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İKTİSAT ANABİLİM DALI
İKTİSAT (İNG.) BİLİM DALI

NOWCASTING TURKEY'S TOURIST ARRIVALS AND TOURISM INCOME

M.A. Thesis

UZAY ERYILMAZ

İstanbul, 2022

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ÖZET

TÜRKİYE'YE GELEN TURİST SAYISININ VE TURİZM GELİRLERİNİN ŞİMDİKİ ZAMAN TAHMİNİ

Bu tez, Türkiye'ye gelen turist sayılarını ve Türkiye'nin turizm gelirini tahmin etmek için şimdiki zaman tahmini yapmaktadır. Henüz resmi veriler yayınlanmadan önce yüksek frekanslı Google Trendler arama verilerine ulaşılabilindiğinden, şimdiki zaman tahmininde bu veriler kullanılmaktadır. Haftalık Google Trendler arama verilerinin uygunluğu turizm verilerinin şimdiki zaman tahmini için test edilmektedir. Bu analiz için Eylül 2011 ile Eylül 2021 arasındaki arama verileri kullanılmaktadır. Aylık yayınlanan turist varış verilerini haftalık Google Trendler arama verileriyle tahmin etmek için Mixed-data sampling (MIDAS) modeli kullanılmaktadır. Bu çalışmadan elde edilen bulgular, Google Trendler verilerinin, Türkiye'ye gelen turist sayısını tahmin etme kabiliyetini önemli ölçüde arttırdığını göstermektedir. Birçok MIDAS regresyonlarından en iyi tahmin performansını sergileyen seçilmiş ve Türkiye'ye gelen turist sayıları tahmin edilmiştir. MIDAS modeli kullanılarak kişi başına ortalama turizm harcaması verileri ve tahmini turist sayıları ile turizm geliri tahmin edilmiştir.

Anahtar Kelimeler: Google Trendler, Şimdiki Zaman Tahmini, Turizm, MIDAS

ABSTRACT

NOWCASTING TURKEY'S TOURIST ARRIVALS AND TOURISM INCOME

This thesis is nowcasting to estimate Turkey's tourist arrivals and tourism income. Because the high-frequency Google Trends search data is available before the official data is published, this data is used in the nowcasting. Eligibility of weekly Google Trends search data is tested for nowcasting of tourism data. For this analysis, search data between September 2011 and September 2021 are used. To nowcast monthly published tourist arrivals data with weekly Google Trends search data, the Mixed-data sampling (MIDAS) model is utilized. Findings from this study suggest that Google Trends data significantly improve accuracy for nowcasting tourist arrivals for Turkey. Out of multiple MIDAS regressions, the most accurate ones are chosen and tourist arrivals for Turkey are estimated. With the average tourism expenditure per capita data and estimated tourist arrivals with the MIDAS model, tourism income is estimated.

Keywords: Google Trends, Nowcasting, Tourism, MIDAS

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LIST OF ABBREVIATIONS

MIDAS	Mixed Data Sampling
TURKSTAT	Turkish Statistical Institute
ARIMA	Autoregressive Integrated Moving Average
RMSE	Root Mean Square Error
MSE	Mean Squared Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
GDP	Gross Domestic Product

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1. INTRODUCTION

Tourism has many positive contributions to the country's economy. The developing and growing tourism sector has many effects, such as increasing foreign exports, opening new business areas, contributing to foreign debt payments, providing foreign currency inflow, and increasing growth (Durbarry, 2004). Besides these effects, tourism also plays a role in bringing people from different cultures closer together. A culture of peace and understanding develops in societies that interact with each other. Tourism also has positive effects on local people and businesses, such as increasing regional trade and improving living standards.

Countries competing for a market share in the tourism sector have entered into a serious competition and, especially developing countries like Turkey, have aimed to take part in the competition by giving incentives to tourism investments. With the incentives made in the tourism sector, they are aimed at increasing the attractiveness of domestic and foreign investors. It is important to attract experienced investors to benefit from their experience, knowledge, and capital.

Because of Turkey's geographical location and climate characteristics, tourism is one of the sectors that makes important contributions to the economy. In 2019, international tourism receipts for Turkey were 41.41 Billion $ and its ratio to GDP is 5%. [1] Hence, the tourism sector is a significant part of Turkey's economy.

Nowcasting can be defined as the prediction of the present, near future, and the recent past (Banbura et al., 2013). Nowcasting is an important tool in economic research because of the delayed release of macroeconomic data. The purpose of this method is to predict the dependent variable as early as possible using high frequency and early published data.

In the literature, there are two popular methods for nowcasting. These are mixed-data sampling (MIDAS) models and bridge equations. These two approaches are similar. However, for this study, the deciding difference is the weighting method of high-frequency data. While the MIDAS model uses empirical weighting of high-frequency data based on functional lag polynomials, bridge equations use fixed weights for high-frequency data (Schumacher, 2014). Since bridge equations simply average the weights of high-frequency data to transform it into low-frequency data, high-frequency data experiences

[1] https://data.worldbank.org/indicator/ST.INT.RCPT.CD?locations=TR

a loss of information. The MIDAS model fixes this by using lag polynomials for weighting high-frequency data. Therefore, this thesis uses the MIDAS model for nowcasting.

Mixed-data sampling (MIDAS) is a regression that allows using dependent and independent variables sampled at different frequencies. This method was introduced by Ghysels et al. (2016). Traditional models can not use high-frequency data to estimate low-frequency dependent variables. This study uses the MIDAS model to forecast tourist arrivals in Turkey. Therefore, it provides a direct forecast of the low-frequency variable without losing potentially useful information.

It is important for policymakers, investors, and managers in the tourism sector to get tourism data as soon as possible. For managers and investors, there is serious competition both in domestic and international markets. A competitive advantage can be created by understanding current developments in the tourism sector. For policymakers, high-frequency information in the tourism sector can help make better decisions at the macro level. Traditionally, market participants analyze tourism data published by national statistical institutes to get an idea about the developments in the tourism sector. However, there is a certain delay in the release of official figures. Google Trends provides a solution to this issue by publishing high-frequency search data. Several studies focus on the use of Google Data for nowcasting. (Carriere-Swallow and Labbe (2013), Chadwick MG et al. (2012), Choi and Varian (2012), etc.)

Google Trends is a free Google service that shows how often keywords are searched. Popular searches can be seen intraday and by querying the keywords, it can be seen in which periods the words are most searched according to the date range. From Google Trends, it is possible to understand the popularity of a keyword over time. Google Trends generates a value between 1 and 100, depending on the popularity of the search term among users. In addition, the trends of the keyword in a particular region or the world can be examined. For this study, Google search data from Russia, Germany, Ukraine, the United Kingdom, France, Iran, and the Netherlands are collected.

This study aims to use the nowcasting method to determine the number of tourists coming to Turkey and Turkey's tourism income before official data using Google Trends data. This study analyzes the eligibility of Google Trends data for nowcasting tourist arrivals and tourism income of Turkey and reports whether Google Trends data can improve nowcasting performance when used with mixed-data sampling (MIDAS) regression. It assesses whether high-frequency Google Trends data leads to better nowcasting by comparing weekly Google Trends data using MIDAS regression with the autoregressive integrated moving average (ARIMA) regression model.

This thesis aims to check if it is possible to nowcast the number of tourist arrivals in Turkey using Google Trends data. This study will test whether Google Trends data can improve the nowcasting performance for tourist arrivals and tourism income in Turkey. Finally, the performance of nowcasting

Turkey's tourism income using both the nowcast of tourist arrivals and the expenditure per tourist data will be tested.

All Google keyword searches made in countries from which tourists come to Turkey will be collected and processed. These keywords will consist of the cities that receive the most tourists in Turkey. MIDAS regression, which has examples in the literature, will be used to make predictions. As a result of the analysis, it will be tested whether the models using Google Trends data are performing better or not in the nowcasting of the number of tourists coming to Turkey. Turkey's tourism income will be determined by using the average expenditure data per tourist published by the Turkish Statistical Institute.

Chapter 2 reviews the literature on the use of Google Trends data and the MIDAS model in economics research. Chapter 3 describes Google Trends and tourist arrivals data and presents visualizations of said data. In that chapter, the process of preparation of Google data is explained. Chapter 4 explains the methodology of the MIDAS model. Chapter 5 presents estimations of multiple MIDAS and ARIMA models. This chapter also includes out-of-sample results of conducted regressions and statistical tests. Chapter 6 concludes the study.

2. LITERATURE REVIEW

A lot of work has been done in the literature using Google Trends data. Most of them study the relationship between single or multiple macroeconomic indicators and the Google search data. Askitas and Zimmermann (2009) examine correlations between keyword searches and monthly unemployment rate changes in Germany. The study shows strong correlations between unemployment rates and keyword searches. Pavlicek and Kristoufek (2015) focus on unemployment rate changes by using job-related Google search data for Visegrad countries. This study shows that Google searches improve both forecasting and nowcasting models of the unemployment rate. Fondeur and Karame (2013) examine the youth unemployment rate in France by using a modified version of the Kalman filter with Google search data. They show that Google search data improves predictions of the unemployment rate relative to the model that does not use Google search data. Smith (2016) forecasted changes in the United Kingdom's unemployment by using both Google search data and survey-based variables. D'Amuri and Marcucci (2017) assess the performance of job-search-related Google search data for forecasting the United States unemployment rate. They found that the Google-based models outperformed most of the other models. Carriere-Swallow and Labbe (2013) introduce a Google search volume index of automobile purchases in Chile to test whether it improves the performance of the nowcasting model for automobile sales. The

study shows that models that use Google Trends data outperform benchmark models in both in-sample and out-of-sample nowcasts. Fantazzini and Fomichev (2014) propose a new model for forecasting the real oil price using Google search data and macroeconomic aggregates. Fantazzini and Toktamysova (2015) have developed a new model to forecast monthly car sales data using Google search data and macroeconomic variables. Choi and Varian (2012) examine Google Trends data to evaluate its nowcasting performance using different macroeconomic indicators, such as consumer confidence and unemployment claims. Goel et al. (2010) examine the performance of search engine data to forecast flu trends, the opening weekend box-office revenue for feature films, and first-month sales of video games. They find that Google search data provides useful information for forecasting.

In this study, MIDAS regression will be used for nowcasting. There are many empirical studies in the economics literature using MIDAS regression. Ghysels and Wright (2009) make use of MIDAS regression to forecast several macroeconomic variables, such as GDP growth. They also propose methods for using asset price data to forecast survey releases. They conclude that their methods make it possible to measure the effects of upcoming events. Andreou et al. (2012) review the use of multiple models that deal with data with different frequencies. They also use MIDAS regression for daily or monthly volatility forecasting. Kuzin et al. (2011) assess the performance of MIDAS and mixed-frequency VAR by forecasting Eurozone GDP growth with both models. They find that the two approaches are complementary because the mixed-frequency VAR approach performs better for longer horizons and the MIDAS model performs better for shorter horizons. Clements and Galvão (2008) use the MIDAS model to forecast the United States' output growth. They find that using higher frequency monthly data for the current quarter significantly improves the forecast of current and next quarter output growth. Marcellino and Schumacher (2010) introduce Factor MIDAS, a model that uses mixed-frequency data for forecasting the GDP of Germany. Monteforte and Moretti (2013) assess the performance of the MIDAS regression for the daily forecast of the euro area inflation. They find that models using daily variables perform better than models that use only monthly variables. Andreou et al. (2013) examine several mixed-frequency models and find that MIDAS models improve the forecasts substantially. Armesto et al. (2010) make use of MIDAS and simple averaging to test which one is more effective for the intra-period forecasts. Engle et al. (2013) study the relationship between macroeconomic activity and stock market volatility by utilizing the MIDAS model. They find the MIDAS model outperforms traditional time series volatility models both at short and long time horizons. Li et al. (2015) use the MIDAS model and Google search data to forecast the Chinese consumer price index. In that study, the MIDAS model, including the Google search data, outperforms the selected benchmark model. Rodrigues and Rua (2017) use high-frequency automated teller machines and point-of-sale for nowcasting quarterly private consumption. The study finds that high-frequency data performs

better than conventional predictors for tracking private consumption. Ghysels and Ozkan (2015) make use of a combination of MIDAS-type models with mixed-frequency predictors to predict the annual U.S. federal government budget. They discovered that MIDAS models with quarterly leads that used real-time current year expenditures data outperformed MIDAS models without leads. However, for this study, some results are not significant. Asgharian et al. (2013) studied relations between macroeconomic variables and stock return variance with the MIDAS model. This study shows that using low-frequency macroeconomic data with the MIDAS model improves the prediction ability of the model. Girardin and Joyeux (2013) study the connection between stock market volatility and economic activity in China with the MIDAS model. These studies are examples of the use of MIDAS regression in the economics literature.

There are many studies focused on Turkey using MIDAS, Google Trends, or both. Chadwick MG et al. (2012) demonstrate the effectiveness of Google search data to nowcast the unemployment rate in Turkey for the period from January 2005 to January 2012. With the help of MIDAS regression, Sensoy et al. (2014) constructed a financial fragility index for Turkey. Turhan et al. (2015) implement MIDAS regression to forecast the monthly capacity utilization rate of the manufacturing industry in Turkey. Doğan et al. (2016) use MIDAS regressions to forecast the real GDP growth of Turkey using 204 daily financial series.

The following two studies use a similar methodology as this thesis. Havranek et al. (2021) examine the performance of Google Trends data in forecasting monthly tourist arrivals and overnight stays in Prague. This study shows that the MIDAS model using Google Trends data outperforms models without Google Trends data. With the help of Google Trends search data, Bangwayo-Skeete and Skeete (2015) test the forecasting performance of MIDAS models relative to benchmark models. They find that the MIDAS model outperforms benchmark models in most out-of-sample forecasting experiments. This study focuses on Caribbean countries.

3. TOURISM STATISTICS OF TURKEY

Annual data for Turkey and other tourism-leading countries are presented in this section. Data are obtained from two sources, TURKSTAT and the World Bank. While the data obtained from TURKSTAT covers Turkey's tourism income, the number of visitors to Turkey, and the ratio of tourism income to GDP, the World Bank data covers the number of visitors of the countries that receive the most visitors in the world and the tourism incomes of the countries with the highest tourism income in the world.

TURKSTAT publishes tourism statistics in two ways. The first of these is the number of visitors entering Turkey, and the second is the number of visitors leaving Turkey. The data in this section considers the number of visitors departing from Turkey. Total visitor data includes both abroad residing citizens and foreign visitors. The World Bank defines "International tourism, receipts" data as expenditures by international inbound visitors that include payments to national carriers for international transport and prepayments made for goods or services received in the destination country.

Table 1: Tourism Income And Tourist Arrivals Statistics In Turkey

Year	Tourism Income (000 $)	Tourism Income Rate of Change (%)	Total Visitors	Total Visitors Rate of Change (%)	Foreign Visitors	Foreign Visitors Rate of Change (%)	Share of tourism income in GDP (%)
2001	10450728		13450127		11276531		5.18
2002	12420519	18.85	15214514	13.12	12921982	14.59	5.17
2003	13854868	11.55	16302053	7.15	13701419	6.03	4.40
2004	17076609	23.25	20262640	24.30	17202996	25.56	4.18
2005	20322111	19.01	24124501	19.06	20522621	19.30	4.01
2006	18593950	-8.50	23148669	-4.04	19275948	-6.07	3.34
2007	20942501	12.63	27214988	17.57	23017081	19.41	3.07
2008	25415067	21.36	30979979	13.83	26431124	14.83	3.30
2009	25064481	-1.38	32006149	3.31	27347977	3.47	3.86
2010	24930996	-0.53	33027943	3.19	28510852	4.25	3.21
2011	28115694	12.77	36151328	9.46	31324528	9.87	3.35
2012	29007003	3.17	36463921	0.86	31342464	0.06	3.29
2013	32308991	11.38	39226226	7.58	33827474	7.93	3.37
2014	34305904	6.18	41415070	5.58	35850286	5.98	3.65
2015	31464777	-8.28	41617530	0.49	35592160	-0.72	3.64
2016	22107440	-29.74	31365330	-24.63	25265406	-29.01	2.54
2017	26283656	18.89	38620346	23.13	32079527	26.97	3.06
2018	29512926	12.29	45628673	18.15	38951902	21.42	3.79
2019	34520332	16.97	51860042	13.66	44712970	14.79	4.54
2020	12059320	-65.07	15826266	-69.48	12708265	-71.58	1.68

Source: TURKSTAT

Table 1 shows the number of tourists who came to our country between 2001 and 2020. Tourism revenue, which was 10.4 billion in 2001, increased by 230% to 34.5 billion in 2019. In the same period, the total number of visitors, which was 13.4 million in 2001, increased by 285% to 51.8 million in 2019, while the number of foreign visitors increased from 11.2 million to 44.7 million, an increase of 296%. In some years, both tourism revenues and the number of tourist arrivals decreased. These years are 2006, 2016, and 2020, respectively. The share of tourism income in GDP varied between 5.18% and 1.68% between 2001 and 2020. The share of tourism income was highest in 2001 and lowest in 2020. It entered a downward trend from 2001 to 2007. From 2007 to 2015, the share of tourism revenue remained flat. After the decline in 2016, it entered an upward trend until 2019. It experienced its lowest level in 2020 because of COVID-19.

Table 2: Rankings of Tourist Arrivals for 2019

Rank	Country	Number of arrivals (000)	Share of the number of arrivals in the world (%)
1	France	217877	9.07
2	United States	165478	6.89
3	China	162538	6.76
4	Spain	126170	5.25
5	Mexico	97406	4.05
6	Italy	95399	3.97
7	Poland	88515	3.68
8	Hungary	61397	2.55
9	Croatia	60021	2.50
10	Hong Kong SAR, China	55913	2.33
11	Turkey	51860	2.15
12	United Kingdom	40857	1.70
13	Thailand	39916	1.66
14	Germany	39563	1.65
15	Macao SAR, China	39406	1.64
16	Czech Republic	37202	1.55
17	Greece	34005	1.42
18	Denmark	33093	1.38
19	Canada	32430	1.35
20	Austria	31884	1.33

Source: The World Bank

Based on data published by the World Bank in 2019, Turkey is the eleventh country in the world that attracts the most tourists. Table 2 shows the 20 most visited countries in the world and their share of total visitors for 2019. According to the table, France took first place with 217.8 million visitors and a 9% visitor share. The United States took second place, with 165.4 million visitors and a 6.8% visitor share. China took third place with 162.5 million visitors and a 6.7% visitor share.

Table 3: Rankings of Tourism Income for 2019

Rank	Country	International tourism, receipts (000000 $)	Share of the international tourism, receipts in the world (%)
1	United States	239447	12.85
2	France	70776	3.80
3	Thailand	64371	3.46
4	Germany	58372	3.13
5	Italy	51910	2.79
6	Japan	49209	2.64
7	Australia	47953	2.57
8	Turkey	41415	2.22
9	Macao SAR, China	41166	2.21
10	United Arab Emirates	38413	2.06
11	Hong Kong SAR, China	32697	1.76
12	India	31661	1.70
13	Austria	25924	1.39
14	Mexico	25847	1.39
15	Korea, Rep.	25456	1.37
16	Portugal	24592	1.32
17	Netherlands	23723	1.27
18	Greece	23003	1.23
19	Malaysia	22200	1.19
20	Switzerland	21257	1.14

Source: The World Bank

Table 3 shows the 20 countries with the highest tourism income in the world and their share of the total tourism income for 2019. The United States took first place, with 239 billion in tourism income and a 12.8% share of tourism income. France took second place with a tourism income of 70 billion and a share of 3.8% in tourism income. Thailand took third place with 64 billion in tourism revenues and a 3.4% share of tourism revenue. In 2019, Turkey ranked eighth with 41 billion in tourism revenues and a 2.2% share of tourism revenue.

4. DATA AND DESCRIPTIVE STATISTICS

This thesis uses Google Trends for gathering search volume data. Google Trends provides a measure of search intensity for specific terms across locations and time. The reporting interval for search data varies daily, weekly, and monthly. For this study, weekly search data is used. Search volume data is scaled such that each of the indices' highest values is set to 100. Google Trends data goes as far back as 2004. For this analysis, weekly Google search data between September 2011 and September 2021 is used. Because of the widespread use of the internet and the changes made by Google in the collection of Google Trends data in 2011, only data from the last 10 years have been used.

Google search data from Russia, Germany, Ukraine, the United Kingdom, France, Iran, and the Netherlands are collected. These countries represent 80% of Turkey's tourist arrivals. Indexed search keywords consist of "İstanbul", "Antalya", "İzmir" and "Bodrum". These keywords were chosen because they represent Turkey's tourism central cities, according to the Republic of Turkey Ministry of Culture and Tourism data.

This study uses the monthly number of visitors data provided by the Turkish Statistical Institute as the dependent variable. This variable is reported with a 1-month lag. Therefore, high frequency Google Trends data could be useful for nowcasting tourist arrival numbers in near real-time.

Two indices have been created from raw search data. The first one is a Weighted Google Index. This index is an aggregation of multiple search indices from multiple countries with weights. Weights are calculated using Turkey's past tourist arrival statistics. The second one is the Equal-Weighted Google Index. This index is an aggregation of multiple search indices from multiple countries with equal weighting.

To remove seasonal variation from the dependent variable, the year-on-year difference in the number of visitors is taken. Then the natural logarithm of the difference in the number of visitors is taken to make it stationary. This preprocessing is done for robust MIDAS results. A similar process is done by Havranek et al. (2021) for tourist arrival nowcasting with the MIDAS model.

Table 4: Descriptive Statistics of Google Trends Search Data

Country	Mean	Median	SD	Min	Max
Russia	64.354	67	25.015	18	125
Germany	53.733	52	16.126	24	131
Ukraine	79.562	78	27.488	21	165
The United Kingdom	57.550	57	21.010	22	119
France	10.562	10	6.933	3	102
Iran	61.212	61	29.738	14	148
The Netherlands	48.495	49	14.619	17	133
Weighted Google Index	60.269	61.164	17.858	24.188	110.489
Equal-Weighted Google Index	53.638	54.5	15.005	20.428	94.571

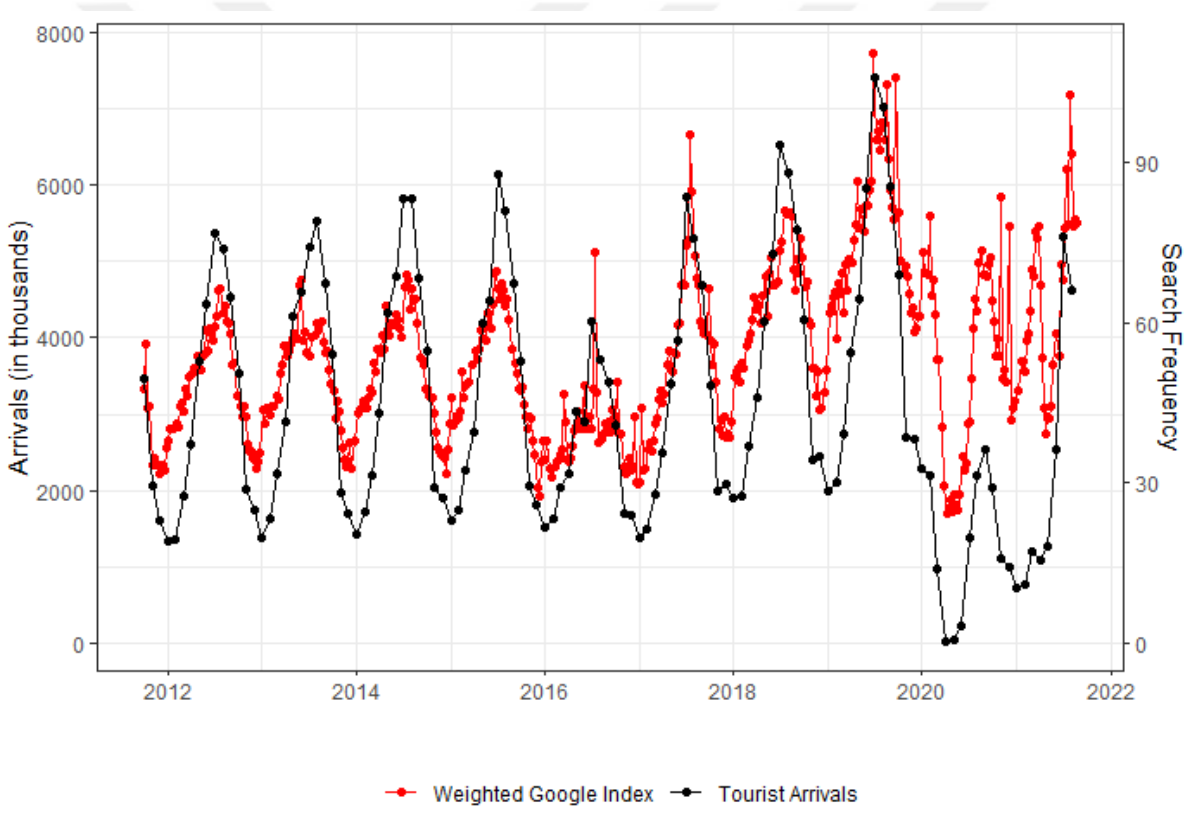
Source: Author's Estimations. Google data is from Google Trends.

Table 4 represents descriptive statistics of listed countries' Google search data between September 2011 and September 2021. To compare with raw search data indices, the Weighted Google Index and Equal-Weighted Google Index are also included. The table shows that the selected keyword search index from Russia's mean is 64.354, the median is 67, the standard deviation is 25.015, the minimum value is 16, and the maximum value is 125. Germany's mean is 53.733, the median is 52, the standard deviation is 16.126, the minimum value is 24 and the maximum value is 131. Ukraine's mean is 79.562, the median is 78, the standard deviation is 27.488, the minimum value is 21 and the maximum value is 165. The United Kingdom's mean is 57.550, the median is 57, the standard deviation is 21.010, the minimum value is 22, and the maximum value is 119. France's mean is 10.562, the median is 10, the standard deviation is 6.933, the minimum value is 3, and the maximum value is 102. Iran's mean is 61.212, the median is 61, the standard deviation is 29.738, the minimum value is 14, and the maximum

value is 148. The Netherlands's mean is 48.495, the median is 49, the standard deviation is 14.619, the minimum value is 17 and the maximum value is 133. The Weighted Google Index's mean is 60.269, the median is 61.164, the standard deviation is 17.858, the minimum value is 24.188, and the maximum value is 110.489. The Equal-Weighted Google Index's mean is 53.638, the median is 54.5, the standard deviation is 15.005, the minimum value is 20.428, and the maximum value is 94.571.

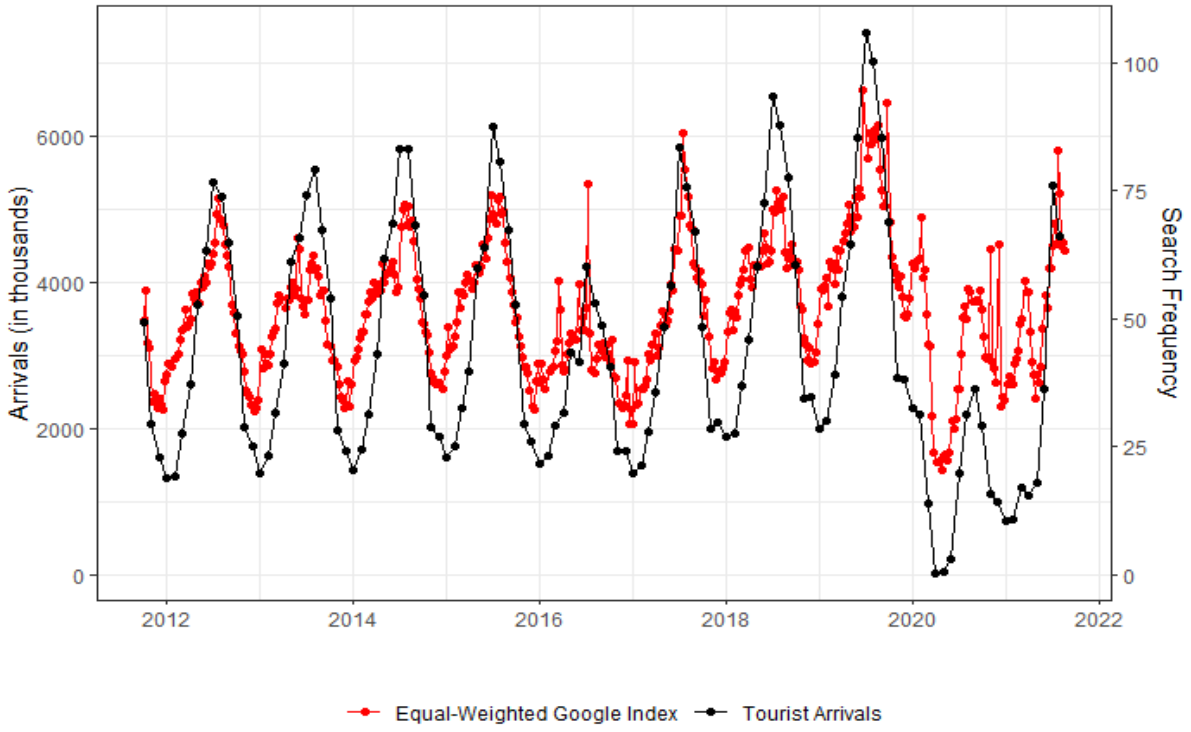
For all indices, all the descriptive metrics are similar except for France. This disparity between France and other indices is because of the extreme values in French search data.

Figure 1: Weighted Google Index and Monthly Tourist Arrivals for Turkey



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure 2: Equal-Weighted Google Index and Monthly Tourist Arrivals for Turkey



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure 1 and Figure 2 represent the Google Index and the Equal-Weighted Google Index, respectively. A visual inspection shows that there is a correlation between indices and tourist arrival data. In both graphs, upward and downward trends appear in the same months. However, both the Google Index and the Equal-Weighted Google Index have multiple outliers. The disparity between tourist arrivals data and search data seems to be higher after 2020. This is likely because of the unusual developments in tourism during the COVID-19 Pandemic.

Figure A1 shows Google Trends search data from Russia and monthly tourist arrivals for Turkey. Similar to the Google Index and the Equal-Weighted Google Index, there is a correlation between search data and tourist arrivals. However, after 2020, the disparity between the two series is high. Compared to the Google Index and Equal-Weighted Google Index, the disparity between tourist arrivals data and search data is higher, especially after 2020. In 2021, search data from Russia is way higher than tourist arrivals data for Turkey.

Figure A2 shows Google Trends search data from Germany and monthly tourist arrivals for Turkey. Seasonal trends in search data and tourist arrivals are in sync. However, compared to search data from Russia, search data and tourist arrivals data are less similar. There are also more outlier data

points. After 2020, general trends of search data from Germany are more similar to tourist arrivals compared to search data from Russia.

Figure A3 shows Google Trends search data from Ukraine and monthly tourist arrivals for Turkey. From 2011 to 2017, search volume was very low compared to the rest of the time series. However, seasonal trends are similar. From 2017 to 2020, the correlation between the two series was higher. After 2020, the disparity between search data from Ukraine and tourist arrival data is higher.

Figure A4 shows Google Trends search data from the United Kingdom and monthly tourist arrivals for Turkey. Except for outliers between 2016 and 2017, trends in search data from the United Kingdom and tourist arrivals are similar until 2020. In 2020, there are a couple of outliers. While there is an increase in tourist arrivals, the volume of search data from the United Kingdom remains low.

Figure A5 shows Google Trends search data from France and monthly tourist arrivals for Turkey. Between search data from France and tourist arrival data, yearly and seasonal trends are similar. In 2016 and 2020, there were few outliers in search data.

Figure A6 shows Google Trends search data from Iran and monthly tourist arrivals for Turkey. Until 2019, the correlation between search data from Iran and tourist arrivals was low. However, there are still seasonal similarities. After 2019, they are more similar.

Figure A7 shows Google Trends search data from the Netherlands and monthly tourist arrivals for Turkey. While there are seasonal similarities, the correlation between search data and tourist data is low. However, after 2020, changes in tourist arrival data and search data are similar.

5. METHODOLOGY

This study analyzes how to get better nowcasts of tourist arrivals and tourism income by using mixed-data sampling (MIDAS) and assesses whether Google Trends data can provide insights into tourism prediction for Turkey. MIDAS regression is a direct forecasting tool that can relate current low-frequency data with current and lagged high-frequency indicators. It can flexibly deal with data sampled at different frequencies and provide a direct forecast of the low-frequency variable. It solves the problem of losing potentially useful information. In this study, the goal is to nowcast monthly tourist arrivals with weekly search data and lagged monthly tourist arrivals data. Since this study deals with different mixed-frequency data, the MIDAS model is used.

The MIDAS models are run both with and without Google Trends data to analyze whether Google can improve tourist arrivals and tourism income nowcasting. The ARIMA model is chosen as the baseline for evaluating the performance of MIDAS models.

5.1. Formulation of MIDAS Regression

This thesis uses the MIDAS regression proposed by Ghysels et al. (2007) and Andreou et al. (2010). Previously, MIDAS was used by Havranek et al. (2021) and Bangwayo-Skeete and Skeete (2015) to study the effects of Google Data for forecasting tourism data.

The following MIDAS model is used:

$$Y_t = \alpha + \sum_{i=1}^{n} \beta_i L^i Y_t + \gamma \sum_{k=1}^{m} B(k;\theta) L_{HF}^k X_t + \varepsilon_t \quad (1)$$

where the function $B(k;\theta)$ a polynomial that determines the weights for temporal aggregation. X_t is a weekly independent variable. Y_t is a monthly dependent variable. L is a polynomial lag operator. L_{HF}^k is a lag operator for the weekly independent variable X_t. α is an intercept. β_i is the effect of lag values of the dependent variable Y_t. γ is the effect of the aggregated weekly independent variable X_t. m represents the number of high-frequency data needed to aggregate to low-frequency data Y_t. Since this thesis uses weekly data as high-frequency data, m = 4 (4 weeks = 1 month).

5.2. MIDAS Regression Variations

In this thesis, two variations of MIDAS regressions are used. The first one is MIDAS Regression with beta formulation proposed by Ghysels et al. (2007) and the second one is MIDAS Regression with Almon formulation proposed by Almon (1965). The difference between these two variations is that the function $B(k;\theta)$ is in a different form.

5.2.1. MIDAS Regression With Beta Formulation

For the $B(k;\theta)$, this thesis uses two different weighting functions proposed by Ghysels et al. (2006). The first one is Beta formulation:

$$B(k;\theta_1,\theta_2) = \frac{f\left(\frac{k}{m},\theta_1,\theta_2\right)}{\sum_{j=1}^{m} f\left(\frac{j}{m},\theta_1,\theta_2\right)} \quad (2)$$

where

$$f(i;\theta_1,\theta_2) = \frac{i^{\theta_t-1}(1-i)^{\theta_2-1}\gamma(\theta_1+\theta_2)}{\gamma(\theta_1)\gamma(\theta_2)} \quad (3)$$

where θ_1 and θ_2 are hyperparameters determining the shape of the weighting function,

$$\gamma(\theta_p) = \int_0^\infty e^{-i} i^{0_p-1}\, di \quad (4)$$

(4) is the standard gamma function.

5.2.2. MIDAS Regression With Almon Formulation

The second formulation is the exponential Almon weighting function proposed by Almon (1965). Ghysels et al. (2007) proposed the following functional form:

$$B(k;\theta_1,\theta_2) = \frac{e^{\theta_1 k+\theta_2 k^2}}{\sum_{j=1}^{m} e^{\theta_1 j+\theta_2 j^2}} \quad (5)$$

where k is the selected lag length. θ_1 and θ_2 are hyperparameters determining the shape of the weighting function.

5.3. Model Selection Criteria

Several techniques and tests have been developed to decide which of the models has the better performance. In this study, the following common metrics are used:

- Mean Square Error
- Root Mean Square Error
- Mean Absolute Percentage Error
- Mean Absolute Scaled Error

Mean square error (MSE) measures the average squared difference between estimations and the actual value.

$$MSE = \frac{1}{n}\sum_{j=1}^{n} e_j^2$$

Root mean square error (RMSE) measures the root of the average squared difference between estimations and the actual value.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} e_j^2}{n}}$$

$$RMSE = \sqrt{MSE}$$

Mean absolute percentage error (MAPE) is a common measure used to forecast error. It measures the accuracy of regression as a percentage.

$$MAPE = \frac{100}{n}\sum_{j}^{n} \frac{|e_j|}{|A_j|}$$

Mean absolute scaled error (MASE) is a forecast accuracy measurement proposed by Hyndman et al. (2006). If the resulting MASE value is less than one, it means regression is better than the average one-step naïve forecast computed in-sample.

$$MASE = \frac{\sum_{t=1}^{n} |e_j|}{\frac{n}{n-1}\sum_{t=2}^{n} |Y_t - Y_{t-1}|}$$

5.4. The Benchmark Model

The autoregressive integrated moving average (ARIMA) method is used in the forward estimation of univariate time series. The major difference between this method and other estimation methods is that it does not require any prior knowledge of the structure of the time series. Instead of using independent values of different indicators, the ARIMA method uses only historical values of dependent value.

This study uses the ARIMA model as a benchmark to measure the performance of MIDAS models. The main reason for choosing ARIMA for comparison is to test if high-frequency Google Trends data improves the nowcast accuracy of tourist arrivals in Turkey.

5.5. Evaluation of the Quality of a Forecast

The Diebold-Mariano test was conducted to test the significance of the predictive accuracy of regressions. This test was developed by Diebold and Mariano (2002) to compare the predictive accuracy of multiple regressions. The null hypothesis of this test is that both regressions have the same accuracy.

6. RESULTS

In this section, the results of multiple MIDAS models are presented. All the models are conducted with Google Trends and lagged tourist arrivals data. This section consists of five separate subsections. The weighted and equal-weighted MIDAS models subsection shows the coefficients of weighted and equal-weighted MIDAS regressions for the period between September 2011 and September 2020. The pre-2020 MIDAS models subsection shows the coefficients of weighted and equal-weighted MIDAS regressions for the period between September 2016 and January 2020. The post-2020 MIDAS models subsection shows the coefficients of weighted and equal-weighted MIDAS regressions for the period between January 2020 and September 2021. The Single Country MIDAS models subsection shows the coefficients of MIDAS regression that use seven different countries' search data separately for the period between September 2011 and September 2020. Finally, the out-of-sample results subsection shows the out-of-sample results of conducted regressions. For out-of-sample analysis, the period between September 2020 and September 2021 was chosen.

6.1. Weighted and Equal-Weighted MIDAS Models

This subsection presents empirical results for the nowcasts of tourist arrivals to Turkey for the period between September 2011 and September 2020. For this analysis, four different MIDAS regressions and one ARIMA regression are used. The ARIMA model was chosen for evaluating the performance of MIDAS models. These MIDAS models are Weighted MIDAS Beta, Weighted MIDAS Almon, Equal-Weighted MIDAS Beta, and Equal-Weighted MIDAS Almon models.

Table 5: MIDAS and ARIMA Estimations of Tourist Arrivals Between September 2011 and September 2020

	Weighted MIDAS Beta	**Weighted MIDAS Almon**	**Equal-Weighted MIDAS Beta**	**Equal-Weighted MIDAS Almon**	**Monthly ARIMA**
β_1	0.761^{***}	0.759^{***}	0.648^{***}	0.648^{***}	
	(0.152)	(0.156)	(0.060)	(0.142)	
β_2	-0.489^{***}	-0.493^{***}	-0.430^{***}	-0.429^{***}	
	(0.095)	(0.093)	(0.075)	(0.085)	
β_3	0.086	0.089	0.049	0.039	
	(0.078)	(0.072)	(0.056)	(0.060)	
β_{12}	-0.219^{***}	-0.220^{***}	-0.228^{***}	-0.224^{***}	
	(0.051)	(0.044)	(0.055)	(0.051)	
γ	1.553^{**}	1.566^{**}	1.888^{***}	1.903^{***}	
	(0.730)	(0.743)	(0.664)	(0.673)	
ar1					0.685^{***}
					(0.075)
ma1					0.534^{***}
					(0.078)
Intercept	**−0.122**	**−0.122**	**−0.087**	**−0.088**	**−0.043**
	(0.090)	**(0.086)**	**(0.063)**	**(0.062)**	**(0.240)**

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.
***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 5 shows the coefficients of the five different models. The second column represents MIDAS regression with the Beta weighting function. The third column represents MIDAS regression with the Almon weighting function. Both regressions use country-weighted Google search data. The fourth and fifth columns represent MIDAS regression with MIDAS Beta and MIDAS Almon weighing functions. These two regressions use equal-weighted Google search data. The ARIMA (1,0,1) model is represented in the sixth column.

Both Weighted MIDAS Beta and Weighted MIDAS Almon regressions' coefficients β_1, β_2 and β_{12} are significant at the 1% level. γ coefficient is significant at the 5% level. The results for Equal-Weighted MIDAS Beta and Equal-Weighted MIDAS Almon are similar. Both of their β_1, β_2, β_{12}, and γ coefficients are significant at 1%.

For all four regressions, while β_2 and β_{12} coefficients are negative, β_1 and γ coefficients are positive. This means that for all four regressions, while the 2 and 12 month lagged versions of the tourist arrivals variable affect the dependent value negatively, the 1-month lagged version of tourist arrivals data and weekly Google Trends search data affect the dependent value positively.

6.2. Pre-2020 MIDAS Models

The goal of this subsection is to analyze the period between September 2011 and January 2020. This period is analyzed separately because of unusual developments in tourism caused by the COVID-19 Pandemic. Pre-2020 Weighted MIDAS Beta, Pre-2020 Weighted MIDAS Almon, Pre-2020 Equal-Weighted MIDAS Beta, and Pre-2020 Equal-Weighted MIDAS Almon regressions are created to analyze and compare their accuracy in the out-of-sample results section.

Table 6: MIDAS and ARIMA Estimations of Tourist Arrivals Between September 2011 and January 2020

	Weighted MIDAS Beta	**Weighted MIDAS Almon**	**Equal-Weighted MIDAS Beta**	**Equal-Weighted MIDAS Almon**	**Monthly Arima**
β_1	0.605^{***}	0.624^{***}	0.676^{***}	0.741^{***}	
	(0.123)	(0.119)	(0.125)	(0.117)	
β_2	0.227^{*}	0.307^{***}	0.265^{**}	0.317^{**}	
	(0.130)	(0.115)	(0.120)	(0.121)	
β_3	-0.212^{**}	-0.223^{**}	-0.258^{**}	-0.293^{***}	
	(0.177)	(0.093)	(0.113)	(0.108)	
β_{12}	0.003	-0.003	-0.002	-0.021	
	(0.051)	(0.066)	(0.065)	(0.074)	
γ	0.296^{***}	0.249^{***}	0.283^{***}	0.181^{**}	
	(0.051)	(0.056)	(0.069)	(0.090)	
ar1					0.908^{***}
					(0.043)
ma1					-0.070
					(0.092)
Intercept	$\mathbf{-0.005}$	$\mathbf{-0.003}$	$\mathbf{-0.0007}$	$\mathbf{-0.002}$	$\mathbf{0.050}$
	$(\mathbf{0.007})$	$(\mathbf{0.009})$	$(\mathbf{0.010})$	$(\mathbf{0.010})$	$(\mathbf{0.067})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.
***, ** and * denote statistical significance at 1%, 5% and 10% level, respectively.

Table 6 shows that for Weighted MIDAS Beta regression coefficients β_1 and γ are significant at the 1% level, β_3 is significant at the 5% level, and β_2 is significant at the 10% level. For Weighted MIDAS Almon regression coefficients β_1, β_2, and γ are significant at the 1% level, and β_3 is significant at the 5% level. For Equal-Weighted MIDAS Beta regression coefficients β_1 and γ are significant at the 1% level. β_2 and β_3 is significant at the 5% level. For Equal-Weighted MIDAS Almon regression coefficients β_1 and β_3 are significant at the 1% level. β_2 and γ is significant at the 5% level.

For all four regressions, while β_3 coefficient is negative, β_1, β_2, and γ coefficients are positive. This means that for all four regressions, while the 3-month lagged version of the tourist arrivals variable

affects the dependent value negatively, the 1 and 2 lagged versions of the tourist data and the weekly Google Trends search data affect the dependent value positively.

6.3. Post-2020 MIDAS Models

In this subsection, the period between January 2020 and September 2021 is analyzed. The purpose of this section is to check γ coefficient's significance. However, the post-2020 model isn't used for out-of-sample analysis because of the limited amount of training data.

Table 7: MIDAS and ARIMA Estimations of Tourist Arrivals Between January 2020 and September 2021

	Weighted MIDAS Beta	Weighted MIDAS Almon	Equal-Weighted MIDAS Beta	Equal-Weighted MIDAS Almon	Monthly Arima
β_1	0.332^{*}	0.375^{**}	0.355^{***}	0.324^{***}	
	(0.154)	(0.154)	(0.116)	(0.083)	
β_2	-0.295^{***}	-0.310^{***}	-0.413^{***}	-0.280^{***}	
	(0.034)	(0.050)	(0.079)	(0.033)	
β_3	-0.024	-0.041	0.004	-0.079	
	(0.050)	(0.044)	(0.069)	(0.050)	
β_{12}	-0.294^{***}	-0.290^{***}	-0.201^{***}	-0.223^{***}	
	(0.028)	(0.030)	(0.038)	(0.063)	
γ	3.052^{**}	2.899^{***}	3.520^{***}	3.216^{***}	
	(0.722)	(0.610)	(0.412)	(0.487)	
ar1					0.661^{***}
					(0.138)
ma1					0.539^{***}
					(0.145)
Intercept	$\mathbf{-0.464}^{***}$	$\mathbf{-0.497}^{***}$	$\mathbf{-0.132}$	$\mathbf{-0.249}^{*}$	$\mathbf{-0.201}$
	$(\mathbf{0.097})$	$(\mathbf{0.098})$	$(\mathbf{0.132})$	$(\mathbf{0.136})$	$(\mathbf{0.704})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 7 shows that for Weighted MIDAS Beta regression coefficients β_2 and β_{12} are significant at 1% level, γ is significant at 5% level, and β_1 is significant at the 10% level. For Weighted MIDAS Almon regression coefficients β_2, β_{12}, and γ are significant at the 1% level, and β_1 is significant at the 5% level. For both Equal-Weighted MIDAS Beta and Equal-Weighted MIDAS Almon regression coefficients β_1, β_2, β_3, and γ are significant at the 1% level.

Signs of coefficients of the post-2020 MIDAS models are the same as the regressions conducted with data between September 2011 and September 2020. For all four regressions, while β_2 and β_{12} coefficients are negative, β_1 and γ coefficients are positive. This means that for all four regressions, while the 2 and 12 month lagged versions of the tourist arrivals variable affect the dependent value negatively, the 1-month lagged version of tourist arrivals data and weekly Google Trends search data affect the dependent value positively.

Like the pre-2020 MIDAS regressions from the previous section, all post-2020 MIDAS regressions' γ coefficients are positive and statistically significant. However, one difference is that post γ coefficients' values are higher. This can be explained by the sharp decline in tourist arrivals caused by the COVID-19 pandemic.

6.4. Single Country MIDAS Models

In this subsection, instead of using indices of multiple countries' search data, single country search data is used. A total of fourteen regressions were conducted for seven different countries. These countries are Russia, Germany, Ukraine, the United Kingdom, France, Iran, and the Netherlands.

Table A1 shows that for MIDAS Beta regression coefficients β_1, β_2, and β_{12} are significant at the 1% level. β_3 is significant at the 5% level, and β_2 is significant at the 10% level. For MIDAS Almon regression coefficients β_1, β_2, and β_{12} are significant at the 1% level. β_3 is significant at the 10% level. γ coefficient is not significant. Table A2-A7 illustrates MIDAS regressions using only search data from Germany, Ukraine, the United Kingdom, France, Iran, and the Netherlands, respectively. For search data from Germany, both MIDAS Beta and MIDAS Almon regressions' γ coefficients are significant at the 5% level. For Ukraine, both regressions' γ coefficients are insignificant. For the United Kingdom, MIDAS Beta regression is insignificant but MIDAS Almon regression regressions' γ coefficient is significant at the 5% level. For France, MIDAS Beta regressions' γ coefficient is significant at the 5% level and MIDAS Almon regression regressions' γ coefficient is significant at the 10% level. For Iran, both MIDAS Beta and MIDAS Almon regressions' γ coefficients are significant at the 10% level. For

the Netherlands, both MIDAS Beta and MIDAS Almon regressions' γ coefficients are significant at the 5% level.

6.5. Out-of-Sample Results

In this subsection, out-of-sample results of the models made in the study are analyzed. For the out-of-sample nowcast evaluation, the period between September 2020 and September 2021 was chosen. Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE) are used to determine the nowcasting ability of multiple MIDAS regressions. Lower RMSE, MSE, MAPE, and MASE values indicate that given models offer better nowcasting performance than other models do.

Table 8 shows the results of MIDAS regressions' estimates of tourist arrivals for the period between September 2020 and September 2021. Equal-Weighted MIDAS Almon regression has lower RMSE, MSE, and MASE. Equal-Weighted MIDAS Beta has a lower MAPE. Weighted MIDAS Beta and Weighted MIDAS Almon regressions are close third and fourth in terms of all metrics. Out of MIDAS regressions with individual search indices, Russia and the United Kingdom MIDAS regressions perform better than others.

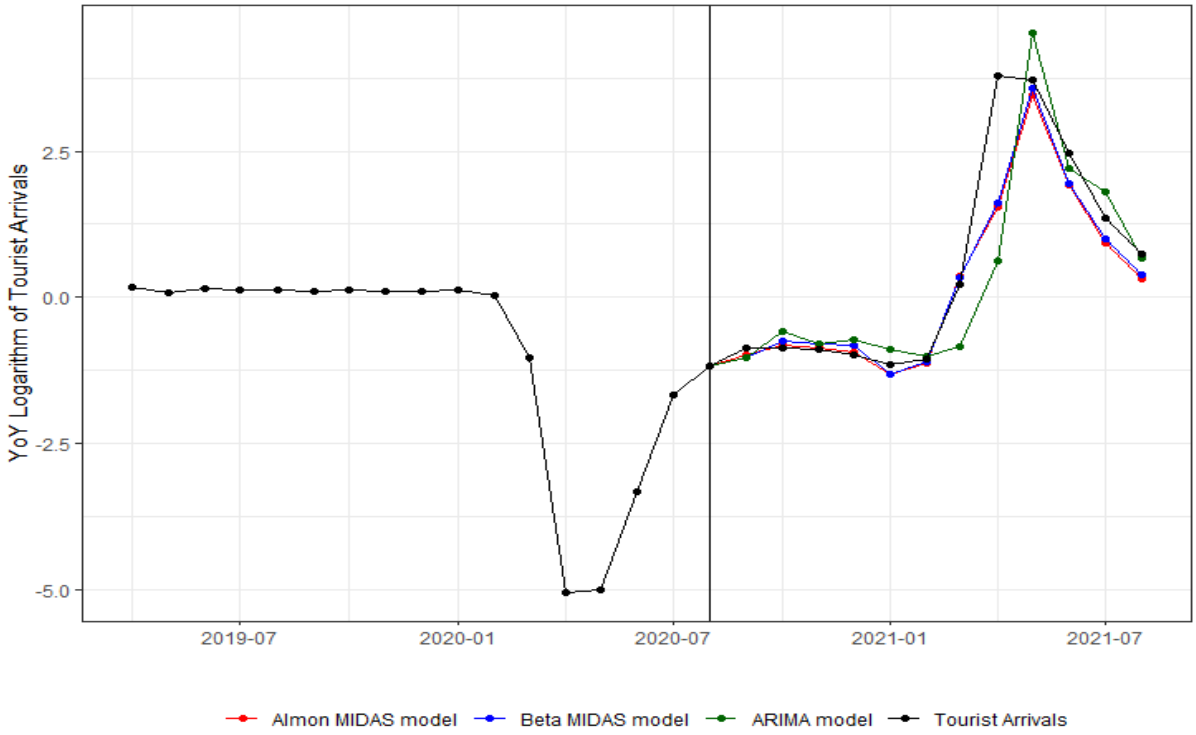
These findings suggest that individual search indices are ineffective compared to both equal-weighted and weighted methods in the period used in this research. However, search indices from Russia, the United Kingdom, and Iran perform better than the Monthly ARIMA model. Pre-2020 models also underperform compared to the main models.

Table 8: Evaluations of MIDAS Estimates Of Tourist Arrivals for The Period Between September 2020 and September 2021

	RMSE	MSE	MAPE	MASE
Russia MIDAS Beta	0.895	0.802	0.410	0.655
Russia MIDAS Almon	0.884	0.782	0.413	0.651
Germany MIDAS Beta	1.905	3.629	0.963	1.857
Germany MIDAS Almon	1.977	3.910	1.027	1.938
Ukraine MIDAS Beta	1.245	1.551	0.612	0.944
Ukraine MIDAS Almon	1.242	1.543	0.613	0.939
The United Kingdom MIDAS Beta	0.812	0.660	0.443	0.701
The United Kingdom MIDAS Almon	0.774	0.600	0.485	0.664
France MIDAS Beta	1.211	1.468	0.519	1.075
France MIDAS Almon	1.465	2.147	0.688	1.362
Iran MIDAS Beta	0.967	0.936	0.485	0.657
Iran MIDAS Almon	0.968	0.937	0.493	0.659
The Netherlands MIDAS Beta	2.104	4.427	1.279	2.025
The Netherlands MIDAS Almon	2.214	4.903	1.287	2.110
Pre-2020 Weighted MIDAS Beta	1.148	1.318	0.632	0.945
Pre-2020 Weighted MIDAS Almon	1.165	1.357	0.677	0.987
Pre-2020 Equal-Weighted MIDAS Beta	1.126	1.269	0.657	0.936
Pre-2020 Equal-Weighted MIDAS Almon	1.160	1.347	0.699	0.953
Weighted MIDAS Beta	0.811	0.657	0.281	0.602
Weighted MIDAS Almon	0.843	0.711	0.276	0.644
Equal-Weighted MIDAS Beta	0.697	0.486	**0.246**	0.501
Equal-Weighted MIDAS Almon	**0.667**	**0.445**	0.251	**0.493**
Monthly ARIMA	1.012	1.025	0.642	0.768

Source: Author's Estimations. The bold values represent the lowest values for each measure.

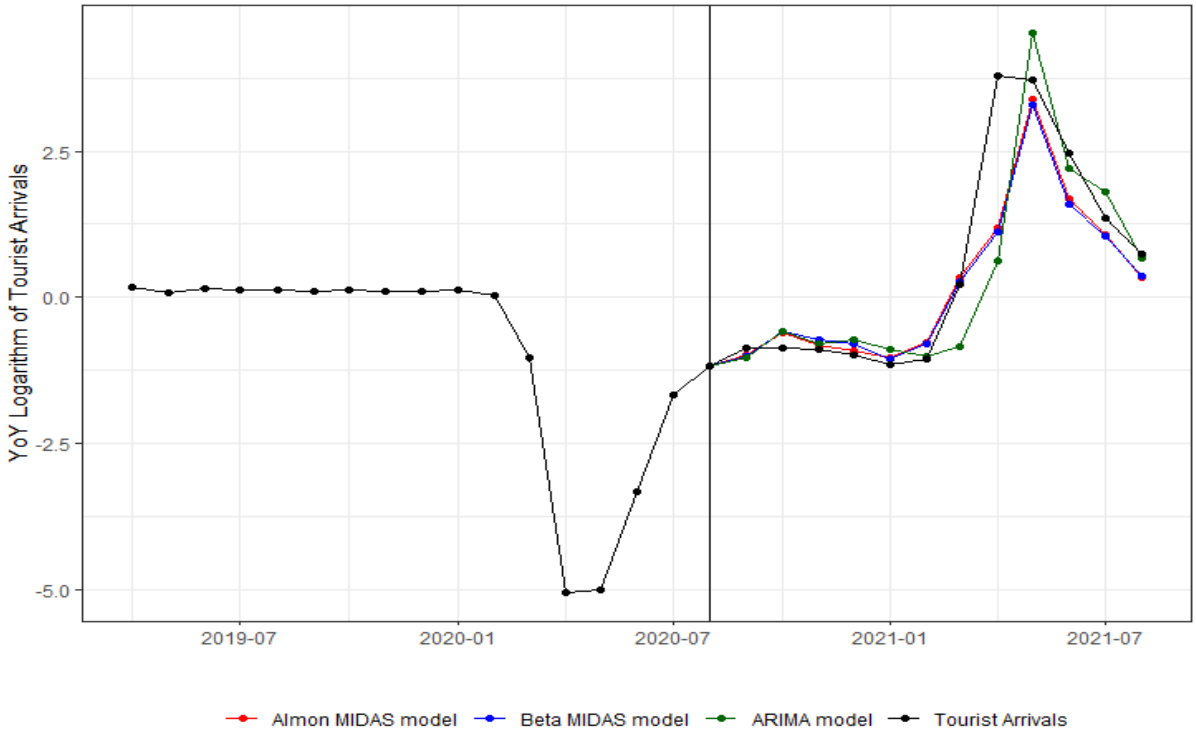
Figure 3: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: Equal-Weighted MIDAS



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure 3 shows the out-of-sample results of the Equal-Weighted MIDAS Beta, Equal-Weighted MIDAS Almon, and ARIMA models. The period between September 2020 and September 2021 was selected for this out-of-sample analysis. From September 2020 to February 2021, the annual rate of change in tourist arrivals data is stable. In this time interval, MIDAS regressions can predict the data better than the ARIMA model. In the increase from February 2021 to May 2021, MIDAS regressions responded more quickly to sudden change than the ARIMA model, as it predicted changes early with the help of Google Trends search data. After May 2021, the nowcasts of MIDAS regressions and the ARIMA model have been realized at close levels.

Figure 4: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: Weighted MIDAS



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure 4 shows the out-of-sample results of the Weighted MIDAS Beta, Weighted MIDAS Almon, and ARIMA models. The period between September 2020 and September 2021 was selected for this out-of-sample analysis. From September 2020 to February 2021, the annual rate of change in tourist arrivals data is stable. In this time interval, MIDAS regressions can predict the data better than the ARIMA model. In the increase from February 2021 to May 2021, MIDAS regressions responded more quickly to sudden change than the ARIMA model, as it predicted changes early with the help of Google Trends search data. After May 2021, the nowcasts of MIDAS regressions and the ARIMA model have been realized at close levels.

Visual inspection of two figures shows that regressions with Google Trends data fit better to out-of-sample monthly tourism arrivals data than the ARIMA model. As results from Table 8 suggest, Equal-Weighted MIDAS regressions perform better than Weighted MIDAS regressions in terms of out-of-sample accuracy.

Figure A8 visualizes the out-of-sample results of the ARIMA model and MIDAS regressions with only Russian data. Compared to Figures 4 and 5, MIDAS regression results are more similar to

ARIMA results. This can be explained by the insignificant and less effective γ coefficient from Table A1. Figures A9, A10, A11, A12, A13, and A14 show similar out-of-sample results for Germany, Ukraine, the United Kingdom, France, Iran, and the Netherlands. Germany, the United Kingdom, France, and the Netherlands estimated values overshoot tourist arrivals data. Other ones are looking better, but they are still worse than MIDAS with multi-country Google data.

Table 9: Values of Diebold and Mariano Test for The Period Between September 2020 and September 2021

Monthly ARIMA	Weighted MIDAS Beta	Weighted MIDAS Almon	Equal-Weighted MIDAS Beta	Equal-Weighted MIDAS Almon
Tourist arrivals	**2.280***	**2.192***	**2.292***	**2.306***

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. * denote statistical significance at 10% level.

The Diebold-Mariano Test is used to test whether the accuracy of both equal-weighted and weighted MIDAS regressions is significantly better than the ARIMA model. The ARIMA model is used as a benchmark to compare the performance of regressions in terms of accuracy. RMSE is chosen as a measure of forecast accuracy.

Table 9 shows the Diebold-Mariano test results. All four MIDAS regressions are significantly more accurate than the Monthly ARIMA model at the 10% confidence level. These results show that models with multiple countries' Google Trends search data perform better than models that use only past data. These results are consistent with the results of Havranek et al. (2021) and Bangwayo-Skeete and Skeete (2015). In all three studies of tourism nowcasting with Google Trends data, models with Google Trends data significantly increase the performance of estimations.

Using both average expenditure per capita data from TURKSTAT and selected MIDAS models, tourism income values are estimated. The selected average expenditure per capita value for the period between September 2020 and September 2021 was $834. This value was chosen because, in 2021, the average expenditure per capita was 834.

Table 10: Actual and Estimated Tourist Arrivals Data for Turkey

Months	Tourist Arrivals	ARIMA	Weighted MIDAS Beta	Weighted MIDAS Almon	Equal-Weighted MIDAS Beta	Equal-Weighted MIDAS Almon
2020-09	2534376	2159670	2145806	**2239025**	2182487	2227759
2020-10	2044001	2713251	2305920	**2114065**	2674281	2614558
2020-11	1104834	1216766	1224410	**1126776**	1295800	1191141
2020-12	990896	1285501	1180357	**1051043**	1215388	1075194
2021-01	727301	939126	608640	611811	**802758**	821636
2021-02	764314	**803363**	723661	720714	981262	1019341
2021-03	1198371	417141	1370181	1391820	**1254691**	1350998
2021-04	1072496	45315	**123246**	113872	74373	79891
2021-05	1254673	2790649	**1094627**	967040	827365	903517
2021-06	2540872	**1951524**	1533013	1474646	1053772	1166174
2021-07	5319992	8488949	3776223	3464125	3980160	**4069952**
2021-08	4630334	**4310611**	3202951	3001125	3151448	3094042

Source: Author's Estimations. Tourist arrival data is from TURKSTAT. The bold values are closest to the actual data.

Table 10 shows the out-of-sample results of Weighted MIDAS Beta, Weighted MIDAS Almon, Equal-Weighted MIDAS Beta, Equal-Weighted MIDAS Almon regressions, and the ARIMA model. Out of the selected 12 months of data, the ARIMA model performed best in 3 months, Weighted MIDAS Beta regression performed best in 2 months, Weighted MIDAS Almon regression performed best in 4 months, Equal-Weighted MIDAS Beta regression performed best in 2 months, and Equal-Weighted MIDAS Almon regression performed best in 1 month. These results show that, out of 12 months, regressions with Google Trends data performed better in 9 months.

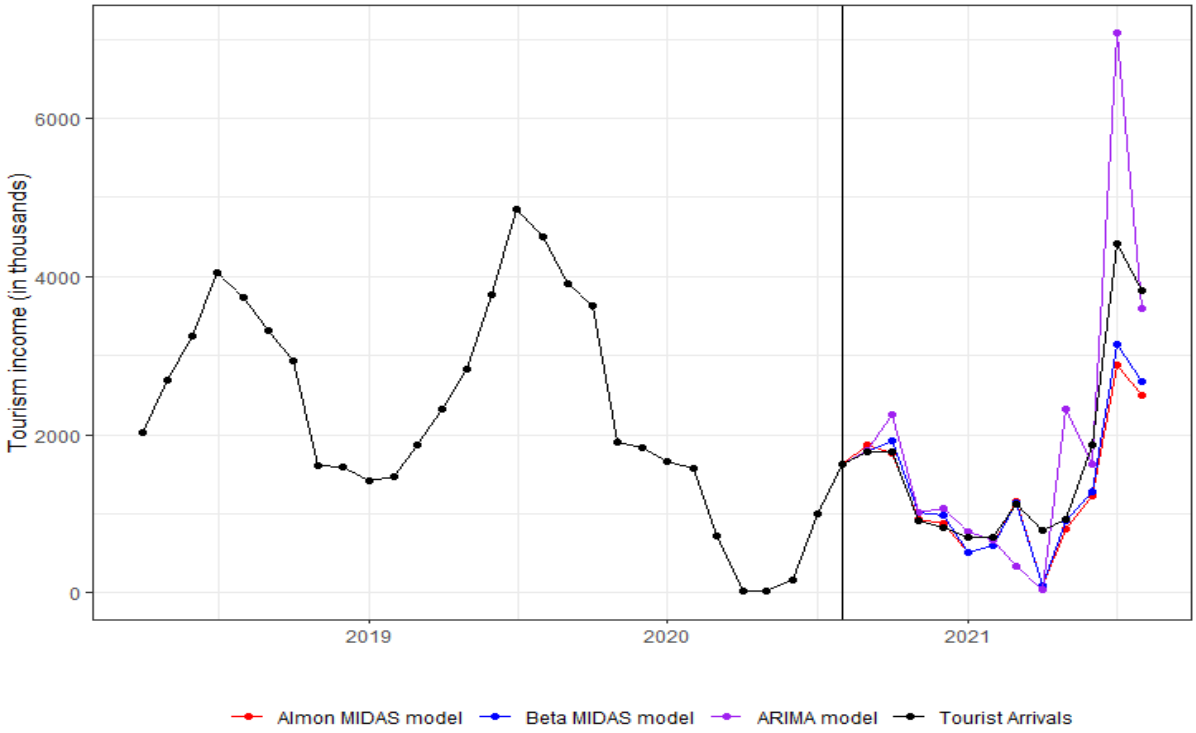
Table 11: Actual and Estimated Tourism Income Data for Turkey

Months	Tourism Income (000)	ARIMA (000)	Weighted MIDAS Beta (000)	Weighted MIDAS Almon (000)	Equal-Weighted MIDAS Beta (000)	Equal-Weighted MIDAS Almon (000)
2020-09	1789.26	1801.2	1867.34	**1789.6**	1820.19	1857.95
2020-10	1784.41	2262.9	**1763.13**	1923.13	2230.35	2180.54
2020-11	920.32	1014.8	**939.73**	1021.15	1080.69	993.41
2020-12	828.38	1072.1	**876.57**	984.41	1013.63	896.71
2021-01	696.75	783.23	510.25	507.6	669.5	**685.24**
2021-02	706.22	**670**	601.07	603.53	818.37	850.13
2021-03	1131.26	347.89	1160.77	1142.73	1046.41	**1126.73**
2021-04	796.86	37.79	94.96	**102.78**	62.02	66.62
2021-05	927.2	2327.4	806.51	**912.91**	690.02	753.53
2021-06	1870.08	**1627.6**	1229.85	1278.53	878.84	972.58
2021-07	4415.59	7079.8	2889.08	3149.37	3319.45	**3394.34**
2021-08	3829.28	**3595**	2502.93	2671.26	2628.3	2580.43

Source: Author's Estimations. Tourist arrival data is from TURKSTAT. The bold values are closest to the actual data.

Table 11 shows the out-of-sample estimations of monthly tourism income for Turkey using Weighted MIDAS Beta, Weighted MIDAS Almon, Equal-Weighted MIDAS Beta, Equal-Weighted MIDAS Almon regressions, and the ARIMA model. Out of the selected 12 months of data, the ARIMA model performed best in 3 months, Weighted MIDAS Beta regression performed best in 3 months, Weighted MIDAS Almon regression performed best in 3 months, Equal-Weighted MIDAS Beta regression did not perform best in any month, and Equal-Weighted MIDAS Almon regression performed best in 3 months. As in tourist arrival results, out of 12 months, regressions with Google Trends data performed better in 9 months.

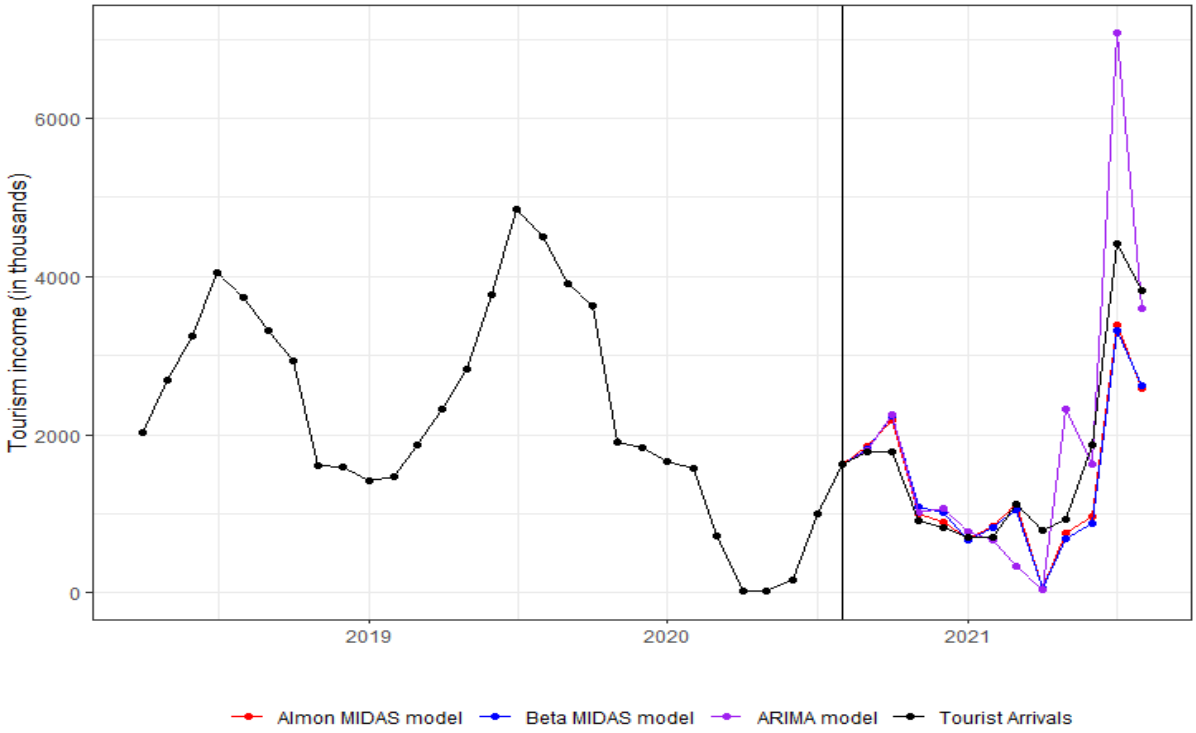
Figure 5: Tourism Income Nowcasts Between September 2020 and September 2021: Equal-Weighted MIDAS



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure 5 shows the estimated values of the Equal-Weighted MIDAS regression and ARIMA model compared to tourist arrivals data. The period between September 2020 and September 2021 was selected for this out-of-sample analysis. The figure shows that the Equal-Weighted MIDAS regression is more accurate than the ARIMA model for the same period.

Figure 6: Tourism Income Nowcasts Between September 2020 and September 2021: Weighted MIDAS



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure 6 shows the estimated values of the Weighted MIDAS regression and the ARIMA model compared to tourist arrivals data. As in the Equal-Weighted MIDAS analysis, the period between September 2020 and September 2021 is selected for out-of-sample analysis. The figure shows that the Weighted MIDAS regression is more accurate than the ARIMA model for the same period. In both figures 7 and 8, the Beta and Almon MIDAS models generate similar results.

In summary, the results in this section show that MIDAS regressions using Google Trends search data are useful in nowcasting the number of tourists coming to Turkey and Turkey's tourism income. Especially Weighted MIDAS regressions performed better than their alternatives in the selected time frame. If the methods used in this thesis are used with the new Google Trend data, both the number of tourists coming to Turkey and Turkey's tourism income can be successfully estimated before the official data are announced.

7. CONCLUSION

The main aim of this thesis is to analyze the eligibility of weekly Google Trends search data for nowcasting tourist arrivals and tourism income in Turkey. Accurately and quickly estimating tourist arrivals is vital for policymakers, investors, and managers in the tourism sector. Since there is a delay in the announcement of official figures, estimating current developments with higher frequency data creates value for the sector. This thesis used MIDAS regression to nowcast monthly tourist arrivals with weekly search data.

Findings from this study show that using Google Trends data with MIDAS regression improves nowcasting accuracy. These results are consistent with the results of similar studies. Twenty-two different MIDAS models and an ARIMA model are evaluated. Among all of them, Weighted MIDAS Beta, Weighted MIDAS Almon, Equal-Weighted MIDAS Beta, and Equal-Weighted MIDAS Almon regressions performed better than the others. It should be noted that these four regressions are models that use multiple country search data. In terms of estimation accuracy, the four best-performing regressions are selected. The significance of the performance of the said models is tested with the Diebold-Mariano test. All four MIDAS regressions performed significantly better compared to the benchmark Monthly ARIMA model at the 10% confidence level.

With average expenditure per capita data, Turkey's monthly tourism income is estimated with selected four models. For the average expenditure per capita value, the period between September 2020 and September 2021 was selected. Estimating Turkey's monthly tourism income can be improved by nowcasting or forecasting data on average expenditure per capita. This thesis did not estimate average expenditure per capita but instead used data on average historical average expenditure per capita. Future research can improve this shortcoming by studying factors that affect the monthly average expenditure per capita.

Results from this study highlight the potential of using internet search data to improve nowcasting accuracy for the tourism sector. With the help of MIDAS regressions and Google Trends data, the information set available to policymakers, investors, and managers in the tourism sector can be improved.

To sum up, the results from this study support the use of MIDAS regression with Google Trends data to nowcast both tourist arrivals in Turkey and Turkey's tourism income. The results confirm that using this method improves nowcasting performance and allows the estimation of both tourist arrivals and tourism income before the release of official data.

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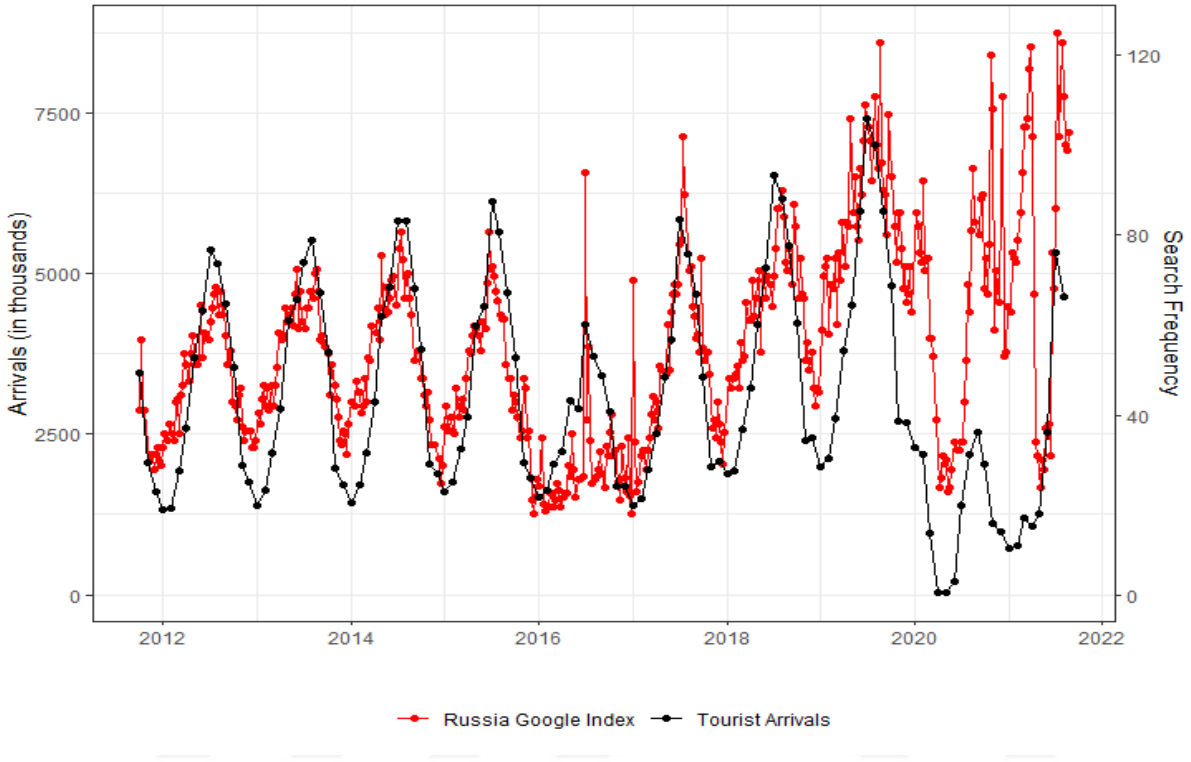
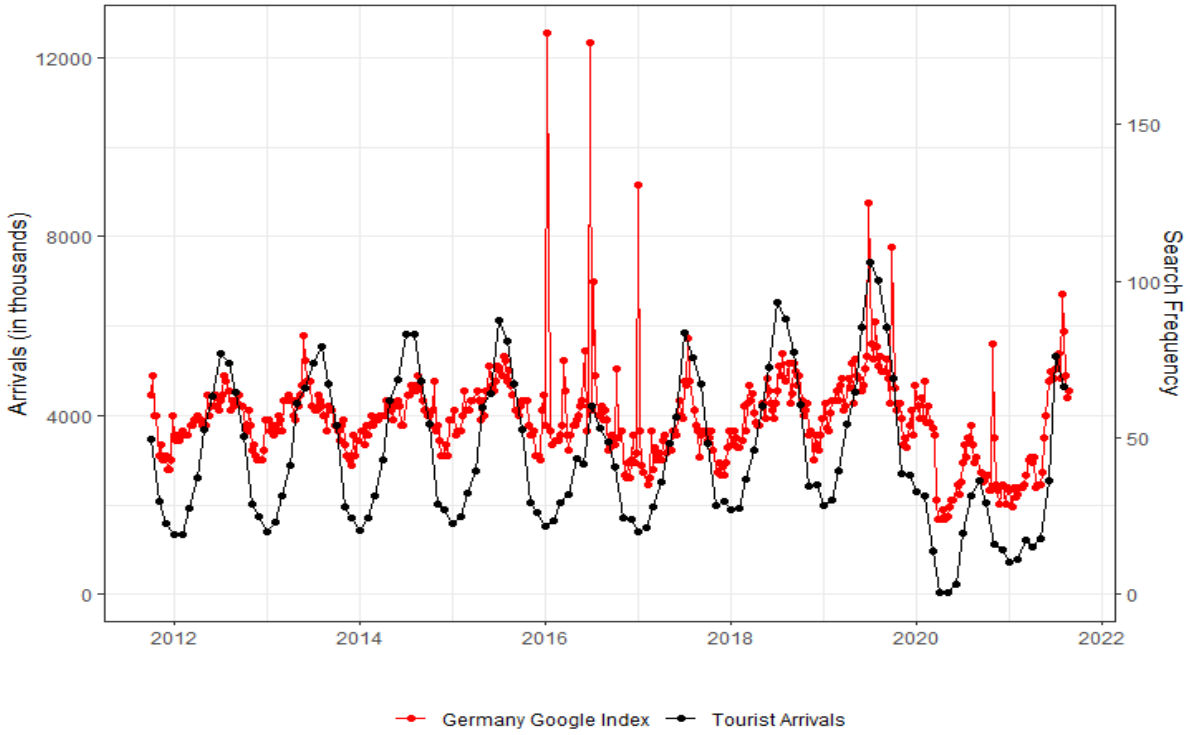
APPENDIX

Figure A1: Google Trends Search Data From Russia and Monthly Tourist Arrivals for Turkey



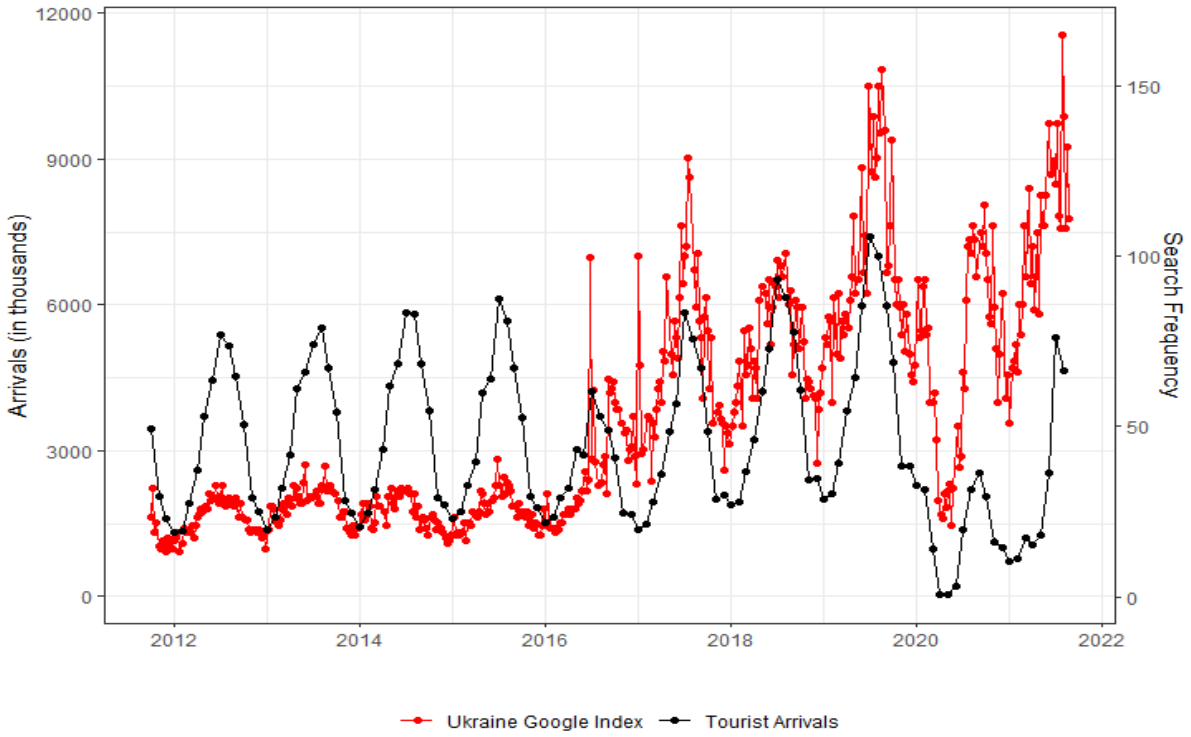
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A2: Google Trends Search Data From Germany and Monthly Tourist Arrivals for Turkey



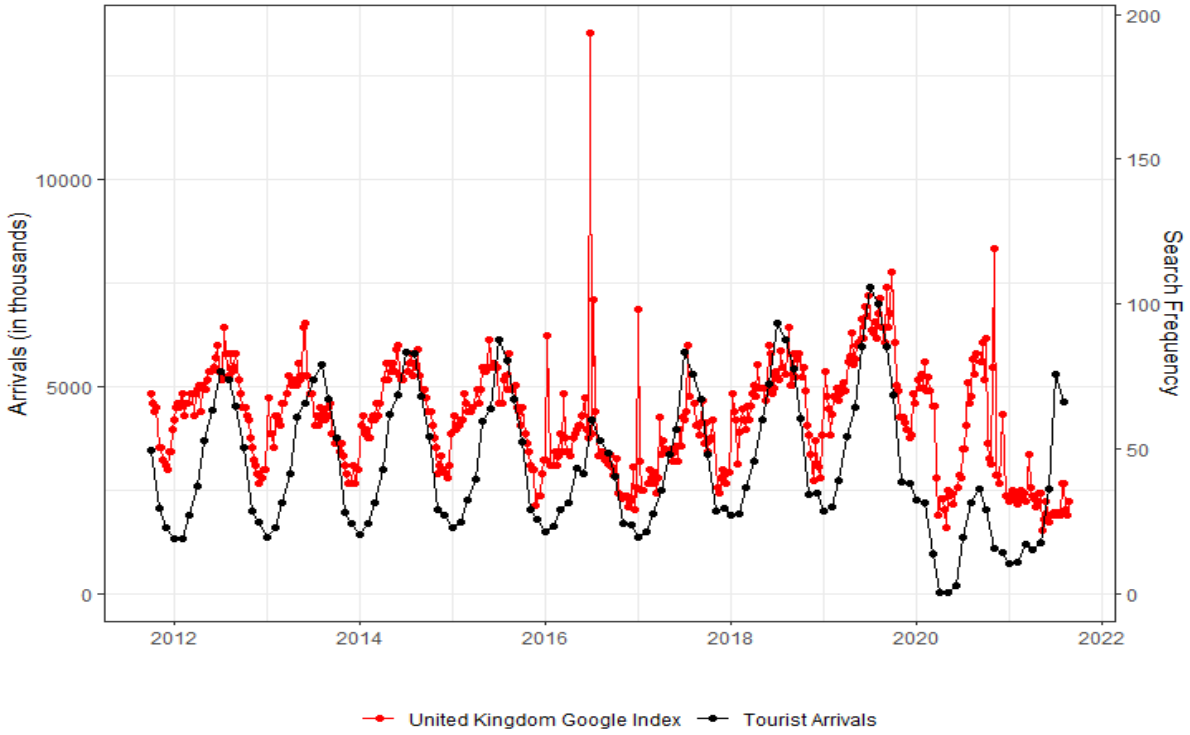
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A3: Google Trends Search Data From Ukraine and Monthly Tourist Arrivals for Turkey



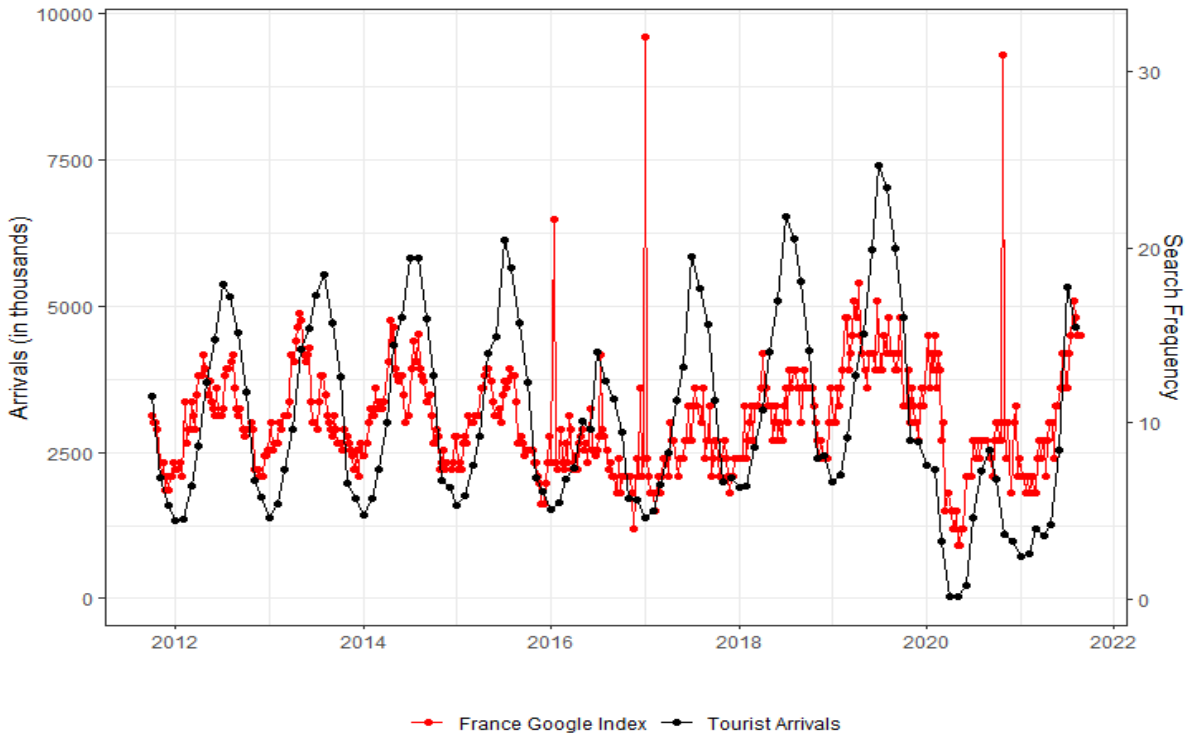
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A4: Google Trends Search Data From The United Kingdom and Monthly Tourist Arrivals for Turkey



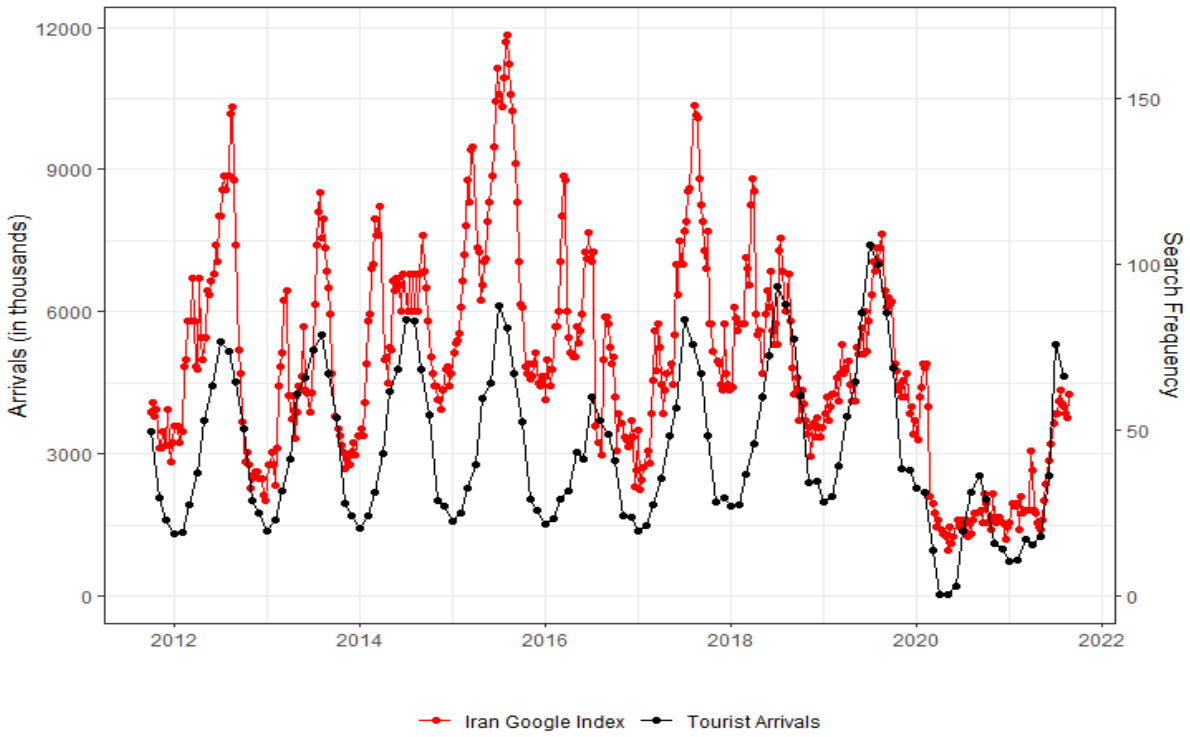
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A5: Google Trends Search Data From France and Monthly Tourist Arrivals for Turkey



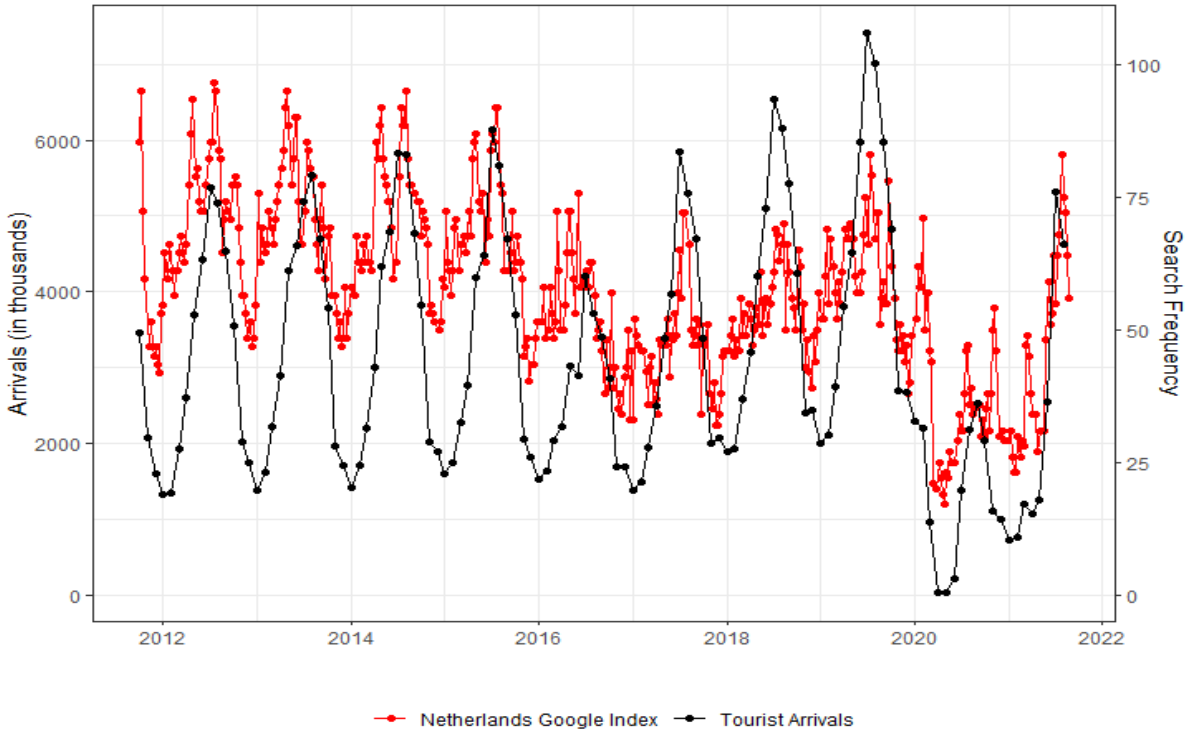
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A6: Google Trends Search Data From Iran and Monthly Tourist Arrivals for Turkey



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A7: Google Trends Search Data From The Netherlands and Monthly Tourist Arrivals for Turkey



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Table A1: Estimates for MIDAS With Search Data From Russia Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	1.014^{***}	1.012^{***}
	(0.122)	(0.150)
β_2	-0.617^{***}	-0.612^{***}
	(0.067)	(0.151)
β_3	0.166^{**}	0.160^{*}
	(0.082)	(0.086)
β_{12}	-0.267^{***}	-0.266^{***}
	(0.060)	(0.056)
γ	0.595	0.592
	(0.481)	(0.504)
Intercept	$\mathbf{-0.095}$	$\mathbf{-0.096}$
	$(\mathbf{0.105})$	$(\mathbf{0.107})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

***, ** and * denote statistical significance at 1%, 5% and 10% level, respectively.

Table A2: Estimates for MIDAS With Search Data From Germany Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	0.738^{***}	0.734^{***}
	(0.153)	(0.144)
β_2	-0.493^{***}	-0.479^{***}
	(0.113)	(0.102)
β_3	0.054	0.050
	(0.081)	(0.068)
β_{12}	-0.275^{***}	-0.280^{***}
	(0.069)	(0.064)
γ	1.780^{**}	1.738^{**}
	(0.741)	(0.715)
Intercept	$\mathbf{-0.035}$	$\mathbf{-0.035}$
	$(\mathbf{0.034})$	$(\mathbf{0.033})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table A3: Estimates for MIDAS With Search Data From Ukraine Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	0.967^{***}	0.958^{***}
	(0.187)	(0.183)
β_2	-0.560^{***}	-0.549^{***}
	(0.118)	(0.118)
β_3	0.204^{***}	0.195^{***}
	(0.056)	(0.060)
β_{12}	-0.203^{*}	-0.202^{*}
	(0.102)	(0.102)
γ	0.597	0.609
	(0.469)	(0.472)
Intercept	$\mathbf{-0.151}$	$\mathbf{-0.154}$
	$(\mathbf{0.127})$	$(\mathbf{0.128})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table A4: Estimates for MIDAS With Search Data From The United Kingdom Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	0.801^{***}	0.791^{***}
	(0.233)	(0.207)
β_2	-0.437^{*}	-0.423^{**}
	(0.206)	(0.202)
β_3	0.183	0.172
	(0.207)	(0.125)
β_{12}	-0.486^{***}	-0.481^{***}
	(0.088)	(0.071)
γ	1.096	1.116^{**}
	(0.855)	(0.528)
Intercept	$\mathbf{-0.026}$	$\mathbf{-0.029}$
	$(\mathbf{0.079})$	$(\mathbf{0.054})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table A5: Estimates for MIDAS With Search Data From France Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	0.690^{***}	0.745^{***}
	(0.151)	(0.181)
β_2	-0.329^{***}	-0.370^{***}
	(0.098)	(0.122)
β_3	0.019	0.057
	(0.064)	(0.069)
β_{12}	-0.221^{***}	-0.258^{***}
	(0.081)	(0.076)
γ	1.273^{**}	1.082^{*}
	(0.503)	(0.556)
Intercept	$\mathbf{-0.047}$	$\mathbf{-0.077}$
	$(\mathbf{0.041})$	$(\mathbf{0.050})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table A6: Estimates for MIDAS With Search Data From Iran Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	0.961^{***}	0.949^{***}
	(0.144)	(0.158)
β_2	-0.547^{***}	-0.551^{***}
	(0.141)	(0.137)
β_3	0.036	0.032
	(0.070)	(0.080)
β_{12}	-0.277^{***}	-0.271^{***}
	(0.085)	(0.092)
γ	0.509^{*}	0.576^{*}
	(0.305)	(0.651)
Intercept	$\mathbf{-0.043}$	$\mathbf{-0.036}$
	$(\mathbf{0.044})$	$(\mathbf{0.048})$

Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

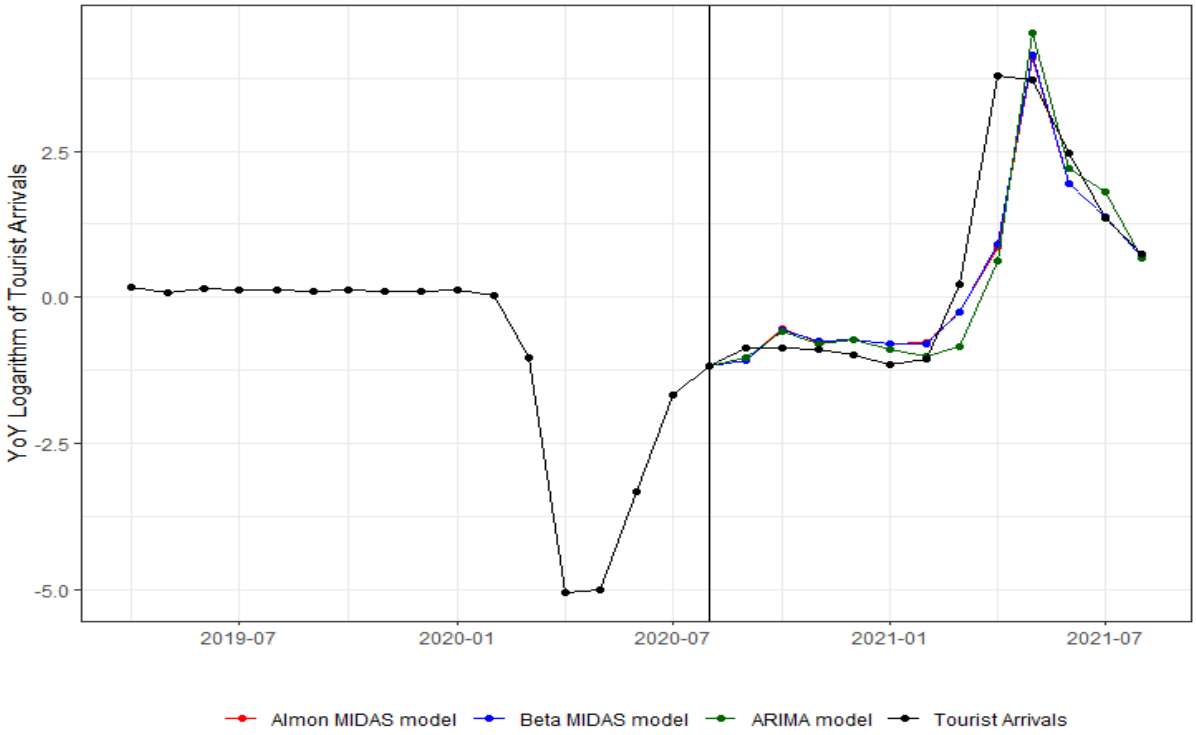
***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table A7: Estimates for MIDAS With Search Data From The Netherlands Between September 2011 and September 2020

	MIDAS Beta	**MIDAS Almon**
β_1	0.839^{***}	0.838^{***}
	(0.114)	(0.120)
β_2	-0.510^{***}	-0.517^{***}
	(0.111)	(0.113)
β_3	0.034	0.051
	(0.074)	(0.068)
β_{12}	-0.243^{***}	-0.243^{***}
	(0.056)	(0.061)
γ	1.499^{**}	1.426^{**}
	(0.641)	(0.632)
Intercept	**0.023**	**0.018**
	(**0.034**)	(**0.033**)

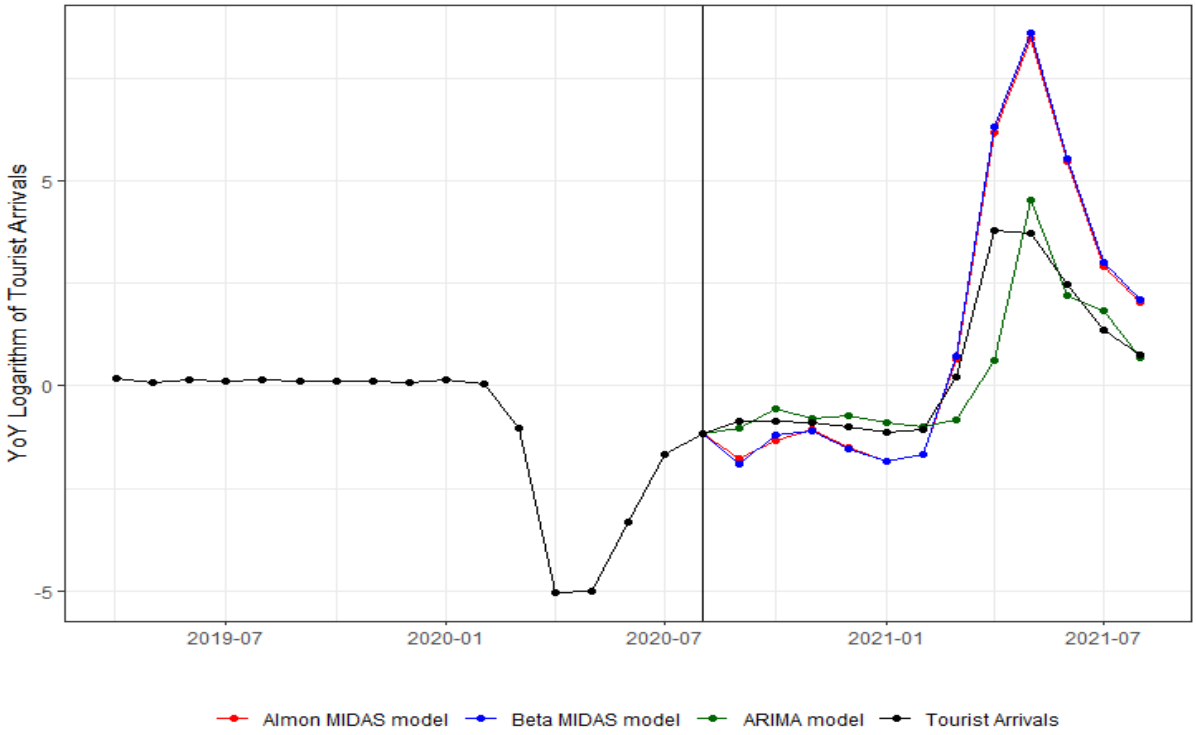
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Figure A8: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: Russia MIDAS



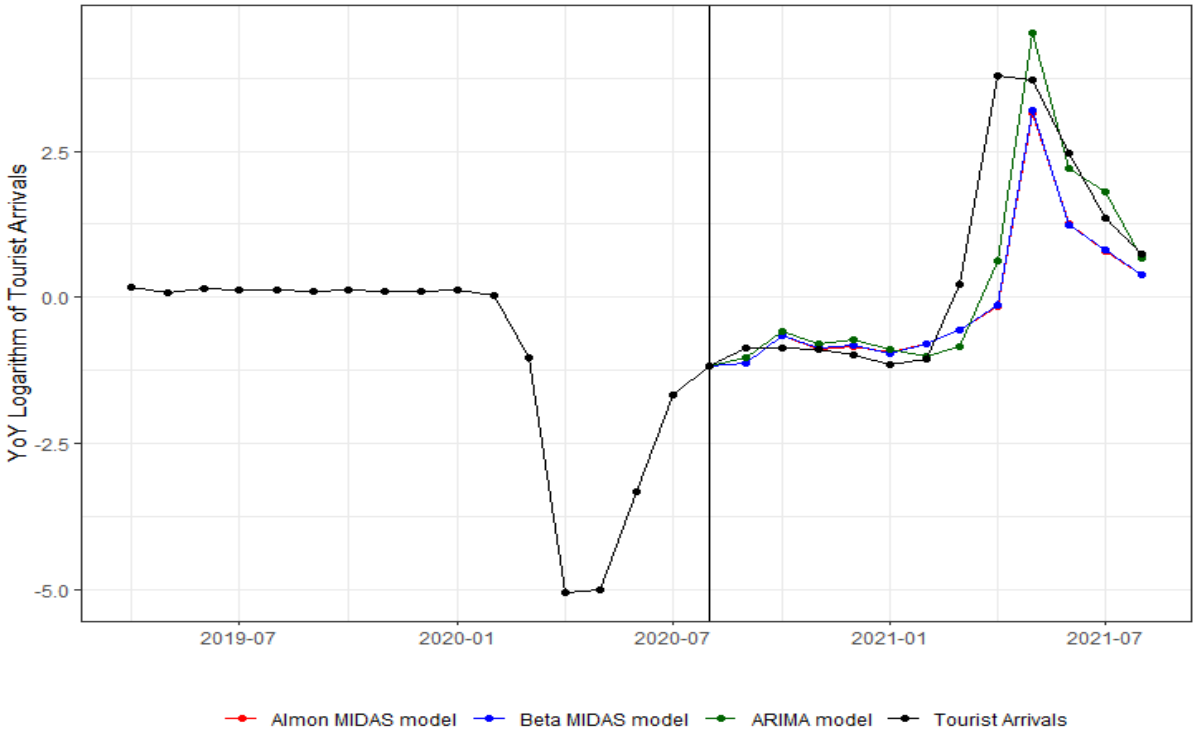
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A9: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: Germany MIDAS



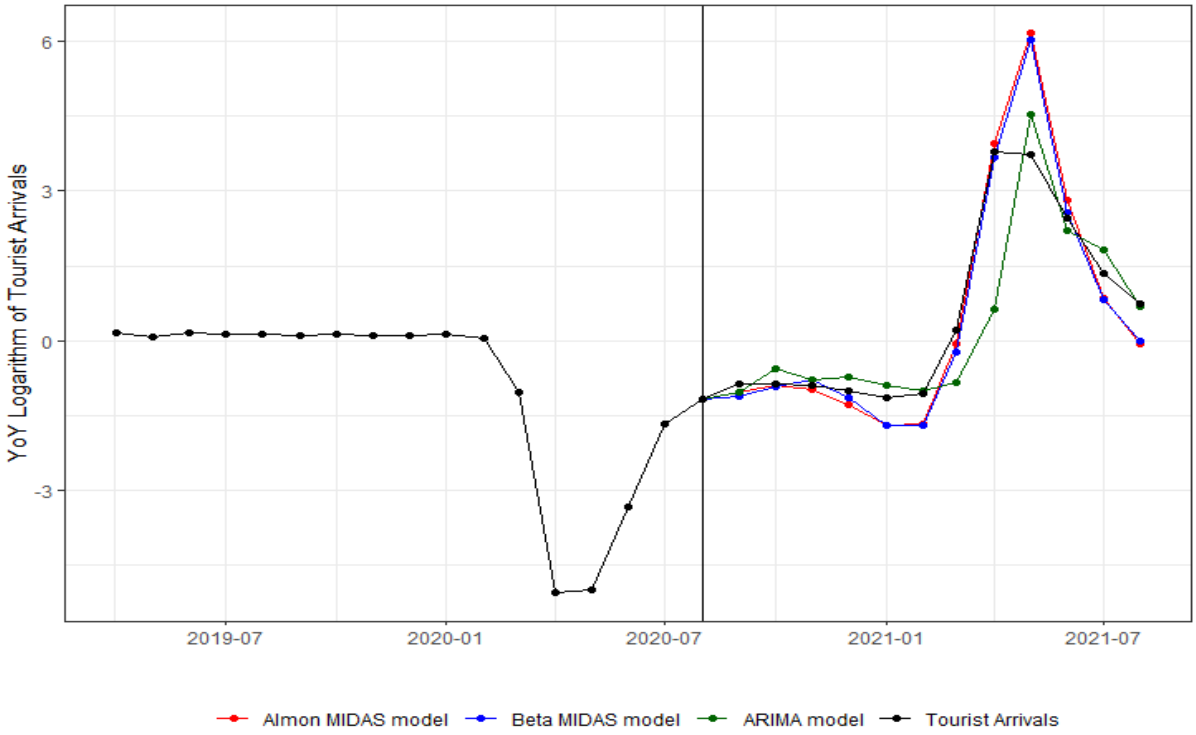
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A10: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: Ukraine MIDAS



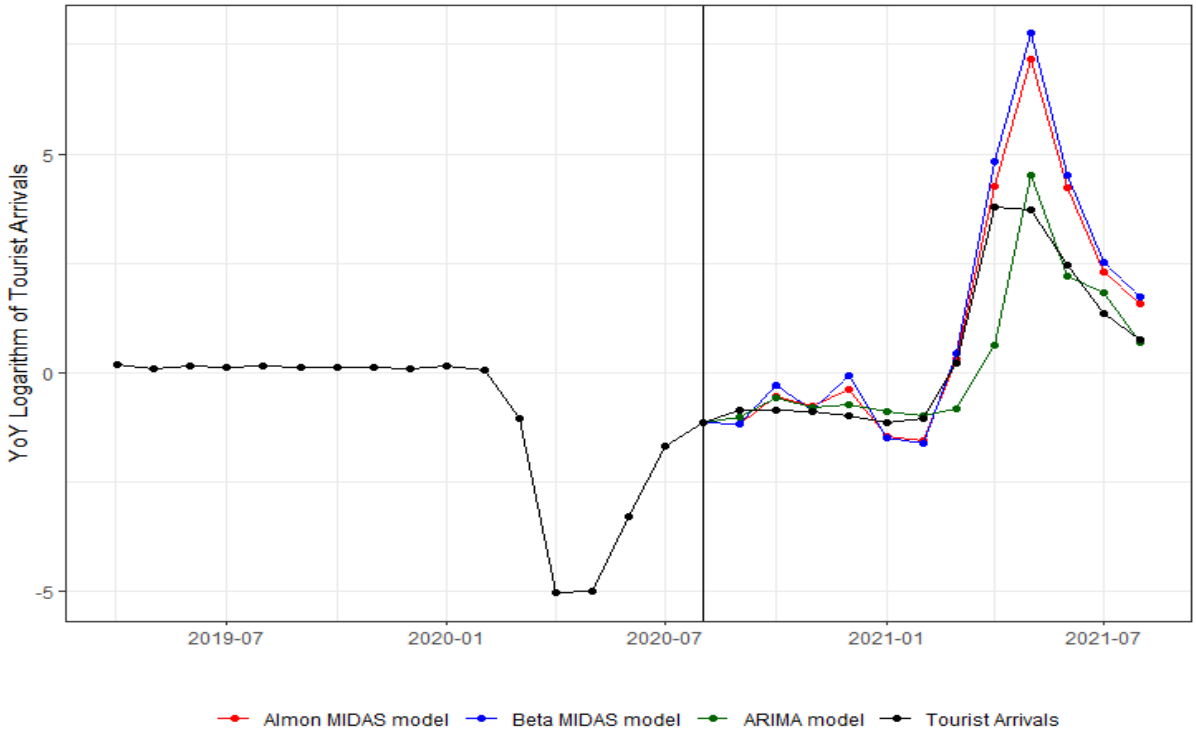
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A11: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: The United Kingdom MIDAS



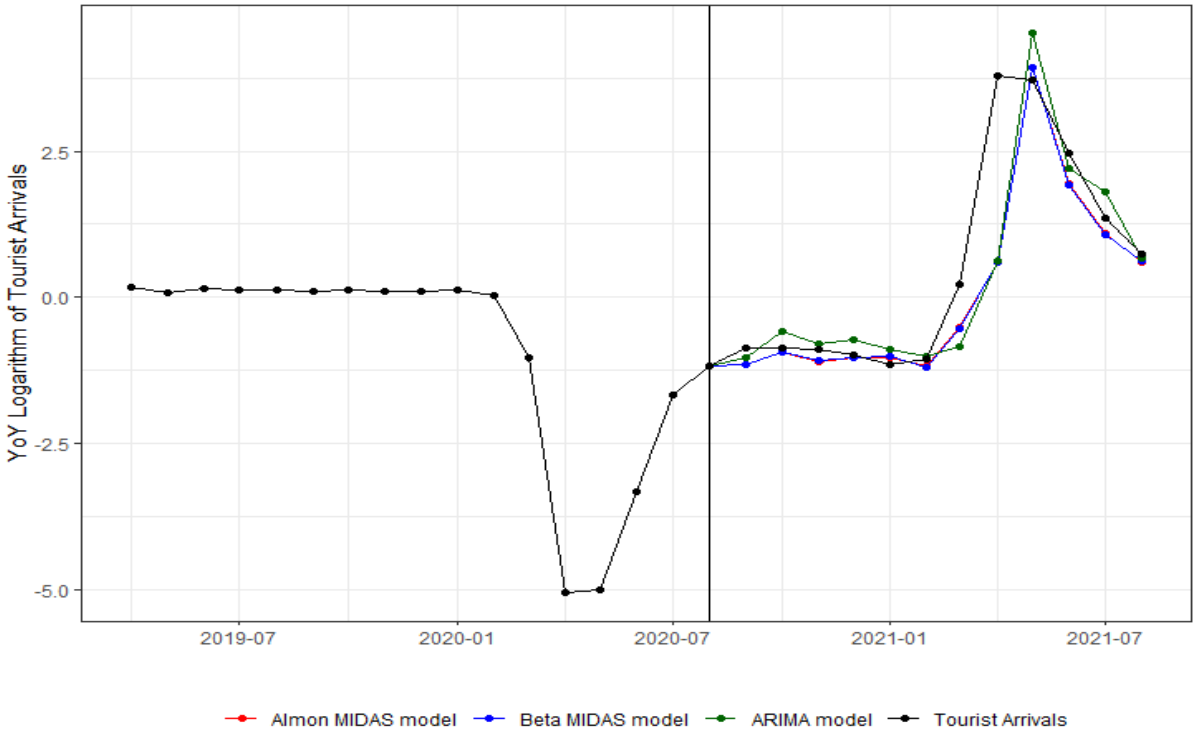
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A12: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: France MIDAS



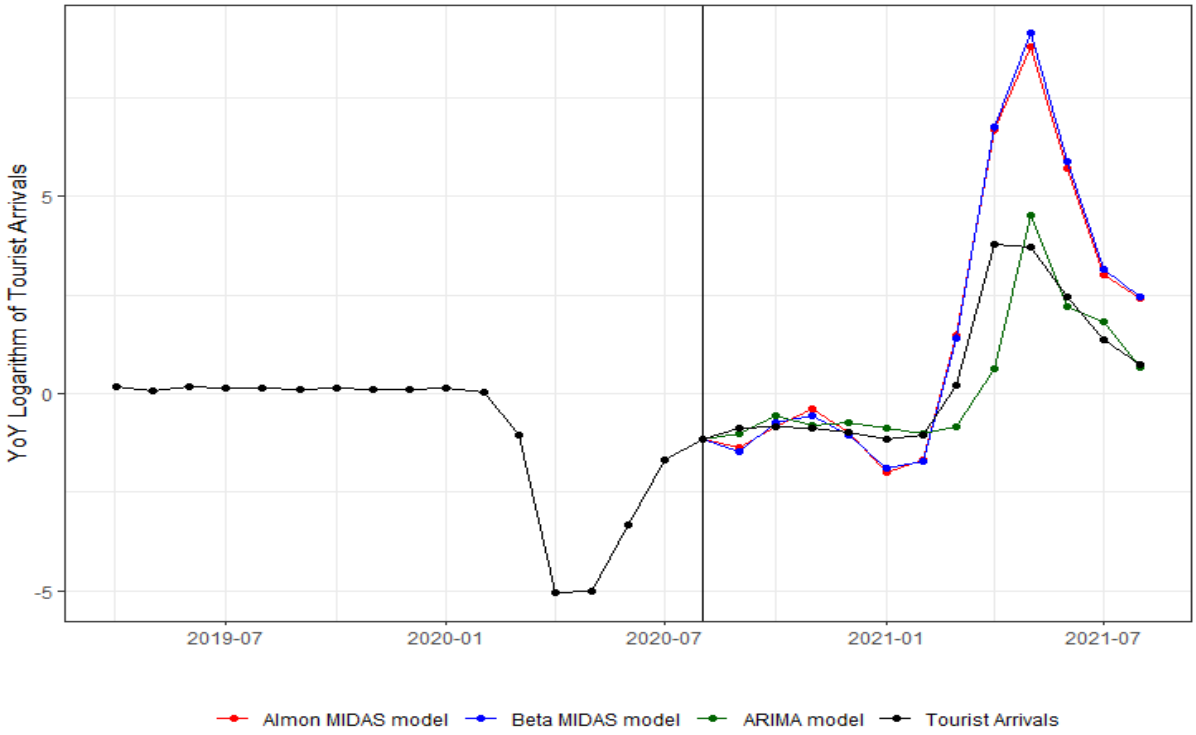
Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A13: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: Iran MIDAS



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.

Figure A14: Year-On-Year Change of Logarithm of Tourist Arrivals Nowcasts Between September 2020 and September 2021: The Netherlands MIDAS



Source: Author's Estimations. Google data is from Google Trends. Tourist arrival data is from TURKSTAT.