The impact of Covid-19 on G7 stock markets volatility: Evidence from a ST-HAR model

Marwan Izzeldin
Lancaster University, Lancaster, LA1 4YW, UK
Email: m.izzeldin@lancaster.ac.uk

Gulnur Muradoglu
Queen Mary University of London, E1 4NS, UK
Email: y.g.muradoglu@qmul.ac.uk

Vasileios Pappas[1]
University of Kent, Kent, ME4 4TE, UK
Email: v.pappas@kent.ac.uk

Sheeja Sivaprasad
University of Westminster, London, NW1 5LS, UK
Email: s.sivaprasad@westminster.ac.uk

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Abstract

We investigate the impact of Covid-19 on stock markets across G7 countries (the US, the UK, Canada, France, Germany, Italy and Japan) and sectors (Consumer Goods, Consumer Services, Financials, Healthcare, Industrials, Materials, Oil & Gas, Technology, Telecommunications and Utilities) and highlight the synchronicity and severity of this unprecedented crisis. We find strong transition evidence to a crisis regime for all countries and all sectors suggesting the universal impact of Covid-19. However, not all business sectors were affected with the same intensity or at the same time. The Health Care and Consumer services sectors were the most severely affected; a reflection of the Covid-19 drug-race and the dire situation of the airlines. Technology were among those sectors that was hit the latest and least severely, as imposed lockdown measures forced people to explore various web-based entertainment and distraction options. Country-wise the UK and the US were hit the hardest, while exhibiting the highest heterogeneity in their business sectors' response; a possible reflection on the financial markets of the ambiguity of these countries' political response to the pandemic crisis.

Keywords: Covid-19, financial markets, HAR model, smooth transition, business sectors

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[1] *Corresponding author*: email: v.pappas@kent.ac.uk
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1. Introduction

The Covid-19 pandemic affected almost every country in the world, with the medical part of the crisis gaining (some) control and governments tentatively entering a post-lockdown phase. The economic and financial implications may take years to unfold with recent IMF forecasts suggesting that the global economy will contract by 3% in 2020 - 6% in advanced economies. The start of the Covid-19 financial crisis may be traced back to 24/2/2020 when stock markets worldwide entered a period of record-breaking losses. The crisis unfolds further in March 2020 where jumps are recorded in stock markets around the world in response to the sheer escalation of the coronavirus situation and following the WHO designation of pandemic. The 9/3/2020 stock markets plunge is comparable in scale to what was observed after the Lehman Brothers' collapse in 2008, while trading was halted in NYSE. Spikes in stock market volatility observed during the Covid-19 crisis are comparable to that of the 2008 global financial crisis (2008 GFC, hereafter), the Black Monday and even the Great Crash of 1929 (Baker et al., 2020).

Financial markets are known to be affected by epidemics (Page et al., 2012), terrorist attacks (Llussá & Tavares, 2011) and natural (Toya & Skidmore, 2007) – or otherwise – disasters such as plane crashes (Ho et al., 2013). A strand of literature investigates the impact of epidemics such as the foot and mouth disease (Blake et al., 2003), the severe acute respiratory syndrome (SARS) (Chen et al., 2007), the bird flu (H5N1) (Kuo et al., 2009) and the swine flu (H1N1) (Page et al., 2012) on the economy. Some recent studies compare the financial markets response in light of the Covid-19 financial crisis to past pandemics and/or financial crisis (Baker et al., 2020; Correia et al., 2020; Eichenbaum et al., 2020; Ma et al., 2020). Another strand of literature sheds light on what drives the delay in the response to disease outbreaks drawing from the experience of H1N1, Ebola and Zika epidemics (Hoffman & Silverberg, 2018). (Pastor-Satorras et al., 2015) highlight the importance of network, big data, and social media analyses in attempting to understand the spread of the contagion diseases, while (Saker et al., 2004) suggest that globalisation increases the spread of infectious diseases.

As far as the Covid-19 impact on the financial markets is concerned the literature is still thin. The study of (Ji et al., 2020) investigates how traditionally safe-haven assets have behaved during the Covid-19 financial crisis only to find gold and soybean to retain their status. (Sharif et al., 2020) examine how Covid-19 affected the geopolitical risk and economic policy uncertainty indices in the US. Despite the thin literature on this front, some similarities and differences to earlier crises, most notably the 2008 GFC, are expected insofar as multiple countries/business sectors are affected with a certain lead/lag.[2] In particular, the 2008 GFC spread from the US, starting with a disruption to the real estate and financial markets, with other countries and business sectors followed after a certain time lag. The US committed two large economic stimulus packages, totalling around $1.5 trillion, targeting first the heavily hit financial sector (TARP program) and then the economy (Recovery Act). By contrast during the COVID-19 financial crisis multiple countries were hit simultaneously, while an unprecedented impact on the real economy coupled with severe disruptions to supply and demand was observed. This may be largely attributed to the pandemic nature of the crisis and the government measures taken, such as school and business closures, employee furloughs and layoffs, travel restrictions and lockdowns, that prioritised the control of the virus infection rate. However, these measures distorted economic activity in manufacturing and service sectors, while also limiting productivity. To boost the economy

[2] In this paper we treat the Covid-19 as a financial crisis rather than an epidemic event due to the magnitude of the response in the stock markets. We are aware that there is certain evidence towards classifying the Covid-19 as a black swan event however (Yarovaya et al., 2020).

extraordinary economic stimulus packages included direct transfers to affected households and businesses, funds for the healthcare system, extended outreach of the social safety net, and even prohibiting of layoffs in certain jurisdictions. The Covid-19 stimulus packages in the US stands at \$3 trillion according to the latest figures (IMF, 2020). Financial institutions were more capitalised and with better liquidity compared to previous crises; an array of regulatory measures was taken to avoid procyclical effects, such as a relief in capitalisation requirements and a flexibility to the classification of defaulted loans due to the Covid-19 (BIS, 2020; ECB, 2020). Therefore, we expect business sectors such as Health Care, Consumer Goods/Services and Technology to be under the spotlight of attention – a striking difference to the Financials sector during the 2008 GFC. Hence, we argue that in order to properly assess the impact of the Covid-19 crisis it is essential to undertake a sectoral analysis. Our study addresses this research gap and investigates the sectoral impact of the Covid-19 financial crisis.

This paper is an early attempt to address the impact of Covid-19 on financial markets in the G7 economies. We focus on the 10 business sectors of the Industrial Classification Benchmark (ICB) classification and model the market sentiment against the rising cases of Covid-19 worldwide using a smooth transition heterogenous autoregressive model (ST-HAR). Thereby, we gauge the intensity, timeliness and homogeneity of the volatility shift from a calm to a crisis regime for the G7 countries and sectors. Our results verify the transition to a crisis regime for all countries and sectors. However, not all business sectors were affected with the same intensity or at the same time. The Health Care and Consumer Services sectors were the most severely affected; a reflection of the Covid-19 drug-race and the dire situation of the airlines. Technology and Materials were among those that were hit the latest and least severely, as people sought distraction and entertainment elsewhere (Forbes, 2020). Country-wise the UK and the US were hit the hardest, while exhibiting the highest heterogeneity in their business sectors' response; a possible reflection on the financial markets of the indecisiveness and ambiguity of the political response to the pandemic crisis.

The rest of the paper is organised as follows. The next section presents the methodology and data. Section 3 presents the empirical findings. A final section concludes.

2. Methodology and Data

A key characteristic of volatility is its latent nature and high persistence. Volatility modelling prefers FIGARCH and ARFIMA models over ARIMA processes that are inadequate to capture long-memory in a parsimonious way. But long-memory models have certain drawbacks: they are nontrivial to estimate, mainly univariate, and require a large sample size to obtain accurate estimates of the fractional differencing parameter. We use the heterogeneous autoregressive model (HAR) that builds on the property that the summation of short memory models can generate the hyperbolic decay patterns that the autocorrelation function of volatility estimates typically exhibits (Corsi, 2009). The superior performance of the HAR in modelling and forecasting realised volatility is well-established (Andersen et al., 2007, 2011; Bollerslev et al., 2016). Compared to ARFIMA, HAR models are more trivial to estimate and forecast from. To outline our research design, consider a $T \times 1$ vector of demeaned asset returns r_t, where the variance is modelled as a GARCH(1,1) process:

$$r_t | \mathcal{F}_{t-1} \sim N(0, h_t^2) \tag{1}$$

$$h_t^2 = \omega + a u_{t-i}^2 + b r_{t-j}^2 \tag{2}$$

Following Corsi (2009) the HAR model is defined as:

$$h_t = c + \beta^{(d)} h_{t-1} + \beta^{(w)} h_t^{(w)} + \beta^{(m)} h_t^{(m)} + e_t \tag{3}$$

where $e_t \sim iid(0, \sigma^2)$ with $h_t^{(w)}$ and $h_t^{(m)}$ defined as follows:

$$h_t^{(w)} = \frac{1}{5}(h_{t-1} + h_{t-2} + h_{t-3} + h_{t-4} + h_{t-5}) \tag{4}$$

$$h_t^{(m)} = \frac{1}{22}(h_{t-1} + h_{t-2} + \cdots + h_{t-21} + h_{t-22}) \tag{5}$$

To allow for non-linear dynamics in the volatility process we use the family of smooth transition models[3], that allow for observed variables to affect the transition between the regimes, subject to unobservable thresholds. In addition, they allow for a more realistic, analogue transition between the regimes, rather than a discrete one.[4] A two-regime smooth transition model is defined as:

$$y_t = X_t a + G(s_t; \gamma, \psi) Z'_t \beta + \big(1 - G(s_t; \gamma, \psi)\big) Z'_t \delta + \varepsilon_t \tag{6}$$

where G denotes a continuous transition function that returns values (i.e., threshold weights) between 0 and 1; s_t is an observable threshold variable with unknown threshold (ψ) and slope (γ) values; Z_t vector contains variables that are regime dependent (i.e., their slope coefficient vary across regimes); X_t vector contains variables that are regime invariant; ε_t is the stochastic error term.

We model the G transition function using the exponential function[5] given as:

$$G(s_t; \gamma, \psi) = 1 - \exp(-\gamma / \sigma_{s_t}^2 (s_t - \psi)^2) \tag{7}$$

In our specification we use an ST-HAR model that allows for a smooth transition between two regimes governed by an ESTAR function. To allow for more realistic dynamics during the turmoil period of the study we assume that the HAR parameters related to the weekly and monthly volatility are regime invariant. The following equation is estimated via nonlinear least square techniques and Newey-West robust standard errors:

$$\begin{aligned} h_t = \beta_0 + \beta_1 h_{t-1} + \alpha_1 h_t^{(w)} + \alpha_2 h_t^{(m)} + (\delta_0 + \delta_1 h_{t-1}) \\ \times \big(1 - \exp\big(-\gamma / \sigma_{s_t}^2 (s_t - \psi)^2\big)\big) + e_t \end{aligned} \tag{8}$$

The data comprises daily prices of the aggregate and sector equity indices for the G7 economies (Canada, France, Germany, Italy, Japan, UK and US). All indices are value-weighted and exclude dividends. The sectors are the following: Consumer Goods, Consumer Services, Financials, Healthcare, Industrials, Materials, Oil & Gas, Technology, Telecommunications and Utilities. The data source is Datastream and cover the period from 24/4/2018 – 24/4/2020. For every index, we compute the

[3] See Teräsvirta (1994) for more details.
[4] Smooth transition models have been used in financial and economic context (Bradley & Jansen, 2004; Caggiano et al., 2017; Ghoshray, 2010; Huang & Hu, 2012; Tse, 2001; Zhang, 2013).
[5] We compare a logistic transition function (LSTAR) to an exponential (ESTAR) using the (Escribano & Jorda, 1999) test, which confirms the appropriateness of the exponential case.

continuously compounded percentage return as $r_t = \log(p_t/p_{t-1}) \times 100$, where p_t is the closing price at day t. Covid-19 data on identified cases are retrieved from the Johns Hopkins University Coronavirus Research Centre at the daily level for each country.[6] Although cases are observed from 1/1/2020, the data during the month of January are very thin, hence we start the analysis from 1/2/2020 and aggregate the number of observed Covid-19 cases worldwide. Figure 1, panel A plots the annualised time-varying volatility of the aggregate equity indices, while panel B plots the daily number of Covid-19 cases on a log scale. Table 1 presents mean percentage return and annualized volatility for the equity indices under investigation over the period of study (panel A). The statistics show the large increase in the volatility across all sectors and economies.

[Figure 1 around here]

[Table 1 around here]

3. Empirical results

Table 2 presents the sector wise estimation results of the ST-HAR model, where median values across the G7 economies are reported as well as standard goodness-of-fit statistics. In particular, the linearity test shows the appropriateness of a non-linear HAR specification over the linear equivalent. A first inspection finds the slope and threshold coefficients to be highly statistically significant indicating the non-linear smooth transition between the regimes for these sectors and economies. In addition, the statistical significance of the two regime parameters, namely β_0, β_1 and δ_0, δ_1 respectively indicate marked changes on the level and first-lag autocorrelation dynamics of volatility. By contrast, the parameters measuring the dependence of current volatility on weekly and monthly factors are only important for a subset of sectors.

[Table 2 around here]

Table 3 presents key location and dispersion statistics on the slope and threshold of the transition function that characterise the intensity and timeliness of the Covid-19 crisis across sectors and countries. The intensity of the transition to the new regime is highest in the Health Care sector, followed by the Utilities and the Consumer Services according to the mean and median values of the slope coefficients. The uniformity of intensity varies across the sectors with the Health Care and the Consumer Goods being the least and most uniform respectively according to the quartile coefficient of variation (QCV) measure. Furthermore, we find that the financial markets of the UK and the US are the most severely hit by the Covid-19 crisis. It is interesting that these are the markets with the highest heterogeneity in the Covid-19 response, which may reflect the indecisiveness and ambiguity of the political response to the pandemic crisis. In terms of timeliness of the transition we find that the Oil & Gas and Telecommunications sectors were the first to be affected as evidenced by the low mean threshold values. The lower QCV in the Oil & Gas case compared to the Telecommunications shows the homogenous impact of the former sector from the Covid-19 crisis. Country-wise the US has the lowest mean threshold, suggesting that the financial markets there were affected the earliest.

[Table 3 around here]

Figure 2 presents the estimated threshold smoothing weights against the threshold variable for a selection of sectors. The top row presents the cases of the Health Care and the Materials that exhibits

[6] Data may be accessed here: https://coronavirus.jhu.edu/

the highest and lowest crisis intensity, as evidenced by the mean estimated slope coefficients (γ). The bottom row presents the cases of the Oil & Gas and Technology sectors that are those that were affected first and last respectively, according to the estimated thresholds (ψ). In addition, the Oil & Gas sector features a homogenous response to the crisis (see also Table 3). Figure 3 presents estimated threshold smoothing weights against the threshold variable for a selection of countries, with the UK and Germany exhibiting the highest and lowest crisis transition intensity. The bottom row depicts the US and Japan that have, on average, the lowest and highest threshold and exhibit similar degree of homogeneity in terms of their individual sectors' response.

[Figures 2 and 3 around here]

4. Conclusion

The Covid-19 crisis presented itself as a series of economic costs on a scale that is unprecedented in peacetime. Costs that arise both directly and in consequence of policy initiatives to ameliorate the impact upon industrial output, financial markets, social institutions and the public at large. With our study we have applied statistical methods to obtain early insights, most obviously into the initial impact of Covid-19 but also into the long-term resilience of necessary adjustments across markets and industry. Those adjustments must be the focus for on-going analysis

Out initial focus has been upon the financial crisis as manifested across stock markets worldwide, where comparisons may be drawn with the GFC and, indeed, the Great Crash of 1929 and the long-drawn depression that followed. Using the most recently available data from stock markets across the G7 economies, we have assessed aggregate volatility and, more specifically, volatility within 10 business sectors. To capture the impact of the pandemic and associated market reactions, we applied a novel smooth transition heterogenous autoregressive model (ST-HAR) on each volatility series for the daily count of Covid-19 cases. Thereby, our analysis brings unique insight to the intensity, the timeliness and the homogeneity of volatility shifts as well as the rankings of countries and sectors.

The results show a non-linear transition to a crisis regime for all countries and sectors in the analysis. Our findings are that the Health Care and Consumer Services sectors were the most severely affected, with Telecommunications and Technology least affected. Financial markets in the UK and the USA took the largest hits, yet with high response heterogeneity across business sectors. This may be a reflection the indecisiveness and ambiguity of the political response to the pandemic crisis.

Beyond the immediate short-term reactions to the crisis, the world economy faces obvious risks. Not least among these are: that furlough might delay unduly the transition to a post Covid-19 world; and that the provision to ameliorate immediate needs overextends inasmuch as essentially 'zombie' companies receive unwarranted support from government. Sooner, rather than later, governments must pass the initiative to employers and employees within private sectors, where capital investments are more likely to be directed to long-term viable activities.

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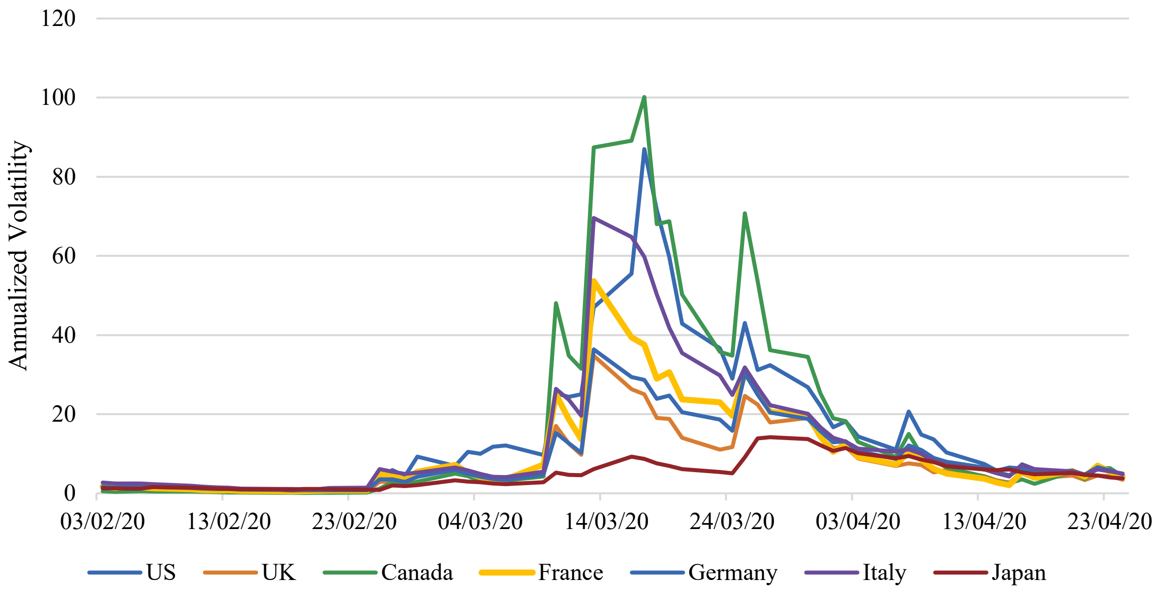
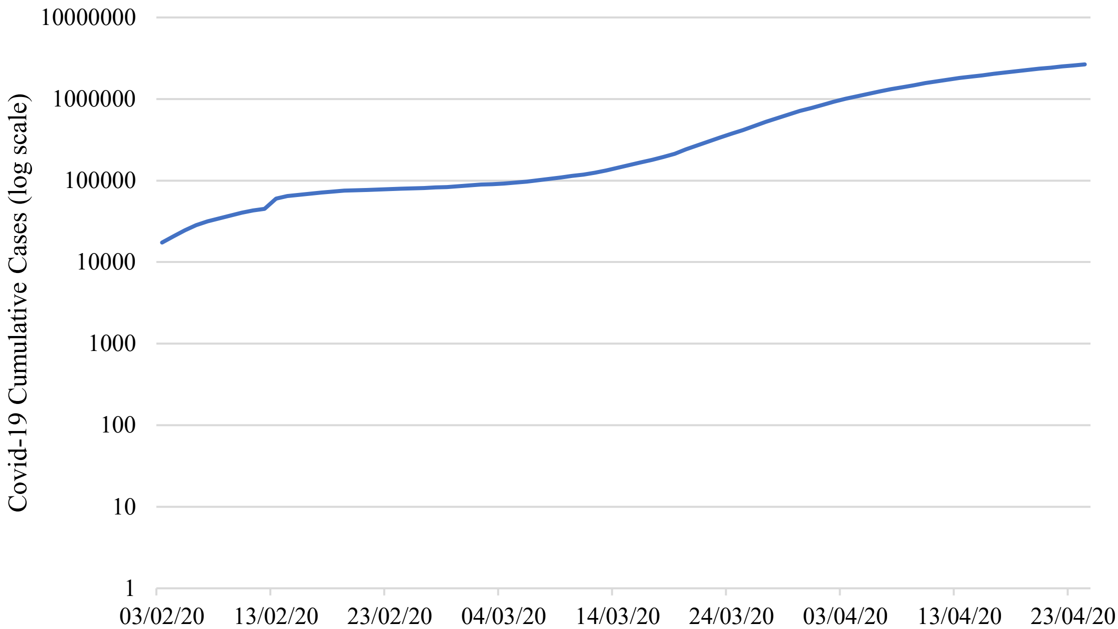
Figure 1. Time evolution of volatilities and Covid-19 cases

Panel A: Time varying annualized volatilities (G7 economies)

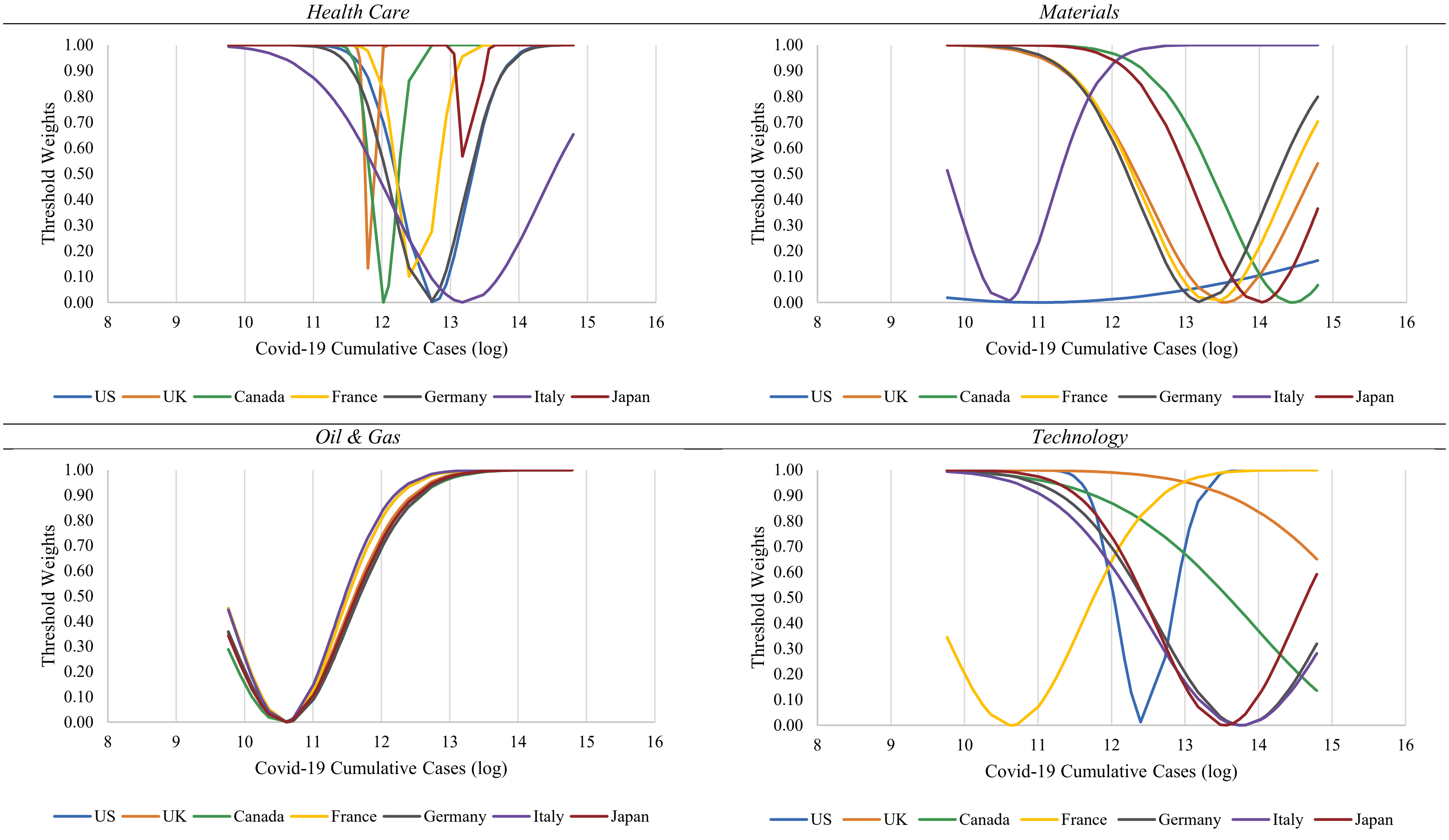


Panel B: Covid-19 Cumulative cases (Worldwide)



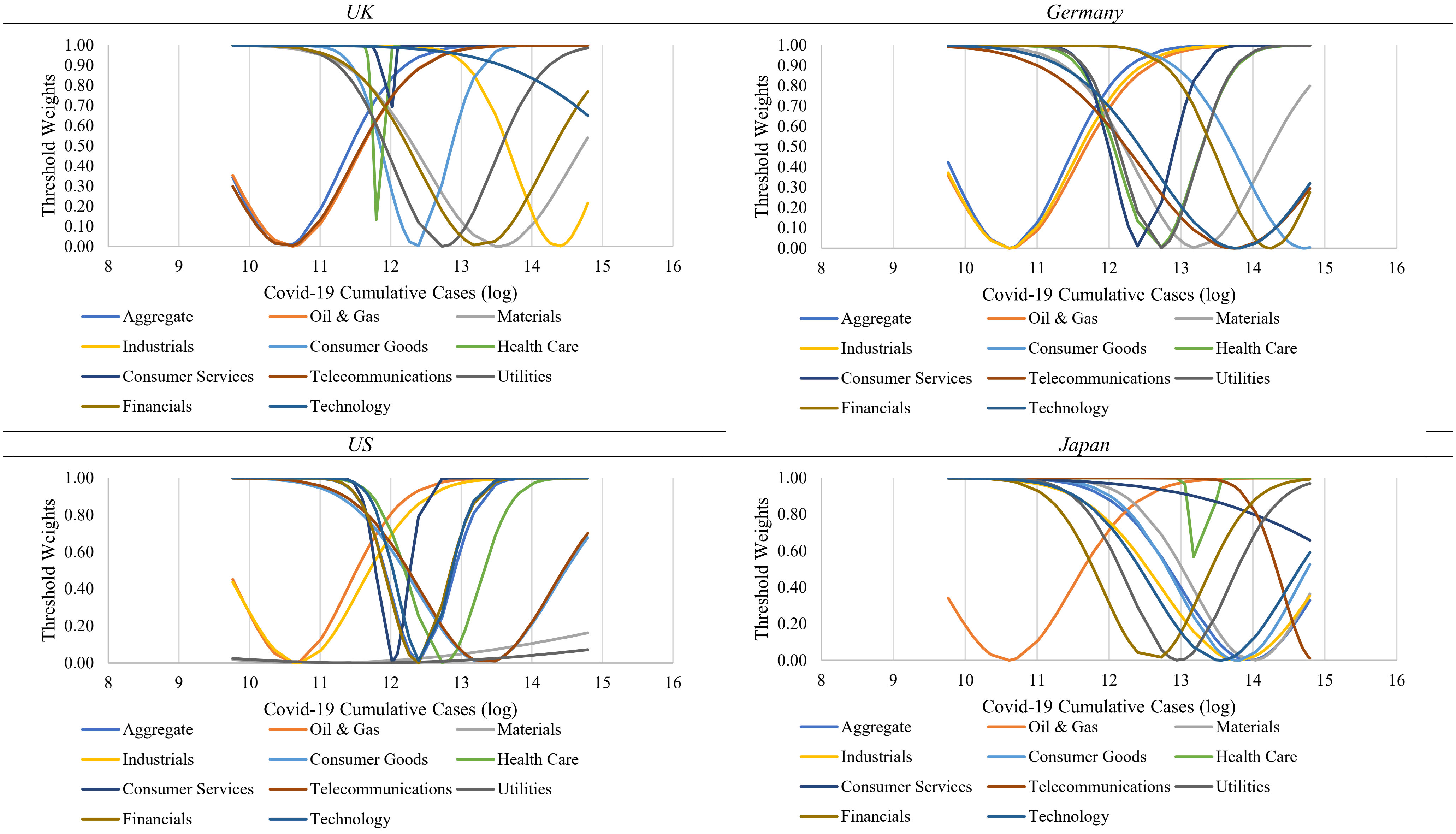
Source: Datastream and Johns Hopkins University Coronavirus Resource Centre.

Figure 2. Threshold weights for selected sectors



Notes: The figure depicts the threshold smoothing weights from the ST-HAR model of equation 11 ploted against the Covid-19 Cumulative worldwide cases (log scaled). Across all sectors, the ones reported here exhibit the highest and lowest crisis intensity (top left, top right respectively), and the earliest and latest affected (bottom right, bottom left respectively).

Figure 3. Threshold weights for selected countries



Notes: The figure depicts the threshold smoothing weights from the ST-HAR model of equation 11 ploted against the Covid-19 Cumulative worldwide cases (log scaled). Across all countries, the ones reported here exhibit the highest and lowest crisis intensity (top left, top right respectively), and the earliest and latest affected (bottom right, bottom left respectively).

Table 1. Descriptive statistics

		Panel A: Covid (01/02/2020-24/4/2020)							Panel B: pre-Covid (24/4/2018-31/1/2020)						
		US	UK	Canada	France	Germany	Italy	Japan	US	UK	Canada	France	Germany	Italy	Japan
Aggregate	Return	0.014	-0.049	-0.014	-0.041	-0.037	-0.068	-0.028	0.044	-0.002	0.024	0.014	0.007	-0.007	0.009
	Volatility	17.845	15.095	13.511	17.401	18.401	21.289	17.835	13.398	12.144	8.768	14.093	15.297	17.689	15.897
Oil & Gas	Return	-0.136	-0.117	-0.094	-0.104	-0.245	-0.095	-0.128	-0.061	-0.048	-0.005	-0.043	-0.143	-0.025	-0.085
	Volatility	27.966	27.202	26.984	25.736	42.653	23.318	30.604	21.578	21.487	20.300	20.371	39.145	18.360	29.988
Materials	Return	-0.036	-0.053	0.049	0.013	-0.082	-0.186	-0.079	-0.011	-0.015	0.026	0.043	-0.039	-0.111	-0.039
	Volatility	22.178	28.015	21.686	19.560	23.493	34.927	21.255	18.138	24.547	18.703	17.045	20.888	32.930	19.703
Industrials	Return	-0.010	-0.030	0.042	-0.044	-0.058	-0.089	-0.049	0.036	0.021	0.080	0.043	-0.001	-0.026	-0.007
	Volatility	20.307	19.229	21.265	20.827	21.686	27.558	20.002	15.931	16.058	18.075	16.184	18.497	23.641	18.347
Consumer Goods	Return	0.010	-0.013	-0.088	-0.008	-0.086	-0.038	-0.043	0.039	0.016	-0.029	0.021	-0.031	0.003	-0.017
	Volatility	15.270	15.829	25.948	18.404	22.197	24.950	16.684	11.846	14.123	22.698	16.097	18.410	22.161	15.146
Health Care	Return	0.043	0.055	-0.100	0.042	-0.056	0.078	0.025	0.044	0.060	-0.027	0.052	-0.034	0.078	0.042
	Volatility	17.777	18.281	43.023	16.872	22.696	23.320	19.545	14.376	16.774	40.812	15.300	21.270	20.934	18.166
Consumer Services	Return	0.031	-0.041	0.014	-0.038	-0.063	-0.107	-0.026	0.048	0.012	0.046	0.014	-0.037	-0.068	0.001
	Volatility	18.072	15.705	15.783	19.137	21.548	30.567	15.665	14.646	12.939	12.149	16.470	19.433	27.923	14.051
Telecommunications	Return	0.000	-0.128	-0.018	-0.041	-0.031	-0.141	0.013	0.025	-0.076	0.020	-0.023	-0.004	-0.106	0.022
	Volatility	19.319	24.155	17.379	18.088	17.596	31.122	22.507	17.091	21.944	13.526	16.227	15.209	28.769	20.863
Utilities	Return	0.027	0.004	0.027	-0.062	0.013	0.023	-0.035	0.067	0.035	0.063	0.027	0.056	0.083	-0.041
	Volatility	17.998	20.411	15.471	19.361	18.351	21.350	19.577	13.704	18.188	10.941	16.252	16.127	18.319	18.631
Financials	Return	-0.024	-0.099	-0.061	-0.135	-0.031	-0.128	-0.084	0.034	-0.028	0.010	-0.033	0.021	-0.049	-0.034
	Volatility	19.213	19.802	17.018	21.640	16.935	27.458	16.811	14.097	16.423	11.686	17.311	13.575	24.065	15.001
Technology	Return	0.061	-0.039	0.085	0.002	0.016	0.052	-0.006	0.082	0.027	0.071	0.039	0.041	0.082	0.026
	Volatility	24.147	27.551	22.595	26.702	25.472	40.441	18.844	19.896	25.365	19.124	23.486	23.856	37.270	16.945

Notes: The table shows average percentage daily returns and annualised volatility for the equity indices in the respective countries and sectors.

Table 2. Estimation results

	Aggregate	Oil & Gas	Materials	Industrials	Consumer Goods	Health Care	Consumer Services	Telecommunications	Utilities	Financials	Technology
β0	6.066**	-5.527	16.376**	-2.407	15.737**	50.920***	20.833**	-2.485	10.583***	-2.990	23.345***
	(1.651)	(2.110)	(1.043)	(-1.904)	(1.149)	(2.037)	(3.218)	(2.172)	(0.263)	(-4.344)	(1.005)
β1	0.426*	0.888**	0.109	0.650*	0.088	-1.199*	-0.032	-0.029	0.028	0.517*	-0.322
	(0.304)	(1.369)	(2.213)	(0.304)	(1.619)	(-0.228)	(-1.576)	(-0.131)	(0.109)	(0.106)	(-1.271)
δ0	-6.388**	38.440**	-17.203**	10.915**	-16.039**	-50.959***	-22.062**	1.988	-17.780***	11.621	-21.505***
	(-1.622)	(2.174)	(-1.874)	(2.212)	(-1.748)	(-1.988)	(-3.009)	(2.171)	(-0.215)	(4.369)	(-1.039)
δ1	0.933**	-0.551	0.998***	0.437	1.118***	1.870***	1.138	0.927*	1.413***	0.677	1.299***
	(1.835)	(-1.633)	(0.946)	(2.684)	(1.161)	(2.432)	(3.418)	(1.016)	(1.438)	(2.698)	(0.526)
α1	0.341*	0.488**	0.309	0.403**	-0.177	-0.027	0.075	0.577	-0.060**	0.015	0.248
	(0.825)	(1.334)	(1.741)	(0.825)	(-2.091)	(-0.736)	(0.171)	(0.621)	(-1.100)	(1.722)	(0.058)
α2	-0.462**	-0.511**	-0.584**	-0.337*	-0.483*	-0.070	0.011	-0.434**	0.005	-0.219*	-0.811**
	(-1.455)	(-1.766)	(-1.667)	(-1.962)	(-1.384)	(-1.395)	(1.186)	(-0.171)	(1.941)	(-0.375)	(-1.259)
γ	3.914***	3.277**	2.950***	3.368**	3.487***	35.775***	4.354***	3.057**	5.851***	4.242**	1.884***
	(2.998)	(2.998)	(1.754)	(3.828)	(2.226)	(4.123)	(4.257)	(3.950)	(1.934)	(4.831)	(2.277)
ψ	5.555***	4.734***	5.977***	5.373***	5.968***	5.670***	5.382***	5.910***	5.684***	5.539***	6.159***
	(100.891)	(103.877)	(120.973)	(47.227)	(93.006)	(81.434)	(307.775)	(116.207)	(95.155)	(89.256)	(93.965)
Adj-R^2	0.856	0.856	0.856	0.856	0.856	0.856	0.856	0.856	0.856	0.856	0.856
BIC	5.801	5.801	5.789	5.789	5.783	5.789	5.789	5.789	5.789	5.789	5.789
Q(8)	11.759	10.197	11.119	12.142	12.870	8.274	15.346*	14.212*	17.607**	10.115	12.876
Linearity Test	2.410*	2.583**	2.739**	3.072**	3.033**	2.248*	3.083**	3.067**	2.486**	2.603**	4.276***
EJ Test	3.027*	3.688**	2.462*	3.176**	3.666**	3.774**	3.390**	3.738**	3.247*	3.467**	3.241**

Notes: The table reports median estimated coefficients and t-statistics in parenthesis from equation 8. BIC is the Schwarz information criterion. Q(8) is the Ljung-Box test for serial correlation up to lag 8. Linearity Test is the F-statistic where the null hypothesis of linearity is tested against the alternative of a non-linear model. EJ Test is the Escribano-Jorda test for the appropriateness of an exponential transition function in the non-linear specification. ***, **, * denote statistical significance at the 1, 5 and 10% levels.

Table 3. Slope and threshold by sectors and countries

	Slope coefficient (γ)			Threshold coefficient (ψ)		
	Mean	Median	QCV	Mean	Median	QCV
Panel A: Business Sectors						
Aggregate	4.794 [7]	3.910 [5]	2.871 [7]	5.413 [3]	5.550 [5]	1.157 [7]
Oil & Gas	3.581 [10]	3.280 [8]	1.598 [10]	4.737 [1]	4.730 [1]	0.021 [1]
Materials	3.033 [11]	2.950 [10]	1.993 [8]	5.757 [9]	5.980 [10]	1.199 [9]
Industrials	9.303 [4]	3.370 [7]	5.078 [6]	5.477 [4]	5.370 [2]	1.311 [11]
Consumer Goods	4.626 [8]	3.490 [6]	1.572 [11]	6.023 [10]	5.970 [9]	0.258 [2]
Health Care	147.7 [1]	35.78 [1]	9.382 [1]	5.644 [6]	5.670 [6]	0.469 [4]
Consumer Services	126.9 [3]	4.350 [3]	9.236 [2]	5.711 [8]	5.380 [3]	1.132 [6]
Telecommunications	5.063 [6]	3.060 [9]	6.184 [4]	5.710 [7]	5.910 [8]	1.276 [10
Utilities	141.4 [2]	5.850 [2]	6.699 [3]	5.580 [5]	5.680 [7]	0.444 [3]
Financials	5.927 [5]	4.240 [4]	1.667 [9]	5.399 [2]	5.540 [4]	1.103 [5]
Technology	4.361 [9]	1.880 [11]	5.574 [5]	6.221 [11]	6.160 [11]	1.187 [8]
Panel B: Countries						
Canada	13.73 [4]	4.080 [2]	3.402 [6]	5.446 [2]	5.370 [1]	1.252 [6]
France	8.600 [6]	3.800 [4]	5.758 [3]	5.464 [4]	5.650 [4]	1.103 [3]
Germany	5.644 [7]	3.490 [6]	5.077 [4]	5.666 [6]	5.680 [5]	1.300 [7]
Italy	88.08 [2]	2.870 [7]	3.507 [5]	5.456 [3]	5.860 [6]	1.167 [4]
Japan	30.39 [3]	3.610 [5]	3.053 [7]	6.166 [7]	6.170 [7]	0.381 [1]
UK	132.1 [1]	3.910 [3]	6.324 [2]	5.653 [5]	5.530 [2]	1.224 [5]
US	12.10 [5]	4.210 [1]	7.090 [1]	5.395 [1]	5.540 [3]	0.743 [2]

Notes: The table reports the mean, the median and the quartile coefficient of dispersion of the slope and threshold estimates related to equation 11, per sector and country. The number in square brackets is the relative rank ranging from 1-11 and reflecting from the lowest to highest intensity (slope) of transition, and from the lowest to highest timeliness (threshold) of transition. A rank of 1 (10) in the QCV measures indicate a homogenous (heterogenous) intensity and timeliness.

Highlights

- Investigate the Covid-19 impact on G7 countries and 10 sectors
- A smooth transition HAR model estimates intensity, timeliness and homogeneity
- Health Care and Consumer Services were the most severely affected
- Materials and Technology weathered the crisis
- Country-wise the UK and the US were hit the hardest