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

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Abstract

We investigate the impact of Covid-19 on stock markets across G7 countries and their business sectors. We highlight the synchronicity and severity of this unprecedented crisis. We find strong transition evidence to a crisis regime in all countries and sectors, yet crisis intensity and timings vary. The Health Care and Consumer services sectors were the most severely affected; a reflection of the Covid-19 drug-race and international travel restrictions. The Technology sector 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 the most affected with the highest heterogeneity in their business sectors' response; a possible reflection of the ambiguity in the initial response and adoption of lockdown measures. Financial markets' response to Covid-19 is akin to response in previous financial crisis rather than previous pandemics. A series of robustness checks confirms our findings.

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

JEL classification: G15, C24

Declarations of interest: None

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1. Introduction

Financial markets periodically reflect major events retrospectively categorized as either endogenous or exogenous shocks. The most recent of these are the 2008 Global Financial Crisis (GFC) and the Covid-19 pandemic. The GFC was an "endogenous shock"; a banking liquidity crisis that followed as the inevitable consequence of a credit-led housing boom. As financial markets reacted to falling economic activity, monetary and fiscal adjustments attempted to counteract recession. More recently, the "exogenous shock" of an unforeseeable coronavirus prompts fiscal and monetary adjustments to counter rising hardships. As some degree of control began to emerge post-lockdown, long-term financial implications are expected to take years to unfold with recent forecasts suggesting initial economic contraction between 3% and 6% (IMF, 2020). The pandemic was noted early in December 2019 and by the end of February 2020 its impact was widely manifest across financial markets. Thereafter, a variety of lock-down measures impeded economic activity with consequential effects upon financial markets. In little over a month, the Dow Jones and the S&P 500 fell by 35%, where stock market volatility was comparable to that of the 1929 Great Crash 1929, the 1987 Black Monday and the 2008 Global Financial Crisis (Baker, Bloom, Davis, Kost, et al., 2020).

This paper is an early attempt to highlight the impact of Covid-19 on financial markets in the G7 economies, which produce about forty percent of the world GDP and have the highest market capitalisations and trading volumes worldwide. We focus on the 10 business sectors of the Industrial Classification Benchmark (ICB) classification and investigate the volatility shift from a calm to a crisis regime, as Covid-19 unfolds and governments respond with unprecedented measures to mitigate the adverse economic effects. We apply a novel heterogenous autoregressive model (ST-HAR) which allows a smooth transition switch in volatility regimes, so allowing inferences on the intensity, timeliness and homogeneity.

Our results verify the transition to a crisis regime for all countries and sectors, with varying intensity and timing. The Health Care and the Consumer Services were the most severely affected, reflecting both the Covid-19 "drug-race" and international travel restrictions. That Technology was the last and least adversely affected sector may reflect a rise in web-based entertainment and other distractions (Forbes, 2020). Shutdowns and the vaccine race are possible causes of sectoral diversity. The UK and the US were the most affected, where the heterogeneity among business sectors may reflect early variations in the adoption of lockdown measures upon the financial markets. Countries that engaged sooner and more thoroughly in containment measures against Covid-19 weathered the financial crisis better. A series of robustness checks confirms our results. Our analysis permits important and timely lessons with respect to the resilience of business sectors in this exogenous shock. Hence, implications for market participants, regulators and policy makers ahead of a follow-up wave of Covid-19 cases are warranted.

Our paper offers two main contributions to the literature. First, we examine the impact of Covid-19 upon stock market volatility at both aggregate and sectorial levels. Second, we use a new approach to identify the transition between distinctive volatility regimes. Thus, our econometric approach extends the heterogenous autoregressive (HAR) model to allow for a smooth transition between regimes, thereby allowing for diverse responses, as indicated by metrics for intensity and timeliness at country/sectorial levels.

The rest of the paper is organised as follows. The next section presents a synopsis of the relevant literature. Section 3 presents the data and the methodology. Section 4 presents the empirical findings. A comparison to other major events is offered in Section 5. Robustness checks are presented in section 6. A final section concludes.

2. Literature Review

2.1 Volatility in financial markets

Although instrumental to the measurement of financial risk, the non-observability of market volatility is traditionally proxied by non-parametric measures such as squared returns, and by parametric measures that draw support from GARCH models (Bollerslev, 1986; Engle, 1982; Nelson, 1991), and stochastic volatility (SV) models (Ghysels et al., 1996; S. J. Taylor, 1994). Owing to volatility importance, the search for superior predictors and models has always been of great importance. One important advancement has been the introduction of realised measures of volatility estimated using high frequency data. Realised volatility (RV) that is defined as the sum of squared intraday returns, is an efficient estimator of volatility and improves volatility forecasting, which typically relies on effective modelling of the persistence inherent in volatility processes (Andersen et al., 2001; Andersen & Bollerslev, 2003; Barndorff-Nielsen & Shephard, 2002; Corsi, 2009). Moreover, the use of RV in conjunction with HAR models circumvents the computational burden and complexity of the earlier ARCH/ARFIMA/SV approaches.

Non-linearities and regime changes are common within financial time series. Several models capture these phenomena, such as the Markov-switching models (Hamilton, 1994), the (SE-)TAR (Tong, 2005) and the STAR models (Teräsvirta, 1994) among others. Where Markov and (SE-)TAR models assume an instantaneous transition between the regimes, at an estimated breakpoint date, STAR models allow a gradual transition between regimes, with an estimated parameter to gauge the intensity of the transition. Although two regimes (e.g., calm/crisis) are commonly used, all models can accommodate multiple, subject to data limitations. Contrarily to Markov models where the switching process is endogenously determined, the TAR/STAR models can accommodate exogenous factors that may drive the regime change.[2] Such non-linear models may be embedded within other models to allow non-linearities and/or regime changes. Pappas et al. (2016) combine a Markov-switching model with the multivariate DCC-GARCH models, to incorporate the delay and intensity to a crisis regime following the 2008 Global Financial Crisis. Papanicolaou and Sircar (2014) combine a Markov-switching model with the Heston stochastic volatility model to capture the option strikes that lie in the tail of the distribution of the volatility process.

Although the HAR model is simple to estimate and captures the persistence of volatility,[3] it fails to indicate any transition between regimes. As a remedy Y. Wang et al. (2017) introduce a time-varying parameter (TVP) specification into the HAR model. Although this TVP-HAR can portray the impact of financial crises on volatility, it provides no indication of the timing and/or the intensity of the transition. To accommodate the diversity of volatility across financial markets, that is likely at the onset

[2] For empirical applications on these models we direct you to (Caggiano et al., 2017; Chkili, 2017; Elliott et al., 2016; Ghoshray, 2010; Moore & Wang, 2007; Nademi & Nademi, 2018; Umer et al., 2018)

[3] For studies using the HAR model across different asset classes we direct you to Santos and Ziegelmann (2014) for Spanish equity index data, Y. Wang et al. (2017) for US equity index data, Buncic and Gisler (2016) for global equity index data; Čech and Baruník (2017) and Audrino et al. (2020) for empirical applications using individual firm data; Mazzeu et al. (2019) and Li et al. (2020) for commodities.

of an unfamiliar pandemic, we introduce a specification based around the HAR model to capture regime change. This specification, which we refer to as ST-HAR, is a combination of a smooth transition model and the heterogenous autoregressive model.[4] The smooth transition allows for a continuum of intermediate states between the two extreme volatility regimes. Not only does this specification model non-linear dynamics[5] that are inherent in the volatility process, it provides estimates of the intensity and the timeliness of the transition.

2.2 Volatility applications and pandemics

The empirical literature on volatility modelling is extensive; focusing upon commodities including, silver (Li et al., 2020), gold (Chkili, 2017; Lucey & O'Connor, 2013), electricity (Ciarreta et al., 2020) and oil (Nademi & Nademi, 2018); and upon financial instruments, namely options Elliott et al. (2016), bonds (Tamakoshi & Hamori, 2014), futures (N. Taylor, 2019) and equity indices (Pappas et al., 2016). Other studies focus upon key political events, economic uncertainty, macroeconomic announcements and financial crises upon volatility (Moore & Wang, 2007; Tiwari et al., 2020). Watugala (2019) finds that periods of economic uncertainty have significant predictive power for the volatility of commodity future returns. Omrane and Savaşer (2017) document a varying impact of macroeconomic news upon the volatility of major exchange rates for the duration of the 2008 GFC. Using high frequency data Chuliá et al. (2010) find that only unexpected changes in the Federal Open Market Committee (FOMC) announcements affect the volatility of the federal fund rate.

A host of factors are relevant to financial market volatility. Extant research relates to pandemics and financial crisis (Baker, Bloom, Davis, Kost, et al., 2020; Correia et al., 2020; Eichenbaum et al., 2020; Ma et al., 2020); terrorist attacks (Llussá & Tavares, 2011); natural disasters (Toya & Skidmore, 2007); plane crashes (Ho et al., 2013); 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); the swine flu (H1N1) (Page et al., 2012) and the H1N1, Ebola and Zika epidemics (Hoffman & Silverberg, 2018). Also relevant are networks, big data, and social media in attempting to understand the spread of the contagion diseases (Pastor-Satorras et al., 2015), and the relevance of globalisation to the spread of infectious diseases (Saker et al., 2004).

A quickly emerging literature investigates the impact of the Covid-19 upon financial fraud (Karpoff, 2020), financial stability (Gortsos et al., 2020), fiscal and monetary policies (Benmelech & Tzur-Ilan, 2020) as well as financial markets. Stock market returns are affected by health related news Salisu and Vo (2020) and Covid-19 confirmed cases (Ashraf, 2020; W. Wang & Enilov, 2020). Across a multitude of assets, only gold and soybean have retained the safe-haven status (Ji et al., 2020). Stock market volatility, geopolitical risk indicators and economic policy uncertainty indices are greatly affected by policymakers' actions and developments at the Covid-19 front (Baker, Bloom, Davis, & Terry, 2020; Baker, Bloom, Davis, Kost, et al., 2020; Sharif et al., 2020). Barro et al. (2020) conclude that the impact of the Spanish flu in the 1920s provide guidance on how the Covid-19 pandemic may impact mortality and economic contraction.

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

[4] Cheikh et al. (2020) use a smooth transition GARCH specification for the conditional variance of cryptocurrencies.
[5] We are aware that over long time periods the linearity of a HAR model may not be rejected (Lahaye & Shaw, 2014).

lead/lag.[6] 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 the impact on the economy was more direct. This may be largely attributed to the exogenous nature of the shock and the 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 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.[7] Our study addresses this research gap and investigates the sectoral impact of the Covid-19 financial crisis.

3. Data and Methodology

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 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.[8] 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]

[6] In this paper we treat the Covid-19 as a financial crisis rather than an epidemic event due to the magnitude of the shutdowns and response in the stock markets. We are aware of other classifications of Covid-19 as a black swan event (Yarovaya et al., 2020).

[7] Examining the sectorial impact of a crisis can give important insights on how the crisis has spread across the economy. Efthyvoulou (2012) study the impact of financial stress in the production and market services sectors and find that although both sectors are affected, the channels of the impact differ. Rioja et al. (2017) provide evidence that recession accompanied by banking crises have a profound negative effect across all business sectors.

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

[Table 1 around here]

To outline our research design, consider a $T \times 1$ vector of demeaned asset returns r_t, where the variance is estimated as a GARCH(1,1) process:

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

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

Subsequent modelling of the conditional variance relies on the heterogeneous autoregressive model (HAR). This exploits the property that the summation of short-memory models can generate the hyperbolic decay patterns typical of the autocorrelation function of volatility estimates (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, estimation and forecasting is more easily obtained from HAR models. 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.[9] These allow 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.[10] 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 is a vector containing regime dependent variables (i.e., slope coefficients that vary across regimes); X_t is a vector containing regime invariant variables; ε_t is the stochastic error term.

We model the G transition function using the exponential function[11] given as:

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

[9] See Teräsvirta (1994) for more details.
[10] 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).
[11] 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.

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, we assume 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:

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

4. 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. In addition, the statistical significance of the two regime parameters (β_0, β_1 and δ_0, δ_1) respectively indicate marked changes in the level and first-lag autocorrelation dynamics of volatility. Parameters measuring the dependence of current volatility on weekly and monthly factors are only important for a subset of sectors.

[Table 2 around here]

Figure 2 presents estimated threshold smoothing weights against threshold variables for selected sectors. In the top row Health Care and Materials respectively show the highest and lowest crisis intensity (estimated slope coefficients (γ)). By analogous metrics, in the bottom row Oil & Gas and Technology were respectively affected first and last (estimated slope thresholds (ψ)). Also note that the Oil & Gas sector shows a homogenous response to the crisis (see also Table 3). Of particular relevance are the estimated slope (γ) and threshold (ψ) coefficients. These are highly statistically significant, further corroborating the non-linear smooth transition between the volatility regimes. High values of the slope coefficient indicate an abrupt transition between volatility regimes. By contrast, lower values indicate a smoother transition. The threshold coefficient indicates the degree of tolerance until the volatility shifts to another regime. Low values indicate sectors that are among the first to be affected as Covid-19 cases increase. Due to the importance of these parameters in understanding the evolution of the crisis, we now elaborate further upon them.

[Figures 2 and 3 around here]

Table 3 presents key location and dispersion statistics relating to the slope and threshold of the transition function. These characterise the intensity and timeliness of Covid-19 across sectors and countries. As indicated by the mean and median values of slope coefficients, the intensity of the transition is highest in the Health Care sector, then followed by Utilities and Consumer Services. 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. 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.

Technology sectors were the last to be affected as the Covid-19 lockdown measures have accelerated the adoption of remote working platforms, while people sought distraction and entertainment elsewhere online. The US and the UK exhibit the highest crisis transition intensity. It is interesting that these are the markets with the highest heterogeneity in the Covid-19 response, as indicated by the high values in the QCV metric. This may be a reflection upon the financial markets of the initial indecisiveness and ambiguity of the political response to the pandemic crisis as far as lockdown measures are concerned. Both the US and the UK were among the slowest countries in adopting containment measures, and which were often met with civilian unrest. At the other end of the spectrum lay Germany and Japan that exhibit the lowest intensity and lowest timelines respectively.

[Table 3 around here]

Country-wise the US has the lowest mean threshold, suggesting that the financial markets there were affected the earliest. This may have been catalytic to a faster and mightier when compared to the 2008 GFC policy response in the US. For instance, the Fed cut interest rates and announced economic support packages, including the $1200 rebate checks, the $600 per week supplement to unemployment benefits, and the Paycheck Protection Program (Humphries et al., 2020). The unprecedented in terms of scale, scope and speed response have partially aided the speedy recovery of the financial markets. The UK also followed a similar strategy by providing funds directly to the business sectors. By contrast, Germany and Japan were among the least affected economies by the Covid-19 financial crisis, which may have partially affected the nature of the economic packages that were offered. Contrary to a “going direct/whatever-it-takes” strategy of the Fed and the Bank of England, the financial stimuli offered by the ECB and the Bank of Japan focused on the commercial banking sector, which would in turn incentivise bank lending to the business sectors hit by Covid-19. But weathering the Covid-19 financial crisis has not only been affected by the economic stimuli. Policy responses regarding containment and closure of businesses, movement restrictions, testing and tracing are also important. We use the Oxford COVID-19 Government Response Tracker (OxCGRT) that tracks government responses across countries and over time. Policy responses with regards to an extended array of parameters including the aforementioned ones are aggregated into four indicators, of which the Government Response Index and the Containment and Health Index are the most comprehensive. For more information about the construction of these indices see (Hale et al., 2020).

Table 4 presents the mean values of the Government Response Index and the Containment and Health Index for the G7 countries over the 1/2/2020 – 24/4/2020, to maintain comparability with the estimation period of our model as well as the crisis intensity estimate for each country (see also Table 3). The negative relationship between each of the policy response indices to the crisis intensity, evidenced by the negative correlation coefficient, suggests that countries that engaged sooner and more thoroughly in across the scale containment measures against Covid-19 weathered the financial crisis better.

[Table 4 around here]

5. Stock markets, Covid-19 and other major events

The Covid-19 has given rise to an unprecedented crisis. In figure 4 we compare the impact of the Covid-19 to that of other major events during the last century on the financial markets. Using the S&P 500 index due to the long timespan of data availability that extends as far back as 1927, we calculate two volatility proxies, namely the realised volatility as the sum of squared returns over the past 22 trading days, and the conditional volatility estimated from a GARCH(1,1) model. In addition, we use the CBOE

Volatility Index (VIX) that is a well-known proxy for the expectation of volatility based on S&P 500 index options. We also plot the Economic Policy Uncertainty (EPU) that is a news-based indicator of economic uncertainty.[12]

[Figure 4 around here]

Stock market volatility is a key indicator to assess the magnitude of financial/economic crisis (Baker, Bloom, Davis, Kost, et al., 2020). A first inspection of Figure 5 suggests that the Covid-19 pandemic has unleashed an extensive and massive uncertainty to financial markets. Compared against other epidemic/pandemic outbreaks such as Ebola, SARS, H1N1, the impact on volatility of Covid-19 is considerably larger. A similar conclusion is reached when comparing against notable terrorist attacks, such as the 9/11 and the Paris bombings of Bataclan. A comparison against other financial crises is more revealing about the true magnitude of the Covid-19 impact on financial markets. Compared against the 2008 GFC at the time of the Lehman Brothers collapse, the Covid-19 financial crisis has posed a larger uncertainty. Hence, the impact of the Covid-19 financial crisis may be directly comparable to the 1929 Great Crash and the 1987 Black Monday event.

6. Robustness checks

As a first robustness check we substitute the GARCH conditional volatility, used in the main part of the analysis, with realised measures. In particular, we use the realised variance (RV) and the robust to microstructure noise *realised kernel variation* (RKV).[13] *Realised variance* (RV) is calculated as the sum of squared intraday returns (Andersen et al., 2001; Andersen & Bollerslev, 2003; Barndorff-Nielsen & Shephard, 2002) as:

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2 \tag{9}$$

where j subscripts each of the M equally-spaced 5-minute subintervals in each day.

The realised kernel variance is given as:

$$RKV_t = \sum_{h=-H}^{H} k\left(\frac{h}{H+1}\right)\gamma_h \tag{10}$$

where

$$\gamma_h = \sum_{j=|h|+1}^{H} r_{j,t} r_{j-|h|}, t \tag{11}$$

Using the RV and the RKV, Table 5 shows estimated slope (γ) and threshold (ψ) coefficients for the G7 countries. The main results - where the GARCH conditional volatility is used - are reported for comparison purposes and labelled accordingly. Although we do not report other estimated coefficients pertaining to Equation 8, these are in line with those when GARCH volatility is used.

[Table 5 around here]

[12] Due to data limitations VIX data are available from 1990 onwards, and EPU data from 1985 onwards.
[13] The realised measures are obtained from the Oxford Man Institute of Quantitative Finance database here: https://www.oxford-man.ox.ac.uk/our-research/realized-library/

A first inspection of Table 4 shows that both the slope and the threshold estimates obtained from the realised measures are highly aligned to those pertaining to the main results of the paper. The last row of table 5 reports a Spearman correlation coefficient between the estimated coefficients that verifies the high alignment. In particular, the Covid-19 has hit the US markets with the highest intensity. As such, the use of alternative volatility proxies does not change the conclusions reached in the main part of the paper.

As a second robustness check we apply a time varying parameter (TVP) HAR model with the period 24/4/2018 – 24/4/2019 as our initial estimation window, which we roll over by one day. We direct you to Todorova (2017) and Y. Wang et al. (2017) for similar approaches. The key attribute of this approach is the intuitive way it can capture the dynamics of the Covid-19 crisis unfolding, while the limitations of this technique in comparison to the ST-HAR model are presented in the main part of the paper.

The following equation is estimated via least squares and Newey-West robust standard errors:

$$h_t = c_i + \beta_i^{(d)} h_{t-1} + \beta_i^{(w)} h_t^{(w)} + \beta_i^{(m)} h_t^{(m)} + e_t \qquad (12)$$

where i denotes the time varying coefficients.

Figure 5 reports the estimated coefficients of the TVP-HAR model for the G7 countries and the ten business sectors under consideration. The grey shaded area represents the Covid-19 financial crisis and is assumed to span from 1/2/2020 onwards to maintain comparability with the main paper results. A cursory inspection reveals that during the Covid-19 financial crisis the coefficients of the TVP-HAR are found to be highly variable. The goodness of fit markedly deteriorates, thus indicating the inability of a linear model to capture the volatility transition effect. In addition, while it is not possible to accurately reflect on the intensity and/or timeliness of the Covid-19 impact upon countries/sectors volatilities, we can clearly infer a certain heterogeneity in the countries' and sectors' responses to the crisis. As such and in the broadest of strokes the results of the TVP-HAR model are similar to those of the ST-HAR.

[Figure 5 around here]

7. Discussion and Conclusions

Our investigation is based upon data from stock markets and business sectors of the G7 economies. To capture the impact of Covid-19 and the associated market reactions, we apply a novel smooth transition heterogenous autoregressive model (ST-HAR) to identify transition between regimes. Thereby, our analysis brings early insights to the intensity, the timeliness and the homogeneity of volatility shifts as well as the rankings of countries and business sectors. Our results are robust to the use of alternative realised measures of volatility and dynamic models.

Our results show a non-linear transition to a crisis regime for all countries and sectors. Our findings are that the Healthcare and Consumer Services sectors were the most severely affected, with Telecommunications and Technology the least. The Healthcare sector is under immense scrutiny in its attempts to develop an effective vaccine. Consumer services were directly targeted by shut down measures to limit the contagion by inhibiting travel and avoiding restaurants and hotels. Households generally were forced to rely upon online entertainment and novel services to cope with the disruptions.

Financial markets in the UK and the US took the largest hits, yet with high response heterogeneity across business sectors. This may be an early reflection upon the financial markets of the indecisiveness and ambiguity of the initial political response to the pandemic crisis, mainly revolving around lockdown measures. Yet, it may have cemented in what culminated to be an unprecedented economic response in terms of scale, scope and speed.

Beyond immediate short-term reactions to the crisis, the world economy faces a host of uncertainties. Furlough schemes only delay the transition to a post Covid-19 world. In the short term, provisions to ameliorate immediate needs may protect essentially ‘zombie’ companies whose demise is inevitable. Eventually the initiative must pass to employers and employees in directing capital investments to long-term viable activities. More work will be needed as the Covid-19 crisis unfolds.

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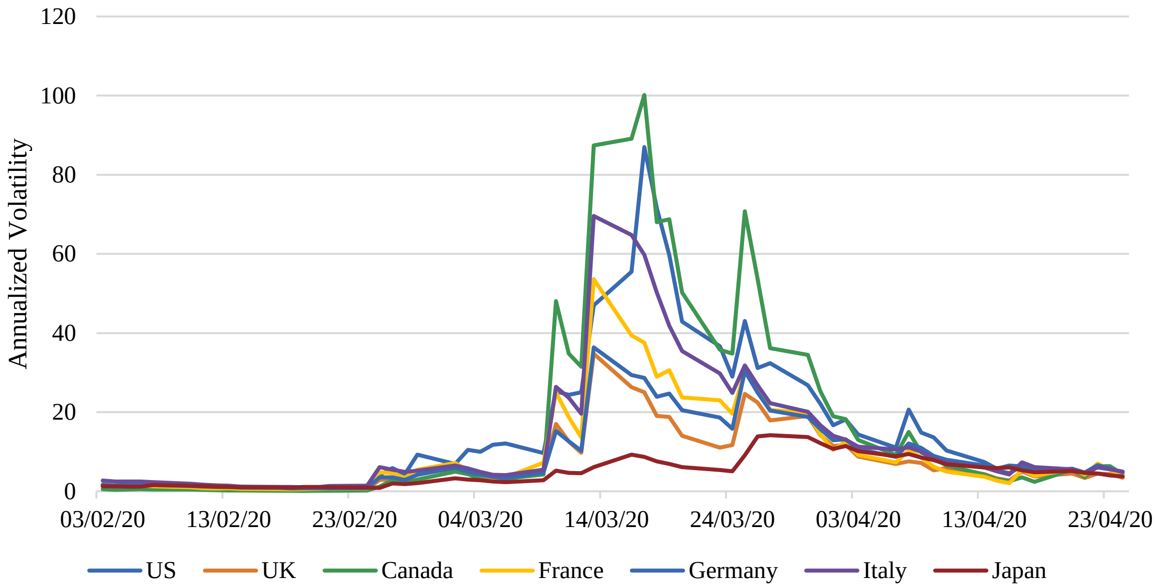
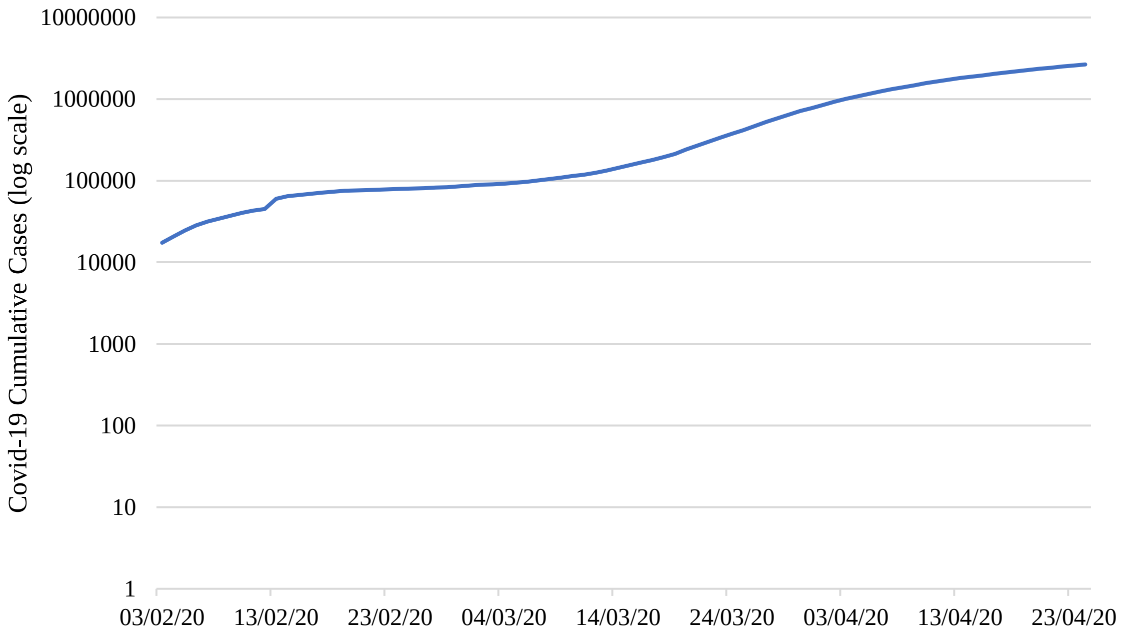
Figure 1. Time evolution of volatilities and Covid-19 cases

Panel A: Time varying annualized volatilities (G7 economies)

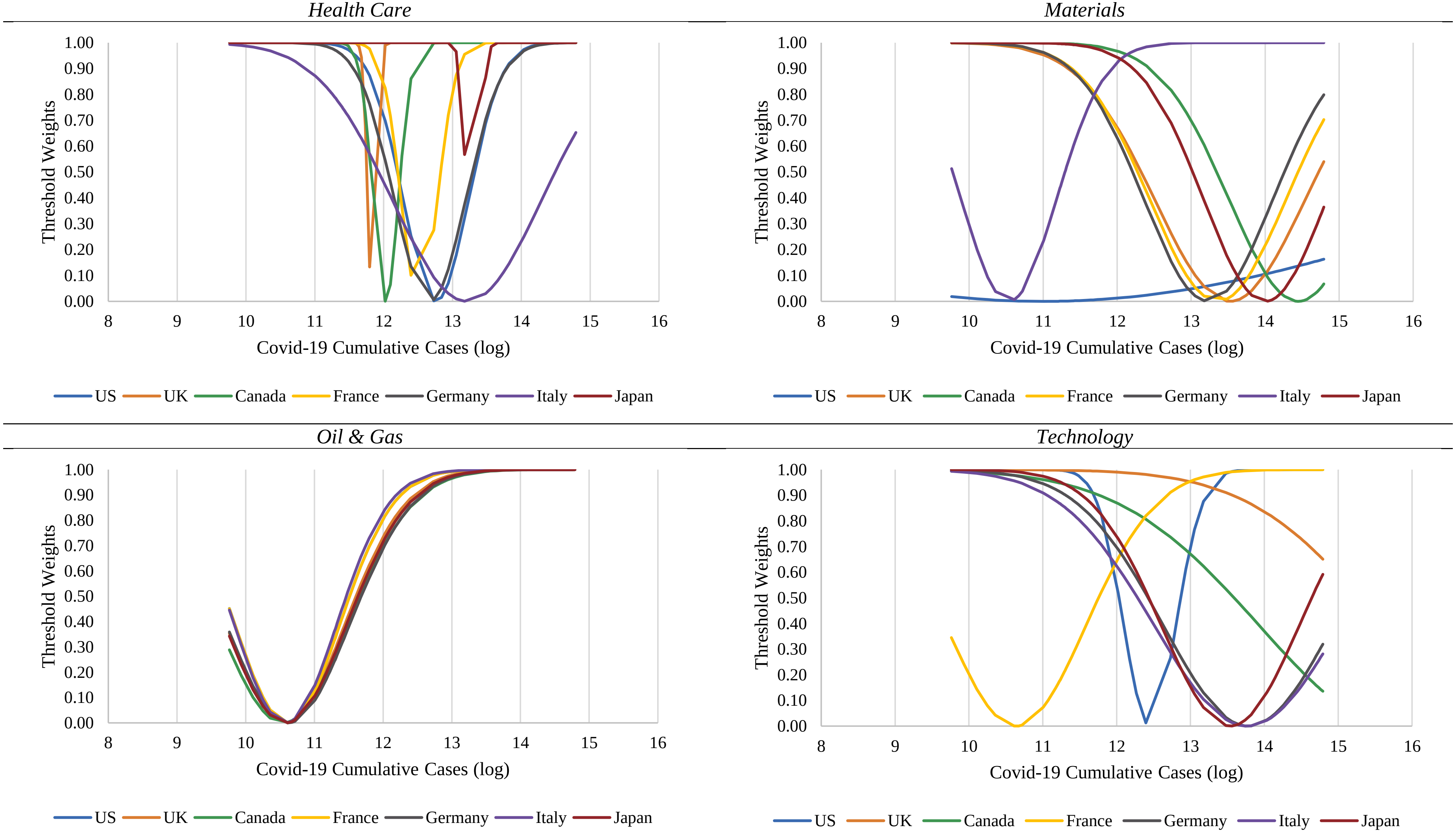


Panel B: Covid-19 Cumulative cases (Worldwide)



Source: Datastream and Johns Hopkins University Coronavirus Resource Centre.

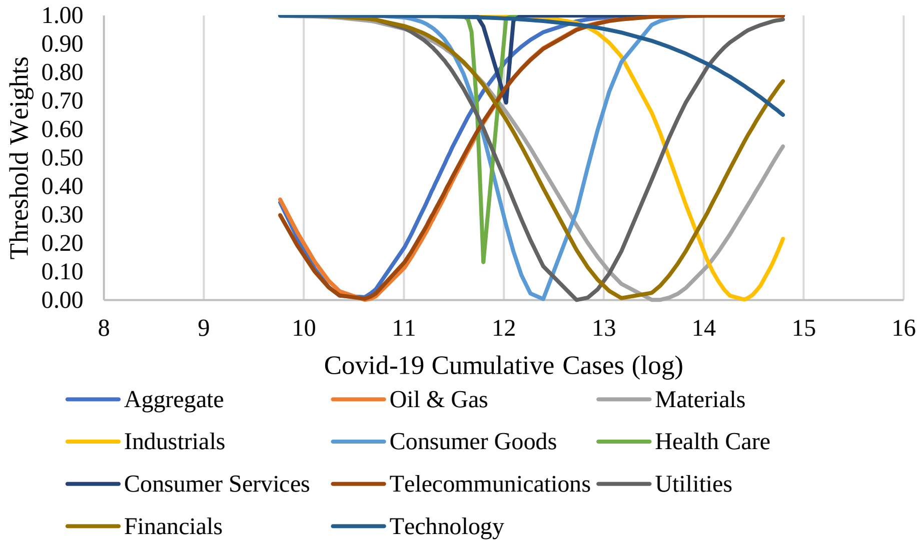
Figure 2. Threshold weights for selected sectors



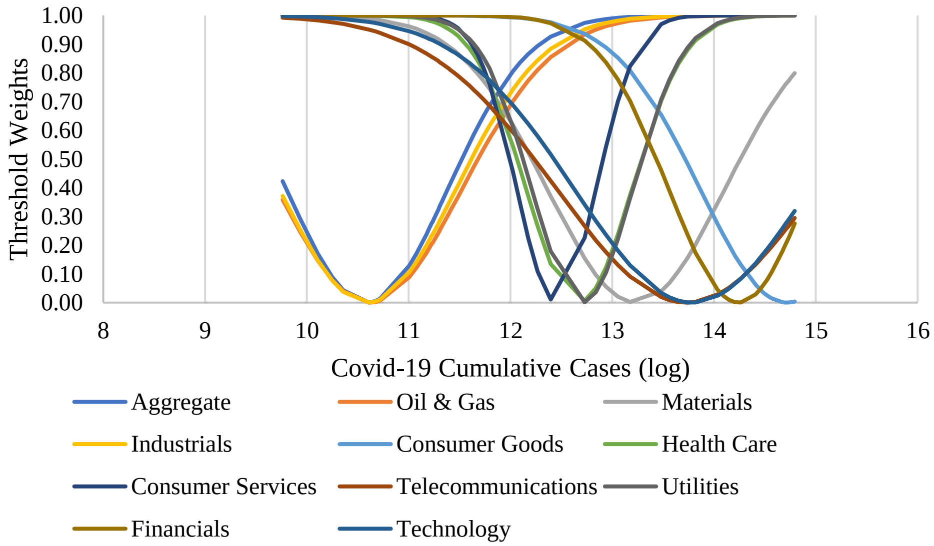
Notes: The figure depicts the threshold smoothing weights from the ST-HAR model of equation 11 ploted against the Covid-19 Cumulative worldwide cases (log scaled). Across all sectors, the ones reported here exhibit the highest and lowest crisis intensity (top left, top right respectively), and the earliest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

Figure 3. Threshold weights for selected countries

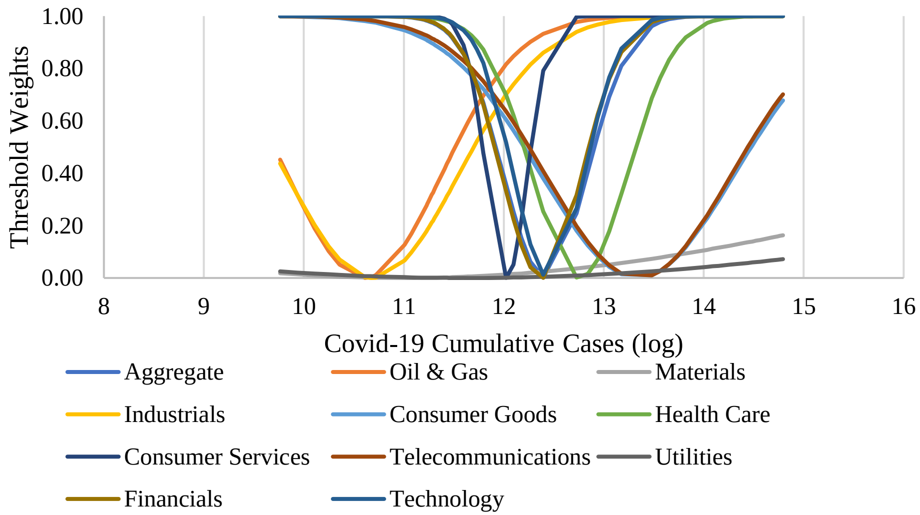
UK



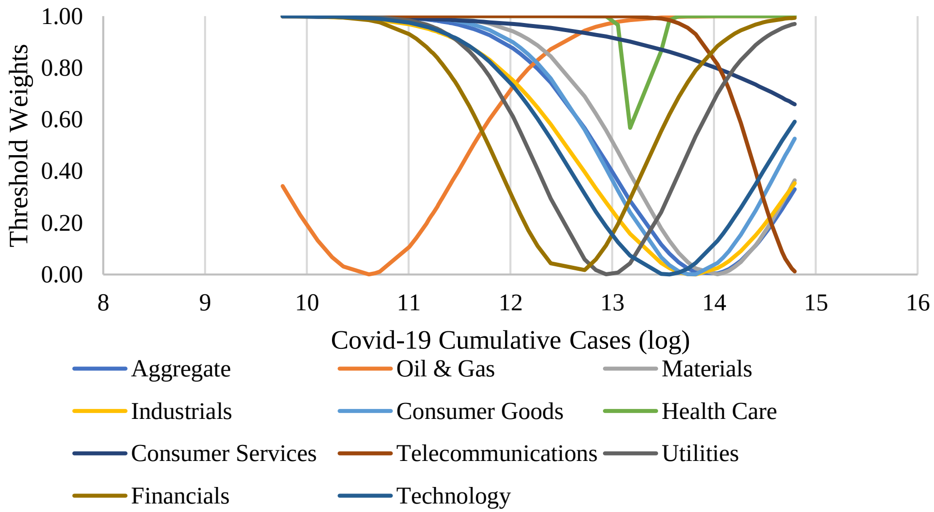
Germany



US

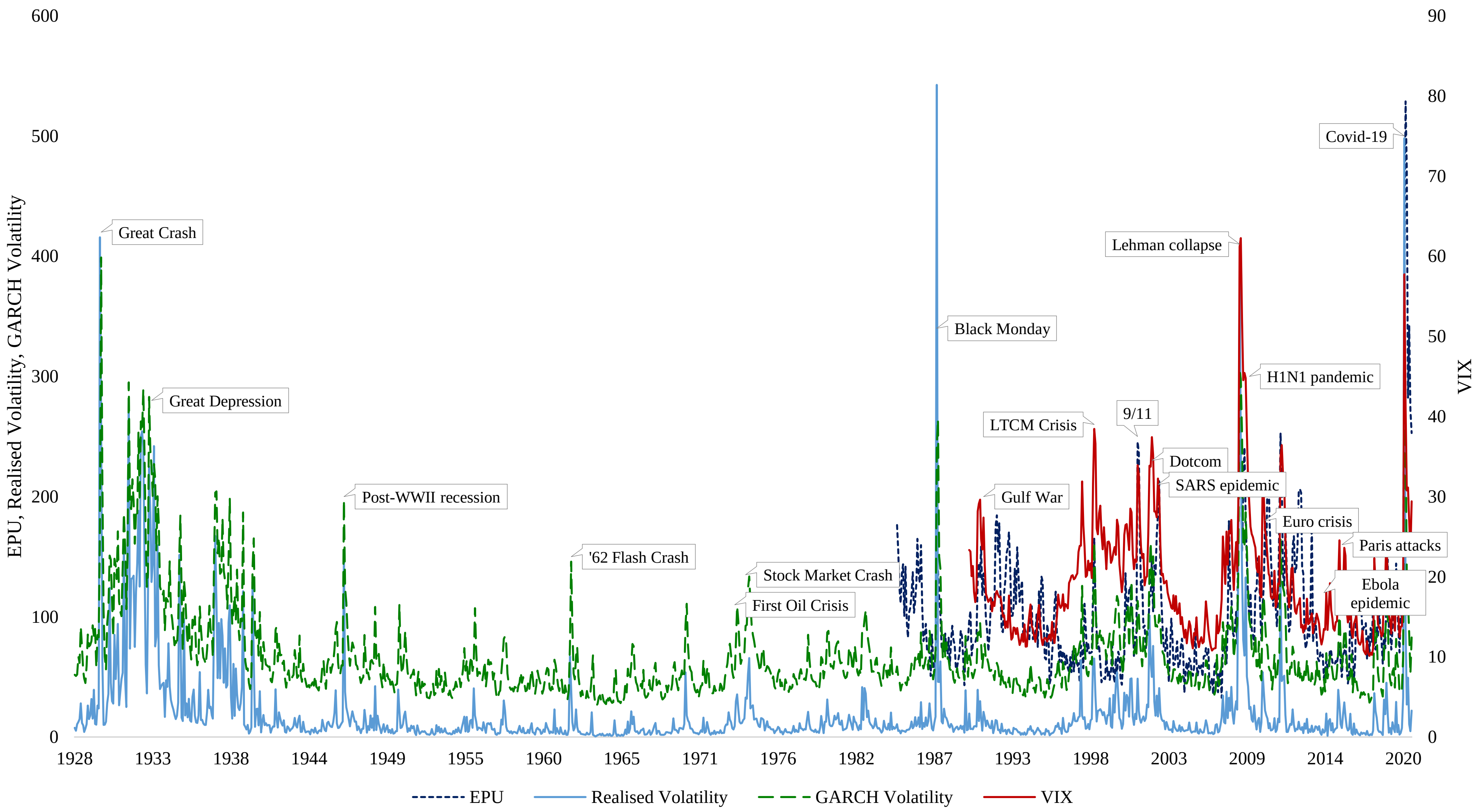


Japan



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).

Figure 4. Volatility across time and major events



Notes: We use the S&P 500 returns to calculate the realised volatility, as the sum of squared returns over the past 22 trading days, and the GARCH Volatility. VIX is a proxy for the expectation of volatility based on S&P 500 index options and is available from 1990 onwards. The Economic Policy Uncertainty (EPU) is a news-based indicator of economic uncertainty and is available from 1985 onwards.

Figure 5. Time varying parameter HAR estimation results

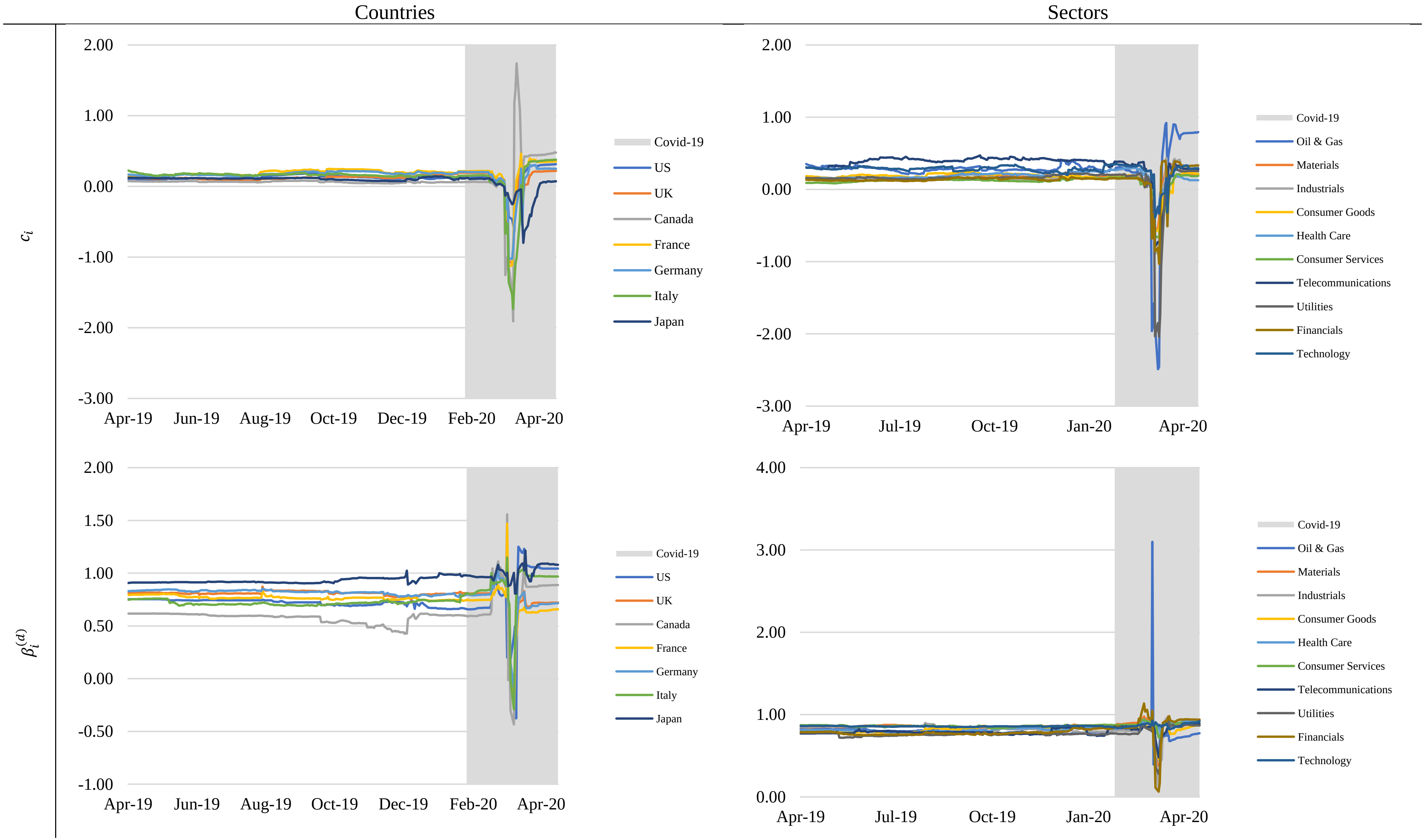
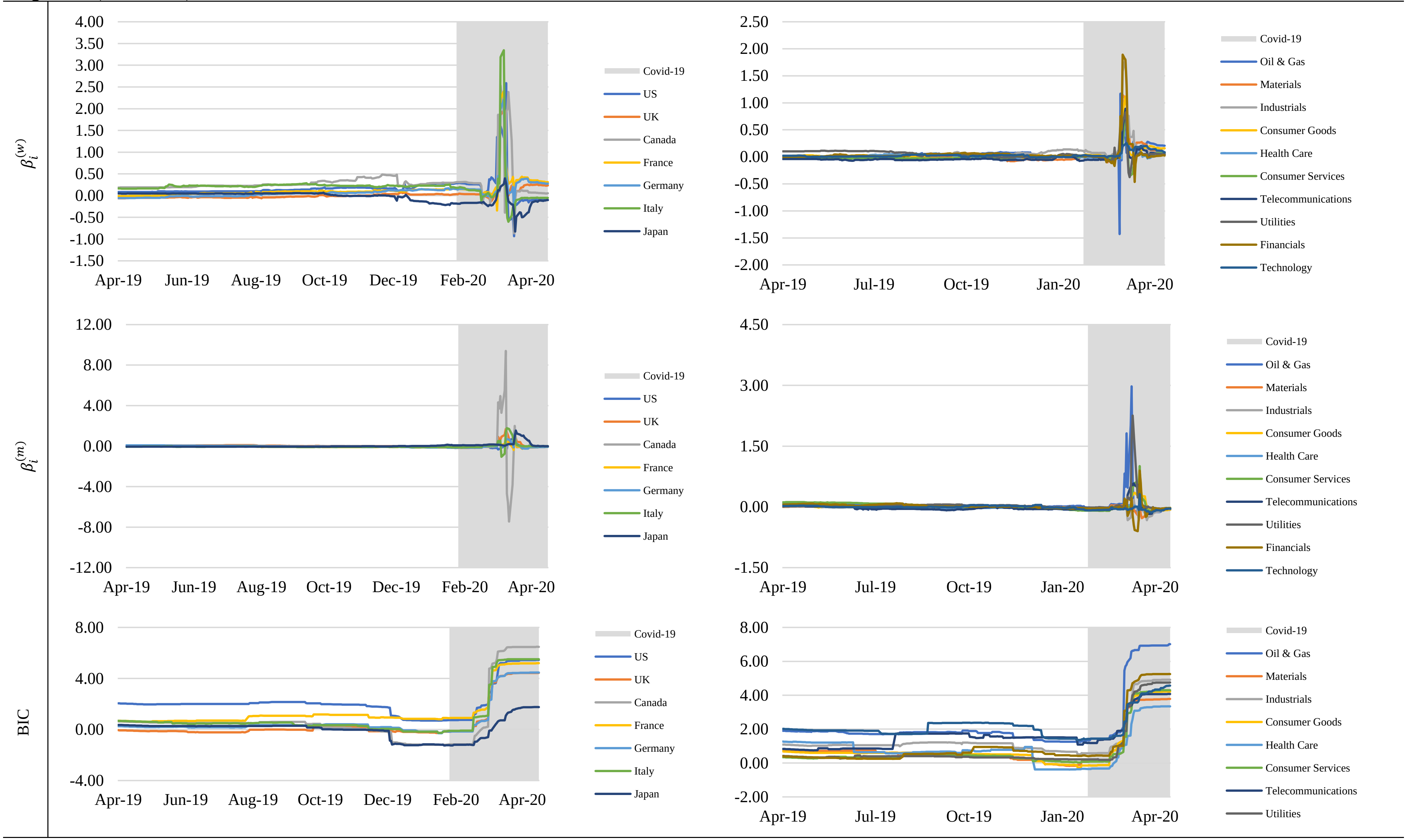


Figure 5. (continued)



Notes: The graphs depict estimated coefficients from the time varying parameter HAR model in eq11.

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	0.833	0.785	0.901	0.844	0.849	0.949	0.900	0.810	0.885	0.843	0.880
BIC	6.167	8.542	5.305	6.561	5.825	4.472	5.184	5.422	3.481	6.545	5.940
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.

Table 4. Crisis intensity and policy response

Country	Government Response Index	Containment and health index	Crisis intensity
Canada	39.54	40.24	4.080
France	50.67	51.22	3.800
Germany	42.45	45.62	3.490
Italy	62.92	70.41	2.870
Japan	35.19	36.77	3.610
UK	40.61	40.15	3.910
US	39.13	42.32	4.210
ρ	-0.742*	-0.787**	—

Notes: The Government Response Index and the Containment and Health Index track government responses in regard to COVID-19 and are obtained from the Oxford COVID-19 Government Response Tracker (OxCGRT) website. Crisis intensity is the median slope coefficient from the ST-HAR model across all business sectors in each country. ρ denotes the correlation coefficient between the each of the Government Response Index and the Containment and health index to the crisis intensity respectively. ***, **, * denote statistical significance at the 1, 5 and 10% levels.

Table 5. ST-HAR with realised measures

	Slope coefficient (γ)			Threshold coefficient (ψ)		
	GARCH	RV	RKV	GARCH	RV	RKV
Canada	4.080**	3.316**	4.746***	4.754***	4.593***	4.642***
	(1.833)	(2.302)	(3.353)	(84.706)	(42.427)	(78.136)
France	2.129***	2.518***	4.287***	5.932***	6.278***	4.711***
	(2.998)	(3.103)	(4.013)	(66.601)	(114.599)	(80.587)
Germany	3.999	2.316***	3.882***	4.739***	5.939***	4.720***
	(1.940)	(4.942)	(2.946)	(117.727)	(101.668)	(52.670)
Italy	2.261***	2.787***	2.176	5.977***	6.243***	5.139***
	(4.979)	(6.432)	(2.128)	(103.877)	(154.393)	(46.646)
Japan	2.807***	2.921***	1.922***	6.240***	6.332***	5.809***
	(4.842)	(3.979)	(3.848)	(102.444)	(104.598)	(102.922)
UK	3.914*	6.100*	3.967***	4.695***	4.681***	4.636***
	(1.510)	(1.619)	(3.178)	(109.450)	(103.267)	(46.218)
US	14.374***	20.649***	7.248**	5.555***	5.321***	4.685***
	(3.194)	(2.824)	(1.995)	(193.381)	(120.638)	(103.777)
ρ	—	0.979	0.845	—	0.778	0.708

Notes: The table reports estimated slope (γ) and threshold (ψ) coefficients and t-statistics in parenthesis from equation 8 using realised measures. ρ denotes the Spearman rank correlation coefficient between the GARCH estimated slope and threshold coefficients and each of the three realised measures respectively.

Highlights

- Investigate the Covid-19 financial crisis on G7 countries and 10 sectors
- A smooth transition HAR model estimates intensity and timeliness of the crisis
- Health Care and Consumer Services were hit the hardest
- Technology was the last and least adversely affected sector
- Countries that engaged sooner have initially weathered the financial crisis better