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

MAMATZAKIS, emmanuel and MAMATZAKIS, E

Birkbeck College, University of London

6 May 2022

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

Emmanuel C. Mamatzakis[a]

May 2022

Abstract

The paper investigates whether the wellbeing in Great Britain, measured by life satisfaction and happiness, is affected by the dramatic decline in travelling during the pandemic. I employ a Bayesian vector autoregression (VAR) that includes wellbeing, travel, and Covid-19 as endogenous variables while it controls for exogenous variables. I include in the VAR various modes of travel, like flying, car, rail, and cycling and various Covid-19 related variables like confirmed infections, confirmed deaths and hospitalisations. The empirical findings of impulse response functions provide detailed responses of wellbeing and traveling in Great Britain to shocks in Covid-19 while testing for the direction of causality. 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. So, while the decline in travel reduces wellbeing, it does little to combat Covid-19. The forecast error variance decomposition analysis confirms the importance of travel for wellbeing and shows that while the pandemic has caused an unprecedented decline in traveling, this is not going to persist beyond the medium term. However, the decline in traveling in Great Britain would have a negative effect on life satisfaction and a positive effect on anxiety and such effects could persist. Lastly, the paper provides forecasting of the main endogenous variables.

Keywords: Wellbeing; Travel in Great Britain; Covid 19; Bayesian VAR.

[a] I certify that I have the right to deposit the contribution with MPRA.Professor of Finance, Department of Management, Birkbeck, University of London, Malet Street, Bloomsbury, London WC1E 7HX, UK. E-mail: e.mamatzakis@bbk.ac.uk. The Author acknowledges financial support from ESRC ES/V015826/1.

1. Introduction

The paper investigates whether the wellbeing in Great Britain, measured by life satisfaction and happiness, is affected by the dramatic decline in travelling during the pandemic. The focus is on how Covid-19 would affect travel in Great Britain and thereby wellbeing. Kock, et al. (2020) and Zenker and Kock (2020) propose that it is worth studying whether Covid-19 could have an impact on consumer behaviour, identifying factors such as safety and risk as key to understanding changes in behaviour. The authors further highlighted the significance of future research revealing the psychological traits of travellers during the pandemic. So, it is worth examining whether decline in travelling during the pandemic would have an impact on wellbeing as measured, for example, by happiness.

The link between happiness and travel is not new in the literature (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 impact on travel, and it could be case that has shifted consumer behavior and the steady state of the industry a decline of travel due to the shock in Covid-19 could enhance life satisfaction. In addition, there have been exogenous governments interventions that impose draconian lockdowns and severe restrictions to travel. To this end, th

To investigate the above, we follow Kock, et al. (2020) and focus on wellbeing implications of decline in travel during the pandemic. The main hypothesis is related to the literature that shows a positive correlation between travel and wellbeing (Kwon and Hoon 2020; Gilbert and Abdullah, 2004; Filep and Deery, 2010), that is the observed sharp decline in Great Britain travelling during the pandemic would have a detrimental impact on wellbeing. To test this hypothesis, I employ a novel methodology where a Bayesian simultaneous vector autoregression system of equations, without imposing exogeneity assumptions, nests all available socio-economic information whether refers to survey data such as happiness and life satisfaction, or hard data such as infections, mortality, and flights. Government interventions to control the pandemic are treated as exogenous.[1] The model allows disentangling the impact of the pandemic and government interventions on travelling in Great Britain and in turn its impact on wellbeing.

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 (see for a review Sun, et al., 2020). Previous research (Sun, 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

[1] 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.

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.[2]

Following the above, it is worth studying the implications of decline in various modes of travel on the wellbeing in UK. The modelling is challenging due to endogeneity concerns and the interconnections across variables. The paper opts for a unique Bayesian Vector Autoregressive (Bayesian VAR) model that treats for endogeneity while accommodating all variables. This model provides responses in wellbeing and travelling to shocks due to Covid-19 such as infections, hospitalisations, deaths as well as social and economic restrictions. To estimate the model's parameters, we employ Bayesian estimations. It is well known that Bayesian estimation of VAR is superior to other VAR estimations due to the overparameterisation. This paper contributes in many ways: first, I collect recent data of

[2] 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).

weekly frequency that allows the estimation of a VAR model; second, I perform simulations to choose the best model; third, given the variety of COVID-19 related data as well as various government interventions I estimate impulse response functions for each variable in the model, including the wellbeing variables. I also 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 intervention household behaviour which is key to overcome the crisis.

In what follows section 2 presents the Bayesian panel VAR model and the identification strategy while section 3 and 4 presents the data section and results respectively. The last section presents some concluding remarks.

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

The starting point of the Bayesian vector autoregression (VAR) specification is to select the endogenous variables. For the purposes of this study, I select three endogenous variables: COVID-19 related variables, i.e., infections, hospitalisations, deaths; modes of travel in Great Britain that include flights, car journeys, rail journeys, cycling; as well as wellbeing variables like life satisfaction and happiness. All the endogenous variables are in a vector $y_t = [y_{t,1}, \dots, y_{t,m}]'$ $(t = 1, \dots, T)$. In addition, I include $z_t = [z_{t,1}, \dots, z_{t,m}]'$ exogenous variables such as government interventions to control the pandemic, like closing the schools, restrictions in travelling etc.[3] The above variables feed into a Bayesian vector autoregression (VAR):

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

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

where μ is a vector of constant terms, matrix B contains unknown coefficients, $\boldsymbol{\Sigma}$ is an unknown covariance matrix, y_t contains information on m endogenous variables that is modes of travelling, Covid-19, and wellbeing. $\mathbf{z}_t$ 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.[4]

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

[3] 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.
[4] The Bayesian VAR models have been steadily gaining popularity since the seminal paper of Doan et al (1984). Its popularity is justified given that treats for the overparameterization of standard VAR models that results to big losses of degrees of freedom in maximum likelihood estimation. In terms of the present model given that the period under examination is the Covid-19 pandemic period and observations are therefore limited the Bayesian VAR model does not suffer from overparameterization because it considers all VAR parameters as random with prior distributions. In detail, the Minnesota prior (see Litterman, 1980) assists to reduce the necessary lags in the VAR. In addition, the Bayesian VAR models produce superior forecasts compared to frequentist VARs (see Banbura, et al. 2008; Dieppe et al. 2016).

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:

$$\underset{(m\times1)}{\mathbf{y}_t} = \mathrm{B}_{(m\times s_t)} \underset{(m\times1)}{X_t} + \underset{(m\times1)}{\mathbf{u}_t}, \qquad (2)$$

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, I 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.

In terms of the variables in y_t, the focus is on wellbeing and travelling, though Covid-19 is also endogenous. Both wellbeing and travelling rely on resilience and recovery in the aftermath of an extreme shock like the Covid-19 one. As the VAR treats wellbeing, travel, and Covid-19 as endogenous, I relate various modes of travel to address how Covid-19 shocks are reshaping them and in turn how wellbeing is affected.

One of the advantages of opting for Bayesian VAR is that I could compare across VARs of different lags based on based on their posterior probabilities rather than imposing a specific lag structure.[5] In the empirical section, I 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.[6]

3. The data set.

3.1 Covid 19 related data (daily).

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, I 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, I include the stringency index that provides a composite measure based on nine response indicators of government interventions to control the pandemic. This stringency index

---

[5] It is worth noting that the Bayesian analysis is based on a posterior model with a defined probability distribution of parameters. This probability distribution is posterior, and it is conditional on the observed data and on the priors. The posterior distribution consists of a likelihood, that has information about all parameters based on the data, and a prior, that includes prior information about parameters. The Base rule simply combines the likelihood with priors so as estimate the posterior distribution. This posterior distribution is given by posterior $\propto$ Likelihood $\times$ Prior
In practice is difficult to derive the posterior distribution in a closed form. Hence, I estimate the posterior distribution using MCMC sampling.

[6] The MCMC generates values from a transition kernel so that draws from that kernel would converge to a stationary distribution. I select the Metropolis–Hastings algorithm because it is flexible and allows any distribution to be applied as a proposal distribution. The Metropolis–Hastings algorithm generates many states, while each single state comes from the previous state, and it is simply based on a Gaussian distribution centred at the corresponding state level.

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). I also consider the economic support index that provides information about governmental support in the form of income and debt relief.

<< Insert Table 1: Covid-19 related data here>>

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.

3.2 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.[7] The largest number of visits was made to Europe (396,000), but they still 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.

I 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.

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

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

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.

<< Insert Table 2 here>>

3.3 Life satisfaction (weekly data)

Figure 3 presents the survey questions of the Office of National Statistics of wellbeing variables in Great Britain and their diagrams (see Table 3 for descriptive statistics). The survey questions refer to life satisfaction, happiness, and anxiety. There is a survey question that focuses on whether what Great Britain residents do is worthwhile.

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, and while there is some recovery in recent weeks, the happiness and life satisfaction in Great Britain remains below the pre-lockdown levels.

<< Insert Figure 3 here>>

<< Insert Table 3 here>>

4. Empirical results.

4.1 Bayesian VAR: model selection

In this section, I 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, I 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.[8]

draw

---

[8] As discussed in Section 2, I opt for the Metropolis–Hastings (MH) algorithm for sampling from a posterior distribution. MH algorithm includes several stages. During the first stage, the posterior probability distribution $q(\cdot)$ and the starting state θ_0 within the posterior, $p(\theta_0|y) > 0$, are defined.
The MH algorithm produces a Markov chain $\{\theta_t\}^{T-1}{}_{t=0}$ so that at each step *t* a proposal state θ_* is generated that is conditional on the current state.
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.

The above stages are steps of MH algorithm.
In addition, I opt for Markov chain simulated because it safeguards that $p(\theta|y)$ is stationary distribution. What is left is to define the acceptance rate of the Markov chain and the degree of autocorrelation. An acceptance rate near zero means that proposals should be rejected. An acceptance rate near one it means that the Markov chain is confined within a small region and is not exploring the whole posterior domain. This the acceptance rate should not approach neither one nor zero for efficiency and low autocorrelation to be valid.

The first column in the output table reports the log-marginal likelihoods. The second reports the prior model probabilities, which are all equal to 0.25 by default, and the third column reports the posterior model probabilities. The simplest model with two lags has a probability of 0.88, and it is overwhelmingly the best one. To this end, in my empirical application a select a Bayesian VAR with two lags.

<< Insert Table 4 here>>

Note that for all Bayesian VAR models in Table 4 I include priors for all parameters. 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 I select a Minnesota prior as the default prior.[9] From economic interpretation point of view the parameters of VAR models are not interpretable. Instead, I proceed with the estimations of impulse–response functions (IRFs). Prior to IRFs, as with any MCMC method, I check that MCMC converged before moving on to impulse response functions. To test for stability, I 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.

<< Insert Figure 4 here>>

[9] In the empirical Bayesian estimation, which uses the Gibb's sampling for simulation, converges. I select RSEED to be equal to 21 and the MCMC sample size equal to 2,000. I have had a very high sampling efficiency of 0.99. The MCMC sample of size 2,000 is equivalent to about 1990 independent draws from the posterior, which generates sufficient estimation precision. Because the output of Bayesian VAR includes all parameters it takes a lot of space and I opt not to include (results are available under request).

Postestimation VAR analysis such as impulse–response functions are only meaningful for stable VAR models. To check the stability of a Bayesian VAR model, I estimate the eigenvalue stability condition for a MCMC sample size of 2000. To facilitate the presentation, I 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 the moduli of the eigenvalues of the companion matrix of the VAR model, which refers to unit circle tests but accounting for the fact that, in a Bayesian context, these moduli are random numbers.

<< Insert Table 5 here>>

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, I also estimate the posterior probability of unit circle inclusion which is 0.88. Thus, the posterior probability is close to one, assuring the stability of the model. If the inclusion probability is significantly lower than one, then there could be instability.

4.2 IRFs of the impact of Covid shocks.

Having selected the appropriate Bayesian VAR model, I present next responses to shocks in the endogenous variables. Impulse response functions (IRFs) provide the main toolbox for exploring a VAR model. They consider a shock to one variable (the impulse) for example in

Covid-19 infections and how this shock affects an endogenous variable (the response) for example flights in Great Britain.

Below, I 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 I 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. I estimate orthogonal IRFs because they have an advantage over the regular IRFs in that the impulses are guaranteed to be independent.[10] 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, but in the case of cycling that appears not to show any response.

<< Insert Figure 5 here>>

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

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

anxiety. Similarly, the shock in confirmed infections would increase anxiety but statistical significance is low.

<< Insert Figure 6 here>>

As the Bayesian VAR has three main endogenous sets of variables: travel, Covid-19 data, and well-being, I 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.

<< Insert Figure 7 here>>

Lastly, I 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.

<< Insert Figure 8 here>>

For completeness of the analysis the Appendix I reports the IRFs of responses of Covid-19 data, like confirmed infections, to shocks in wellbeing life satisfaction. 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.

4.3 Forecast Error Variance Decomposition

In this section, I 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 I 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.

<< Insert Figure 9 here>>

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 I 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.

<< Insert Figure 10 here>>

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.

<< Insert Figure 11 here>>

The forecast error variance decompositions shows that while the pandemic has caused an unprecedented decline in traveling, this is not going to persist beyond the short term. However, the decline in traveling in Great Britain would reduce life satisfaction and increase anxiety and such effects could persist.

5. Bayesian forecasting

Finally, I 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 I compute Bayesian forecasts based on information about lower and upper significance levels, posterior mean estimates, posterior standard deviations for all the endogenous variables.[11]

I 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 I fit VAR (2)) to compute dynamic forecast. In Figure 12, I provide that computed Bayesian forecasts starting from 2021 week 39 into the future.

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

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 capture the observed 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, I 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.

<< Insert Figure 12 here>>

6. Conclusions

The paper employs a unique Bayesian Vector Autoregressive model. This model provides responses in wellbeing, travelling in Great Britain to shocks in Covid-19 related data. It also provides reverse responses as endogeneity is treated within the VAR while I 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.

References

Anyu Liu, Yoo Ri Kim, John Frankie O'Connell, (2021). COVID-19 and the aviation industry: The interrelationship between the spread of the COVID-19 pandemic and the frequency of flights on the EU market, Annals of Tourism Research, Volume 91.

Banbura, M., D. Giannone, and L. Reichlin. 2008. Large Bayesian VARs. Working Paper Series 966, European Central Bank.

Dieppe, A., R. Legrand, and B. van Roye. 2016. The BEAR toolbox. Working Paper Series 1934, European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1934.en.pdf.

Doan, T., R. B. Litterman, and C. Sims. 1984. Forecasting and conditional projection using realistic prior distributions. Econometric Reviews 1: 1–100.

Filep, S. and M. Deery, (2010). Towards a picture of tourists' happiness, Tourism Analysis, 15 (4), pp. 399-410.

Gilbert, D. and J. Abdullah (2004). Holiday taking and the sense of well-being Annals of Tourism Research, 31 (1) (2004), pp. 103-121.

Ghysels, E., Santa-Clara, P., Valkanov, R. (2004). The MIDAS Touch: Mixed Data Sampling Regression Models.

Ghysels, E., P. Santa-Clara, and R. Valkanov (2006) Predicting volatility: getting the most out of return data sampled at different frequencies, Journal of Econometrics, 131, 59–95.

Ghysels, E., and J. Wright (2009). Forecasting professional forecasters, Journal of Business and Economic Statistics, 27, 504–516.

Hornik, K., M. Stinchcombe, H. White (1989). Multi-layer feedforward networks are universal approximators, Neural Networks 2, 359–366.

ICAO (2022). 2021 global air passenger totals show improvement from 2020, but still only half pre-pandemic levels. ICAO, News Release, March.

Kadiyala, K. R., and S. Karlsson. 1997. Numerical methods for estimation and inference in Bayesian VAR-models. Journal of Applied Econometrics 12: 99–132.

Karlsson, S. 2013. Forecasting with Bayesian vector autoregression. In Handbook of Economic Forecasting, vol. 2B, ed. G. Elliott and A. Timmermann, 791–897. Amsterdam: North-Holland. https://doi.org/10.1016/B978-0-444-62731- 5.00015-4.

Kock, F., Assaf, A. G., Tsionas, M. G. (2020). Developing Courageous Research Ideas. Journal of Travel Research 59:1140–46.

Kock, F., Nørfelt, A., Josiassen, A., Assaf, A. G., Tsionas, M. G. (2020). Understanding the COVID-19 Tourist Psyche: The Evolutionary Tourism Paradigm. Annals of Tourism Research 85:103053.

Kwon, Jangwook and Hoon Lee, (2020). Why travel prolongs happiness: Longitudinal analysis using a latent growth model, Tourism Management, Volume 76.

Litterman, R. B. 1980. A Bayesian procedure for forecasting with vector autoregressions. MIT working paper, Massachusetts Institute of Technology. 1984.

Lutkepohl, H. 2005. ¨ New Introduction to Multiple Time Series Analysis. New York: Springer.

Oh, Dong Hwan and Patton, Andrew J., Better the Devil You Know: Improved Forecasts from Imperfect Models (August 31, 2021). Available at SSRN:

Sun, X., S. Wandelt, A. Zhang. How dis COVID-19 impact air transportation? A first peek through the lens of complex networks. Journal of Air Transport Management, 89 (2020), Article 101928.

UNTWO (2020). Impact assessment of the COVID-19 outbreak on international tourism Available at https://www.unwto.org/impact-assessment-of-the-covid-19-outbreak-on-international-tourism.

White, H. (1989). Learning in artificial neural networks: A statistical perspective. Neural Computation, 1, 425–464.

White, H. (1990). Connectionist nonparametric regression: Multilayer feedforward networks can learn arbitrary mappings, Neural Networks 3, 535–549.

Zabai Anna, (2020). How are household finances holding up against the Covid-19 shock? BIS Bulletin, No 22, June.

Zellner, A. (1971). Introduction to Bayesian inference in econometrics. Wiley, New York.

Zenker, S., Kock, F. (2020). The Coronavirus Pandemic—A Critical Discussion of a Tourism Research Agenda. Tourism Management 81:104164.

Table 1: Covid-19 related data.

	OBS	Mean	Std. Dev.	Min	Max
Mortality	104	6.710533	1.361091	1.609438	9.158521
Hospital	83	9.096626	8.076435	0.5	36.68
Infections	83	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).

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.

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.

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.

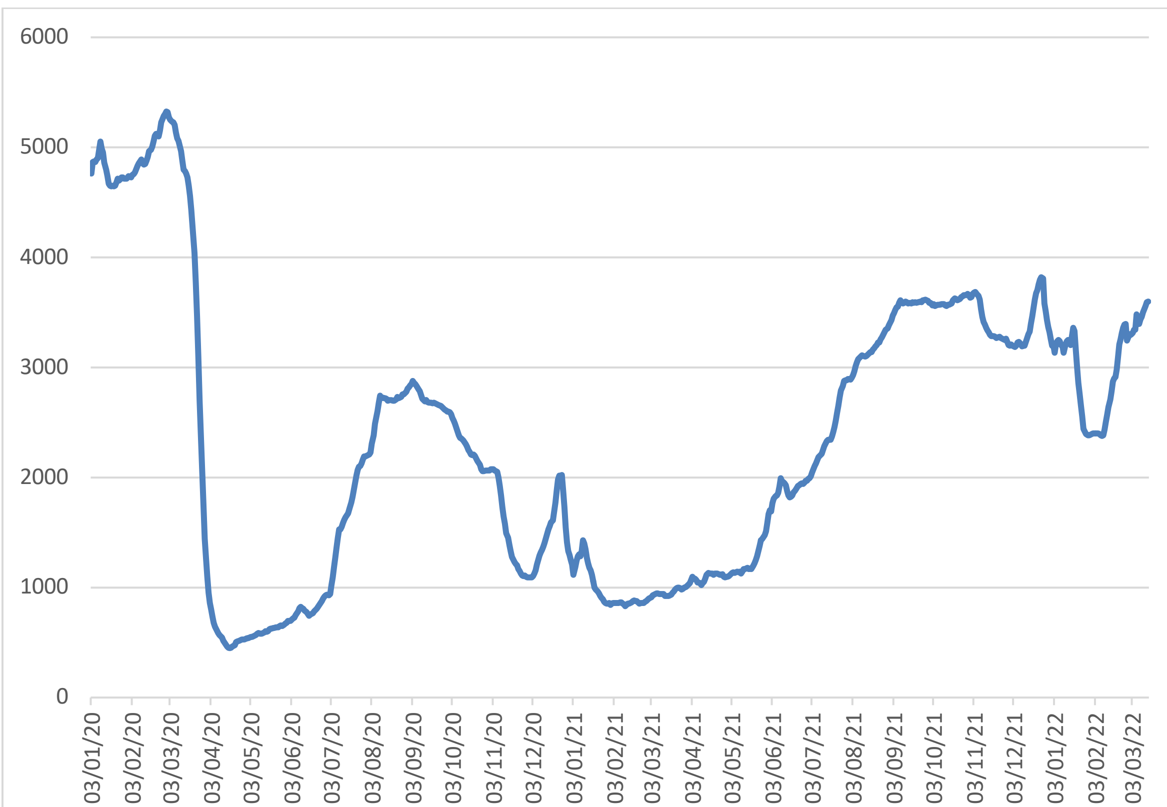
Table 5: Lag order selection of Bayesian VAR

	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

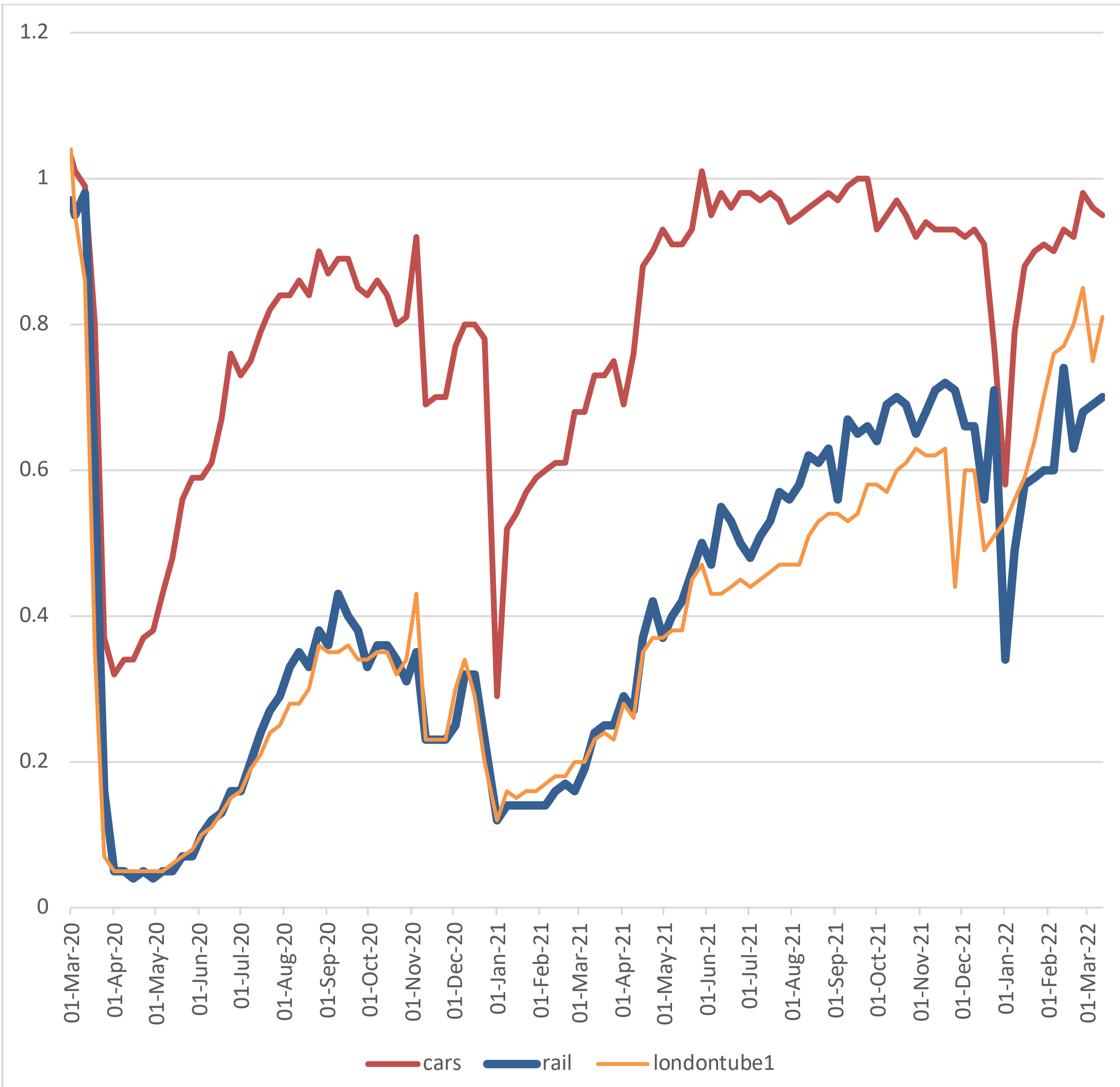
Source: Author's estimations.

Figure 1: Great Britain flights during the pandemic.



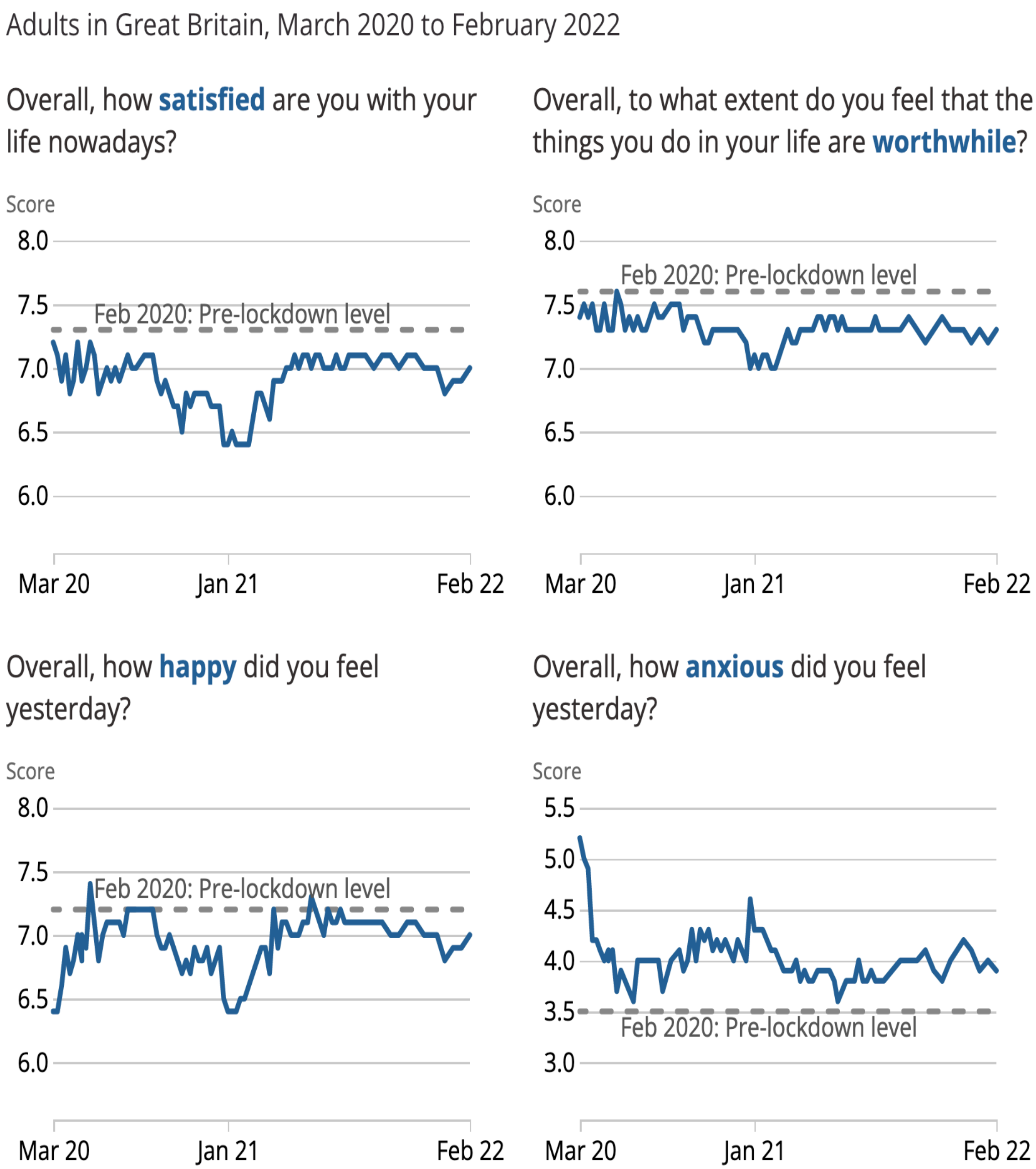
Source: ONS. Figure is in thousands.

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



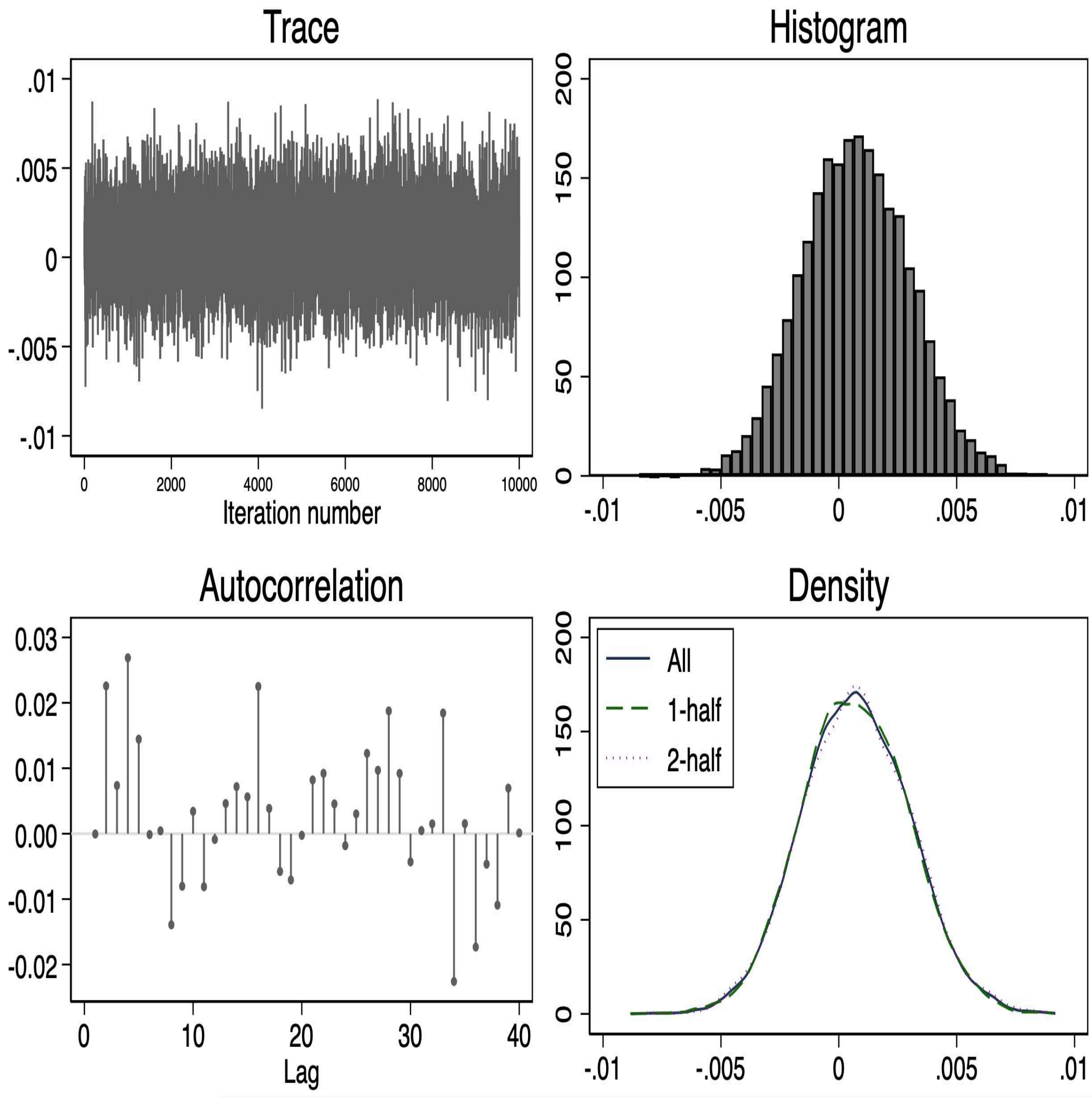
Source: Transport GREAT BRITAIN, DfT provides statistics on transport use by mode.

Figure 3: Wellbeing of Great Britain residents.



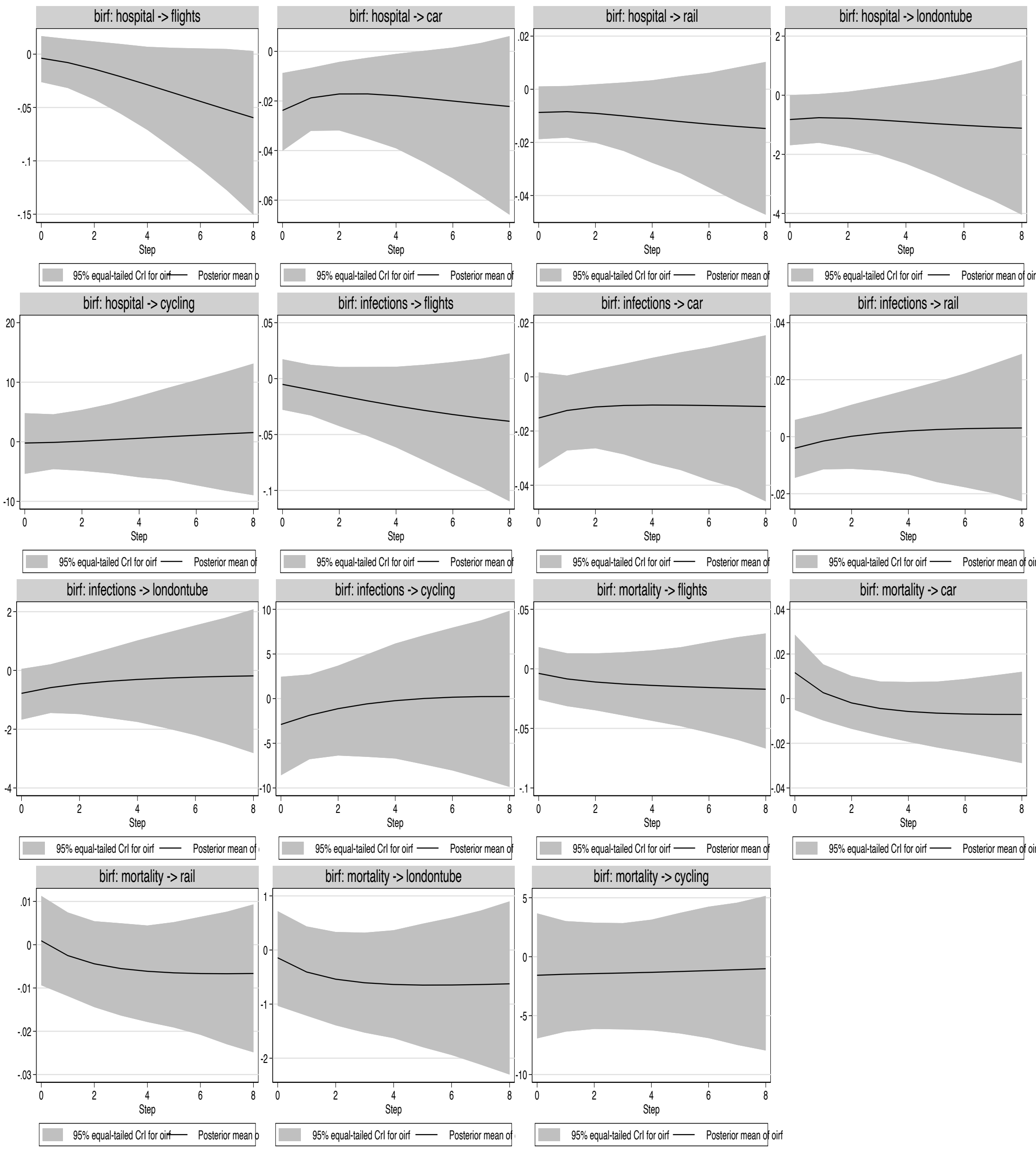
Source: Office for National Statistics – Opinions and Lifestyle Survey

Figure 4: MCMC convergence testing.



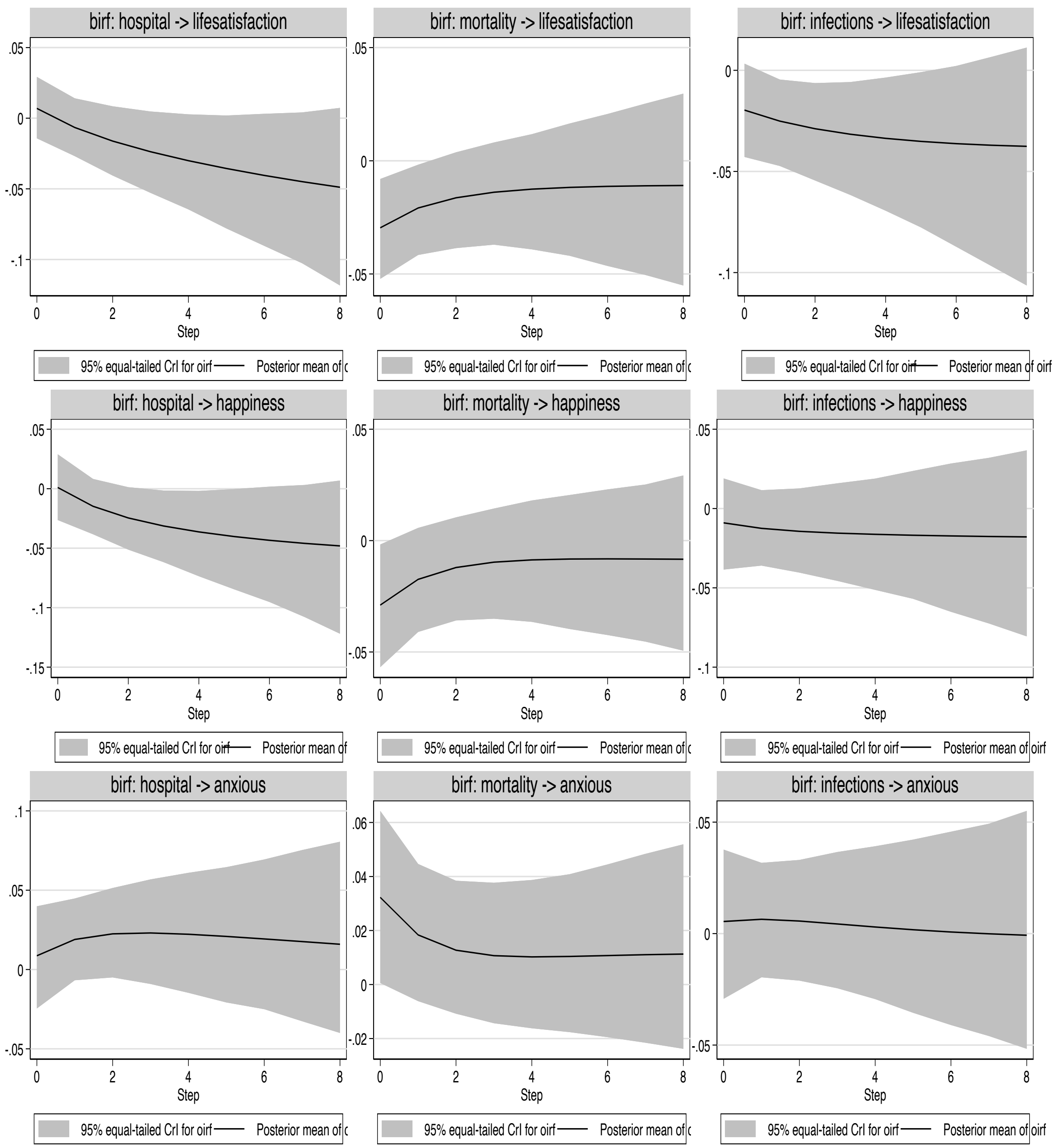
Source: Author's estimations.

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



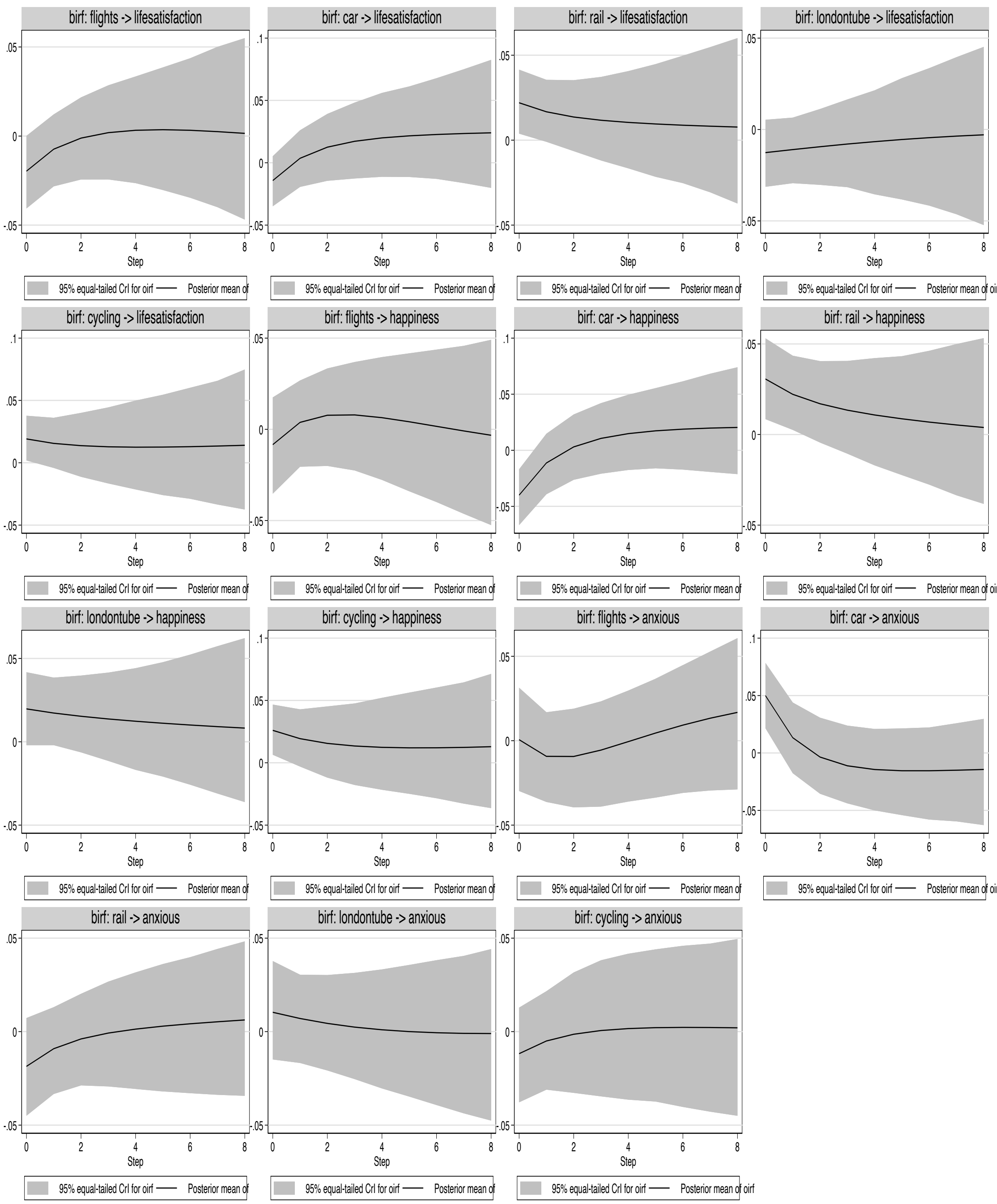
Source: Author's estimations. Hospitals refer to hospitalisation, mortality to confirmed deaths, and infections to confirmed infections.

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



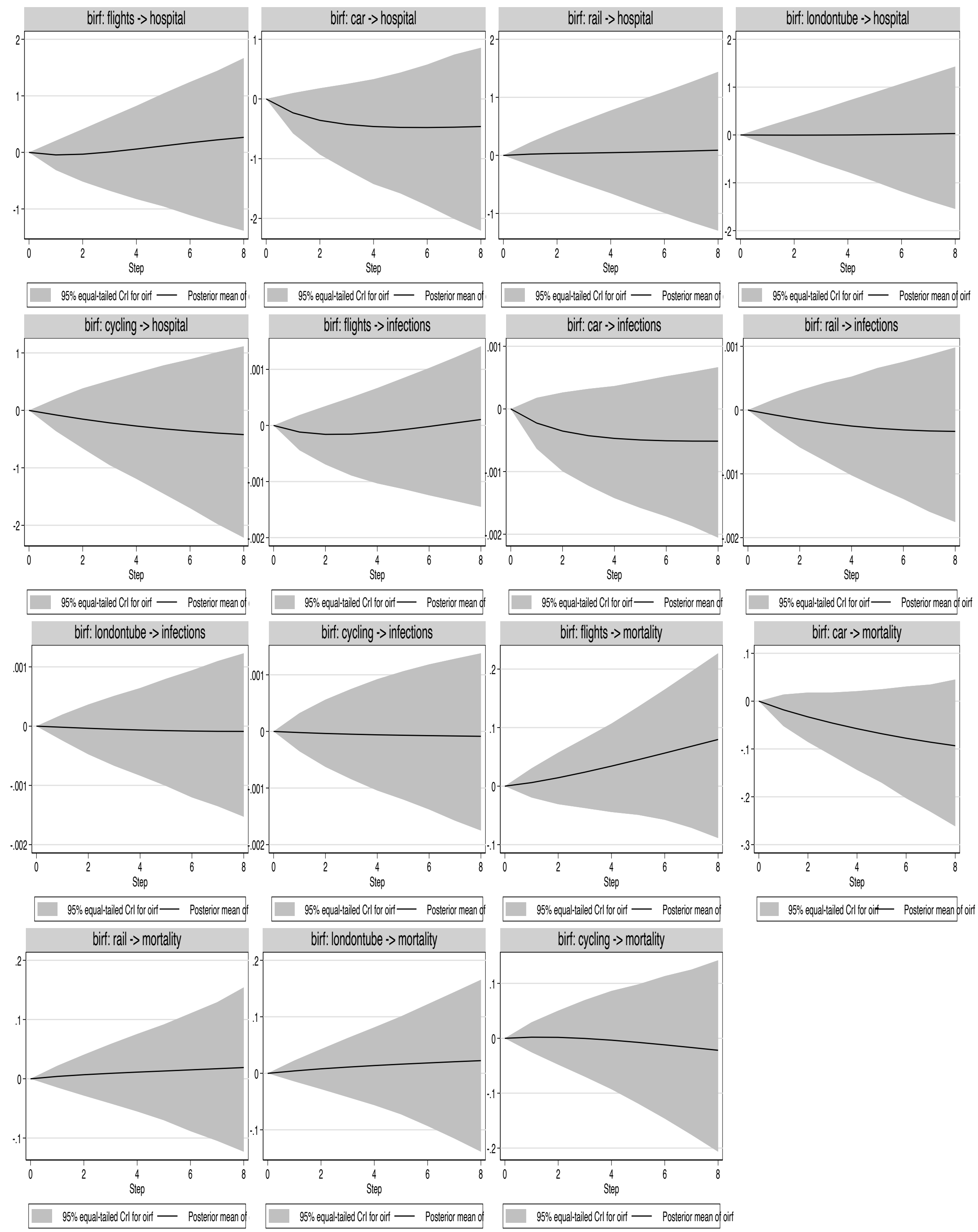
Source: Author’s estimations. Hospitals refer to hospitalisation, mortality to confirmed deaths, and infections to confirmed infections.

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



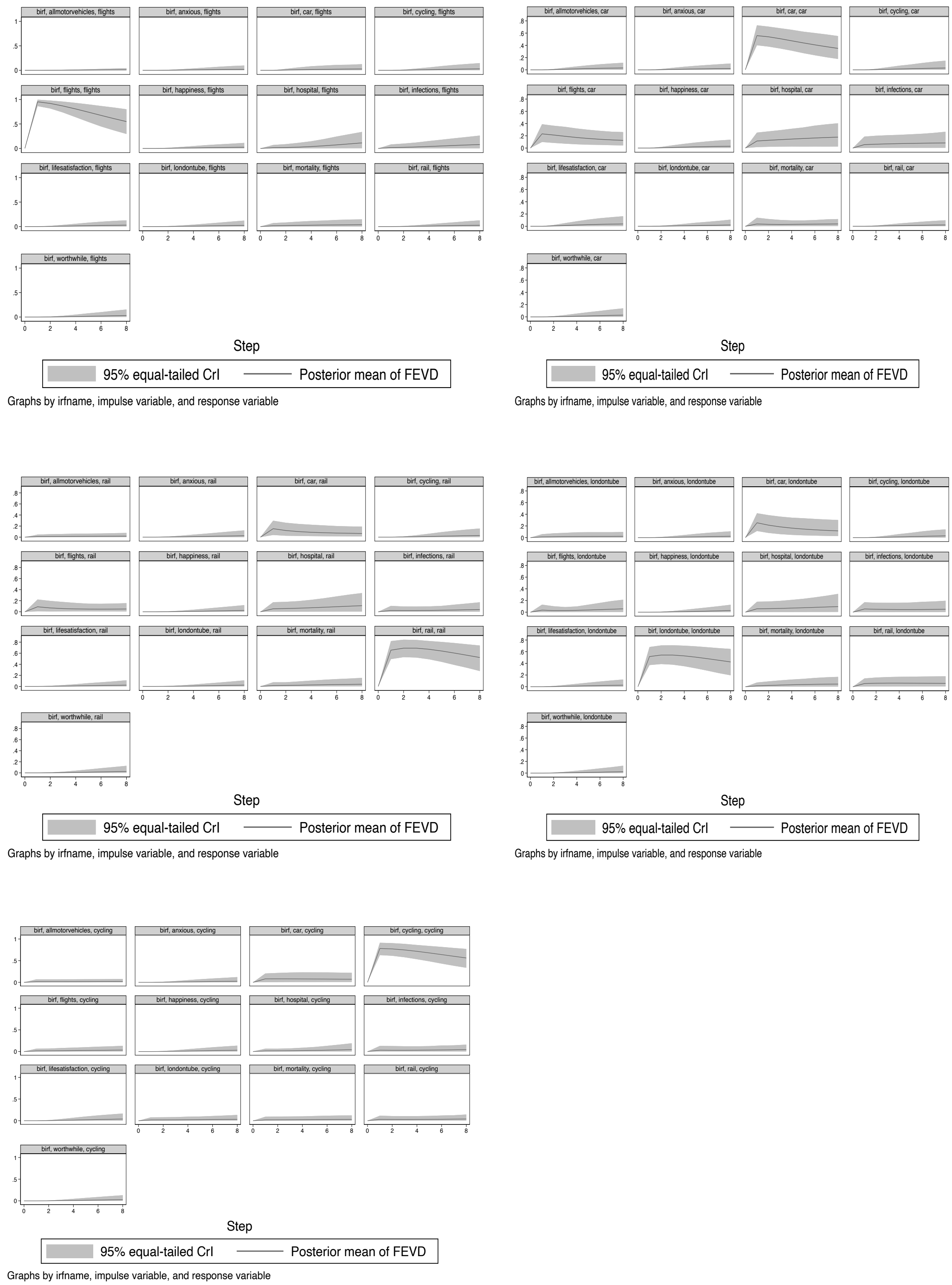
Source: Author's estimations.

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



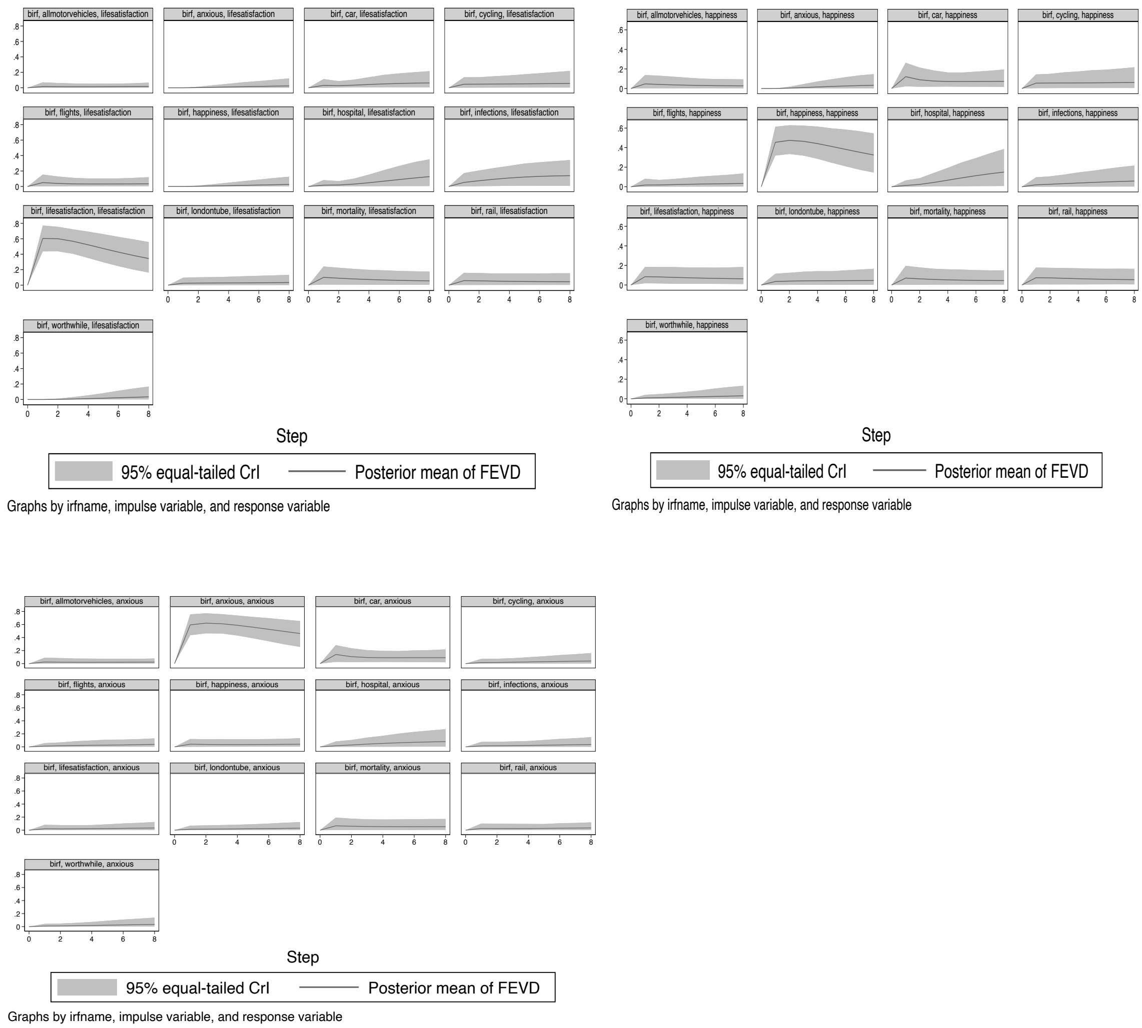
Source: Author's estimations.

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



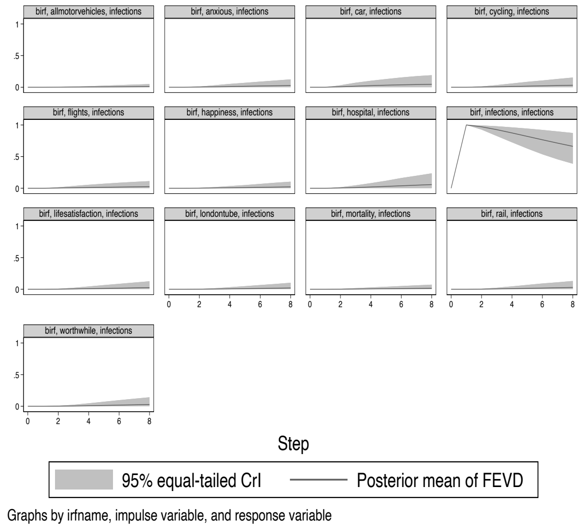
Source: Author's estimations.

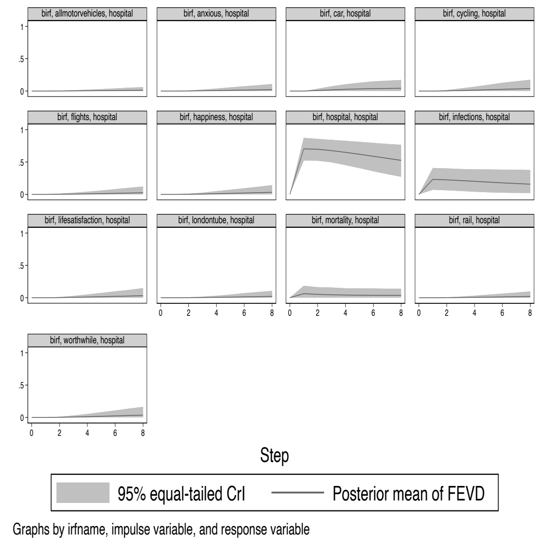
Figure 10: Forecast Error Variance Decomposition: response wellbeing.

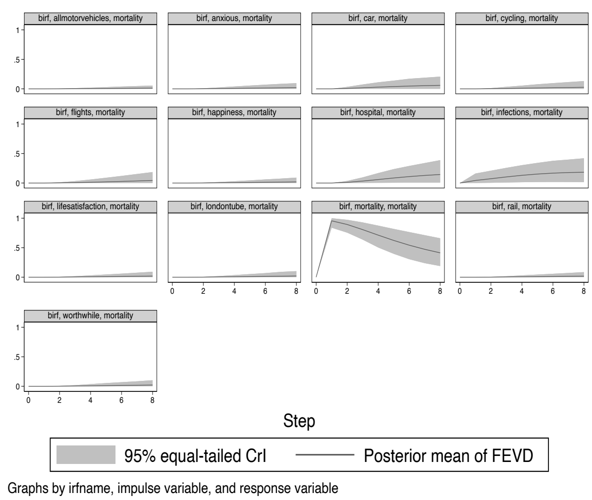


Source: Author's estimations.

Forecast 11: Forecast Error Variance Decomposition: response Covid 19

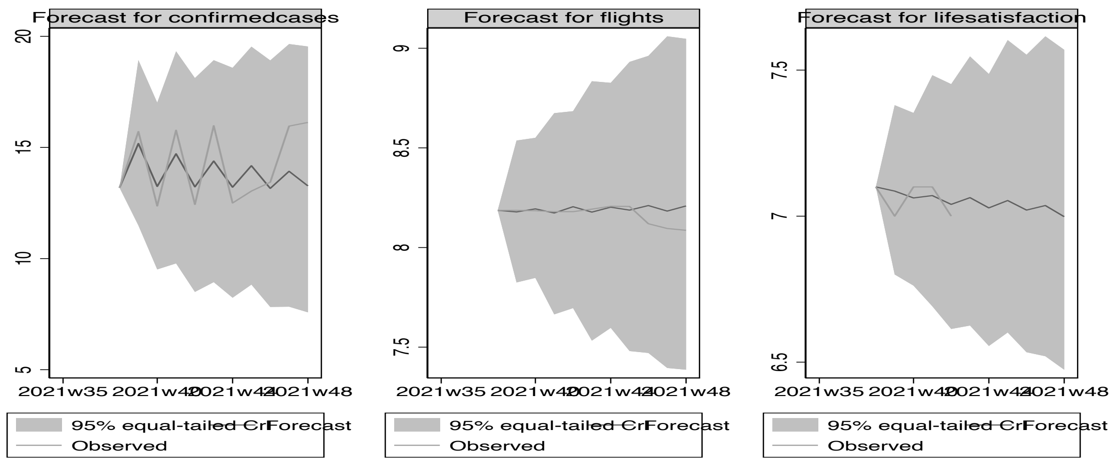




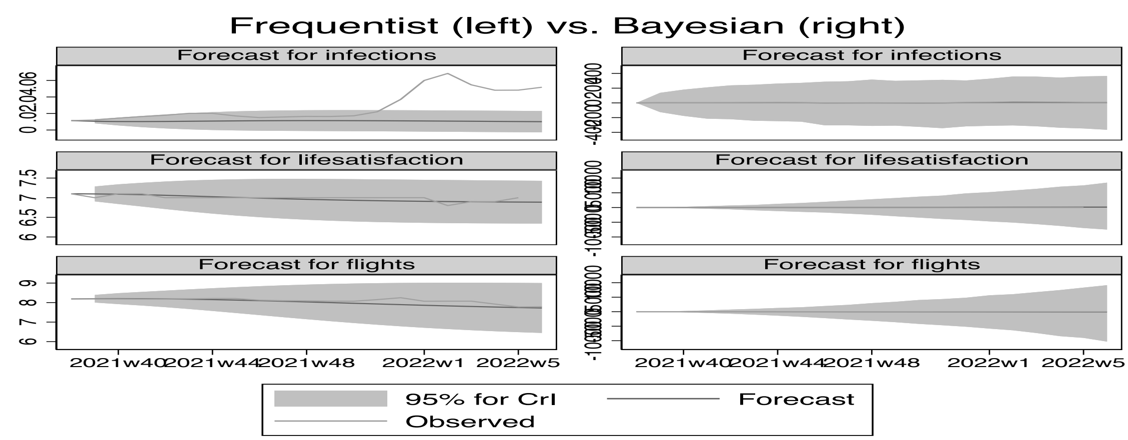


Source: Author's estimations.

Figure 12: (a) Forecasting based on Bayesian VAR



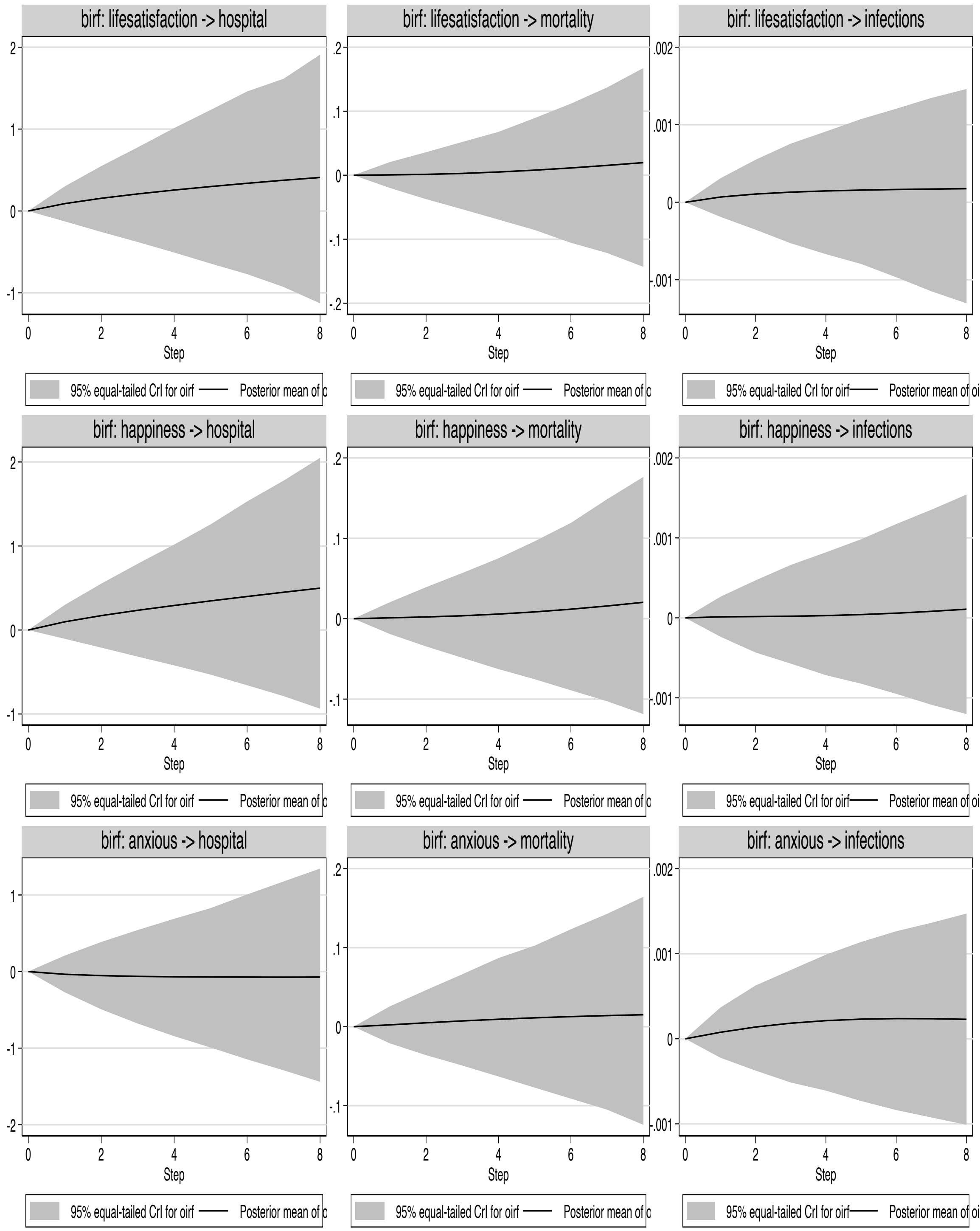
(b) Comparing forecasting of Bayesian VAR vs frequentist forecasting.



Source: Author's estimations.

Appendix I

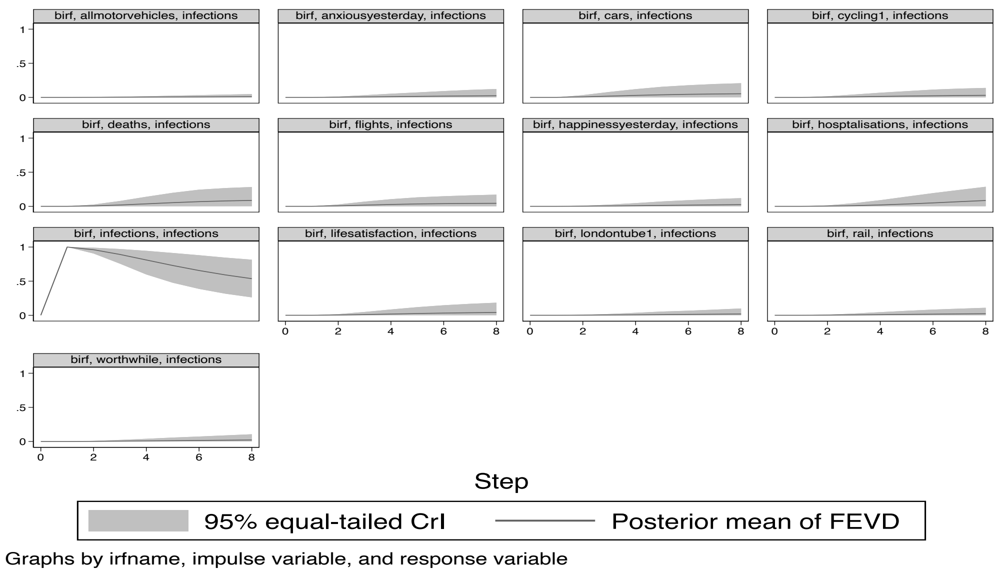
Figure I.1: response to Covid-19 variables to shocks in wellbeing.



Source: Author’s estimations.

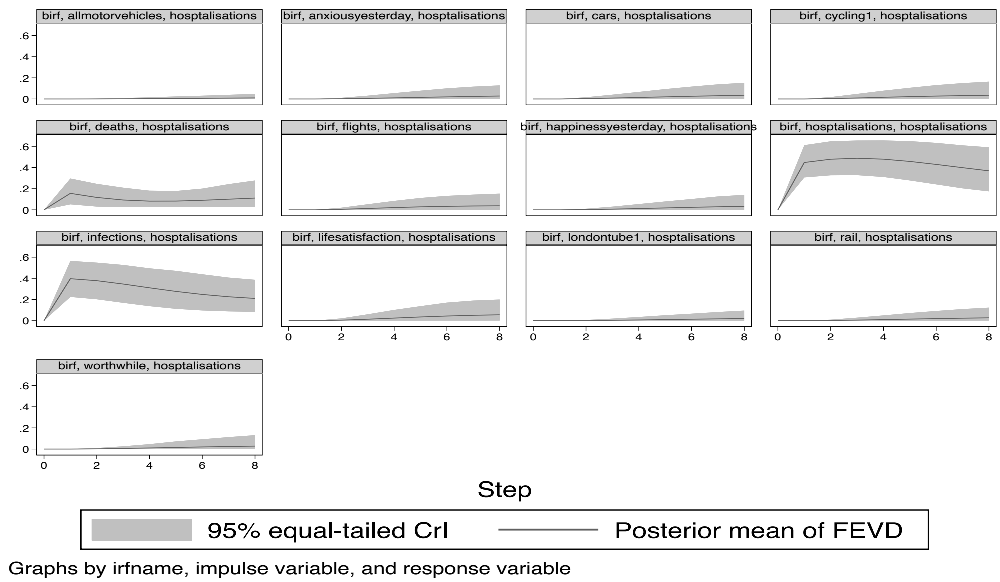
Appendix II

Figure Appendix AII.1: Forecast Error Variance Decomposition: response infections



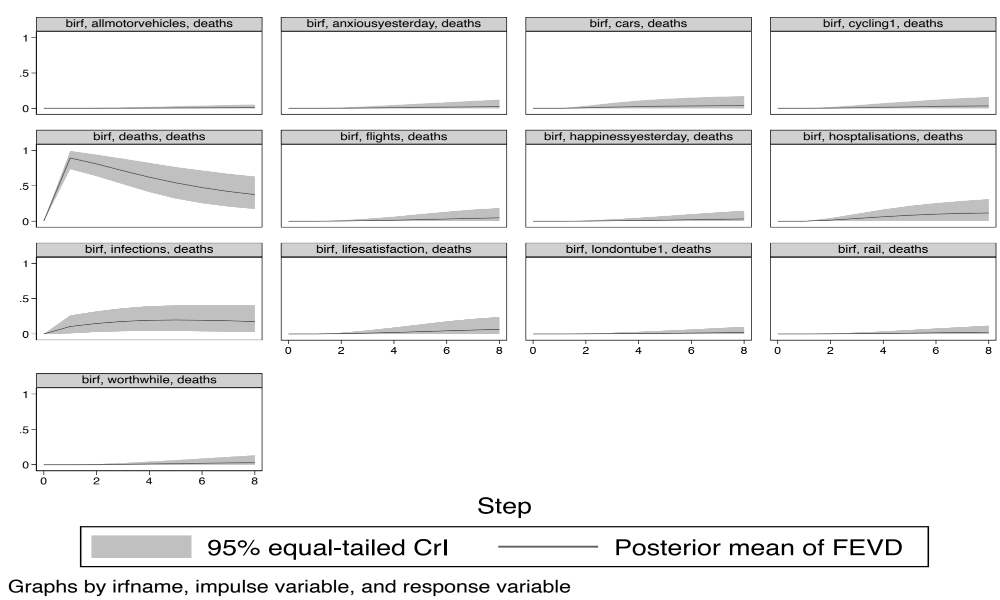
Source: Author’s estimations.

Figure Appendix AII.2: Forecast Error Variance Decomposition: response hospitalisations.



Source: Author's estimations.

Figure Appendix AII.3: Forecast Error Variance Decomposition: response deaths



Source: Author's estimations.