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A TGARCH Quantification of the Average Effect of COVID-19 Cases on Share Prices by Sector: Comparing the US and the UK

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A TGARCH Quantification of the Average Effect of COVID-19 Cases on Share Prices by Sector: Comparing the US and the UK

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Abstract

This paper proposes an econometric algorithm that quantifies by a single number (in the interval from 0 to –1) the average negative effect of the daily news regarding COVID-19 cases on stock-market prices by business sector. We apply it to the US and the UK, which results in a data-driven, 'objective' ranking of the adverse overall impact of the huge and persistent COVID-19 shock to sectoral share prices in these two leading economies that account for some 45% of global equity market capitalisation. Our quantification is based on a sample covering the full duration of the pandemic (1 January 2020 – 20 October 2022) and on a TGARCH approach, which we justify as particularly appropriate for the task at hand. Consequently, we establish three ranges of such an average impact: weak, moderate and strong. We, then, compare the sectors in the two countries and uncover similarities as well as differences. The most affected sector in both countries is technology, while industry comes next when both countries are considered together. Yet, there are sectoral differences too, with the specificity that the share prices of financials and utilities in the UK were the least affected of all business sectors in both economies. Our empirical quantification and comparison by sector, thus, points not only to some common patterns but also to the importance in explaining the differences of country-specific production and trade structures as well as of institutions and policies when dealing with the pandemic and its influence on stock-market prices.

Keywords: COVID-19 cases, sectoral stock-market prices, TGARCH quantification, daily correlations, US, UK
JEL codes: E71, G18, G41

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1 Introduction

The COVID-19 pandemic has had a deep impact globally, leading to significant disruptions in public health, economies and social systems. Understanding and comparing the experiences of different countries and business sectors during the pandemic is crucial for identifying effective strategies, evaluating policy interventions, and improving potential future responses. In an earlier paper, Hassan *et al.* (2022), aiming at a broad and global picture, we empirically uncovered, via a recent GARCH-based estimation technique due to Gibson *et al.* (2017) addressing the problem of dimensionality, volatility correlations and Granger causality between the daily COVID-19 cases and the share price indices in all 11 sectors of the Global Industry Classification Standard (GICS) across 11 major world economies accounting for 83.1% of the global stock market capitalisation and during the initial two worst years of the global pandemic (i.e., throughout January 2020 – December 2021). In essence, we documented a shift of density mass from dominantly negative correlations by sector from the first and second halves of 2020, with no vaccines to reassure human fear, to dominantly positive correlations in the first and second halves of 2021, with the population vaccinated two or three times and recovering its optimism.

In this sequel paper, we narrow down our interest and zoom into a very specific and data-driven research question. In effect, we apply the empirical TGARCH (Threshold Generalised Autoregressive Conditional Heteroskedasticity) approach to daily data to quantify the varying average extent to which stock-market prices by sector were negatively affected by the news for new COVID-19 cases in the United States (US) and the United Kingdom (UK). Employing TGARCH models is particularly appropriate for our purposes here, as it enables the empirical – and, hence, data-informed or 'objective' – analysis of volatility patterns, factors driving volatility, breaking points, effectiveness of policy measures and economic implications by sector. In essence, we devise and implement in this paper a novel econometric algorithm that characterises, or quantifies, by a single average numerical value the negative impact of the newly reported daily COVID-19 cases on daily share prices by sector in the two advanced economies we focus on, namely the US and the UK, where the financial sector is most highly developed and plays an overwhelming role.

The COVID-19 pandemic brought about unprecedented challenges to governments worldwide, requiring immediate responses to restrain the spread of the virus and its mutations, protect public health, and limit the huge and adverse socio-economic consequences. The US and the UK, as two highly developed nations and part of G7, have both advanced healthcare systems and faced similar challenges but acted with somewhat different strategies and policies in response to the pandemic. Comparing, on average for the duration of the pandemic, their experiences and outcomes by stock-market price sector can provide valuable insights into the effectiveness of various approaches and inform evidence-based decision-making for future pandemics or similar events.

The TGARCH approach is particularly useful to employ in analysing the dynamics of COVID-19 and comparing different industries within a country as well as across countries. The reason is that TGARCH models allow for the examination of time-varying volatility and conditional heteroskedasticity, capturing the nonlinear and asymmetric responses of volatility to shocks. A fundamental aspect of comparing the US and the UK during the COVID-19 pandemic involves examining the volatility patterns in their respective datasets. Notably, TGARCH models have been widely applied to analyse volatility clustering, which in our case matches the presence of persistence in the pandemic's impact. Understanding this persistence can help policymakers anticipate and respond to future outbreaks or fluctuations, enabling them to implement appropriate measures in a timely manner to minimise the impact on public health and the economy.

Government interventions via public health, fiscal and monetary policies, such as lockdown measures, testing strategies, vaccination campaigns and financial aid to the most vulnerable, play a pivotal role in shaping the pandemic's trajectory. For example, the timing and stringency of lockdown measures may have different impacts on volatility reduction, allowing policymakers to refine their strategies based on empirical evidence. By understanding the similarities and differences between the US and the UK, policymakers can learn from each other's experiences, identify successful strategies, and improve global preparedness for future pandemics.

In a preview of our results, we established three ranges of an average impact of the pandemic (over its duration in daily data) on share prices by sector: weak (0 to –0.1, in our quantification), moderate (–0.1 to –0.3) and strong (below –0.3). We then compared the sectors in the two countries and revealed common features but also disparities. The most heavily affected stock prices by sector in both countries were in technology, while industry came next when both countries were considered together. Yet, there were also important differences across these countries, with the specificity that the stock prices in financials and utilities in the UK were the least affected by the pandemic of all sectors and in both compared advanced economies.

The rest of this paper is organised as follows. We begin by densely summarising the closest literature in section 2. Section 3 then presents the data, while the methodological approach is summarised in section 4. Section 5 reports the numerical results from our quantification exercise by sector and for the two compared advanced economies, the US and the UK. Section 6 suggests our main interpretations in the light of related studies, and section 7 concludes. An online appendix collects additional figures and tables.

2 Related Literature

The literature has extensively examined the effects of the COVID-19 pandemic on the US stock market using various approaches. Some studies focus on stock-market returns, such as Ashraf (2020). He investigates the impact of confirmed COVID-19 cases and deaths on stock-market returns through panel data analysis. Other research concentrates on the influence of the spread of COVID-19 on stock-market volatility, as in Albulescu (2021) and Chaudhary *et al.* (2020). Albulescu (2021) employs a simple Ordinary Least Squares regression to measure the impact of the COVID-19 spread on US financial volatility. Chaudhary *et al.* (2020), in contrast, utilises a GARCH model to examine the influence of COVID-19 on both return and volatility in various stock markets. Lúcio and Caiado (2022) study how the COVID-19 pandemic affected some of the conditional volatilities of S&P 500 industries, using a new model feature-based clustering method on a fitted TARCH model. Rather than using the estimated model parameters to compute a distance matrix for the stock indices, they suggest using a distance based on the autocorrelations of the estimated conditional volatilities. Both hierarchical and non-hierarchical algorithms are used to assign the set of industries into clusters. The results show a clear change in the composition of each cluster between the period before the first US COVID-19 case and the period during the pandemic.

Duttilo *et al.* (2021) employ a TGARCH-in-Mean model with exogenous dummy variables. They use daily returns of the euro area stock-market indices from 4 January 2016 to 31 December 2020. Their results reveal that euro area stock markets responded differently to the COVID-19 pandemic. Specifically, the first wave of COVID-19 infections had a notable impact on stock market volatility in euro area countries with middle-large financial centres while the second wave had a significant impact only on stock-market volatility in Belgium.

According to the Bureau of Transportation Statistics (2022), the COVID-19 pandemic and associated lockdowns and restrictions resulted in a USD 35 billion and USD 2.8 billion net losses in 2020 and 2021, respectively, for the US airlines compared to net profit of USD 14.7 billion in 2019. Achille and Zipser (2020) predict a negative shock for the apparel, accessories and luxury goods industry due to the pandemic, as a significant portion of luxury sector revenues comes from international consumers, whose spending is expected to decline due to travel restrictions.

Krishnan *et al.* (2020) highlight the hotels, resorts, and cruise lines industry as one of the most adversely affected sectors, mainly due to travel restrictions, consumer sentiment, and a decrease in willingness to travel. Statista (2023) shows that e-commerce as a share of total retail sales increased from 11% before the pandemic to 22% in the early months of the pandemic (March to April 2020) due to restrictions and lockdowns, indicating a shift towards online shopping. Despite the closure of many US theatres, companies in the movie and entertainment industry with streaming platforms like Netflix and Disney+ experienced a surge in subscribers at the start of the pandemic. Mittal and Sharma (2022) examined the impact of COVID-19 on the stock returns of the Indian pharmaceutical sector and found positive and statistically significant returns between February 1, 2020, and April 24, 2020. Their study aims to investigate whether similar effects occurred in the US context. Additionally, Song *et al.* (2021) suggests that increased leverage in restaurant companies during COVID-19 impacted positively stock returns, as shareholders could benefit from tax advantages resulting from leverage.

Bouazizi *et al.* (2020) examine volatility patterns in Brent crude oil simulation during the COVID-19 crisis that significantly affected the oil market volatility. Employing a GARCH model with different parameters pre- and post-coronavirus peaks, they find that oil prices are strongly and negatively influenced by the COVID-19 crisis. The downward movement post-COVID-19 crisis is very noticeable in energy volatility.

Table 1: Descriptive Statistics for the US

	3M	Basic	Cases	Cons Disc	Cons Stap	Energy	Fin	Gen Indx	Health	Ind	RE	Tech	Telco	Util	BTC	Brent	EUR	Gold
Mean	0.5788	1.0180	0.3710	0.9196	1.0237	1.3455	1.0865	1.0277	1.0115	0.9732	1.0814	1.0028	0.9366	1.0365	1.0105	1.3475	1.0841	0.9455
Med	0.1010	1.0550	0.2217	0.9451	1.0467	1.3104	1.1122	1.0427	1.0394	0.9875	1.0831	1.0083	0.9345	1.0389	1.0037	1.3315	1.0763	0.9486
Max	4.0010	1.3093	5.3665	1.2063	1.2085	2.1952	1.3929	1.2770	1.1921	1.1657	1.3523	1.3753	1.1085	1.2222	2.2977	2.4696	1.2718	1.0834
Min	−0.0460	0.5215	0.0000	0.5100	0.7050	0.5974	0.6041	0.5957	0.6341	0.5378	0.6639	0.5267	0.6955	0.7150	0.1647	0.3180	0.9947	0.7772
SD	0.9268	0.1696	0.5253	0.1592	0.0963	0.3768	0.1931	0.1513	0.1099	0.1409	0.1365	0.1997	0.0933	0.0839	0.5923	0.4885	0.0656	0.0545
Skew	1.868	−0.613	4.669	−0.405	−0.421	0.287	−0.377	−0.443	−0.619	−0.538	−0.186	−0.232	−0.218	−0.217	0.247	0.191	0.864	−0.418
Kurt	5.440	2.531	32.048	2.238	2.565	2.081	1.978	2.344	2.729	2.544	2.206	2.304	2.430	2.966	1.754	2.147	2.992	3.140
J-B	606.31	52.50	28356.15	37.68	27.35	35.76	49.13	37.00	48.84	41.66	23.41	21.29	15.65	5.77	54.71	26.58	91.01	21.93
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0558	0.0000	0.0000	0.0000	0.0000
Sum	423.13	744.19	271.18	672.21	748.30	983.59	794.25	751.27	739.44	711.37	790.47	733.08	684.69	757.70	738.68	985.04	792.48	691.19
SSD	627.09	21.00	201.47	18.50	6.77	103.63	27.22	16.71	8.82	14.50	13.60	29.12	6.36	5.14	256.09	174.23	3.14	2.17
Obs	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731

Notes: The table reports descriptive statistics for all variables entering our TGARCH specifications in the US estimations, including the 11 GICS sectors: (1) Basic = basic materials; (2) Cons Disc = consumer products and services; (3) Cons Stap = consumer staples; (4) Energy = energy; (5) Fin = financials; (6) Health = healthcare; (7) Ind = industrials; (8) RE = real estate; (9) Tech = technology; (10) Telco = telecommunications; and (11) Util = utilities; as well as (12) Gen Indx = general stock-market index, (13) 3M = 3-month interset rate, (14) Cases = COVID-19 new cases, (15) BTC = Bitcoin price, (16) Brent = Brent oil price, (17) EUR = USD exchange rate against the EUR, and (18) Gold = gold price. For the sources of these daily data series see the subsection on Sources and Definitions in section 3.

Table 2: Descriptive Statistics for the UK

	3M	Basic	Cases	Cons Disc	Cons Stap	Energy	Fin	FX	Gen Indx	Health	Ind	RE	Tech	Telco	Util	BTC	Brent	Gold
Mean	0.4554	1.0087	0.3278	0.9752	1.0027	1.2634	1.0053	1.0498	1.0592	1.1257	1.0096	1.0470	1.0002	1.0537	1.1049	1.0105	1.3475	0.9455
Med	0.0800	1.0608	0.1483	0.9855	1.0047	1.1571	1.0355	1.0387	1.0880	1.1278	1.0162	1.0480	0.9990	1.0632	1.0819	1.0037	1.3315	0.9486
Max	3.1410	1.3183	3.8199	1.2009	1.1079	1.8049	1.1642	1.2720	1.1879	1.3453	1.2293	1.2561	1.3052	1.2897	1.3997	2.2977	2.4696	1.0834
Min	−0.0940	0.5374	0.0000	0.6093	0.8360	0.7148	0.7366	0.9616	0.7729	0.8951	0.6193	0.7228	0.6685	0.7936	0.8524	0.1647	0.3180	0.7772
SD	0.7138	0.1744	0.4638	0.1365	0.0360	0.2808	0.1034	0.0620	0.0932	0.0930	0.1277	0.1257	0.1275	0.1066	0.1201	0.5923	0.4885	0.0545
Skew	2.058	−0.608	3.215	−0.2709	−0.477	0.324	−0.715	0.971	−0.687	0.236	−0.383	−0.209	0.189	−0.141	0.463	0.247	0.191	−0.418
Kurt	6.688	2.449	18.052	1.921	5.694	2.007	2.266	3.578	2.434	2.858	2.786	2.073	2.584	2.309	2.141	1.754	2.147	3.140
J-B	930.13	54.26	8159.81	44.40	248.75	42.88	78.75	125.09	67.23	7.40	19.24	31.52	9.60	16.98	48.62	54.71	26.58	21.93
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0247	0.0001	0.0000	0.0082	0.0002	0.0000	0.0000	0.0000	0.0000
Sum	332.89	737.39	239.59	712.87	732.96	923.57	734.88	767.41	774.33	822.88	737.99	765.32	731.18	770.22	807.71	738.68	985.04	691.19
SSD	371.89	22.22	157.04	13.61	0.95	57.55	7.82	2.81	6.34	6.31	11.91	11.531	11.86	8.30	10.53	256.09	174.23	2.17
Obs	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731	731

Notes: The table reports descriptive statistics for all variables entering our TGARCH specifications in the UK estimations, including the 11 GICS sectors: (1) Basic = basic materials; (2) Cons Disc = consumer products and services; (3) Cons Stap = consumer staples; (4) Energy = energy; (5) Fin = financials; (6) Health = healthcare; (7) Ind = industrials; (8) RE = real estate; (9) Tech = technology; (10) Telco = telecommunications; and (11) Util = utilities; as well as (12) Gen Indx = general stock-market index, (13) 3M = 3-month interset rate, (14) Cases = COVID-19 new cases, (15) BTC = Bitcoin price, (16) Brent = Brent oil price, (17) FX = GBP exchange rate against the USD, and (18) Gold = gold price. For the sources of these daily data series see the subsection on Sources and Definitions in section 3.

None of the literature, to our knowledge, has aimed to quantify the *average* sectoral impact of COVID-19 cases on share prices in a single number and in a data-driven, algorithmic and transparent way. We, therefore, attempt to fill in this gap with our present study, which focuses on comparing the US and the UK, as representing nearly half of the global stock-market capitalisation.

3 Data

3.1 Sources and Definitions

The selected countries – the US and the UK – are chosen based on their systemic character in the global financial markets. The US ranks first in terms of stocks market capitalisation globally, while the UK is fourth. As mentioned, the two of them represent around 45% of the global equity market capitalisation.

The data consist of daily observations from 1st January 2020 to 20th October 2022, excluding the weekends and official holidays (731 observations in total, for each of the two countries). The variable of registered COVID-19 cases is sourced from the WHO database. All other variables are extracted from Refinitiv (Thomson Reuters) and have their values as the closing for the day. The "control" variables are five for each country, and standard in similar work: bitcoin, Brent oil, and gold prices, the daily exchange rate of the USD against the GBP for the UK and the daily exchange rate of the USD against the EUR for the US, and the 3-months sovereign bonds yield, which is for local currency bonds. All 11 GICS sectoral indices are used, consisting of the following business sectors: technology; telecommunications; healthcare; financials; consumer products and services; consumer staples; industrials; basic materials; energy; utilities; and real estate. As the two countries under consideration have more than one stock exchange, the stock exchange with the highest market capitalisation was selected, namely Standard and Poor's 500 for the US and FTSE 100 for the UK.

The main contribution of our study is to estimate empirically, by using a Threshold GARCH (TGARCH) due to its specificity of capturing negative events through the introduction of a dummy variable in the conditional variance, the *average* effect of COVID-19 cases on *sectoral* equity prices in two major economies compared with each other.

3.2 Descriptive Statistics

Table 1 reports descriptive statistics for the US. The reported variables are the general stock-market index, the 11 GICS subsector indices, the prices of Bitcoin, oil Brent and gold. Moreover, it contains the EUR/USD rate and the 3-month interest rate. Apart from the 3-month interest rate, for all other variables, the value has been transformed into an index, with a base period 1 January 2021. Overall, these results indicate that means are positive and close to one for the general index and subindices; standard deviations are generally much smaller than means; and the distributions are mixed left and right-skewed, and mainly platykurtic. Based on the Jarque-Bera normality test, the null hypothesis is rejected for all variables, i.e., all of them are not normally distributed.

Table 2 reports the same descriptive statistics for a similar set of variables as in Table 1, but this time for the UK. The only different variable is the exchange rate, which now represents the GBP/USD rate. Again, the results show that means are positive and close to one – but smaller than in the case of the US – for the 3-month interest rate, basics, COVID-19 cases, consumer staples, energy, financials, real estate and technology. Similarly, for all of the indices, the means remain around one. Standard deviations in most of the cases tend to be smaller for the UK variables than for the respective US ones, while remaining much smaller than the means. The distributions remain – similarly to Table 1 – mixed, left and right-skewed and platykurtic. As it was for the US, none of the UK variables is normally distributed based on the Jarque-Bera test.

4 Methodology

To investigate which stock-market subindices have been affected the most by the news about COVID-19 cases in both of the US and the UK, daily time-varying conditional covariances and correlations are estimated and analysed using a newly developed GARCH technique suggested by Gibson *et al.* (2017). This technique introduces a simple computational way for constructing large conditional covariance matrices. The key motivation behind using the GARCH family of models here rather than other models is the ability of GARCH models to estimate the time-varying conditional variances that are considered the true measures of risk, and which are rarely similar to the constant unconditional variances estimated by other models (Morelli, 2002; Gibson *et al.*, 2017).

Traditionally, the BEKK-GARCH model – due to Baba *et al.* (1987)[1] and Engle and Kroner (1995) – is considered the best Multivariate GARCH model in estimating the time-varying conditional variances for three reasons. Firstly, the BEKK-GARCH model ensures the positive semi-definiteness of the estimated conditional covariance matrices by imposing a restriction implied automatically within the model structure compared with other Multivariate GARCH models such as the Vector-GARCH (VEC-GARCH) model, which does not ensure the positive semi-definiteness. Secondly, the BEKK-GARCH model allows for a more complex interaction between covariances, thus allowing for more dynamics than other Multivariate GARCH models such as the Constant Conditional Correlation GARCH (CCC-GARCH) model, in which the time-varying conditional covariances are parameterised to be proportional to the product of the corresponding conditional standard deviations or the Dynamic Conditional Correlation GARCH (DCC-GARCH) model that imposes a constant dynamic structure for all conditional correlations. Finally, the BEKK-GARCH model allows for more time variation in covariances compared with other Multivariate GARCH model such as the Factor-GARCH (FGARCH) model, which not only limits the amount of time variation in covariances but also the number of the underlying factors for the variables being studied (Gibson *et al.*, 2017).

Having said that, one of the key problems of the BEKK-GARCH model is the dimensionality problem. As the number of included variables in a system increases, the model quickly generates

[1] "BEKK" is an acronym originating in the first letters of the respective family names of the four coauthors of this discussion paper of 1987.

a very large number of parameters. For a BEKK-GARCH (1,1) model, if the number of included variables in a system is N, the estimated number of parameters is equal to $2N^2 + \frac{N(N+1)}{2}$: see, among others, Caporin and McAleer (2012) and Gibson *et al.* (2017). As N increases, the number of parameters grows exponentially. For example, if the number of the included variables is equal to 17, the BEKK-GARCH (1,1) model requires to estimate 731 parameters in the variance equation, which is a very large number.

Another problem with the BEKK-GARCH model is the nonlinearity in parameters, which makes its convergence very difficult for large N (Caporin and McAleer, 2012). To reduce these problems, two restrictions can be imposed, namely the diagonal or the scalar versions. However, these restrictions eliminate the interaction between the covariances and limit their time variation (Gibson *et al.*, 2017).

All of the above in mind, this newly suggested GARCH technique by Gibson *et al.* (2017) allows us to estimate larger conditional covariance matrices, sidesteps the dimensionality problem of the traditional Multivariate GARCH family of models and drops all of the restrictions imposed by the pervious literature. This new technique rests on the following three simple equations (1)–(3), which explain the relationship between the conditional variance of any two variables, say x and y, and the conditional variance of the summation of those two variables as follows:

$$E\left(x_t + y_t \mid \Omega_t\right)^2 = E\left(x_t^2 \mid \Omega_t\right) + E\left(y_t^2 \mid \Omega_t\right) + 2E(x_t y_t \mid \Omega_t) \tag{1}$$

In conditional variance terms:

$$Var\left(x_t + y_t \mid \Omega_t\right) = Var\left(x_t \mid \Omega_t\right) + Var\left(y_t \mid \Omega_t\right) + 2Cov(x_t y_t \mid \Omega_t) \tag{2}$$

Hence:

$$Cov\left(x_t y_t \mid \Omega_t\right) = \frac{1}{2}\left[Var\left(x_t + y_t \mid \Omega_t\right) - Var\left(x_t \mid \Omega_t\right) - Var(y_t \mid \Omega_t)\right], \tag{3}$$

where, $Var\left(\cdot \mid \Omega_t\right)$ is the conditional variance of $(\cdot)$ and $Cov\left(\cdot \mid \Omega_t\right)$ is the conditional covariance of $(\cdot)$. The only assumption made here is that both x and y are zero-mean processes. Given these three equations, it is clear that in order to calculate the conditional covariance between any two variables, we need to estimate the conditional variance for each individual variable and the conditional variance for the summation of those two variables. These conditional variances can simply be estimated using a univariate GARCH (1,1) model for each single variable and for the summation of both variables.

Since the GARCH family of models uses the maximum likelihood to estimate conditional variances, each of the three estimated conditional variances mentioned above are expected to be consistent, and hence the calculated conditional covariance using equation (3) is expected to be consistent as well. However, by estimating these conditional variances using univariate GARCH models rather than Multiple GARCH ones, this could lead to an omitted variable bias problem due to omitting the covariance terms. Following Gibson *et al.* (2017) argument, it is true that the parameters of a univariate GARCH model are not consistent estimates for the parameter matrices of Multiple GARCH ones. But it is not required here to have consistent estimate for the parameter matrices of a Multiple GARCH model, we simply require a consistent estimate of the three conditional variances in equation (3). The consistency of these three conditional variances can be proved by the fact of the Wold Decomposition Theorem, which states that any process can be represented by an infinite order of a Moving Average univariate model. Given that the GARCH model is a time series representation of the variance process and the Wold Decomposition Theorem assumption of the existence of a valid univariate representation even if the underlying model is a multivariate one, a univariate GARCH (1,1) model which is equivalent to an infinite order of Moving Average model ensures the consistency of the conditional variances subject to including an adequate number of lags in the univariate GARCH model.

To apply this new approach and to answer our question of interest, daily time-varying conditional variances for each of the 11 subindices and for the summation of the COVID-19 cases with each of the remaining variables are estimated using the Threshold GARCH (TGARCH) model up to its 9th threshold order. Then, the optimum TGARCH models for each individual variable and each summation are used to construct their conditional variances. At this step, simply applying equation (3) gives us the conditional covariances and correlations. Following the academic financial literature, these univariate GARCH models are limited to the GARCH (1,1) specification. The mean equation for these univariate GARCH models takes the following error correction form:[2]

$$\Delta y_{it} = c_i + \sum_{i=1}^{17}\sum_{j=1}^{p}\delta_{ij}\Delta y_{it-j} + \sum_{i=1}^{17}\lambda_i y_{it-1} + \varepsilon_{it}, \qquad \varepsilon_t \mid I_{t-1} \sim N\left(0, h_t\right), \tag{4}$$

where Δy_{it} and Δy_{it-j} are the current and lagged return (growth rate) of the variable i, respectively. In addition, c is the deterministic component and p is the optimum lag length. Moreover, ε_{it} represents the current innovation of the variable i which is conditional on a previous information set I_{t-1} and is normally distributed with zero mean and h_t time-dependent variance. On the other hand, the variance equation for the TGARCH models is specified as:[3]

$$h_{it} = \omega + \alpha\varepsilon_{it-1}^2 + \gamma\varepsilon_{it-j}^2\iota_{it-j} + \beta h_{it-1}, \qquad \omega > 0, \alpha > 0, \beta \geq 0, \mid \alpha + \beta \mid < 1, \alpha + \gamma \geq 0, \tag{5}$$

where h_{it} denotes the time-varying conditional variance of the variable i and ω is a constant, which is restricted to be positive.[4] In addition, α, restricted to be positive, and β, restricted to be nonnegative, are the coefficients of the lagged squared residuals ε_{it-1}^2 generated from

[2] specified as follows:

$$\Delta y_{(x+i)t} = c_{x+i} + \sum_{i=1}^{17}\sum_{j=1}^{p}\delta_{ij}\Delta y_{it-j} + \sum_{i=1}^{17}\lambda_i y_{it-1} + \varepsilon_{(x+i)t}, \qquad \varepsilon_t \mid I_{t-1} \sim N\left(0, h_t\right),$$

where x is the natural logarithm of the daily COVID cases and i represents the natural logarithm of each of the remaining 16 variables.

[3] For the theoretical background of these univariate GARCH models, see Bollerslev (1986), Nelson (1991) and Glosten *et al.* (1993), among others.

[4] In the variance equation of univariate GARCH models for the summation terms, each h_i and ε_i will be replaced by $h_{(x+i)}$ and $\varepsilon_{(x+i)}$, respectively.

the mean equation and the lagged conditional variance h_{it-1}, respectively. $\mid \alpha + \beta \mid < 1$ is the required condition for stationarity. The TGARCH model is extended to include an asymmetry component, ι_{it-j}, with γ being its coefficient. For bad news, ι_{it-j} takes the value of one while for good news it takes the value of zero. Conditional on the existence of leverage effects, γ will be positive and statistically significant and thus good news will have an impact of α on the conditional variance. On the other hand, bad news will have a higher impact, $\alpha + \gamma$. Given the conditional normality of residuals, these univariate GARCH models specified by equation (4) and (5) above, can be estimated by maximising the following likelihood function:

$$\mathcal{L} = -\frac{T}{2} \ln (2\pi) - \frac{1}{2} \sum_{t=1}^{T} \ln |h_t| - \frac{1}{2} \sum_{t=1}^{T} \frac{\varepsilon_t^2}{\ln |h_t|}, \tag{6}$$

where T is the total number of observations and all other variables are as defined earlier. The reason for using the absolute value for h_t in equation (6) is to ensure including positive conditional variances in this log-likelihood function.

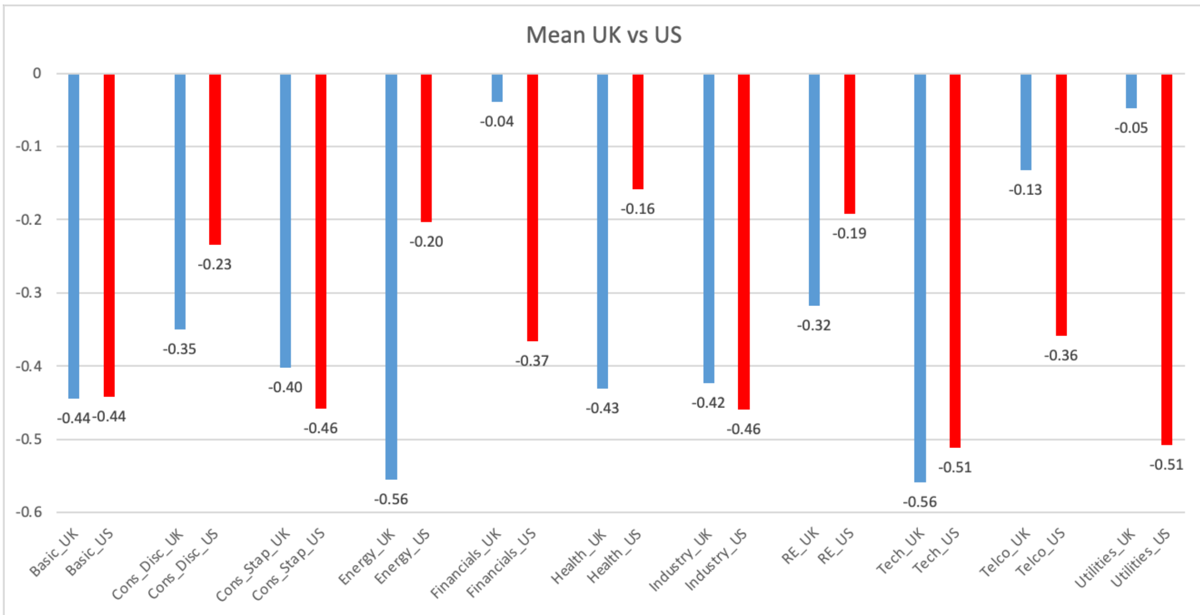
As we discussed above, the TGARCH (1,1) model, with up to 9 threshold orders, specified by equation (5) is estimated for each of the 17 included individual variables and for the summation of the COVID-19 cases with each of the remaining 16 variables. The optimum time-varying conditional variances are then generated using the TGARCH (1,1) model, which are found to satisfy four main conditions. These are: (i) the models with a statistically significant ARCH effect in residuals, (ii) the models that satisfy the stationarity condition, (iii) the models which satisfy the variance non-negativity condition and (iv) the models with appropriate (i.e., not extremely noisy) graph representations. Depending on these optimum generated time-varying conditional variances, the time-varying conditional covariances between the COVID-19 cases and the growth rate (return) of each of the subindices are calculated using equation (3). Given the fact that covariances can only tell us about the direction of the relationship between any two variables, and following the literature, the time-varying conditional correlations are also calculated to eliminate the scaling problem of the conditional covariances and to make the interpretation of results much easier. Then, given these optimum time-varying conditional correlations for both the US and the UK, the average of these correlations is calculated to explore and compare the most and least affected subindex in both nations.

5 Results

5.1 Empirical Algorithm

To quantify the average negative effect of the pandemic in terms of new daily COVID-19 cases on stock-market prices by sector in the US and the UK, we employed a data-driven "algorithm" we designed. In order to have a stationary TGARCH model, there are conditions that need to be satisfied, as mentioned. In addition, as we have nine different threshold terms checked for each of the 11 business sectors, the Schwarz Information Criteria (SIC) is also used in the selection process of the optimal lag in the empirical specifications.[5] Hence, we used the following algorithm.

Figure 1: Preferred TGARCH Quantification



Notes: This figure depicts and compares our preferred TGARCH-quantified average negative effect (or correlation) over our sample, 1 January 2020 – 20 October 2022, of the daily news on COVID-19 cases on stock-market prices by the 11 GICS sectors in the US (red bars) and the UK (blue bars), as follows: (1) basic materials; (2) consumer products and services; (3) consumer staples; (4) energy; (5) financials; (6) healthcare; (7) industrials; (8) real estate; (9) technology; (10) telecommunications; and (11) utilities. For details on the computation, see sections 4 and 5.

1. As a first step, we test for the presence of an ARCH effect, which is a precondition to employ a TGARCH model.
2. For the equations where we confirm its presence, we select the equation with the minimal SIC, as is common in econometrics when determining the optimal lag length.
3. We, then, confirm that the (i) nonnegativity and (ii) stationarity conditions, which the TGARCH model requires, are indeed satisfied.
4. An additional step is that, based on the conditional variances, we calculate the conditional correlations and graphically discard any very noisy observations.
5. Finally, we repeat the algorithm by selecting the second lowest SIC in step 2, and then proceed to steps 3 and 4 (as above).

We eventually chose the second-lowest SIC results to illustrate and discuss further down, referring to them as our 'preferred' TGARCH quantification. The reason is that the second-lowest SIC results turned out to satisfy better than the minimal SIC results the criteria of the empirical selection algorithm we outlined. This quantitative assessment of the average negative

[5]The output from the 11 sectors with the nine possible threshold terms is presented in the appendix.

effect of the COVID-19 pandemic on the stock-market prices by sector in the US and the UK is summarised in Figure 1. Table 3 reports, in turn, the optimal selected threshold terms by sector and country. The appendix contains illustrative graphs for all examined cases (11 sectors by country with up to 9 thresholds), as well as respective tables documenting the econometric results for each case examined by our data-driven quantification algorithm.

Table 3: Optimally Selected Threshold Terms by Sector in the TGARCH

Country	Basic	Cons Disc	Cons Stap	Energy	Fin	Health	Ind	RE	Tech	Telco	Util
US	6	5	5	5	6	5	5	5	6	5	5
UK	9	6	9	5	7	9	6	9	6	6	8

Notes: This table reports and compares the optimally selected threshold in the TGARCH estimations over our sample, 1 January 2020 – 20 October 2022, of the correlation of the daily news on COVID-19 cases and daily stock-market prices by the 11 GICS sectors in the US and the UK, as follows: (1) Basic = basic materials; (2) Cons Disc = consumer products and services; (3) Cons Stap = consumer staples; (4) Energy = energy; (5) Fin = financials; (6) Health = healthcare; (7) Ind = industrials; (8) RE = real estate; (9) Tech = technology; (10) Telco = telecommunications; and (11) Util = utilities. For details on the computation, see sections 4 and 5.

5.2 Quantified Average Impact by Sector

What one could infer from Figure 1 are several important quantitative findings that our methodological approach uncovers empirically. We analyse the illustrative summary in the figure by roughly delineating three regions, namely: strongly negatively affected sectors, where the value of the average negative effect is quantified in the range below –0.3; moderately negatively affected sectors, where this value is in the range –0.1 < –0.3; and weakly negatively affected sectors, where this value is between 0 and –0.1.

First, the US and the UK tend to share some important similarities. In three sectors, namely technology (–0.51 for the US and –0.56 for the UK), industry (–0.46 and –0.42, respectively), and basics (–0.44 for both countries), the COVID-19 pandemic has, on average for the period of our sample, strongly and negatively affected the share prices in both countries.

Second, on the other extreme, only in the UK and in only two sectors, financials (–0.04, UK minimum) and utilities (–0.05), has the pandemic weakly and negatively affected share prices. This is, notably, never the case in the US.

Third, in the US, share prices in the majority of sectors, 7 in number, were strongly negatively affected by the COVID-19 new cases: technology and utilities (–0.51 for both, in a double maximum), industry and consumer staples (-0.46 each), basics (–0.44), financials (–0.37) and telecommunications (–0.36). Similarly in the UK, the majority of sectors, 8 in number, were all affected in a strong negative way: technology and energy (–0.56 each, a double maximum, again), basics (–0.44), health (–0.43), industry (–0.42), consumer staples (–0.40), consumer products and services (–0.35) and real estate (-0.32).

Fourth, all remaining 4 sectors in the US were moderately negatively affected: consumer products and services (–0.23), energy (–0.20), real estate (–0.19) and health (–0.16, US minimum). In this range of moderate negative influence falls as well the last remaining UK sector, telecommunications (–0.13).

In the next section, we try to interpret these numerical values by business sector and their relative similarities and differences in the US and the UK. We point to some features of the production and trade structures, as well as to the role of institutions and policies in their endeavours to mitigate the negative shock of the COVID-19 pandemic, in these compared countries.

6 Discussion and Some Interpretations

The subindices in the US that typically were more heavily impacted during COVID-19 include sectors such as telecommunications, utilities, industrials, consumer staples and basics (Baek *et al.*, 2020; Arbogast and Wen, 2021), which our quantification generally captures (except for utilities in the UK) – see Figure 1. These sectors were particularly vulnerable during the pandemic due to disruptions in global supply chains, reduced demand for commodities, and decreased industrial activity (Szczygielski *et al.*, 2022). The significant decline in oil prices, coupled with lower demand for raw materials and manufacturing slowdowns, heavily impacted them in the US (Standard & Poors, 2023). In contrast, in the UK, these subindices – except the similarly strongly affected industrials subindex – had a different sectoral composition, with relatively lower exposure to the shocks, which could have mitigated the negative impact (Standard & Poors, 2018). Differences in market structure and the weightings of individual stocks within the subindices can also influence their performance, explaining the country specificity. The US stock market, with its larger market capitalisation and more diverse range of listed companies, may have experienced greater volatility due to the higher number of constituents in these subindices. The UK market, with a smaller number of constituents, could have exhibited relatively more stable subindices.

In addition, the international trade exposure is more elevated in the US. The US economy is highly interconnected with global markets, and many companies in these subindices have significant exposure to international trade (UNCTAD, 2021). Disruptions in global supply chains and reduced international trade flows during the pandemic would have had a substantial impact on these companies' revenues and profitability. In comparison, the UK's subindices have a relatively lower degree of international trade exposure, potentially mitigating the negative impact on its constituent companies.

Government support and stimulus measures also varied across countries. These policy actions can play a vital role in mitigating the impact of the pandemic on businesses and industries (Chen *et al.*, 2020). The timing, scale, and effectiveness of such measures can vary between countries. The US implemented various fiscal stimulus measures, such as the CARES Act, to support businesses and individuals, but the magnitude of the economic shock and the challenges in implementing these measures may have limited their effectiveness in cushioning the impact on the basic subindex (Efraim and Tzur-Ilan, 2020; Gourinchas *et al.*, 2021). The UK government also provided support to businesses through initiatives like the Coronavirus Job Retention Scheme, which could have contributed to some stability to the subindices.

Investor sentiment and market psychology would have significantly influenced stock market movements too. The uncertainty and fear surrounding the COVID-19 pandemic may have resulted in more pronounced selling pressure and heightened volatility in the mentioned US subindices (Szczygielski *et al.*, 2022). The perception of higher risk and the prevailing sentiment among investors in the US market may have contributed to sharper declines compared to the UK. The marked outperformance of the financial stock market subindex on average in the UK compared to the US during the COVID-19 pandemic, as also sharply reflected in Figure 1, could be attributed mainly to the regulatory environment, financial sector composition and different forms of government interventions (European Central Bank, 2022).

The regulatory landscape and government policies in the UK may have played a role in bolstering the financial sector. The UK regulatory framework, including the Financial Conduct Authority and the Bank of England, implemented measures to support the stability of financial institutions and maintain market confidence (Bank of England, 2023). These actions may have provided reassurance to investors and contributed to the relatively much better performance of the UK financial stock market subindex (quantified by our empirical algorithm at –0.04 vs –0.37 in the US). The composition of the financial sector in the UK, which includes major global banks and financial institutions, may have contributed to its resilience as well. These institutions have established risk management practices, diversified revenue streams, and strong capital positions, which would have helped them navigate the challenges posed by the pandemic. In comparison, the US financial sector is more diverse and includes a broader range of institutions, some of which have faced greater challenges during the crisis (Bowman, 2023).

The consumer product and services subindex in the UK performed worse (–0.35 in our numerical value) than in in the US (–0.23). The composition of this particular sector in the UK market may have played a role in its relative underperformance. The UK consumer product and services sector is more heavily weighted towards industries such as travel and leisure, hospitality, and retail, which were severely impacted by lockdowns, travel restrictions, and reduced consumer spending during the pandemic (Office for National Statistics, 2021). These industries faced significant challenges, including temporary closures, supply chain disruptions, and reduced consumer demand, leading to weaker financial and stock-market performance. Yet, it is worth noting that the US consumer product and services sector has a larger exposure to international markets compared to the UK. During the pandemic, global travel restrictions and reduced international trade had a particularly adverse impact on sectors such as tourism, airlines, and luxury goods. The US companies in the consumer product and services sector, with their larger international presence and diversified revenue streams, may have been better positioned to withstand the domestic challenges and benefit from pockets of strength in global markets. Consumer behaviour and preferences during the pandemic also varied between the US and the UK. In the US, there was a greater shift towards online shopping, which benefited e-commerce and technology companies in the consumer product and services sector. The UK, on the other hand, had a higher reliance on physical retail and hospitality sectors, which faced more significant disruptions due to lockdown measures (International Monetary Fund, 2022).

The underperformance of consumer staple stocks in the US market (–0.40 in our quantification) compared to the UK (–0.26) during the COVID-19 pandemic can be attributed to the composition of the consumer staple sector in the US market. The latter is more heavily weighted towards industries such as food and beverages, household products, and personal care items. While these industries were considered essential during the pandemic, they still faced challenges such as supply chain disruptions, increased production costs, and changing consumer preferences. In the US, there is a higher presence of large supermarket chains and discount retailers that faced intense competition and price pressures during the pandemic. These factors, combined with changing consumer behaviour and increased reliance on online shopping, may have affected the financial performance and stock market performance of consumer staple companies in the US (Standard & Poors, 2019).

7 Concluding Remarks

The contribution of the present paper was to propose an econometric algorithm to quantify and compare by a single numerical value – on average along the duration of our pandemic sample – the negative effect of the daily news about COVID-19 cases on stock-market prices by sector in two leading economies, the US and the UK, accounting for nearly a half of the global equity market capitalisation. Employing the TGARCH approach, which we justified as being particularly appropriate for such a task, we established three ranges of such average impact: weak (0 to –0.1, in our quantification), moderate (–0.1 to –0.3) and strong (below –0.3). We then compared the sectors in the two countries and revealed common patterns but also differences.

The most affected sector in both countries when it comes to the negative impact of COVID-19 cases to share prices was technology, and industry ranked next when both countries were considered. Yet, there were several important sectoral differences across these countries, with the specificity that the stock prices of financials and utilities in the UK were the least affected by the pandemic of all sectors and in both compared advanced economies. Our empirical quantification and comparison by business sector, thus, pointed not just to the similarities, but also to the importance of country-specific production and trade structures, institutions and policies in dealing with the pandemic and its influence on stock-market prices.

We made a broad attempt to interpret these numerical findings and link them to the conclusions from the related literature. Of course, further work needs to be done to provide a narrower and more focused account of the similarities as well as the differences across sectors in the US and the UK, and possibly other major economies.

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Online Appendix to

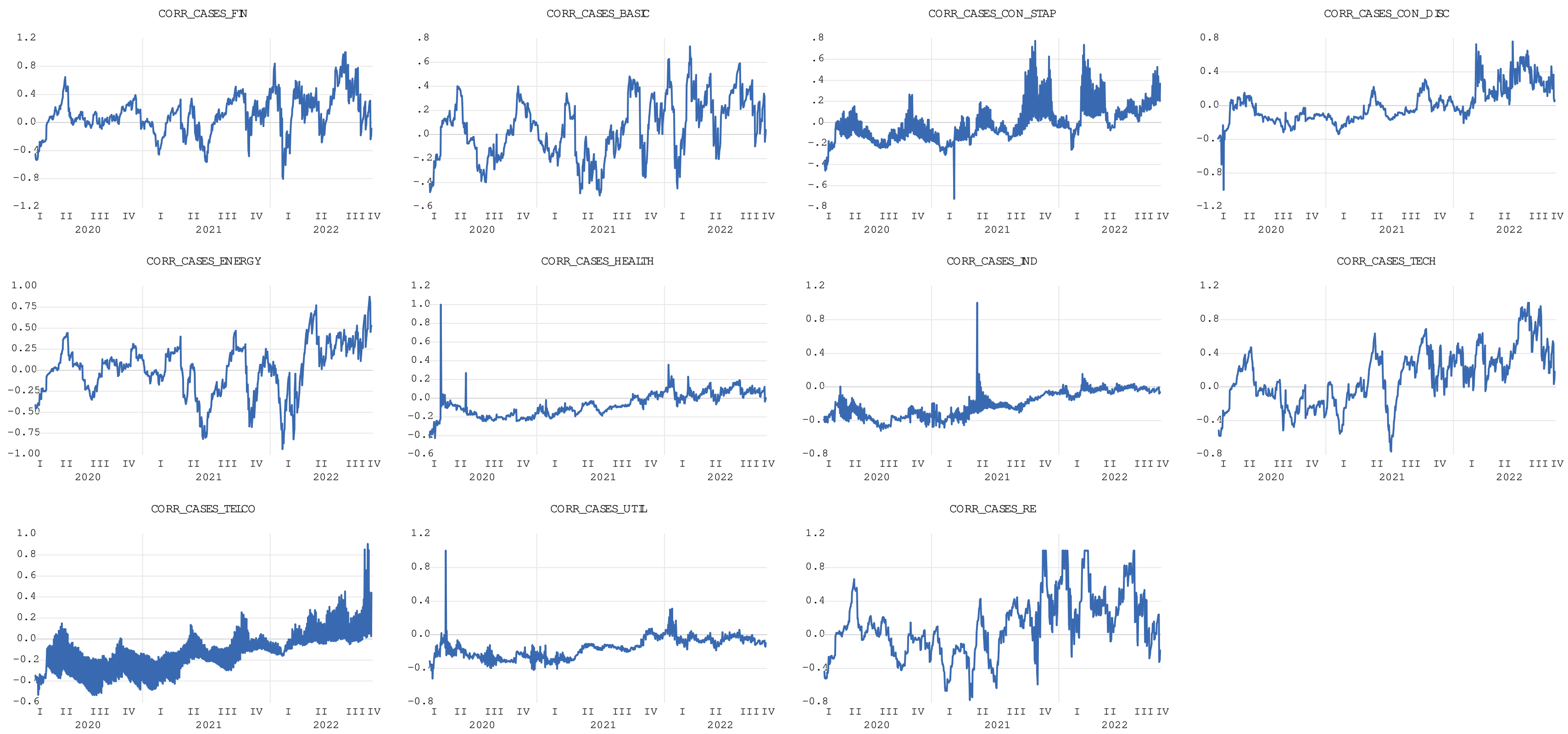
"A TGARCH Quantification of the Average Effect of COVID-19 Cases on Share Prices by Sector: Comparing the US and the UK"

Hussein Hassan, Minko Markovski and Alexander Mihailov

September 2023

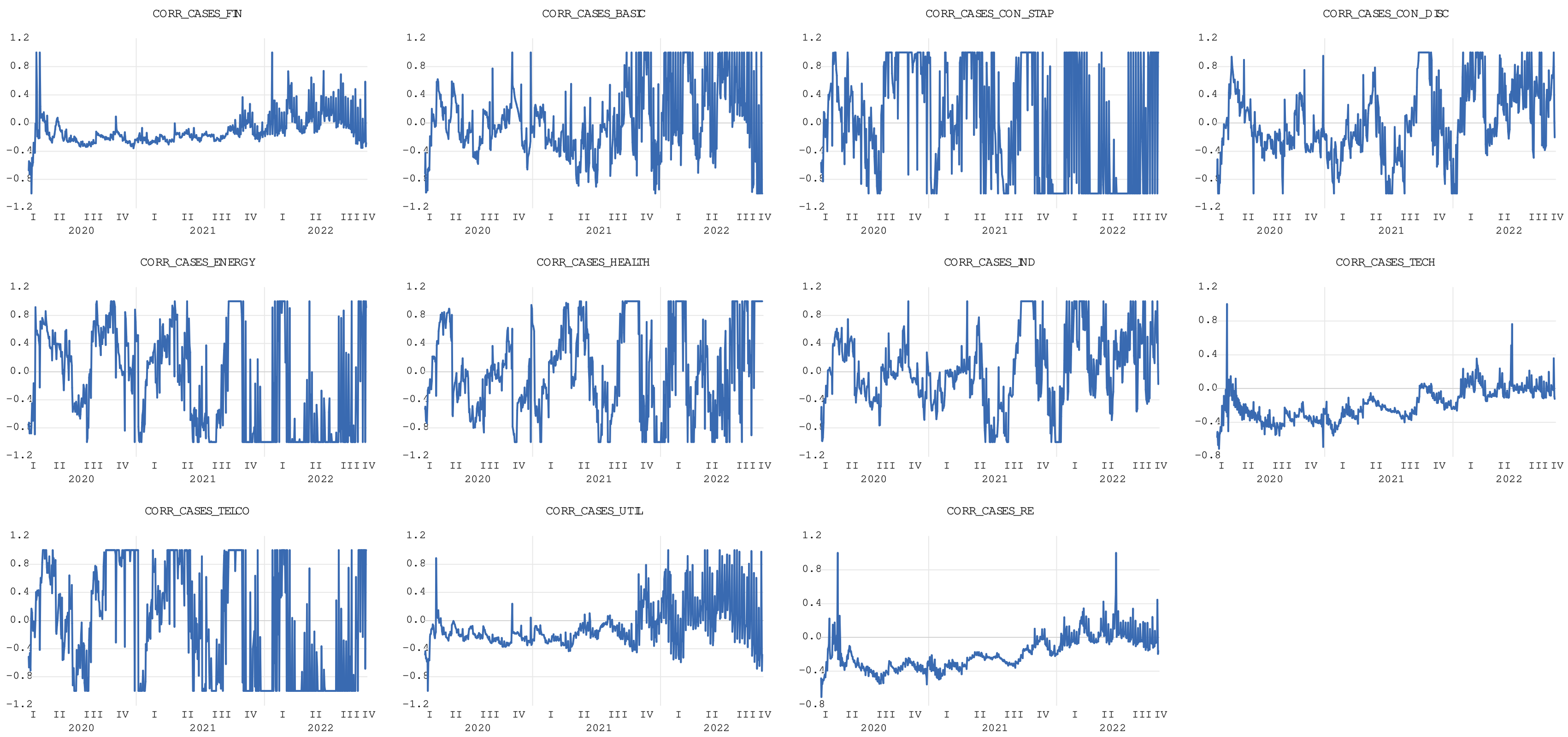
This appendix, intended for online publication, contains additional figures and tables.

Figure A1: TGARCH(1) for the US



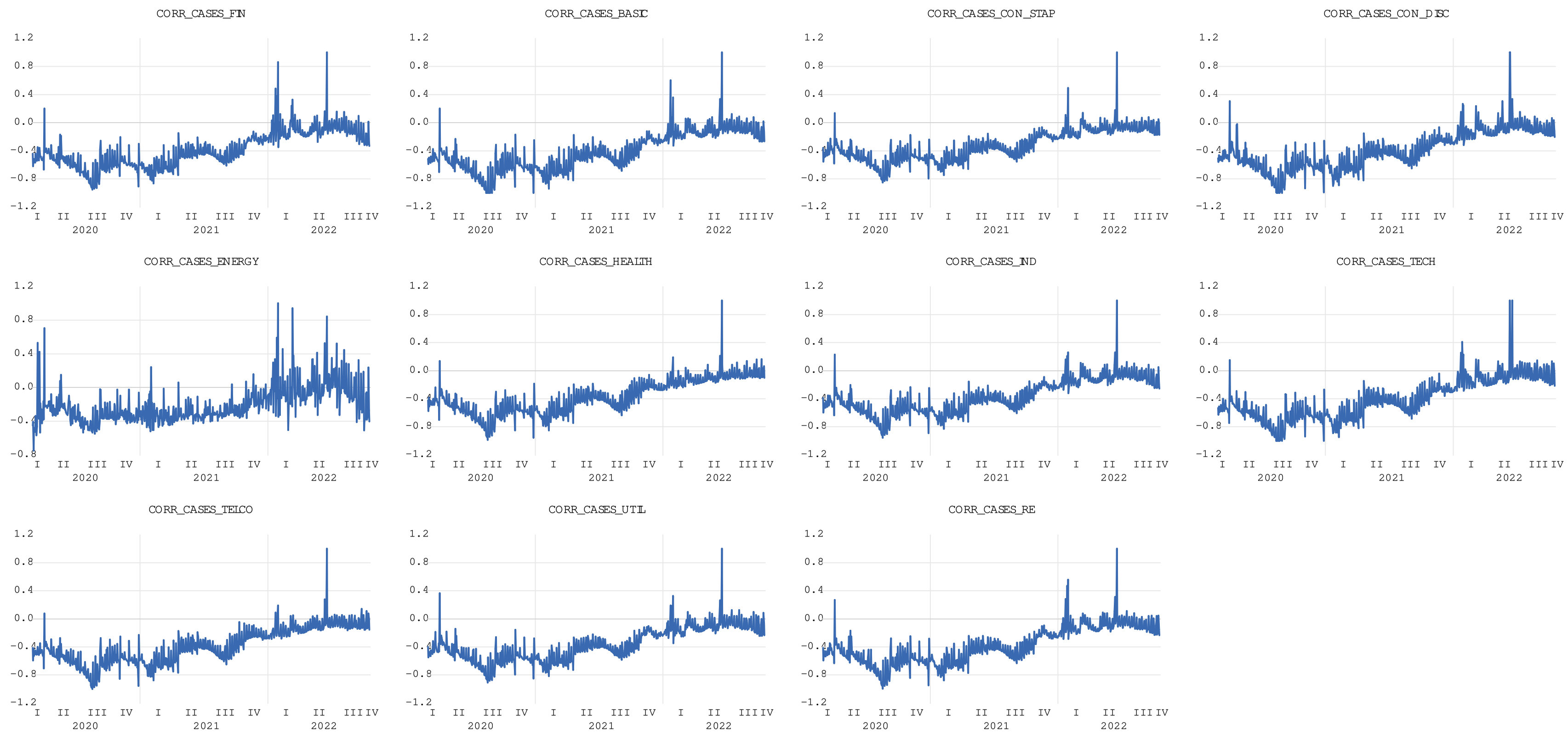
Notes: The figure contains 11 panels and depicts in each the TGARCH(1)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A2: TGARCH(2) for the US



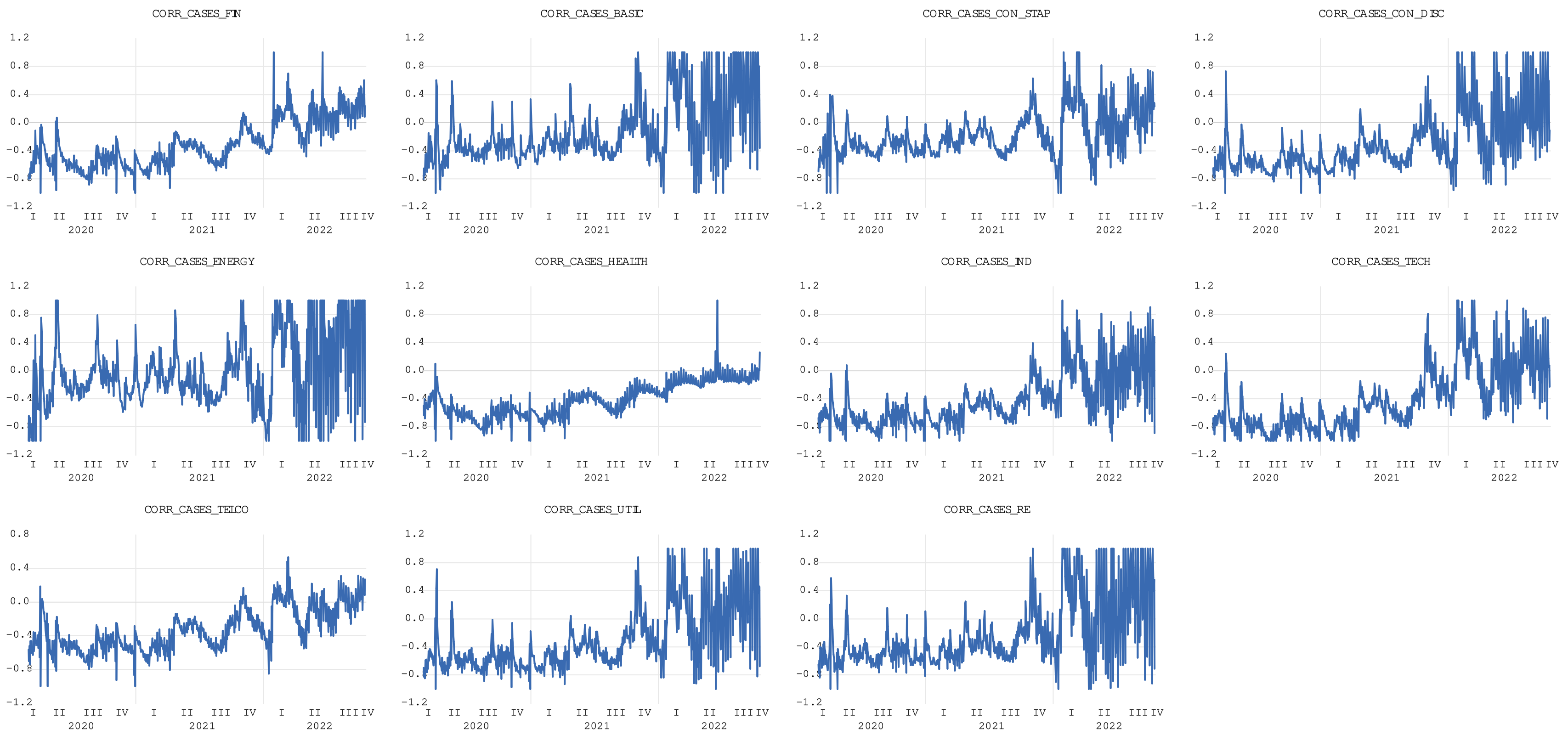
Notes: The figure contains 11 panels and depicts in each the TGARCH(2)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A3: TGARCH(3) for the US



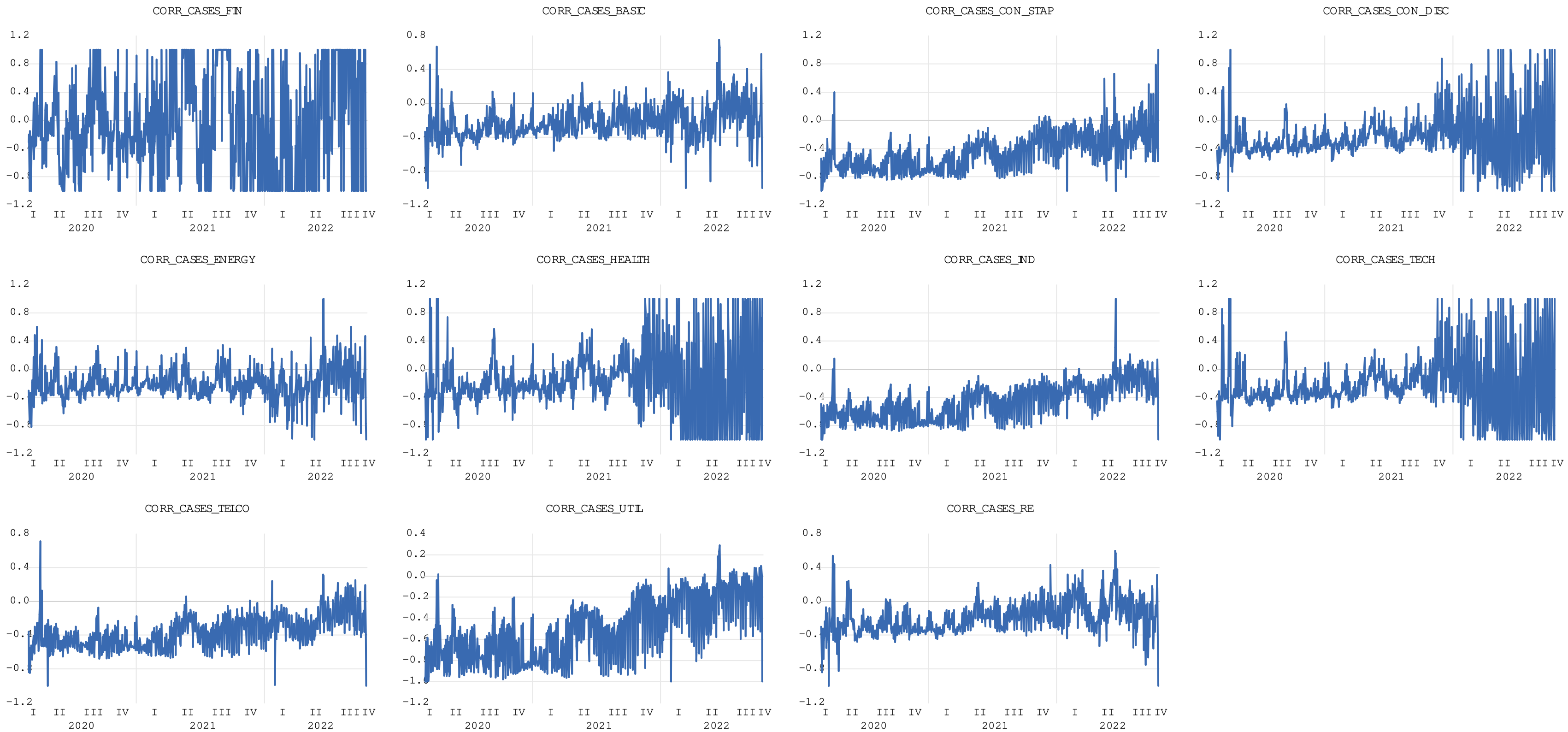
Notes: The figure contains 11 panels and depicts in each the TGARCH(3)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A4: TGARCH(4) for the US



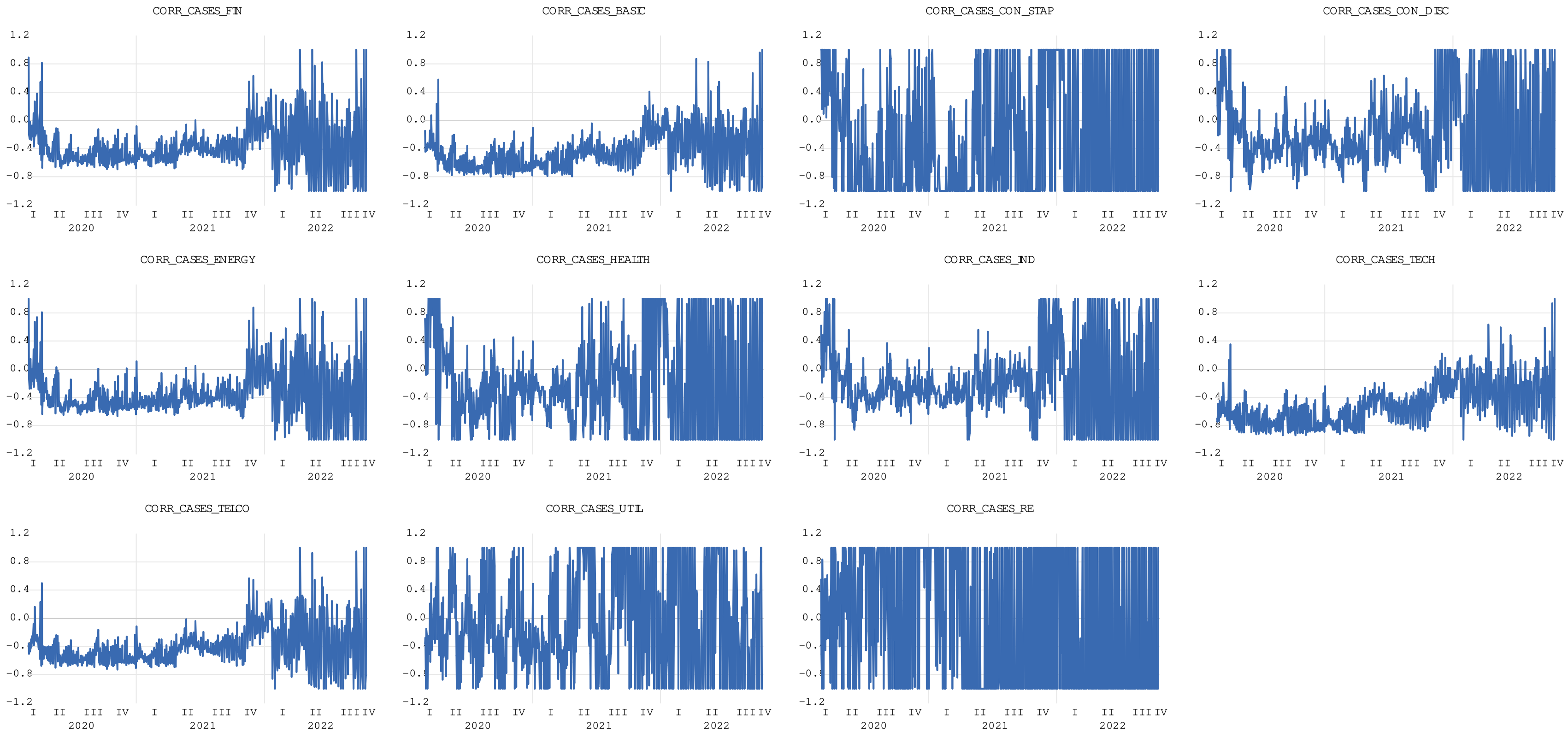
Notes: The figure contains 11 panels and depicts in each the TGARCH(4)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A5: TGARCH(5) for the US



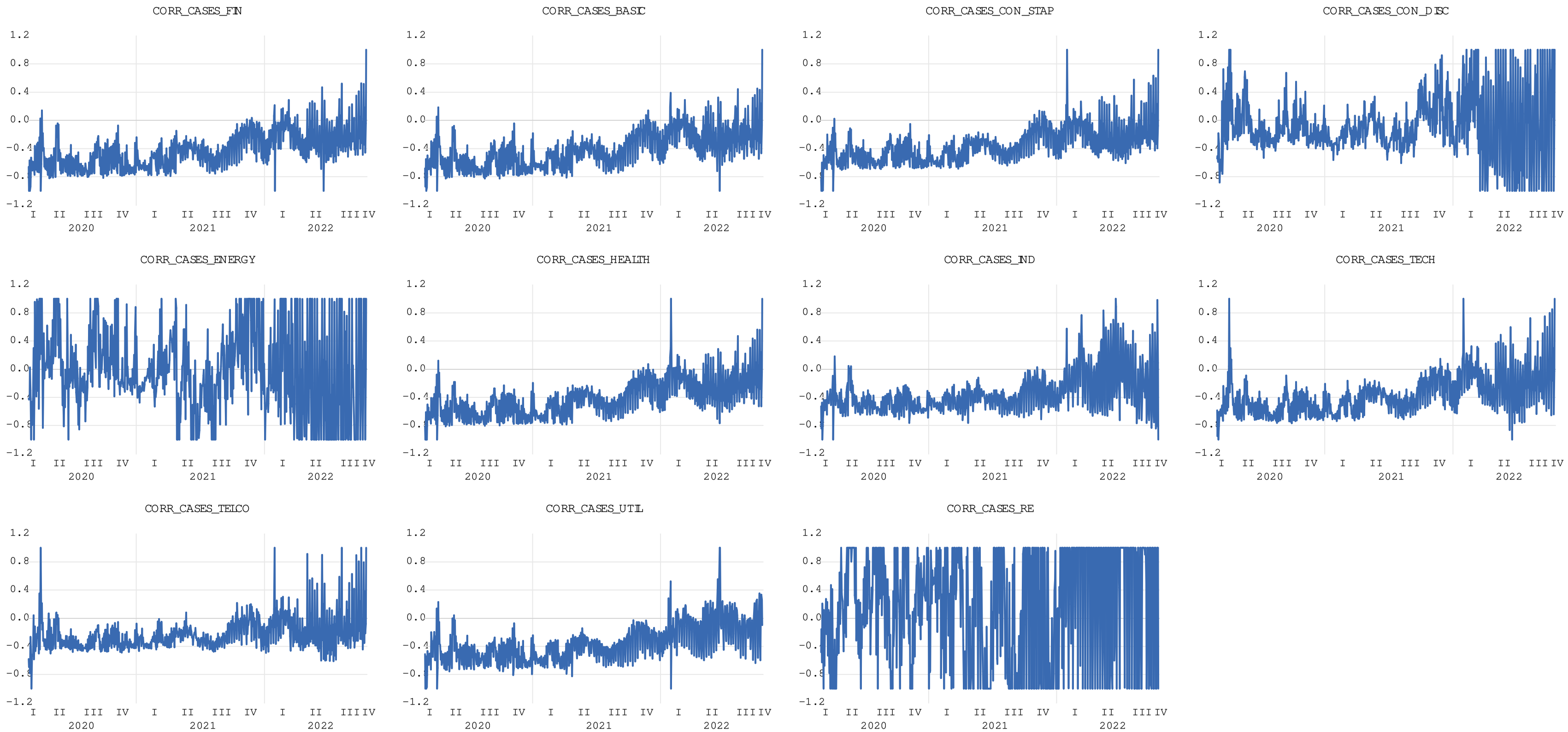
Notes: The figure contains 11 panels and depicts in each the TGARCH(5)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A6: TGARCH(6) for the US



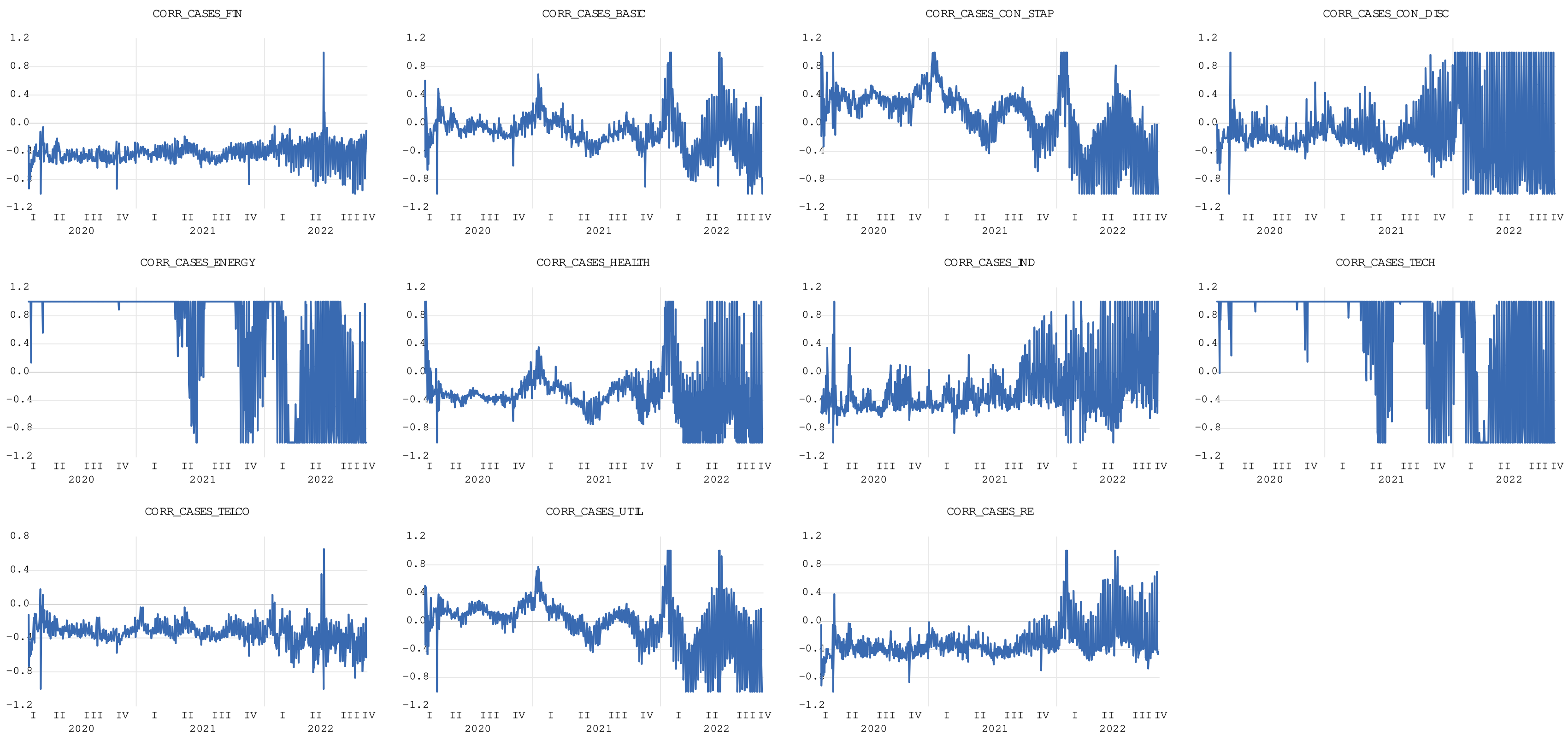
Notes: The figure contains 11 panels and depicts in each the TGARCH(6)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A7: TGARCH(7) for the US



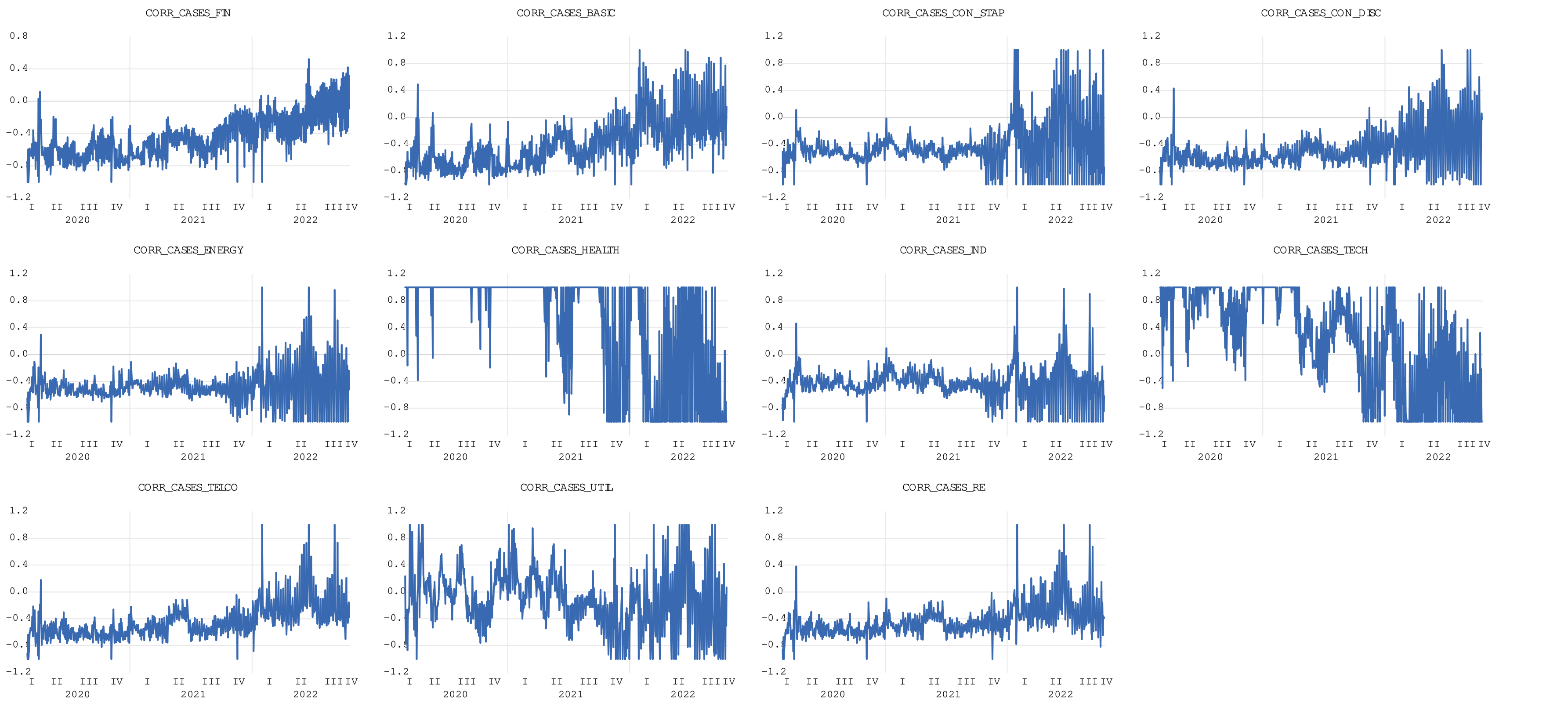
Notes: The figure contains 11 panels and depicts in each the TGARCH(7)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A8: TGARCH(8) for the US



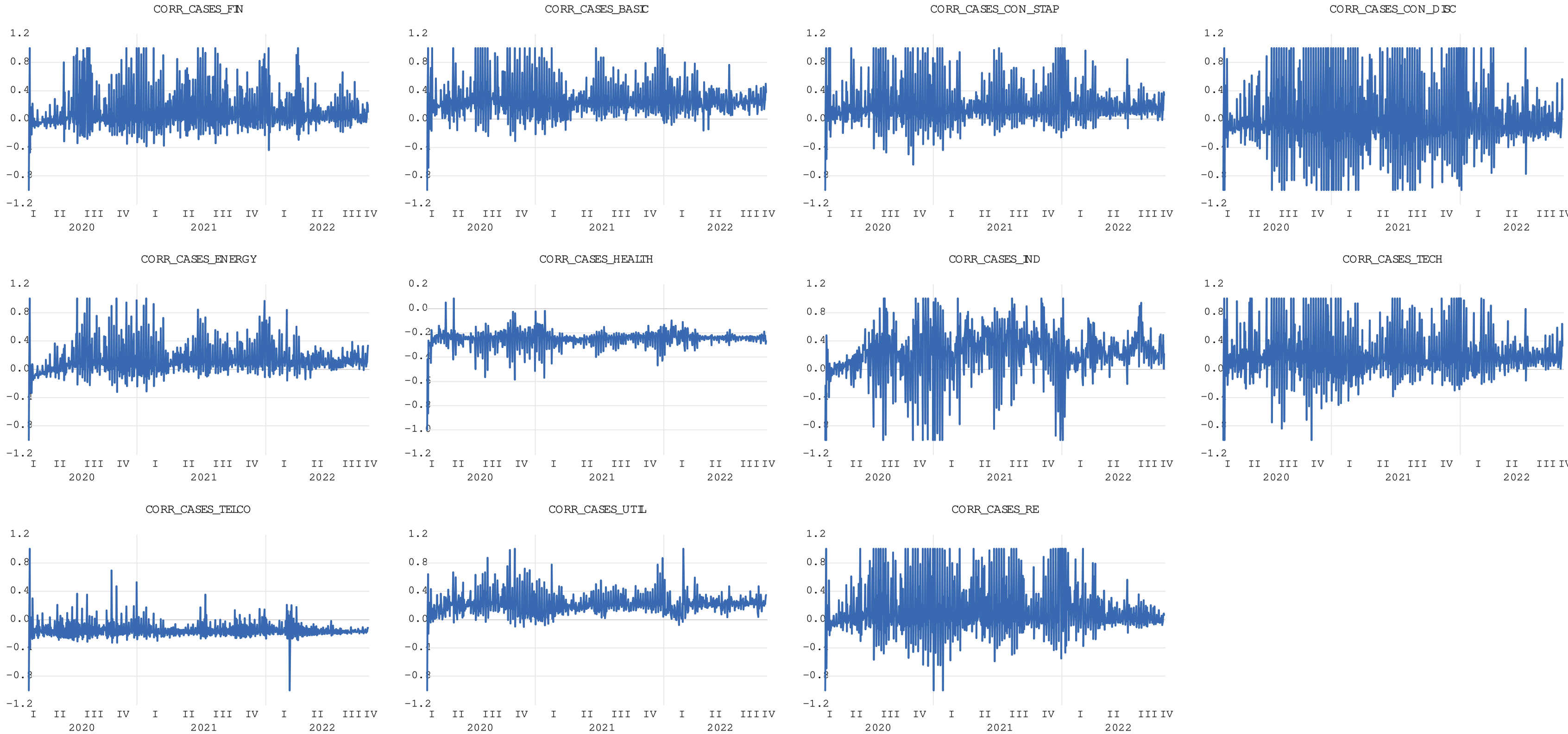
Notes: The figure contains 11 panels and depicts in each the TGARCH(8)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A9: TGARCH(9) for the US



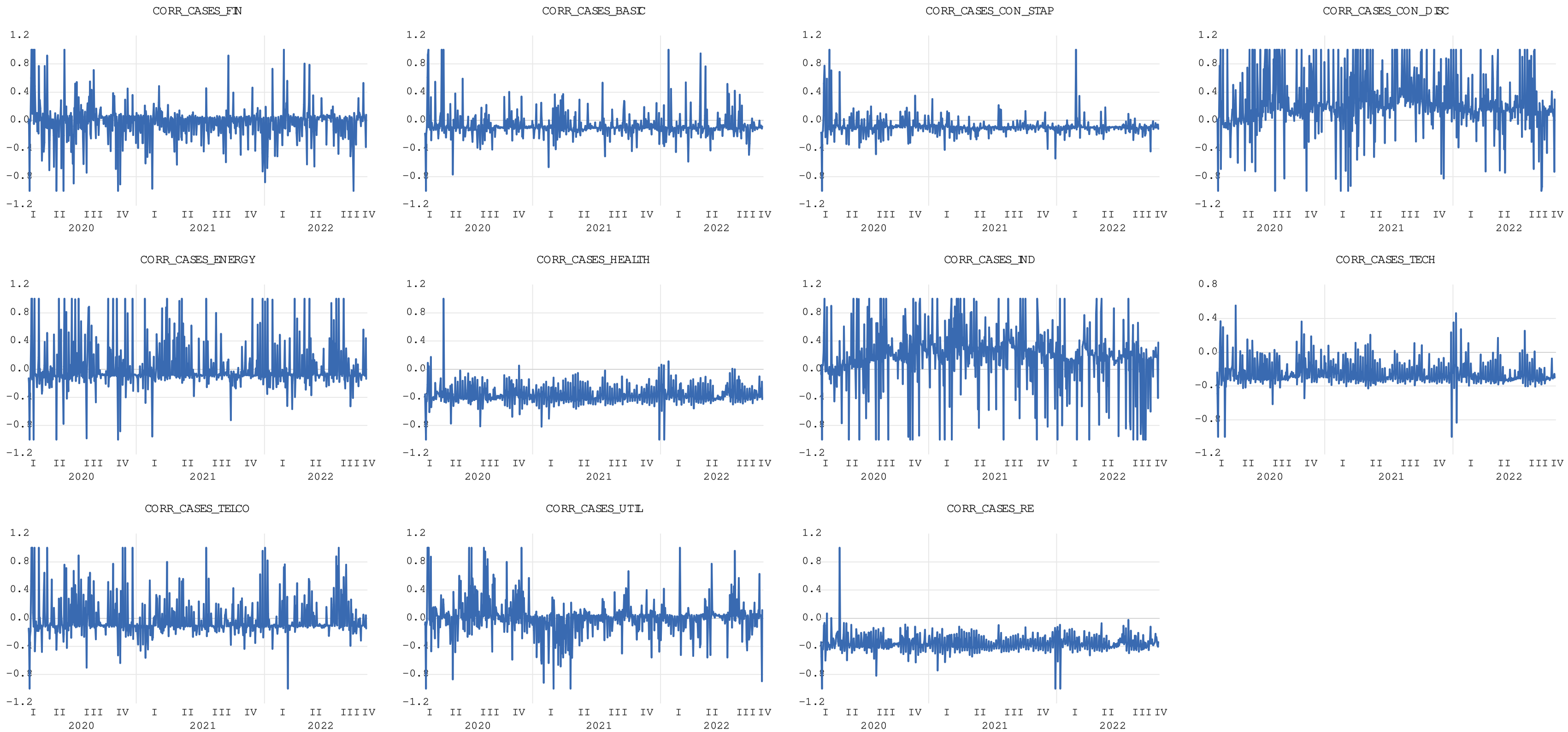
Notes: The figure contains 11 panels and depicts in each the TGARCH(9)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the US, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A10: TGARCH(1) for the UK



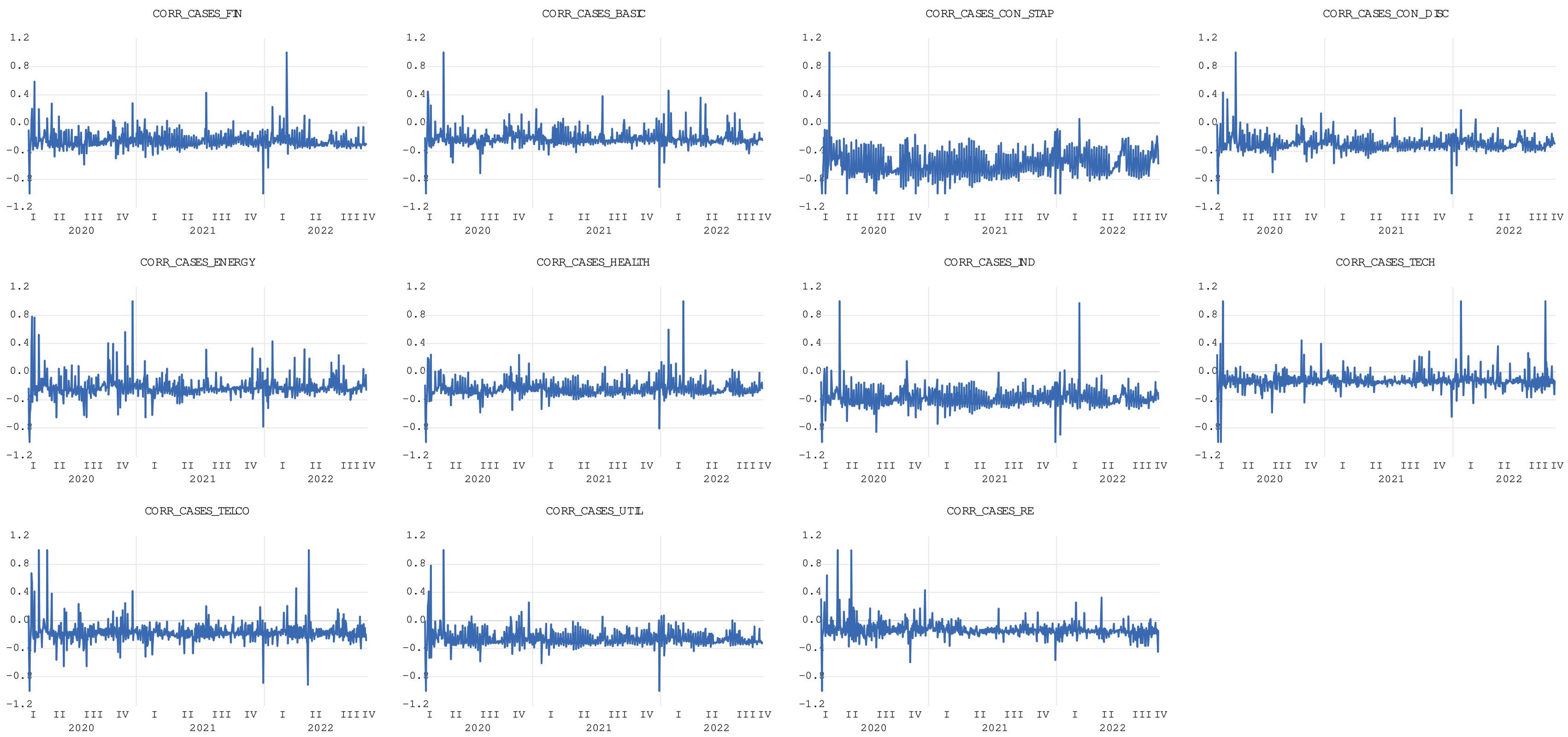
Notes: The figure contains 11 panels and depicts in each the TGARCH(1)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A11: TGARCH(2) for the UK



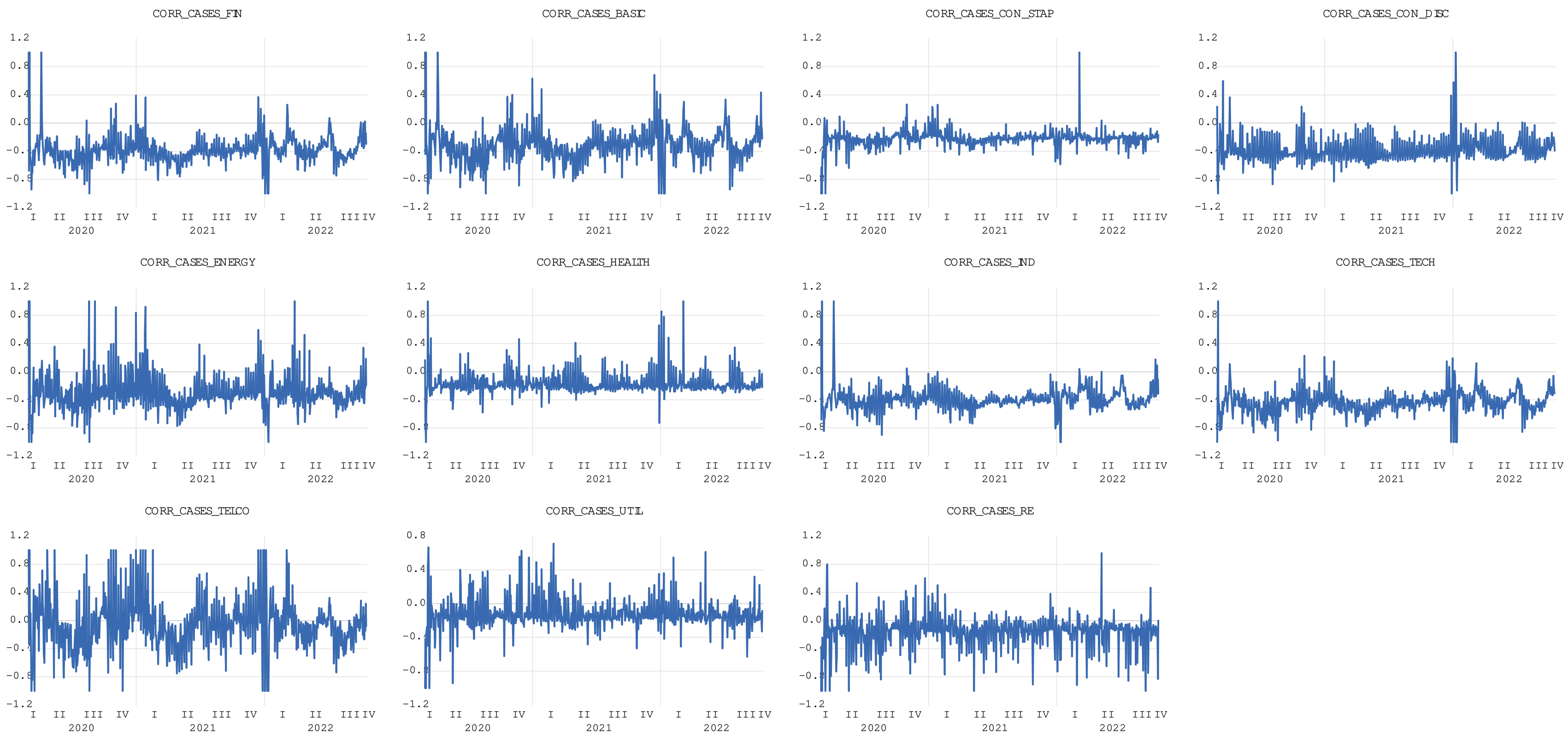
Notes: The figure contains 11 panels and depicts in each the TGARCH(2)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A12: TGARCH(3) for the UK



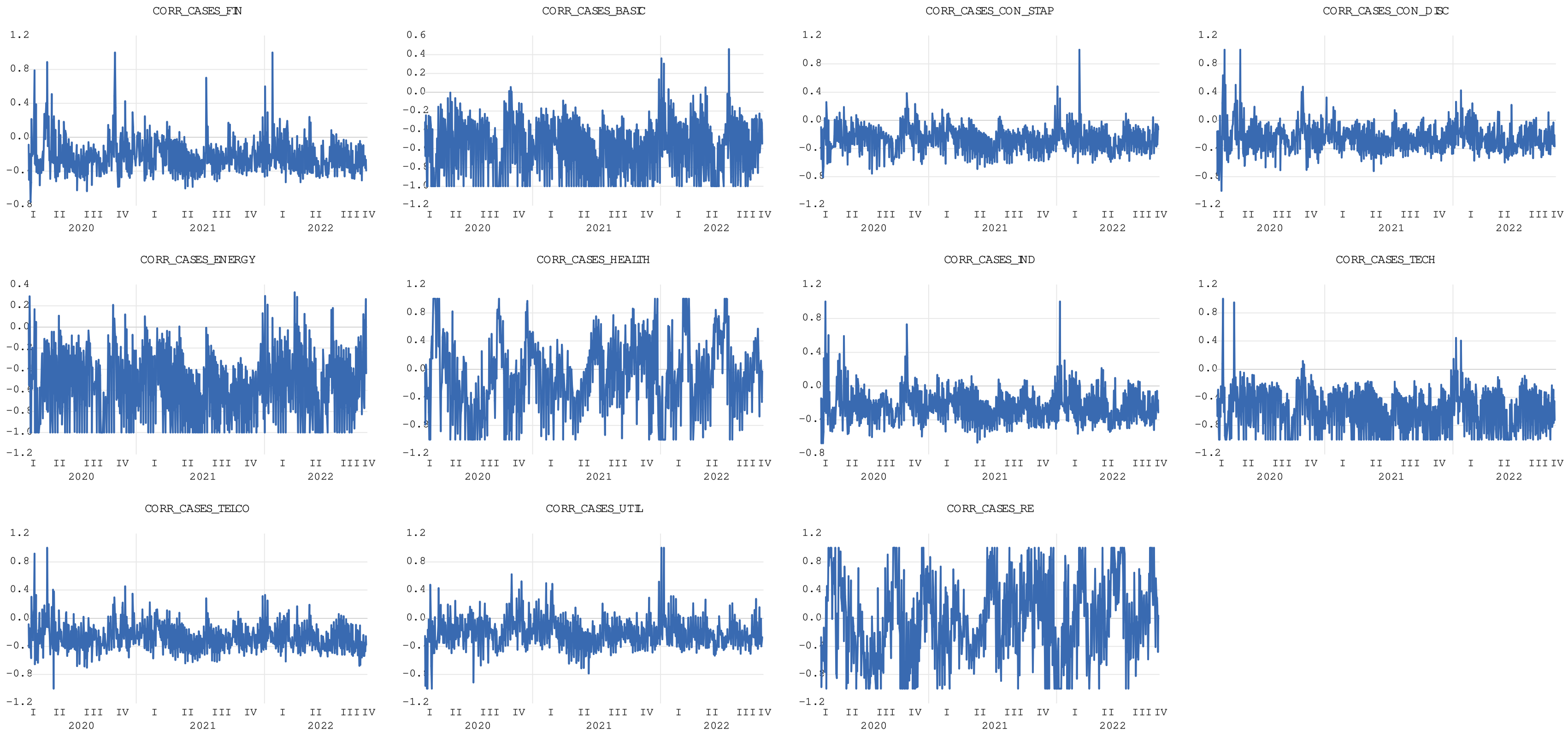
Notes: The figure contains 11 panels and depicts in each the TGARCH(3)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A13: TGARCH(4) for the UK



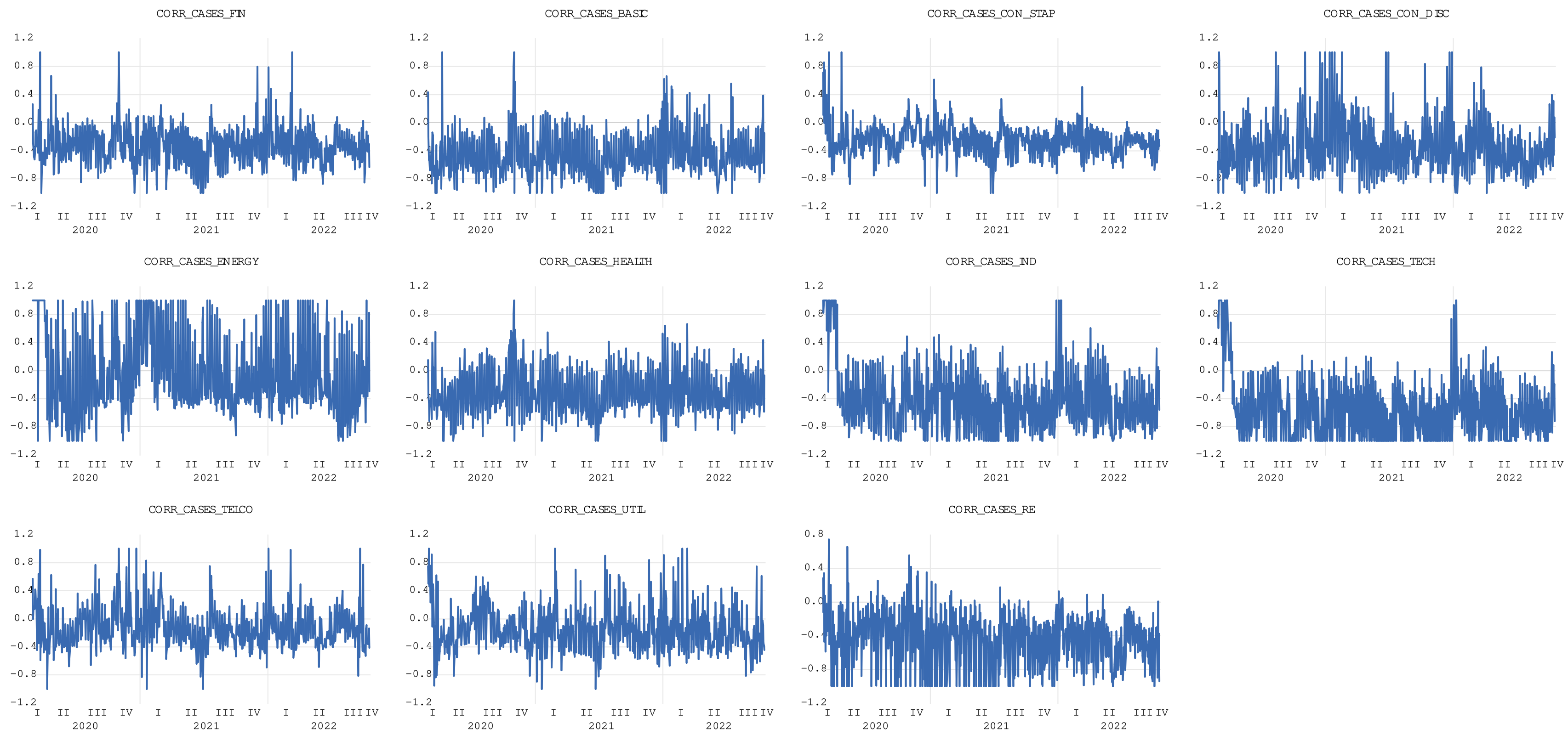
Notes: The figure contains 11 panels and depicts in each the TGARCH(4)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A14: TGARCH(5) for the UK



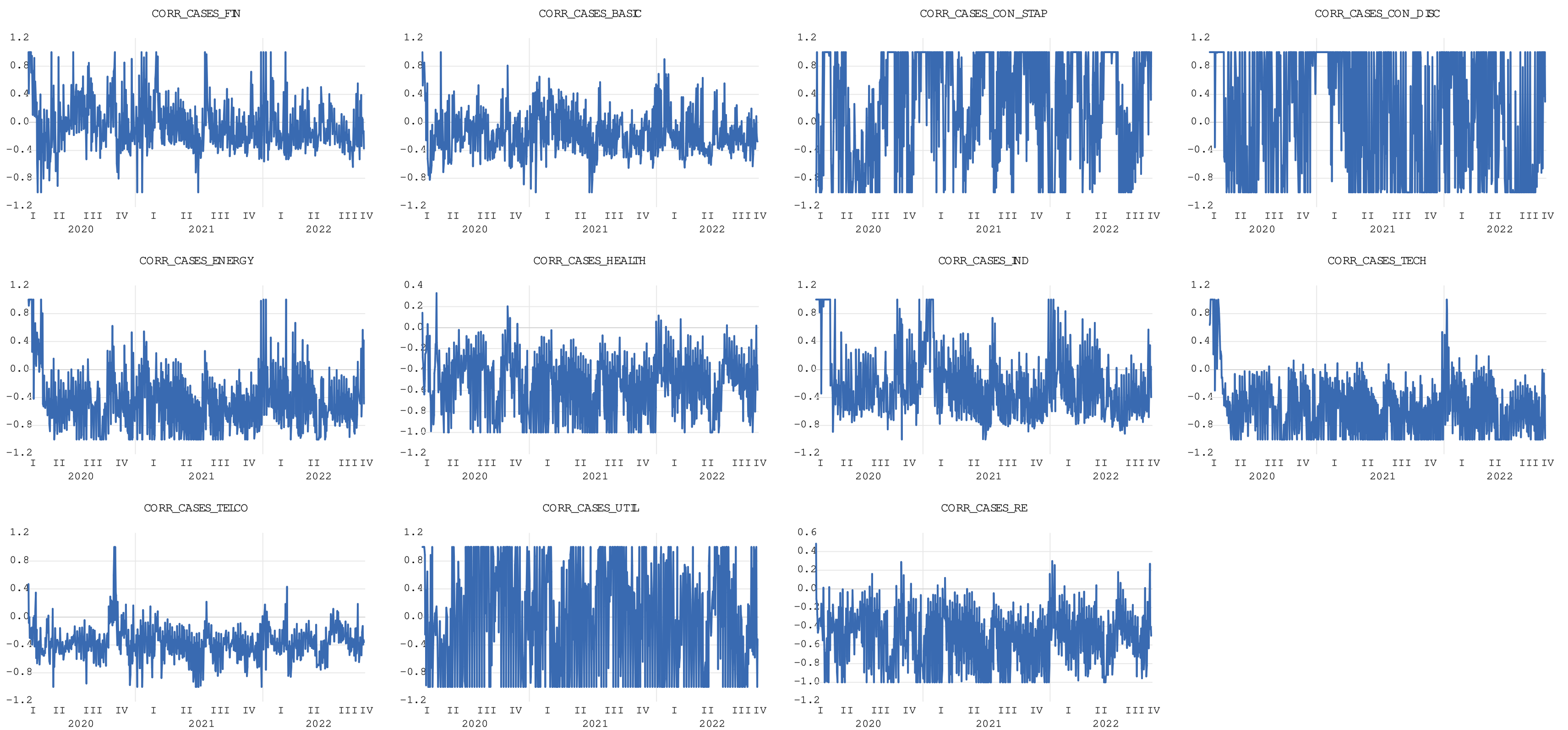
Notes: The figure contains 11 panels and depicts in each the TGARCH(5)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A15: TGARCH(6) for the UK



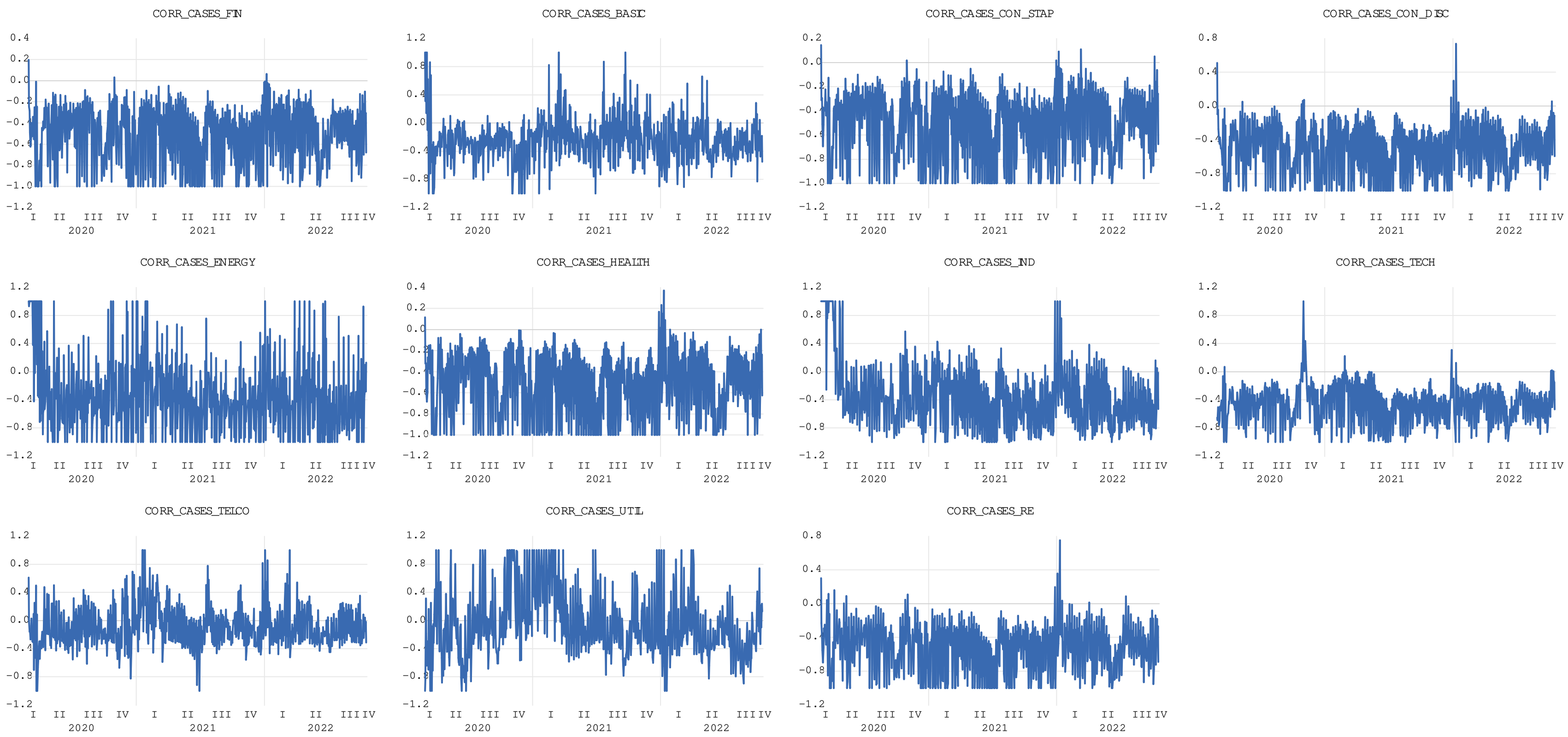
Notes: The figure contains 11 panels and depicts in each the TGARCH(6)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A16: TGARCH(7) for the UK



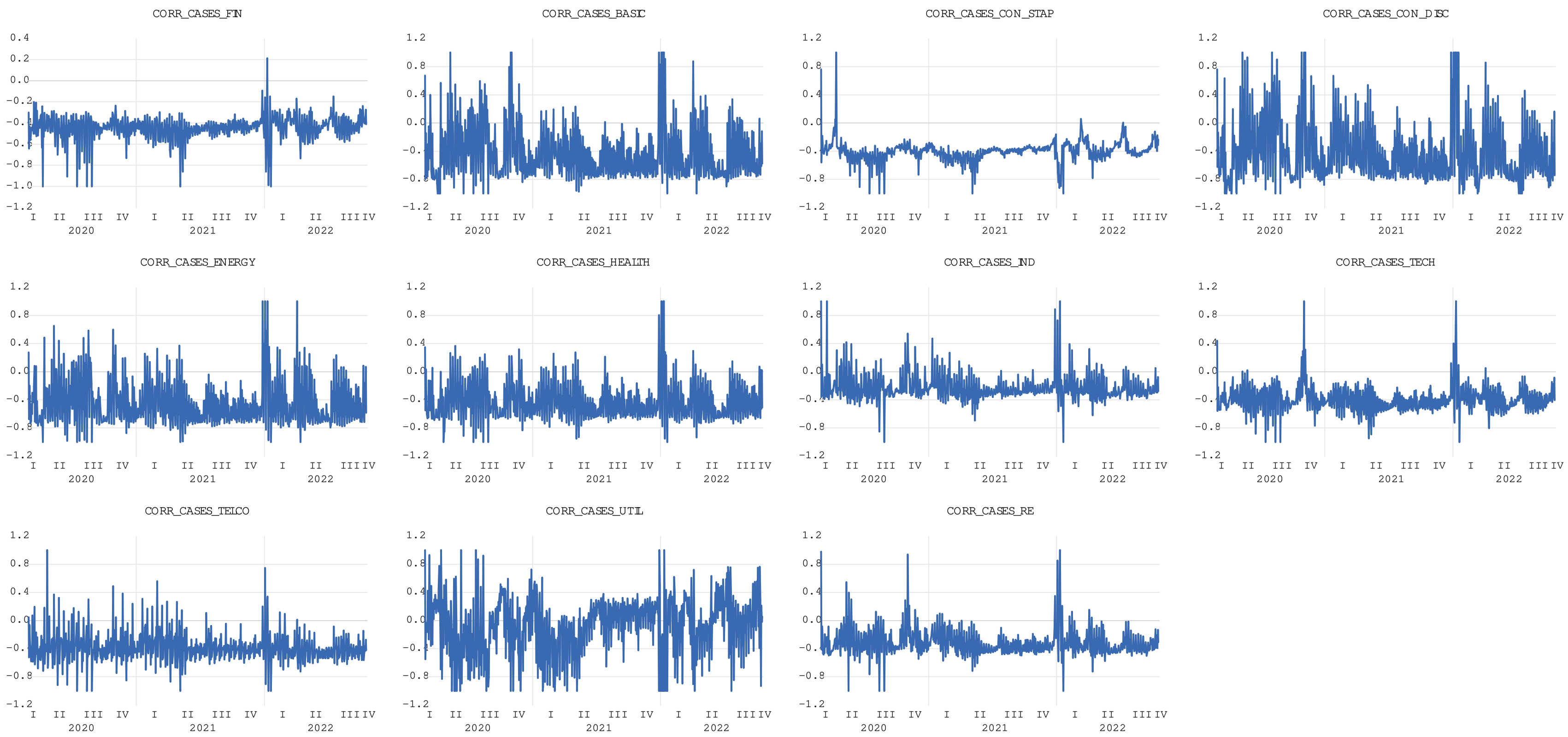
Notes: The figure contains 11 panels and depicts in each the TGARCH(7)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A17: TGARCH(8) for the UK



Notes: The figure contains 11 panels and depicts in each the TGARCH(8)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A18: TGARCH(9) for the UK



Notes: The figure contains 11 panels and depicts in each the TGARCH(9)-inferred daily correlations within our pandemic sample between new COVID-19 cases, on one hand, and the respective 11 GICS sectoral stock-market indexes in the UK, on the other, as follows: (1,1) financials; (1,2) basic materials; (1,3) consumer staples; (1,4) consumer products and services; (2,1) energy; (2,2) healthcare; (2,3) industrials; (2,4) technology; (3,1) telecommunications; (3,2) utilities; and (3,3) real estate. For details on the computation, see section 4 in the main text.

Figure A19: TGARCH with 1-3 Thresholds for the US

TGARCH - 1	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
α	0.0235	0.0226	0.0221	0.0198	0.0247	0.0248	0.0237	0.0267	0.0242	0.0206	0.0286
β	0.9494*	0.9488*	0.9490*	0.9516*	0.9497*	0.9495*	0.9496*	0.9485*	0.9497*	0.9501*	0.9480*
γ	0.0701*	0.0736*	0.0741*	0.0732*	0.0674**	0.0674**	0.0694**	0.0658**	0.0685**	0.0750*	0.0629**
$\alpha+\beta$	0.9729	0.9713	0.9711	0.9714	0.9744	0.9743	0.9734	0.9752	0.9740	0.9707	0.9765
F-LM	10.852*	10.975*	11.888*	10.500*	10.893*	12.418*	10.975*	10.448*	10.837*	12.216	9.874*
LL	-178.90	-176.89	-178.03	-180.92	-181.43	-178.70	-178.80	-178.59	-178.75	-178.11	-180.52
SIC	0.8892	0.8834	0.8867	0.8951	0.8966	0.8886	0.8889	0.8883	0.8888	0.8869	0.8939
TGARCH - 2	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0008***	0.0009***	0.0012	0.0012	0.0008***	0.0008***	0.0009***	0.0008***	0.0009***	0.0011*	0.0006
α	-0.0120	-0.0271	-0.0438	-0.0556	-0.0109	-0.0325	-0.0271	-0.0142	-0.0262	-0.0512*	0.0055
β	0.9073*	0.9111*	0.9071	0.9134	0.9073*	0.9167*	0.9116*	0.9096*	0.9120*	0.9179*	0.9103*
$\gamma1$	-0.0601	-0.0576	-0.0751	-0.0600	-0.0556	-0.0692	-0.0589	-0.0593	-0.0538	-0.0697	-0.0595
$\gamma2$	0.2764*	0.2990*	0.3595	0.3486	0.2695*	0.3119*	0.2988*	0.2766*	0.2916*	0.3512*	0.2354*
$\alpha+\beta$	0.8953	0.8840	0.8633	0.8578	0.8964	0.8843	0.8845	0.8954	0.8859	0.8667	0.9158
F-LM	5.016**	4.690**	4.571**	1.696	5.446**	5.196**	5.112**	4.868**	4.861**	4.533**	4.344**
LL	-173.92	-171.91	-171.08	-175.00	-176.69	-173.60	-174.02	-174.07	-174.22	-172.48	-176.55
SIC	0.8842	0.8784	0.8760	0.8874	0.8923	0.8833	0.8845	0.8847	0.8851	0.8801	0.8919
TGARCH - 3	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
α	-0.0105	-0.0145	-0.0140	-0.0110	-0.0087	-0.0160	-0.0121	-0.0108	-0.0135	-0.0168***	-0.0104
β	0.9651*	0.9660*	0.9662*	0.9671*	0.9649*	0.9680*	0.9658*	0.9652*	0.9681*	0.9689*	0.9659*
$\gamma1$	-0.0376	-0.0397	-0.0442	-0.0297	-0.0359	-0.0496	-0.0388	-0.0418	-0.0374	-0.0420	-0.0377
$\gamma2$	0.9964*	1.0246*	1.0130*	0.9654*	0.9618*	1.0361*	0.9914*	0.9980*	1.0298*	1.0316*	0.9871*
$\gamma3$	-0.8312*	-0.8483*	-0.8345*	-0.8134*	-0.8046*	-0.8503*	-0.8233*	-0.8282*	-0.8624*	-0.8537*	-0.8244*
$\alpha+\beta$	0.9545	0.9516	0.9522	0.9561	0.9562	0.9520	0.9537	0.9544	0.9545	0.9521	0.9555
F-LM	0.952	1.052	1.161	0.900	1.229	1.404	1.169	1.062	1.025	1.341	0.865
LL	-158.98	-157.05	-158.15	-161.68	-162.15	-158.61	-159.38	-159.28	-158.95	-157.90	-161.34
SIC	0.8504	0.8448	0.8480	0.8582	0.8596	0.8493	0.8515	0.8512	0.8503	0.8472	0.8572

1. *, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
2. F-LM: ARCH test F-statistics for heteroskedasticity.
3. LL: Log-likelihood ratio.
4. SIC: Schwarz Information Criterion.

Indicates the minimum SIC when the stationarity criteria are met.

Indicates the second minimum SIC when the stationarity criteria are met.

Figure A20: TGARCH with 4-6 Thresholds for the US

TGARCH - 4	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0034	0.0031	0.0020	0.0031	0.0016	0.0010	0.0036	0.0043	0.0028	0.0017	0.0034
α	0.0530	0.0216	0.0201	0.0350	0.0254	0.0124	0.0618	0.0728	0.0932	0.0189	0.0650
β	0.7298	0.7617	0.8370	0.7760	0.8605	0.9118	0.7584	0.6808	0.7385	0.8588	0.7100
$\gamma 1$	-0.0898	-0.0760	-0.0905	-0.0744	-0.0810	-0.0856	-0.1274	-0.1118	-0.1448	-0.0867	-0.0984
$\gamma 2$	0.4641	0.4428	0.5286	0.5320	0.4872	0.5300	0.5063	0.4915	0.4890	0.5185	0.4806
$\gamma 3$	-0.3711	-0.3626	-0.4641	-0.4536	-0.4570	-0.5069	-0.4187	-0.3669	-0.3890	-0.4660	-0.3763
$\gamma 4$	0.3663	0.3582	0.2821	0.3202	0.2649	0.2027	0.3260	0.4011	0.3439	0.2551	0.3635
$\alpha+\beta$	0.7828	0.7833	0.8570	0.8110	0.8859	0.9242	0.8202	0.7536	0.8317	0.8777	0.7749
F-LM	2.292	1.623	3.073***	2.180	5.171**	4.184**	2.239	1.988	4.309**	2.597	3.152***
LL	-162.05	-158.06	-155.15	-162.79	-160.89	-153.68	-161.91	-165.94	-163.14	-155.34	-166.08
SIC	0.8688	0.8572	0.8487	0.8709	0.8654	0.8445	0.8684	0.8801	0.8719	0.8493	0.8805
TGARCH - 5	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0156*	0.0147*	0.0152*	0.0169*	0.0160*	0.0152*	0.0158*	0.0155*	0.0149*	0.0159*	0.0167*
α	0.0371	0.0219	0.0262	0.0318	0.0339	0.0233	0.0310	0.0406*	0.0136	0.0271	0.0316
β	0.0363	0.0363	0.0367	0.0274	0.0400	0.0343	0.0398	0.0502	0.0355	0.0375	0.0291
$\gamma 1$	0.0019	-0.0002	0.0020	0.0094	-0.0012	-0.0007	0.0048	-0.0157	0.0043	0.0079	0.0060
$\gamma 2$	0.6350*	0.6256*	0.6054*	0.6223*	0.6448*	0.6234*	0.6426*	0.6412*	0.6287*	0.6332*	0.6835*
$\gamma 3$	-0.0300	0.0181	0.0054	-0.0237	-0.0327	0.0108	-0.0322	-0.0397	0.0292	-0.0296	-0.0265
$\gamma 4$	0.0092	0.0110	0.0078	0.0094	0.0103	0.0097	0.0104	0.0084	0.0121	0.0089	0.0077
$\gamma 5$	0.8105*	0.8291*	0.8205*	0.8097*	0.8126*	0.8214*	0.8179*	0.8011*	0.8299*	0.8132*	0.8252*
$\alpha+\beta$	0.0734	0.0581	0.0629	0.0592	0.0739	0.0576	0.0708	0.0907	0.0491	0.0646	0.0607
F-LM	0.112	0.027	0.004	0.057	0.126	0.025	0.141	0.034	0.074	0.117	0.048
LL	-102.86	-105.28	-105.51	-107.17	-105.83	-105.94	-103.33	-104.18	-106.92	-102.43	-105.48
SIC	0.7064	0.7135	0.7141	0.7189	0.7151	0.7154	0.7078	0.7103	2.0598	0.7052	0.7140
TGARCH - 6	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0010	0.0010	0.0011	0.0010	0.0010	0.0010	0.0009	0.0181	0.0009	0.0011	0.0152*
α	0.0098	0.0097	0.0099	0.0101	0.0088	0.0094	0.0086	0.1118	0.0093	0.0104	0.0291
β	0.9246*	0.9210*	0.9187*	0.9265*	0.9269*	0.9268*	0.9271*	0.1678	0.9266*	0.9184*	0.0848
$\gamma 1$	-0.0120	-0.0140	-0.0143	-0.0116	-0.0135	-0.0176	-0.0106	-0.1652	-0.0117	-0.0127	-0.0004
$\gamma 2$	0.5906*	0.6028*	0.5883*	0.5712*	0.5935*	0.6062*	0.5868*	0.2957	0.6079*	0.5949*	0.6378*
$\gamma 3$	-0.5358*	-0.5344*	-0.5250*	-0.5135*	-0.5343*	-0.5448*	-0.5277*	-0.0190	-0.5430*	-0.5343*	-0.0608
$\gamma 4$	-0.0259	-0.0328	-0.0311	-0.0292	-0.0306	-0.0295	-0.0311	-0.0129	-0.0337	-0.0288	0.0084
$\gamma 5$	0.8061*	0.8044*	0.7978*	0.8057*	0.7951*	0.7937*	0.8091*	0.4968	0.8060*	0.7932*	0.8038*
$\gamma 6$	-0.7186*	-0.7144*	-0.7028*	-0.7226*	-0.7081*	-0.7063*	-0.7241*	0.0579	-0.7217*	-0.6997*	-0.0304
$\alpha+\beta$	0.9344	0.9307	0.9286	0.9366	0.9357	0.9361	0.9357	0.2795	0.9358	0.9288	0.1139
F-LM	0.001	0.001	0.008	0.000	0.028	0.001	0.006	0.163	0.002	0.011	0.099
LL	-99.89	-98.94	-99.43	-104.01	-103.30	-99.69	-100.67	-133.56	-100.94	-99.63	-105.57
SIC	0.7073	0.7045	0.7060	0.7193	0.7172	0.7067	0.7096	0.8050	0.7103	0.7065	0.7238

1. *, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
2. F-LM: ARCH test F-statistics for heteroskedasticity.
3. LL: Log-likelihood ratio.
4. SIC: Schwarz Information Criterion.

Indicates the minimum SIC when the stationarity criteria are met.

Indicates the second minimum SIC when the stationarity criteria are met.

Figure A21: TGARCH with 7-9 Thresholds for the US

TGARCH - 7	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0102*	0.0103*	0.0108*	0.0108*	0.0112*	0.0107*	0.0127	0.0130	0.0108*	0.0111*	0.0112
α	0.0154	0.0123	0.0131	0.0119	0.0140	0.0115	0.0352	0.0617	0.0029	0.0134	0.0310
β	0.2946***	0.2642***	0.2506***	0.2955***	0.2565***	0.2535***	0.1817	0.2026	0.2376***	0.2397***	0.2421
$\gamma 1$	-0.0223	-0.0213	-0.0187	-0.0187	-0.0239	-0.0190	-0.0316	-0.0498	-0.0145	-0.0162	-0.0267
$\gamma 2$	0.4206*	0.4018*	0.3967*	0.4336*	0.4141*	0.3871*	0.4065	0.4250	0.3913*	0.3972*	0.4179
$\gamma 3$	-0.1210	-0.1025	-0.0930	-0.1131	-0.0947	-0.0952	-0.1104	-0.1260	-0.0751	-0.0907	-0.1342
$\gamma 4$	0.0037	0.0069	0.0048	0.0018	0.0040	0.0062	0.0074	0.0028	0.0081	0.0060	0.0066
$\gamma 5$	0.8442*	0.8471*	0.8387*	0.8445*	0.8313*	0.8397*	0.7599	0.7985	0.8479*	0.8382*	0.8250
$\gamma 6$	-0.2185	-0.1925	-0.1784	-0.2227	-0.1782	-0.1827	-0.0917	-0.1261	-0.1685	-0.1706	-0.1659
$\gamma 7$	0.2136**	0.2563**	0.2410**	0.1882**	0.2274**	0.2634**	0.2319	0.2245	0.2764**	0.2431**	0.2438
$\alpha+\beta$	0.3100	0.2765	0.2637	0.3074	0.2705	0.2651	0.2169	0.2644	0.2404	0.2531	0.2731
F-LM	0.047	0.063	0.085	0.005	0.119	0.076	0.204	0.243	0.080	0.100	0.160
LL	-102.20	-100.18	-101.09	-106.56	-105.08	-101.35	-100.98	-104.16	-102.23	-101.33	-100.93
SIC	0.7235	0.7176	0.7203	0.7361	0.7318	0.7210	0.7199	0.7292	0.7236	0.7210	0.7198

TGARCH - 8	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0419	0.0429	0.0752*	0.0700*	0.0257	0.0372*	0.0163	0.0287	0.0603*	0.0260	0.0649*
α	0.0824	0.0961	0.0989	0.0938	0.0813	0.0846*	0.0845	0.0914	0.0916	0.0958	0.0980
β	0.0234	0.0799	0.0632***	0.0511	0.0067	0.0954	0.0469	0.0491	0.0631	0.0504	0.0442
$\gamma 1$	-0.1122	-0.1201	-0.1322	-0.1168***	-0.1061	-0.0584	-0.0991	-0.1113	-0.1193**	-0.1102	-0.1259***
$\gamma 2$	0.2548	0.1724	0.1833***	0.2022**	0.2910	0.1722**	0.4090	0.2677	0.1833**	0.3128	0.2048**
$\gamma 3$	-0.0953	-0.1031	-0.0970	-0.1003	-0.0626	-0.1037**	-0.0609	-0.0723	-0.1056***	-0.0762	-0.1037
$\gamma 4$	0.0204	-0.0009	0.0092	0.0116	0.0349	0.0269*	0.0227	0.0232	0.0131	0.0260	0.0161
$\gamma 5$	0.4214	0.6826	0.3640*	0.3733*	0.3079	0.2143*	0.5893	0.4658	0.4018*	0.3431	0.3939*
$\gamma 6$	0.0432	-0.0115	0.0259	0.0195	0.0537	0.0287	0.0117	0.0249	0.0184	0.0204	0.0305
$\gamma 7$	0.2616	0.1837	0.1876**	0.2044**	0.3109	0.1745*	0.2707	0.2746	0.1934**	0.3089	0.2075**
$\gamma 8$	0.1267	0.0839	0.0767	0.0873	0.1344	0.0897***	0.1090	0.1006	0.0922***	0.0960	0.0953**
$\alpha+\beta$	0.1058	0.1760	0.1620	0.1449	0.0880	0.1800	0.1314	0.1405	0.1548	0.1463	0.1422
F-LM	0.191	0.155	0.223	0.293	0.156	0.028	0.184	0.002	0.697	0.237	0.092
LL	-188.72	-186.76	-249.50	-243.55	-149.27	-275.99	-108.40	-159.72	-236.54	-147.30	-224.82
SIC	0.9841	0.9784	1.1605	1.1433	0.8696	1.2374	0.7510	0.8999	1.1229	0.8639	1.0889

TGARCH - 9	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0125	0.0206	0.0245	0.0291	0.0162	0.0818*	0.0315	0.0259	0.0745**	0.0227	0.0212
α	0.0431	0.0848	0.1010	0.0923	0.0839	0.1017***	0.0933	0.0900	0.0896***	0.0985	0.0895
β	0.0453	0.0456	0.1376	0.0306	0.0357	0.0729	0.0444	0.0520	0.0833	0.0429	0.0819
$\gamma 1$	-0.0575	-0.1127	-0.0819	-0.1161	-0.1036	-0.1279**	-0.1166	-0.1153	-0.1036***	-0.1192	-0.1139
$\gamma 2$	0.4086	0.3496	0.1871	0.3290	0.4309	0.2097*	0.2620	0.3045	0.1725**	0.3313	0.3189
$\gamma 3$	-0.0201	-0.0677	-0.0924	-0.0762	-0.0494	-0.0996	-0.0772	-0.0748	-0.1160	-0.0696	-0.0767
$\gamma 4$	0.0738	0.0461	0.0471	0.0402	0.0494	0.0329***	0.0453	0.0440	0.0236	0.0393	0.0350
$\gamma 5$	0.7756	0.4117	0.2596	0.3428	0.6205	0.2838*	0.3380	0.4783	0.2573*	0.5047	0.4785
$\gamma 6$	0.0087	0.0420	0.0085	0.0372	0.0265	0.0166	0.0359	0.0307	0.0036	0.0334	0.0185
$\gamma 7$	0.2263	0.3281	0.2337	0.2761	0.1748	0.2244**	0.2627	0.3055	0.1774**	0.2929	0.2905
$\gamma 8$	0.0946	0.1352	0.0894	0.1253	0.1150	0.0686	0.1157	0.1163	0.1001	0.1151	0.1140
$\gamma 9$	-0.0554	-0.0328	-0.0312	-0.0275	-0.0383	-0.0376	-0.0337	-0.0315	-0.0189	-0.0295	-0.0375
$\alpha+\beta$	0.0885	0.1304	0.2386	0.1229	0.0357	0.1746	0.1377	0.1421	0.1730	0.1414	0.1715
F-LM	0.076	0.301	0.826	0.120	0.134	1.506	0.002	0.227	0.114	0.185	0.764
LL	-93.88	-114.88	-191.90	-138.10	-102.47	-276.61	-155.81	-126.68	-264.11	-121.98	-125.74
SIC	0.7183	0.7793	1.0028	0.8467	0.7433	1.2487	0.8981	0.8135	1.2124	0.7999	0.8108

1. *, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
2. F-LM: ARCH test F-statistics for heteroskedasticity.
3. LL: Log-likelihood ratio.
4. SIC: Schwarz Information Criterion.

Indicates the minimum SIC when the stationarity criteria are met.

Indicates the second minimum SIC when the stationarity criteria are met.

Figure A22: TGARCH with 1-3 Thresholds for the UK

TGARCH - 1	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0859	0.0848	0.0850	0.0835	0.0819	0.0803	0.0807	0.0830	0.0871	0.0848	0.0861
α	0.0463	0.0764	0.0457	0.0426	0.0304	-0.0417	-0.0117	0.0460	0.0704	0.0585	0.0325
β	-0.3348	-0.3878	-0.3505	-0.3220	-0.3165	-0.2614	-0.2590	-0.3352	-0.3740	-0.3367	-0.3361
γ	-0.1000	-0.1193	-0.0945	-0.0912	-0.0757	-0.0100	-0.0424	-0.0897	-0.1219	-0.1097	-0.0847
$\alpha+\beta$	-0.2885	-0.3115	-0.3048	-0.2794	-0.2860	-0.3031	-0.2707	-0.2893	-0.3036	-0.2782	-0.3036
F-LM	3.719***	4.575**	3.607***	3.643***	3.680***	1.678	2.525	3.714***	3.851***	4.821**	3.224***
LL	-22.05	-23.99	-20.23	-24.48	-20.35	-18.06	-20.30	-24.05	-22.48	-20.47	-21.05
SIC	0.4339	0.4396	0.4287	0.4410	0.4290	0.4223	0.4289	0.4397	0.4352	0.4293	0.4310
TGARCH - 2	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0483	0.0490	0.0484	0.0478	0.0492	0.0480	0.0492	0.0490	0.0470	0.0473	0.0489
α	-0.0572	-0.0563	-0.0588	-0.0595	-0.0634	-0.0608	-0.0567	-0.0539	-0.0533	-0.0622	-0.0637
β	-0.0523	-0.0528	-0.0550	-0.0472	-0.0556	-0.0507	-0.0550	-0.0565	-0.0472	-0.0469	-0.0531
$\gamma 1$	0.0672	0.0721	0.0688	0.0706	0.0656	0.0650	0.0689	0.0635	0.0658	0.0750	0.0700
$\gamma 2$	0.9106	0.9502	0.8940	1.0013	0.8775	0.9384	0.8931	0.8895	0.9924	0.9800	0.9002
$\alpha+\beta$	-0.1095	-0.1091	-0.1138	-0.1067	-0.1191	-0.1115	-0.1118	-0.1104	-0.1005	-0.1090	-0.1169
F-LM	1.405	2.072	1.601	1.165	0.890	1.380	2.601	2.062	1.453	1.245	1.191
LL	16.02	17.30	18.10	15.12	16.88	18.55	16.65	14.76	15.78	18.71	19.08
SIC	0.3329	0.3292	0.3269	0.3355	0.3304	0.3256	0.3311	0.3366	0.3336	0.3251	0.3240
TGARCH - 3	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0439	0.0431	0.0424	0.0436	0.0438	0.0432	0.0431	0.0435	0.0431	0.0416	0.0424
α	-0.0579	-0.0546	-0.0570	-0.0613	-0.0582	-0.0596	-0.0539	-0.0541	-0.0565	-0.0601	-0.0581
β	0.0420	0.0646	0.0668	0.0566	0.0517	0.0524	0.0564	0.0623	0.0699	0.0855	0.0683
$\gamma 1$	0.0690	0.0663	0.0697	0.0701	0.0688	0.0683	0.0653	0.0649	0.0699	0.0734	0.0712
$\gamma 2$	0.9532	0.9196	0.9536	0.9415	0.9675	0.9637	0.9439	0.9190	0.9269	0.9377	0.9689
$\gamma 3$	-0.0852	-0.1058	-0.1093	-0.0980	-0.0943	-0.0946	-0.0997	-0.1040	-0.1108	-0.1253	-0.1116
$\alpha+\beta$	-0.0159	0.0100	0.0098	-0.0046	-0.0065	-0.0072	0.0025	0.0082	0.0134	0.0254	0.0102
F-LM	1.644	1.275	1.258	0.374	0.643	0.856	1.615	1.398	1.709	1.116	1.056
LL	17.46	16.70	19.39	16.08	16.34	17.93	16.72	14.89	17.36	19.11	19.05
SIC	0.3382	0.3404	0.3326	0.3422	0.3415	0.3368	0.3404	0.3457	0.3385	0.3334	0.3336

1. *, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
2. F-LM: ARCH test F-statistics for heteroskedasticity.
3. LL: Log-likelihood ratio.
4. SIC: Schwarz Information Criterion.

Indicates the minimum SIC when the stationarity criteria are met.

Figure A23: TGARCH with 4-6 Thresholds for the UK

TGARCH - 4	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0707	0.0496	0.0582	0.0555	0.0638	0.0525	0.0566	0.0578	0.0715	0.0689	0.0575
α	0.0879	-0.0597	-0.0463	0.1149	0.0873	-0.0662	0.0162	-0.0456	0.0576	0.0837	-0.0458
β	-0.1259	-0.0074	-0.1940	-0.0279	-0.1030	-0.0783	-0.0382	-0.1877	-0.2956	-0.1078	-0.1954
$\gamma1$	-0.1413	0.0647	0.0360	-0.1464	-0.1250	0.0653	-0.0420	0.0370	-0.0872	-0.1525	0.0365
$\gamma2$	0.2783	0.8524	0.6605	0.6199	0.3907	0.8112	0.5923	0.6397	0.3029	0.4539	0.7508
$\gamma3$	-0.0980	-0.0443	0.0705	-0.0984	-0.0771	0.0127	-0.0694	0.0652	-0.0076	-0.0794	0.0917
$\gamma4$	-0.1166	-0.0581	-0.0775	-0.0925	-0.1068	-0.0646	-0.0950	-0.0797	-0.1098	-0.1127	-0.0762
$\alpha+\beta$	-0.0381	-0.0671	-0.2403	0.0870	-0.0158	-0.1445	-0.0220	-0.2333	-0.2380	-0.0241	-0.2412
F-LM	0.321	0.140	0.155	0.049	0.008	0.099	1.105	0.143	0.833	0.097	0.054
LL	-0.76	19.98	26.69	0.32	2.60	23.88	9.40	22.85	14.24	7.94	26.85
SIC	0.4006	0.3404	0.3209	0.3974	0.3908	0.3291	0.3711	0.3320	0.3570	0.3753	0.3204
				1.7201							
TGARCH - 5	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0102*	0.0119*	0.0103*	0.0104	0.0113*	0.0570	0.0108*	0.0383	0.0107*	0.0111*	0.0094*
α	0.1709*	0.1803*	0.1857*	0.2661	0.1747*	0.1749	0.1760*	0.1596	0.1690*	0.1735*	0.1807*
β	-0.0148	-0.0467	-0.0361	0.0081	-0.0365	-0.1074	-0.0367	-0.0509	-0.0280	-0.0326	-0.0317
$\gamma1$	-0.0867***	-0.0785	-0.0812	-0.2042	-0.0787	-0.1648	-0.0782	-0.1377	-0.0797	-0.0789	-0.0716
$\gamma2$	0.8256*	0.7249*	0.7737*	0.8642	0.7724*	0.1284	0.7628*	0.3544	0.7966*	0.7929*	0.8127*
$\gamma3$	0.0060	0.0317	0.0283	-0.0527	0.0261	-0.1038	0.0263	-0.0637	0.0210	0.0254	0.0256
$\gamma4$	-0.0048	-0.0047	-0.0024	-0.0207	-0.0045	-0.0851	-0.0035	-0.0651	-0.0029	-0.0036	-0.0015
$\gamma5$	0.8421*	0.8427*	0.8471*	0.8674	0.8372*	0.4972	0.8569*	0.5962	0.8500*	0.8331*	0.8576*
$\alpha+\beta$	0.1562	0.1336	0.1496	0.2742	0.1382	0.0675	0.1393	0.1087	0.1410	0.1409	0.1490
F-LM	0.061	0.154	0.119	0.122	0.177	0.498	0.175	0.003	0.183	0.152	0.243
LL	93.31	89.61	93.72	94.56	91.91	29.80	94.03	59.09	92.09	91.98	95.49
SIC	0.1370	0.1477	0.1358	0.1334	0.1411	0.3214	0.1349	0.2363	0.1405	0.1409	0.1307
TGARCH - 6	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0033	0.0112*	0.0031	0.0009**	0.0033	0.0034	0.0004	0.0033	0.00040	0.0024	0.0032
α	-0.0590	0.2038*	-0.0462	-0.0047	-0.0452	-0.0557	0.0013	-0.0468	0.00463	-0.0424	-0.0472
β	0.7387	0.1151***	0.7268	0.8964*	0.7081	0.7484	0.9152*	0.7237	0.9200*	0.7614	0.7291
$\gamma1$	0.0995	-0.1387***	0.1015	0.0551**	0.1041	0.0969	0.0583**	0.1010	0.0554**	0.0969	0.1114
$\gamma2$	0.2711	0.6122*	0.5288	0.8383*	0.5891	0.3030	0.8307*	0.5643	0.8444*	0.5851	0.5673
$\gamma3$	-0.1718	-0.0949**	-0.3961	-0.7830*	-0.4299	-0.2304	-0.7989*	-0.4180	-0.8166*	-0.4620	-0.4296
$\gamma4$	-0.0181	-0.0327*	0.0085	-0.0018	0.0076	0.0055	-0.0042	0.0071	-0.00666	0.0102	0.0074
$\gamma5$	0.9094	0.8021*	0.8579	0.8968*	0.8638	0.9421	0.9179*	0.8723	0.9077*	0.8576	0.8648
$\gamma6$	-0.6781	-0.0978***	-0.6322	-0.8068*	-0.6197	-0.7118	-0.8428*	-0.6382	-0.8371*	-0.6484	-0.6424
$\alpha+\beta$	0.6797	0.3189	0.6806	0.8917	0.6629	0.6927	0.9165	0.6769	0.92459	0.7189	0.6820
F-LM	0.035	0.152	0.025	0.212	0.104	0.051	0.396	0.027	0.259	0.069	0.001
LL	116.56	86.26	137.48	136.82	135.28	126.54	142.31	133.25	141.42	135.94	138.28
SIC	0.0790	0.1670	0.0183	0.0202	0.0247	0.0500	0.0042	0.0305	0.0068	0.0227	0.0159

1. *, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
2. F-LM: ARCH test F-statistics for heteroskedasticity.
3. LL: Log-likelihood ratio.
4. SIC: Schwarz Information Criterion.

Indicates the minimum SIC when the stationarity criteria are met.

Figure A24: TGARCH with 7-9 Thresholds for the UK

TGARCH - 7	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0028	0.0003	0.0644	0.0008**	0.0023	0.0029	0.0003	0.0027	0.0003	0.0022	0.0032
α	-0.0480	-0.0027	0.1170	-0.0071	-0.0413	-0.0447	-0.0025	-0.0476	-0.0010	-0.0443	-0.0503
β	0.7656	0.9206*	-0.0886	0.9002*	0.7805	0.7248	0.9214*	0.7389	0.9227*	0.7299	0.7235
γ1	0.1090	0.0860**	-0.1226	0.0664**	0.1175	0.1101	0.0877**	0.1193	0.0833**	0.1159	0.1205
γ2	0.6340	0.7911*	0.1057	0.8238*	0.6692	0.5249	0.7966*	0.5614	0.8079*	0.4835	0.4668
γ3	-0.5006	-0.7881*	-0.1232	-0.7834*	-0.5521	-0.3998	-0.7960*	-0.4343	-0.8060*	-0.3775	-0.3567
γ4	0.0051	-0.0004	-0.1100	0.0017	0.0085	0.0081	0.0007	0.0073	0.0007	0.0106	0.0068
γ5	0.9305	0.9221*	0.4489	0.9004*	0.9005	0.8935	0.9360*	0.9387	0.9222*	0.8488	0.8681
γ6	-0.7312	-0.8897*	-0.0175	-0.8299*	-0.7305	-0.6671	-0.9059*	-0.7215	-0.8924*	-0.6438	-0.6524
γ7	0.0106	0.0381	0.0410	0.0184	0.0231	0.0198	0.0403	0.0272	0.0374	0.0429	0.0179
α+β	0.7177	0.9179	0.0283	0.8931	0.7392	0.6801	0.9189	0.6912	0.9217	0.6856	0.6732
F-LM	0.014	0.184	2.012	0.124	0.000	0.014	0.246	0.072	0.141	0.004	0.022
LL	136.34	140.65	23.86	137.23	139.61	137.22	143.74	134.56	142.63	136.72	136.58
SIC	0.0311	0.0186	0.3576	0.0285	0.0216	0.0285	0.0096	0.0362	0.0128	0.0300	0.0304
											1.1551
TGARCH - 8	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0043	0.0039	0.0041	0.0010*	0.0038	0.0037	0.0004	0.0039	0.0072	0.0037	0.0085
α	-0.0508	-0.0446	-0.0469	-0.0062	-0.0469	-0.0443	0.0014	-0.0490	-0.0023	-0.0472	0.0704
β	0.7270	0.7244	0.7008	0.8903*	0.7005	0.7001	0.9219*	0.7116	0.4212	0.7060	0.2206
γ1	0.0974	0.1144	0.1142	0.0601***	0.1148	0.1102	0.0694**	0.1162	0.0659	0.1175	-0.0123
γ2	0.3139	0.3711	0.3177	0.4955**	0.3101	0.3964	0.5327**	0.3875	0.3760	0.3830	0.5085
γ3	-0.2381	-0.2846	-0.2311	-0.4734**	-0.2295	-0.2912	-0.5405*	-0.2917	-0.1369	-0.2873	-0.0849
γ4	0.0065	0.0073	0.0049	-0.0026	0.0061	0.0077	-0.0044	0.0090	-0.0059	0.0082	-0.0101
γ5	0.8052	0.8316	0.8530	0.9054*	0.8419	0.8655	0.9260*	0.7759	0.8053	0.8795	0.7875
γ6	-0.6072	-0.6325	-0.6303	-0.8181*	-0.6178	-0.6279	-0.8788*	-0.5762	-0.3572	-0.6494	-0.1811
γ7	0.2454	0.2626	0.2396	0.2782***	0.2378	0.2161	0.2279	0.2397	0.1992	0.2342	0.1481
γ8	-0.1836	-0.1936	-0.1746	-0.2415***	-0.1677	-0.1545	-0.1896	-0.1704	-0.1149	-0.1615	-0.0709
α+β	0.6762	0.6799	0.6539	0.8842	0.6536	0.6558	0.9233	0.6626	0.4190	0.6588	0.2909
F-LM	0.020	0.018	0.000	0.080	0.072	0.015	0.141	0.073	1.148	0.026	0.103
LL	140.00	139.94	142.08	140.49	141.02	142.38	145.09	141.17	127.03	140.81	109.96
SIC	0.0299	0.0301	0.0239	0.0285	0.0270	0.0230	0.0152	0.0265	0.0676	0.0276	0.1171
TGARCH - 9	Basic	Consumer Discretionary	Consumer Staplers	Energy	Financials	Health	Industry	RE	Tech	Telco	Utilities
ω	0.0205	0.0200	0.0614	0.0276	0.0535	0.0318	0.0523	0.0450	0.0468	0.0480	0.0715
α	0.1432	0.1423	0.1037	0.1397	0.1045	0.1498	0.1166	0.1168	0.1118	0.1195	0.0971
β	0.0470	0.0437	0.0242	-0.0017	-0.0829	0.0046	-0.0146	0.0095	-0.0125	-0.0569	0.0338
γ1	-0.0920	-0.0850	-0.1073	-0.1008	-0.0729	-0.1185	-0.1157	-0.0967	-0.0986	-0.1107	-0.1173
γ2	0.4684	0.3513	0.0419	0.4270	0.1099	0.3052	0.2216	0.1874	0.1937	0.2473	-0.0261
γ3	-0.0529	-0.0411	-0.0692	-0.0485	-0.0521	-0.0407	-0.0604	-0.0586	-0.0537	-0.0676	-0.0099
γ4	0.0015	-0.0091	-0.0202	-0.0214	-0.0294	-0.0251	-0.0253	-0.0154	-0.0179	-0.0290	-0.0256
γ5	0.7406	0.6850	0.3613	0.6619	0.3801	0.6144	0.4821	0.5081	0.5198	0.4971	0.2202
γ6	-0.0572	-0.0527	-0.0790	-0.0263	-0.0362	-0.0301	-0.0458	-0.0577	-0.0405	-0.0129	-0.0851
γ7	0.1080	0.2038	0.0570	0.1359	0.0885	0.1540	0.0637	0.1207	0.1134	0.0783	0.0996
γ8	-0.0126	-0.0240	-0.0457	-0.0096	-0.0233	-0.0357	-0.0342	-0.0239	-0.0257	-0.0123	-0.1145
γ9	-0.0448	-0.0359	-0.0940	-0.0416	-0.0759	-0.0493	-0.0782	-0.0715	-0.0716	-0.0722	-0.0952
α+β	0.1902	0.1860	0.1279	0.1380	0.0216	0.1543	0.1021	0.1263	0.0993	0.0627	0.1309
F-LM	0.015	0.092	2.087	0.185	0.101	0.348	2.519	1.679	1.408	1.773	3.225***
LL	91.00	87.44	28.74	82.15	51.43	76.01	44.53	51.03	54.25	48.46	7.41
SIC	0.1816	0.1920	0.3624	0.2073	0.2965	0.2252	0.3165	0.2977	0.2883	0.3051	0.4243

1. *, ** and *** denote the rejection of the null hypotheses at 1, 5 and 10%, respectively.
2. F-LM: ARCH test F-statistics for heteroskedasticity.
3. LL: Log-likelihood ratio.
4. SIC: Schwarz Information Criterion.

Indicates the minimum SIC when the stationarity criteria are met.