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The Summer's Call [*preliminary draft*]*

A Forecasting Framework for Tourism Demand in Corsica

Jean-Toussaint Battestini[†] Marc-Antoine Faure[‡]

April 9, 2024

Abstract

Tourism is a vital resource for small island economies, and Corsica is no exception. Although it is difficult to estimate precisely the contribution of tourism to Corsica's gross domestic product, official statistics highlights the importance of the sector for the island's economy. The analysis we are proposing, one of the first to focus specifically on Corsican tourism to the best of our knowledge, uses several econometric models (SARIMA, SVAR, DCC-GARCH) to lay the foundations for a monitoring and forecasting framework. Using data on air and sea arrivals between January 2001 and July 2023, SARIMA shows a positive effect of past tourist arrivals, French, Italian and German household confidence, and oil prices. Covid-19 harms demand, while inflation has no effect. The results obtained from the S(easonal)VAR show only a positive effect from past arrivals and a negative effect from Covid-19. While the pandemic had an immediate effect on arrivals to Corsica in 2020 and 2021 (−43% of arrivals during the tourist season - April-August - 2020 compared with 2019; −16% for 2021), we note that the consequences of Covid-19 are not persistent, demonstrating a significant level of resilience. The SARIMA model has better forecasts than the SVAR model, with an average error (underestimation of real demand) of 2% and 5%, which seems reasonable for a first draft. In the future, further modelling involving AI models, sentiment analysis and high frequency data could enhance our monitoring and forecasting capabilities.

JEL codes: L83, Z3, P25

Keywords: Tourism Economics, Time Series, Demand forecasting, Transportation, Corsica

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Résumé non technique

Après une analyse descriptive de l'évolution des trafics aériens et maritimes vers la Corse de 2001 à 2021¹, il convient d'élargir l'analyse aux facteurs explicatifs de la demande touristique en Corse et de poser les bases d'un outil de prévision des flux touristiques pour les saisons à venir.

Cette étude contribue à l'analyse de la demande touristique pour la Corse en identifiant certains facteurs qui l'influencent positivement ou négativement. Nous tentons ensuite d'évaluer l'impact sur la demande touristique d'un choc sur le prix du Brent, sur la confiance des ménages français, italiens et allemands, sur l'inflation et sur le retour brutal des restrictions de voyage. Enfin, nous construisons un outil de prévision des arrivées en Corse qui pourrait être réutilisé par le gouvernement régional, les transporteurs aériens et maritimes et les associations professionnelles du tourisme pour simplifier le suivi, la gestion et la planification stratégique du tourisme en Corse.

Les résultats montrent que la demande touristique sur l'île au cours des vingt dernières années a été faiblement influencée par des facteurs externes (prix du pétrole, inflation, confiance des ménages), mais fortement par la Covid-19 et les arrivées touristiques passées. Pour ces derniers, cela pourrait s'expliquer par un 'effet de fidélité' des visiteurs ou un 'effet de bouche à oreille' en faveur de la Corse. La demande touristique pourrait également être alimentée par d'autres facteurs, tels que la fréquence/amplitude des campagnes de promotion de la destination Corse, les transports aériens/maritimes disponibles vers l'île, ou encore la réputation de la Corse sur les réseaux sociaux. Ces hypothèses devront faire l'objet d'une étude plus approfondie. Cette analyse a vocation à être complétée par l'ajout de nouvelles variables susceptibles d'affiner notre compréhension de la demande touristique de l'île. Elle ne constitue pour l'instant qu'une première tentative d'explication par la modélisation économétrique.

¹L'article est accessible à l'adresse suivante : [Évolution du trafic aérien et maritime en Corse entre 2001 et 2021 : les grandes tendances \(substack.com\)](https://substack.com).

Non-technical summary

Following a descriptive analysis of the development of air and sea traffic to Corsica from 2001 to 2021², it is opportune to widen the analysis to the factors explaining tourist demand in Corsica and to lay the foundations for a tool to forecast tourist flows for the coming seasons.

This study contributes to the analysis of tourism demand for Corsica by identifying certain factors that influence it positively or negatively. We then attempt to assess the impact on tourism demand of a shock to the price of Brent crude oil, French, Italian and German household confidence, inflation and a sudden return to travel restrictions. Finally, we are building a tool for forecasting arrivals in Corsica that could be re-used by the regional government, air and sea carriers and tourism professional associations to simplify the monitoring, management and strategic planning of tourism in Corsica.

The results show that tourist demand on the island over the last twenty years has been weakly influenced by external factors (oil prices, inflation, household confidence), but strongly by Covid-19 and past tourist arrivals. For the latter, this could be explained by a 'loyalty effect' among visitors or a 'word-of-mouth effect' in favour of Corsica. Tourism demand could also be driven by other factors, such as the frequency/amplitude of campaigns promoting Corsica as a destination, the air/sea transport available to the island, or Corsica's reputation on social networks. These hypotheses will have to be the subject of further study. This analysis is intended to be supplemented by the addition of new variables likely to refine our understanding of the demand for tourism on the island. For the moment, it is only a first attempt to explain it through econometric modelling.

²The article can be accessed at the following address: [Évolution du trafic aérien et maritime en Corse entre 2001 et 2021 : les grandes tendances \(substack.com\)](https://substack.com/p/evolution-du-traffic-aerien-et-maritime-en-corse-entre-2001-et-2021-les-grandes-tendances).

Introduction

Corsica has obviously not escaped the decision by the President Macron to lockdown the country in March 2020. By bringing France to a standstill for two months, all the ports and airports stopped their activities with the exception of emergency evacuations. Health restrictions in 2020 and 2021 have significantly reduced air and sea traffic to Corsica. However, despite a delay, the tourist season was able to proceed in the euphoria of the end of the first wave of the pandemic. The following year, despite a second and third lockdown, the island's tourist season passed off almost normally, with entry to the island conditional on presentation of a health or vaccination pass on boarding, and less severe restrictions than in 2020.

Tourism is one of the island's main industries, and therefore one of the driving forces behind its economic growth. According to INSEE and the Corsican Tourism Agency (Agence de tourisme de la Corse - ATC - in French), tourism expenditures account for an average of a third of Corsica's GDP. The region is therefore heavily dependent on tourism. Unless the economy is diversified, any negative shock to demand for air and sea transport during the high season (from June to the end of August) represents a threat to employment and economic health in the short term; in the long term, the question arises of the risks of a persistent economic shock to the unemployment rate, business failure, poverty and social exclusion. Tourism is both the strength and the Achilles heel of the island economy.

In recent years, small island tourism economies (SITEs) have become a dynamic subject of study in the field of tourism economics. Based on the standard framework of dynamic macroeconomics, numerous theoretical models have been proposed. On the other hand, advances in theoretical econometrics and increased computing capacity have made it possible to study the empirical dynamics of SITEs in greater detail. Despite this, the weight of tourism in the economic structure of SITEs in general, and Corsica in particular, remains a statistical 'great unknown'.

In this respect, our contribution to the study of the Corsican tourism economy is twofold. First, we have built a monthly database over more than twenty years (January 2001 - July 2023) of total tourist arrivals in Corsica (boats and planes; continental and foreign tourists). This database enables economists and researchers to study air and sea flows to Corsica over the long term, whether in terms of observation, explanation of the factors influencing these flows, or forecasting flows for the months and years ahead.

Our second contribution concerns the modelling and forecasting of tourist

arrivals. A draft econometric forecasting framework is proposed. This type of modelling is usual in large states and regions where tourism is predominant; however, to our knowledge, this would appear to be the first time that a public study has proposed a tool for forecasting arrivals to Corsica. The empirical strategy has two main objectives:

- Take into account the seasonal nature of tourist arrivals;
- Model the reaction of tourism demand to a series of exogenous shocks (Covid-19, increase in oil prices, etc.).

For the time being, we limit our approach to the best-established models in the literature. This concerns the extension of ARIMA models to seasonal data, SARIMA, and the use of Autoregressive Vector models (VAR) and their seasonal variation. In this way, we propose an ‘econometric base’, from which it is possible to develop a tool for forecasting and monitoring island tourism demand. This study aims to contribute to recent work on the tourism economy in Corsica.

The rest of the article is organized into seven parts: (i) We begin by recalling some results of the recent literature on small island tourism economies; (ii) then, we detail the construction of the database and its structure; (iii) our third part details the empirical strategy; (iv) the presentation of the results is then divided into three blocks: (a) modelling a SARIMA augmented with covariates ; (b) estimating a vector autoregression model (VAR) and simulating several shocks to our control variables; (v) pitting our SARIMA against our seasonal VAR to determine which best predicts arrivals in Corsica; and (vi) a brief analysis of the volatility of tourism demand; (vii) finally, we conclude with the results obtained and their socio-economic and political implications, and we detail the empirical prospects for future work.

1 Related Literature

In this section, we briefly present some recent work that inspired the approach of our paper. This having above all an operational vocation, and the construction of a demand monitoring framework, we wanted to establish these foundations on these robust and well-known models from the literature in econometrics of tourist demand. The construction of the data, the econometric models selected and the treatment of seasonality are based on previous work that is well established in the literature. In addition, this literature review allows us to outline the prospects for our research. Indeed, as this paper is a preliminary work, it

aims to pave the way for the application of other, more advanced and ‘at the frontier methods. Thus, the questions of *nowcasting*, the application of machine learning and alternative data (satellites, textual data, etc.) are at the heart of the perspectives opened up by this contribution. If one is interested in a more comprehensive review of the literature in econometrics of tourism demand, please refer to Song and Li (2008), Athanasopoulos et al. (2011), Goh and Law (2011), Jiao and Chen (2019) and Commission (2021).

1.1 Review of tourism demand forecasting methods

We begin with a review of the main methods used in econometrics and tourism demand forecasting. This part has a dual purpose: (i) to enlighten us on the most established methods, which are therefore desirable to use in the context of an empirical paper; (ii) open up perspectives for future research based on more recent work on methods allowing more detailed investigation of certain complex mechanisms of tourism demand, such as household confidence or the role of substitution between destinations.

Jiao and Chen (2019) identify three types of approaches to modelling and forecasting tourism demand: causal econometric techniques, non-causal time series models, and artificial intelligence (AI) and *machine learning* (ML) approaches.

1.1.1 Econometric models

The “econometric models”³ identified by the authors fall into four groups: *error correction models* (ECMs), *autoregressive distributed lag models* (ADLMs and ARDLs), *autoregressive vector models* (VARs) and *time-varying parameter models* (TVPs). These models were particularly popular over the period 2000-2007 (Song and Li 2008); this popularity in academic research continues over the period 2007-2018 (Jiao and Chen 2019) although new methods, linked to progress in AI and machine learning, complement the methodological base established during the previous decade. The use of these models over the 2007-2018 decade has been facilitated by the availability of new data sources, advances in econometric techniques (particularly Bayesian econometrics) and increased comput-

³The distinction in terminology between “econometric models” and “time series” made by Jiao and Chen (2019) is counter-intuitive at first glance. Indeed, ARMA models (and their variants ARIMA, SARIMA(X) etc.) could also be considered as econometric approaches. Nevertheless, we follow the distinction made by the authors, which allows us to distinguish between the VAR and ARIMA approaches, as we do later in the econometric section.

ing power. More recently, Assaf et al. (2019), Bilgili et al. (2021) and H. Liu, Liu, and Wang (2021) used a VAR-type approach to model tourism demand in various geographical and temporal contexts.

1.1.2 The time series approach

As noted by Jiao and Chen (2019) non-causal time series models have continued to grow in popularity during the 2010s. The main positive points of time series are threefold: (i) predicting the series from historical *patterns*, (ii) taking seasonality into account, (iii) having less constraint on data collection, compared to causal econometrics models. A large number of papers use autoregressive (AR), moving average (MA) processes and their variants (ARMA, ARIMA, SARIMA(X) etc.) to model and forecast tourism demand. Recent publications include Chang and Liao (2010), Balli, Tsui, and Balli (2019), Abellana et al. (2020), Wu et al. (2021) and He et al. (2021). Our work is mainly related to this branch of literature. These papers allows us to have efficient and robust tools to deal with the seasonality of tourist arrivals. This point is the main challenge for Corsican tourism, and must therefore be addressed with the greatest possible rigor.

1.1.3 The emergence of AI and machine learning

Artificial intelligence (AI) methods, sometimes referred to as *machine learning*, have become popular in the field of *forecasting* since the mid-2000s. Song and Li (2008) already highlights the emergence of these methods; since 2008, considerable progress has been made, thanks both to new theoretical developments and to the increased computing power of computers. Claveria, Monte, and Torra (2015) and more recently A. Liu et al. (2021) and Li et al. (2023) are examples of papers introducing *machine learning* and *deep learning* methods into tourism forecasting. The paper by Guizzardi et al. (2021) proposes an interesting approach, based on *big data* and cross-referenced with simple, high-performance economic theories. In the case of Corsica, it is valid to question the usefulness of this type of method. If we consider, given its geographical position and the structure of tourist arrivals, that the factors explaining Corsican tourism are well explained by (S)ARIMA(X) and/or (S)VAR models, it is not necessarily necessary to add a layer of complexity. Nevertheless, in future work we will test the relevance of these models by placing them in competition with the approaches proposed here. This will enable us to assess the relevance of a machine/deep learning approach to modelling Corsican tourism demand.

1.2 Some results from recent literature

Let us now summarise the results of some recent works in the academic literature. The authors Athanasopoulos et al. (2011) offer an important (albeit slightly dated) review of methods and results in the field of tourism forecasting. In particular, they show that approaches based on ARIMA processes are particularly relevant in the case of seasonal and monthly data. This paper broadens our perspective: by evaluating the results of 366 monthly series, 427 quarterly series and 518 annual series, as well as a wide range of econometric techniques (ARIMA, exponential smoothing, TVP, VAR...), Athanasopoulos et al. (2011) show a state of the art of established and robust methods. Having passed through the many filters of academic discussion, these methods can be used in operational problems such as the one we are dealing with in this paper.

More recently Balli, Tsui, and Balli (2019) uses a SARIMAX/(E)GARCH approach to model the volatility of tourist arrivals in New Zealand. The authors show that the SARIMA approach, i.e. a seasonal ARIMA plus exogenous regressors, can provide accurate forecasts of monthly tourist arrivals in the case of a series marked by strong seasonality. It is also interesting to note that the authors include an exogenous epidemic shock, with SARS in 2003, whose similarities with Covid-19 are obvious⁴. In addition, Balli, Tsui, and Balli (2019) wishes, as in this paper, to propose an operational approach, feeding into the decision-making of public and private players in the tourism industry. They also offer some interesting perspectives on the challenges of modelling tourism volatility and better anticipating and taking into account exogenous shocks to demand.

Corsica's tourism economy has also attracted the attention of researchers. These include Mantovani, Piga, and Reggiani (2021), Casamatta et al. (2022) and Brunstein, Casamatta, and Giannoni (2023), who are conducting an econometric study of the dynamics of accommodation booking platforms; and the collective work ESTATE (Prunetti and Jouve 2023), which proposes a multi-disciplinary approach to the issues of sustainability and the development of tourism. In this work, Prunetti et al. (2023) looks at land-related conflicts within the framework of an agent-based model, and Giannoni, Noblet, and Bisgambiglia (2023) at the issues of 'over-tourism' and 'hyper-concentration' of tourists in time and space. Finally, we might mention the more systematic approach of A. Liu et al. (2021), focusing on the Covid-19 period, and incorporating a wider range of territories.

⁴Considering, of course, the difference in scale between the two shocks.

1.3 Data and descriptive statistics

Five variables were used to model tourism demand on the island: (i) monthly arrivals to Corsica (ships and planes; from mainland France and abroad); (ii) the average monthly price of a barrel of Brent crude oil, (iii) a monthly index of the severity of health restrictions with regard to Covid-19, which varies from 0 (total absence of restrictions, or recommendations during the Covid-19 pandemic) to 100 (total ban on travel or other economic activities); (iv) a weighted consumer confidence index (CCI) based on the weight of French, Italian and German tourist demand for Corsica (see below for details of the calculation method), and (v) the monthly inflation rate in France measured year-on-year (*year to year; y/y*).

1.4 Dependent Variable: Monthly Arrivals to Corsica

Monthly arrivals to Corsica include arrivals by boat (excluding cruise passengers) and by air from the mainland and abroad. The data used covers the period from January 2001 to July 2023. The data for the period 2001-2020 were collected manually from the former site of the Corsican Regional Transport Office (ORTC), which listed data from 2001 to 2020, now unavailable, and from the new DREAL Corsica website, which now centralizes all information on passenger transport to Corsica.

Fig. 1 represents gross tourist arrivals (not seasonally adjusted) over the analysis period. Firstly, arrivals in Corsica are highly seasonal, peaking at the height of the summer season (July/August) with a dip at the end of the year. An upward trend can be seen over the period 2001-2019, with no negative impact from the 2008 crisis on tourist demand. The Covid-19 pandemic causes tourism demand to plummet, to a level close to 0, before catching up in the 2021 and 2022 seasons, returning it to a pre-pandemic trend. Incomplete data for the 2023 tourist season show a slight decline in arrivals to Corsica. Arrivals in Corsica are still above their pre-pandemic level and the 2015-2019 average (see *Appendix*).

Figure 1: Total arrivals to Corsica (not seasonally adjusted; January 2001-July 2023)

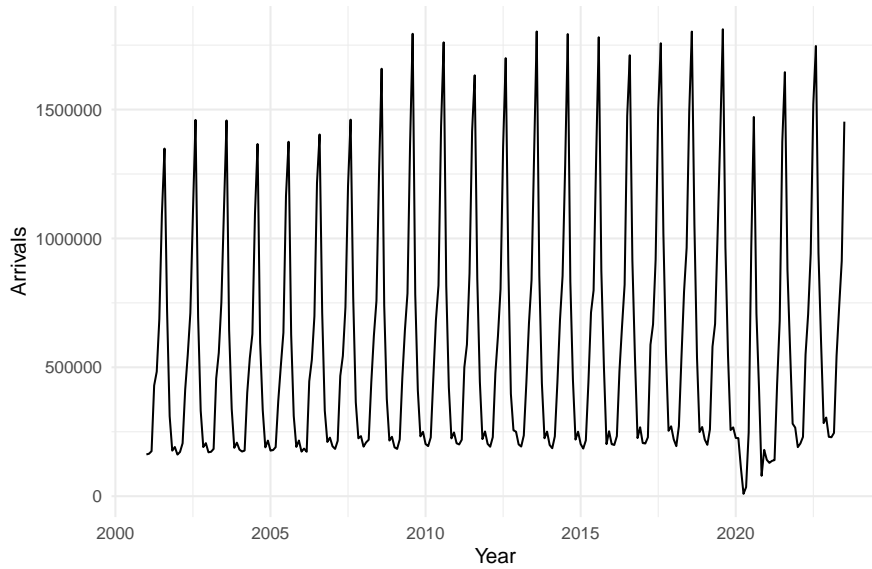
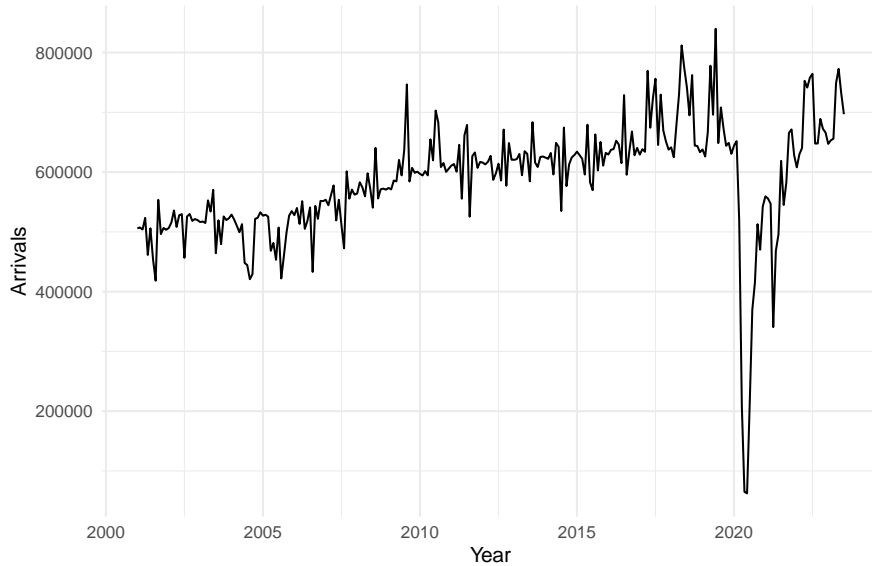


Fig. 1 shows seasonally adjusted monthly tourist arrivals, a finer measure of arrivals in Corsica. This series makes it possible to focus on the trend purged of variations attributable to the seasonality of demand. Demand for the destination therefore increased over the period 2001-2019, before collapsing in 2020 and then rebounding in the 2021 and 2022 tourist seasons. By 2023, demand had returned to its pre-Covid trend. This confirms the observations made for Fig. 1, the non-seasonally adjusted series.

Figure 2: Total arrivals to Corsica (seasonally adjusted; January 2001-July 2023)



1.5 Presentation of the explanatory variables

We present the explanatory variables that are included in the SARIMA and SVAR models. We have decided to retain only a few variables. This is partly due to the justification for the project given in the introduction, i.e. to propose a relatively simple and operational approach, and partly to avoid the risk of “overfitting” our models. Consequently, we introduce sparingly a few variables that we feel are important in explaining arrivals to Corsica.

1.5.1 Average monthly price of a barrel of Brent crude oil

The monthly price of a barrel of Brent for the period January 2001-July 2023 was collected from the US Energy Agency (EIA) website⁵. Fig. 3 illustrates the fluctuations in the price of Brent over our analysis period. The variable is used to identify the extent to which the price of oil discourages tourists from coming to Corsica (petrol prices too high, more expensive plane/boat tickets).

⁵See: [Europe Brent Spot Price FOB \(Dollars per Barrel\) \(eia.gov\)](https://www.eia.gov/finance/brent/).

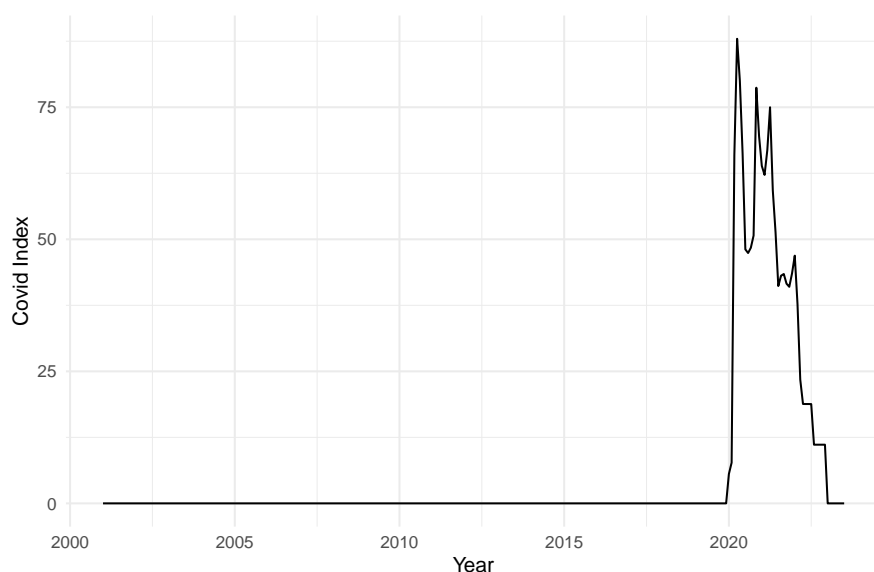
Figure 3: Average monthly Brent crude oil price (January 2001-July 2023)



1.5.2 Index measuring the level of restriction in France in the face of Covid-19

Fig. 4 represents the measure of the level of restriction in the face of the Covid-19 pandemic. This variable was retrieved from the *Oxford Coronavirus Government Response Tracker* (OxCGRT) project. The index aggregates nine parameters of government response to Covid-19: closure of schools, closure of workplaces, cancellation of public events, restrictions on public gatherings, closure of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements and controls on international travel. This index records only the stringency of government policies and their effects on people's mobility, not their actual effectiveness against Covid-19. It ranges from 0 (no restrictions) to 100 (absolute restrictions).

Figure 4: Index measuring restrictions on Covid-19 (January 2001-July 2023)



1.5.3 Weighted consumer confidence index for France, Italy and Germany

The OECD's Consumer Confidence Index (CCI)⁶ is a monthly indicator that measures consumers' confidence in the economy and their expectations about the future financial situation. The index is calculated from household surveys. Households are asked about their perception of the economy, their personal financial situation, their purchasing intentions, etc.

An indicator above 100 signals a strengthening of consumer confidence in the future economic situation, meaning that they are more inclined to consume over the next 12 months. Values below 100 indicate a pessimistic attitude towards the future development of the economy, which may translate into a tendency to save more and consume less.

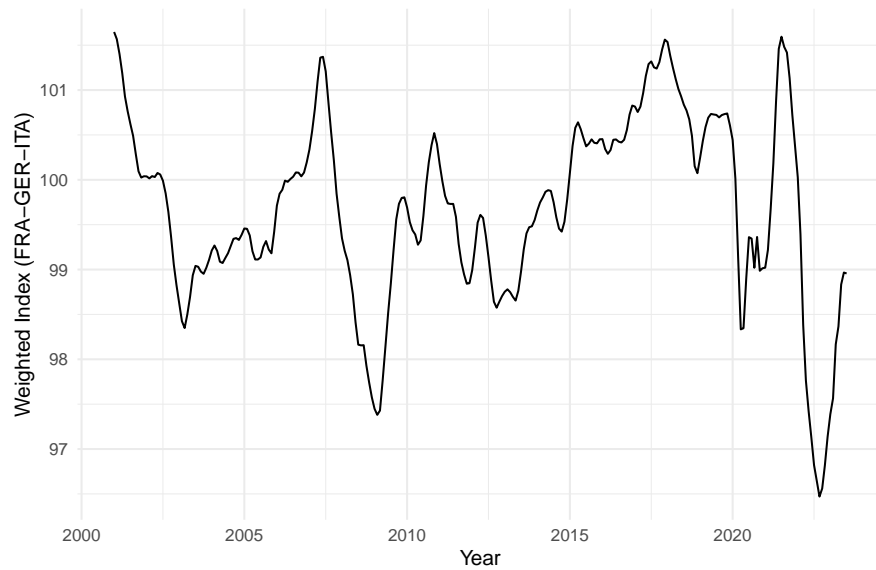
A weighted household confidence index for France, Italy and Germany has been calculated. These three markets account for more than 90% of tourism demand on the island, which is why we have restricted ourselves to these three countries when calculating our aggregate household confidence index.

The weighted index is calculated as follows: for each given month, the share of French and foreign arrivals (Italian and German together) in total arrivals in Corsica is estimated. The CCI for each of these countries is multiplied according

⁶See <https://data.oecd.org/leadind/consumer-confidence-index-cci.htm>

to its weight and then summed. Given the importance of the continental market in island tourism demand (75%), it is essentially French household confidence that guides the aggregate index.

Figure 5: Weighted index of French, Italian and German household confidence (January 2001-July 2023)



1.5.4 Year-on-year inflation rate for France

Finally, the year-on-year monthly inflation rate for France has been collected from the INSEE website, which provides a history of the inflationary dynamics of countries between 1991 and 2023. 6 illustrates inflation trends over the period 2001-2023. This variable is used to test the hypothesis that tourism demand declines when inflation is high. It is expected that high inflation will have a negative effect on household disposable income, resulting in a reduction in the volume of household consumption, in particular by not going on holiday to Corsica.

Figure 6: Year-on-year inflation rate (January 2001-July 2023)



As stated above, econometric modelling means that not too many variables need to be included. In the future, other variables could be tested to assess their impact on demand, such as the average monthly price of a return air or sea ticket to Corsica, the number of days of heatwave per year to take into account the environmental aspect, the presence of Corsica as a destination in the traditional media and on social networks, the number of departure points to Corsica, etc. The possibilities are numerous. The possibilities are endless. The rest of the paper details the empirical strategy and the results obtained.

2 Empirical strategy

In this section, we provide a comprehensive overview of the various models employed to simulate and forecast tourism demand in the region of Corsica. Our analysis begins with an examination of the most fundamental models in this domain, specifically the autoregressive (AR) and moving average (MA) models. These models, owing to their simplicity and foundational nature, serve as the initial step in our exploration. Following this, we delve into more sophisticated and complex models to refine our understanding and predictions regarding tourism demand in Corsica. In particular, we are interested in the effects of seasonality on tourism demand and ways of dealing with it. This progression from basic

to advanced models allows us to systematically assess the efficacy and applicability of each model in capturing the dynamics of tourism demand within the island.

2.1 Moving average (MA) process

A moving average $MA(q)$ process of order q , $X(t)_{t \in \mathbb{Z}}$, can be written as :

$$X_t = m + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q}$$

Which is equivalent to :

$$X_t = m + \Theta(L)\varepsilon_t$$

With $\theta(L) = 1 - \theta_1 L - \dots - \theta_q L^q$. In a $MA(q)$ we have $\theta_i \in \mathbb{R}$, $i = 1, \dots, q$, $\theta_q \neq 0$ and the errors are white noise, i.e. $\varepsilon_t \sim BB(0, \sigma_\varepsilon^2)$.

In other words, if a time series follows a moving average process of order q , then the value at time t depends solely on the errors of the q previous periods. This relatively simple model can be used to capture shocks or disturbances in the time series. For example, an unforeseen event, such as a financial (or health) crisis, may affect the economy for an extended period. Moving average models can capture these kinds of dynamics⁷.

2.2 Autoregressive process

An autoregressive process of order p ($AR(p)$) is the process $X(t)_{t \in \mathbb{Z}}$ such that:

$$X_t = c + \phi_1 X_{t-1} + \dots + \phi_p X_{t-p} + \varepsilon_t$$

This relationship can be rewritten as follows:

$$\Phi(L)X_t = c + \varepsilon_t \quad \text{with} \quad \Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p$$

With $\phi_i \in \mathbb{R}$.

In the case of an autoregressive process, we explain the present value of the series (X_t) by its past values. This captures the “dependency” effect of the series. The challenge lies in the number of *lags* to be introduced (the order p).

To specifically address the modeling of tourist arrivals in Corsica using this autoregressive framework, it is imperative to account for the region’s distinctive

⁷Indeed, an unforeseen event (the Covid-19 pandemic, for example) will enter into the measurement error of the previous period. By aggregating all these errors, we can approach the desired value.

characteristics that influence tourism demand. The determination of the optimal number of lags (p) is crucial in capturing the dependency of current tourist arrivals on past figures. This includes considering the impact of various factors such as promotional campaigns, changes in accessibility to the region (e.g., new flight routes or ferry services), and global or regional economic trends. By carefully selecting p , we can ensure the model is sensitive enough to reflect short-term fluctuations in tourist arrivals while avoiding the pitfalls of overfitting. This step is particularly important in our context, where tourism dynamics may be influenced by a blend of traditional appeal and modern factors, such as digital marketing effectiveness and international travel trends and global economic events.

2.3 (S)AR(I)MA

The two previous models may be considered too restrictive, poorly capturing the dynamics of our time series. In this case, the model can be made more refined by combining the two processes, $MA(q)$ and $AR(p)$, and adding additional mechanisms. The main challenge is to take full account of the seasonal component of the series: tourist arrivals are very low in winter and peak sharply in July and August.

2.3.1 ARMA process

From the two processes mentioned above, we can construct the $ARMA(p,q)$ process. Thus, a process $(X_t)_{t \in \mathbb{Z}}$ follows an $ARMA(p,q)$ if :

$$X_t = c + \phi_1 X_{t-1} + \dots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \phi_q \varepsilon_{t-q}$$

We can simplify this expression thanks to the polynomials Φ et Θ de with degree p et q respectively, hence:

$$\Phi(L)X_t = \Theta(L)\varepsilon_t$$

Où $\phi \in \mathbb{R}, i = 1, \dots, p; \theta_j \in \mathbb{R}, j = 1, \dots, q; \phi_p \neq 0, \theta_q \neq 0$ et $\varepsilon_t \sim BB(0, \sigma_\varepsilon^2)$.

In this expression, the polynomials Φ and Θ must have no common roots. Otherwise, the appearance of redundant terms is contrary to the need for a *minimal expression*⁸.

⁸For mathematical details on process invertibility and stationarity, we refer the reader to Master's-level textbooks on time-series econometrics.

2.3.2 Non-Seasonal and Seasonal ARIMA Processes

An ARIMA process(p, d, q) is written as follows:

$$\Phi(L)(1-L)^d X_t = c + \Theta(L)\varepsilon_t$$

Where $c \in \mathbb{R}$, $\Phi(L) = 1 - \sum_{i=1}^p \phi_i L^i$, $\Theta(L) = 1 - \sum_{j=1}^q \theta_j L^j$, $\phi_i \in \mathbb{R}$, $\theta_j \in \mathbb{R}$, $\phi_p \neq 0$, $\theta_q \neq 0$ and $\varepsilon_t \sim BB(0, \sigma_\varepsilon^2)$. Note also that all roots of the polynomials $\Phi(L)$ and $\Theta(L)$ must be greater than 1 in modulus.

Seasonal ARIMA is simply a refinement of the non-seasonal ARIMA(p, d, q) process:

$$\text{SARIMA}_{S,S'}(p, d, q) \Rightarrow \Phi(L^S)(1-L^S)^d X_t = c + \Theta(L^{S'})\varepsilon_t$$

Vector Auto-Regressive Model

A VAR(Vector Autoregressive) model of order p , denoted VAR(p), can be described as follows:

$$Y_t = c + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + \varepsilon_t$$

where Y_t is a k -dimensional vector of time series, c is our constant, A_i are $k \times k$ matrices of real coefficients, and ε_t is a k -dimensional vector of multivariate white noise with a defined positive \square covariance matrix. White noise in different series can be correlated with each other.

Note that each equation in a VAR(p) system can be seen as a multiple linear regression of the variables of the i -th time series on p past values of all k series, with the addition of an error term. VAR models are often used to capture dynamic linear relationships between several time series, and are particularly useful for analyzing systems of interdependent endogenous economic variables.

3 Econometric results

In this section, we summarize the results of the various models and present some forecasting tests based on this econometric *framework*. This relatively simple econometric framework is motivated by three reasons: (i) the readability of the results, (ii) we believe that the dynamics of Corsican tourism do not necessarily require excessively complex models to be accurately monitored, and (iii) it is a starting framework that we hope to enrich in the months to come. Additional econometric specifications are presented in appendices [A.4](#) and [A.5](#).

3.1 Taking Seasonality into Account in our Estimates: the SARIMA Model

We estimate a SARIMA(X) model, i.e. an ARIMA that takes the series' seasonality into account. The table below shows the results of four SARIMAX models. In the first model, we include the Covid-19 index and the average monthly Brent crude oil price as covariates; the second model includes the aggregate German-French-Italian confidence index and the Brent crude oil price; the third model includes these two variables and the Covid-19 index; finally, the fourth model includes these three variables and the inflation rate. In this way, we limit ourselves to a maximum of four covariates, which we introduce progressively into the model. We can control our estimates of the introduction of different variables together. In this context, the challenge of time-series econometrics is both not to *over*-explain certain phenomena and not to *under*-explain them. We use the `auto.arima` function from the `forecast` package on R to estimate our SARIMA(X) models.

The model selected is a SARIMA(1, 0, 0)(2, 1, 2)[12]. This model is made up of the following components:

1. AR(1): there is an autoregressive component of order 1 in the model.
2. I(0): there is no non-seasonal differentiation in the model. From this point of view, the data are considered stationary for the purpose of selecting the best model.
3. MA(0): time series values do not take into account past errors.
4. SAR(2): there is a *seasonal autoregressive component* of order 2. Thus, each value in t is related to the values of the same season in periods $t - 1$ and $t - 2$.
5. SI(1): seasonal *differentiation* of order 1 is performed. In this way, the data are differentiated once for each seasonal period. This makes the series seasonally stationary.
6. SMA(2): the errors of the previous two seasons are taken into account to predict the t value of the time series.
7. The [12] refers to the fact that the seasonal period is 12. In this way, seasonality is matched to the months of the year.

| | SARIMA1(1,0,0)(2,1,2)[12] | SARIMA2(1,0,0)(2,1,2)[12] | SARIMA3(1,0,0)(2,1,2)[12] | SARIMA4(1,0,0)(2,1,2)[12] |
|----------------|---------------------------|---------------------------|---------------------------|---------------------------|
| ar1 | 0.6462*** (0.0483) | 0.747*** (0.042) | 0.6244*** (0.0498) | 0.6264*** (0.0499) |
| sar1 | 0.8253*** (0.0783) | 0.812*** (0.079) | 0.8348*** (0.0768) | 0.8344*** (0.0763) |
| sar2 | -0.7107*** (0.0658) | -0.7078*** (0.0619) | -0.7238*** (0.0637) | -0.7247*** (0.0638) |
| sma1 | -1.2242*** (0.0978) | -1.2623*** (0.0944) | -1.2280*** (0.0974) | -1.2285*** (0.0969) |
| sma2 | 0.6547*** (0.0832) | 0.6673*** (0.0905) | 0.6672*** (0.0839) | 0.6686*** (0.0836) |
| covid.index | -3971*** (495) | | -3703*** (497) | -3655*** (505) |
| Brent | 524+ (300) | 998** (382) | 691* (301) | 596+ (349) |
| CCI.FRITDE | | 29 193*** (8643) | 13 609* (6435) | 15 252* (7123) |
| inflation.rate | | | | 415 001 (760 469) |
| Num.Obs. | 259 | 259 | 259 | 259 |
| AIC | 6398.0 | 6435.7 | 6395.8 | 6397.5 |
| BIC | 6426.5 | 6464.2 | 6427.8 | 6433.1 |
| RMSE | 51 441.06 | 55 016.36 | 50 975.10 | 50 935.97 |
| x | 0.987780489075617 | 0.98588620672641 | 0.988038600601742 | 0.988048470649155 |

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

In the first specification (and the other three as well), the model parameters are all highly significant (with a p -value below 0.001). On the side of the regressors we have added, the Covid index has a negative and highly significant coefficient. Thus, a one-unit increase in the Covid index translates into a 4090 drop in tourist arrivals. The price of Brent crude oil is significant at 10% and positive. So, as the price of Brent increases, so do tourist arrivals. This result seems seemingly counter-intuitive as an increase in oil price should lead to an increase in the price of plane ticket, thus having a negative effect on the demand. We conjecture that an increase in oil prices implies an increase in ticket prices, particularly for certain *low cost* airlines which are more sensitive to variations in the price of their inputs than airlines with a better *standing*. As a result, we suspect that consumers are substituting Corsica for a more distant destination that has become too expensive. Corsica thus appears as a fallback solution and would explain these additional arrivals.

Finally, we note that the aggregate household confidence index also has a positive and significant effect on arrivals to Corsica.

3.2 SVAR: another demand model for Corsica

Given the structure of the data (strong seasonal component), we decided to apply a seasonal VAR, or SVAR. This is the most common type of model used in competition with an AR/SARIMA model. This specification allows us to take into account the strong differences of the time series between the seasonal tourist peak (July-August) and the rest of the year.

Table 2: SVAR results

| Variables | Estimate | Std..Error | t.value | p.value |
|--------------------|--------------|-------------|---------|-------------|
| Covid Index l.1 | -1825.6027 | 354.5653 | -5.149 | < 0.001 *** |
| Brent l.1 | 198.0987 | 160.5828 | 1.234 | 0.218493 |
| Inflation rate l.1 | 252092.0951 | 349440.7514 | 0.721 | 0.471322 |
| Aggregated CCI L.1 | 4820.8062 | 4410.7526 | 1.093 | 0.275452 |
| TOTAL l.1 | 0.5584 | 0.0524 | 10.663 | < 0.001 *** |
| Const | -282062.8414 | 440913.2712 | -0.640 | 0.522933 |
| trend | 392.8414 | 78.9593 | 4.975 | < 0.001 *** |
| sd1 | -59774.9116 | 19032.8812 | -3.141 | 0.001887 ** |
| sd2 | -38164.1989 | 18844.4274 | -2.025 | 0.043899 * |
| sd3 | -16693.0940 | 18873.9510 | -0.884 | 0.377296 |
| sd4 | 203162.1979 | 18804.8712 | 10.804 | < 0.001 *** |
| sd5 | 231571.9908 | 22266.9010 | 10.400 | < 0.001 *** |
| sd6 | 327400.5634 | 27223.5684 | 12.026 | < 0.001 *** |
| sd7 | 745429.2165 | 34616.0797 | 21.534 | < 0.001 *** |
| sd8 | 780584.5442 | 59270.2364 | 13.170 | < 0.001 *** |
| sd9 | -215387.0343 | 75785.5248 | -2.842 | 0.004849 ** |
| sd10 | -142787.1128 | 36299.1396 | -3.934 | < 0.001 *** |
| sd11 | -145802.2273 | 21946.6522 | -6.643 | < 0.001 *** |

^a Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

^b Residual standard error: 63010 on 252 degrees of freedom

^c Multiple R-Squared: 0.9826, Adjusted R-squared: 0.9814

^d F-statistic: 837 on 17 and 252 DF, p-value: < 0.0001

Table 2 presents the results of a level SVAR(1), *i.e.*, evaluating the effect of explanatory variables, with a one-period lagged effect, on the variable to be explained at period t . Our dependent variable (y) corresponds to total tourist arrivals, while the independent variables are the one-period lagged values of the Covid restriction index, Brent crude oil, aggregate household confidence (Germany-France-Italy) and tourist arrivals. We also include seasonal terms, ranging from 1 to 11, with December as the reference month. The variables are

ordered from the most exogenous (the Covid-19 shock) to the most endogenous (total tourist arrivals). The model also includes a constant, a *trend* and the seasonal terms mentioned above.

We can interpret the SVAR results as follows:

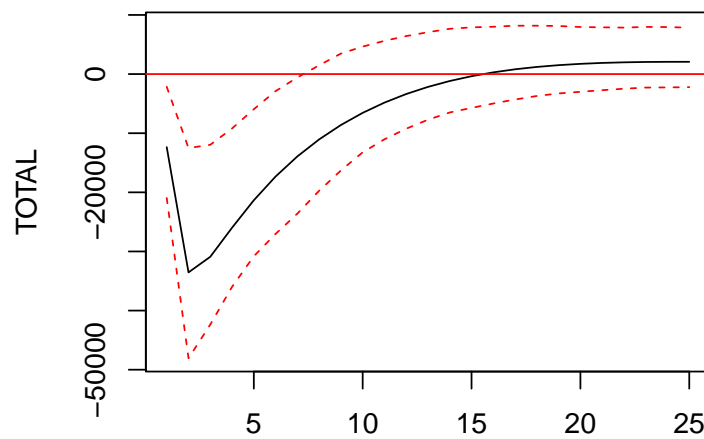
- The index of Covid-19 restrictions is the variable with the strongest effect: a one-unit increase in Covid-19 restrictions in the previous month reduces arrivals in Corsica by 1826 units. This suggests that an increase in restrictions has a strong short-term impact on tourist arrivals. This variable is significant at all levels considered, reinforcing the credibility of the result.
- The positive coefficient suggests that an increase in the price of Brent slightly increases tourist arrivals. This could be due to the higher cost of more distant destinations, encouraging consumers to prefer a closer destination. However, the effect of the price of a barrel of Brent oil is not significant at the 5% and 10% thresholds, which means that the SVAR does not detect any significant effect of the price of oil on arrivals in Corsica.
- The SVAR points to the absence of any effect of the inflation rate on arrivals on the island. However, it is difficult to conclude on the effect of inflation on arrivals to Corsica in the medium and long term: if the inflationary surge persists over time, we may end up observing that inflation has a negative effect on demand for Corsica as a destination.
- European household confidence with a one-period lag has a positive effect, which is expected but not significant, pointing to the absence of any impact of this variable on arrivals in Corsica.
- The delayed value of a period of tourist arrivals has a positive, slight and highly significant effect. This probably reflects the build-up of the tourist period from April to August. Island tourism thus seems to be characterized by a fairly strong trail dependency.
- We also note that there is a significant positive *trend* over time. In other words, the seasons are on average, in terms of number of arrivals, better each year.
- Finally, the indicator variables for the months of the year are almost all highly significant. They are alternately positive or negative, depending on which month they are compared with the reference month (December). Logically, arrivals in Corsica are definitely influenced by a seasonal effect.

4 Response of tourism demand to various shocks from the SVAR model

To analyze the impact of explanatory variables (Covid-19, inflation, household confidence, oil prices) on arrivals to Corsica, we examine impulse response functions (IRFs for short) and the historical decomposition obtained using SVAR for the variable of interest: arrivals to Corsica. The IRFs provide information on the propagation of a possible shock and the response of the variables over several months, while the historical decomposition captures the sources of fluctuations in each of the tourism arrivals variables throughout the analysis period (2001-2023). All numerical results are expressed in number of arrivals. It should be noted that these simulations depend essentially on past observations, which means that recent major upheavals (price of oil and other commodities structurally high since the outbreak of the Russo-Ukrainian war, China/US tensions) could have a lasting effect on inflation and therefore be more important in the modelling when more data becomes available.

4.1 How would arrivals to Corsica be affected by a sudden resurgence of health restrictions?

Figure 7: Non-cumulative IRF, shock Covid over 24 months

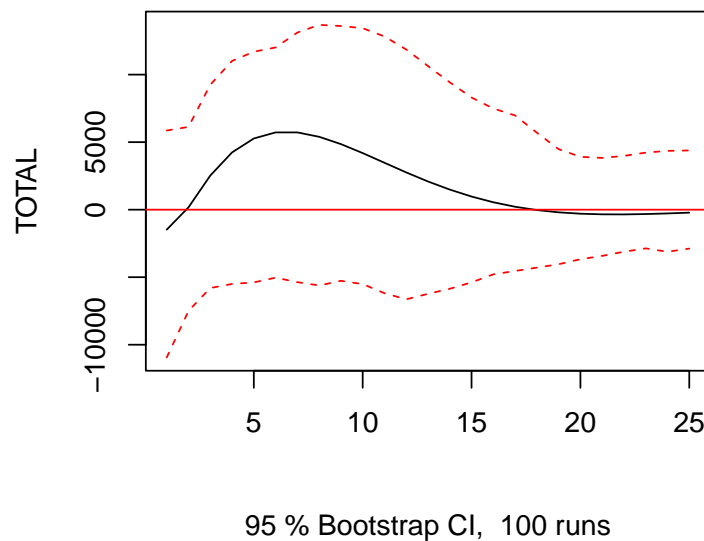


95 % Bootstrap CI, 100 runs

Fig. 7 shows that a resurgence of Covid-19 (or a disease with similar consequences), forcing the Government to reintroduce sanitary restrictions, would have a definite negative effect on arrivals to Corsica. The reintroduction of sanitary restrictions would lead to a reduction of 15,000 arrivals in the first month, followed by a reduction of over 30,000 arrivals the following month. Tourism demand began to recover in the third month after the shock. Demand fully absorbs the shock from the seventh month onwards, when the upper bound of the IRF (red dotted line) leaves the zone of significance (above 0). Beyond the seventh month, the effect of the shock is no longer statistically significant.

4.2 How would arrivals to Corsica be affected by a sudden rise in French, German and Italian household confidence?

Figure 8: Non-cumulative IRF, shock to household confidence over 24 months



The IRF for French, German and Italian household confidence is not significant at the 5% level (as the two dotted red bounds are on either side of the significance level: 0). The VAR therefore points to the absence of any significant effect of a positive shock to household confidence on tourism demand for Corsica.

4.3 How would arrivals to Corsica be affected by a sudden rise in the price of oil?

Figure 9: Non-cumulative IRF, 24-month Brent crude shock

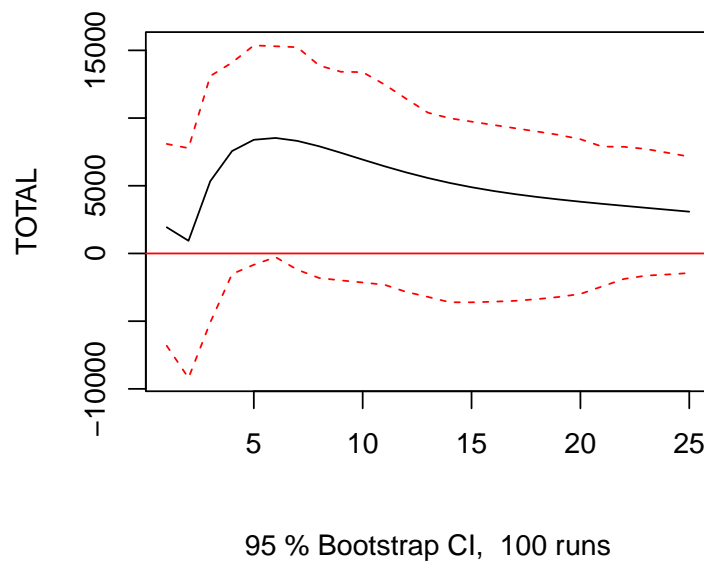
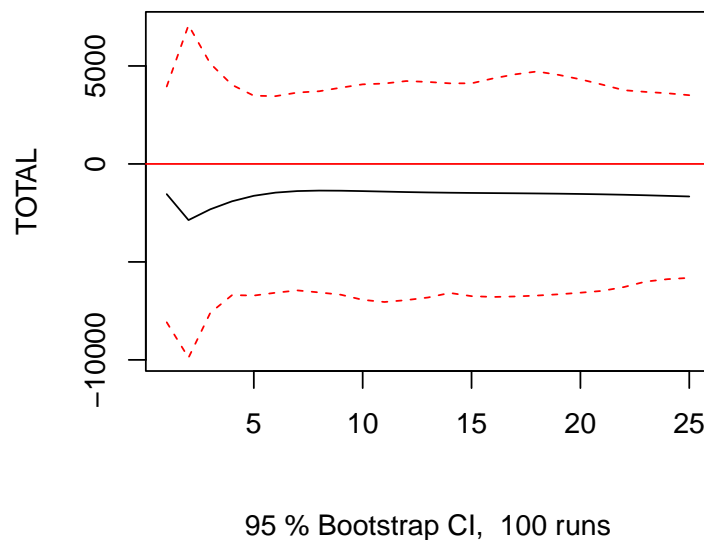


Fig. 9 illustrates the response of tourism demand to a sudden rise in the price of oil. The effect is non significant : there is no significant effect on tourism demand at the 5% error level (red dotted line on either side of 0, the significance level) in the first three months after the shock, although the IRF moves closer to the zone of significance between the fourth and the seventh month after the shock. The following months fell back into the insignificance zone. This is contradictory to the intuition we had identified through the estimation of a SARIMA model in the previous section.

4.4 How would arrivals to Corsica be affected by a sudden rise in inflation?

Figure 10: Non-cumulative IRF, inflationary shock over 24 months

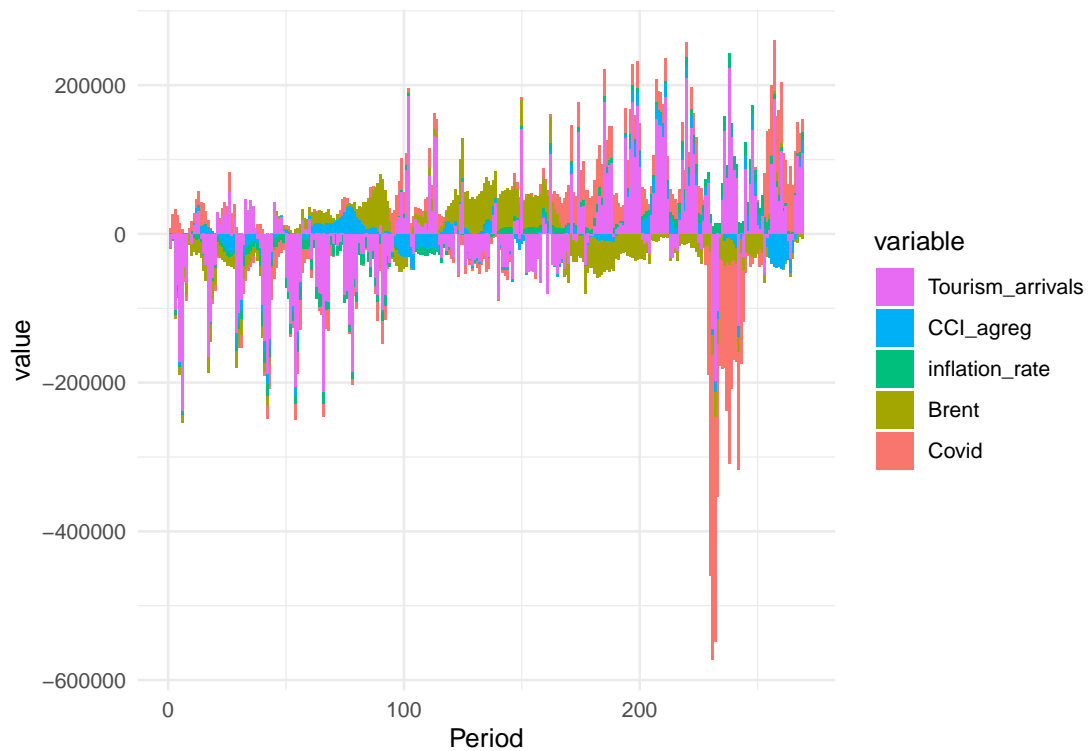


The tourism demand response function following a sudden rise in inflation in France (Fig. 10) shows the absence of any immediate significant effect of inflation on tourist arrivals to Corsica. We note a fairly relative approach to the zone of significance 18 months after the shock. This means that the negative effect of a sudden rise in inflation on tourist arrivals to Corsica is not significant. However, as the models presented are based on past observations (2000-2023), they probably do not sufficiently capture the effect of the inflationary surge observed since the end of 2021. As a reminder, inflation has always been within the European Central Bank's inflation target until 2022. It will therefore be quite possible to observe, when more data become available, a negative effect of inflation on arrivals in Corsica.

4.5 Evaluating the weight of each explanatory variable over time: historical decomposition of arrivals in Corsica

Historical decomposition enables us to analyze the contributions of each of the variables in our SVAR to the evolution of arrivals in Corsica over the period 2001-2023, and to identify periods when the model's variables have had a significant impact on the variable of interest. Fig. 11 shows that tourist arrivals in Corsica over the analysis period are partly influenced by their past values. Arrivals in Corsica would be determined in part by recurrent visitor behavior (loyalty effect, notably on the part of the Corsican diaspora or regular tourists) or positive "word-of-mouth" effects, where previous visitors positively influence future visitors to choose Corsica as a destination. According to Fig.11, this effect would be rather negative over the period 2001-2010 before becoming positive over the period 2011-2023. The confidence of French, Italian and German households has little influence on arrivals in Corsica over our analysis period: a positive effect is identified over the 2007-2009 period, followed by a negative effect over the 2010-2013 period. From 2022 onwards, household confidence seems to have a downward influence on arrivals in Corsica. This may be explained by the deterioration in macroeconomic conditions in France, Germany and Italy, which are in a fragile macroeconomic situation due to the inflationary crisis exacerbated by the Russian-Ukrainian war.

Figure 11: Historical breakdown of tourist arrivals



According to Fig. 11, low inflation levels in France would have had a slightly positive effect on arrivals to Corsica between mid-2013 and mid-2016. What's more, the graph illustrates the strong upturn in arrivals to Corsica as health restrictions were lifted. All in all, the low level of inflation at the start of the post-pandemic recovery, combined with an effect of frustrated demand due to the months of confinement would have supported the restart of the Corsican tourism industry in 2021, when vaccinated French tourists were able to travel freely throughout France. In 2022, this effect can be explained by the more marked return of vaccinated foreign tourists and non-vaccinated French and foreign tourists, who were once again able to travel freely. The historical breakdown illustrates the counter-cyclical effect of the Brent price on arrivals in Corsica. During the months preceding the Great Recession of 2008 and the period 2011-2015, two periods when the price of Brent was close to USD 100 per barrel, there was a positive effect on tourist arrivals in Corsica, while the fall in the price of Brent from 2016 onwards is illustrated by a negative contribution from Brent to arrivals in Corsica. This counter-cyclicity of the oil price could indicate that Corsica is considered by part of the demand as a "safety destination",

or as a “fallback destination” in case other, more distant destinations become too expensive.

Note, however, that this model is not perfect. Some variations that the model was unable to explain by our included variables may be falsely attributed to other variables: this is sometimes the case for our index measuring health restrictions. Fig. 11 sometimes shows positive contributions from the Covid-19 index to arrivals in Corsica, even though it did not exist. The inclusion of other variables in the model, or better calibration in the future, will correct this identified flaw.

4.6 What is the best model for forecasting arrivals to Corsica? (*in-sample & out-sample forecast*)

Having studied the variables that positively or negatively influence arrivals in Corsica, it is now time to determine which of the SARIMA and SVAR models we have modeled is the most effective for forecasting purposes. To do this, we split our sample in two: a training run (January 2001-March 2022) and a test run (April 2022-July 2023). We have not opted for a rolling forecast, in order to stick to the simplest methods for a first forecasting exercise. We re-estimate our SARIMA and SVAR on the training series, then calculate Corsican arrival forecasts on our test series, between January 2022 and July 2023. The test series allows us to evaluate the effectiveness of our models over two tourist seasons: 2022, and 2023 (which has not yet been completed at the time of writing). The idea is to see how our two models fare in predicting actual arrivals over the period of the test series. We then calculate the prediction errors between our estimates and actual arrivals, and summarize this by calculating the root-mean-square error (RMSE) for SARIMA and SVAR. The model with the lowest RMSE is the one that produces the least forecast error, and will therefore be the preferred model for future estimates of arrivals to Corsica.

Figure 12: SARIMAX forecast error

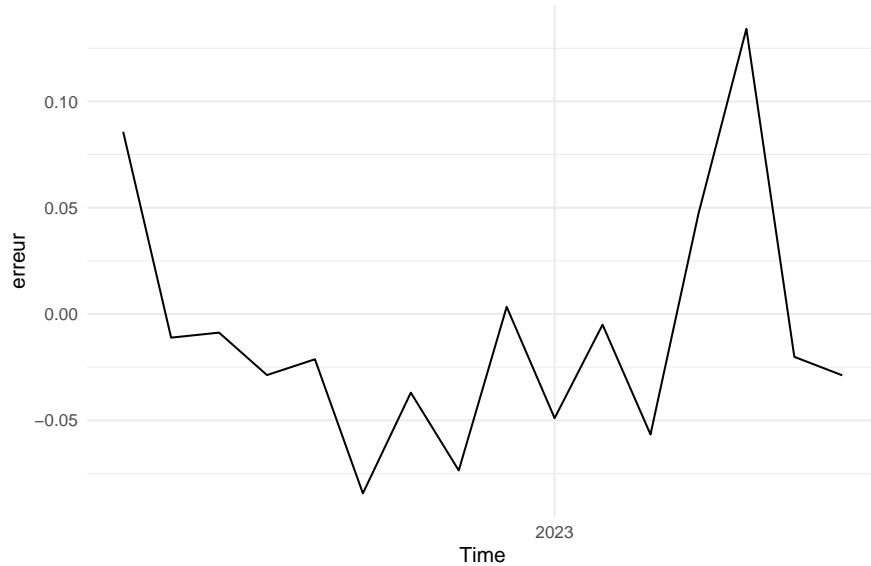


Fig. 12 illustrates the rate of forecast errors between the SARIMA model's predictions for the period April 2022-July 2023 and the observations actually recorded. When the errors are greater than 0, this means that there were actually more arrivals in Corsica than our model had predicted; conversely, if the errors are less than 0, there were fewer arrivals than our model had predicted.

Over the entire test period, with the exception of the months of April 2022 and May 2023, where the forecast error is close to 10%, the average error of the modelled SARIMA oscillates between 2% and 5% of actual observations. More precisely, SARIMA forecasts for our test sample (April 2022-July 2023) are 2% to 5% more optimistic than actual arrivals in Corsica.

This is a relatively satisfactory level of error for an initial model. The variables in this model are 'simple' for a model forecasting arrivals in Corsica. These forecasts could be further improved with the inclusion of more refined variables, such as the average price of a return air or sea ticket to Corsica, or a Corsica promotion index, which would measure the intensity of campaigns to promote the island as a tourist destination, for example.

Figure 13: SVAR(1) forecast error

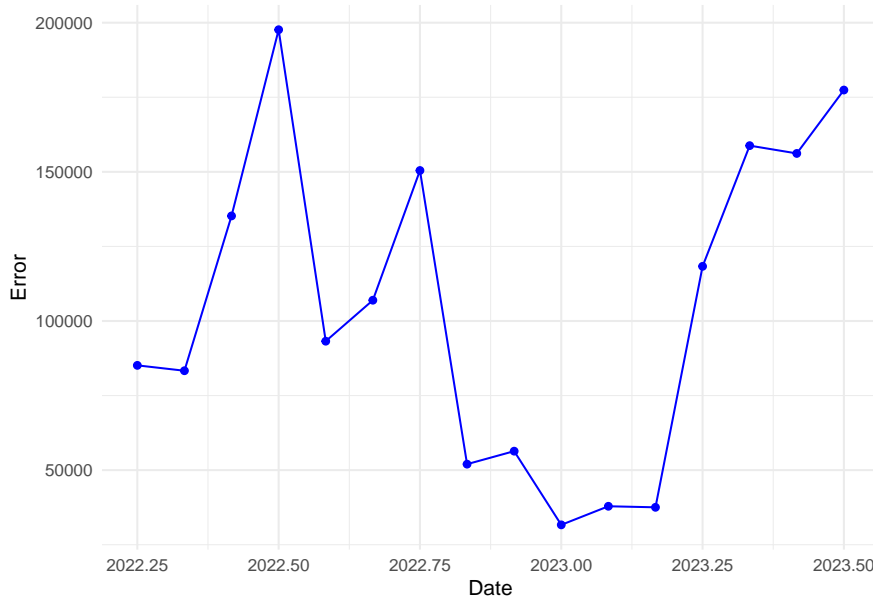


Fig. 13 shows the forecast error rate between the forecasts made by the SVAR model for the period April 2022-July 2023 and the observations actually recorded. Here again, an error rate greater than 0 means that there were more arrivals in Corsica than our model predicted, and vice versa.

We can see here that the error rate is much higher than our SARIMA for each of the months in our test sample. On average, the error rate is close to 10%. The error rate even reaches 25% for July 2022 and 15% for March 2023, the two highest error levels for our test sample. With the exception of January 2023, the error rate systematically exceeds the error of the SARIMAX model. This means that the SVAR clearly underestimates the number of arrivals destined for Corsica. In this case, the SVAR does not appear to be the most appropriate model for forecasting arrivals to Corsica.

This observation is mechanically confirmed by a comparison of the RMSEs for SARIMA and SVAR. The RMSE, a measure of the average error, for our SARIMA is 39,363.54 people compared with 75,463.13 for the SVAR; We conclude that with these explanatory variables, SARIMA is the most accurate model for forecasting tourist arrivals in Corsica.

Figure 14: Forecasting tourist arrivals with an S(easonal)VAR

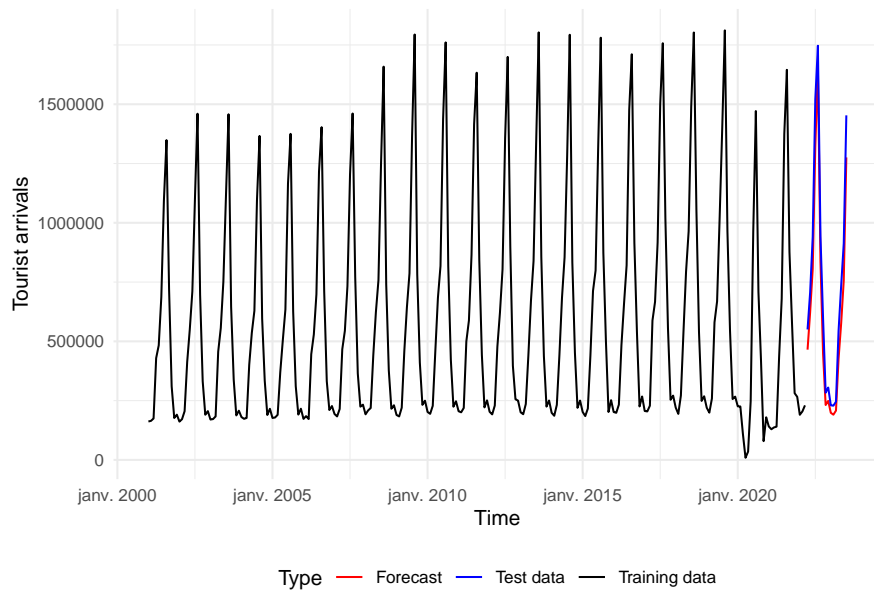
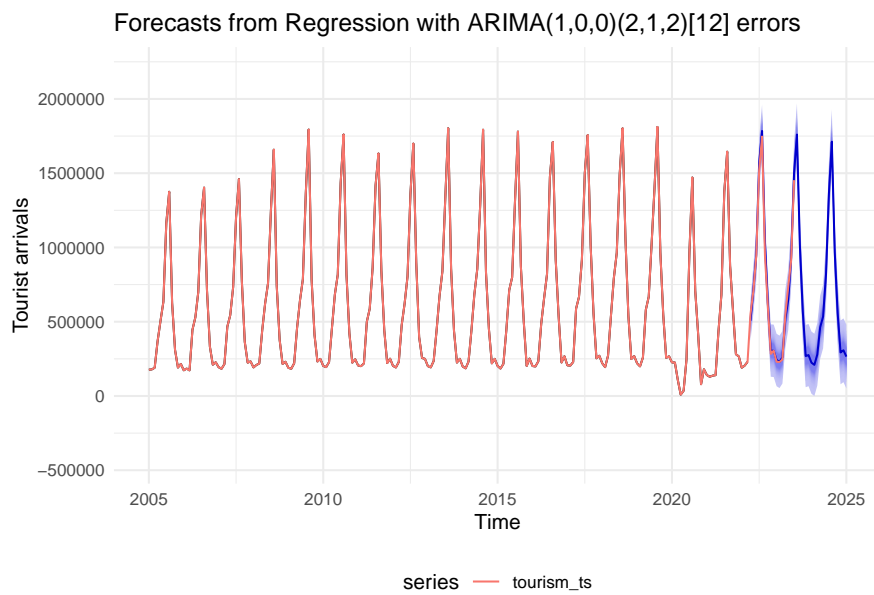


Figure 15: Forecasting tourist arrivals with SARIMAX



By way of illustration, Fig. 15 shows the *in-sample* (see above) and out-sample (see below) forecasts for arrivals in Corsica for the end of the 2023 tourist season and the coming season in 2024. In the light of the variables included in

the model, SARIMA suggests a slight decline in arrivals in Corsica for the 2024 season. It should be noted that this result, like all forecasts, should be treated with caution: the 95% confidence interval, which measures the margin of error at 5, indicates that it is possible that the tourist peak in the 2024 season will be equal to or even greater than that of 2022. Data from the coming months, which may be included in this model, will enable these forecasts to be refined. Similarly, the inclusion of new variables could further minimise our RMSEs, thereby improving the accuracy of our forecasts.

5 Analysis of the persistence of short- and long-term volatility in response to past shocks (DCC-GARCH)

In this section, we delve into the analysis of the persistence of short- and long-term volatility in response to past shocks, employing the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. This statistical framework allows us to examine how volatility, both in the short run and the long run, adapts and persists following the Covid-19 shock. By leveraging the DCC-GARCH model, we can identify the evolving correlations between the pandemic's progression and tourism demand fluctuations, offering a detailed perspective on how these correlations shift over time. This analysis is pivotal in understanding the resilience of the tourism sector in Corsica to the profound disruptions caused by the pandemic. It also provides insights into the recovery trajectory and potential long-lasting effects of such a global health crisis on regional tourism dynamics.

5.1 Test to identify an ARCH effect

Table 3: Test series

| Test | Statistic | DF | PValue |
|---------------------|-----------|------|-------------------------|
| Portmanteau | 519.5537 | 250 | 0*** |
| ARCH (multivariate) | 3241.568 | 2700 | 0.000000000002007394*** |

^a + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First, let's check for the presence of an ARCH effect in our series of arrivals

to Corsica. Table 3 presents the results of two statistical tests: the *Portmanteau* test and the *ARCH* test. For the *Portmanteau* test, the test statistic is 519.55 with a critical probability of less than 0.001. Thus, we can strongly reject the null hypothesis of *independence of residuals*. In other words, the series is characterised by autocorrelation of the residuals. This can affect the efficiency of parameter estimation and the reliability of forecasts. Models such as ARIMA/SARIMA, which take account of time dependence in the data, are used to deal with this type of problem.

The second result from the table is the ARCH test: the p -value also tends towards 0, which allows us to reject the null hypothesis of homoscedasticity with a high degree of confidence. This result suggests that the model's residuals show signs of conditional volatility. When this type of result emerges from the data, it is consistent to apply a (G)ARCH model. This is what we do in the remainder of this study.

The presence of an ARCH effect in the model means that past shocks are influencing current volatility. The presence of an ARCH effect is largely explained by the scale of the shock caused by the Covid-19 pandemic, which the SARIMA and VARmodels are unable to deal with in full (Fig. 16). By excluding the pandemic period from the series, the test for detecting an ARCH effect no longer leads to rejection of the null hypothesis at the 5% threshold.

Fig 16 illustrates the variation in volatility over time: between 2001 and 2019, the level of volatility follows the tourist seasons. From March 2020 onwards, volatility explodes in response to health restrictions and the confinement of the population. This volatility continues into 2021 with the continuation of certain travel restrictions (curfews, health passes, etc.). From 2022 onwards, volatility converges towards pre-pandemic levels. If we look at the volatility graph alone, we can see that there is no lasting "pandemic effect" on arrivals in Corsica in the months following the lifting of health restrictions.

Figure 16: Volatility of tourist arrivals

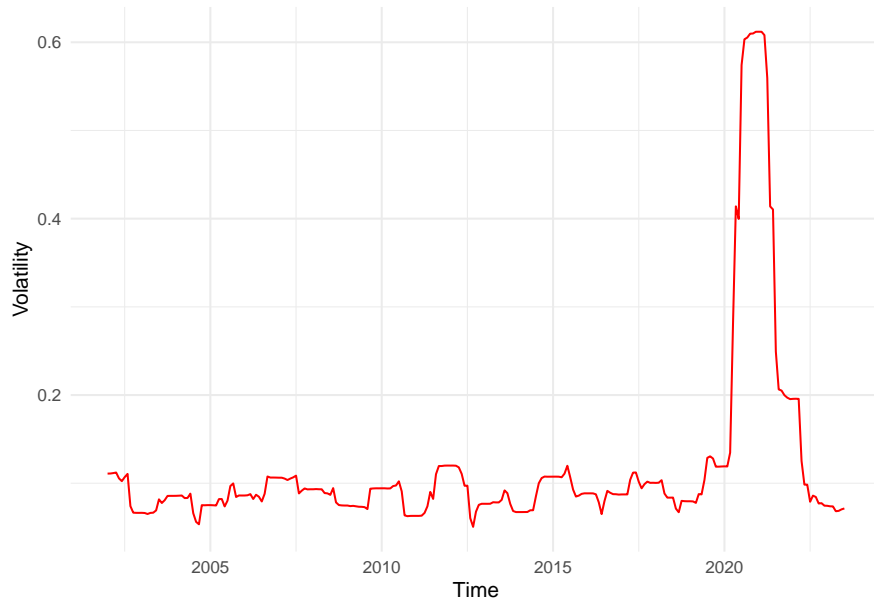


Fig. 16 illustrates a certain constancy (with the exception of the Covid-19 pandemic) in volatility over time, averaging around 0.1 over the period 2001-2019. In our view, this does not call for the specification of a GARCH model, which would be trivial. However, the table showing the results of a DCC-GARCH model with arrivals in Corsica and the index measuring health restrictions against Covid-19 as variables is available in Appendix VI.

6 Conclusion

This paper makes several contributions to the work on modelling tourism in Corsica. First of all, data collection and construction work has been carried out. We took each monthly report from the Corsican Prefecture's Transport Observatory between 2001 and 2023 and plotted the values for French and foreign arrivals, by boat and by plane. We selected certain variables in order to test hypotheses to explain certain determinants of tourism demand on the island. By restricting ourselves to a small number of variables that are consistent with each other and with tourist arrivals, we seek to avoid *overfitting* and confusion between variables. We conclude that there is a significant effect of autoregressive processes on tourism demand and of the Covid-19 pandemic. Indicators measuring household confidence and the inflation rate do not seem to be very decisive. The case

of the oil price is more interesting given the counter-intuitive result observed. A more in-depth analysis of this point could be carried out in the future. Finally, the series of arrivals in Corsica is not marked by any underlying volatility, with the exception of the pandemic period and, of course, tourism cycles. The end of the health restrictions allowed a return to normal, demonstrating that the health crisis had no lasting impact on demand.

This work is an interesting starting point in the construction of an econometric framework for monitoring and forecasting demand for tourism in Corsica. In the future, other variables, other hypotheses and other competing models could be mobilised, making it possible in the long term to build a solid body of literature around the explanation of Corsican tourism demand.

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A Appendices

A.1 Update on the 2023 tourist season

This appendix provides a brief update on the results for the 2023 tourist season, which is still in progress at the time of writing (only results up to July are available). Comparisons will be made on the basis of combined results for May, June and July. The inclusion of May is justified by the start of the pre-season period, when tourist flows to Corsica begin to intensify.

Flows to Corsica fell slightly in 2023 compared with the previous tourist season. Over the months of May, June and July 2023, non-seasonally adjusted data from the Corsican DREAL counted 3.1 million arrivals to Corsica (boats and planes; French and foreign), 2.1% fewer than in 2022 for the same period. The result is similar when we look at the seasonally adjusted figures: between May-June-July 2022 and May-June-July 2023, arrivals in Corsica fell by 2.8%, to 2.2 million people. A breakdown of arrivals by air and sea shows that the drop for the months of May-June-July 2023 compared with 2022 is explained by the 4.3% fall in air arrivals, while sea arrivals rose by 0.4% year-on-year. For the months of May-June-July 2023, compared with the months of May-June-July 2019, maritime arrivals are stable (-0.04%) and are very slightly above (0.3%) the level for the months of May-June-July 2019. A breakdown by market shows a clear drop in arrivals from France (-6.9%), both by air (-5.1%) and by sea (-9.5%). This decline on the continental market has not been offset by the post-pandemic recovery seen on foreign markets (+12.2%), where there has been a notable increase by sea (+18%).

With these results, the 2023 season seems to be avoiding the worst when measured in terms of arrivals in Corsica. Despite this drop, demand remains above the average for the years 2015 to 2018 over the same period and is stable compared to the months of May-June-July 2019. Non-seasonally adjusted arrivals in Corsica for the months of May-June-July 2023 are 0.8% above the months of May-June-July 2019 and 4.9% above the average for the same months for the 2015 to 2019 tourist seasons. Tourism in Corsica therefore appears to be resilient, insofar as it has not fallen back below 2019 levels and, above all, is still above the trend that prevailed in the years preceding the Covid-19 pandemic.

However, analysis solely through the prism of arrivals in Corsica is incomplete. It is certain that while arrivals in Corsica have not fallen, they are likely to have been accompanied by a marked decline in tourist spending, an important variable that could refine the assessment of the season. In concrete terms, this drop in tourist spending could be reflected in a smaller number of tourist

activities being carried out once on site, shorter stays, less expenditure on food and drink, and a different choice of accommodation than usual. In this respect, INSEE notes a 1.9% drop in hotel occupancy, and a net 8.8% decline in other collective tourist accommodation (ACHT) for the 2023 tourist season. Similarly, greater attention needs to be paid to the variable of tourist spending in the future, and it would seem appropriate to make this data freely available on a monthly basis.

| | Tot. may-jul. 2022 | Tot. may-jul. 2023 | Evol. may-jul. 2022-23 |
|---------------|--------------------|--------------------|------------------------|
| Ship_France | 939,626 | 850,244 | -9.5% |
| Plane_France | 1,436,141 | 1,361,631 | -5.2% |
| Total_France | 2,375,767 | 2,211,875 | -6.9% |
| Ship_Foreign | 527,206 | 622,452 | 18.1% |
| Plane_Foreign | 264,821 | 266,612 | 0.7% |
| Total_Foreign | 792,027 | 889,064 | 12.3% |
| Total | 3,167,794 | 3,100,939 | -2.1% |

A.2 Disaggregated descriptive statistics

A.2.1 Arrivals by origin and means of transport

Fig. 17 and Fig. 18 show the evolution of disaggregated tourist arrivals. These data have not been used in the econometric models above, which focus on total data, i.e. grouping sea and air arrivals, French and foreign.

Figure 17: Tourist arrivals by origin and means of transport

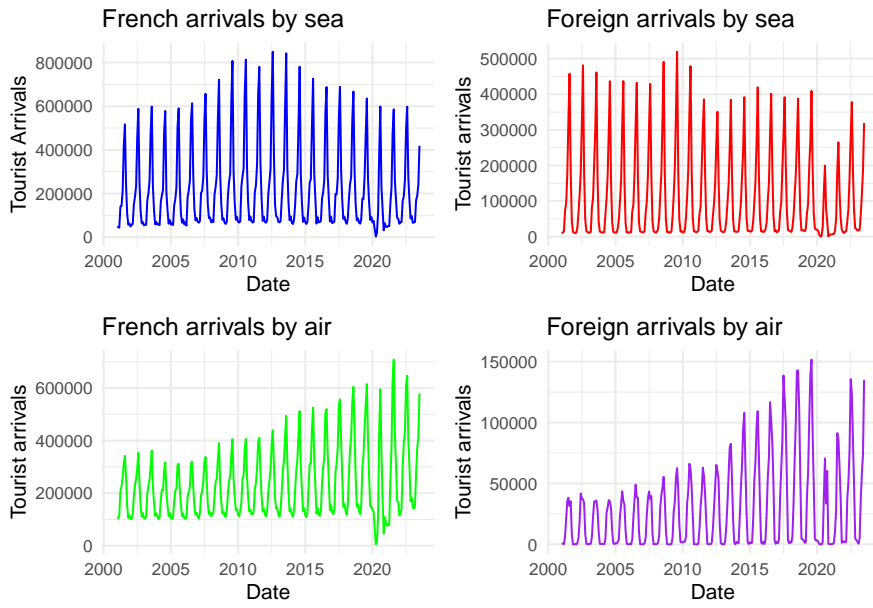
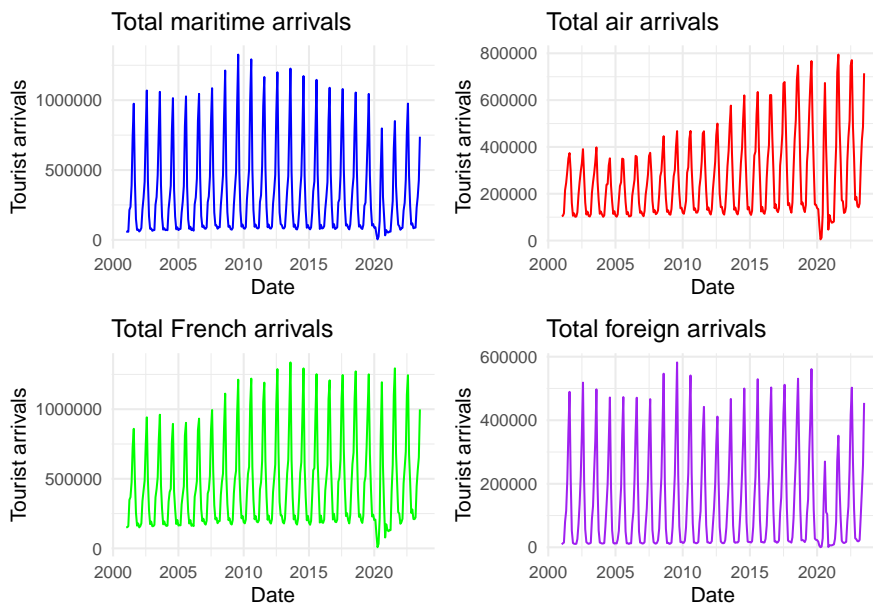


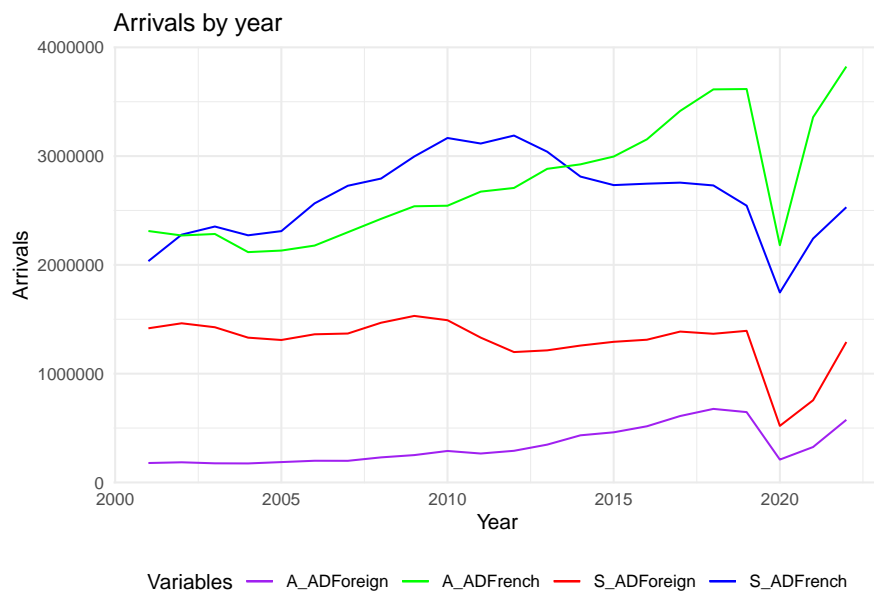
Figure 18: Total arrivals by origin and means of transport



A.2.2 Averaging arrivals

Fig@ref(fig:combinedplot3) is constructed as follows: we sum the data by year for each origin/transport mode, then plot the corresponding curve.

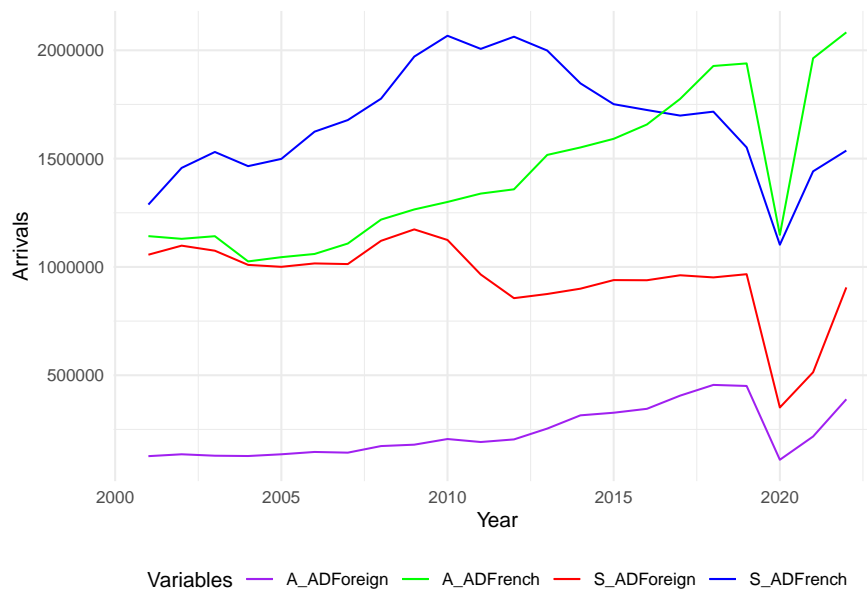
Figure 19: Annual arrivals by origin and means of transport



A.2.3 Seasonal arrivals

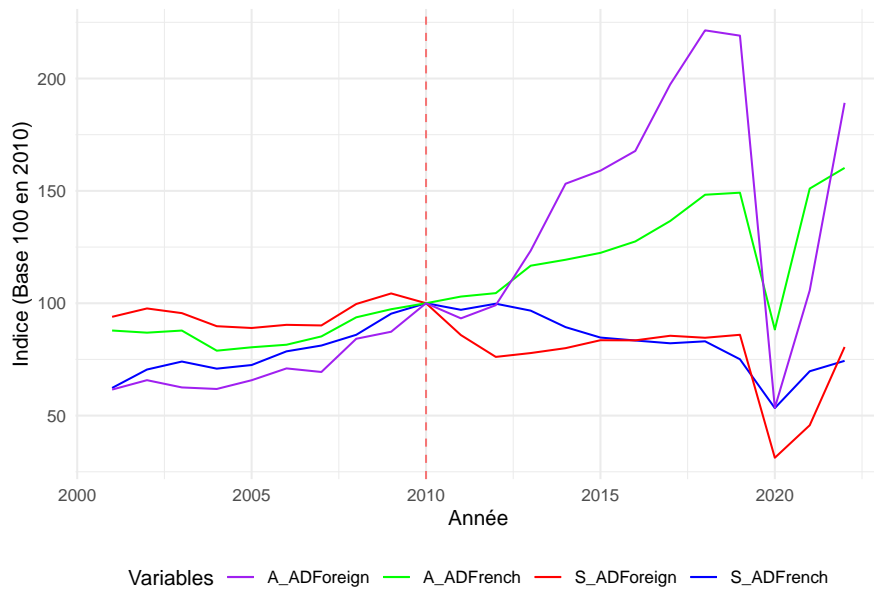
Fig. 20 focuses on the summer period (May - August) from 2001 to 2022. The decline in maritime transport is more visible than in the annual data. This decline concerns both French and foreign arrivals. The increase in air transport is very marked in the case of French arrivals.

Figure 20: Change in arrivals for the months of May to August (2001-2022)



Another way of looking at these trends is to define a 'reference' (or base) year, in this case 2010, and observe how arrivals evolve around that year. Fig. 21 highlights the marked decline in foreign arrivals by ship, with a clear shift towards air (purple curve).

Figure 21: Change in arrivals from May to August, base 100 (2010)



Finally, figures 22 and 23 apply the same approach to the November - February period. We see a significant increase in foreign arrivals over this period ((ref?) (fig:combinedplot7)) while the other three variables are relatively stable over the period. This could reflect the implementation of new commercial strategies aimed at attracting foreign tourists/providing air connections to foreign destinations during the winter period.

Figure 22: November to February arrivals (2001-2022)

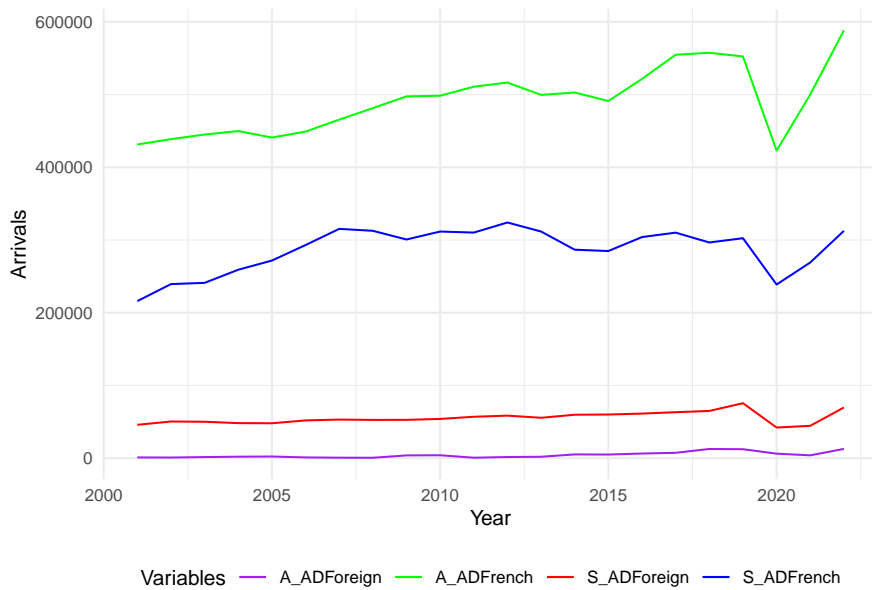
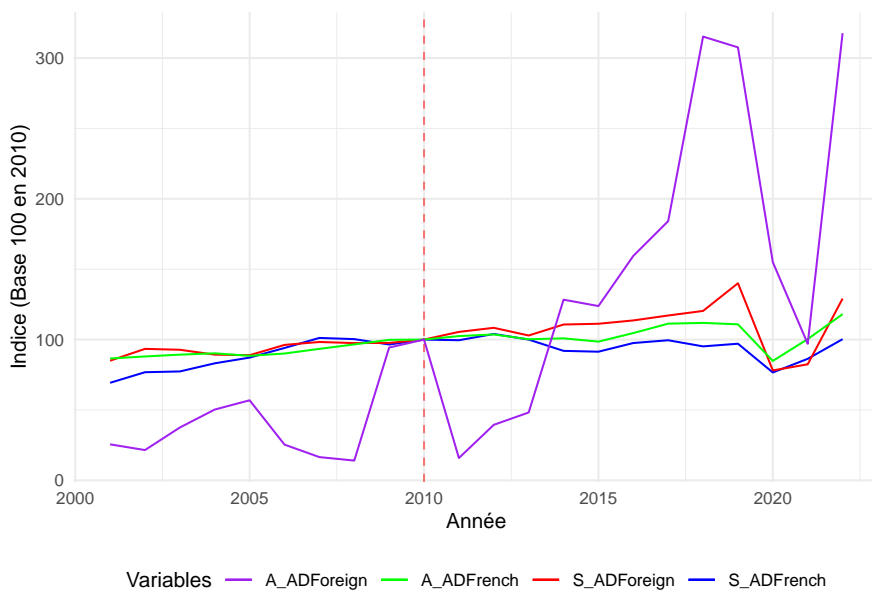


Figure 23: Change in arrivals based on 100 (2010) for Nov-Feb.



A.3 ARIMA model

The table below summarises the estimation results:

| | AR(1) | MA(1) | ARIMA1(0,1,4) | ARIMA2(0,1,4) | ARIMA3(4,1,1) | ARIMA4(4,1,1) |
|----------------|---------------------|--------------------|------------------------|------------------------|------------------------|------------------------|
| ar1 | 0.814 (0.035) | | | | 0.3646*** (0.0736) | 0.3692*** (0.0759) |
| intercept | 586 471 (18 300) | 586 010 (7280) | | | | |
| ma1 | | 0.6175 (0.0423) | -0.4931*** (0.0608) | -0.3416*** (0.0612) | -0.8768*** (0.0518) | -0.882*** (0.055) |
| ma2 | | | 0.0217 (0.0679) | 0.0660 (0.0651) | | |
| ma3 | | | -0.1282+ (0.0763) | -0.139+ (0.074) | | |
| ma4 | | | -0.2580*** (0.0681) | -0.2412*** (0.0676) | | |
| Covid.index | | | -3820*** (464) | | -3846*** (449) | -3803*** (485) |
| Brent | | | 611+ (322) | 1310** (426) | 659* (317) | 604 (395) |
| CCI.FRITDE | | | | 19 992+ (10 310) | 9745 (6710) | 10 373 (7238) |
| ar2 | | | | | 0.230*** (0.066) | 0.2320*** (0.0667) |
| ar3 | | | | | -0.0416 (0.0643) | -0.0399 (0.0648) |
| ar4 | | | | | -0.233*** (0.064) | -0.2317*** (0.0641) |
| inflation.rate | | | | | | 207 287 (889 013) |

| | | | | | | |
|----------|-----------|-----------|-------------------|-------------------|-------------------|-------------------|
| Num.Obs. | 271 | 271 | 270 | 270 | 270 | 270 |
| R2 | 0.663 | 0.477 | | | | |
| AIC | 6710.5 | 6853.8 | 6616.2 | 6661.5 | 6616.2 | 6618.1 |
| BIC | 6721.3 | 6864.6 | 6641.3 | 6686.7 | 6648.6 | 6654.1 |
| RMSE | 56 892.83 | 74 199.04 | 49 178.09 | 53 545.09 | 48 819.17 | 48 812.63 |
| x | | | 0.750570700747664 | 0.703386545973775 | 0.754035339202552 | 0.754155379824957 |

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

A.3.1 Result of the autoregressive process

We start with a 1 autoregressive process and a 1 moving average process. These are our *baseline models*, i.e. the starting point for our econometric examination. Recall that AR(1) can be written as follows:

$$\text{Tourist arrivals}_t = \beta_0 + \beta_1 \text{Tourist arrivals}_{t-1} + \varepsilon_t$$

By replacing with our values:

$$\text{Tourist arrivals}_t = 583282 + 0.8083 \times \text{Tourist arrivals}_{t-1} + \varepsilon_t$$

The constant term β_0 has a value of 583282, which gives the value, in the equation, of the variable Tourist arrivals in t in the case where the value in $t - 1$ is zero. This value can be better understood by considering the *long-term* value of tourist arrivals from the expectation $\mathbb{E}(Y_t)$:

$$\mathbb{E}(Y_t) = \mathbb{E}(Y_{t-1}) = \mu$$

Where the error term is assumed to be normally distributed and to have zero mean, i.e. $\mathbb{E}(\varepsilon_t) = 0$. Rearranging the equation:

$$\mathbb{E}(Y_t) = \left(\frac{1}{1 - \beta_1} \right) \beta_0$$

By replacing with the estimated values:

$$\mathbb{E}(Y_t) = \frac{583282}{1 - 0.8083} \approx 3045550$$

In other words, over the long term, we expect around three million tourist arrivals on average. The coefficient $\beta_1 = 0.8083$ is also important. It tells us that tourist arrivals in period t “retain” around 80% of the value in $t - 1$. The series is therefore characterised by a strong autoregressive component: arrivals in period t are strongly influenced by arrivals in the previous month (period $t - 1$).

A.3.2 Using a moving average process

View table.

A.3.3 Refining our estimate: using an ARIMAX process

These initial models provide some insight into how time series models work, and into the dynamics of tourist arrivals in Corsica. However, these initial results must be interpreted with caution. The value of tourist arrivals in month t depends on a large number of factors. This is why more complex models are introduced, such as ARIMAX, which combines an autoregressive process (AR), a moving average process (MA) and integration (I). In time series econometrics, a series is said to be “integrated of order d ” when it becomes stationary after d differentiation.

The third column summarises the results of an ARIMAX(4, 1, 1). This is a combination of an AR(4), a MA(1) and a differentiation of order 1. The X indicates that additional regressors are added to the model parameters. In the case of this model, the Covid index and the price of Brent. The Covid index is negative and highly significant (at the highest threshold): a one-unit increase in Covid restrictions reduces tourist arrivals by 4025 units. The change in the price of Brent positively affects tourist arrivals (significant at the 10 threshold). The proposed intuition can be summarised as follows: the increase in the price of Brent results in higher transport costs. This shock to transport costs will be passed on to air and sea fares. As a result, going on holiday will become more expensive. In this context, tourists will substitute Corsica for a more distant destination that would be too expensive.

The next three columns present three alternative specifications of ARIMA processes. Note, for example, that by introducing all variables except the Covid-19 index, the selected ARIMA does not contain an autoregressive process. This means that past values of arrivals have little influence on present and future values. By not controlling for the Covid-19 shock, we introduce a lot of “noise” into the model. These disturbances can bias the results, because of an omitted variable. It should also be noted that the model includes errors from the four previous periods. Given that this ARIMA(p, d, q) has a very different shape to the other models estimated, it seems obvious that controlling the Covid shock is necessary. Also, using a composite index that varies over time provides a finer-grained analysis of the persistence of the shock, compared with a binary pandemic/non-pandemic or containment/non-containment variable.

The results of the last two models are similar to those of the first ARIMA. Compared with the 1 autoregressive process, the effect of past values is weaker (but highly significant). The Covid-19 index is negative and highly significant. On the other hand, the household confidence index is not significant at any of the thresholds. The same is true for Brent crude and the inflation rate.

A.4 Seasonal VAR(2)

We present here the results of a seasonal VAR with two lags (SVAR(2)), while the model used in the text is a S(easonal)VAR(1).

Table 5: SVAR(2) results

| Variables | Estimate | Std..Error | t.value | p.value |
|--------------------|---------------|---------------|---------|-------------|
| Const | -425643.24401 | 944.67187 | -5.920 | 0.3495 |
| Covid Index l.1 | -5592.58692 | 733.98140 | 0.097 | < 0.001 *** |
| Brent l.1 | 71.42348 | 1561289.21055 | -0.438 | 0.9226 |
| Inflation rate l.1 | -684474.51198 | 20164.71057 | 0.438 | 0.6615 |
| Aggregated CCI L.1 | 8838.97815 | 0.06201 | 9.997 | 0.6615 |
| TOTAL l.1 | 0.61999 | 959.93404 | 5.554 | < 0.001 *** |
| Covid Index l.2 | 5331.55509 | 735.50099 | 0.324 | < 0.001 *** |
| Brent.l2 | 238.24954 | 1585502.23627 | 0.463 | 0.7463 |
| Inflation rate l.2 | 733309.57575 | 19531.43701 | -0.176 | 0.6441 |
| Aggregated CCI l.2 | -3437.78497 | 0.06302 | 2.453 | 0.8604 |
| TOTAL l.2 | 0.15461 | 454061.05948 | -0.937 | 0.0148 * |
| sd1 | -35252.49676 | 23543.70879 | -1.497 | 0.1356 |
| sd2 | -14393.87287 | 21649.64612 | -0.665 | 0.5068 |
| sd3 | 15551.00020 | 23019.45499 | 0.676 | 0.5000 |
| sd4 | 244763.17696 | 24197.74254 | 10.115 | < 0.001 *** |
| sd5 | 248964.57648 | 31814.93536 | 7.825 | < 0.001 *** |
| sd6 | 289979.94072 | 29344.78958 | 9.882 | < 0.001 *** |
| sd7 | 674986.63155 | 33490.83193 | 20.154 | < 0.001 *** |
| sd8 | 648443.39115 | 55948.46234 | 11.590 | < 0.001 *** |
| sd9 | -442772.51031 | 62833.26987 | -7.047 | < 0.001 *** |
| sd10 | -369450.37553 | 57696.36338 | -6.403 | < 0.001 *** |
| sd11 | -222480.90459 | 25406.83321 | -8.757 | <0.001 *** |

^a Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

^b Residual standard error: 63010 on 252 degrees of freedom

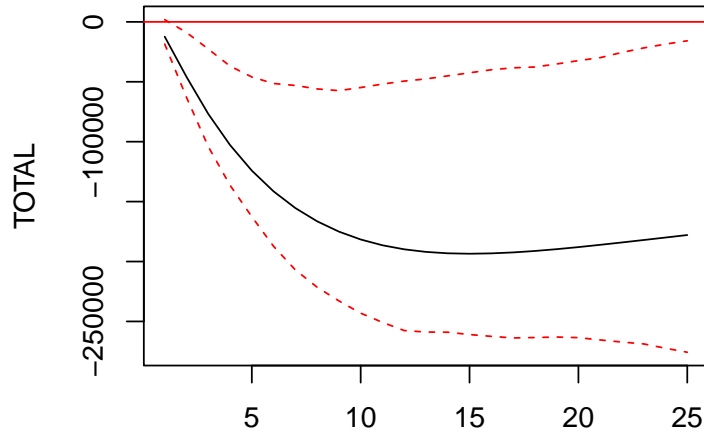
^c Multiple R-Squared: 0.9826, Adjusted R-squared: 0.9814

^d F-statistic: 837 on 17 and 252 DF, p-value: < 0.0001

A.5 Cumulative IRF

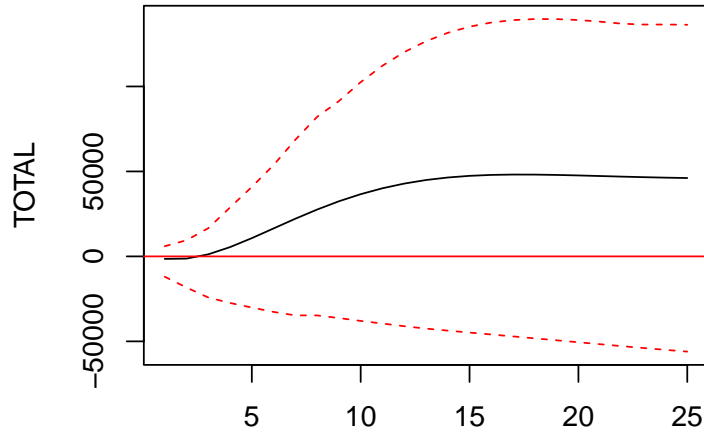
The cumulative shocks over 24 months are shown below.

Orthogonal Impulse Response from Covid_index (cumulative)



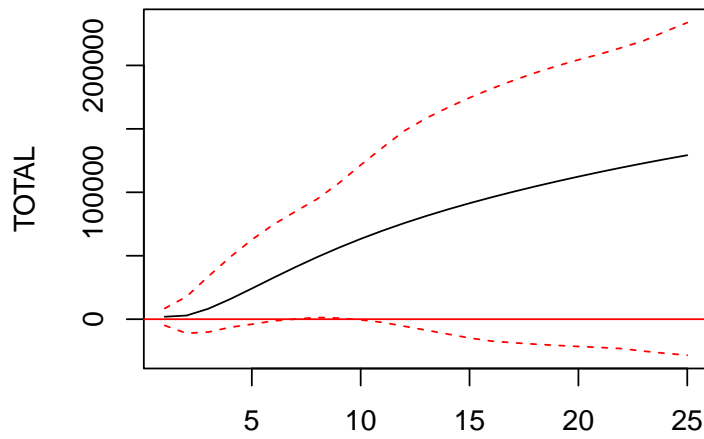
95 % Bootstrap CI, 100 runs

Orthogonal Impulse Response from CCI_agreg (cumulative)



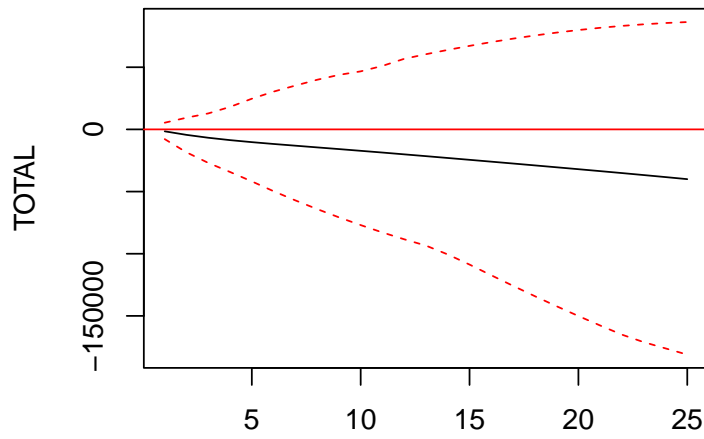
95 % Bootstrap CI, 100 runs

Orthogonal Impulse Response from Brent (cumulative)



95 % Bootstrap CI, 100 runs

Orthogonal Impulse Response from inflation_rate (cumulative)



95 % Bootstrap CI, 100 runs

A.6 DCC-GARCH results

Table 6: DCC-GARCH results

| Variable | Estimate | Std.Error | t_value | Pr |
|-------------------|-----------|-----------|-----------|----------|
| [arrivals].mu | 49.595046 | 1.005416 | 49.32786 | 0.000000 |
| [arrivals].ar1 | 1.142180 | 0.003087 | 369.94426 | 0.000000 |
| [arrivals].ar2 | -0.134109 | 0.001978 | -67.81285 | 0.000000 |
| [arrivals].ma1 | -0.866828 | 0.025493 | -34.00299 | 0.000000 |
| [arrivals].omega | 6.507688 | 2.228305 | 2.92047 | 0.003495 |
| [arrivals].alpha1 | 0.708620 | 0.246672 | 2.87272 | 0.004070 |
| [arrivals].beta1 | 0.242265 | 0.082895 | 2.92255 | 0.003472 |
| [Covid].mu | -0.024863 | 0.026213 | -0.94847 | 0.342890 |
| [Covid].ar1 | -0.144274 | 0.285393 | -0.50553 | 0.613189 |
| [Covid].ar2 | 2.032049 | 0.398703 | 5.09666 | 0.000000 |
| [Covid].ma1 | 0.005019 | 0.004816 | 1.04212 | 0.297356 |
| [Covid].omega | 0.132856 | 0.130989 | 1.01425 | 0.310463 |
| [Covid].alpha1 | 0.998999 | 0.200544 | 4.98144 | 0.000001 |
| [Covid].beta1 | 0.000000 | 0.000380 | 0.00000 | 1.000000 |
| [Joint]dcca1 | 0.155154 | 0.088236 | 1.75839 | 0.078680 |
| [Joint]dccb1 | 0.742353 | 0.132803 | 5.58986 | 0.000000 |