Brunel University London

Department of
Economics and Finance

Working Paper No. 2115

Economics and Finance Working Paper Series

Guglielmo Maria Caporale, Abdurrahman Nazif Çatık,
Mohamad Husam Helmi, Coşkun Akdeniz and Ali İlhan

The Effects of the COVID-19 Pandemic on Stock Markets, CDS and Economic Activity: Time-Varying Evidence from the US and Europe

September 2021

http://www.brunel.ac.uk/economics

THE EFFECTS OF THE COVID-19 PANDEMIC ON STOCK MARKETS, CDS AND ECONOMIC ACTIVITY: TIME-VARYING EVIDENCE FROM THE US AND EUROPE

Guglielmo Maria Caporale[a]

Abdurrahman Nazif Çatık[b]

Mohamad Husam Helmi[c]

Coşkun Akdeniz[d]

Ali İlhan[e]

September 2021

Abstract

This paper examines the effects of the COVID-19 pandemic on stock returns, CDS and economic activity in the US and the five European countries (the UK, Germany, France, Italy, and Spain) which have been most affected. The sample period covers the dates from the first confirmed COVID-19 cases in these countries to February 19, 2021. Specifically, we estimate first benchmark linear VAR models and then, given the evidence of parameter instability, TVP-VAR models with stochastic volatility which are ideally suited to capturing the changing dynamics in both financial markets and the real economy. The empirical findings can be summarised as follows. The linear VAR responses of electricity consumption (a proxy for real economic activity) to a one-standard-deviation shock to the number of COVID-19 cases are statistically insignificant, except for France, whilst the CDS ones are positive and significant only in a few periods, and there are very mixed results for those of stock returns. As for the TVP-VAR results, these indicate that COVID-19 cases had a negative and significant effect on economic activity in all countries in the early stages of the pandemic (especially in Italy), and a positive one on CDS at the same time (with cross-country differences). Finally, the negative impact on stock markets was felt only initially and it had tapered off by mid-April 2020.

Keywords: COVID-19; Stock markets; CDS; Economic activity; TVP-VAR

JEL classification: G10, G14, G15

---

[a] Corresponding author. Department of Economics and Finance, Brunel University London, Uxbridge, UB8 3PH, UK. Email: Guglielmo-Maria.Caporale@brunel.ac.uk. https://orcid.org/0000-0002-0144-4135

[b] Department of Economics, Ege University, İzmir, Turkey. Email: a.nazif.catik@ege.edu.tr. https://orcid.org/0000-0001-9247-5668

[c] Department of Economics and Finance, Durham Business School, University of Durham, UK, and Rabdan Academy, Abu Dhabi, United Arab Emirates. Email: mohamad.h.helmi@durham.ac.uk. https://orcid.org/0000-0003-0907-7939

[d] Department of Economics, Tekirdağ Namık Kemal University, Tekirdağ, Turkey. Email: cakdeniz@nku.edu.tr. https://orcid.org/0000-0002-3973-754X

[e] Department of Economics, Tekirdağ Namık Kemal University, Tekirdağ, Turkey. Email: ailhan@nku.edu.tr. https://orcid.org/0000-0001-6201-5353

1. Introduction

The COVID-19 outbreak started with the reporting to the World Health Organization (WHO) on the last day of 2019 of pneumonia cases of unknown cause in Wuhan, Hubei province of China. The WHO declared a Public Health Emergency of International Concern on January 30, 2020, after the virus was found to be transmitted from human to human and was also detected outside China (WHO, 2020a). Because of the international spread and alarming levels of COVID-19 cases as well as the inertia of policy makers, WHO classified the COVID-19 outbreak as a global pandemic on March 11, 2020 (WHO, 2020b). As of August 18, 2021, the number of confirmed COVID-19 cases had surpassed 200 million, with over 4 million deaths in the world as a whole (WHO, 2021) and devastating effects on public health, the real economy and financial markets.

Following the easing of trade tensions between the US and China investor sentiment had been bullish in late 2019 but quickly became bearish in early 2020 when increasing evidence of the global spread of the Coronavirus drastically changed positioning and pricing in the international financial markets (BIS, 2020; FSB, 2020). Owing to the higher degree of uncertainty, investors rushed to purchase safe and liquid assets, which led to sharp declines in stock market indices (IMF, 2020). Specifically, stocks in the US and euro area lost around 35% of their value between February 19 and March 23 (Ampudia et al., 2020). The S&P 500 fell by 20% from its previous peak in just 16 trading sessions (IMF, 2020), and 18 stock market jumps occurred in the 22 trading sessions between February 24 and March 24, despite the mortality rate being much lower than during the Spanish Flu, when there was no single daily stock market jump (Baker et al., 2020).[1]

The COVID-19 pandemic also had real effects, both on the supply and demand side. Workers reduced their labour supply, consumers were reluctant to spend, and the containment measures aimed at saving human lives had further negative effects on economic activity (Eichenbaum et al., 2020). All these factors combined resulted in the worst global recession since the Great Depression of 1929 (Gopinath, 2020). The International Monetary Fund (IMF) and the World Bank (WB) respectively estimated that the global economy contracted by 3.3% and 4.3% in 2020 (IMF, 2021; World Bank, 2021).

[1] Baker et al. (2020) define a stock market jump as a situation when daily stock market movements are greater than |2.5%|.

It is well known that economies and stock markets respond to political and geopolitical events (Chau et al., 2014, Al-Maadid et al., 2021, Elsayed and Helmi, 2021), terrorist attacks (Chesney et al., 2011; Phan et al., 2021), and natural disasters (Cavallo and Noy, 2011; Horvath, 2021). There is less evidence on the impact of pandemics, which are relatively rare compared to those other types of events and whose effects are often confined to specific regions. However, the global nature of the COVID-19 pandemic made it immediately apparent that both the world economy and financial markets would be severely affected (Al-Awadhi et al., 2020; Sharif et al., 2020).

The present paper aims to provide new evidence on the effects of the COVID-19 pandemic on the stock returns, CDS and economic activity in the US and five European countries (the UK, Germany, France, Italy, and Spain) which have been among the hardest hit developed economies. Specifically, it uses a time-varying parameter VAR (TVP-VAR) model with stochastic volatility to capture the volatile dynamics of financial markets and the changes in economic activity during the pandemic. This approach is the most appropriate to examine the evolution over time of the parameters of interest and the error terms (Primiceri, 2005; Koop et al., 2009; Nakajima, 2011) and thus is ideally suited for examining the impact of the current pandemic given the fact that there have been several COVID-19 waves since the initial outbreak. Although their dates differ across countries, two main global waves starting in the Spring and Autumn of 2020 have been identified by the WHO on the basis of the number of confirmed cases. COVID-19 uncertainty and lockdowns caused sharp drops in stock markets and economic activity during the first wave; the easing of restrictions in June 2020 then led to a moderate recovery. Although the number of confirmed cases was much higher during the second compared to the first wave (around 70 million cases were recorded between October 2020 and February 2021 as opposed to 6 million between March and June 2020 - WHO, 2021), the impact on the real economy and stock markets was less pronounced in the former case (see Figure 1).

<Insert Figure 1 about here>

The layout of the paper is as follows. Section 2 provides a brief review of the relevant literature. Section 3 describes the data and the TVP-VAR methodology. Section 4 discusses the empirical findings. Section 5 offers some concluding remarks.

2. Literature Review

Following the COVID-19 outbreak, various studies were soon carried out to analyse its consequences for financial markets. Al-Awadhi et al. (2020) investigated the effects of COVID-19 on the Chinese stock market during the period from January 10 and March 16, 2020, and found that the daily growth rate of total cases and total deaths affected negatively stock returns in all sectors. Ashraf (2020a) examined the impact on stock markets of daily COVID-19 cases and deaths in 64 countries between January 22 and April 17, 2020, and reported that the former had a stronger effect and that there was evidence of time variation. Haroon and Rizvi (2020) concluded that the increasing number of COVID-19 cases had reduced liquidity in emerging equity markets during the period from January 1 to April 30, 2020. Xu (2021) explored the effects of COVID-19 on the US and Canadian stock markets from the initial outbreak to July 2, 2020, and found a less pronounced negative effect in the case of the former country.

Another strand of the literature has explored the impact on stock markets of the restrictive measures adopted by governments to contain the spread of the virus. D'Orazio and Dirks (2020) showed that lockdown policies had substantial, adverse effects on stock market indices in the eurozone during the period from January, 1 to May 17, 2020. Aggarwal et al. (2021) found that between December 2019 and May 2020 lockdowns affected stock returns in 12 countries negatively through market risk premiums and positively through growth projections. Ambros et al. (2020) concluded that COVID-19 news increased volatility in eight major European stock markets between January 1 and March 31, 2020. Chundakkadan and Nedumparambil (2021) analysed investor sentiment using benchmark stock market indices for 59 countries as well as the Google Search Volume Index over the period from February 1 to April 30, 2020; they found an inverse relationship between the research volume of pandemic news and daily stock returns. Ali et al. (2020) provided further evidence that the situation in the stock markets of nine countries (the US, the UK, Germany, France, Italy, Spain, Switzerland, China, and South Korea) had deteriorated quickly from January 1 to March 30, 2020, by which time the epidemic had become a pandemic.

Other studies report that the initial negative effects on stock markets subsequently disappeared. For instance, Capelle-Blancard and Desroziers (2020) found that 79 stock markets were no longer affected by the number of COVID-19 cases between March 23 and April 30, 2020. Topcu and Gulal (2020) showed that the negative effect of COVID-19 on stock markets decreased gradually and had tapered off by mid-April 2020 in 26 emerging market economies. Anh and Gan (2021) found that in Vietnam, negative stock return responses to COVID-19 turned positive in the lockdown period between April 1 and April 15, 2020. Harjoto and Rossi (2021) also reported that the stock market recovery during the COVID-19 pandemic was faster than during the global financial crisis for both emerging and developed economies.

One of the main reasons for this rebound is the massive monetary expansion and fiscal stimulus packages announced at the national and international level since mid-March 2020. Klose and Tillmann (2021) analysed the impact of monetary and fiscal policy announcements on financial markets in 29 European countries during the period from February 17 to April 24, 2020. They reported that those concerning asset purchase programmes led to higher stock returns while those about fiscal stimulus packages resulted in lower stock prices. Ashraf (2020b) found that income support announcements had a positive impact on stock returns in 77 countries from January 22 to April 17, 2020. Chang et al. (2021) showed that income support packages and other fiscal measures increased stock returns in 20 countries between January 2 and July 21, 2020. Narayan et al. (2021) concluded that stimulus packages introduced in March 2020 positively affected stock returns in Canada, the UK, and the US between July 1, 2019, and April 16, 2020.

Whilst the support package announcements soon led to a recovery in stock markets, the negative impact of containment measures on economic activity was more severe and lasted longer. There was a substantial contraction, especially in the spring of 2020, when national lockdowns were widely imposed. Several studies have investigated the effects of the pandemic on the real economy using different proxies as real-time indicators and confirmed the sharp drop in economic activity. Lewis et al. (2020) investigated the early effects of the pandemic in the US up to April 2, 2020, using a weekly economic index; they found that the decline in economic activity started in the week ending March 21 and that there was a further slump in the week ending March 28, with a 6.17% drop in the quarterly GDP growth rate. Chen et al. (2020) analysed the impact of COVID-19 on economic activity in Europe and the US from January to May 2020 using several high-frequency indicators such as unemployment insurance claims, electricity consumption, and the Google Community Mobility Index; they reported significant contractions prior to the adoption of economic support policies. Fezzi and Fanghella (2020) examined daily electricity load data in Italy from January 1 to June 30, 2020, and found that the three weeks of strictest lockdown in March and April led the output losses of approximately 30% of GDP. Beyer et al. (2021) showed that the negative growth effect of the decline in electricity consumption in India in the second quarter of 2020 was 20.8%. Janzen and Radulescu (2020) estimated that the 4.6% decrease in electricity consumption during the lockdown in Switzerland corresponded to a 7% decline in output. Finally, Carvalho et al. (2020) analysed BBVA-mediated sales transactions in Spain for the period from January 1, 2019, to March 30, 2020; they found that from March 14, 2020, when a nationwide lockdown was announced, to March 30, 2020, daily average nominal expenditure decreased by 49% compared to the same period of the previous year.

3. Data and Methodology

3.1. Data

We employ daily data for the US and the five European countries most affected by the pandemic, i.e., the UK, Germany, France, Italy, and Spain, to investigate the impact of COVID-19 on stock returns, CDS, and economic activity. The sample covers the period from the first confirmed COVID-19 cases in each of these countries to February 19, 2021.[2] The vector of endogenous variables for the estimated TVP-VAR model is defined as follows.

$$Y_t' = [case_t \; ec_t \; cds_t \; ret_t] \quad (1)$$

where $case_t$ indicates the cumulative number of confirmed COVID-19 cases, and ec_t represents electricity consumption, more precisely the average hourly electricity load measured in megawatt, which is a proxy for economic activity. This follows the large empirical literature showing the existence of a link between electricity consumption and economic growth (Narayan et al., 2008; Yoo and Kwak, 2010; Sarwar et al., 2017).[3] Various studies have also employed electricity consumption specifically to examine the impact of COVID-19 on economic activity (Chen et al., 2020; Fezzi and Fanghella, 2020; Janzen and Radulescu, 2020; Beyer, 2021; Menezes et al., 2021). cds_t is the 5-year credit default swap (CDS) spreads reflecting the change in country risk. Finally, ret_t denotes the stock market index of each country. The series are obtained from various databases. In particular, the electricity load data have been collected from the European Network of Transmission System Operators for Electricity[4] and the US Energy Information Administration[5]. COVID-19 cases, CDS spreads, and stock returns have been retrieved from the Thomson Reuters DataStream database. First differences of the logged series are used for the analysis.

[2] The starting dates are January 21, 2020 for the US, January 30, 2020 for the UK, January 27, 2020 for Germany and France, February 24, 2020 for Italy, and January 31, 2020 for Spain.
[3] For a detailed survey of the literature on the nexus between electricity consumption and economic growth, see Payne (2010).
[4] The data for European countries are available at https://transparency.entsoe.eu/load-domain/r2/totalLoadR2/show (Accessed: 21.02.2021)
[5] The data for the US is obtained from https://www.eia.gov/opendata/qb.php?category=3389935&sdid=EBA.US48-ALL.D.H (Accessed: 21.02.2021)

<Insert Table 1 about here>

Table 1 reports descriptive statistics of the variables in levels. It can be seen that the US had the highest number of COVID-19 cases and Germany the lowest. Also, CDS and stock returns have been most volatile in Italy during the pandemic, whilst electricity consumption has been highest and most volatile in the US.

Prior to the TVP-VAR estimation, we examine the time series properties of the variables employing the Lumsdaine and Papell (1997) unit root test allowing for two structural breaks. The test statistics indicate that all series exhibit a unit root whilst their differences are stationary at the 1% significance level (see Table A1 in the Appendix). We also analyse the break dates using a specification with an intercept and a time trend. The first significant break is found for stock returns, CDS, and economic activity around the beginning of April when there was a rebound in most countries (the exceptions being Italy in the case of stock returns and CDS, and Italy as well as the US in the case of economic activity); as for COVID-19 cases, two significant breaks are found in most cases towards the end of the summer of 2020 and just before the second COVID-19 wave.

3.2. Methodology

This section briefly outlines the structure of the TVP-VAR model used to estimate the time-varying responses. As argued by Primiceri (2005) and Koop et al. (2009), this model has important advantages compared to other nonlinear specifications. First, in contrast with threshold models, it does not require a transition variable governing the behaviour of the variables across the regimes. Second, time-varying parameters capture gradual changes in the relationship among the variables. Finally, the time-varying variance-covariance matrix of the error terms can account for the impact of unanticipated exogenous shocks.

The TVP-VAR model is based on the Bayesian estimation of state-space equations and consists of a measurement equation and state equations for the time-varying coefficients. The measurement equation is specified as follows (Nakajima, 2011; Primiceri, 2005):

$$y_t = c_t + \xi_{1t} y_{t-1} + \cdots + \xi_{st} y_{t-s} + \epsilon_t, \quad \epsilon_t \sim N(0, \Omega_t) \tag{2}$$

where ξ_{it} and c_t are the time-varying coefficients and intercept terms, respectively. The error terms are assumed to follow a normal distribution with a zero mean and a time-varying variance-covariance matrix Ω_t. In order to extract time-varying shocks, this matrix is decomposed into $\Omega_t = C_t^{-1} \Sigma_t (C_t^{-1})'$ through a Cholesky decomposition based on a recursive ordering of the variables. The matrix, C_t , which measures the simultaneous relationship among variables, is a lower-triangular one, whereas Σ_t is a diagonal matrix reflecting the time-varying idiosyncratic shocks:

$$\Sigma_t = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix} \qquad C_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \delta_{21,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \delta_{k1,t} & \cdots & \delta_{k,k-1,t} & 1 \end{bmatrix} \tag{3}$$

Once the time-varying shocks have been identified, the model in Equation (2) can be reformulated through a Kronecker product conversion, as outlined by Nakajima and Watanabe (2011):

$$y_t = X_t\beta_t + C_t^{-1} \Sigma_t e_t, \qquad e_t \sim N(0, I) \tag{4}$$

To estimate the above equation, the time-varying parameters and error variances must be modelled; specifically, the following state equations are assumed to govern their behaviour:

$$\begin{aligned} \beta_{t+1} &= \beta_t + \varepsilon_{\beta t}, \\ \delta_{t+1} &= \delta_t + \varepsilon_{\alpha t}, \\ h_{t+1} &= h_t + \varepsilon_{ht}, \end{aligned} \qquad \begin{bmatrix} e_t \\ \varepsilon_{\beta_t} \\ \varepsilon_{\delta_t} \\ \varepsilon_{h_t} \end{bmatrix} \sim N \left[0, \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\delta & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix} \right] \tag{5}$$

The equations β_{t+1} and δ_{t+1} imply that the parameters of the measurement equation β and C_t matrix governing the impact of instantaneous shocks follow a random walk without an intercept.[6] In the equation for the standard deviations of the residuals, a geometric (exponential) random walk is employed, similar to the ARCH specification in the financial econometrics literature, where the estimated time-varying variances are placed on the diagonals of H_t.[7] Furthermore, the error terms of the equations above are assumed to be independent of one another and to follow the normal distribution.

4. Empirical Results

4.1. Linear VAR Results

Before analysing the TVP-VAR models, benchmark linear VAR models are estimated. The cumulative responses of electricity consumption, CDS, and stock returns to COVID-19 cases shocks are shown in Figure 2. First, we examine the effects to a one-standard-deviation shock to the number of COVID-19 cases on electricity consumption. All responses are statistically

[6] The random walk model is not stationary, hence we impose the stability restriction on the parameters as suggested by Cogley and Sargent (2005).
[7] Using a geometric (exponential) random walk implies that the logarithm of the standard deviations follows a random walk.

insignificant, except in the case of France, where the response is positive and significant in the first two periods but then becomes insignificant. Second, we analyse the impact of shocks on the sovereign risk of countries. The results suggest that an increase in the number of cases has a positive and significant effect on the CDS after the fourth and sixth periods, with the exception of Italy. The highest positive impact is observed in France.

<Insert Figure 2 about here>

The results for the cumulative responses of stock returns to the one-standard-deviation shock to COVID-19 cases are mixed. The response is insignificant in all periods in the US and Germany, it is positive and significant until the fourth period in the UK, it is only significant in the third period in Italy and from the ninth and tenth periods in France and Spain, respectively.

4.2. TVP-VAR Results

To motivate the estimation of a TVP-VAR model we investigate first parameter constancy in the linear VAR model. To this end, we plot the recursive residuals of the time-invariant VARs along with their two standard error confidence intervals (see Figures A1 to A6 in the Appendix). These plots indicate clearly the presence of parameter instability, as the recursive residuals are often outside the confidence intervals, especially during the early months of the COVID-19 pandemic. The implication is that a linear approach is not suitable for analysing the possible effects of the pandemic on stock markets, CDS and economic activity, and thus we proceed to estimate TVP-VAR models using the set of signal and transition equations described in the previous section.[8] This involves the estimation of several parameters which could result in over-parameterisation and inconsistent estimates. To prevent this problem a Bayesian approach based on the Markov Chain Monte Carlo (MCMC) algorithm is used.[9] Of the various sampling procedures employed in the estimation of Bayesian VARs, we choose the multi-move sampling one developed by Shephard and Pitt (1997) and Watanabe and Omori (2004) following Nakajima (2011); specifically, we draw samples of 50,000 from the posterior distribution to achieve convergence of the time-varying parameters in the signal equations and the transition

[8] To find the optimal number of lags, we used the Akaike Information Criterion (AIC). The same priors in Nakajima (2011) are employed in the TVP-VAR estimates.

[9] Previous research (e.g., Primiceri, 2005; Nakajima, 2011) has shown that the Bayesian method minimizes the risk of parameter instability by specifying the prior probability densities of the coefficients before assessing the joint posterior distributions of the parameters.

equations. In addition, the first 5,000 samples are reserved for the convergence of the parameters.[10]

<Insert Table 2 about here>

The stability of the estimated TVP-VAR models investigated with the posterior means, standard deviations, and 95 percent confidence intervals of the chosen parameters can be inferred from Table 2. The convergence diagnostics (CD) by Geweke (1992) are low, and the posterior mean of the estimated parameters lies in the confidence intervals; in addition, the inefficiency factors imply that the null hypothesis of convergence to the posterior distribution is not rejected for any of the parameters of the models. Therefore, the diagnostic results confirm that the MCMC algorithm generates posterior draws efficiently.[11]

After establishing the stability of the estimates for each country, we compute time-varying responses based on the identifying shocks derived from the time-varying variance-covariance matrix in Equation 3. These are shown in Figures 3-5. Panel (a) in each figure displays the time-varying cumulative responses for the time horizons $t = 0, 1, 2, \ldots, 15$.[12] Such responses are entirely different from the time-invariant ones in that they require an additional dimension to plot them over time. Panel (b) shows instead in each case the accumulated responses over the fifteenth-day horizon, $h = 15$, with two standard error confidence bands to evaluate their significance over the sample period.

First, we analyse the time-varying responses of electricity consumption to COVID-19 cases shocks (see Figure 3). These are negative in all countries and significant in the early stages of the pandemic. The largest impact of COVID-19 cases on economic activity is found in Italy. By April 2020, responses had become insignificant and remain so till the end of the sample. As for the CDS responses, these are positive in all countries (see Figure 4); however, they are significant only at the beginning of the pandemic, and vary across countries. The highest CDS response is found in Germany, followed by Italy and Spain; the lowest response is estimated in

[10] Unlike the other sampling methods, e.g. the Metropolis-within-Gibbs sampler applied by Primiceri (2005), the multi-move sampler does not require putting aside some initial observations to calibrate the starting values of the parameters, and thus the full sample can be used for the TVP-VAR estimation.

[11] The CD test is used to evaluate the convergence of the Markov Chain in Bayesian models by comparing the first and last draws. If the MCMC sampling yields stable estimations, the posterior distribution of the parameters should converge to standard normal, and the null hypothesis of posterior distribution convergence cannot be rejected. Together with the CD test, we provide additional diagnostics in Figures A7-A12 for all countries' TVP-VAR models. These findings corroborate the posterior distribution's convergence. First, the chosen parameters' sample paths exhibit steady behavior since their autocorrelation functions rapidly converge to zero. Second, the shape of the distribution of the chosen parameters is near to the standard normal, as demonstrated by the CD test.

[12] According to Nakajima (2011), time-varying responses are calculated by setting the initial shock magnitude identical to the average stochastic volatility over the estimation sample to make responses comparable over time.

the US. Finally, in the case of stock returns (see Figure 5) significant negative responses are found in the early stages of the pandemic, namely before mid-April 2020, in all countries (though their time profile differs across countries) – just as in the case of electricity consumption, which indicates that in periods when stock returns decreased significantly, economic activity also did.

5. Conclusions

The COVID-19 pandemic has caused havoc around the world through the loss of human lives and severe damage to the economy. The measures adopted to contain the spread of the Coronavirus reduced economic activity sharply. In 2020, real GDP contracted by 6.8 percent in Western Europe while unemployment reached 8.1 percent in the US (IMF, 2021). Stock markets also plunged in the early stages of the pandemic when uncertainty was very high. Global stock prices dropped 40% between February 17, 2020, and March 23, 2020, when the volatility index reached above 80 (CBOE, 2021; Davis et al., 2020).

This paper examines the effects of COVID-19 cases on stock returns, CDS and economic activity in the US and the five European countries (the UK, Germany, France, Italy, and Spain) which have been most affected. The sample period covers the dates from the first confirmed COVID-19 cases in these countries to February 19, 2021. We estimated first benchmark linear VAR models and then, given the evidence of parameter instability, TVP-VAR models with stochastic volatility which are ideally suited to capturing the changing dynamics in both financial markets and the real economy (Primiceri, 2005; Koop et al., 2009; Nakajima, 2011).

The empirical findings can be summarised as follows. The linear VAR responses of electricity consumption (a proxy for economic activity) to a one-standard-deviation shock to the number of COVID-19 cases are statistically insignificant, except for France, whilst the CDS responses are positive and significant only in a few periods, and there are very mixed results for those of stock returns. As for the TVP-VAR results, these indicate that COVID-19 cases had a negative and significant effect on economic activity in all countries in the early stages of the pandemic (especially in Italy), and a positive one on CDS at the same time (with cross-country differences). Finally, the negative impact on stock markets was felt only initially and it had tapered off by mid-April 2020. There are various possible explanations for this rapid recovery of the international financial markets, such as the effects of economic support packages and monetary expansion (Avalos and Xia, 2020; Igan et al., 2020; Su, 2020), or the rising demand for saving which drove up stock prices (Herrenbrueck, 2021; Andre, 2021). Future research should investigate more thoroughly cross-country differences in terms of economic performance, policy responses to COVID-19 including containment measures, and vulnerability to external shocks, to explain the asymmetric effects of the COVID-19 pandemic.

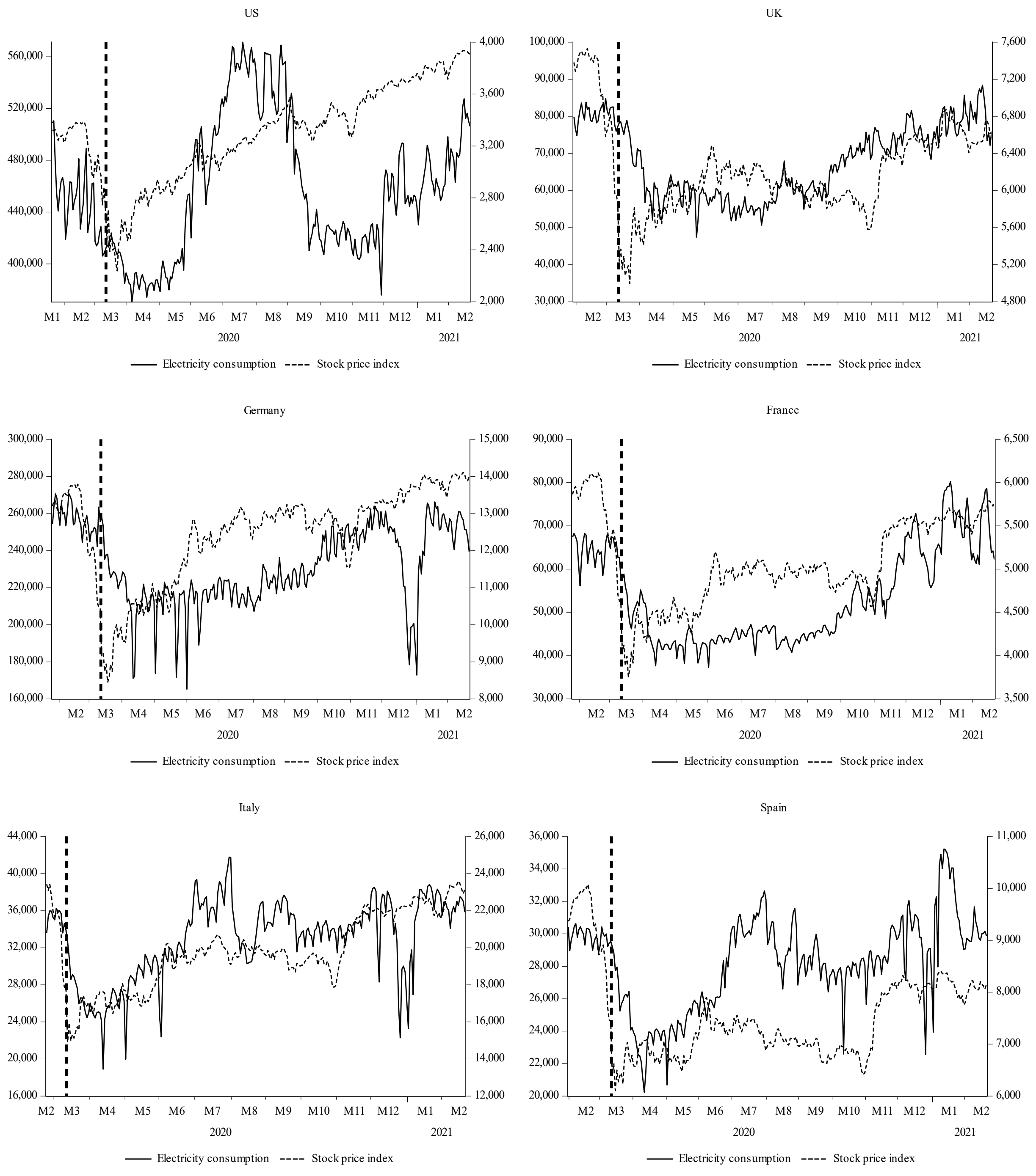
Table 1. Descriptive Statistics

Variables	Obs.	Mean	Min.	Max.	Std. Dev.	Jarque-Bera	Prob.
US							
$case_t$	284	7546557	1	28046275	8312653	63.857	0.000
ec_t	284	457163.9	370770.4	571229.1	52259.41	17.348	0.000
cds_t	284	14.136	8.510	22.759	3.480	5.651	0.059
ret_t	284	3295.276	2237.400	3934.830	368.709	9.139	0.010
UK							
$case_t$	277	915721.4	2	4095269	1184062	117.9764	0.000
ec_t	277	68020.59	47424.04	88367.29	9827.199	18.949	0.000
cds_t	277	16.872	10.660	37.110	6.235	58.364	0.000
ret_t	277	6224.557	4993.890	7534.370	482.092	23.422	0.000
Germany							
$case_t$	280	570925.5	1	2373685	712001.7	96.117	0.000
ec_t	280	232457.1	165228.8	270823.7	21284.47	7.573	0.022
cds_t	280	7.027	4.780	13.780	2.505	61.023	0.000
ret_t	280	12465.09	8441.710	14109.48	1282.361	60.381	0.000
France							
$case_t$	280	920619.3	3	3560764	1121655	53.865	0.000
ec_t	280	53654.68	37252.13	80243.67	10881.54	25.130	0.000
cds_t	280	9.787	5.020	26.140	5.613	92.703	0.000
ret_t	280	5085.621	3754.840	6111.240	508.212	4.253	0.119
Italy							
$case_t$	260	762429.1	221	2780882	869095	58.461	0.000
ec_t	260	33016.67	18905.63	41777.67	4278.590	22.967	0.000
cds_t	260	81.712	31.100	169.350	32.306	20.703	0.000
ret_t	260	19843.31	14894.44	23604.31	2027.008	6.417	0.040
Spain							
$case_t$	276	827701.4	1	3133122	883460.2	56.920	0.000
ec_t	276	28240.02	20234.00	35234.79	2814.145	3.872	0.144
cds_t	276	33.082	10.440	86.720	15.182	64.902	0.000
ret_t	276	7523.090	6107.200	10083.60	853.748	68.918	0.000

Table 2. Estimation results for selected parameters of the TVP-VAR models

Parameters	Mean	Std. Dev.	95%L	95%U	CD	Inefficiency
			US			
$(\Sigma_\Theta)_1$	0.016	0.001	0.014	0.019	0.031	6.67
$(\Sigma_\Theta)_2$	0.022	0.002	0.018	0.028	0.554	13.57
$(\Sigma_\alpha)_1$	0.085	0.023	0.049	0.142	0.137	68.56
$(\Sigma_\alpha)_2$	0.076	0.020	0.045	0.126	0.790	67.48
$(\Sigma_h)_1$	0.264	0.044	0.187	0.360	0.909	72.11
$(\Sigma_h)_2$	0.322	0.056	0.220	0.442	0.277	95.44
			UK			
$(\Sigma_\Theta)_1$	0.017	0.001	0.014	0.020	0.329	8.59
$(\Sigma_\Theta)_2$	0.022	0.002	0.018	0.028	0.700	12.02
$(\Sigma_\alpha)_1$	0.082	0.022	0.048	0.136	0.136	65.07
$(\Sigma_\alpha)_2$	0.071	0.019	0.043	0.117	0.633	52.32
$(\Sigma_h)_1$	0.252	0.041	0.180	0.343	0.833	63.77
$(\Sigma_h)_2$	0.277	0.052	0.187	0.391	0.009	107.02
			Germany			
$(\Sigma_\Theta)_1$	0.016	0.001	0.014	0.019	0.306	5.91
$(\Sigma_\Theta)_2$	0.022	0.002	0.018	0.028	0.383	15.42
$(\Sigma_\alpha)_1$	0.090	0.026	0.051	0.152	0.602	73.15
$(\Sigma_\alpha)_2$	0.078	0.021	0.046	0.132	0.191	62.87
$(\Sigma_h)_1$	0.271	0.043	0.192	0.364	0.673	56.66
$(\Sigma_h)_2$	0.284	0.052	0.189	0.393	0.519	86.24
			France			
$(\Sigma_\Theta)_1$	0.017	0.001	0.014	0.020	0.164	7.31
$(\Sigma_\Theta)_2$	0.022	0.002	0.018	0.028	0.150	14.92
$(\Sigma_\alpha)_1$	0.080	0.023	0.046	0.137	0.918	71.43
$(\Sigma_\alpha)_2$	0.077	0.022	0.044	0.129	0.613	73.08
$(\Sigma_h)_1$	0.265	0.046	0.185	0.366	0.054	66.69
$(\Sigma_h)_2$	0.342	0.060	0.235	0.470	0.226	72.96
			Italy			
$(\Sigma_\Theta)_1$	0.016	0.001	0.0144	0.019	0.782	7.60
$(\Sigma_\Theta)_2$	0.022	0.002	0.018	0.028	0.033	15.88
$(\Sigma_\alpha)_1$	0.087	0.026	0.049	0.150	0.820	62.12
$(\Sigma_\alpha)_2$	0.078	0.021	0.045	0.129	0.278	53.91
$(\Sigma_h)_1$	0.251	0.043	0.176	0.346	0.610	65.84
$(\Sigma_h)_2$	0.266	0.055	0.173	0.392	0.643	73.67
			Spain			
$(\Sigma_\Theta)_1$	0.016	0.001	0.014	0.019	0.004	7.94
$(\Sigma_\Theta)_2$	0.022	0.002	0.018	0.028	0.803	13.79
$(\Sigma_\alpha)_1$	0.084	0.023	0.048	0.139	0.750	72.77
$(\Sigma_\alpha)_2$	0.077	0.020	0.046	0.126	0.646	51.80
$(\Sigma_h)_1$	0.273	0.045	0.195	0.373	0.126	63.35
$(\Sigma_h)_2$	0.283	0.054	0.188	0.404	0.053	97.57

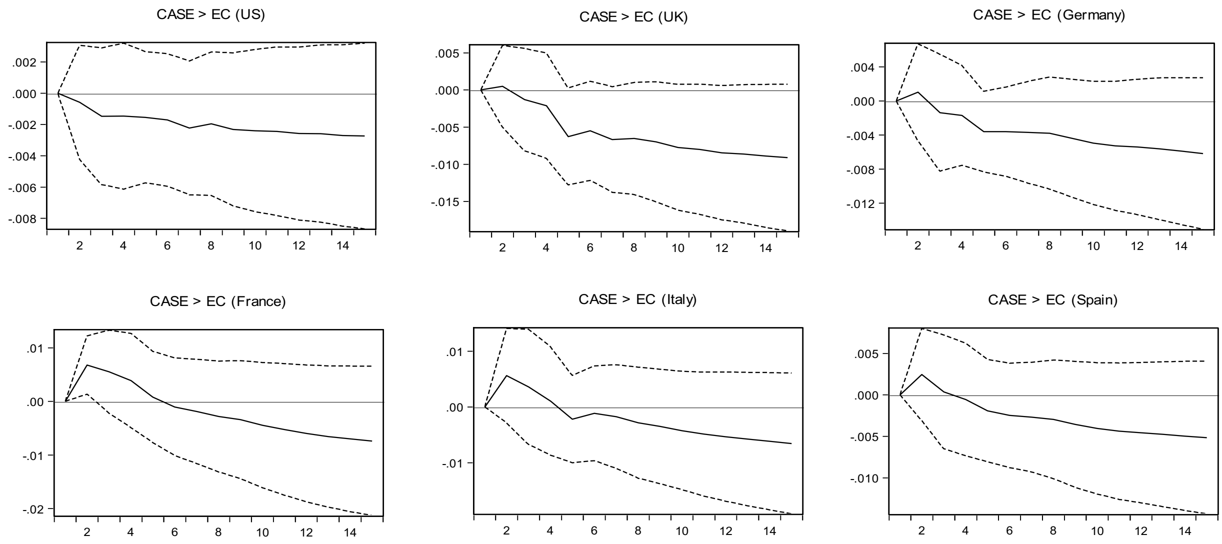
Figure 1. Time series plots of electricity consumption and stock price indices



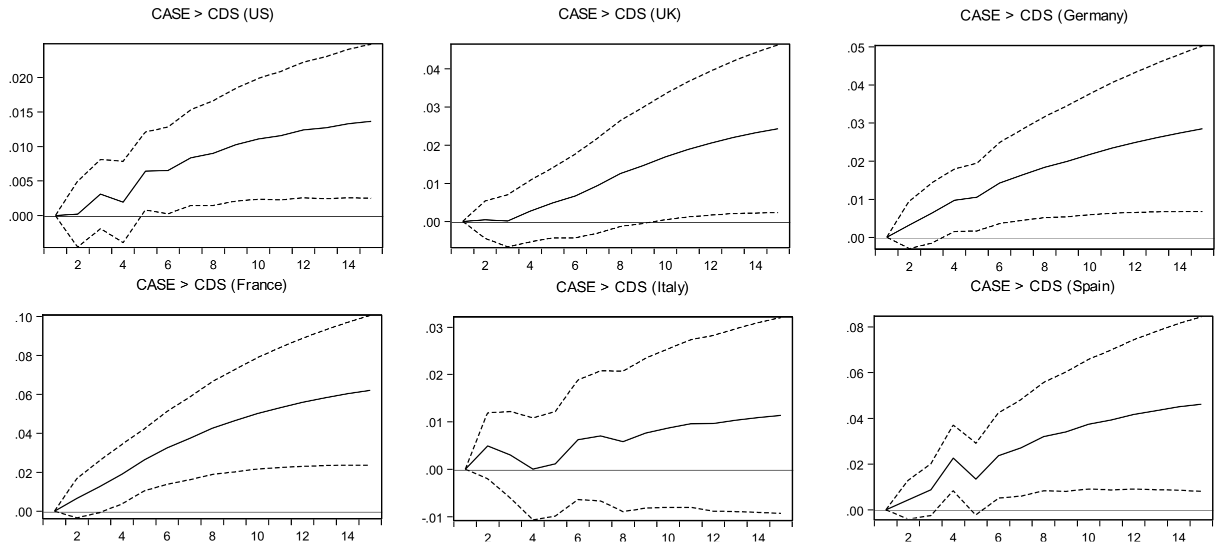
Notes: The left axis shows electricity consumption while the right axis is for the stock price index. Electricity consumption data is the average hourly electricity load measured in megawatt, and weekends are excluded for consistency with stock price index data. The vertical dashed black line represents the date March 11, 2020, on which WHO declared the COVID-19 as a global pandemic.

Figure 2. Linear VAR responses to COVID-19 cases shocks

Panel A. Cumulative responses of electricity consumption to COVID-19 cases shocks



Panel B. Cumulative responses of CDS to COVID-19 cases shocks



Panel C. Cumulative responses of stock return to COVID-19 cases shocks

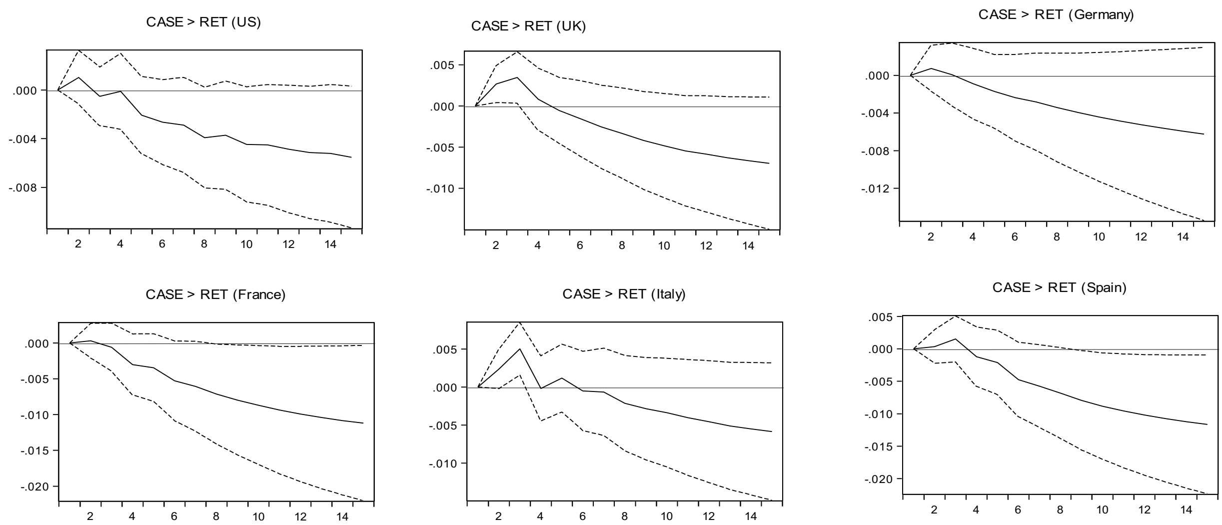
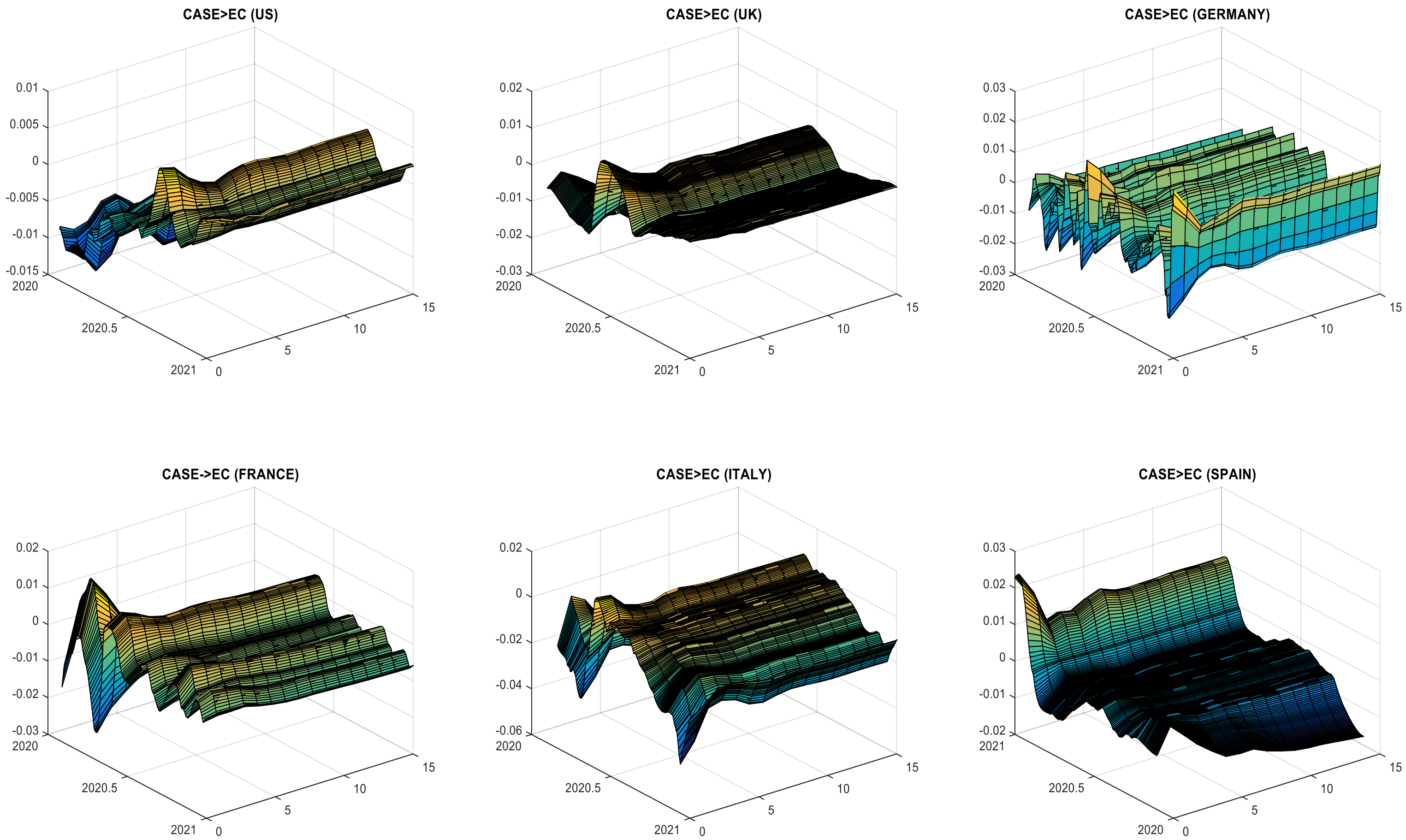


Figure 3. Time-varying responses of electricity consumption to COVID-19 cases shocks

Panel A. Time-varying cumulative responses



Panel B. Cumulative responses at h=15 with $\pm$ 2 standard error bands

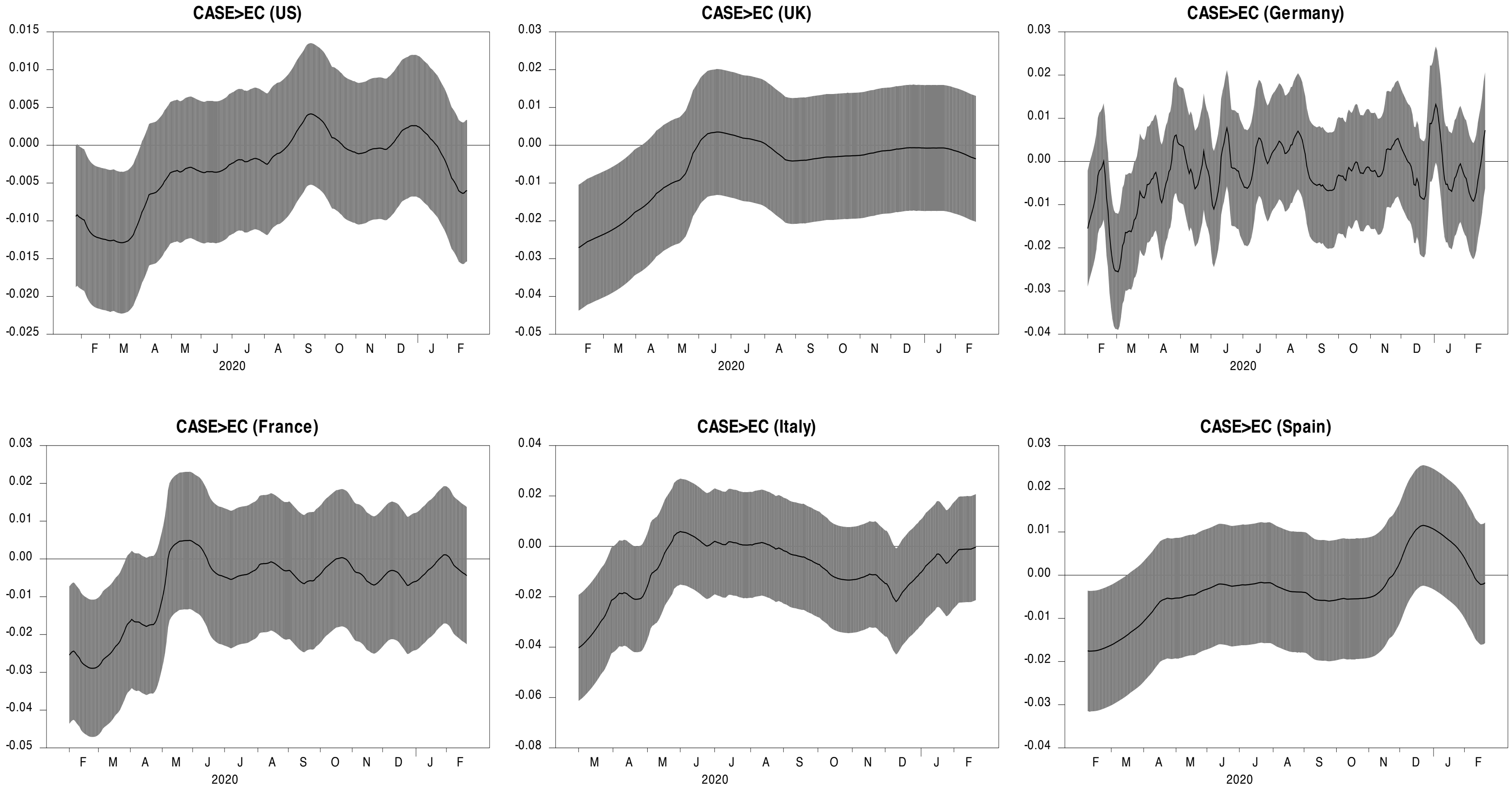
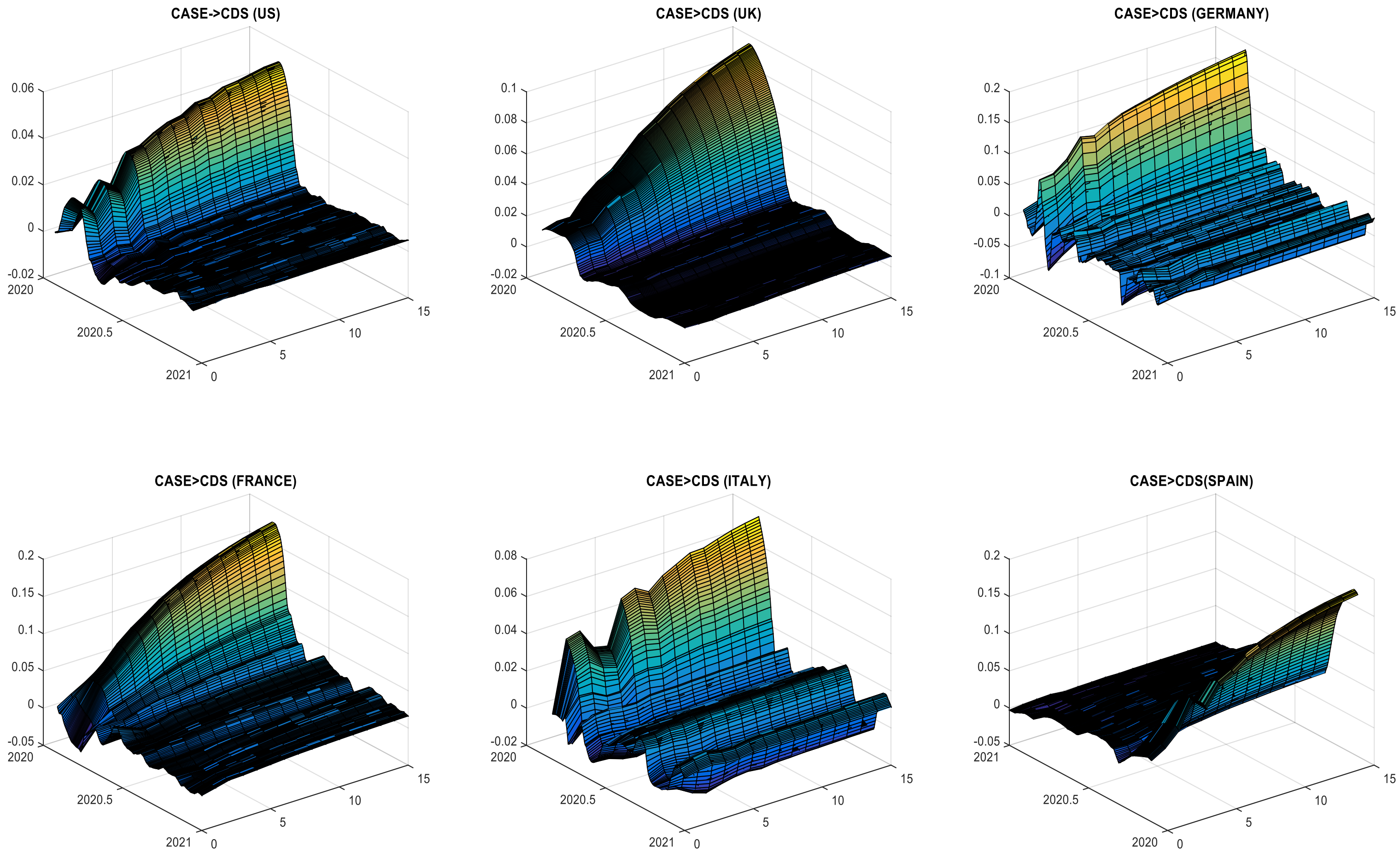


Figure 4. Time-varying responses of CDS to COVID-19 cases shocks

Panel A. Time-varying cumulative responses



Panel B. Cumulative responses at h=15 with $\pm$ 2 standard error bands

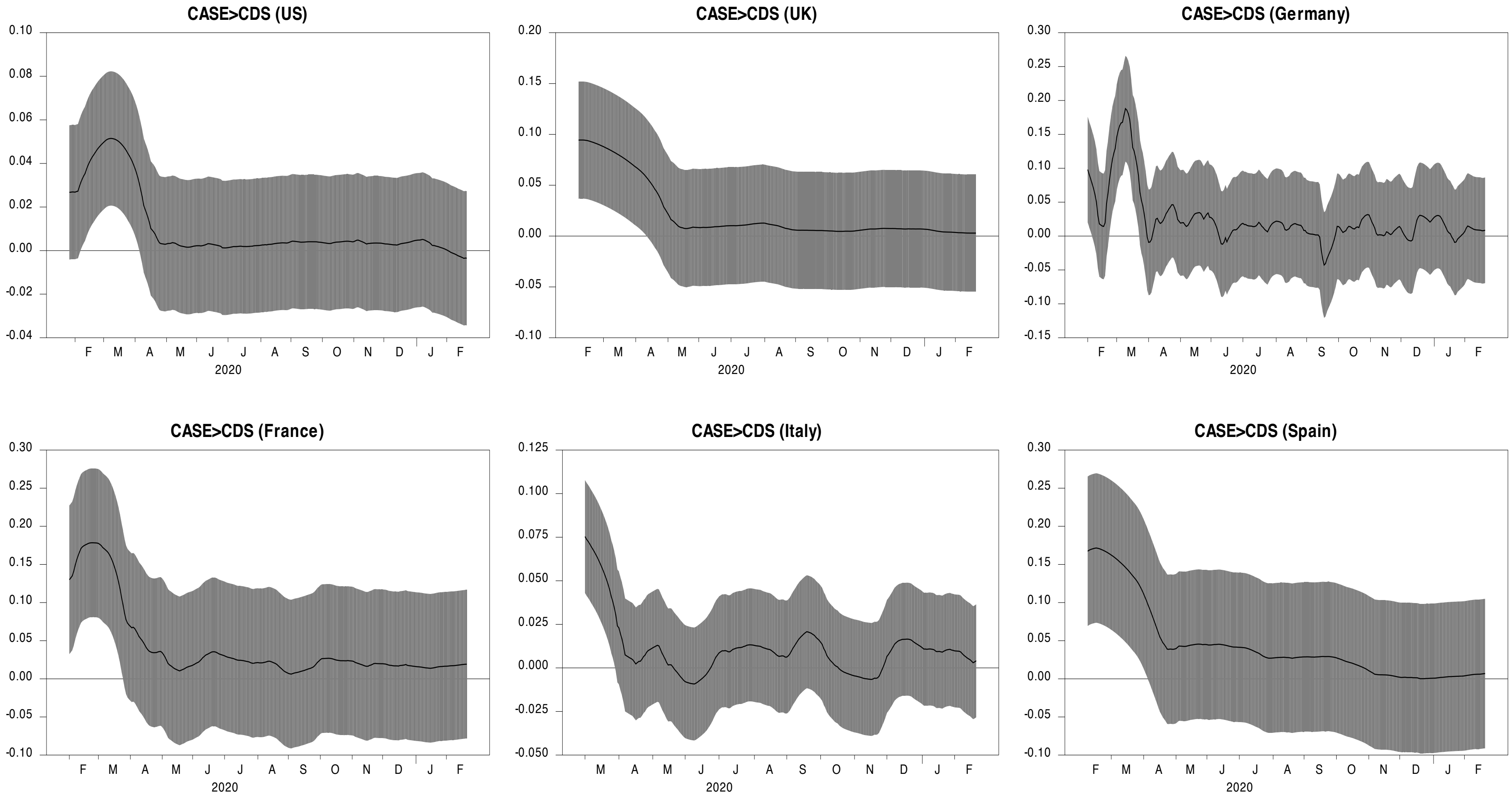
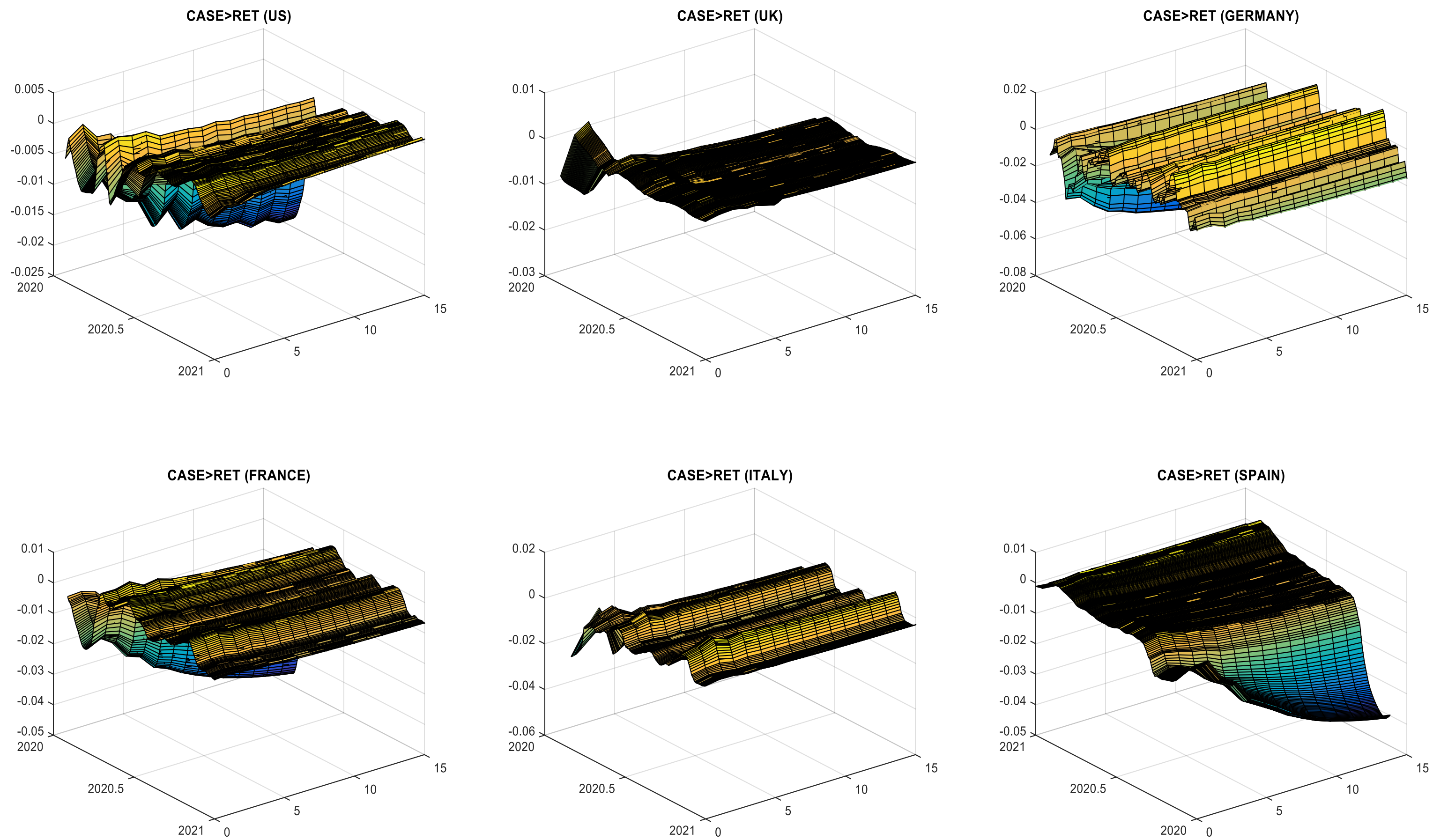
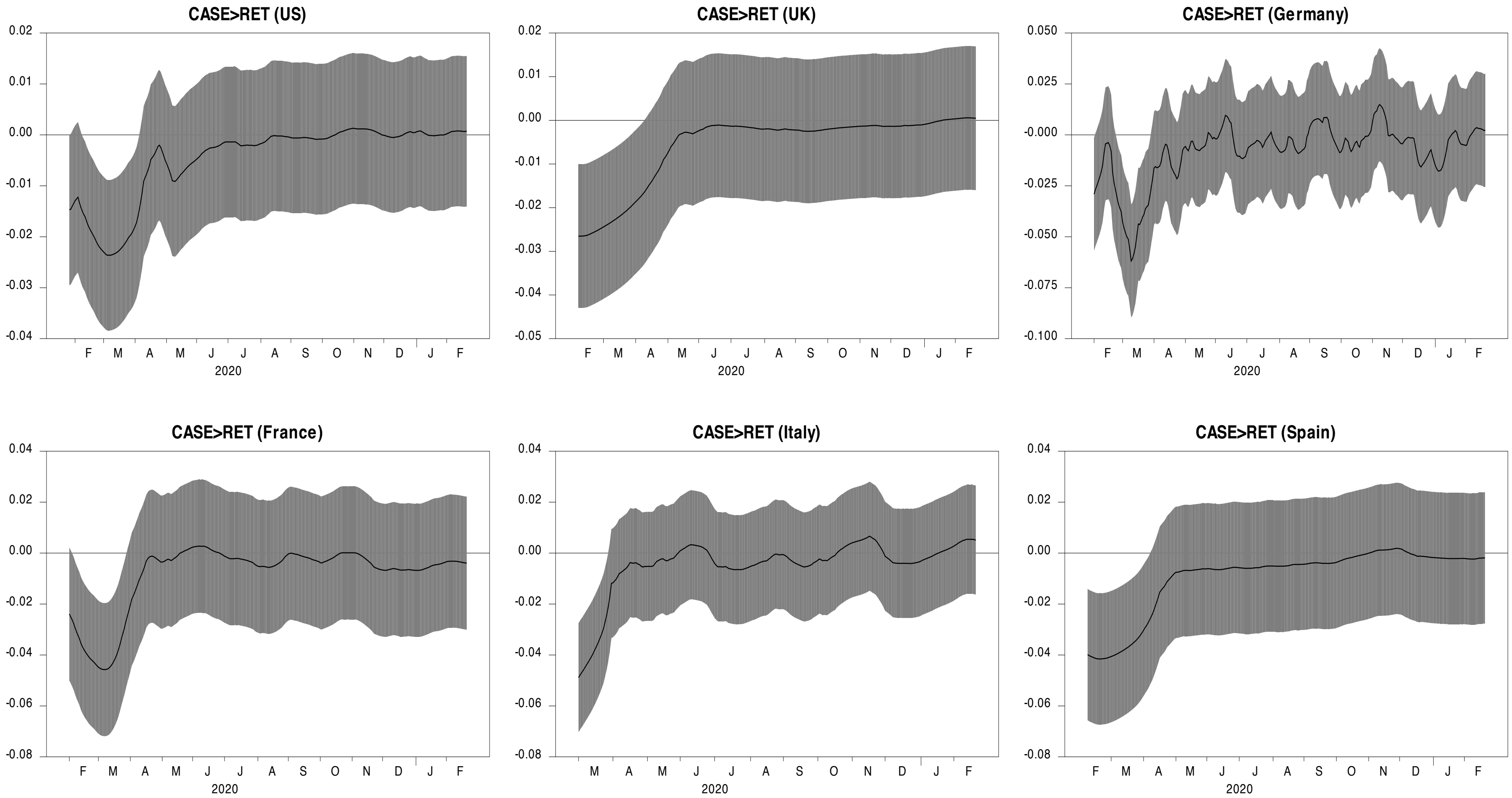


Figure 5. Time-varying responses of stock return to COVID-19 cases shocks

Panel A. Time-varying cumulative responses



Panel B. Cumulative responses at h=15 with ± 2 standard error bands



References

Aggarwal, S., Nawn, S., and Dugar, A. (2021). What caused global stock market meltdown during the COVID pandemic-Lockdown stringency or investor panic?, *Finance Research Letters,* 38, https://doi.org/10.1016/j.frl.2020.101827

Al-Awadhi, A. M., Alsaifi, K., Al-Awadhi, A., and Alhammadi, S. (2020). Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns, *Journal of Behavioral and Experimental Finance,* 27. https://doi.org/10.1016/j.jbef.2020.100326

Al-Maadid, A., Caporale, G. M., Spagnolo, F., and Spagnolo, N. (2021). Political tension and stock markets in the Arabian Peninsula. International Journal of Finance & Economics, 26(1), 679-683. https://doi.org/10.1002/ijfe.1810

Ali, M., Alam, N., and Rizvi, S. A. R. (2020). Coronavirus (COVID-19) – An epidemic or pandemic for financial markets, *Journal of Behavioral and Experimental Finance,* 27. https://doi.org/10.1016/j.jbef.2020.100341

Ambros, M. Frenkel, M., Huynh, T. L. D., and Kilinc, M. (2020). COVID-19 pandemic news and stock market reaction during the onset of the crisis: evidence from high-frequency data, *Applied Economic Letters,* https://doi.org/10.1080/13504851.2020.1851643

Ampudia, M., Baumann, U., and Fornari, F. (2020). Coronavirus (COVID-19): market fear as implied by options prices, *ECB Economic Bulletin,* 4, 51-55.

André, V. C. (2021). Rising Stocks during Lockdown Economic Recessions: Explaining the Phenomenon, *MPRA Paper,* 106710. https://mpra.ub.uni-muenchen.de/id/eprint/106710

Anh, D. L. T., and Gan, C. (2021). The impact of the COVID-19 lockdown on stock market performance: evidence from Vietnam, *Journal of Economic Studies,* 48(4), 836-851. https://doi.org/10.1108/JES-06-2020-0312

Ashraf, B. N. (2020a). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance,* 54. https://doi.org/10.1016/j.ribaf.2020.101249

Ashraf, B. N. (2020b). Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets, *Journal of Behavioral and Experimental Finance,* 27. https://doi.org/10.1016/j.jbef.2020.100371

Avalos, F., and Xia, D. (2020). The short and long end of equity prices during the pandemic: Valuations and the shift in interest rates, *BIS Quarterly Review,* September, 9-10.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C., and Viratyosin, T. (2020). The Unprecedented Stock Market Impact of COVID-19, *NBER Working Paper Series,* 26495. https://www.nber.org/papers/w26945

Beyer, R. C. M., Franco-Bedoya, S., and Galdo, V. (2021). Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity, *World Development,* 140. https://doi.org/10.1016/j.worlddev.2020.105287

BIS. (2020). BIS Quarterly Review: International banking and financial market developments, March.

Capelle-Blancard, G., and Desroziers, A. (2020). The stock market is not the economy? Insights from the Covid-19 crisis, *Covid Economics: Vetted and Real-Time Papers,* CEPR Press, 28. June 12. https://cepr.org/

Carvalho, V., Juan, G., Hansen, S., Ortiz, A., Rodrigo, T., Mora, J. V. R., and Ruiz, J. (2020). Tracking the COVID-19 Crisis with High-Resolution Transaction Data, *Cambridge Working Papers in Economics,* 2030. https://www.econ.cam.ac.uk/research-files/repec/cam/pdf/cwpe2030.pdf

Cavallo, E., and Noy, I. (2011). Natural disasters and the economy—a survey. *International Review of Environmental and Resource Economics*, 5(1), 63-102. http://dx.doi.org/10.1561/101.00000039

CBOE. (2021) Chicago Board Options Exchange Volatility Index Historical Price Data. https://www.cboe.com/tradable_products/vix/vix_historical_data/

Chang, C-H., Feng, G-F., and Zheng, M. (2021). Government Fighting Pandemic, Stock Market Return, and COVID-19 Virus Outbreak, *Emerging Market Finance and Trade.* https://doi.org/10.1080/1540496X.2021.1873129

Chau, F., Deesomsak, R., and Wang, J. (2014). Political uncertainty and stock market volatility in the Middle East and North African (MENA) countries. *Journal of International Financial Markets, Institutions and Money*, 28, 1-19. https://doi.org/10.1016/j.intfin.2013.10.008

Chen, S., Igan, D., Pierri, N., and Presbitero, A. F. (2020). Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States, *IMF Working Paper,* 125. https://www.imf.org/en/Publications/WP/Issues/2020/07/10/Tracking-the-Economic-Impact-of-COVID-19-and-Mitigation-Policies-in-Europe-and-the-United-49553

Chesney, M., Reshetar, G., and Karaman, M. (2011). The impact of terrorism on financial markets: An empirical study. *Journal of Banking & Finance*, 35(2), 253-267. https://doi.org/10.1016/j.jbankfin.2010.07.026

Chundakkadan, R., and Nedumparambil, E. (2021). In search of COVID-19 and stock market behavior, *Global Finance Journal,* https://doi.org/10.1016/j.gfj.2021.100639

Cogley, T., and Sargent, T. J. (2005). Drifts and volatilities: monetary policies and outcomes in the post WWII US, *Review of Economic Dynamics,* 8(2), 262-302. https://doi.org/10.1016/j.red.2004.10.009

D'Orazio, P., and Dirks, M. W. (2020). COVID-19 and financial markets: Assessing the impact of the coronavirus on the Eurozone, *Ruhr Economic Papers,* 859. http://dx.doi.org/10.4419/86788995

Davis, S. J., Liu, D., and Sheng, X. S. (2020). Stock Prices, Lockdowns, and Economic Activity in the Time of Coronavirus, *The Becker Friedman Institute Working Paper Series,* 156. https://repec.bfi.uchicago.edu/RePEc/pdfs/BFI_WP_2020156.pdf

Eichenbaum, M. S., Rebelo, S., and Trabandt, M. (2020). The Macroeconomics of Epidemics, *NBER Working Paper Series,* 26882. http://www.nber.org/papers/w26882

Elsayed, A. H., and Helmi, M. H. (2021). Volatility transmission and spillover dynamics across financial markets: the role of geopolitical risk. *Annals of Operations Research*, 1-22. https://doi.org/10.1007/s10479-021-04081-5

Fezzi, C., and Fanghella V. (2020). Real-Time Estimation of the Short-Run Impact of COVID-19 on Economic Activity Using Electricity Market Data, *Environmental and Resource Economics,* 76, 885-900. https://doi.org/10.1007/s10640-020-00467-4

FSB. (2020). COVID-19 pandemic: Financial stability implications and policy measures taken, April 15.

Geweke, J. (1992). *Evaluating the Accuracy of Sampling-Based Approaches to the Calculation of Posterior Moments,* In Bayesian Statistics, 4, edited by J. M. Bernardo, J. O. Berger, A. P. Dawid, and A. F. M. Smith, 169-193. Oxford: Oxford University Press.

Gopinath, G. (2020). The Great Lockdown: Worst Economic Downturn Since the Great Depression. https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/

Harjoto, M. A., and Rossi, F. (2021). Market reaction to the COVID-19 pandemic: evidence from emerging markets, *International Journal of Emerging Markets.* https://doi.org/10.1016/j.frl.2020.101691

Haroon, O., and Rizvi, S. A. R. (2020). Flatten the Curve and Stock Market Liquidity – Inquiry into Emerging Economies, *Emerging Markets Finance and Trade,* 56(10), 2151-2161. https://doi.org/10.1080/1540496X.2020.1784716

Herrenbrueck, L. (2021). Why a pandemic recession boosts asset prices, *Journal of Mathematical Economics,* 93. https://doi.org/10.1016/j.jmateco.2021.102491

Horvath, R. (2021). Natural catastrophes and financial depth: An empirical analysis. *Journal of Financial Stability*, 53. https://doi.org/10.1016/j.jfs.2021.100842

Igan, D., Kirti, D., and Peria, S. M. (2020). The Disconnect between Financial Markets and the Real Economy, *IMF Special Notes Series on COVID-19.* https://www.imf.org/en/Publications/SPROLLs/covid19-special-notes

IMF. (2020). Global Financial Stability Report: Markets in the Time of COVID-19, April.

IMF. (2021). World Economic Outlook: Managing Divergent Recoveries, April.

Janzen, B., and Radulescu, D. (2020). Electricity Use as a Real-Time Indicator of the Economic Burden of the COVID-19-Related Lockdown: Evidence from Switzerland, *CESifo Economic Studies,* 66(4), 303-321. https://doi.org/10.1093/cesifo/ifaa010

Klose, J., and Tillmann, P. (2021). COVID-19 and Financial Markets: A Panel Analysis for European Countries, *Journal of Economics and Statistics.* https://doi.org/10.1515/jbnst-2020-0063

Koop, G., Leon-Gonzales, R., and Strachan, R. (2009). On the evolution of the monetary policy transmission mechanism. *Journal of Economic Dynamics and Control,* 33(4), 997-1017. https://doi.org/10.1016/j.jedc.2008.11.003

Lewis, D., Mertens, K., and Stock, J. H. (2020). US Economic Activity during the Early Weeks of the SARS-COV-2 Outbreak, *NBER Working Papers,* 26954. https://www.nber.org/papers/w26954

Lumsdaine, R. L., and Papell, D. H. (1997). Multiple Trend Breaks and the Unit-Root Hypothesis, *The Review of Economics and Statistics,* 79(2), 212-218. https://doi.org/10.1162/003465397556791

Menezes, F., Figer, V., Jardim, F., and Medeiros, P. (2021). Using electricity consumption to predict economic activity during COVID-19 in Brazil, *Discussion Papers Series from University of Queensland, School of Economics,* 641. http://www.uq.edu.au/economics/abstract/641.pdf

Nakajima, J. (2011). Time-Varying Parameter VAR Model with Stochastic Volatility: An Overview of Methodology and Empirical Applications. *Monetary and Economic Studies***,** 29, 107-142.

Nakajima, J., and Watanabe, T. (2011). Bayesian Analysis of Time-Varying Parameter Vector Autoregressive Model with the Ordering of Variables for the Japanese Economy and Monetary Policy, *Global COE Hi-Stat Discussion Paper Series,* 196.

Narayan, P. K., Narayan, S., and Prasad, A. (2008). A structural VAR analysis of electricity consumption and real GDP: Evidence from the G7 countries, *Energy Policy,* 36, 2765-2769. https://doi.org/10.1016/j.enpol.2008.02.027

Narayan, P. K., Phan, D. H. B., and Liu, G. (2021). COVID-19 lockdowns, stimulus packages, travel bans, and stock returns, *Finance Research Letters,* 38. https://doi.org/10.1016/j.frl.2020.101732

Payne, J. E. (2010). A survey of the electricity consumption-growth literature, *Applied Energy,* 87, 723-731. https://doi.org./10.1016/j.apenergy.2009.06.034

Phan, D. H. B., Narayan, P. K., and Gong, Q. (2021). Terrorist attacks and oil prices: Hypothesis and empirical evidence. *International Review of Financial Analysis*, 74, 101669. https://doi.org/10.1016/j.irfa.2021.101669

Primiceri, G. E. (2005). Time-varying Structural Vector Autoregressions and Monetary Policy. *Review of Economic Studies, 72*(3), 821 - 852. https://doi.org/10.1111/j.1467-937X.2005.00353.x

Sarwar, S., Chen, W., and Waheed, R. (2017). Electricity consumption, oil price and economic growth: Global perspective, *Renewable and Sustainable Energy Reviews,* 76, 9-18. https://doi.org/10.1016/j.rser.2017.03.063

Sharif, A., Aloui, C., and Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 70, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Shephard, N., and Pitt, M. K. (1997). Likelihood analysis of non-Gaussian measurement time series, *Biometrika,* 84(3), 653-667. https://doi.org/10.1093/biomet/84.3.653

Su, E. (2020). Why Have Stock Market and Real Economy Diverged During the COVID-19 Pandemic? *Congressional Research Service Reports.* https://www.everycrsreport.com/reports/IN11494.html

Topcu, M., and Gulal, O. S. (2020). The impact of COVID-19 on emerging stock markets, *Finance Research Letters*, 36. https://doi.org/10.1016/j.frl.2020.101691

Watanabe, T., and Omori, Y. (2004). A multi-move sampler for estimating non-Gaussian time series models: Comments on Shephard & Pitt (1997), *Biometrika,* 91(1), 246-248. https://doi.org/10.1093/biomet/91.1.246

WHO. (2020a). WHO Director-General's statement on IHR Emergency Committee on Novel Coronavirus (2019-nCoV). https://www.who.int/dg/speeches/detail/who-director-general-s-statement-on-ihr-emergency-committee-on-novel-coronavirus-(2019-ncov)

WHO, (2020b). WHO Director-General's opening remarks at the media briefing on COVID-19. https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

WHO. (2021). WHO Coronavirus Disease (COVID-19) Dashboard. https://covid19.who.int/

World Bank. (2021). Global Economic Prospects, January.

Xu, L. (2021). Stock Return and the COVID-19 pandemic: Evidence from Canada and the US, *Finance Research Letters,* 38. https://doi.org/10.1016/j.frl.2020.101872

Yoo, S-H., and Kwak, S-Y. (2010). Electricity consumption and economic growth in seven South American countries, *Energy Policy,* 38, 181-188. https://doi.org/10.1016/j.enpol.2009.09.003

Appendix

Table A1. Lumsdaine and Papell (1997) unit root test

		Breaks in intercept			Breaks in trend			Breaks in intercept and trend		
		$t-stat$	D_{1t}	D_{2t}	$t-stat$	DT_{1t}	DT_{2t}	$t-stat$	DT_{1t}	DT_{2t}
						Level				
US	$case_t$	-5.028	2020:05:04	2020:11:13	-5.755	2020:05:22	2020:10:14	-5.184	2020:05:25	2020:09:21
	ec_t	-4.921	2020:05:25	2020:08:28	-3.174	2020:08:06	2020:10:02	-4.972	2020:05:25	2020:08:28
	cds_t	-3.076	2020:09:22	2020:11:27	-4.308	2020:03:20	2020:09:03	-5.343	2020:04:06	2020:07:06
	ret_t	-3.113	2020:06:26	2020:10:30	-5.160	2020:03:25	2020:05:21	-6.237	2020:04:01	2020:09:02
						First difference				
	$case_t$	-13.063***	2020:04:06	2020:07:27	-13.039***	2020:03:23	2020:05:20	-14.203***	2020:03:23	2020:05:20
	ec_t	-8.831***	2020:06:09	2020:08:28	-8.694***	2020:06:23	2020:09:07	-9.240***	2020:05:25	2020:09:21
	cds_t	-23.949***	2020:03:20	2020:09:18	-23.340***	2020:03:20	2020:05:18	-24.622***	2020:03:20	2020:11:27
	ret_t	-9.454***	2020:04:01	2020:10:30	-8.833***	2020:05:18	2020:09:08	-9.591***	2020:03:25	2020:10:30
						Level				
UK	$case_t$	-6.920***	2020:10:16	2020:12:18	-4.714	2020:04:20	2020:09:18	-3.859	2020:04:03	2020:08:31
	ec_t	-5.024	2020:04:01	2020:09:22	-5.095	2020:04:13	2020:06:29	-6.132	2020:04:01	2020:09:22
	cds_t	-3.774	2020:05:25	2020:07:22	-6.136	2020:04:01	2020:08:26	-6.659*	2020:04:01	2020:09:18
	ret_t	-3.703	2020:05:15	2020:10:30	-3.247	2020:03:27	2020:05:22	-4.922	2020:04:03	2020:11:06
						First difference				
	$case_t$	-9.332***	2020:04:06	2020:06:01	-8.672***	2020:03:31	2020:05:26	-9.940***	2020:03:31	2020:05:26
	ec_t	-14.479***	2020:04:13	2020:07:22	-14.303***	2020:04:01	2020:08:06	-14.861***	2020:04:13	2020:12:25
	cds_t	-8.065***	2020:09:07	2020:11:27	-7.770***	2020:04:30	2020:07:24	-8.056***	2020:06:09	2020:09:07
	ret_t	-17.514***	2020:04:03	2020:10:30	-17.121***	2020:05:18	2020:07:13	-17.494***	2020:04:03	2020:10:30
						Level				
Germany	$case_t$	-6.037*	2020:05:11	2020:10:30	-6.689**	2020:04:02	2020:09:24	-5.404	2020:03:26	2020:09:07
	ec_t	-3.992	2020:04:02	2020:12:11	-4.159	2020:04:13	2020:11:11	-5.581	2020:04:03	2020:12:17
	cds_t	-3.532	2020:05:27	2020:09:24	-5.279	2020:04:01	2020:08:05	-5.248	2020:03:30	2020:06:30
	ret_t	-3.398	2020:05:15	2020:10:30	-4.544	2020:03:25	2020:06:04	-4.727	2020:03:25	2020:05:22
						First difference				
	$case_t$	-7.475***	2020:03:30	2020:12:21	-6.766**	2020:03:27	2020:05:25	-8.114***	2020:03:30	2020:10:21
	ec_t	-14.853***	2020:04:13	2020:12:25	-14.242***	2020:03:27	2020:06:04	-15.292***	2020:10:30	2020:12:25
	cds_t	-18.494***	2020:03:31	2020:05:27	-18.186***	2020:03:25	2020:05:28	-18.759***	2020:03:25	2020:05:27
	ret_t	-10.574***	2020:04:02	2020:10:30	-10.185***	2020:05:25	2020:07:24	-10.541***	2020:04:02	2020:10:30

Note: D_{1t} and D_{2t} refer to the first and second break dates, while DT_{1t} and DT_{2t} indicate the first and second break dates when allowing for the trend. ***, **, and * show significance at 1%, 5%, and 10%, respectively.

Table A1. (Continued)

		Breaks in intercept			Breaks in trend			Breaks in intercept and trend		
		$t-stat$	D_{1t}	D_{2t}	$t-stat$	DT_{1t}	DT_{2t}	$t-stat$	DT_{1t}	DT_{2t}
						Level				
France	$case_t$	-7.304***	2020:05:06	2020:10:21	-5.608	2020:09:16	2020:11:12	-7.728***	2020:08:25	2020:10:21
	ec_t	-5.161	2020:03:30	2020:11:11	-4.749	2020:04:10	2020:08:14	-5.448	2020:04:02	2020:11:18
	cds_t	-3.897	2020:03:26	2020:05:26	-5.391	2020:04:21	2020:06:22	-5.374	2020:03:26	2020:05:26
	ret_t	-3.607	2020:05:22	2020:10:30	-3.659	2020:03:25	2020:06:01	-4.563	2020:04:03	2020:11:06
						First difference				
	$case_t$	-7.302***	2020:03:31	2020:11:09	-6.856**	2020:03:27	2020:05:25	-7.991***	2020:03:30	2020:08:13
	ec_t	-7.825***	2020:04:13	2020:08:17	-7.695***	2020:04:06	2020:06:02	-8.462***	2020:04:13	2020:12:25
	cds_t	-18.265***	2020:05:04	2020:07:02	-18.079***	2020:03:25	2020:05:20	-18.410***	2020:03:31	2020:07:01
	ret_t	-10.473***	2020:04:03	2020:10:29	-10.128***	2020:05:27	2020:07:22	-10.463***	2020:04:03	2020:10:29
						Level				
Italy	$case_t$	-8.844***	2020:05:11	2020:10:23	-8.713***	2020:10:08	2020:12:01	-5.535	2020:09:29	2020:12:09
	ec_t	-4.750	2020:06:02	2020:07:31	-4.352	2020:04:21	2020:06:25	-5.408	2020:05:01	2020:07:31
	cds_t	-5.188	2020:06:02	2020:10:28	-5.098	2020:04:20	2020:06:11	-5.217	2020:05:15	2020:10:13
	ret_t	-6.664**	2020:05:22	2020:11:06	-5.826	2020:07:21	2020:09:24	-6.365	2020:07:31	2020:10:30
						First difference				
	$case_t$	-5.918*	2020:04:21	2020:10:02	-11.811***	2020:04:21	2020:11:09	-12.929***	2020:04:21	2020:10:16
	ec_t	-16.550***	2020:05:01	2020:12:25	-16.169***	2020:05:06	2020:08:05	-16.659***	2020:11:02	2020:12:25
	cds_t	-16.754***	2020:04:21	2020:06:11	-16.743***	2020:04:24	2020:12:30	-16.818***	2020:06:08	2020:08:07
	ret_t	-9.678***	2020:04:21	2020:10:29	-10.033***	2020:04:20	2020:07:28	-10.354***	2020:04:29	2020:10:29
						Level				
Spain	$case_t$	-2.575	2020:10:21	2020:12:25	-4.428	2020:08:07	2020:12:23	-4.207	2020:07:27	2020:12:07
	ec_t	-4.412	2020:06:19	2020:12:25	-4.529	2020:04:07	2020:07:01	-5.128	2020:04:02	2020:07:31
	cds_t	-3.244	2020:05:15	2020:11:02	-6.181	2020:04:14	2020:06:09	-6.245	2020:04:13	2020:06:09
	ret_t	-3.980	2020:05:22	2020:10:30	-3.420	2020:04:01	2020:09:29	-5.710	2020:04:01	2020:11:06
						First difference				
	$case_t$	-7.846***	2020:04:01	2020:07:31	-7.289***	2020:05:13	2020:09:07	-7.711***	2020:04:01	2020:07:15
	ec_t	-8.405***	2020:04:10	2020:10:12	-7.748***	2020:06:22	2020:08:17	-8.805***	2020:04:10	2020:12:25
	cds_t	-18.299***	2020:04:22	2020:11:02	-17.885***	2020:03:31	2020:05:26	-18.334***	2020:04:22	2020:07:10
	ret_t	-9.839***	2020:04:02	2020:10:29	-9.511***	2020:05:27	2020:07:22	-9.898***	2020:06:08	2020:10:29

Note: D_{1t} and D_{2t} refer to the first and second break dates, while DT_{1t} and DT_{2t} indicate the first and second break dates when allowing for the trend. ***, **, and * show significance at 1%, 5%, and 10%, respectively.

Figure A1. Recursive residuals of the Linear VAR: US

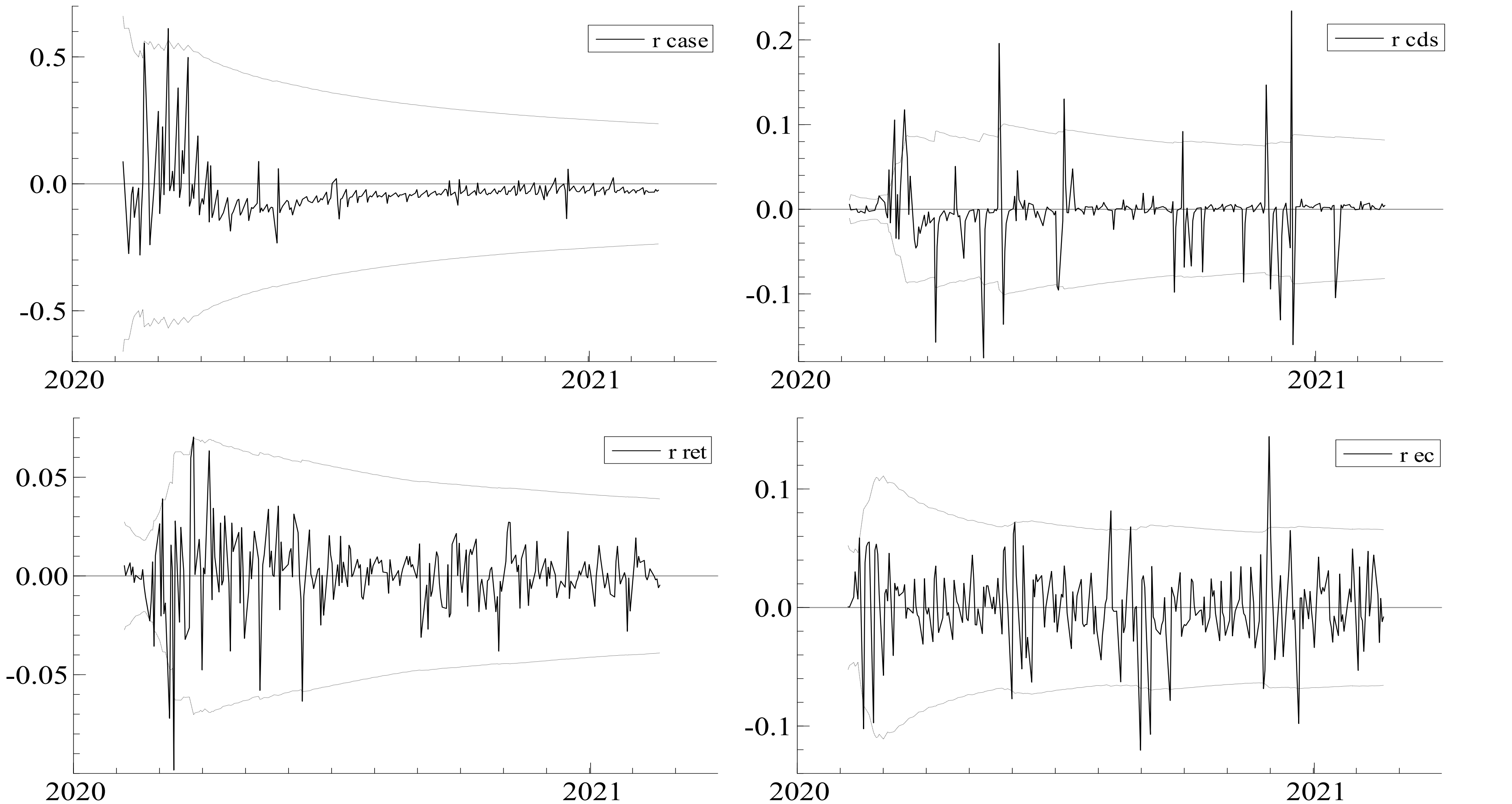


Figure A2. Recursive residuals of the Linear VAR: UK

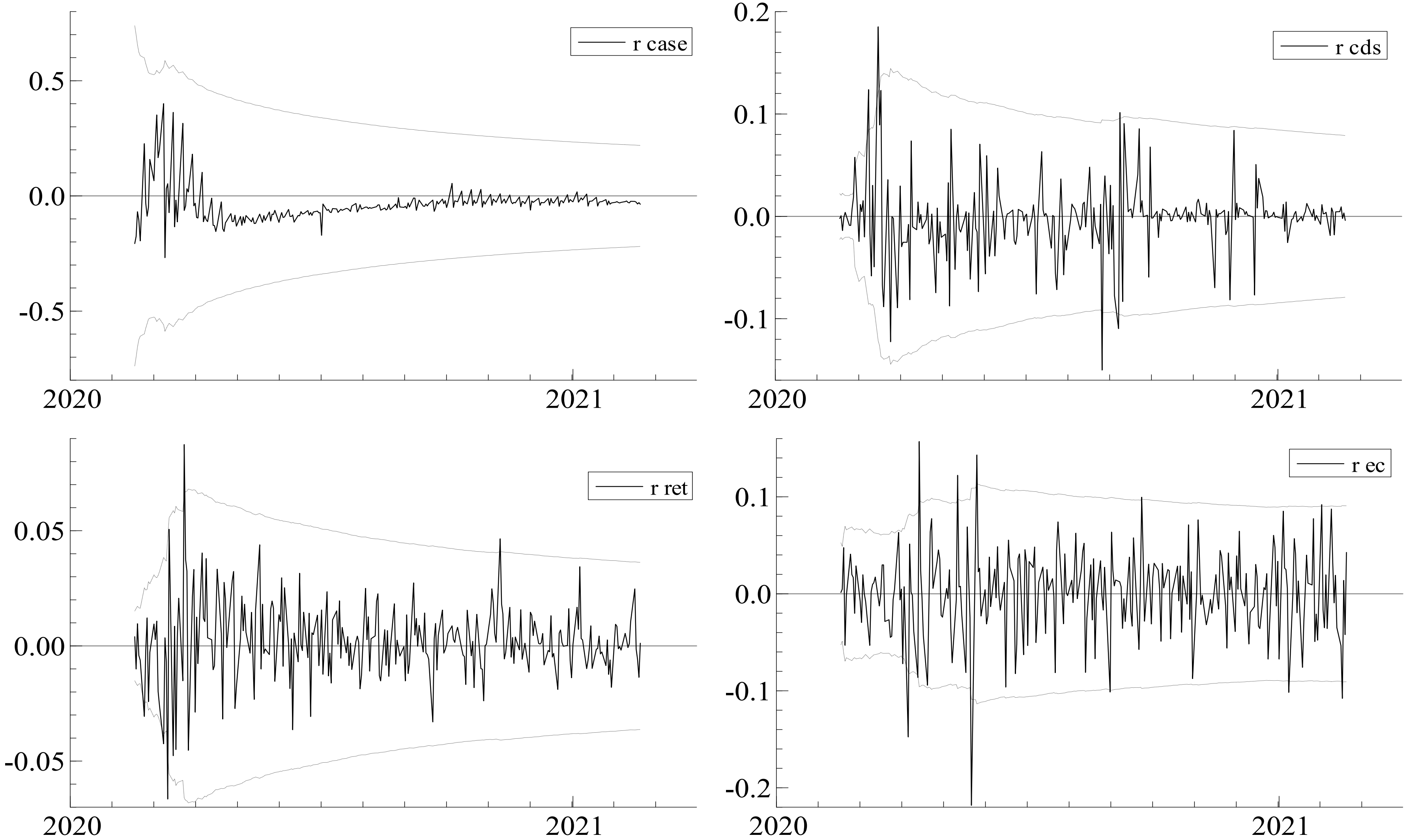


Figure A3. Recursive residuals of the Linear VAR: Germany

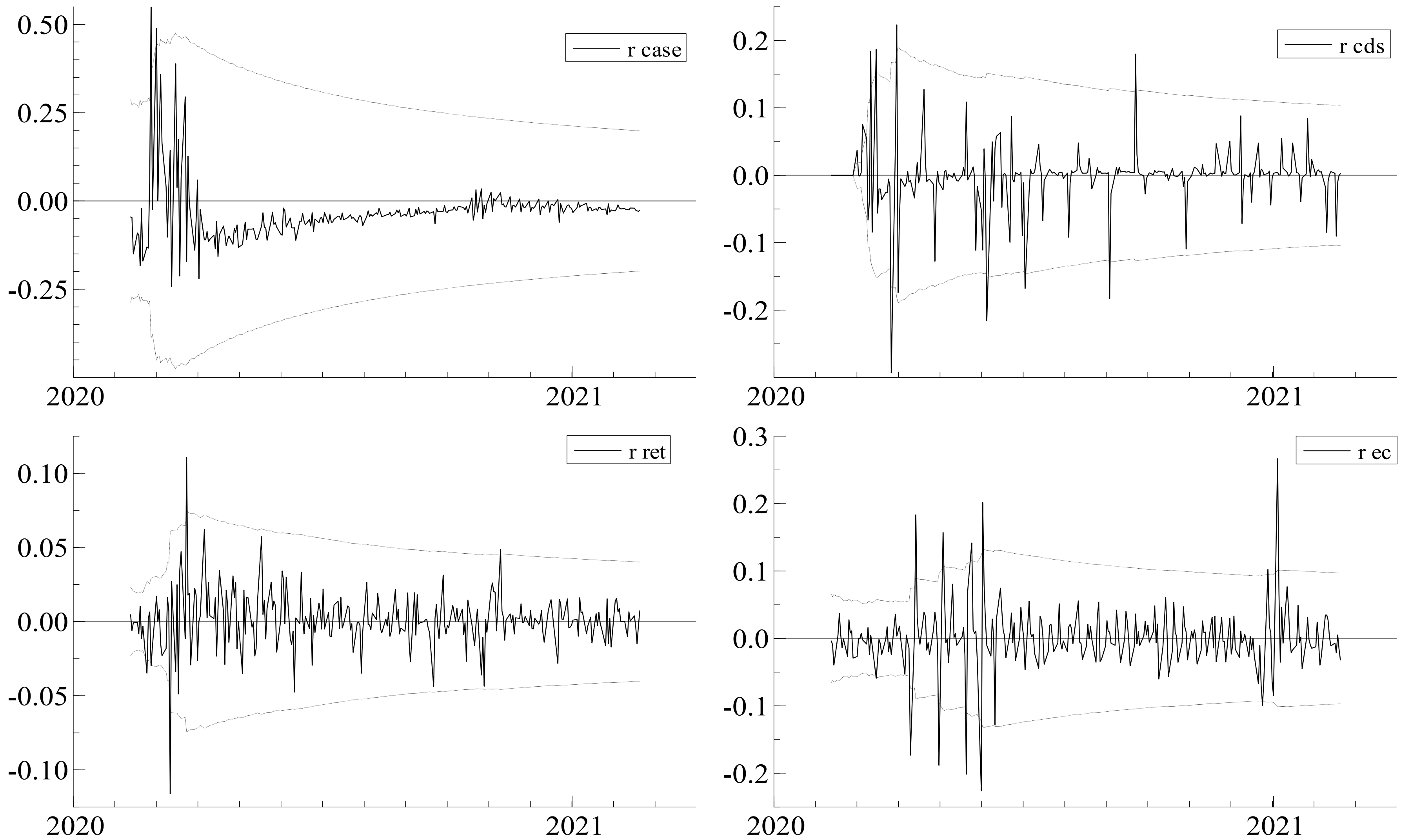


Figure A4. Recursive residuals of the Linear VAR: France

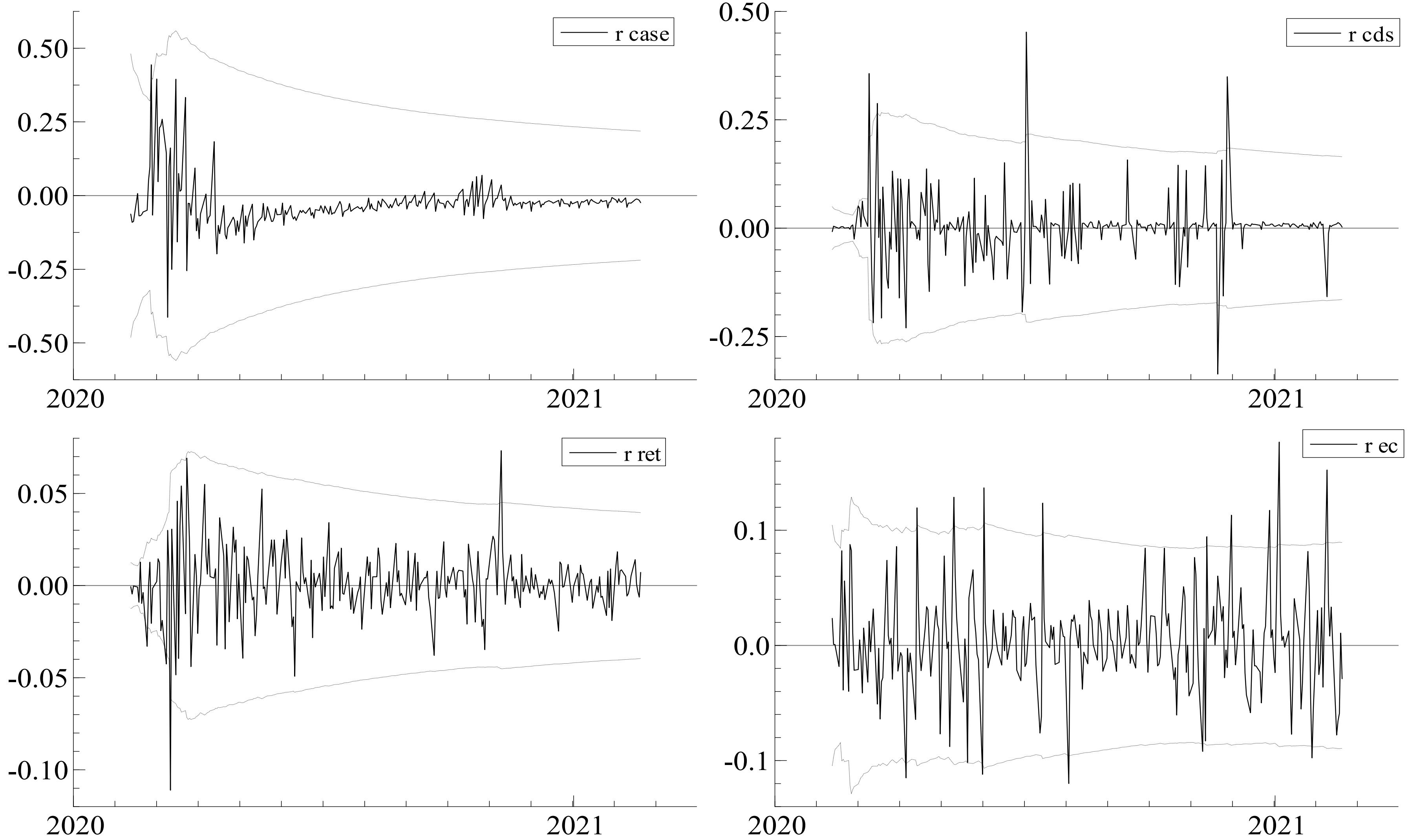


Figure A5. Recursive residuals of the Linear VAR: Italy

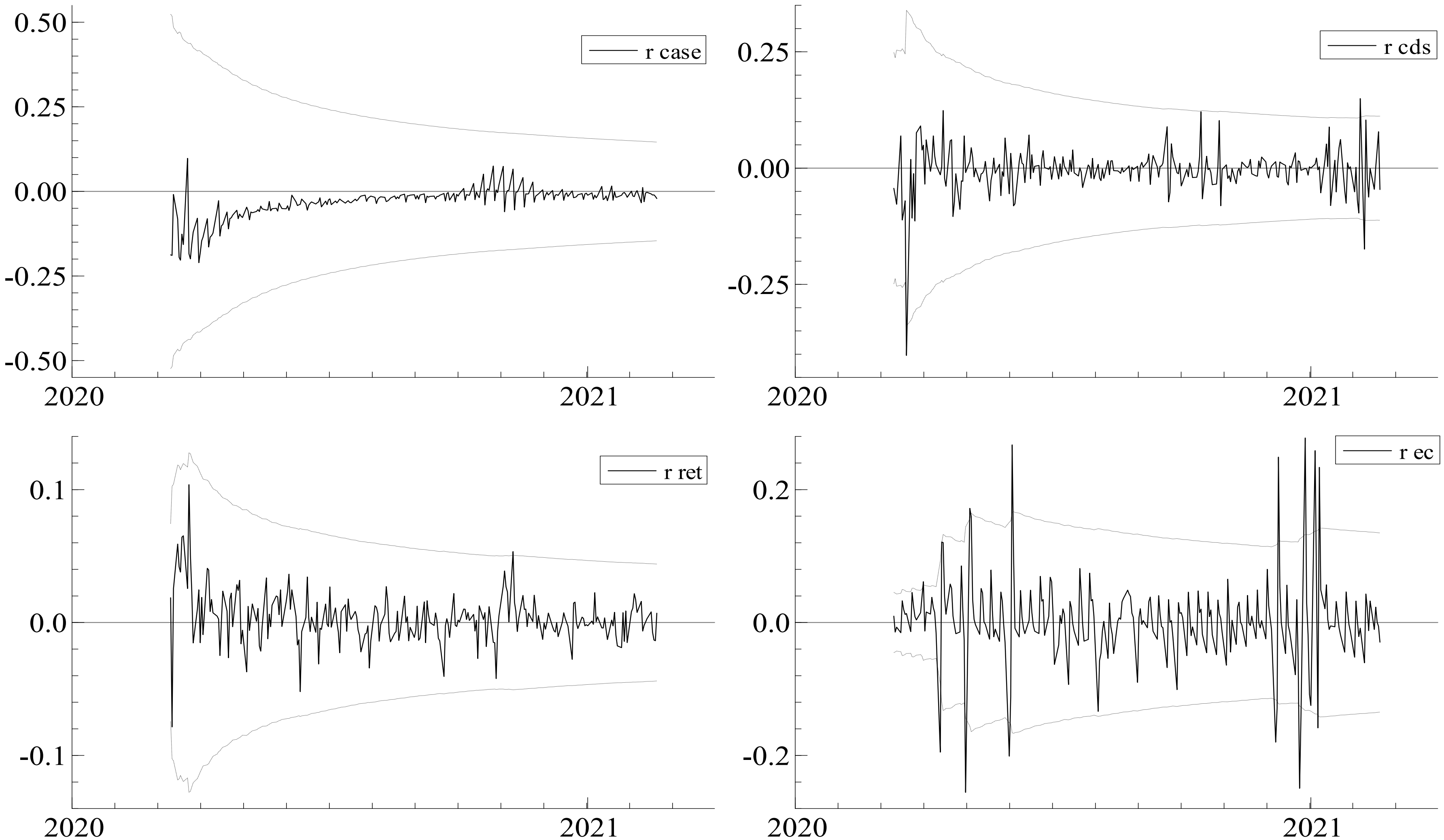


Figure A6. Recursive residuals of the Linear VAR: Spain

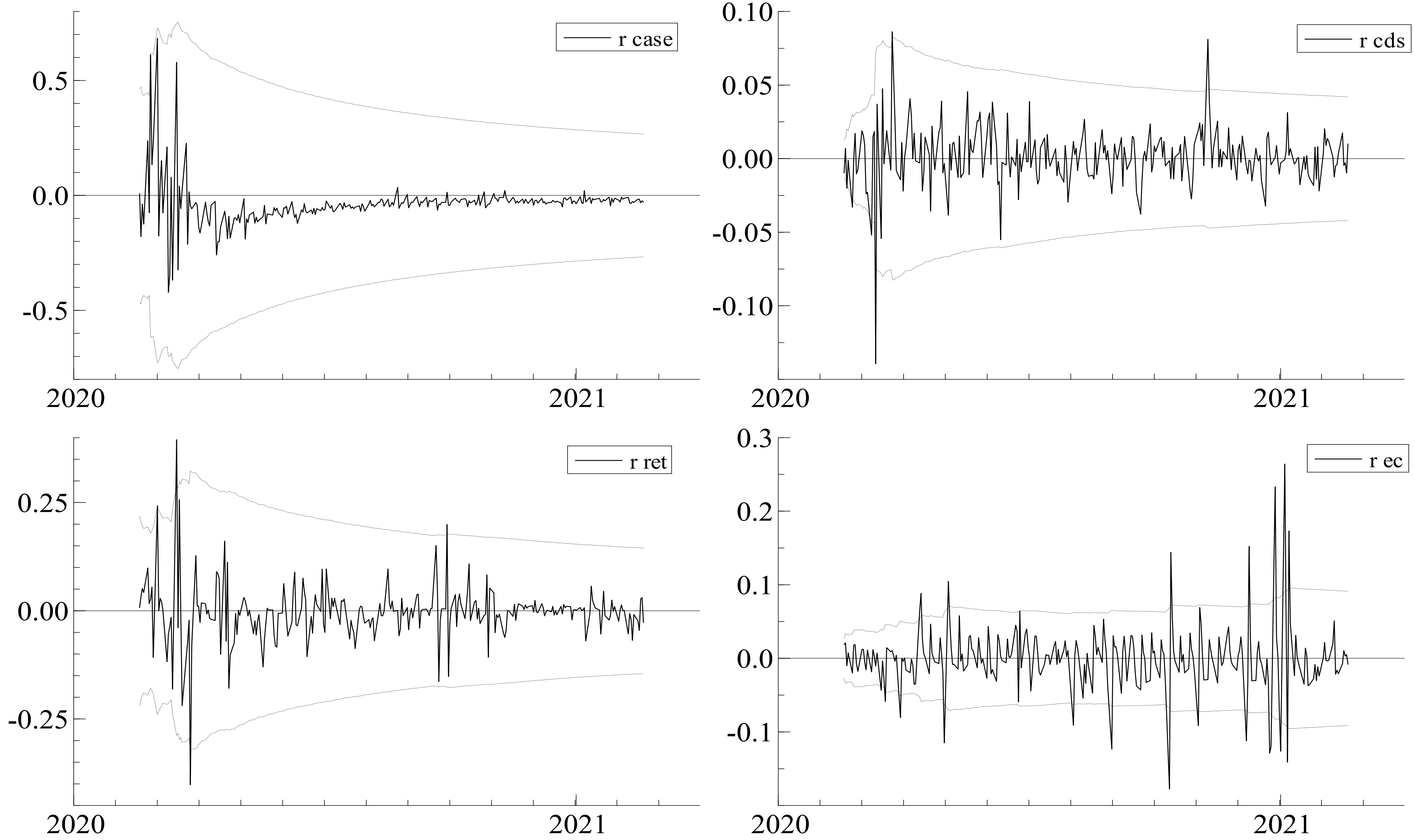


Figure A7. Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters: US

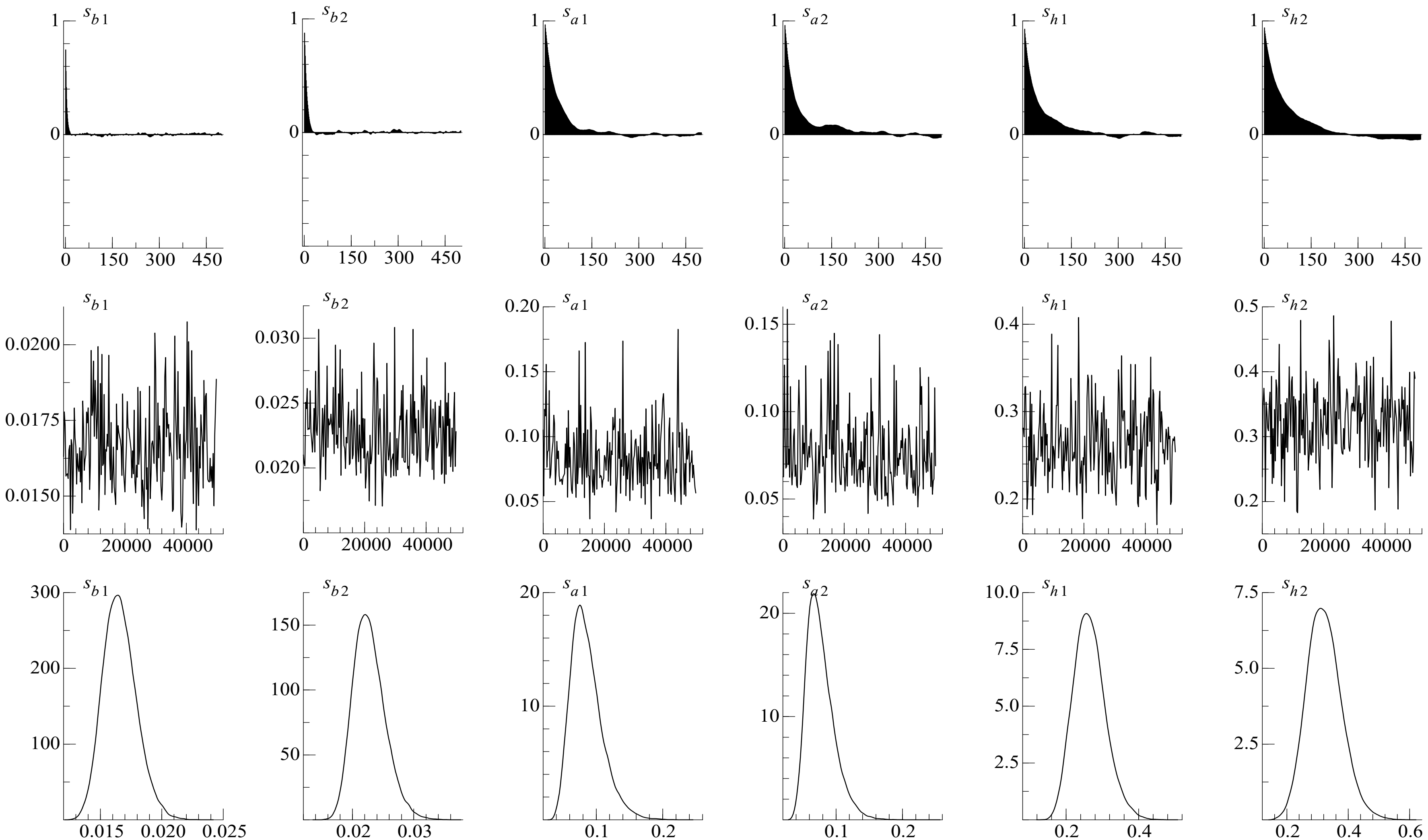


Figure A8. Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters: UK

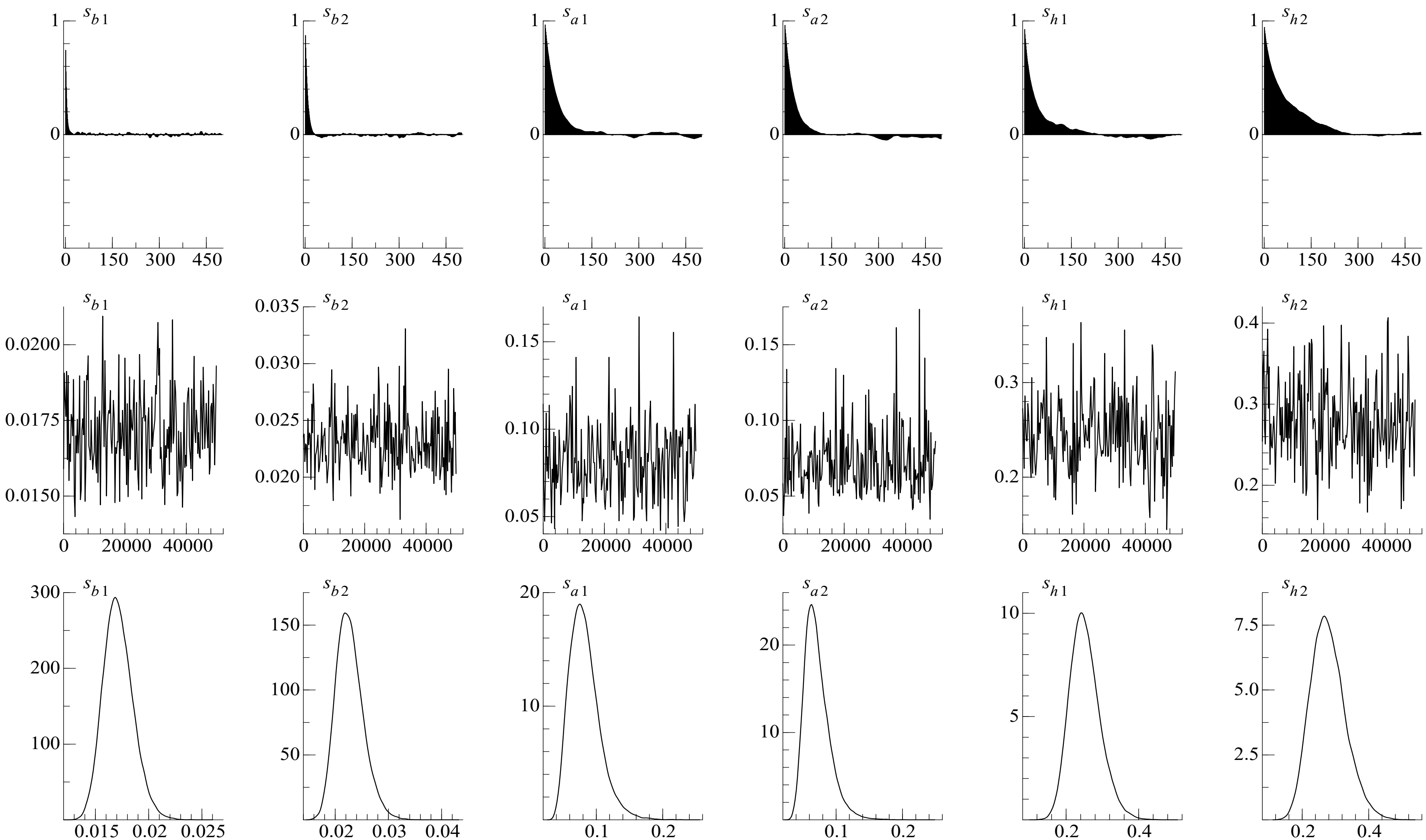


Figure A9. Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters: Germany

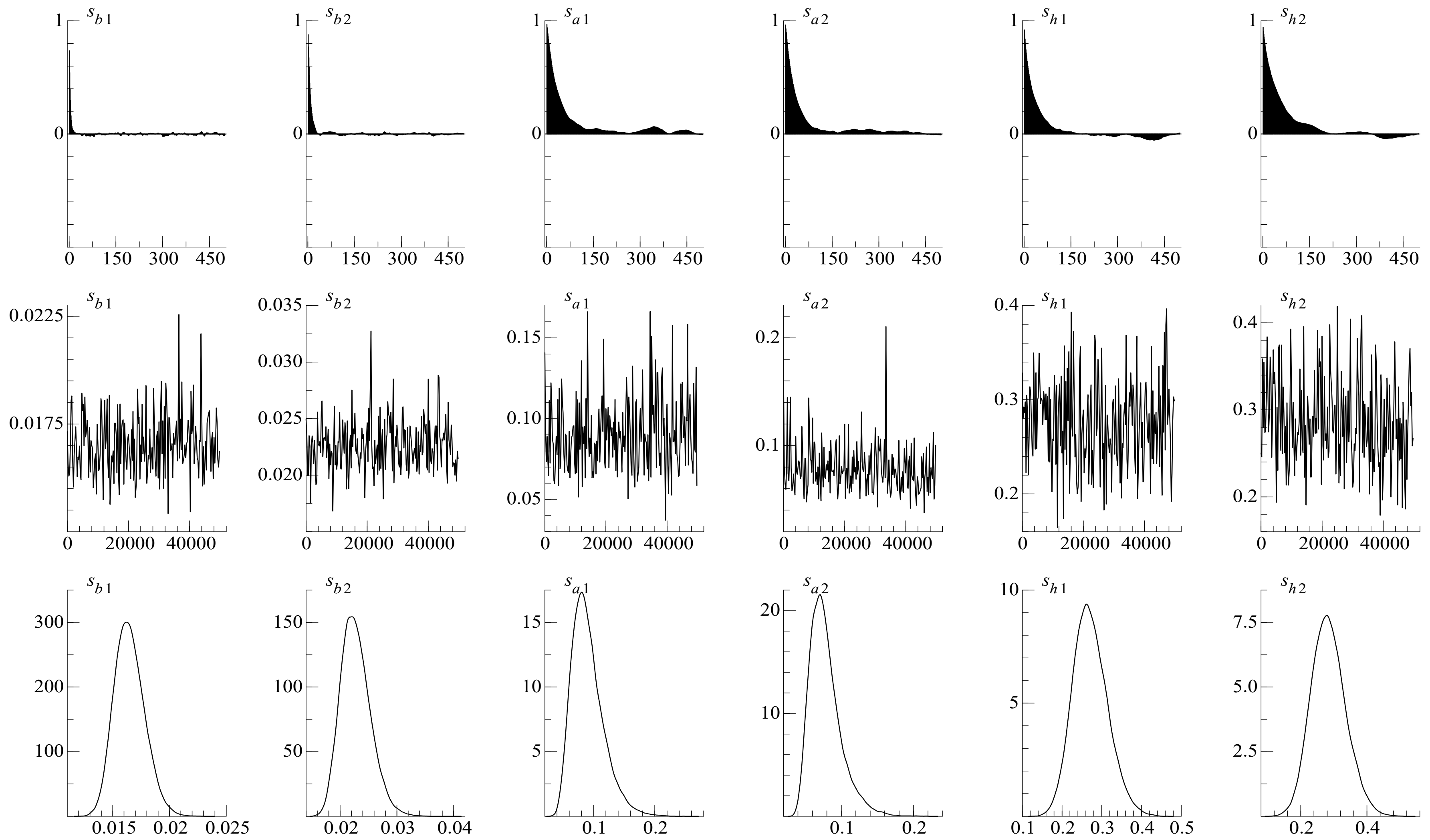


Figure A10. Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters: France

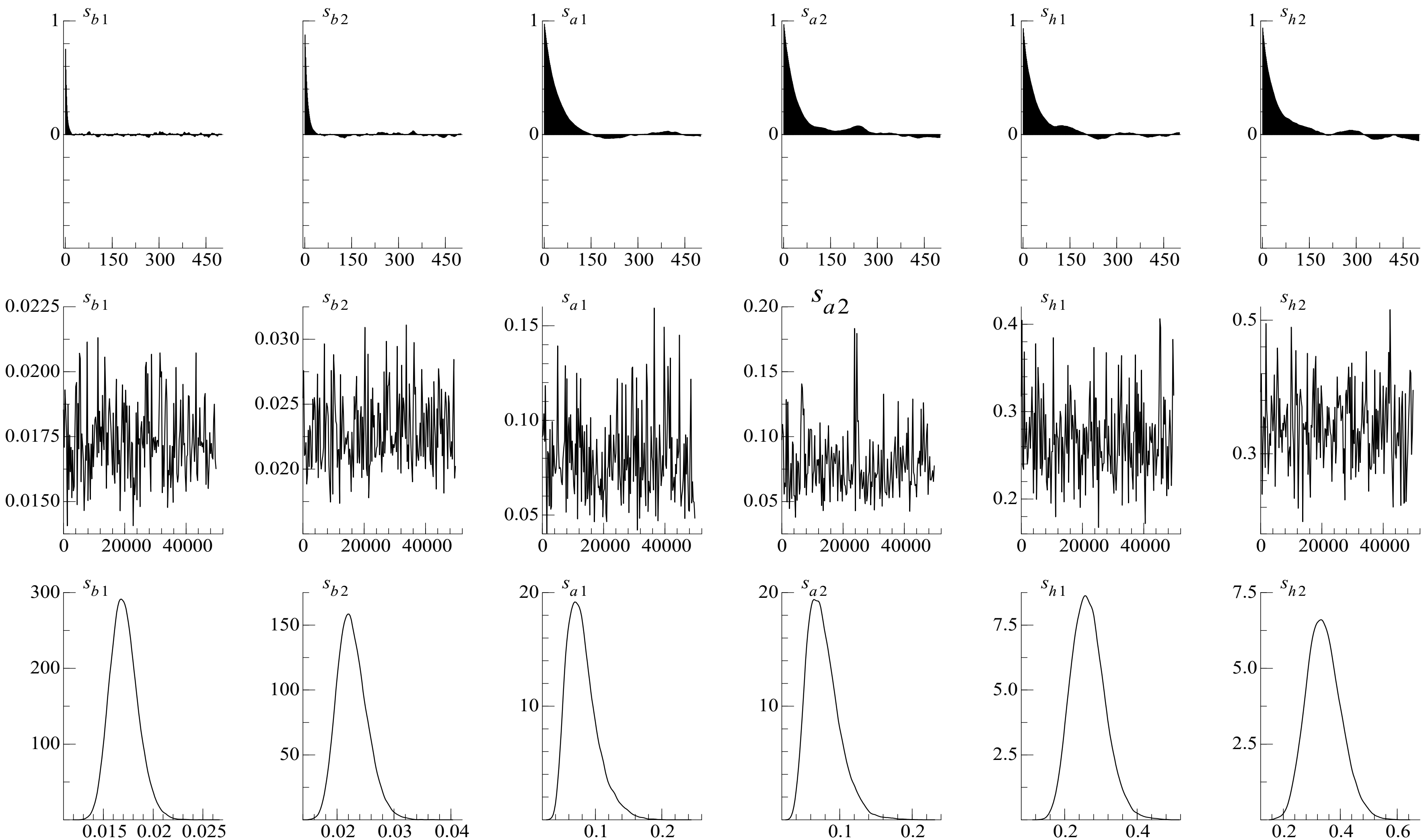


Figure A11. Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters: Italy

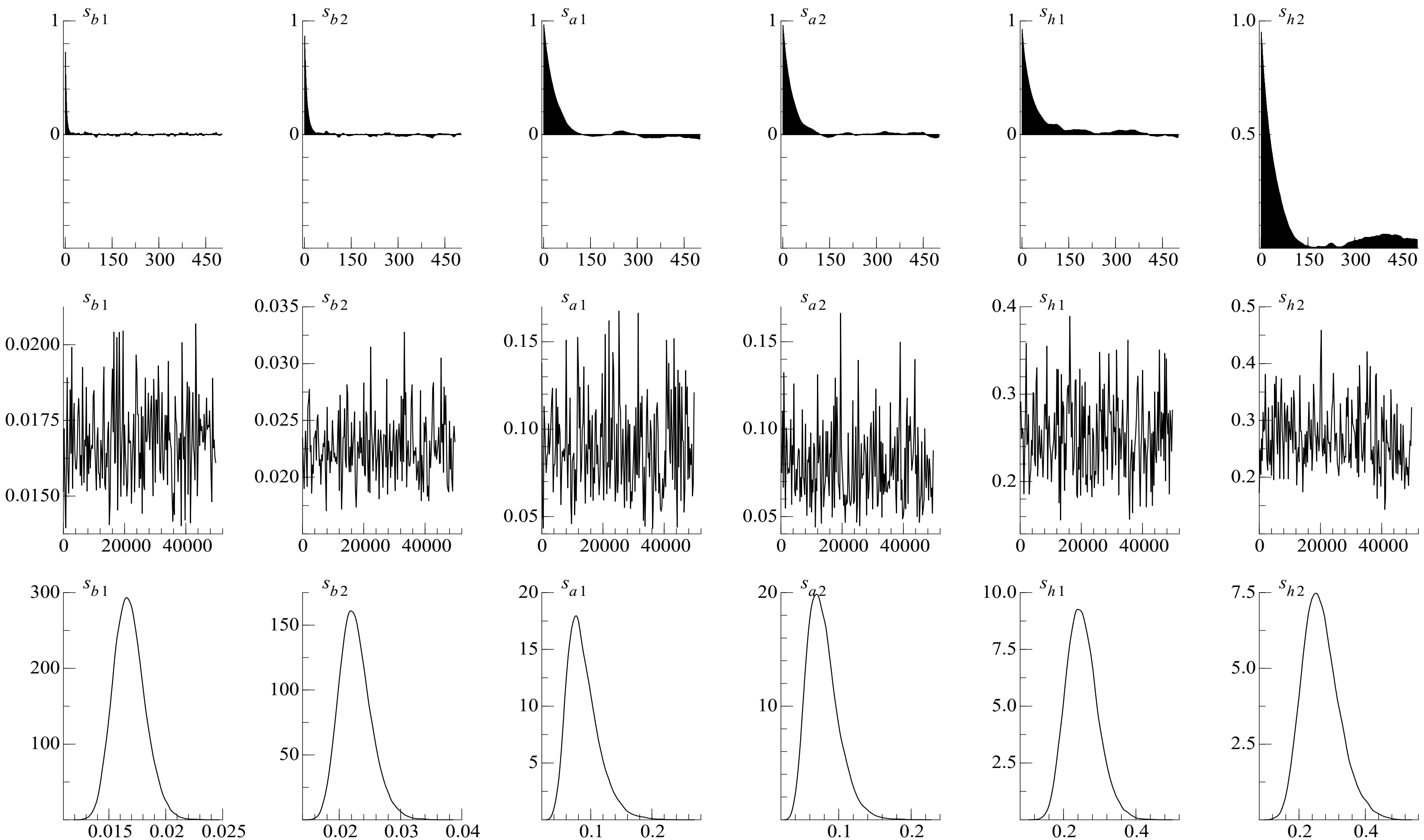


Figure A12. Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters: Spain