.18) | (0.16) |
| L2.GT | X | X | X | X | X | X | X | X | X |
| | X | X | X | X | X | X | X | X | X |
| D.vixmax | X | X | X | X | X | X | X | X | X |
| | X | X | X | X | X | X | X | X | X |
| IC | X | X | X | X | X | X | X | X | X |
| | X | X | X | X | X | X | X | X | X |
| Constant | 62.56*** | 62.43*** | 62.45*** | 63.27*** | 63.23*** | 63.26*** | -9.31 | -9.38 | -10.99 |
| | (5.79) | (6.21) | (6.10) | (5.51) | (5.91) | (5.73 | (15.17) | (15.27) | (13.67) |
| L1.ar | 0.91*** | 0.17 | 0.15 | 0.90*** | 0.19 | 0.11 | 0.94*** | 1.05*** | 0.05 |
| | (0.04) | (0.22) | (0.10) | (0.04) | (0.48 | (0.11 | (0.02) | (0.15) | (0.06) |
| L2.ar | X | 0.69*** | 0.71*** | X | 0.67 | 0.73*** | X | -0.09 | 0.85*** |
| | X | (0.18) | (0.08) | X | (0.44 | (0.09 | X | (0.14) | (0.05) |
| L1.ma | 0.17 | 0.90*** | 0.94*** | 0.19 | 0.89** | 0.99*** | -0.26 | -0.35* | 0.69*** |
| | (0.27) | (0.10) | (0.17) | (0.27) | (0.31 | (0.2 | (0.14) | (0.17) | (0.14) |
| L2.ma | X | X | 0.03 | X | X | 0.07 | X | X | -0.31* |
| | X | X | (0.17) | X | X | (0.19 | X | X | (0.14) |
| SD | 6.99*** | 6.88*** | 6.88*** | 6.92*** | 6.84*** | 6.83*** | 5.22*** | 5.22*** | 5.08*** |
| LL | -711.8 | -709.5 | -709.3 | -649.2 | -649.1 | -647.8 | -644.4 | -644.2 | -644.2 |
| AIC | 1484.9 | 1480.3 | 1482.2 | 1455.7 | 1452.9 | 1454.5 | 1332.4 | 1334.1 | 1331.6 |
| SWILK | 0.82*** | 0.82*** | 0.82*** | 0.81*** | 0.80*** | 0.81*** | 0.96*** | 0.95*** | 0.96*** |

**Table A3-2 (cont). Tourist arrivals to Aruba — Auxiliary Models w/RPCE (Sample: 2004m1-2021m12)**

| Ex. regr. | RPCE, CAP & GT | | | RPCE, CAP, GT & VIX | | | RPCE, CAP, GT, VIX & COV19 | | |
|---|---|---|---|---|---|---|---|---|---|
| ARIMA | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| i1 | 16.75*** | 16.75*** | 16.45*** | 16.82*** | 16.83*** | 16.49*** | 15.35*** | 15.33*** | 15.03*** |
| | (1.72) | (1.71) | (1.72) | (1.73) | (1.71) | (1.77) | (1.51) | (1.50) | (1.49) |
| i2 | 12.12*** | 12.12*** | 11.98*** | 12.33*** | 12.33*** | 12.28*** | 11.04*** | 11.01*** | 10.81*** |
| | (1.64) | (1.63) | (1.60) | (1.67) | (1.66) | (1.61) | (1.52) | (1.51) | (1.49) |
| i3 | 16.90*** | 16.86*** | 16.90*** | 16.97*** | 16.94*** | 16.94*** | 17.69*** | 17.65*** | 17.55*** |
| | (1.99) | (1.99) | (1.90) | (1.94) | (1.94) | (1.90) | (1.68) | (1.64) | (1.60) |
| i4 | 13.55*** | 13.55*** | 13.62*** | 13.41*** | 13.40*** | 13.52*** | 13.67*** | 13.69*** | 13.60*** |
| | (1.67) | (1.67) | (1.65) | (1.69) | (1.69) | (1.67) | (1.66) | (1.66) | (1.64) |
| i5 | 2.44 | 2.44 | 2.36 | 2.48 | 2.48 | 2.36 | 3.21* | 3.21* | 3.08 |
| | (1.67) | (1.68) | (1.70) | (1.67) | (1.68) | (1.73) | (1.55) | (1.59) | (1.59) |
| i6 | 4.08** | 4.10** | 4.00* | 3.95* | 3.96* | 3.99* | 5.23*** | 5.23*** | 5.08*** |
| | (1.58) | (1.58) | (1.58) | (1.59) | (1.59) | (1.59) | (1.41) | (1.44) | (1.40) |
| i7 | 13.02*** | 13.01*** | 12.76*** | 12.74*** | 12.73*** | 12.32*** | 14.77*** | 14.71*** | 14.45*** |
| | (1.67) | (1.69) | (1.71) | (1.75) | (1.75) | (1.64) | (1.32) | (1.34) | (1.36) |
| i8 | 11.59*** | 11.59*** | 11.52*** | 11.63*** | 11.63*** | 11.65*** | 12.95*** | 12.93*** | 12.78*** |
| | (1.31) | (1.29) | (1.31) | (1.27) | (1.25) | (1.29) | (1.03) | (1.00) | (0.99) |
| i10 | 1.19 | 1.19 | 1.06 | 1.24 | 1.24 | 1.16 | 2.33* | 2.29 | 2.16 |
| | (1.43) | (1.44) | (1.40) | (1.40) | (1.42) | (1.37) | (1.16) | (1.19) | (1.15) |
| i11 | 10.62*** | 10.65*** | 10.45*** | 10.43*** | 10.45*** | 10.17*** | 10.32*** | 10.32*** | 10.27*** |
| | (1.41) | (1.42) | (1.45) | (1.39) | (1.40) | (1.42) | (1.28) | (1.33) | (1.36) |
| i12 | 23.91*** | 23.93*** | 23.81*** | 23.88*** | 23.90*** | 23.73*** | 23.06*** | 23.05*** | 23.08*** |
| | (1.46) | (1.46) | (1.43) | (1.43) | (1.43) | (1.45) | (1.32) | (1.33) | (1.32) |
| L3.dRPCE | 1.58 | 1.55 | 1.39 | 1.53 | 1.49 | 0.97 | 1.35* | 1.26* | 1.18 |
| | (0.90) | (0.91) | (0.78) | (0.87) | (0.89) | (0.71) | (0.60) | (0.59) | (0.61) |
| CAP | 0.94*** | 0.95*** | 0.96*** | 0.98*** | 0.98*** | 1.00*** | 0.71*** | 0.71*** | 0.74*** |
| | (0.16) | (0.17) | (0.16) | (0.18) | (0.18) | (0.15) | (0.07) | (0.07) | (0.07) |
| L2.GT | 0.14** | 0.14** | 0.13** | 0.14** | 0.14** | 0.12** | 0.13** | 0.13** | 0.12** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| D.vixmax | X | X | X | -0.06 | -0.06 | -0.08** | -0.02 | -0.02 | -0.02 |
| | X | X | X | (0.05) | (0.05) | (0.03) | (0.03) | (0.03) | (0.03) |
| IC | X | X | X | X | X | X | -38.54*** | -38.75*** | -37.30*** |
| | X | X | X | X | X | X | (3.39) | (3.25) | (3.34) |
| Constant | -13.85 | -14.06 | -15.02 | -16.18 | -16.38 | -17.24 | 13.96 | 14.72 | 10.84 |
| | (14.80) | (14.96) | (13.68) | (15.56 | (15.70) | (13.07) | (12.20) | (13.33) | (11.11) |
| L1.ar | 0.95*** | 1.08*** | 0.08 | 0.94*** | 1.08*** | 0.09 | 0.98*** | 1.31*** | 0.58 |
| | (0.02) | (0.14) | (0.06 | (0.02) | (0.16) | (0.07) | (0.02) | (0.18) | (0.36) |
| L2.ar | X | -0.12 | 0.82*** | X | -0.12 | 0.82*** | X | -0.32 | 0.4 |
| | X | (0.13 | (0.06 | X | (0.15) | (0.06) | X | (0.17) | (0.35) |
| L1.ma | -0.28* | -0.40* | 0.62*** | -0.28* | -0.40* | 0.66*** | -0.23* | -0.55** | 0.2 |
| | (0.14) | (0.16) | (0.12) | (0.14) | (0.18) | (0.14) | (0.10) | (0.17) | (0.36) |
| L2.ma | X | X | -0.32* | X | X | -0.34* | X | X | -0.23** |
| | X | X | (0.13) | X | X | (0.14) | X | X | (0.08) |
| SD | 5.11*** | 5.10*** | 5.02*** | 5.06*** | 5.06*** | 4.90*** | 4.54*** | 4.52*** | 4.51*** |
| LL | -642.7 | -642.5 | -644.2 | -642.7 | -642.5 | -640.4 | -620.2 | -619.3 | -621.9 |
| AIC | 1324.9 | 1326.4 | 1328.3 | 1323.5 | 1325.1 | 1320.8 | 1280.4 | 1280.5 | 1287.8 |
| SWILK | 0.95*** | 0.95*** | 0.97*** | 0.96*** | 0.96*** | 0.97*** | 0.99 | 0.99 | 0.99 |

**Table A3-3. Contributions of Exogenous Regressors to the Model Fit**

(estimation sample: 2004m1 – 2021m12) [31]

| Ex. Regr. (1) | None (2) | RPCE (3) | RPCE & CAP (4) | RPCE, CAP & GT (5) | RPCE, CAP, GT & VIX (6) | RPCE, CAP, GT, VIX & IC (7) | Change before IC (8)=(6)-(2) | Change after IC (9)=(7)-(6) |
|---|---|---|---|---|---|---|---|---|
| | | | | ARIMA 101 | | | | |
| SD | 6.99 | 6.92 | 5.22 | 5.11 | 6.84 | 4.54 | -2.45 | -2.45 |
| LL | -711.8 | -649.2 | -644.4 | -642.7 | -649.1 | -620.2 | 91.6 | 91.6 |
| AIC | 1484.9 | 1455.7 | 1332.4 | 1324.9 | 1452.9 | 1280.4 | -204.5 | -204.5 |
| | | | | ARIMA 201 | | | | |
| SD | 6.88 | 6.84 | 5.22 | 5.1 | 5.06 | 4.52 | -2.36 | -2.45 |
| LL | -709.5 | -649.1 | -644.2 | -642.5 | -642.7 | -619.3 | 90.2 | 91.6 |
| AIC | 1480.3 | 1452.9 | 1334.1 | 1326.4 | 1323.5 | 1280.5 | -199.8 | -204.5 |
| | | | | ARIMA 202 | | | | |
| SD | 6.88 | 6.83 | 5.08 | 5.02 | 4.9 | 4.51 | -2.37 | -2.45 |
| LL | -709.3 | -647.8 | -644.2 | -644.2 | -640.4 | -621.9 | 87.4 | 91.6 |
| AIC | 1482.2 | 1454.5 | 1331.6 | 1328.3 | 1320.8 | 1287.8 | -194.4 | -204.5 |

[31] Results in column 2 correspond to the model in equation [5]. Results in column 7 correspond to the full model with RPCE in equation [7]. Results in columns 3-6 correspond to the model in equation [6], where vector $X_l$ includes only $d1RPCE_{t-3}$ (col. 3), $d1RPCE_{t-3}$ and $GT_{t-2}$ (col. 4), $d1RPCE_{t-3}$, $GT_{t-2}$ and $CAP_t$ (col. 5), or $d1RPCE_{t-3}$, $GT_{t-2}$, $CAP_t$, and $d1VIX_t$ (col. 6) respectively.

## Table A3-4. Forecast Evaluation — Contributions of Regressors to Forecast Accuracy

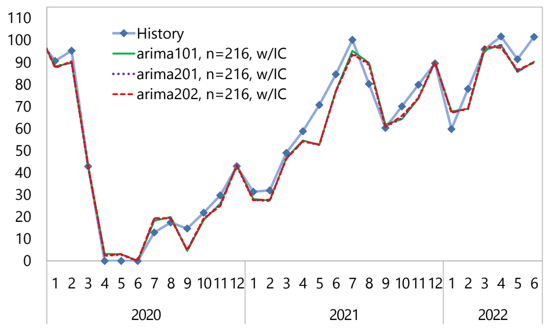
| Estimation sample | 2004m1-2019m12 | | | 2004m1-2020m12 | | | 2004m1-2021m12 | | |
|---|---|---|---|---|---|---|---|---|---|
| Test sample | 2020m1-2022m6 | | | 2021m1-2022m6 | | | 2022m1-2022m6 | | |
| Arima class | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| | ***Full sample: 2004m1-2022m6*** | | | | | | | | |
| | ***RMSE*** | | | | | | | | |
| Pure ARIMA | 8.508 | 8.481 | 8.354 | 7.400 | 7.261 | 7.277 | 7.364 | 7.246 | 7.244 |
| RPI | 8.302 | 8.277 | 8.183 | 7.278 | 7.160 | 7.173 | 7.244 | 7.151 | 7.140 |
| RPI, GT | 6.726 | 6.699 | 6.652 | 5.299 | 5.298 | 5.194 | 5.271 | 5.269 | 5.167 |
| RPI, GT, CAP | 6.556 | 6.535 | 6.497 | 5.182 | 5.178 | 5.104 | 5.156 | 5.152 | 5.079 |
| RPI, GT, CAP, VIX | 6.521 | 6.497 | 6.387 | 5.136 | 5.133 | 5.035 | 5.113 | 5.109 | 4.987 |
| RPI, GT, CAP, VIX, IC | 6.521 | 6.497 | 6.387 | 4.843 | 4.843 | 4.817 | 4.712 | 4.705 | 4.687 |
| | ***Theil's U*** | | | | | | | | |
| Pure ARIMA | 0.934 | 0.902 | 0.891 | 0.684 | 0.663 | 0.675 | 0.661 | 0.654 | 0.652 |
| RPI | 0.931 | 0.916 | 0.914 | 0.672 | 0.657 | 0.662 | 0.655 | 0.645 | 0.639 |
| RPI, GT | 0.788 | 0.782 | 0.721 | 0.499 | 0.498 | 0.471 | 0.478 | 0.475 | 0.429 |
| RPI, GT, CAP | 0.741 | 0.740 | 0.702 | 0.485 | 0.485 | 0.460 | 0.468 | 0.465 | 0.427 |
| RPI, GT, CAP, VIX | 0.710 | 0.704 | 0.650 | 0.490 | 0.490 | 0.452 | 0.469 | 0.466 | 0.409 |
| RPI, GT, CAP, VIX, IC | 0.710 | 0.704 | 0.650 | 0.506 | 0.497 | 0.499 | 0.472 | 0.464 | 0.462 |
| | ***Training sample (same as estimation sample)*** | | | | | | | | |
| | ***RMSE*** | | | | | | | | |
| Pure ARIMA | 4.620 | 4.609 | 4.548 | 6.914 | 6.765 | 6.750 | 7.083 | 6.977 | 6.976 |
| RPI | 4.415 | 4.397 | 4.363 | 6.772 | 6.634 | 6.631 | 6.940 | 6.861 | 6.855 |
| RPI, GT | 4.247 | 4.229 | 4.187 | 5.148 | 5.146 | 5.033 | 5.245 | 5.243 | 5.152 |
| RPI, GT, CAP | 4.180 | 4.166 | 4.133 | 5.059 | 5.057 | 4.975 | 5.123 | 5.120 | 5.059 |
| RPI, GT, CAP, VIX | 4.148 | 4.136 | 4.041 | 5.009 | 5.007 | 4.838 | 5.083 | 5.080 | 4.980 |
| RPI, GT, CAP, VIX, IC | 6.521 | 6.497 | 6.387 | 4.843 | 4.843 | 4.817 | 4.712 | 4.705 | 4.687 |
| | ***Theil's U*** | | | | | | | | |
| Pure ARIMA | 0.468 | 0.468 | 0.462 | 0.664 | 0.642 | 0.653 | 0.646 | 0.643 | 0.640 |
| RPI | 0.467 | 0.465 | 0.462 | 0.651 | 0.634 | 0.639 | 0.639 | 0.632 | 0.626 |
| RPI, GT | 0.442 | 0.439 | 0.435 | 0.509 | 0.508 | 0.477 | 0.485 | 0.482 | 0.435 |
| RPI, GT, CAP | 0.433 | 0.431 | 0.429 | 0.496 | 0.496 | 0.468 | 0.474 | 0.471 | 0.432 |
| RPI, GT, CAP, VIX | 0.430 | 0.429 | 0.423 | 0.503 | 0.502 | 0.455 | 0.475 | 0.472 | 0.415 |
| RPI, GT, CAP, VIX, IC | 0.430 | 0.429 | 0.423 | 0.484 | 0.468 | 0.475 | 0.474 | 0.466 | 0.464 |
| | ***Test sample*** | | | | | | | | |
| | ***RMSE*** | | | | | | | | |
| Pure ARIMA | 19.978 | 19.908 | 19.597 | 11.559 | 11.472 | 11.693 | 14.142 | 13.783 | 13.772 |
| RPI | 19.462 | 19.408 | 19.164 | 11.489 | 11.481 | 11.605 | 14.306 | 13.944 | 13.852 |
| RPI, GT | 14.885 | 14.830 | 14.748 | 6.746 | 6.752 | 6.715 | 6.114 | 6.103 | 5.665 |
| RPI, GT, CAP | 14.434 | 14.391 | 14.321 | 6.383 | 6.366 | 6.357 | 6.213 | 6.173 | 5.737 |
| RPI, GT, CAP, VIX | 14.375 | 14.318 | 14.120 | 6.376 | 6.362 | 6.840 | 6.081 | 6.036 | 5.233 |
| RPI, GT, CAP, VIX, IC | 14.375 | 14.318 | 14.120 | 8.961 | 9.101 | 9.040 | 7.301 | 7.207 | 7.254 |
| | ***Theil's U*** | | | | | | | | |
| Pure ARIMA | 1.241 | 1.191 | 1.178 | 0.779 | 0.767 | 0.782 | 0.901 | 0.853 | 0.857 |
| RPI | 1.233 | 1.212 | 1.209 | 0.771 | 0.765 | 0.774 | 0.918 | 0.863 | 0.868 |
| RPI, GT | 1.025 | 1.016 | 0.924 | 0.439 | 0.442 | 0.434 | 0.312 | 0.312 | 0.281 |
| RPI, GT, CAP | 0.956 | 0.955 | 0.897 | 0.419 | 0.420 | 0.414 | 0.335 | 0.334 | 0.299 |
| RPI, GT, CAP, VIX | 0.909 | 0.899 | 0.817 | 0.416 | 0.418 | 0.436 | 0.321 | 0.320 | 0.259 |
| RPI, GT, CAP, VIX, IC | 0.909 | 0.899 | 0.817 | 0.607 | 0.629 | 0.609 | 0.424 | 0.420 | 0.419 |

# Annex 4. Panel Charts: Projected Arrivals

## Figure A4-1. Projected Arrivals: Comparison across ARIMA classes, before and after IC[32]

**Projected Monthly Tourism Arrivals to Aruba**

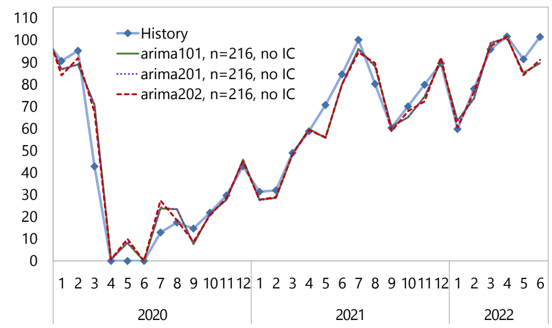
(Thousand persons, w/intercept correction; training sample: 2004m1-2021m12)




Sources: Author's calculations

**Projected Monthly Tourism Arrivals to Aruba**

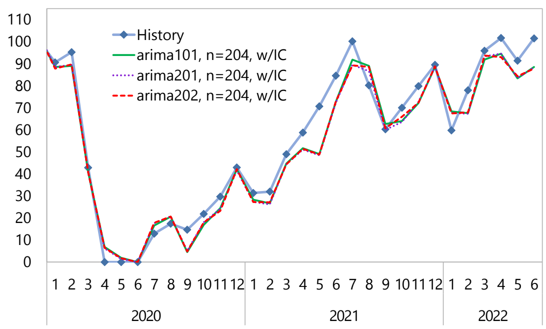
(Thousand persons, no intercept correction; training sample: 2004m1-2021m12)




Sources: Author's calculations

**Projected Monthly Tourism Arrivals to Aruba**

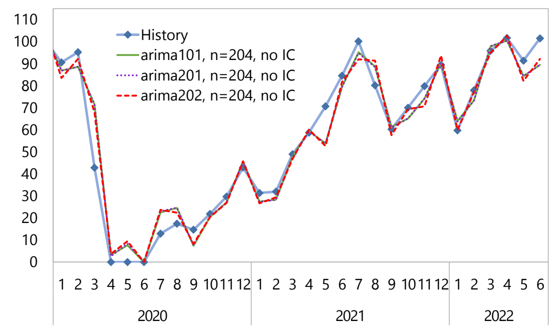
(Thousand persons, w/intercept correction; training sample: 2004m1-2020m12)




Sources: Author's calculations

**Projected Monthly Tourism Arrivals to Aruba**

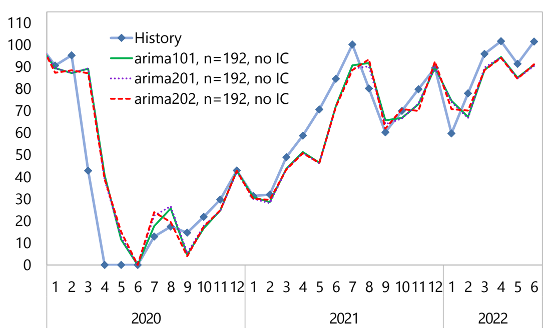
(Thousand persons, no intercept correction; training sample: 2004m1-2020m12)




Sources: Author's calculations

**Projected Monthly Tourism Arrivals to Aruba**

(Thousand persons, no intercept correction; training sample: 2004m1-2019m12)




Sources: Author's calculations

Source: Author's calculations.

[32] IC stands for intercept correction.

# Annex 5. Robustness Check

### Table A5-1. Tourist Arrivals to Aruba—Model w/RPI, GT, CAP, VIX, IC and Monthly Dummies

| Sample | 2004m1-2019m12 | | | 2004m1-2020m12 | | | 2004m1-2021m12 | | |
|---|---|---|---|---|---|---|---|---|---|
| ARIMA | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| i1 | 13.48*** | 13.44*** | 13.47*** | 14.65*** | 14.54*** | 14.47*** | 15.16*** | 15.15*** | 15.05*** |
| | (1.45) | (1.45) | (1.47) | (1.48) | (1.51) | (1.48) | (1.55) | (1.53) | (1.51) |
| i2 | 9.30*** | 9.25*** | 9.56*** | 10.52*** | 10.38*** | 10.40*** | 10.88*** | 10.86*** | 10.81*** |
| | (1.40) | (1.39) | (1.38) | (1.49) | (1.52) | (1.48) | (1.57) | (1.54) | (1.52) |
| i3 | 16.23*** | 16.21*** | 16.29*** | 17.78*** | 17.74*** | 17.77*** | 17.61*** | 17.59*** | 17.62*** |
| | (1.42) | (1.38) | (1.37) | (1.59) | (1.59) | (1.53) | (1.72) | (1.66) | (1.62) |
| i4 | 13.58*** | 13.62*** | 13.63*** | 13.26*** | 13.28*** | 13.26*** | 13.62*** | 13.66*** | 13.64*** |
| | (1.43) | (1.46) | (1.38) | (1.59) | (1.65) | (1.57) | (1.73) | (1.73) | (1.69) |
| i5 | 2.49 | 2.48 | 2.59 | 2.19 | 2.17 | 2.17 | 3.01 | 3.03 | 3.02 |
| | (1.30) | (1.33) | (1.33) | (1.48) | (1.56) | (1.50) | (1.63) | (1.65) | (1.63) |
| i6 | 5.10*** | 5.08*** | 5.31*** | 4.29** | 4.18** | 4.27** | 5.22*** | 5.21*** | 5.26*** |
| | (1.25) | (1.29) | (1.23) | (1.44) | (1.51) | (1.40) | (1.51) | (1.53) | (1.46) |
| i7 | 15.81*** | 15.79*** | 15.91*** | 13.94*** | 13.80*** | 13.81*** | 14.29*** | 14.24*** | 14.23*** |
| | (1.22) | (1.27) | (1.28) | (1.42) | (1.46) | (1.47) | (1.34) | (1.35) | (1.36) |
| i8 | 14.24*** | 14.19*** | 14.59*** | 13.37*** | 13.30*** | 13.33*** | 13.03*** | 13.00*** | 13.01*** |
| | (0.89) | (0.87) | (0.83) | (1.18) | (1.13) | (1.13) | (1.05) | (1.01) | (1.00) |
| i10 | 3.62** | 3.59** | 3.88** | 2.60* | 2.53 | 2.55* | 2.30* | 2.25 | 2.24 |
| | (1.25) | (1.32) | (1.26) | (1.26) | (1.32) | (1.27) | (1.16) | (1.20) | (1.16) |
| i11 | 9.23*** | 9.20*** | 9.27*** | 9.72*** | 9.64*** | 9.58*** | 10.14*** | 10.13*** | 10.06*** |
| | (1.21) | (1.28) | (1.17) | (1.31) | (1.43) | (1.40) | (1.31) | (1.36) | (1.37) |
| i12 | 21.58*** | 21.54*** | 21.74*** | 22.50*** | 22.43*** | 22.35*** | 22.85*** | 22.85*** | 22.78*** |
| | (1.33) | (1.34) | (1.30) | (1.34) | (1.41) | (1.34) | (1.35) | (1.37) | (1.33) |
| L3.dRPI | 2.68*** | 2.77*** | 2.22*** | -0.07 | 0.03 | 0.03 | -0.13 | -0.14 | -0.17 |
| | (0.52) | (0.54) | (0.56) | (0.51) | (0.55) | (0.55) | (0.31) | (0.31) | (0.29) |
| CAP | 0.37*** | 0.37*** | 0.37*** | 0.59*** | 0.60*** | 0.59*** | 0.70*** | 0.71*** | 0.71*** |
| | (0.10) | (0.10) | (0.10) | (0.09) | (0.09) | (0.09) | (0.07) | (0.07) | (0.07) |
| L2.GT | 0.09* | 0.08** | 0.09** | 0.10** | 0.10** | 0.09** | 0.12** | 0.13** | 0.12** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) |
| D.vixmax | -0.03 | -0.03 | -0.06* | -0.02 | -0.02 | -0.02 | -0.03 | -0.03 | -0.03 |
| | (0.03) | (0.03) | (0.02) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| IC | X | X | X | -43.90*** | -43.88*** | -43.52*** | -38.90*** | -39.15*** | -38.85*** |
| | X | X | X | (3.92) | (3.95) | (3.99) | (3.53) | (3.48) | (3.40) |
| Constant | 34.50*** | 34.32** | 34.67*** | 18.17 | 17.51 | 18.23 | 14.50 | 15.41 | 15.3 |
| | (10.4 | (10.79) | (10.38) | (9.40) | (9.65) | (9.59) | (11.96) | (13.58) | (12.99) |
| L1.ar | 0.97*** | 1.29*** | 0.10* | 0.97*** | 1.41*** | 0.47 | 0.98*** | 1.39*** | 0.59 |
| | (0.02) | (0.24) | (0.05) | (0.02) | (0.20) | (0.39) | (0.02) | (0.18) | (0.42) |
| L2.ar | X | -0.31 | 0.86*** | X | -0.42* | 0.49 | X | -0.40* | 0.39 |
| | X | (0.23) | (0.05) | X | (0.20) | (0.37) | X | (0.18) | (0.42) |
| L1.ma | -0.31** | -0.60** | 0.62*** | -0.31** | -0.71*** | 0.24 | -0.20 | -0.61*** | 0.22 |
| | (0.10) | (0.21) | (0.09) | (0.10) | (0.17) | (0.39) | (0.11) | (0.16) | (0.43) |
| L2.ma | X | X | -0.38*** | X | X | -0.31** | X | X | -0.24** |
| | X | X | (0.09) | X | X | (0.10) | X | X | (0.09) |
| SD | 3.99*** | 3.97*** | 3.88*** | 4.31*** | 4.27*** | 4.25*** | 4.60*** | 4.56*** | 4.53*** |
| LL | -528.1 | -527.2 | -524.2 | -574.4 | -572.8 | -571.6 | -622.9 | -621.4 | -620.1 |
| AIC | 1094.2 | 1094.3 | 1088.4 | 1188.8 | 1187.6 | 1187.2 | 1285.8 | 1284.9 | 1284.2 |
| SWILK | 0.99** | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 | 0.99 |

**Table A5-2. Tourist Arrivals to Aruba—Models with alternative risk measures—2004m1-2021m12**

| Exog. Var. | RPCE, CAP, GT, IC, & **UR** | | | RPCE, CAP, GT, IC, & **EPU1** | | | RPCE, CAP, GT, IC, & **EPU2** | | |
|---|---|---|---|---|---|---|---|---|---|
| ARIMA | 101 | 201 | 202 | 101 | 201 | 202 | 101 | 201 | 202 |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| i1 | 15.31*** | 15.29*** | 15.23*** | 15.25*** | 15.22*** | 15.13*** | 15.25*** | 15.22*** | 15.14*** |
| | (1.50) | (1.50) | (1.48) | (1.53) | (1.52) | (1.51) | (1.53) | (1.52) | (1.51) |
| i2 | 10.93*** | 10.89*** | 10.85*** | 11.03*** | 11.00*** | 10.99*** | 11.03*** | 11.00*** | 10.98*** |
| | (1.51) | (1.50) | (1.49) | (1.52) | (1.51) | (1.51) | (1.52) | (1.51) | (1.51) |
| i3 | 17.70*** | 17.66*** | 17.67*** | 17.68*** | 17.65*** | 17.67*** | 17.68*** | 17.65*** | 17.67*** |
| | (1.66) | (1.62) | (1.59) | (1.67) | (1.63) | (1.60) | (1.67) | (1.63) | (1.60) |
| i4 | 13.65*** | 13.66*** | 13.63*** | 13.80*** | 13.82*** | 13.83*** | 13.80*** | 13.82*** | 13.83*** |
| | (1.70) | (1.70) | (1.69) | (1.67) | (1.67) | (1.65) | (1.67) | (1.67) | (1.65) |
| i5 | 3.21* | 3.20* | 3.18* | 3.24* | 3.25* | 3.24* | 3.24* | 3.24* | 3.24* |
| | (1.54) | (1.58) | (1.57) | (1.54) | (1.58) | (1.57) | (1.54) | (1.57) | (1.57) |
| i6 | 5.21*** | 5.20*** | 5.19*** | 5.32*** | 5.33*** | 5.33*** | 5.33*** | 5.33*** | 5.33*** |
| | (1.44) | (1.47) | (1.42) | (1.42) | (1.45) | (1.40) | (1.41) | (1.45) | (1.40) |
| i7 | 14.77*** | 14.69*** | 14.62*** | 15.01*** | 14.96*** | 14.93*** | 15.01*** | 14.96*** | 14.93*** |
| | (1.40) | (1.43) | (1.49) | (1.32) | (1.35) | (1.38) | (1.32) | (1.34) | (1.37) |
| i8 | 12.86*** | 12.82*** | 12.80*** | 13.06*** | 13.05*** | 13.07*** | 13.07*** | 13.06*** | 13.08*** |
| | (1.10) | (1.07) | (1.08) | (1.02) | (0.99) | (0.98) | (1.01) | (0.99) | (0.98) |
| i10 | 2.2 | 2.14 | 2.1 | 2.43* | 2.40* | 2.40* | 2.44* | 2.40* | 2.40* |
| | (1.25) | (1.28) | (1.27) | (1.17) | (1.20) | (1.17) | (1.17) | (1.20) | (1.17) |
| i11 | 10.33*** | 10.31*** | 10.24*** | 10.41*** | 10.40*** | 10.33*** | 10.41*** | 10.40*** | 10.33*** |
| | (1.31) | (1.36) | (1.37 | (1.31) | (1.36) | (1.37) | (1.31) | (1.35) | (1.37) |
| i12 | 23.03*** | 23.02*** | 22.96*** | 23.05*** | 23.04*** | 22.96*** | 23.05*** | 23.04*** | 22.96*** |
| | (1.32) | (1.34) | (1.32) | (1.34) | (1.36) | (1.35) | (1.34) | (1.36) | (1.35) |
| L3.dRPCE | 1.39* | 1.31* | 1.24* | 1.44* | 1.36* | 1.33* | 1.45* | 1.37* | 1.34* |
| | (0.59) | (0.58) | (0.60) | (0.63) | (0.63) | (0.64) | (0.65) | (0.65) | (0.66) |
| CAP | 0.71*** | 0.72*** | 0.73*** | 0.68*** | 0.69*** | 0.68*** | 0.68*** | 0.69*** | 0.69*** |
| | (0.09) | (0.10) | (0.10) | (0.07) | (0.07) | (0.07) | (0.07) | (0.07) | (0.07) |
| L2.GT | 0.13** | 0.13** | 0.12** | 0.13** | 0.13** | 0.12** | 0.13** | 0.13** | 0.12** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| D.UR | 0.20 | 0.22 | 0.24 | X | X | X | X | X | X |
| | (0.36) | (0.35) | (0.39) | X | X | X | X | X | X |
| D.EPU1 | X | X | X | 0.00 | 0.00 | 0.01 | X | X | X |
| | X | X | X | (0.01) | (0.01) | (0.01) | X | X | X |
| D.EPU2 | X | X | X | X | X | X | 0.00 | 0.00 | 0.00 |
| | X | X | X | X | X | X | (0.01) | (0.01) | (0.01) |
| IC | -38.97*** | -38.93*** | -38.32*** | -39.94*** | -40.17*** | -39.96*** | -39.94*** | -40.16*** | -39.91*** |
| | (3.61) | (3.68) | (3.88 | (3.65) | (3.54) | (3.54) | (3.69) | (3.55) | (3.53) |
| Constant | 13.99 | 14.42 | 13.9 | 16.45 | 17.33 | 17.38 | 16.45 | 17.3 | 17.29 |
| | (13.01) | (14.17) | (14.11 | (12.47) | (13.67) | (13.45) | (12.54) | (13.73) | (13.47) |
| L1.ar | 0.98*** | 1.30*** | 0.62* | 0.98*** | 1.31*** | 0.59* | 0.98*** | 1.31*** | 0.59* |
| | (0.01) | (0.16) | (0.30) | (0.01) | (0.17) | (0.29) | (0.01) | (0.17) | (0.29) |
| L2.ar | X | -0.31* | 0.36 | X | -0.32 | 0.39 | X | -0.32 | 0.39 |
| | X | (0.16) | (0.29) | X | (0.17) | (0.29) | X | (0.17) | (0.28) |
| L1.ma | -0.24* | -0.54*** | 0.16 | -0.23* | -0.54*** | 0.2 | -0.23* | -0.54*** | 0.20 |
| | (0.10) | (0.15) | (0.31) | (0.10) | (0.16) | (0.30) | (0.10) | (0.16) | (0.30) |
| L2.ma | X | X | -0.22** | X | X | -0.22** | X | X | -0.22** |
| | X | X | (0.07) | X | X | (0.07 | X | X | (0.07) |
| SD | 4.54*** | 4.52*** | 4.50*** | 4.54*** | 4.52*** | 4.50*** | 4.54*** | 4.52*** | 4.50*** |
| LL | -620.4 | -619.4 | -618.5 | -620.4 | -619.5 | -618.4 | -620.4 | -619.5 | -618.4 |
| AIC | 1280.8 | 1280.9 | 1280.9 | 1280.9 | 1280.9 | 1280.9 | 1280.9 | 1280.9 | 1280.9 |
| SWILK | 0.99** | 0.99** | 0.99** | 0.99** | 0.99** | 0.99** | 0.99** | 0.99** | 0.99** |

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