Understanding the impact of travel on wellbeing: evidence for Great Britain during the pandemic.

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Exploring the Link Between Travel and Wellbeing Amidst the Pandemic.

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Abstract

This study examines the impact of the COVID-19 on the wellbeing of individuals in Great Britain, as measured by life satisfaction and happiness, by analysing the dramatic drop in travel during this time. The Bayesian VAR model considers a range of exogenous and endogenous variables, including COVID-19, modes of transportation, and wellbeing variables. Results indicate that shocks in COVID-19 have a negative impact on travel, which subsequently affects wellbeing. However, there is limited evidence to suggest that COVID-19 responses to shocks in various forms of transportation have a significant impact on COVID-19 outcomes. Additionally, the study provides forecasts for key endogenous variables, which can inform evidence-based policymaking during the pandemic. The study emphasizes the importance of considering the relationship between travel and wellbeing amidst the pandemic and highlights the need for policies that balance the public health risks of travelling with the benefits of mobility and travel for wellbeing.

Keywords: Travelling; wellbeing; Covid 19; Great Britain; Bayesian VAR.

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1. Introduction

The pandemic has significantly impacted the tourism industry, with many businesses and destinations struggling to adapt to the changing circumstances (Ma et al. 2022; Hu and Chen, 2021; Habib and Anik, 2021; Kock, et al. 2020). Travelling during the pandemic has become a complex issue as health, safety, and wellbeing are critical factors to consider (Mamatzakis et al. 2023; Zhang, 2022). The Great Britain government, in line with governments worldwide, implemented various measures to control the spread of COVID-19, including restrictions on travel and social activities (Mamatzakis et al. 2023; Gholipour, et al. 2023; Zhang, 2022). From a wellbeing perspective, travelling during the pandemic has been stressful and may have increased anxiety levels due to the uncertainty and risks involved. However, travelling can also have positive effects on wellbeing, such as reducing stress, increasing creativity, and providing opportunities for personal growth and self-reflection. Nevertheless, it is essential to balance these benefits with the potential risks and take measures to protect oneself and others. Therefore, further research is necessary to understand the specific ways in which the pandemic has affected wellbeing, both in the context of travel and more broadly. Such research can inform interventions and policies aimed at promoting mental health and wellbeing during and after the pandemic. Overall, it is crucial to acknowledge the complex nature of travelling during the pandemic and develop evidence-based strategies to support individuals' health and wellbeing while travelling.

This study investigates the impact of the significant decrease in travel during the pandemic on the welfare of individuals in Great Britain, as measured by life satisfaction and happiness. The study primarily focuses on how Covid-19 has affected travel patterns and attitudes towards travel, which may subsequently impact wellbeing. Additionally, the study examines changes in travel behaviour and measures of life satisfaction over time. Through this research, valuable insights can be gained into the complex relationship between travel and wellbeing in Great Britain. The findings of this study can inform policies and interventions aimed at promoting sustainable and healthy travel practices during and after the pandemic, ultimately contributing to the overall welfare of individuals in Great Britain.

Existing research has explored the impact of the pandemic on travel behavior, including studies by Ma et al. (2022), Hu and Chen (2021), Habib and Anik (2021), and Kock et al. (2020) and Zhang, (2022). Ma et al. (2022) argue that it is crucial to investigate how Covid-19 has influenced travel habits, considering factors such as safety, perceived racism, sociodemographic characteristics, and risk. For instance, Ma et al. (2022) found that perceived racism negatively affected the walking behaviour of people of Asian origin in Australia. Hu and Chen (2021) highlighted the influence of socioeconomic disparities on ridership during the pandemic. While prior research (Kock et al., 2020) has emphasized the importance of investigating the role of travel in wellbeing during the pandemic, no evidence of this role has been reported to date. Therefore, understanding the impact of travel on wellbeing during the pandemic is critical, especially given the stringent travel restrictions and lockdowns. This study proposes that the decline in various forms of travel in Great Britain during the pandemic has had a negative impact on wellbeing, as measured by happiness and other related factors.

This study aims to investigate the potential impact of the pandemic-induced drop in travel on wellbeing in Great Britain. Previous research has suggested that travel can have a positive effect on wellbeing, but testing this theory can be challenging due to the complexity of travel behaviour and potential endogeneity issues (Mamatzakis et al. 2023). Building on this previous research, this study examines the association between various modes of travel and wellbeing during the pandemic. To address endogeneity issues, the study employs a model that treats all variables as endogenous, allowing for a more comprehensive assessment of the relationship between travel and wellbeing. The findings of this study could have important implications for understanding the role of travel in promoting wellbeing, particularly during times of crisis such as the pandemic. To this end, this study employs a novel methodology to examine the impact of the pandemic and government interventions on travelling in Great Britain and its subsequent impact on wellbeing. The proposed methodology employs a Bayesian simultaneous vector autoregression system of equations that nests all available socio-economic information, including survey data on happiness and life satisfaction and hard data such as infections, mortality, and number of flights. The model allows for the disentanglement of the impact of Covid-19 shocks, including infections, hospitalisations, deaths, and social and economic restrictions, on wellbeing and travelling. The Bayesian Vector Autoregressive (Bayesian VAR) model provides Impulse Response Functions that measure the responses of wellbeing and travelling to these shocks. Bayesian methods are opted to estimate the model's parameters due to their superiority in handling over-parameterisation compared to other VAR estimations. This approach will provide valuable insights into the complex relationship between Covid-19, travelling, and wellbeing, and inform evidence-based policies and interventions to promote sustainable and healthy travel practices during and after the pandemic.

This study contributes in many ways: first, we collect recent data of weekly frequency to test the hypothesis whether Covid-19 has had a detrimental impact on travelling and thereby on wellbeing; second, we employ a Bayesian VAR analysis and perform simulations to choose the best Bayesian VAR model; third, given the plethora of COVID-19 related data as well as various government interventions we estimate Impulse Response Functions for each variable in the model, treating variables as endogenous without imposing any a-priory causation. Fourth, we provide simulations for future paths of travel in UK and wellbeing based on different scenarios that would also control for new health developments such as test and trace applications, drag, and vaccine discovery. The results are useful for policymakers as they provide evidence of how government interventions due to Covid-19, i.e., travel restrictions, adversely affected wellbeing in Great Britain through their impact on travelling. A key policy implication of present study is to allow safe travelling that safeguards health protocols regarding Covid-19, rather than imposing draconian measures that ban travelling all together.

In what follows section 2 discusses prior research and travelling in the Great Britain; section 3 presents the Bayesian panel VAR model and the identification strategy while section 4 and 5 presents the data section and results respectively. Section 6 offers the main discussion of results, and the last section presents some concluding remarks.

2. Literature Review

The negative impact of COVID-19 on the tourism industry is well-documented ICAO 2022; UNTWO, 2020; Kock, et al. 2020). However, there is limited research on the specific implications of the pandemic on the mental health and wellbeing of travellers and the broader population in Great Britain. The pandemic has disrupted social connections and support networks, leading to increased rates of anxiety, depression, and stress worldwide. Additionally, travel restrictions and social distancing measures have limited opportunities for social interaction and leisure activities, which can also impact mental health and wellbeing. The impact of the pandemic on wellbeing may vary depending on individual circumstances, such as social support, financial stability, and access to healthcare. Studies have shown that the pandemic has had a significant impact on mental health and wellbeing worldwide, with increased rates of anxiety, depression, and stress reported (Ma et al. 2022; Qu et al. 2022). The pandemic has also disrupted social connections and support networks, which can have negative effects on mental health and wellbeing (Hu and Chen, 2021; Habib and Anik, 2021; Kock, et al. 2020). In the context of travel, the pandemic has forced many individuals to cancel or postpone travel plans, leading to disappointment and frustration. Additionally, travel restrictions and social distancing measures may limit opportunities for social interaction and leisure activities, which can also impact mental health and wellbeing. However, it is important to note that the impact of the pandemic on wellbeing may vary depending on individual circumstances and factors such as social support, financial stability, and access to healthcare. Therefore, it is necessary to conduct research specifically focused on the wellbeing implications of the pandemic on travellers and the broader population in Great Britain.

The link between happiness and travel is not new in the literature though (see Kwon and Hoon 2020; Gilbert and Abdullah, 2004; Filep and Deery, 2010). Filep and Deery, (2010) provided evidence that the experience of travelling increases life satisfaction which is confirmed by Kwon and Hoon (2020) (see also Gilbert and Abdullah, 2004). However, the pandemic has had a major negative impact on travel that could have reduced life satisfaction. In addition, there have been exogenous governments interventions that impose draconian lockdowns and severe restrictions to travel that could further reduce life satisfaction. There is also an emerging strand of the literature that shows that the pandemic impacted upon the travelling behavior (Ma et al. 2022; Qu et al. 2022; Hu and Chen, 2021; Habib and Anik, 2021; Kock, et al. 2020). A plethora of factors such as safety, perceived racism, sociodemographic factors, and risk are reported to affect how the pandemic affected travelling behaviour (Ma et al. 2022; Hu and Chen, 2021; Qu et al. 2022). Notably, Ma et al. (2022) reported that the perceived racism is responsible for less walking of people of Asian origin in Australia compared to White people. Qu et al. (2022) and Hu and Chen (2021) argue that less privileged sociodemographic affected walking and ridership during the pandemic. In addition, unequivocally, prior research (Kock, et al. 2020) theorise that travelling restrictions would negatively affect wellbeing during the pandemic. Therefore, to study the impact of travelling on wellbeing during the pandemic is warranted.

Clearly, the harmful impact of Covid-19 on all aspects of both society and economy has been unprecedented in modern history and surpasses any previous health emergencies whether they refer to an epidemic or pandemic (Kock, et al. 2020). Previous research (Kock, et al. 2020) argues that the aviation industry has contributed to the spread of the pandemic in the early stages of the pandemic as it spread rapidly to more than 200 countries. It is no surprise that most countries around the world, some more strictly than others, imposed travel restrictions. These restrictions have resulted in an unparalleled decline in world total passengers. In 2020 the number of passengers worldwide was 60 percent below pre-pandemic in 2019 according to ICAO (2022). There is a slow recovery in 2021, though the number of passengers worldwide was 2.3 billion, or 49 percent below pre-pandemic. In terms of travel data for the UK, the seven-day average of flights in the first week of March 2022 was 69% of the level in the equivalent week of 2020. Overseas residents made 1.3 million visits by air to the UK in the third quarter of 2021, which was 86% less than quarter 3 of 2019. UK residents made 774,000 visits abroad by air in the first quarter of 2021, which was 94% fewer than the corresponding period in the previous year, while holidays were the least likely reason for UK residents' visits abroad. Similar negative trends in other modes of travel, like car and rail, have been observed during the pandemic as strict draconian restrictions were imposed. It is worth noting that the importance of tourism and travel industries for the UK economy is unequivocal and the recorded dramatic fall in those industries have had a negative impact upon the whole economy. The travel and tourism industries contributed 6.7% of all gross value added in the UK in 2018 and are substantial contributors to jobs and growth in the UK, indirectly employing 4 million people and making a direct economic contribution of £75 billion a year pre-pandemic. According to Oxford Economics the fall in contribution of tourism on gross value added was 64% between 2019 and 2020, from £75 billion to £27.2 billion. This fall in tourism's economic output over 2020 is estimated to have led to a 1.5% fall in UK GDP. To add a perspective, the loss caused by COVID-19 in 2020 was eight times more than that of the Global Financial Crisis of 2008-09 (UNTWO, 2020).

3. The Bayesian VAR identification of Covid-19, travel, and wellbeing.

The methodology employed in this study utilizes Bayesian vector autoregression (BVAR), a versatile statistical technique that is particularly useful in modelling relationships between multiple variables in the presence of endogeneity. Specifically, the study focuses on three sets of endogenous variables: COVID-19-related variables, modes of travel in Great Britain, and wellbeing variables. The COVID-19-related variables include infections, hospitalizations, and deaths, which are crucial indicators of the pandemic's impact on public health in Great Britain. The modes of travel in Great Britain considered are flights, car journeys, rail journeys, and cycling, which provide insight into how travel patterns have been affected by the pandemic and how changes in travel behaviour may affect public health and wellbeing. Additionally, the study considers two wellbeing variables, namely life satisfaction and happiness, which are commonly used indicators of wellbeing. These variables enable researchers to understand the broader impact of the pandemic on individual and societal wellbeing.

The use of Bayesian vector autoregression (BVAR) specification in this study allows for the estimation of causal relationships between the selected endogenous variables, including the strength and direction of these relationships. This approach enables researchers to identify the key factors that influence public health and wellbeing during the pandemic, facilitating the development of targeted interventions to support positive outcomes. By selecting endogenous variables such as COVID-19 related variables, modes of travel, and wellbeing variables, the study provides a comprehensive understanding of the impact of the pandemic on these factors. In particular, the study focuses on infections, hospitalizations, deaths, flights, car journeys, rail journeys, cycling, life satisfaction, and happiness as key indicators.

The identification of these key factors and their interrelationships can help guide policymakers and public health officials in developing evidence-based interventions to mitigate the negative impacts of the pandemic on public health and wellbeing.

Following research conducted by Ma et al. (2022), Qu et al. (2022), Hu and Chen (2021) that show the significant impact the COVID-19 pandemic has had on the tourism industry, I model the main variables of the study as endogenous. That is endogenous variables are in a vector $y_t = [y_{t,1}, \dots, y_{t,m}]'$ $(t = 1, \dots, T)$ include all modes of travelling and wellbeing. The literature (Ma et al. 2022; Qu et al. 2022; Hu and Chen, 2021; Habib and Anik, 2021; Kock, et al. 2020) highlights a key criticism related to identification issues in estimating the causal relationships between variables like travel and wellbeing, which are likely to be endogenous. Endogeneity occurs when variables are correlated with the error term in the regression model, leading to biased estimations. This is a common issue in studies related to travel and wellbeing during the pandemic, as factors such as travel restrictions, changes in behavior, and public health outcomes are all likely to be interrelated. Addressing endogeneity is crucial to ensure that the estimated effects of the pandemic on travel and wellbeing are accurate and unbiased. To address this issue, researchers can use statistical techniques like instrumental variables or fixed effects models to control for unobserved heterogeneity and reduce the potential bias in estimations. In addition, I include $z_t = [z_{t,1}, \dots, z_{t,m}]'$ exogenous variables related to Covid-19 such as government interventions to control the pandemic (i.e., closing the schools, restrictions in travelling etc).[1] These variables feed into a Bayesian vector autoregression (VAR):

$$\underset{(m\times 1)}{\mathrm{y}_t} = \underset{(m\times 1)}{\mu} + \underset{(m\times m)}{\mathrm{B}}\, y_{t-1} + \Gamma_{0,(m\times s_t)} \underset{(m\times 1)}{z_t} + \underset{(m\times 1)}{\mathrm{u}_t},$$

$$\mathrm{u}_t \sim \mathcal{N}_m(0, \Sigma), t = 1, \dots, T, \qquad (1)$$

where μ is a vector of constant terms, matrix B contains unknown coefficients, Σ is an unknown covariance matrix, y_t contains information on m endogenous variables that is

[1] In the next section that is discussing data I provide details of all variables and the exogenous ones that include: close of public transport; international travel controls; restrictions on internal movement; close public transport; school closing; workplace closing and restrictions on gatherings and economic support index.

modes of travelling, Covid-19, and wellbeing. z_t is a vector that contains all exogenous control variables, such as government interventions of containment and closure of the economy, for a given t whose dimensionality is $s_t \times 1$. Moreover, $\Gamma_{0,(m\times s_t)}$ contains unknown parameters relating the endogenous variables to the exogenous one.

The Bayesian VAR models are increasingly being used in empirical research due to their ability to handle overparameterization issues and produce more accurate forecasts. Overparameterization occurs when the number of parameters in a model is greater than the number of observations, resulting in a loss of degrees of freedom and poor estimation accuracy. In the case of the present study, the Bayesian VAR model is well-suited for the limited observation period of the COVID-19 pandemic. The Bayesian VAR model treats all parameters as random with prior distributions, which allows for more flexible modeling of complex relationships among variables (see also Koutsomanoli-Filippaki & Mamatzakis, 2011; Mamatzakis, 2011 and Mamatzakis & Remoundos 2011). Additionally, the use of the Minnesota prior helps to reduce the number of necessary lags in the VAR model, which further helps to mitigate the overparameterization issue. Compared to frequentist VAR models, Bayesian VAR models have been shown to produce superior forecasts, as they incorporate prior knowledge and are more flexible in their modeling assumptions. This is supported by research conducted by Banbura et al. (2008) and Dieppe et al. (2016), which found that Bayesian VAR models outperformed frequentist VAR models in terms of forecasting accuracy.

Overall, the use of Bayesian VAR models in this study is justified given their ability to handle overparameterization issues, incorporate prior knowledge, and produce accurate forecasts, which will provide valuable insights into the relationship between travel and wellbeing during the COVID-19 pandemic in Great Britain. The Bayesian estimation of the VAR in the system of equations (1) is simply based on a likelihood function given the probability density function of the data that is conditional on the VAR' parameters. To demonstrate the simplicity of Bayesian VAR vis a vis the overfitting of classical frequentist VAR, I simplify the system of equations (1) to:

$$\underset{(m\times 1)}{\mathbf{y}_t} = \mathrm{B}_{(m\times s_t)} \underset{(m\times 1)}{X_t} + \underset{(m\times 1)}{\mathbf{u}_t}, \qquad (2)$$

where $X_t = (I_n \otimes W_{t-1})$ is a $n \times nk$, $W_{t-1I_n} = (y'_{t-1}, \ldots, y'_{t-p}, z'_t)'$ is $k\times 1$ and $B = vec(\mathrm{B}_1, \mathrm{B}_1, \ldots, \mathrm{B}_1, D)$ is $nk\times 1$.

The following likelihood function provides the probability density function of the data conditional on the unknown parameters estimates.

$$L(y/\beta, \Sigma) \propto |\Sigma|^{-T/2} exp\left\{-\frac{1}{2}\sum_t (y_t - X_t\beta)'\Sigma^{-1}(y_t - X_t\beta)\right\} \qquad (3)$$

whereas the joint prior distribution on the unknown parameters is $p(\beta, \Sigma)$ and the joint posterior distribution conditional on the data using the Bayes theorem is:

$$p(\beta, \Sigma/y) = \frac{p(\beta, \Sigma)L(y/\beta, \Sigma)}{p(y)}$$
$$\propto p(\beta, \Sigma)L(y/\beta, \Sigma), \qquad (4)$$

and thus, the joint probability density is:

$$p(\beta, \Sigma, y) = L(y/\beta, \Sigma)p(\beta, \Sigma)$$
$$= p(\beta, \Sigma/y)p(y), \qquad (5)$$

Given the above, the marginal posterior distributions conditional on the data $p(\Sigma/y)$ and $p(\beta/y)$ can be estimated by integrating out β *and* Σ from $p(\beta, \Sigma/y)$. Then, location and dispersion of $p(\Sigma/y)$ and $p(\beta/y)$ can be further processed to estimate the unknown parameter estimates of β *and* Σ.

In the empirical implementation the integration of $p(\beta, \Sigma/y)$ could be challenging to implement. Numerical integrations based on Monte Carlo simulations methods has been used to ease the integration process in practice. Herein, we opt for the Metropolis–Hastings algorithm that is flexible while the Markov Chain Monte Carlo (MCMC) produces values from a transition kernel so its draws then converge to a distribution that is stationary.

One of the advantages of opting for Bayesian VAR is that we could compare across VARs of different lags based on based on their posterior probabilities rather than imposing a specific lag structure. In Bayesian analysis, the goal is to obtain a posterior distribution for the parameters of interest, given the observed data and the prior distribution. The posterior distribution provides a complete summary of the uncertainty in the parameters, and it can be used for inference, model selection, and forecasting. To estimate the posterior distribution, Bayesian analysis uses Bayes' rule to combine the likelihood function, which quantifies the probability of observing the data given the parameters, with the prior distribution, which quantifies our prior knowledge or belief about the parameters. The resulting posterior distribution is proportional to the likelihood times the prior, and it provides the updated probability distribution for the parameters after observing the data. In practice, it is often difficult to derive the posterior distribution in closed form, especially for complex models with many parameters. Therefore, Bayesian analysis uses Markov Chain Monte Carlo (MCMC) sampling methods to approximate the posterior distribution. MCMC algorithms generate a sequence of random samples from the posterior distribution, which can be used to estimate the posterior mean, variance, quantiles, and other summary statistics.

In the empirical section, we estimate various Bayesian VAR models and opt for Bayes 2000 iterations for reducing the Markov chain Monte Carlo (MCMC) sample size with random-number seed equals to 21 for reproducibility.[2]

4. The data set.

4.1 Covid 19 related data (daily).

[2]To clarify, the Metropolis-Hastings algorithm is a Markov chain Monte Carlo (MCMC) method that generates a sequence of states, each of which is proposed based on the previous state and a proposal distribution. The proposed state is then either accepted or rejected based on a comparison of the posterior probability of the proposed state and the previous state. If the proposed state is accepted, it becomes the new state for the next iteration, otherwise, the previous state is retained. The proposal distribution is often chosen to be a Gaussian distribution centred at the corresponding state level, but other distributions can also be used. The MCMC process allows us to estimate the posterior distribution by generating a large number of samples that converge to the target distribution.

The Covid-19 related data come from three data sources: the Oxford COVID-19 Government Response Tracker (OxCGRT); the Johns Hopkins University's Center for Civic Impact and the Office of National Statistics in the UK and Great Britain.

In terms of the data, we measure exposure to the pandemic using three main variables: confirmed infections, hospitalisations of patients with Covid-19 and confirmed deaths noted as mortality thereafter (see Table 1). In the Bayesian VAR models, those three variables are modelled as endogenous. As a control variable of exogenous government interventions, we include the stringency index that provides a composite measure based on nine response indicators of government interventions to control the pandemic. This stringency index includes information such as school closures, workplace closures, and travel bans. And it is scaled from 0 to 100 with 100 being the strictest regime of imposed restrictions as defined by Hale et al. (2020). In addition, as part of the empirical identification, the Bayesian VAR includes the following exogenous variables: close of public transport; international travel controls; restrictions on internal movement; close public transport; school closing; workplace closing and restrictions on gatherings (see Table 1).[3] I also consider the economic support index that provides information about governmental support in the form of income and debt relief.

[3] Unnecessary travel was first discouraged on 16 March 2020 within the UK, before a nationwide lockdown was announced on 23 March. The Foreign and Commonwealth Office advised against all non-essential overseas travel on 17 March. Since then, the UK economy experience a wave of relaxing restrictions and imposing further lockdowns. In summer 2020, some restrictions were gradually relaxed with the opening of non-essential retail, followed by the implementation of quarantine-free travel corridors. Travel was again impacted by the second and third lockdowns in November 2020 and January 2021 and travel corridors were suspended in January 2021.

Table 1: Covid-19 related data.

	OBS	Mean	Std. Dev.	Min	Max
Mortality	110	6.710533	1.361091	1.609438	9.158521
Hospital	110	9.096626	8.076435	0.5	36.68
Infections	110	0.0144446	0.014947	0.0005	0.0685
Stringency	110	55.85418	22.81549	0	87.96
Close Public Transport	110	0.7818182	0.4149017	0	1
International Travel Controls	110	2.036364	1.140797	0	3
Restrictions on Internal Movement	110	0.8272727	0.90725	0	2
Close Public Transport	110	0.7818182	0.4149017	0	1
School Closing	110	1.490909	0.9553851	0	3
Workplace Closing	110	1.890909	0.9418453	0	3
Restrictions on Gatherings	110	3	1.597016	0	4
Economic Support Index	110	76.36364	38.43802	0	100

Source: Oxford COVID-19 Government Response Tracker (OxCGRT).

All the above data are available on a daily base. However, given that the remaining data of this paper are available on a weekly base, the reported data in Table 1 are weekly. Therefore, in the subsequent empirical estimations of Bayesian VAR the time unit will be the week.

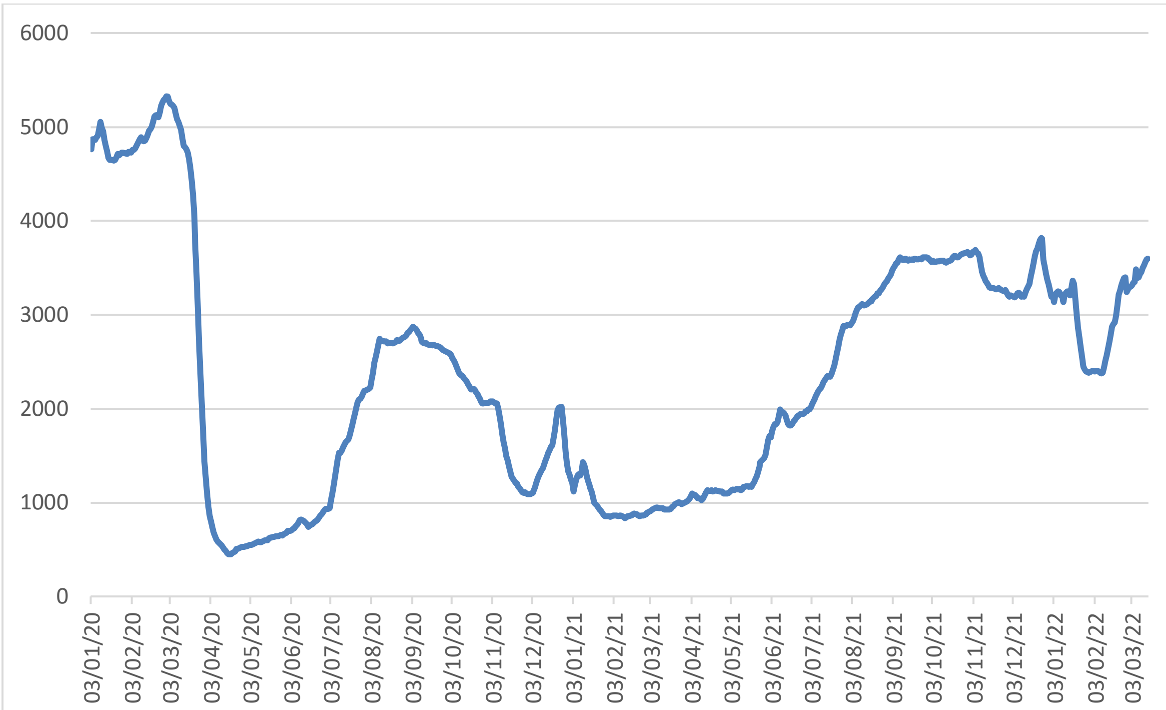
4.2 Travel in Great Britain.

Great Britain experiences a dramatic decline in travel in 2020 and 2021, while only in early 2022 a reversal of the negative trend was observed. In detail, Great Britain residents made 774,000 visits abroad by air in the first quarter of 2021, which was 94% fewer than the corresponding period the previous year. Expenditure by Great Britain residents as results also falls to £817 in the first quarter of 2021. This represents 90% less expenditure than in Quarter 1 2020.[4] The largest number of visits was made to Europe (396,000), but they still

[4] Due to Covid-19 restrictions there are insufficient data for sea and tunnel data.

saw a fall of 95%, while holidays were the least likely reason for Great Britain residents' visits abroad. In Quarter 1 of 2021, there were just 49,000 holidays. Visits to friends or relatives were the most common reason for travelling accounting for 76% of all visits (587,000). In Figure 1 we show the dramatic decline in Great Britain flights residents due to the draconian measures to combat Covid-19, such as lock downs, restrictions to travel.

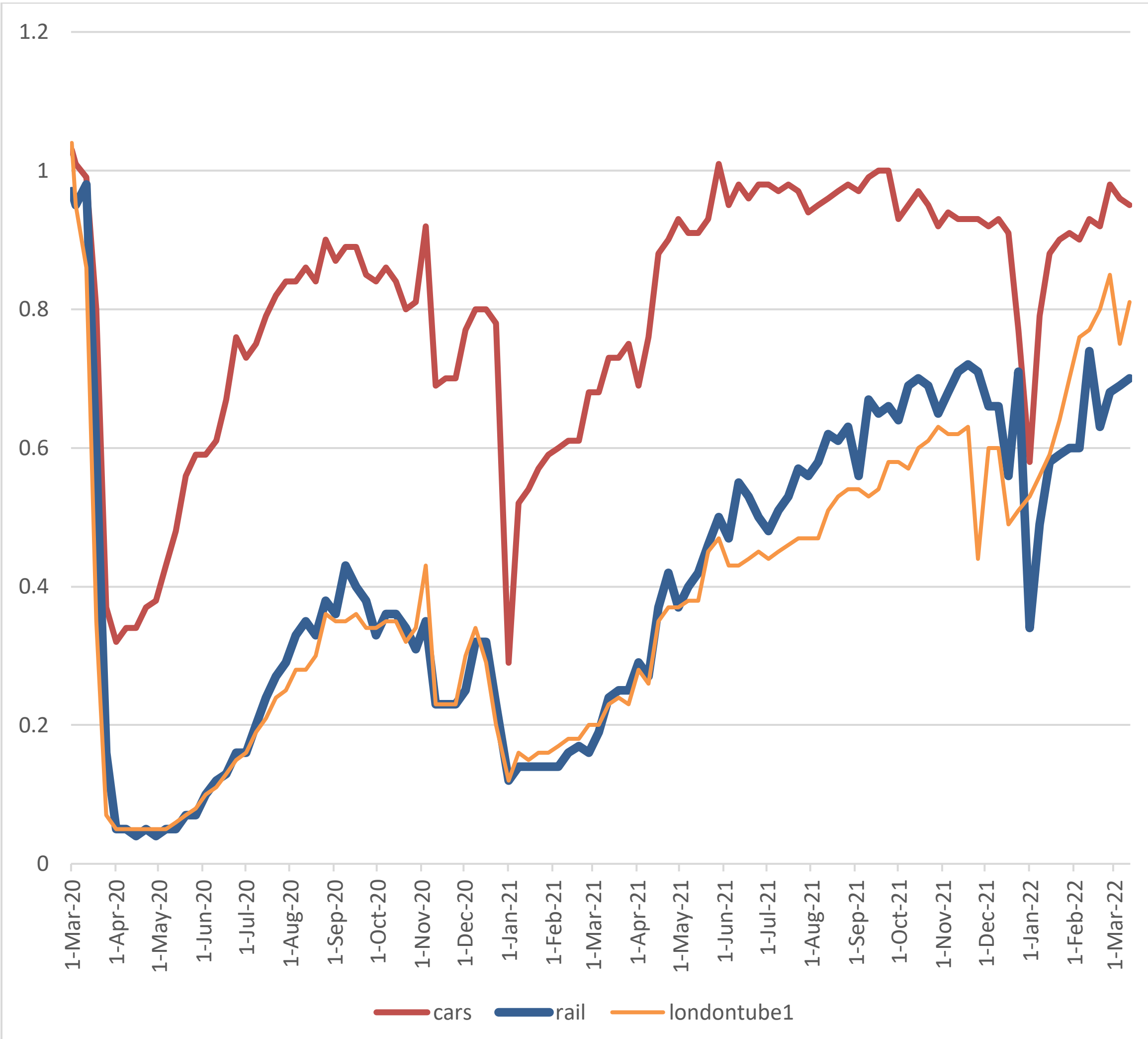
Figure 1: Great Britain flights during the pandemic.



Source: ONS. Figure is in thousands.

We also use data from Transport Great Britain, Department for Transport (DfT), that publishes travel data for Great Britain during the coronavirus (COVID-19) pandemic. To monitor the use of the transport system during the coronavirus (COVID-19) pandemic, the DfT provides statistics on various transport use by mode. These statistics on transport use are published weekly. In detail, the DfT produces statistics for road traffic in Great Britain; rail passenger journeys in Great Britain; transport for London (TfL) tube and bus routes; bus travel in Great Britain (excluding London); and last cycling in England. The full time series for these statistics have started on 1st March 2020. Figure 2 reports data for car travel, rail travel and London tube travel as percentages of an equivalent day or week. Clearly, once the draconian restrictions in economic and social activity were imposed, that is the first lock down measures, in March 2020, travel in Great Britain dramatically dropped. Rail and London tube travel collapsed to the all-time low of 5% of full capacity while car travel fell below 30%. Such drops in travel have been unprecedented.

Figure 2: Use of transport modes: Great Britain, since 1 March 2020.



Source: Transport GREAT BRITAIN, DfT provides statistics on transport use by mode.

Table 2 reports descriptive statistics for travelling in Great Britain by the different available modes such as: flights, car, rail, London tube, London bus and cycling. The sample period is from January 2020 to April 2022.

Table 2: Descriptive statistics of travel by Great Britain residents.

	Obs	Mean	Std.Dev.	Min	Max
Flights	115	7.581821	0.646171	6.135565	8.567125
Car	107	0.8023364	0.1841174	0.29	1.03
Rail	107	0.4060748	0.2312263	0.04	0.98
LondonTube	107	0.3794393	0.2110613	0.05	0.87
LondonBus	107	0.3695327	0.1971418	0.01	0.75
Cycling	107	0.6092523	0.3563989	0.01	1.59

Source: Transport Great Britain, DfT provides statistics on transport use by mode.

4.3 Life satisfaction (weekly data)

Table 3 presents the descriptive statistics of the Office of National Statistics of wellbeing variables in Great Britain and their diagrams.

Table 3: Descriptive statistics of wellbeing in Great Britain.

	Obs	Mean	SD	Min	Max
Life satisfaction	95	6.901176	0.207877	6.4	7.2
Worthwhile	95	7.307059	0.1172992	7	7.6
Happiness	95	6.934118	0.2275924	6.4	7.4
Anxious	95	4.022353	0.2656423	3.6	5.2

Source: Office of National Statistics, ONS.

Figure 3 reports the survey questions of life satisfaction, happiness, and anxiety of the Office of National Statistics. One of the survey questions pertains to the perceived worthwhileness of the activities carried out by Great Britain residents. Clearly, Figure 3 shows that wellbeing whether measured by life satisfaction or happiness dropped during the first lock down in spring 2020. Anxiety, on the other hand, increased during the first lock down. Ever since there is variability over time.

Figure 3: Wellbeing of Great Britain residents.

Source: Office for National Statistics – Opinions and Lifestyle Survey

It is worth noting that while there has been some recovery in wellbeing measures, the levels remain below pre-lockdown levels, as shown in Figure 3. This suggests that the impact of the pandemic on wellbeing has been significant and may have long-term effects. The continued variability over time may also indicate ongoing challenges and uncertainty related to the pandemic and its impacts.

5. Empirical results.

5.1 Bayesian VAR: model selection

In this section, we proceed with the estimation of Bayesian VAR model which is a system of equations of the endogenous variables travelling in Great Britain, Covid-19, and wellbeing. Given the complexities of dealing with the pandemic, government interventions are treated as exogenous variables within the VAR that would be allowed to asset effects on endogenous variables. As a first step in selecting the appropriate VAR model, we test for the lag order. One of the advantages of Bayesian VAR is that allows the comparison across models of different lags based on their posterior probabilities. One of the main advantages of Bayesian VAR is that it is does not suffer from overparameterization and relies on fewer lags than frequentist VARs. To select the lag order, I opt to estimate Bayes factors to be able to select the best model. To this end, I estimate four Bayesian VAR models for lags from one to four. All model specifications include Bayes 2000 iterations for reducing the Markov chain Monte Carlo (MCMC) sample size with random-number seed equals to 21 for reproducibility.[5]

The output table's first column lists the log-marginal likelihoods. The probability for the prior model is reported in the second column and are all by default equal to 0.25. The probabilities for the posterior model are reported in the third column. With a probability of 0.88, the simplest model with two lags is by far the best. To this end, in my empirical application a select a Bayesian VAR with two lags.

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[5] As discussed in Section 2, we opt for the Metropolis–Hastings (MH) we choose to sample from a posterior distribution using the Metropolis-Hastings (MH) algorithm. To elaborate on the stages of the MH algorithm, in the first stage, an initial state within the posterior probability distribution is defined. This state is denoted as θ_0. In the second stage, a candidate state θ_* is generated based on a proposal distribution $q(\theta_*|\theta_t)$, which is a probability distribution centered at the current state θ_t. In the third stage, the acceptance probability $\alpha(\theta_t, \theta_*)$ is calculated as the ratio of the posterior probabilities of the candidate state and the current state, multiplied by the ratio of the proposal densities of the current and candidate states. In the fourth stage, a uniform random number u is generated from the interval [0,1]. If u is less than or equal to $\alpha(\theta_t, \theta_*)$, then the candidate state θ^* is accepted as the new state θ_{t+1}, otherwise, the current state θ_t is repeated as the new state θ_{t+1}. This process is repeated iteratively for a predetermined number of steps, producing a Markov chain $\{\theta_t\}^{T-1}t=0$, where T is the number of iterations. The resulting Markov chain approximates the posterior distribution of the model parameters, allowing us to estimate credible intervals and make inference about the model. The MH algorithm has numerous stages. The beginning stage θ_0 within the posterior probability distribution $q(\cdot)$ and $p(\theta_0|y) > 0$ are defined in the first stage,.
Also, the proposal state, θ_*, would be either rejected or accepted based on a defined acceptance probability.
Thus, the stages over time, $t = 1, \ldots, T-1$, are:

- define the proposal state: $\theta_* \sim q(\cdot|\theta_{t-1})$.
- estimate the probability $\alpha(\theta_*|\theta_{t-1}) = \min\{r(\theta_*|\theta_{t-1}), 1\}$,
  where $r(\theta_*|\theta_{t-1}) = [p(\theta_*|y)q(\theta_{t-1}|\theta)]/[p(\theta_{t-1}|y)q(\theta_*|\theta_{t-1})]$
- $u \sim \text{Uniform}(0, 1)$.
- $\theta_t = \theta_*$ if $u < \alpha(\theta_*|\theta_{t-1})$, while $\theta_t = \theta_{t-1}$ otherwise.

In addition, Markov chain is chosen because it safeguards that $p(\theta|y)$ is stationary distribution. The acceptance rate is a key factor in the efficiency of the Markov chain Monte Carlo (MCMC) algorithm. If the acceptance rate is too low, the chain will take a long time to converge to the target distribution. If the acceptance rate is too high, the chain may become stuck in a local mode and not explore the full posterior distribution. In general, an acceptance rate between 0.2 and 0.5 is considered optimal for most problems. Additionally, the degree of autocorrelation is also important because high autocorrelation can slow down the convergence of the chain, making it less efficient. To address this issue, techniques such as thinning and burn-in can be used to reduce autocorrelation and improve efficiency.

Table 4: Lag order selection of Bayesian VAR

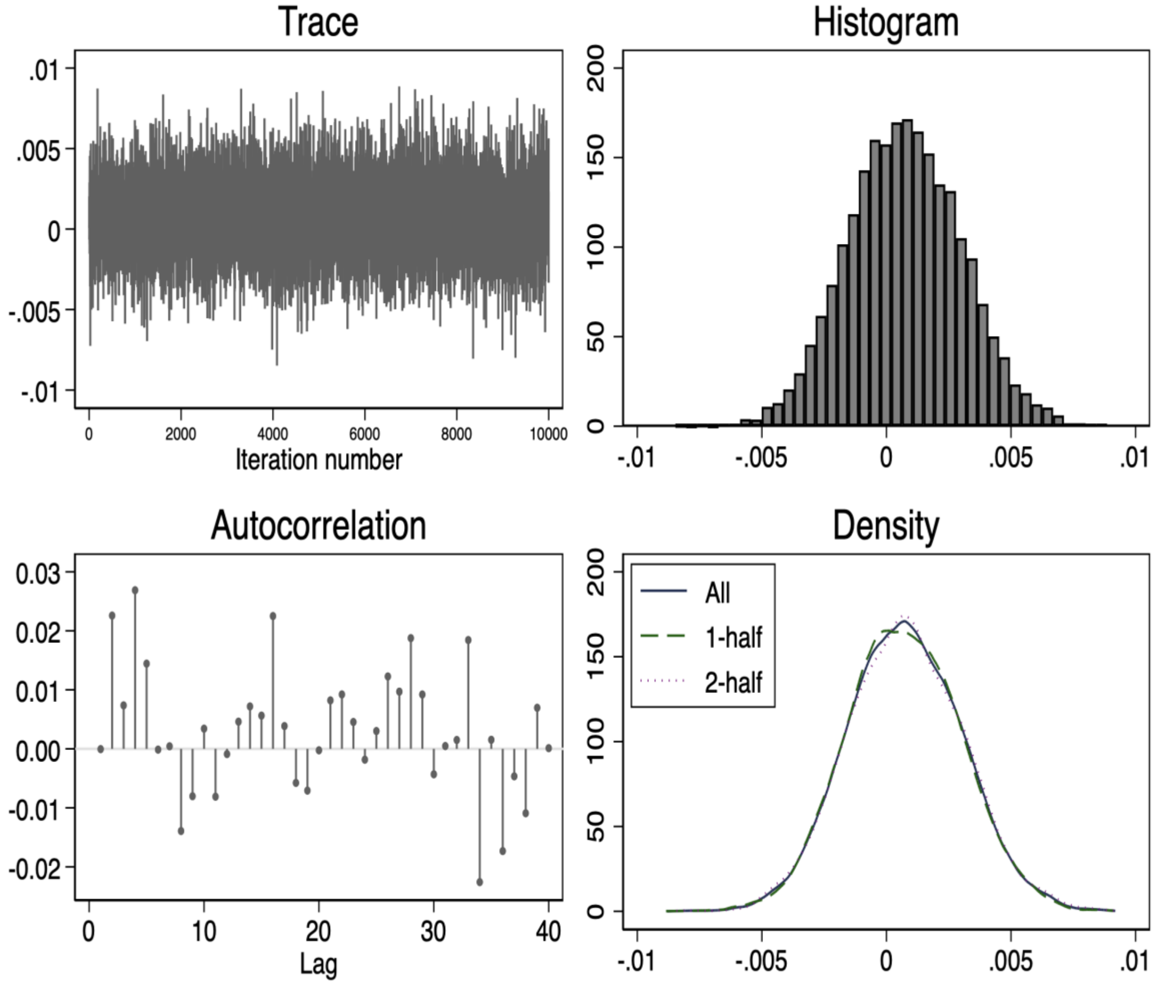
	log(ML)	P(M)	P(M|y)
Lag 1 VAR	96.1081	0.25	0.0025
Lag 2 VAR	90.2462	0.25	0.8811
Lag 3 VAR	92.9371	0.25	0.0598
Lag 4 VAR	92.9901	0.25	0.0567

Source: Author's estimations. I compute Marginal likelihood (ML) using Laplace–Metropolis approximation.

Note that for all Bayesian VAR models' priors for all parameters are included. The regression coefficients of the VAR are grouped for all endogenous variables and the same applies for the variance–covariance matrix of the error terms. For each of the Bayes VAR models we select a Minnesota prior as the default prior.[6] From economic interpretation point of view the parameters of VAR models are not interpretable. Instead, we proceed with the estimations of impulse–response functions (IRFs). Prior to IRFs, as with any MCMC method, we check that MCMC converged before moving on to impulse response functions. To test for stability, we opt for graphical analysis, see Figure 4, which shows that there is stability. In detail Figure 4 reports the trace, the auto correlation, and the density. The trace in Figure 4 indicates that convergence has been achieved, while the correlation shows some variability though it is negligible and zero in less than ten lags.

[6] In the empirical Bayesian estimation, which uses the Gibb's sampling for simulation, converges. We select RSEED to be equal to 21 and the MCMC sample size equal to 2,000. The sampling efficiency at 0.99 is very high. The MCMC sample has a size of 2000 and it has 1990 independent draws from the posterior. Thus, the estimation precision is sufficient. The Bayesian VAR includes all parameters it takes a lot of space, and we opt not to include (results are available under request).

Figure 4: MCMC convergence testing.



Source: Author's estimations.

Only stable VAR models are relevant for postestimation VAR analysis such as impulse-response functions. To evaluate a Bayesian VAR model's stability, we estimate the eigenvalue stability condition for a MCMC sample size of 2000. To facilitate the presentation, we opt not to include the Bayesian VAR parameter estimates (results are available under request). It is also worth noting that I test for ordering of the variables in the VAR and reverse ordering do not alter the main findings. Table 5 reports eigenvalues of VAR's companion matrix, referring to unit circle but are random numbers in a Bayesian context.

Table 5: Lag order selection of Bayesian VAR

	Eigenvalue	Equal-tailed				
Modulus	Mean	Std.Dev.	MCSE	Median	[95%	cred. interval]
1	0.9586793	0.036267	0.000811	0.9566606	0.8954819	1.036839
2	0.8948975	0.0407443	0.000911	0.8962785	0.8147237	0.969641
3	0.8208179	0.0551152	0.001232	0.8258579	0.6999911	0.9121833
Pr(eigenvalues lie inside the unit circle) = 0.871						

Source: Author's estimations.

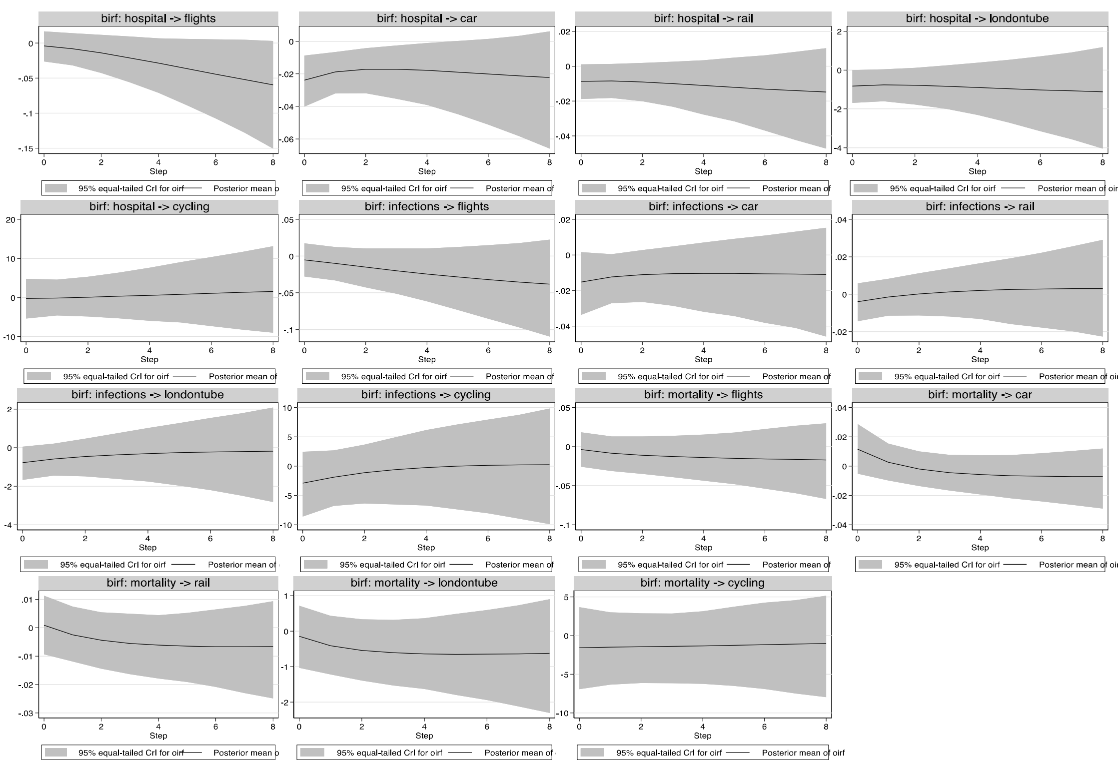
Note that the posterior mean estimated for the eigenvalue of equal tailed modulus are reported in Table 5 in decreasing order from 0.95, 0.89, to 0.82. These eigenvalues are close to one, though just comparing them with one might not suffice for stability. Instead, we also estimate within the unit circle inclusion the posterior probability which is 0.88. Thus, the posterior probability is close to one, implying the model is stable (a probability significantly lower than one would imply). A value close to one indicates that the model is stable and that the shocks will die out over time. The posterior mean estimates for the eigenvalues of equal tailed modulus in Table 5 indicate that the values are close to one, but it's important to also consider the posterior probability of inclusion within the unit circle, which is 0.88. This probability close to one provides additional evidence that the model is stable.

5.2 IRFs of the impact of Covid-19 shocks.

Having selected the appropriate Bayesian VAR model, we present next responses to shocks in the endogenous variables. The primary toolkit for investigating a VAR model consists of impulse response functions (IRFs). They examine how an external shock (the impulse), such as those caused by Covid-19 infections, impacts an internal shock (the response), such as flights in Great Britain.

This study expands on previous research (see Kock, et al. 2020; Kwon and Hoon 2020) that theorise that the pandemic through the decline in travel could negatively impact on wellbeing of individuals. Kock, et al. (2020) and Kwon and Hoon (2020) argue that traveling boost individual's wellbeing and improves life satisfaction. This paper examines this argument as a testable hypothesis rather than accepting it as plausible while we treat all variables as exogenous as causation has not been resolved in the literature. To this end, below, we compute IRFs with a length of 8 steps ahead (that is for eight weeks), equivalent to approximately a two-month period. As a first step of the IRFs analysis we focus on the effects of shocks to Covid-19 related data such as confirmed infections, hospitalisations, mortality, which measures the confirmed deaths, on modes of travel in Great Britain in terms of regular IRFs. We estimate orthogonal IRFs since they are superior to conventional IRFs in that the independence of the impulses is assured.[7]

Figure 5: The response of travelling to shocks in Covid-19.



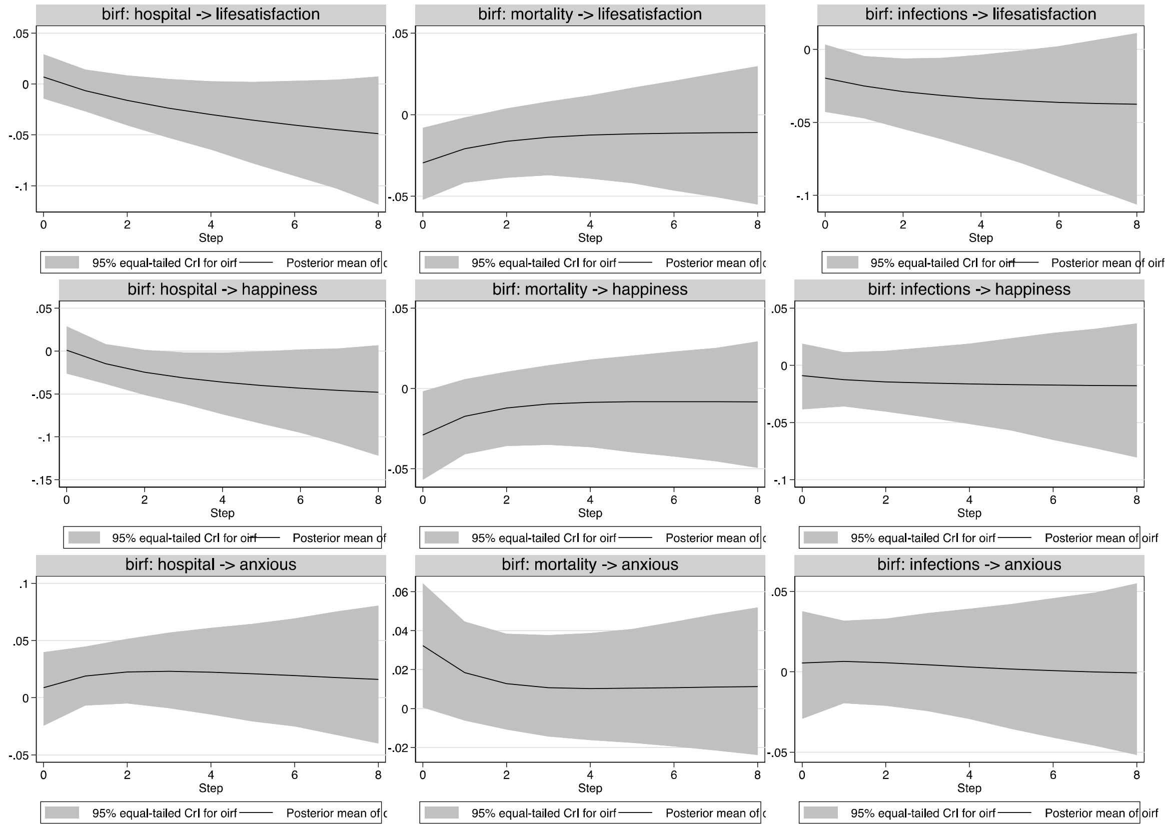
Source: Author's estimations. Hospitals refer to hospitalisation, mortality to confirmed deaths, and infections to confirmed infections.

[7] IRFs that are not orthogonal are available under request. Results remains broadly unchanged.

A shock to confirmed infections has a negative response on all modes of travelling that is flights, car, rail, tube, and cycling. The results conform with the expectation that Covid-19 would assert a negative effect on travelling in Great Britain. Similarly, shocks in hospitalisations and confirmed deaths have negative responses to travelling. It is interesting to note that the response of cycling to shocks in hospitalisations and confirmed deaths is relatively small compared to the other modes of transportation. This could be attributed to the fact that cycling is a relatively safer mode of transportation during the pandemic, as it allows for physical distancing and does not involve being in enclosed spaces with others. Additionally, the government of Great Britain encouraged cycling as a means of transportation during the pandemic by investing in cycling infrastructure and promoting active transportation. Therefore, it is possible that the increase in cycling observed in the data is a result of these policies and initiatives.

Next, Figure 6 reports the response of wellbeing, measured by life satisfaction, happiness, and anxiety to shocks in Covid-19. A shock to confirmed cases has a negative response on life satisfaction and happiness. Clearly, the response of life satisfaction and happiness to shocks in hospitalisations, confirmed deaths, and confirmed infections are all negative and significant for the first two weeks before converging to zero. On the other hand, shocks in hospitalisations and confirmed deaths (that is mortality in the diagram) would increase anxiety. Similarly, the shock in confirmed infections would increase anxiety but statistical significance is low. The negative responses to shocks in Covid-19 on life satisfaction and happiness are concerning, as these factors are important for overall quality of life. The increase in anxiety in response to shocks in hospitalisations and confirmed deaths highlights the psychological toll of the pandemic on individuals. It is important for policymakers and public health officials to consider these impacts when developing interventions and strategies to address the pandemic.

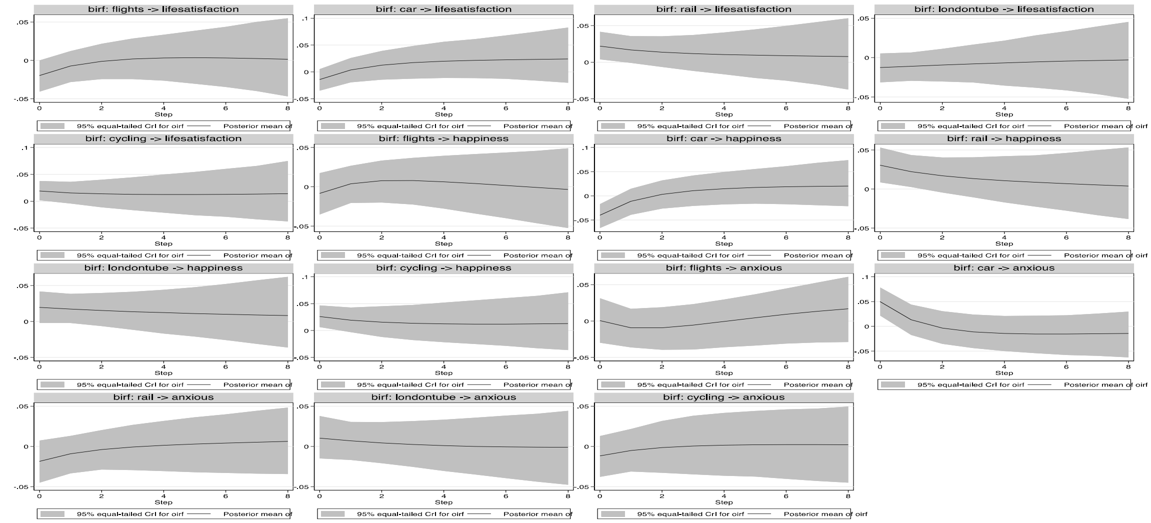
Figure 6: The response of wellbeing to shocks in Covid-19.



Source: Author's estimations. Hospitals refer to hospitalisation, mortality to confirmed deaths, and infections to confirmed infections.

As the Bayesian VAR has three main endogenous sets of variables: travel, Covid-19 data, and wellbeing, we report next the impact of shocks in travel on wellbeing as measured by life satisfaction, happiness, and anxiety. Interestingly, the response of life satisfaction and happiness to rail and cycling are all positive and significant for the first two weeks before converging to zero. The response of life satisfaction to car travelling is negative but it is increasing and crossing the zero line within a week. Similarly, the response of happiness to shocks in car is negative but increase over time and reaches positive values in week two and onwards. Shocks in rail and cycling assert a negative impact on anxiety. Shocks in flights also reduce anxiety, though the latter has a lower magnitude and significance than the effect of cycling and rail. Interestingly, shocks in car and tube would increase anxiety, though these effects last short time and are diminishing.

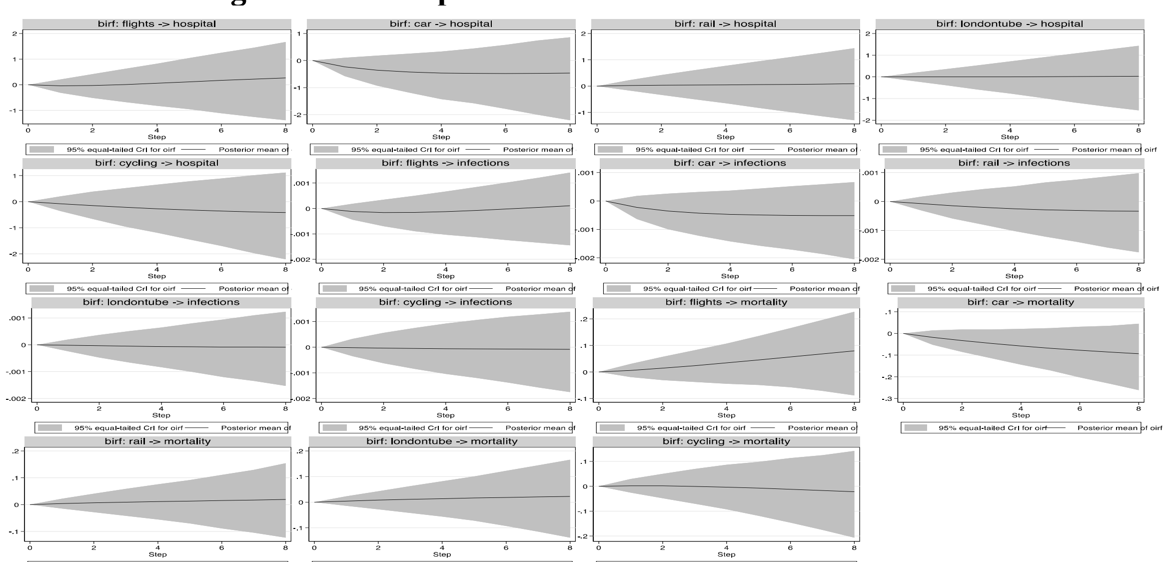
Figure 7: The response of wellbeing to shocks in modes of travel (flights, car, rail, tube, and cycling).



Source: Author's estimations.

Lastly, we report the IRFs of hospitalisations, confirmed infections and confirmed deaths to shocks in travel. The statistical significance of those IRFs is very low and therefore inference is not meaningful. However, the responses of hospitalisations, confirmed deaths to shocks in car travelling are all negative and statistically significant in the first two weeks. The response of confirmed infections to shocks in car is also negative and significant but it carries a low magnitude.

Figure 8: The response of Covid-19 to shocks in travel.



Source: Author's estimations.

For completeness of the analysis the I also estimate the IRFs of responses of Covid-19 data, like confirmed infections, to shocks in wellbeing life satisfaction (results are available under request). Statistical significance is very low, insinuating that there is little causality from wellbeing to Covid-19.

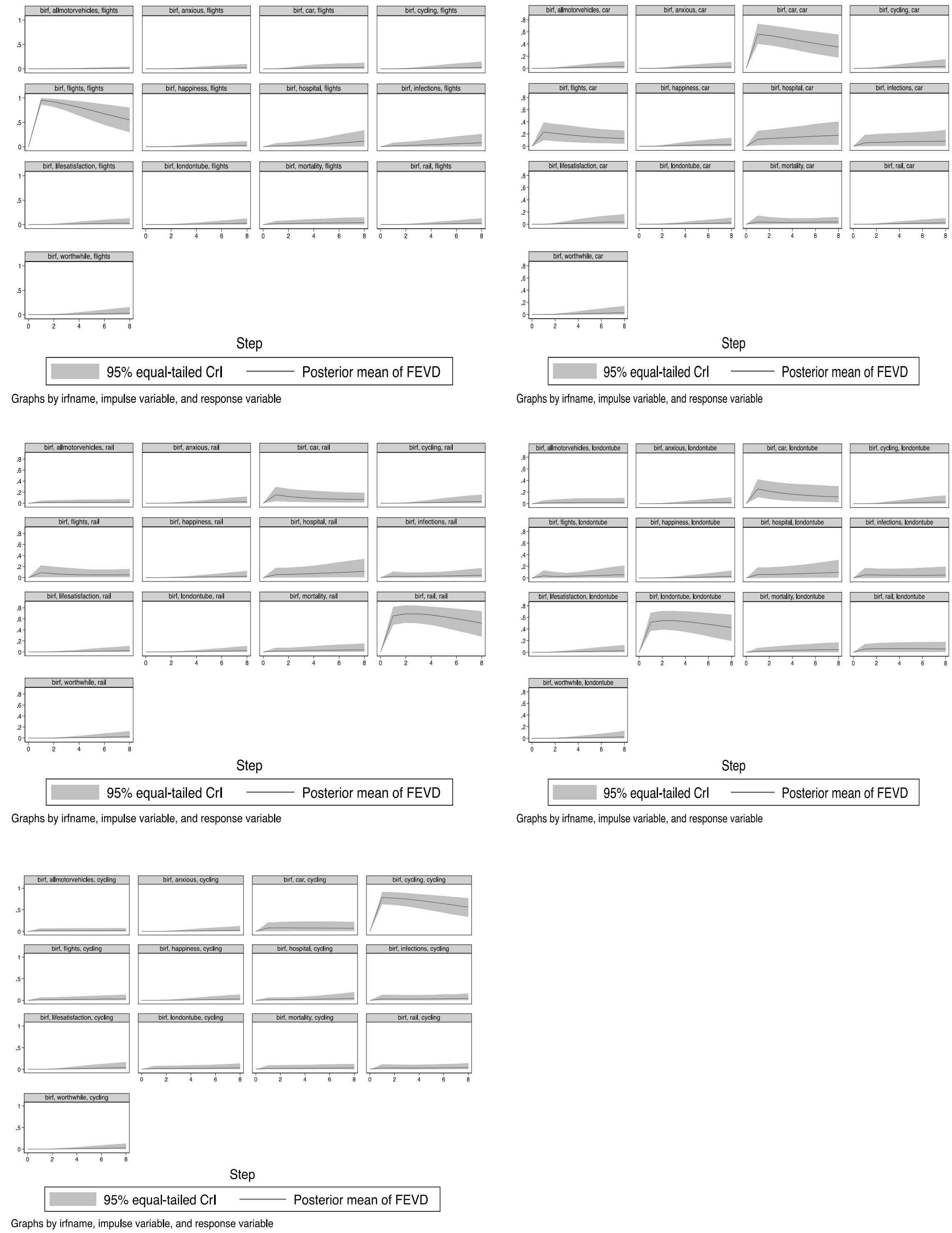
The main results in terms of statistical significance refer to the impact of Covid-19 to travel as expected, but more interestingly the impact of travel on wellbeing. In summary, IRFs show that causality runs from Covid-19 to travelling and from travelling to wellbeing, while and responses of Covid-19 to travelling has little to no statistical significance.

5.3 Forecast Error Variance Decomposition

In this section, we report forecast error variance decompositions (FEVDs). FEVDs provide information on the underlying causal relationships of the response variables. In detail FEVDs estimate the exact variability of the impulse variable that explains the forecast error variance in response variables. To this end, the FEVDs would assist further the identification of the underlying causality among the main three endogenous variables: Covid-19, travel, and wellbeing. Given the plethora of variables as we also include control variables in the Bayesian VAR, I opt to report graphs of FEVDs for simplicity and facilitating the presentation (tables of FEVDs are available under request).

Figure 9 reports the FEVDs of responses in the various modes of travelling in Great Britain such as flights, car, rail, tube, and cycling. In all cases, the FEVDs show that main shocks in travelling explain most of the forecast error variance in travelling. But it is worth noting that hospitalisations due to Covid-19 also explain between 2% and 20% in the forecast error variance of flights and car respectively.

Figure 9: Forecast Error Variance Decomposition: response of travelling.

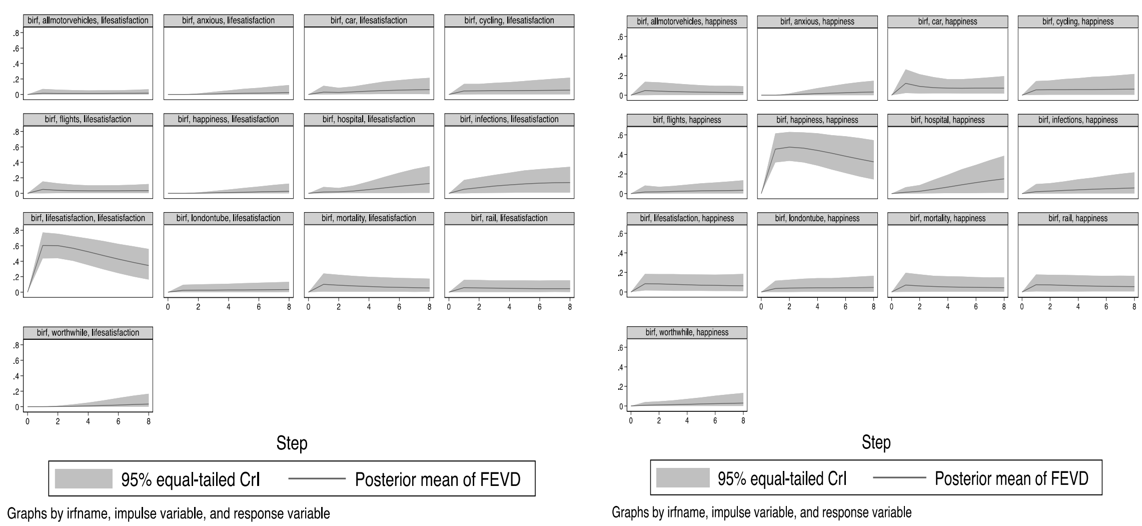


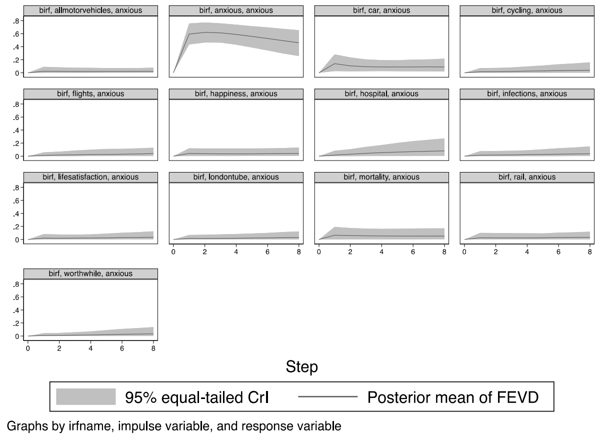
Source: Author’s estimations.

Figure 10 reports the FEVDs of responses in the wellbeing such as life satisfaction, happiness, and anxiety. Again, as expected, the FEVDs show that shocks in wellbeing explain a major proportion of the forecast error variance in wellbeing. In addition, all modes of traveling that are flights, car, rail, London tube, all motor vehicles and cycling help explain the forecast error variance of life satisfaction and happiness whereas Covid-19 related variables, such as hospitalisations, confirmed deaths and confirmed infections, also cause wellbeing. When we measure wellbeing with anxiety the FEVDs confirm the importance of modes of travel for anxiety. The FEVDs show that causal relationship between travel and wellbeing is clearly from the former to the latter. The decline in travel affects wellbeing over the period of eight weeks and shows persistence.

The results suggest that changes in travel modes can have a significant impact on anxiety levels over a period of eight weeks, with the causal relationship going from travel to wellbeing. This persistence in the effect may indicate that the disruption caused by changes in travel modes may have a long-lasting impact on anxiety levels. It is worth noting that while the FEVDs confirm the importance of modes of travel for anxiety, other factors may also play a role in determining wellbeing, such as social and economic factors, and individual coping strategies.

Figure 10: Forecast Error Variance Decomposition: response wellbeing.

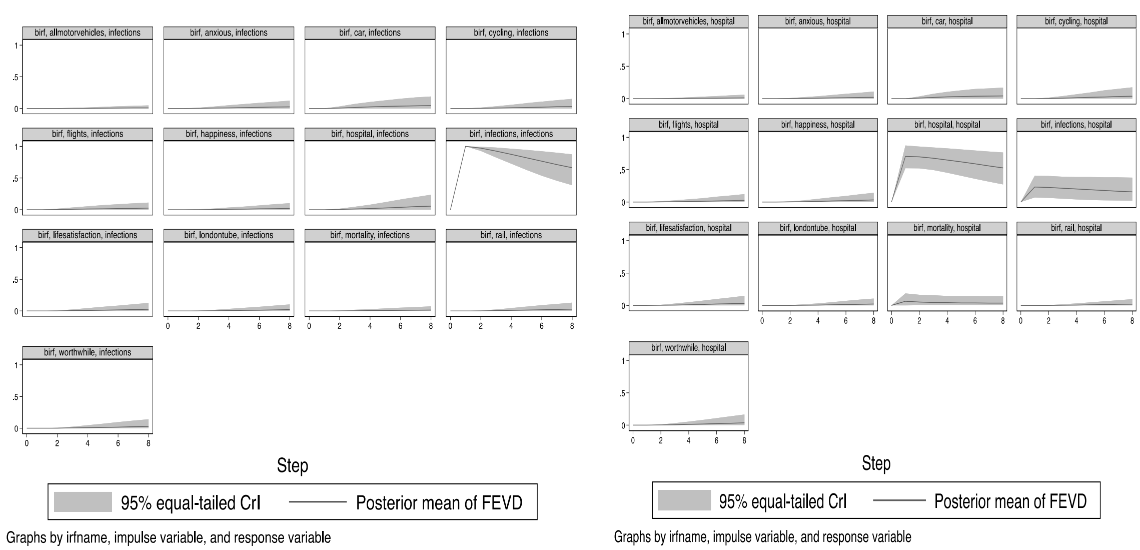


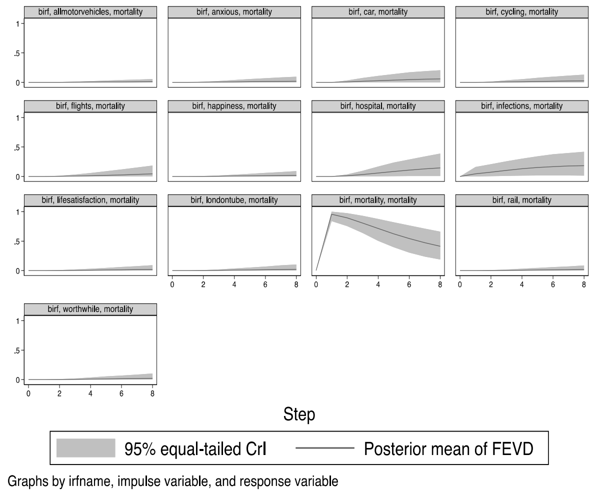


Source: Author’s estimations.

For completeness, Figure 11 reports the FEVDs of responses in Covid-19 related variables. The FEVDs show that shocks in Covid-19 explain most of the proportion of forecast error variance in Covid-19. It is worth noting confirmed infections would explain 70% of confirmed infections, though confirmed infections would also explain a high percentage of 20% of hospitalisations and 5% of confirmed deaths (mortality). Travelling, like flights, explain a very low (less than 0.5%) of forecasts error variance of Covid-19, providing evidence that restrictions in travelling do little to control the pandemic.

Figure 11: Forecast Error Variance Decomposition: response Covid 19





Source: Author's estimations.

The forecast error variance decompositions do not directly show whether the decline in traveling is going to persist beyond the short term or not. Instead, they provide information on the relative importance of each shock in explaining the forecast error variance of the endogenous variables over a certain forecast horizon. Our findings show that the decline in traveling due to the pandemic could have long-lasting effects on wellbeing, particularly on life satisfaction and anxiety, as suggested by the results of the FEVDs. These effects may persist even after the pandemic is over and traveling returns to pre-pandemic levels. It is important to consider these potential long-term effects in policy and decision making.

5.4. Bayesian forecasting

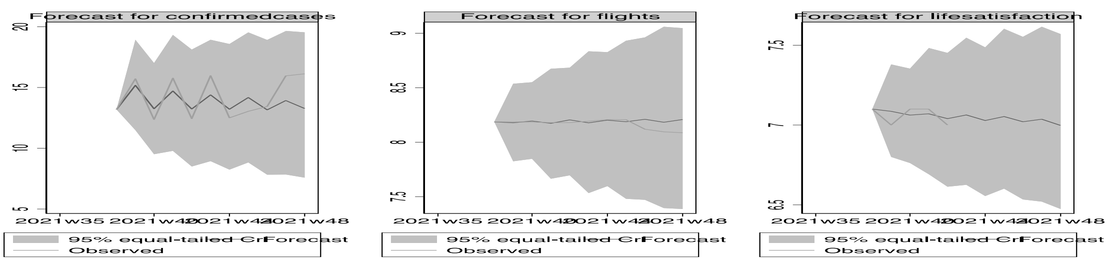
Finally, we use the Bayesian VAR to provide dynamic forecasting for selected endogenous variables such as flight, confirmed cased and life satisfaction. The Bayesian forecasts provide the posterior predictive distributions at certain weeks ahead. Such forecasting exercise is superior to frequentist forecasting, that is based on point estimates. Note that we compute Bayesian forecasts based on information about lower and upper significance levels, posterior mean estimates, posterior standard deviations for all the endogenous variables.[8]

[8] To simplify the reporting, I do not report these estimates and opt instead to summarize results using diagrammatic analysis. Results are available under request.

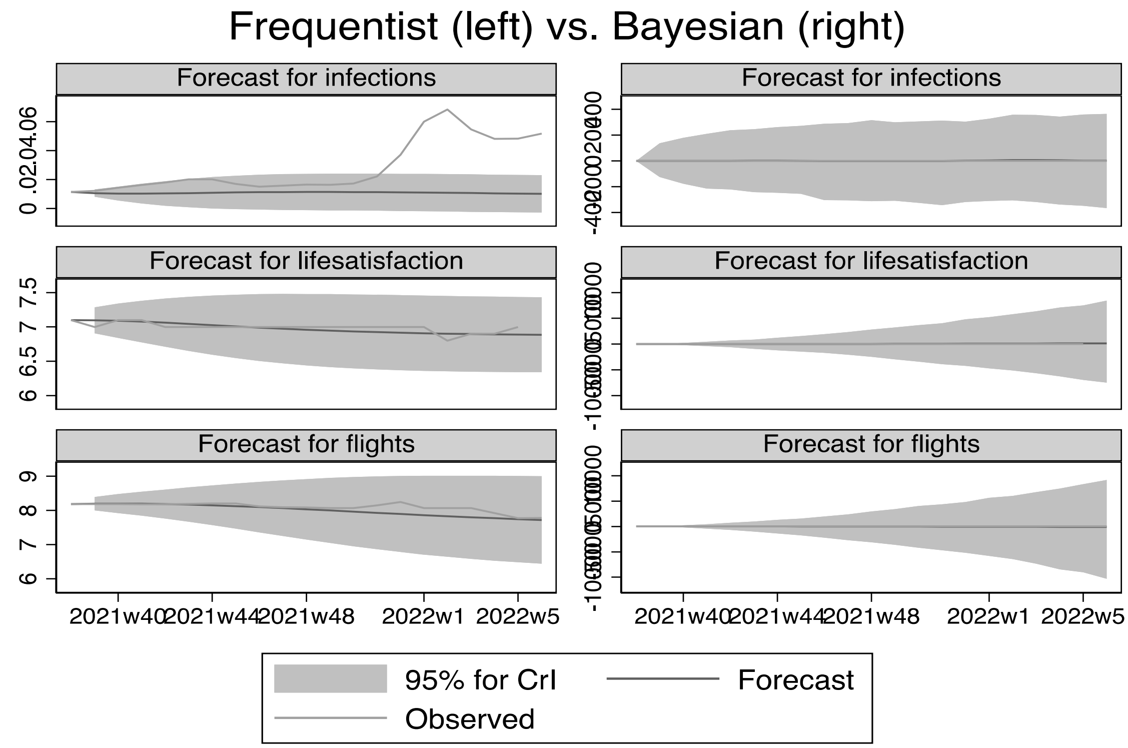
We use observed values of confirmed cases, flights, and life satisfaction at the beginning of the forecast period (week 39 of 2021) and the week before (because we fit VAR (2)) to compute dynamic forecast. In Figure 12, we provide that computed Bayesian forecasts starting from 2021 week 39 into the future.

The posterior mean estimates forecast an initial increase in the confirmed cases and a drop in the flights and life satisfaction, followed by negligible trends of both towards the end of the sample period. The posterior mean forecasts would count for the fluctuations over time. The credible intervals are of 95% level and Figure 12(a) reports them for confirmed cases, flights, and life satisfaction. As a last, step of forecasting accuracy of Bayesian VAR, we report the comparison in forecasting performance between the current Bayesian model and simple frequentist VAR model. Clearly, the Bayesian VAR provides superiors forecasts (see Figure 12 b). The reported evidence shows that the Bayesian forecasting performance is significant and there is sufficient predictive power.

Figure 12: (a) Forecasting based on Bayesian VAR



(b) Comparing forecasting of Bayesian VAR vs frequentist forecasting.



Source: Author's estimations.
The above IRFs suggest show that Covid 19 shocks would negatively impact on all modes of travelling (flights, car, rail, tube, and cycling) and thereafter to individuals' wellbeing, measured by life satisfaction and happiness, while they would increase anxiety further deteriorating life satisfaction and happiness. Testing for reverse causality from wellbeing to travel and Covid -19 shocks is rejected. These results are also confirmed by forecast error variance decompositions (FEVDs). It is worth emphasising that in terms of anxiety the FEVDs show that the decline in travel increase anxiety over the period of eight weeks and it shows some persistence, though this would fade beyond the medium term (i.e., 2 semesters).

These findings augment previous evidence (Kock, et al. 2020) and have important policy implications for the wider world. Clearly, Covid-19 adversely affects the society and the tourism industry. Kock, et al. (2020) postulate that the aviation industry contributed to the spread of the Covid-19 infection while all countries around the world impose draconian travel restrictions. As a result, in 2020 and 2021 the number of passengers worldwide was 60% and 49% respectively below pre-pandemic (see ICAO 2022). The Great Britain travel industry was particularly hit, and recovery has been slow. The seven-day average of flights in UK in the first week of March 2022 was 69% of the level in the equivalent week of 2020. This study, for the first time, shows that Covid -19 pandemic severely reduce travelling and as a result negatively affected the wellbeing of individuals in Great Britain. To this end, the reported results urge for caution when it comes to impose draconian measures against travelling, as such measures would reduce the wellbeing of the society, while from the reported results there is little evidence to substantiate that travelling has been aggravating Covid-19. Key is to have measures in place for safe travelling without resorting to draconian measures of banning travelling. The consequences of banning travelling go beyond their economic impact as it severely affects the wellbeing of the society.

7. Conclusions

The paper employs a unique Bayesian Vector Autoregressive model. This model provides Impulse Response Functions that measures the responses in wellbeing and travelling to shocks due to Covid-19 such as infections, hospitalisations, deaths as well as social and economic restrictions. It also provides reverse responses as endogeneity is treated within the VAR while we control for exogenous government interventions like the closure of the economy and economic support. I also perform forecasting exercise. The main finding shows that the pandemic would cause an unprecedented decline in travelling but this is not going to persist beyond the short term, while lower travelling would reduce life satisfaction and increase anxiety. The causal relationship runs from Covid-19 to models of travel and from the various modes of travelling to life satisfaction and happiness in Great Britain, while Covid-19 reduces life satisfaction and increases anxiety. Interestingly, results report little to no evidence of responses to confirmed cases of Covid-19 and confirmed deaths as well as hospitalisations to shocks in various modes of travel such as flights, car journeys, and rail.

The pandemic has had profound implications across various industries and one industry that has been negatively particularly affected is the travel industry. Previous research shows that travel could enhance life satisfaction and could boost happiness. This paper uses a new data set that allows investigates whether the wellbeing in Great Britain, measured by life satisfaction and happiness, has been affected by the dramatic decline in travelling during the pandemic. Travel is negatively affected by shocks in Covid-19 and in turn, shocks in travel would reduce wellbeing. Interestingly, results show little to no evidence of responses of Covid-19 to shocks in various modes of travel. The forecasting exercise shows that the unprecedented decline in traveling due to pandemic is not going to persist beyond the medium term, though its negative effect on life satisfaction could last in the medium term.

Based on the findings of this study, there are important policy implications for the management of travel during the COVID-19 pandemic in Great Britain. Specifically, the study suggests that safe travel in line with health protocols should be allowed, as draconian measures that ban travel altogether have negatively impacted wellbeing without necessarily being effective in controlling the pandemic. This implies that policymakers should prioritize measures that balance public health concerns with the need to support individual wellbeing and social connectedness through safe travel options. For example, policies could be developed to encourage safe travel practices, such as wearing masks, practicing social distancing, and providing regular testing for travellers. Additionally, policymakers could consider developing targeted interventions to support the wellbeing of individuals affected by travel restrictions, such as providing access to mental health services and social support networks.

The study underscores the need for policymakers to take a balanced approach to managing travel during the COVID-19 pandemic, which recognizes both the importance of protecting public health and the need to support individual wellbeing and social connectedness through safe travel options. By considering a range of COVID-19 related variables, modes of travel, and wellbeing variables, the study provides valuable insights into the complex relationships between travel and wellbeing during the pandemic. These insights can inform evidence-based policymaking that prioritizes the health and wellbeing of individuals while also considering the broader social and economic impacts of travel restrictions. In summary, the study highlights the importance of adopting a nuanced and evidence-based approach to policymaking during the COVID-19 pandemic, which considers the multiple dimensions of travel and wellbeing and balances competing interests to support public health and individual wellbeing.

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