Sovereign credit ratings during the COVID-19 pandemic

Yen Tran,[a] Huong Vu,[a] Patrycja Klusak[b], Moritz Kraemer[c] and Tri Hoang[d]

[a] University of Aberdeen, King's College, UK

[b] Norwich Business School, University of East Anglia and Bennett Institute for Public Policy, University of Cambridge, UK

[c] Goethe-University, Frankfurt, Germany and Centre for Sustainable Finance, SOAS, University of London, UK

[d] School of Finance, University of Economics, Ho Chi Minh City, Vietnam and Faculty of Finance and Commerce, Ho Chi Minh City University of Technology (HUTECH), Vietnam.

This version 22 July 2021

Abstract

Using 603 sovereign rating actions by the three leading global rating agencies between January 2020 and March 2021, this paper shows that the severity of sovereign ratings actions is not directly affected by the intensity of the COVID-19 health crisis (proxied by case and mortality rates) but through a mechanism of its negative economic repercussions such as the economic outlook of a country and governments' response to the health crisis. Contrary to expectations, credit rating agencies pursued mostly a business-as-usual approach and reviewed sovereign ratings when they were due for regulatory purposes rather than in response to the rapid developments of the pandemic. Despite their limited reaction to the ongoing pandemic, sovereign rating news from S&P and Moody's still conveyed price-relevant information to the bond markets.

Keywords: COVID-19, Economic outlook, Sovereign credit ratings, Rating calendars

JEL classification: F3, F5, G2, H1

Declarations of interest: none.

Sovereign credit ratings during the COVID-19 pandemic

Highlights

- This paper examines whether sovereign rating actions by three major rating agencies are affected by the intensity of the COVID-19 health crisis.
- Findings show that sovereign ratings respond to the changes in the economic repercussions caused by the pandemic (economic outlook, government's response to crisis) and not directly by the intensity of the health crisis (proxied by case and mortality rates).
- Contrary to expectations credit rating agencies applied a mostly business-as-usual approach and reviewed sovereign ratings only when they were scheduled for regulatory purposes scheduled ahead of the pandemic.
- Despite credit rating agencies' lack of timeliness, sovereign rating news from S&P and Moody's appear to convey price-relevant information to the bond markets.

Sovereign credit ratings during the COVID-19 pandemic

This version: 22 July 2021

Abstract

Using 603 sovereign rating actions by the three leading global rating agencies between January 2020 and March 2021, this paper shows that the severity of sovereign ratings actions is not directly affected by the intensity of the COVID-19 health crisis (proxied by case and mortality rates) but through a mechanism of its negative economic repercussions such as the economic outlook of a country and governments' response to the health crisis. Contrary to expectations, credit rating agencies pursued mostly a business-as-usual approach and reviewed sovereign ratings when they were due for regulatory purposes rather than in response to the rapid developments of the pandemic. Despite their limited reaction to the ongoing pandemic, sovereign rating news from S&P and Moody's still conveyed price-relevant information to the bond markets.

Keywords: COVID-19, Economic outlook, Sovereign credit ratings, Rating calendars

JEL classification: F3, F5, G2*,* H1

1. Introduction

Media reports of a novel coronavirus first emerged in the international press in January 2020. By March 2020, the World Health Organization (WHO) declared COVID-19 a global pandemic, and by October 2020, the International Monetary Fund (IMF) (2020a) forecast a global economic contraction of 4.4% for the year 2020. For perspective, the Great Financial Crisis saw a global contraction of 0.1% (IMF, 2020b). Fiscal responses to the economic crisis have driven public sector leverage to an all-time high, rendering sovereigns more vulnerable to future shocks, especially if and when interest rates rise from their historic depths.[1] The unusually brisk and synchronised deterioration of economic and fiscal fundamentals across the globe provides an unprecedented opportunity to assess the reactions of credit rating agencies (CRAs) to sudden shocks. CRAs are relied upon as leading sources of credit risk information and act as gatekeepers to global debt markets (Kedia et al., 2014). Analysing ratings actions from January 2020 to March 2021, we are the first to empirically investigate the extent to which CRAs delivered on their remit to inform market participants of changing in creditworthiness in a timely, transparent and independent manner.

We analyse rating actions of the three biggest CRAs (S&P Global Ratings, Moody's Investors Service, and Fitch Ratings), which together represent a market share of more than 90%.[2] Between January 2020 and March 2021, three CRAs issued a total of 99 sovereign rating downgrades on 48 countries, affecting 35% of their rated sovereign portfolio. We find that compared to previous crises, CRAs have reacted with considerable caution. For example, S&P with a coverage of 121 countries, issued 20 (31) downgrades on 19 (26) countries in the six (14) months since February 2020, amounting to 15.7 (21.5)% of its sovereign portfolio. For comparison, in the six months following the collapse of Lehman Brothers in September 2008,

[1] According to the IMF's World Economic Outlook report in April 2021, general government debt for advanced economies stood at 123% of GDP, versus the 90% average during the 2000-2019 period. For emerging and developing countries, the increase of public debt was also pronounced (64% of GDP versus the pre-pandemic average of 43%).

[2] According to the Securities and Exchange Commission (SEC) annual report on Nationally Recognized Statistical Rating Organizations (NRSROs) 2020, the cumulative market share of three leading CRAs in sovereign ratings is 98.7%, whereby S&P leads the market with 54.3% followed by Moody's with 33.4% and Fitch with 11.0% (SEC, 2020).

S&P downgraded 31 sovereigns, or 25% of its (then smaller) sovereign portfolio (Kraemer, 2020).[3]

Why should the severe contraction during COVID-19 induce fewer downgrades than the comparatively mild contraction during the great financial crisis? One potential consideration is the business-as-usual scheduling of ratings reviews by CRAs. The frequency of sovereign ratings reviews is subject to regulation. For example, for sovereign followed by rating analysts based in the EU,[4] CRAs are required to publicly announce ratings reviews on two to three dates in the forthcoming calendar year.[5] Regulations permit CRAs to conduct reviews ahead of schedule when circumstances require (EC, 2013). A reasonable assessment would be that the pandemic constitutes a sufficiently large change in circumstances to merit early ratings reviews from CRAs. CRAs were effectively free to review any rating at any time following the outbreak of the pandemic.

Motivated by these issues we analyse if and how the pandemic influenced global sovereign ratings. To examine whether the severity of the health crisis (case and mortality rates) affected sovereign ratings actions, we compile a novel panel dataset of rating actions for 137 countries issued by three leading CRAs between 30 January 2020 and 31 March 2021. The effect of COVID-19 is measured by the number of confirmed cases per million published by Johns Hopkins database. We establish the starting date of our sample (30 January 2020) as the day when WHO announced COVID-19 a *"Public Health Emergency of International Concern"*. Our identification strategy corrects for the fact that the pandemic did not hit all countries at the same time. Namely, the country enters the sample only after the first confirmed case has been recorded. We regress rating actions against the number of confirmed cases per million, a measure of CRA's timeliness based on the time elapsed since the preceding public ratings review, and country-level controls.

Our results show that negative sovereign rating actions are not directly triggered by the depth of the heath crisis, e.g. the infection cases or mortality rates, but through a mechanism of its negative economic repercussions. Also, government response to the pandemic has unintended

[3] Between January 2020 and March 2021, if we include rated sovereigns excluded from this study for lack of data, we observe 105 downgrades on 54 countries issued by three CRAs.

[4] Or a jurisdiction endorsed by the EU as equivalent for regulatory purposes.

[5] The regulation in other jurisdictions typically requires at least a yearly publication of a ratings update following a credit committee having deliberated on each sovereign.

consequences for sovereign ratings. More decisive measures adopted by countries lead to higher deterioration in creditworthiness.

Our key finding is that rather than proactively issuing early ratings reviews, CRAs in many cases kept coasting in a business-as-usual mode, reviewing ratings close to their scheduled dates set before the pandemic. For each month that the preceding rating review aged, the probability of a downgrade increased by 0.14% and that of a negative outlook or watch by 0.13%. If sovereign credit committees were strictly held on an analytical as-needed basis, the time that has elapsed since the previous review should not have any impact on the likelihood of a rating action. The fact that the coefficient is positive and highly significant (at 1% level) provides evidence that CRAs did in many instances simply wait until a review was due before lowering a rating or outlook. This is an important and surprising finding. In the midst of a disrupting pandemic, which clearly constituted an external unanticipated shock, the case for an accelerated review would have been exceptionally easy to make, both internally as well as externally. Regulators would not have been able to object to the assessment that previous assumptions going into sovereign ratings had been overtaken by events and a fresh look would have been called for. Our finding reveals important and original insights compared with the previous crisis of similar systemic nature. During the sovereign debt crisis in the early 2010s, CRAs were criticised for what some considered to be excessive downgrades on sovereign ratings of Euro area countries. The downgrades have been caused by a common external shock affecting all Euro area sovereigns to varying degrees.[6] Similarly in 2020, almost the entirety of rated sovereigns has been affected by the external shock of the pandemic. Had the CRAs reacted in 2020 in a similar fashion as they did a decade earlier, under what were substantially milder circumstances, we would have obtained insignificant coefficients on the time elapsed since the last review.

Although it is disappointing from the perspective of rating users, we show that market participants have been mostly oblivious to the CRAs' business-as-usual working mode. Namely, they were unable to realise the timing of rating actions according to the CRAs' regulatory review calendar and/or to adjust the spreads accordingly. It follows that rating actions in the pandemic are still treated as 'news'. Sovereign spreads increase by an average

[6] For example, S&P placed all sixteen Euro area sovereigns under negative watch on December 5, 2011. A few weeks later, on January 13, 2012, the CRA lowered ratings on nine Euro area sovereigns on one day and affirmed the remaining seven. See S&P Global Ratings: "Standard & Poor's Takes Various Rating Actions on 16 Eurozone Sovereign Governments", January 13, 2012.

71.06 basis points in the [0; +1] window of a negative outlook announcement compared with the benchmark case of no announcement. Spreads are strongly responsive to S&P's rating actions, whilst moderate if the actions are from Moody's. Similar to episodes of market turbulence in the past (Afonso et al., 2014), negative sovereign rating news give important information value to the capital markets. Additionally, we confirm that there is no relationship between case rates and the bond spreads, which substantiates our earlier findings concerning the muted effects of depth of the pandemic on sovereign risk. On the other hand, we find evidence of an attenuating effect of government measures aiming at containing the virus and bond spreads. Contrary to CRAs' pessimistic view, the government's actions aiming at controlling the virus are perceived by the markets as positive signals.

Our study makes original contributions to the rating literature on three fronts. First and foremost, this is the first empirical study on the effects of COVID-19 pandemic on sovereign credit ratings. The literature on the economic effects of COVID-19 pandemic has been burgeoning since 2020, whereby researchers concentrate on investigating the financial market reactions (Azimli, 2020; Baker et al., 2020), volatility of markets (Lyócsa et al., 2020; Salisu and Vinh, 2020; Zhang and Hamori, 2021) and behavioural aspects of COVID-19 (Binder 2020; Fetzer et al., 2020). However, there is no published study on the response of CRAs to this global pandemic.

Second, we are the first study to highlight a difference in the way CRAs react to the ongoing crisis in comparison to the past crises by observing timing of rating committees. We observe shift from elevating review efforts to stagnant business-as-usual mode. We attribute this change to the CRA regulation in place. This suggests that the tighter regulation since the financial crisis has led to less timely rating behaviour by the CRAs.

Third, we provide the first insights into the information value of sovereign rating news for the debt markets under the influence of the pandemic.

The rest of the paper is structured as follows: Section 2 briefly discusses related literature. Section 3 focuses on methodology employed in this study. Section 4 explains data and summary statistics. Section 5 presents the empirical findings and robustness tests, while Section 6 concludes.

2. Literature review

2.1. Background of the CRA industry and critiques of the paradigm

Credit ratings are forward looking opinions on the probability of default. They provide a common language of credit risk enabling broad comparability of default risk across issuers, industries, geographies and time.[7] Sovereign credit ratings assess the creditworthiness of a country, at the same time affecting the long-term investment and lending decisions across nations. Sovereign downgrades have strong implications for financial markets and institutions alike as they affect the cost of credit available to sovereigns but also other asset classes due to the imposed ceiling effect (Borensztein et al., 2013; Alsakka et al., 2014).

Most ratings are solicited by the issuer, whereby they request the service and pay for the rating. However, there are also a number of unsolicited ratings which are "initiated by parties other than the issuer or its agents" (S&P, 2018; p. 43). Despite their prevalence in the market, unsolicited ratings remain one of the most controversial aspects of the industry[8] (Fulghieri et al., 2014). For example, bank and corporate ratings literature finds that issuers who do not pay for ratings on average receive lower assessment (Poon, 2003; Bannier et al., 2010). The opposite is found in the sovereign ratings market (Gibert, 2019). Following changes in sovereign solicitation disclosure rules, Klusak et al. (2017) find banks domiciled in sovereigns which switched their status to unsolicited rating receive a penalty in a form of lower ratings. Regulators and investors are interested in this feature as both types of ratings are allowed for regulatory purposes.

The rating industry is a regulated business. Part of the regulatory requirement is that methodologies are publicly accessible and that sovereign ratings are reviewed at least once per year, or six-monthly for sovereign that fall under EU-regulation (EC, 2013). The rating decisions are taken by committee process, where committee members apply the appropriate methodology and vote on the final decision of the rating, and/or the outlook on the rating.

---

[7] For a description of the ratings business in general terms see for examples: Moody's "Understanding Moody's Credit Ratings", April 2020; Fitch Ratings "Rating Definitions", April 2021; S&P "S&P Global Rating Definitions" Jan 2021.

[8] Other issues relating to the business model are a lack of competition and conflict of interest problem induced by issuer-pays model, which in turn might trigger rating shopping and rating inflation (Becker and Milbourn, 2011). Moreover, CRAs often release contradicting ratings. Finally, there is a lead-lag relationship in sovereign credit rating announcements whereby S&P leads Moody's in downgrades and Fitch in both upgrades and downgrades (Alsakka and ap Gwilym, 2010).

Because CRAs aim to "rate through the cycle" they find themselves in a constant dilemma between reaching stability versus accuracy in their ratings (Altman and Rijken, 2004). Generally, CRAs intend to give ratings which are stable over time and not influenced by temporary fluctuations due to the nature of the business cycle. One of the key challenges for CRAs is therefore the identification of "fundamental" changes in variables that are expected to have an impact on creditworthiness. To help with their efforts[9] CRAs apply additional credit warnings such as outlook or watch to show possible direction and timing in their rating (Hamilton and Cantor, 2004).

In the recent years CRAs have been put in the spotlight and criticised for their lax ratings and inability to predict the 2007 sub-prime crisis (Stolper, 2009). In a similar vein CRAs were blamed for failing to recognise the 1997 East Asian crisis and aggravating it even further by excessive sovereign downgrades (Mora, 2006). On the other hand, CRAs also stand accused of worsening the 2010 European debt crisis by downgrading ratings of Eurozone sovereigns too far and too fast (Alsakka and ap Gwilym, 2013). Although the inertia during times of sudden shocks might be driven by the underlying business models of CRAs it is also partly related to regulatory negligence on the side of regulators and market players. Users of ratings often over-relied on ratings without making their in-house assessments (House of Commons, 2012). In addition, regulators kept a blind eye for a very long time (BOE, 2011). Finally, the ratings became strongly imbedded into regulations and this assured investors about their reliability and encouraged herd behaviour.

2.2. COVID-19 related literature

There has been an inflow of literature relating to the impact of COVID-19 on the global economy and financial markets. Using the epidemiology model, Eichenbaum et al. (2020) study the interaction between the pandemic and economic decisions and reveal a trade-off between restrictive economic interventions (lockdown) and costs of the spread of the disease. Following, a growing survey literature links how the COVID-19 outbreak affected consumer beliefs, macroeconomic expectations, anxieties and preferences (Binder 2020; Fetzer et al., 2020). Several studies collate how the COVID-19 pandemic affected global economic and financial affairs in comparison with the previous health (e.g., SARS, MERS, Ebola, Zika) and

[9] While regulators, and bond issuers appreciate rating stability, market participants such as investors of hedge funds or traders prefer ratings which are timely and accurate (Cantor and Mann, 2007).

financial crises (Izzeldin et al., 2021; Correia et al., 2020; Goodell, 2020). Treating COVID-19 as a financial crisis rather than an epidemic[10] Izzeldin et al. (2021) apply sectoral analysis to G7 economies and find that the most affected sectors are Health Care and Consumer services with Telecommunications and Technology the least. Moreover, authors find the response of financial markets to COVID-19 resembles that of previous financial crises rather than other pandemics.[11] Wang et al. (2021) estimate the effect of previous pandemics on innovation outputs and find that effects vary between countries and sectors. Sharif et al. (2020) suggest that compared to the Great Depression and the Global Financial Crisis, the COVID-19 crisis is unique, inter alia, in the way it produces a (figurative and literal) contagion effect. Akhtaruzzaman et al. (2020) find that the spillover can be mainly attributed to financial institutions.

The contagion effects of the pandemic resulted in a search for safe haven assets including gold (Ji et al., 2020) and cryptocurrency (Goodell and Goutte, 2020). While the former group yields consistent results, there are some disagreements about 'hedging risk' using latter assets (Conlon and McGee 2020; Corbet et al., 2020; Mnif et al., 2020).

A series of short papers on stock market reactions to the pandemic emerged recently (Azimli, 2020; Baker et al., 2020; Cepoi, 2020). Baker et al. (2020) find the effect of COVID-19 on the US stock market is different from shocks induced by earlier infectious diseases such as SARS or Ebola. Others go a step further and forecast the volatility of stock returns using various predictors. Lyócsa et al. (2020), Salisu and Vinh (2020) study the relevance of health news collected from Google searches in the predictability of stock returns. Using volatility indexes such as EPU and VIX, Wang et al. (2020) conclude that the latter is most useful in predicting stock market volatility during the pandemic. Zhang and Hamori (2021) analyze the return and volatility spillover between the COVID-19 pandemic, crude oil market and stock market and find that return (volatility) spillover occurs in the short (long) term.

The only studies remotely connected to our research are Balajee et al. (2020), Kargar et al. (2020) and Acharya and Steffen (2020). Balajee et al. (2020) in their study of 95 sovereigns

[10] Others consider COVID-19 as a black swan event (e.g., Yarovaya et al., 2020).
[11] When comparing the COVID-19 pandemic to a 2008 Global Financial Crisis, authors find that the pandemic introduced greater uncertainty which makes it comparable to the Great Crash in 1929 and Black Monday Event in 1987.

between January and April 2020, find that sovereign ratings are amongst the most important determinants of fiscal stimulus packages undertaken by governments to tackle the pandemic. Ratings affect not only the amounts raised but also the timing of the stimulus packages being introduced. Authors document that on average, governments with low ratings issued 0.3 % lower fiscal packages and delayed their response by 1.7 days. On the other hand, Kargar et al. (2020) and Acharya and Steffen (2020) investigate the liquidity of US corporate bonds in the wake of Federal Reserve interventions. Kargar et al. (2020) with a sample spanning between January and June 2020 (without access to the latest rating data for all the bonds) find that at the climax of the crisis liquidity conditions depreciated because dealers were unwilling to use their own balance sheets to absorb corporate debt. After Fed facilities such as 'purchase of corporate debt' were announced, the situation reversed. Acharya and Steffen (2020) show how differently the stock market evaluated firms depending on their liquidity. The authors find only firms in the category between A to AAA issued bonds following Fed's quantitative easing. In contrast, the lowest end of the investment grade firms (category BBB-) rushed to convert their commitments into cash. This "dash for cash" behaviour was observed amongst half of the converted credit line commitments and characterised firms with the potential of becoming 'fallen angels'[12] in the future.

3. Data and methodology

3.1. Data sampling

To study factors affecting CRAs' assessments of sovereign creditworthiness in the context of an ongoing health crisis, we collect rating history along with press releases related to rating changes, outlook, credit watch revisions, and rating affirmations by S&P, Moody's, and Fitch during the period 30 January 2020 to 31 March 2021. Data for Moody's is available via their website whereas ratings for S&P and Fitch are collected from subscribed rating data services (S&P Ratings Direct, Fitch Connect). Rating outlooks and credit watches express CRAs' directional view of risks and mitigants which have not yet been sufficient to prompt an immediate rating action but may induce rating changes in the near and intermediate term.[13] Meanwhile, rating affirmations communicate CRAs' judgements that outstanding ratings

[12] This term refers to issuers whose investment grade rating (BBB- and above) is replaced by speculative rating status (BB+ and below).

[13] With watches (outlooks) CRAs indicate the direction into which the rating might be moved during the next three months (year or two) respectively.

continue to be appropriately positioned and are not directly affected by publicly visible credit developments (Moody's, 2020).

Credit rating alphabetic symbols are translated into a 22-point numerical scale, with 22 corresponding to the highest (AAA), and 1 (SD) the lowest credit quality (Appendix A.1). To enter our sample, we require that sovereigns have a long-term foreign currency issuer credit rating issued by at least one of the three CRAs. Countries must have had their 2020 and 2021 economic forecasts in IMF's World Economic Outlook Reports released in October 2019, April 2020 and October 2020. Each country enters the sample when the first COVID-19 case occurs after 30 January 2020.

We calculate the daily changes of ratings, outlooks and watches and form a dataset consisting of all the changes on the first day of each month and any subsequent changes within each month. With this method our sample includes observations of zero changes in ratings (no rating actions) and actual rating actions including changes in rating levels (upgrades or downgrades), revisions of outlooks and watches, and confirmations of ratings. Downgrades to default and upgrades from default are excluded and treated as rating withdrawals and new rating assignments respectively. This is a reflection of the fact that "default" is not a rating but a description of a fact, i.e., a missed payment or a distressed debt exchange.

Our COVID-19 related variables are sourced by the Johns Hopkins University Coronavirus Resources Centre's database. To track the governments' reactions to the outbreak, we use the Oxford Coronavirus Government Response Tracker OxCGRT for which data is accessible from Hale et al. (2021). To account for responsiveness of CRAs via timing of rating committees we use sovereign rating histories found on Moody's website, S&P Ratings Direct, and Fitch Connect. Finally, we obtain the three IMF's World Economic Outlook reports from the IMF official website.

Our final sample encompasses 5,171 observations from 137 sovereigns spanning the period from 30 January 2020 to 31 March 2021. Out of 137 sovereigns, 118 are rated by S&P, 131 by Moody's, and 112 by Fitch.

3.2. Model specification

We study factors affecting CRAs' assessments of sovereign creditworthiness in the context of an ongoing health crisis, which has been declared as a public health emergency of international concern by WHO on 30 January 2020 (WHO, 2020).

To capture the effect of COVID-19 on sovereign rating actions we estimate an ordered probit model. This model is established in the ratings literature whereby it enables to capture ordinal nature of dependent variable(s) (Becker and Milbourn, 2011). Following Williams et al. (2013), we calculate marginal effects (MEs) to estimate the economic significance of variables that are statistically significant for the sovereign rating actions.

When specifying our econometric model, we select several indicators published in CRAs' sovereign rating methodologies (Fitch, 2020; S&P, 2017), recent literature (Salisu and Vinh, 2020; Sharif et al., 2020), as well as economic intuition which can suggest how ratings would move in the context of the pandemic. We look at seven variables including countries' economic outlooks under pressure from COVID-19, the severity of the COVID-19 crisis, governments' responses to the health crisis, the rating surveillance schedule (the time elapsed since the previous public rating pronouncement), and a dummy variable for March 2020-April 2020 period which exhibits the highest uncertainty and fear for the pandemic.[14] The summary statistics and definitions of variables appear in Table 2. We regress sovereign rating actions *(Downaction)* on *CAB_Outlook NetLB_Outlook*, *GDP_Outlook, CaseRates*, *GovtResponse, Count, ShockandAwe* followed by *Region* and *CRA* dummies.[15]

$$Downaction^{*}_{i,j,t} = \beta_1 CAB\_Outlook_{i,t} + \beta_2 NetLB\_Outlook_{i,t} + \beta_3 GDP\_Outlook_{i,t} + \beta_4 CaseRates_{i,t} + \beta_5 GovtResponse_{i,t} + \beta_6 Count_{i,j,t} + \beta_7 ShockandAwe_t + \lambda Region + \theta CRA + \varepsilon_{i,j,t} \quad (1)$$

Where the dependent variable $Downaction^{*}_{i,j,t}$ is a latent variable linked to the observed ordinal daily rating intensity $Downaction_{i,j,t}$ of a sovereign i by CRA j at date t computed by the following model:

[14] Dummy takes value of one during period March-April 2020 and zero otherwise.

[15] We also estimate the results using random effects model similar to Ashraf et al. (2020). The results are mainly consistent and are available on request.

$$Downaction_{i,j,t} = \begin{bmatrix} 0\ (affirmation, pos\ action\ or\ no\ review) & if\ Downaction^{*}_{i,j,t} \leq \mu_1 \\ 1\ (neg\ outlook, neg\ watch) & if\ \mu_1 < Downaction^{*}_{i,j,t} \leq \mu_2 \\ 2\ (downgrade) & if\ \mu_2 < Downaction^{*}_{i,j,t} \end{bmatrix}$$

where the cut-off points μ_m $(\mu_1 < \mu_2)$ and coefficients $\beta, \lambda,$ and θ are parameters to be estimated by Maximum likelihood (ML).

$Downaction_{i,j,t}$ takes the value of 2 for downgrades, 1 for negative outlooks or negative credit watches, and 0 otherwise (i.e., positive rating revisions, rating affirmations, or no rating reviews).[16] As described by S&P (2014; 2005) negative outlooks and credit watch episodes are often a precursor of future rating actions in the indicated direction. Therefore, we consider them in our analysis alongside actual downgrades. Accordingly, we weigh outlook and watch actions less heavily than the actual downgrades. Henceforth outlook refers to both outlook and credit watch actions.

$CAB\_Outlook_{i,t}$, $NetLB\_Outlook_{i,t}$ and $GDP\_Outlook_{i,t}$ are changes in the IMF's forecasts of current account balance (% of GDP), net government lending/borrowing (% of GDP) and GDP growth which capture countries' economic outlook changes as the result of the COVID-19 health crisis. Forecasts for each variable for 2020 and 2021 are obtained from three IMF World Economic Outlook reports published in October 2019 (which did not take into account the impact of COVID-19), April 2020 and October 2020 (which did). For each of these three economic indicators (and in each report) we obtain the average forecast of 2020 and 2021 for each country. We then calculate the change of the average forecast in a report compared to that from the previous report. The IMF lowered the unweighted country average forecast for 2020/2021 of current account balance, net government lending/borrowing and GDP growth by 0.83%, 2.74% and 2.06%, respectively (Table 2, Panel I). Therefore, it is reasonable to assume that a deeper downward revision of economic growth forecast in 2020 would coincide with a higher likelihood of a sovereign's rating being lowered. We expect the coefficients on *CAB_Outlook, NetLB_Outlook* and *GDP_Outlook* to be significant with a negative sign.

$CaseRates_{i,t}$ is the daily cumulative number of confirmed COVID-19 cases per million people for country i at time t. It is our main variable depicting the direct effect of the pandemic's

[16] During our sample period, there were just ten rating upgrades and 56 positive outlook/watch revisions across all three CRAs. Therefore, we merge positive rating actions with confirmations and non-actions into one category.

severity following recent literature (Ashraf et al., 2020; Baig et al., 2020; Fetzer et al., 2020; Hoang et al., 2020; Sharif et al., 2020).[17] We expect a positive sign for *CaseRates* coefficient implying the more severe the pandemic, the higher likelihood of a country facing negative rating revisions.

$GovtResponse_{i,t}$ is an indicator of the ability of governments to effectively manage external shocks (such as a financial crisis or a health emergency), which is an important consideration of institutional strength in sovereign methodologies (Fitch, 2020; S&P 2017). The index is reported daily and tracks different series of policies including closures and containment (school closures; workplace closures; cancelling public events, restrictions on gatherings, closures of public transport, stay at home requirements, international travel controls); economic measures (income support and debt/contract relief for households); and health measures (public information campaigns, testing policy, and contact tracing). The index takes values between 0 and 100, with 100 indicating the most comprehensive government responses to COVID-19. Accounting for substantial unprecedented stimuli packages often in a form of "whatever it takes strategy"[18] is an important consideration when creditworthiness of countries is considered, since strong measures can be a burden on economic activity and public finances. Our choice of an aggregate measure of governments' actions is supported by Izzeldin et al. (2021) who state that the COVID-19 crisis has not only been affected by the economic stimuli, other measures such as containment rules, travel restrictions, test and trace also played an important role. We expect a positive sign on the *GovtResponse* coefficient implying the stronger the government response to COVID-19, the higher likelihood of the sovereign being downgraded.

$Count_{i,j,t}$ measures the number of months elapsed since the last published ratings review for a sovereign. This variable identifies whether rating committees were convened at a date just in time to satisfy regulatory requirements or whether a committee was held earlier to respond to shifting fundamentals in a timely manner. If CRAs bring sovereign credits to a committee review exclusively based on need and urgency, rather than on historically derived review dates, coefficient on this variable should show little or no significance. In a sudden and sharp external

[17] We have also estimated our model using mortality rates, and results remain mainly unchanged (See Appendix B and C). The literature suggests case rates offer advantages over the measure of mortality rates. For example, Ashraf et al. (2020) find that the stock market reacts stronger to the number of confirmed cases than to a number of deceased.

[18] For example, the Fed dropped interest rates and issued support packages. The Bank of England similarly provided funds directly to business sectors (Izzeldin et al., 2021).

shock like the COVID-19 pandemic, it should simply not matter how much time has elapsed since the last rating review: if fundamentals suddenly change, the rating needs to be reviewed immediately. If on the other hand *Count* is positive and significant, it would imply that CRAs wait to release the new rating until the next rating scheduled in the calendar irrespective of the need of urgency caused by the pandemic.

$ShockandAwe_t$ is a binary variable which takes a value one if the observation falls into March 2020 and April 2020, 0 otherwise. The period marks the height of the first wave when the virus spreads exponentially on a global scale. It presents a high level of fear and uncertainty to the CRAs, regulators and financial markets concerning the lasting damage caused to the economies. We predict that sovereign ratings are most vulnerable to downgrades during this most uncertain period, hence the coefficient of *ShockandAwe* is expected to be positive and significant.

IMF *Region* dummies are added to control for the average time-invariant region heterogeneity. The IMF classifies countries into advanced economies (AEs) and five emerging and developing regions (EMDEs, i.e., Emerging & Developing Asia (ED ASIA), Emerging & Developing Europe (ED EUR), Latin America & Caribbean (LAC), Middle East & Central Asia (ME&CA), and Sub-Saharan Africa (SSA)). The economies in emerging and developing countries are less resilient to adverse shocks, while the quality of health care systems and social benefits are less adequate in developing countries than in developed countries. Hence negative revisions for these sovereigns could be anticipated. On the other hand, the economic shock caused by the pandemic was more severe for advanced than for developing countries (see Table 3), which usually hold a rating closer to the top of the scale. This would indicate that if the increase in default risk goes up for these nations, it would lead to more downgrades at the top.

CRA dummies ensure that our results are not driven by the differences in average ratings by the three CRAs.

First, we estimate Eq. (1) using pooled sample containing rating revisions by all the three CRAs to establish the rating industry' general behaviour during the current health crisis. This enables us to exploit differences in the case rates across different CRAs for the same issuer at the same time. Furthermore, we can identify the systematic effect of the case rates on rating actions by disentangling them from the country effects (Fracassi et al., 2016). For instance, it could be possible that the case rates merely reflect a well-designed health system operating in the well-functioning economy.[19]

Secondly, we estimate regressions using individual CRA sub-samples to examine rating agencies' individual reaction to the pandemic. Although this approach has limitations, it is a common practice in the rating literature (Williams et al., 2013). Therefore, we estimate Eq. (2):

$$Downaction^{*}_{i,t} = \beta_1 CAB\_Outlook_{i,t} + \beta_2 NetLB\_Outlook_{i,t} + \beta_3 GDP\_Outlook_{i,t} + \beta_4 CaseRates_{i,t} + \beta_5 GovtResponse_{i,t} + \beta_6 Count_{i,t} + \beta_7 ShockandAwe_t + \lambda Region + \varepsilon_{i,t} \quad (2)$$

Subscripts *i*, *t* stand for countries and months. $Downaction^{*}_{i,t}$ is a latent variable linked to the observed ordinal daily rating intensity $Downaction_{i,t}$ of a sovereign i at date t by one of the three CRAs. The rest of the variables are identified in Eq. (1).

4. Summary statistics

4.1. Full sample

Table 1 shows the distribution of credit rating events in our four samples: pooled, S&P, Moody's and Fitch. We also divide the events by IMF regions (See Section 3.1).[20] The pooled sample of three CRAs contains 5,171 observations for 137 sovereigns (Table 1, Panel I, Columns 2 and 3). We identify 603 sovereign rating events which include 99 downgrades and 121 negative rating outlooks and credit watches with negative implications (Panel I, Columns 8, 6, and 5 respectively). Individually the number of sovereigns receiving negative rating reviews of S&P and Fitch accounts for approximately 47.46% and 64.29% of their sovereign ratings portfolio, respectively (Panel II and IV, Column 10). Surprisingly Fitch leads in all negative revisions with 40 downgrades and 47 negative outlook revisions (Panel IV, Columns 6 and 5). S&P follows with 31 downgrades and 41 negative/watch revisions (Panel II, Columns 6 and 5). Moody's appears the least active amongst the three CRAs. They negatively reviewed ratings of only 48 sovereigns (around 36.64% their sovereign rating portfolio) including 28

[19] It is established that healthcare performance is strongly dependent on the strength of the economy. See OECD Observer:
https://oecdobserver.org/news/archivestory.php/aid/1241/Health_and_the_economy:_A_vital_relationship.html
[20] Additionally, for list of negative rating reviews per country see Appendix A.2.

downgrades and 33 negative rating outlooks/credit watches (Panel III, Columns 7, 10, 6, and 5).

Table 2 depicts the variable definitions and summary statistics of our key variables in four samples (Panel I-IV). The mean and standard deviation of *Downaction* are the largest in Fitch sub-sample (mean=0.08, sd=0.35; Table 2, Panel IV, Column 6), followed by S&P (mean=0.06, sd=0.30, Panel II) and Moody's (mean=0.05, sd=0.28; Panel III). *CAB_Outlook, NetLB_Outlook, GDP_Outlook* and *CaseRates* are winsorised per sub-sample at the top and bottom 1% to prevent outliers from distorting our analyses. All three macroeconomic indicators including current account balance, net government lending/borrowing and GDP growth experience reduction in (average) forecasts of 2020 and 2021 across three IMF's WEO reports. The number of confirmed cases per million stands at the average 9,087 (Panel I, Column 6), with the standard deviation of 16,235 implying a great diversity across countries. There is also a heterogeneity in the responses of governments to the pandemic manifested in a wide range between 0 and 89.69 with the average of 55.53 points and standard deviation of 16.86 points (Panel I, Columns 6 and 7).

On average there was a gap of approximately eight months between rating committees by any of the three CRAs (mean *Count**=7.81*,* Table 2, Panel I, Column 6). Both S&P and Fitch reviewed their sovereign ratings within six months of their previous review dates which is in line with the regulatory requirement (mean *SP_count**=5.88 months, mean *Fitch_count**=6.37 months; Panels II and IV respectively). Meanwhile, Moody's took much longer to reconsider their ratings (mean *Moody's_count** = 14.79 months) (Panel III).

4.2. Regional differences

Table 3 shows a regional breakdown of all independent variables. The number of confirmed cases per million is most severe in the Emerging and Developing Europe (ED EUR) (Table 3, Panel I, Column 7). Advanced economies (AEs), Latin America & Caribbean (LAC), and Middle East & Central Asia (ME&CA) also record large numbers of case rates while Emerging and Developing Asia (ED ASIA) has the lowest rate of COVID-19 infections. Notwithstanding the large variation in the depth of the heath crisis across regions, there is little discrepancy in the average government response index since it just hovers around 55.53 points.

Table 3 also reveals an interesting fact that Moody's, and S&P to a lesser extent, is slower in taking actions on advanced economies (AEs). According to a regional breakdown of *Count** (excluding non-event days), it takes 22.91 (6.24) months since the most recent review date for Moody's (S&P) to announce a rating action, which is longer than the overall average duration of 14.79 (5.88) months across all countries. This is surprising because the AEs were predicted to be hit harder by the pandemic, which is manifested in their net government lending/borrowing forecast being deducted by 3.61%, compared to the global average reduction of 2.74% (Table 3, Panel I, Column 5).

5. Empirical results

5.1. Pooled results

Table 4 presents the results of Eq. (1) using a pooled sample of S&P, Moody's and Fitch. We report specifications 1-3 where the control variables are added sequentially. In the most parsimonious Spec. (1) we include *CaseRates*, *GovtResponse*, *Count* and *ShockandAwe*. This simple model allows us to see the direction of the relationship between COVID-19 case rates and the sovereign rating actions. Moreover, in Spec. (2) we include *CAB_Outlook, NetLB_Outlook* and *GDP_Outlook* which control for the changes in the economic outlook that might be driving the sovereign ratings. Finally, Spec. (3) and our baseline result henceforth, includes the regional dummies controlling for the possibility of regional heterogeneity highlighted in Section 4.2. In columns 5-7 of Table 4 we calculate the marginal effects for the variables with statistically significant coefficients obtained in Spec. (3).[21]

We find an unexpected impact of COVID-19 severity, measured by the number of cases per million people, on sovereign rating actions. The coefficient on *CaseRates* is significant at 5% level with a negative sign in Spec. (1), suggesting the more COVID-19 cases are confirmed per million people, the less likelihood of a negative sovereign rating action. However, *CaseRates* becomes insignificant after we control the model for macroeconomic fundamentals and region fixed effects. It implies that there is little evidence for a causal relationship between the spread of the virus and a sovereign rating action. One possible explanation could be that the CRAs hold the view that the surge in infections will ultimately be a temporary phenomenon. The

[21] Additionally, we check the robustness of our baseline results from the pooled sample using the COVID-19 driven daily cumulative death toll as percentage of the population (*MortalityRates*) and find consistent results. The results are presented in Appendix B.

philosophy of rating "through the cycle", in this case a pandemic cycle, would then call for ratings stability (Altman and Rijken, 2004).

Contrary to *CaseRates,* the degree to which governments respond to the COVID-19 health crisis exerts a strong influence on CRAs' sovereign rating decisions. Countries which employed stronger COVID-19 measures face higher likelihood of adverse rating actions. Coefficient on *GovtResponse* (which is scaled from 1 to 100) has a positive sign and is highly significant at the 1% level across all model specifications. One point increase in the government response index raises the likelihood of a negative outlook and that of a downgrade by approximately 0.03% (Marginal effects, Spec. (3)). Strong COVID-19 measures require a significant amount of financial support which might have immediate and long-term consequences for economic prospects, thus, damaging the sovereign's intermediate and long-term creditworthiness. This finding is somewhat counterintuitive as countries which better weathered the COVID-19 crisis should be better off at least in the long run. As suggested by Izzeldin et al. (2021) those who introduced the rescue packages sooner and more thoroughly overcame the COVID-19 crisis better. The nature of credit ratings is different however as they present the horizons between three to five years into the future.

It is surprising that in the face of an unprecedented crisis, CRAs seem to be largely operating in a business-as-usual mode. The *Count* variable, which measures the time elapsed since the last published sovereign rating review, is significant at the 1% level and with a positive sign in all specifications. With each additional month that the preceding rating review ages, the probability of a downgrade (negative outlook) increases by 0.14% (0.13%) respectively (Marginal effects, Spec. (3)). This result reveals that sovereign ratings are not always reviewed based on the needs and urgency caused by the pandemic observed in the changes of market fundamentals. In contrast, the decision to bring a sovereign rating to a committee seems to be also significantly driven by CRAs regulatory historic review dates and rating schedules. This is especially worrying as there is no obligation to wait until the next possible review date. CRAs can call a committee on any sovereign and change its rating at any time if they can make the argument that a fundamental change to the credit outlook has occurred (EC, 2013).

Consistent with our expectation, there is strong evidence that negative sovereign rating actions are more likely during the first wave of the pandemic (March 2020- April 2020). Specifically, our *ShockandAwe* variable is significant at the 1% level with positive signs across all of the model specifications. Rating downgrades (negative outlooks) were 4.77% (3.96%) more likely to occur in the peak of the first wave than at other times. During that period, maximum uncertainty prevailed on how long the pandemic would last and how much human and economic damage it might have caused.

As anticipated, the coefficient on *GDP_Outlook* has a negative sign indicating that a sharper downward growth revision is associated with a higher likelihood of an adverse rating revision. We detect that growth revision is a strongly statistically significant (at 1% level) determinant of sovereign rating changes in both Spec (2) and (3). Each additional percentage point reduction in *GDP_Outlook* increases the likelihood of a rating downgrade by 0.42%, and that of a negative outlook by 0.40% (Marginal effects, Spec. (3)). Moreover, once controlling for the full set of regional dummies (Spec. (3)), *NetLB_Outlook* presents negative and statistically significant sign (at 5% level) suggesting deeper downward revision in net government lending to borrowing coincides with a higher likelihood of a sovereign's rating being lowered.

The sensitivity of sovereign ratings to the pandemic does vary across the geographic regions. The pooled results reveal favourable rating effects for advanced economies (AEs) and adverse effects for Sub-Saharan Africa (SSA) and Latin America & Caribbean (LAC). Being an AE sovereign increases the chance of successfully escaping a negative rating action (downgrade or negative outlook) between January 2020 and March 2021 by 2.66% (Marginal effects, Table 4). On the other hand, less developed nations in SSA and LAC are more likely to receive a downgrade, by 2.16% and 1.41% respectively, than the countries in the benchmark Middle East and Central Asia (ME&CA). These results are not surprising given significant downward growth revisions of these regions (See Table 3, Panel I).

There are two possible explanations for this rating resilience against negative rating actions for advance economies (AEs). One explanation could be that more prosperous and sophisticated economies have more resources to better absorb shocks without lasting damage to their creditworthiness. This includes their superior ability to mobilise fiscal and monetary support packages to cushion shocks in the short term. This is consistent with an empirical observation that higher ratings have historically been less volatile than lower rated categories (Kraemer and Gunter, 2020). For instance, 73% of S&P's AAA-rated sovereigns will still be rated AAA ten years later. This number will be half (33% and 38%) for sovereigns rated in the BB or B categories respectively.

The alternative explanation is that CRAs might present positive bias toward sovereigns of advanced economies. Some CRAs may still recall the political backlash that followed when they had lowered many AE ratings during the Euro area debt crisis (or, in the case of S&P, the downgrade of the US). In some instances, costly lawsuits in AE courts have been a consequence of downgrades (FT, 2015). A significant tightening of rating regulations is also believed to have been a consequence of what policymakers may have considered excessive AE downgrades (De Haan and Amtenbrink, 2012). The impact on business and operations may subconsciously have lingered in analysts' minds when making decisions on AE ratings, developing a subconscious status-quo bias. Also, CRAs have been told by the EU regulator to avoid quick-fire downgrades during the pandemic in fear of worsening the situation (Reuters, 2020).

5.2. Individual CRAs results

Table 5 presents results from Eq. (2) for each CRA sub-sample. Although our baseline result concerning the effects of macroeconomic variables on sovereign rating actions continue to hold, there is a heterogeneity across the three CRAs concerning the importance of each of the three macroeconomic variables. We find significant coefficients with negative signs on *CAB_Outlook* and *GDP_Outlook* in the sample of S&P's ratings (Spec. (2)). However, they turn insignificant after controlling for region fixed effects (Spec. (3)). In the case of Moody's, *GDP_Outlook* and *NetLB_Outlook* are negative and significant whilst *CAB_Outlook* is insignificant (Spec. (3)). Finally, in the case of Fitch, *GDP_Outlook* is strongly significant with the predicted negative sign but *CAB_Outlook* is weakly significant with a positive sign (Spec. (3)). According to Afonso et al. (2011), the effect of current account balance on sovereign ratings is uncertain. Our obtained result for Fitch indicates that current account deficit is reflective of an accumulation of capital inflows, which fuels growth and improves sovereign creditworthiness. Therefore, deterioration in the *CAB_Outlook* will reduce the likelihood of a negative rating action.

CaseRates is insignificant for S&P and Moody's, which is consistent with the baseline results. However, it is weakly significant at the 10% level with a negative sign for Fitch in all model specifications. One possible explanation for the unexpected negative sign on *CaseRates* is that not all countries record COVID-19 cases reliably. The testing and detection strategy, capacity and effectiveness differ across countries. For example, the COVID-19 positivity rate (i.e., the number of positive results out of total tests) demonstrates that countries' testing adequacy differs significantly.[22] Countries with very high infection rates such as Mexico typically test people who are developing severe symptoms and seeking medical attention (Agren, 2020). Meanwhile, Singapore, Korea and other low-positivity-rate countries extensively test close contacts (and even minor contacts) of COVID-19 cases, vulnerable groups, and incoming travellers (Lee and Lee, 2020).

GovtResponse is only significant in the Fitch model. One point higher index in *GovtResponse*, on average, reduces the chance of avoiding an adverse rating action by 0.13%, raises the higher likelihood of a negative outlook by 0.06%, and increases the probability of a downgrade by 0.07% (Spec. (3), Table 5, Panel II).

Count is positive and highly significant at 1% level in all model specifications for S&P and Fitch. Coefficient is also significant at 5% level for Moody's sub-sample in Spec. (3). This suggests that instead of organising a rating committee based on the needs and urgency reflecting the fundamental changes during the time of crisis, all the three global CRAs wait to review the ratings at the next pre-scheduled event. Notably the marginal effects of *Count* reveal that the business-as-usual mode is more evident in the case of S&P and Fitch than in the case of Moody's.

Consistent with the pool sample's regression in Table 4, we find similar evidence that negative sovereign rating actions are more likely at the height of the first wave due to the uncertainty surrounding the pandemic. *ShockandAwe* variable is significant at 1% level with positive sign in all the three sub-samples and all model specifications.[23]

Once again CRAs' reaction to the pandemic varies across the geographic regions. We find that less developed countries in the Sub-Saharan Africa (SSA) are more likely to get a downgrade from S&P and Moody's than the countries in the benchmark Middle East and Central Asia (ME&CA). This effect is significant at the 5% level. In the case of Moody's, we also find weak evidence that negative sovereign rating actions during the pandemic are more likely to occur to countries from Latin America & Caribbean (LAC). The positive bias to countries of advanced economies (AEs) is prevalent only in the case of S&P and Moody's. The coefficients on AEs dummy variable are negative and significant at the 5% and 1% level respectively. Moody's is 1.46% less likely to give a negative outlook, and 1.23% less willing to downgrade

[22] See the positivity rate comparison per country at: https://coronavirus.jhu.edu/testing/international-comparison
[23] The only exception is Spec. (2) for Moody's, where the coefficient is significant at 5% level.

sovereigns from advanced economies. The corresponding values in the sample of S&P's ratings are 1.16% less downgrades and 1.45% less negative outlooks.[24]

5.3. The business-as-usual approach: a market perspective

In this section, we examine empirically the reactions of three global CRAs to the ongoing pandemic from the perspective of financial market participants. Despite the rapidly changing circumstances of the pandemic, global CRAs have largely continued in a business-as-usual mode instead of elevating the review procedures to provide the timely updates of sovereign creditworthiness to the market participants. In other words, when scheduling sovereign rating committees, the CRAs, even in times of an exceptional crisis, still seem to be driven to a significant extent by the regulatory requirement to bring sovereigns to committee in predetermined intervals. An interesting question that emerges from this issue is whether financial markets are capable of detecting the CRAs' behavioural pattern. If so, this information should be incorporated into the movement of the financial asset prices.

Prior to the onset of the pandemic, CRAs have mostly adhered to that minimal requirement, reviewing and releasing sovereign ratings in roughly yearly intervals (or six-monthly for EU-regulated sovereign credits). We hypothesise that the closer CRAs are to their annual/bi-annual rating committee, the more likely sovereign credit spreads are to change if bond investors realise that CRAs are to release a rating action. Such an outcome is not anticipated if bond investors are oblivious to the CRAs' rating calendars, and in consequence a business-as-usual approach is taken during the pandemic. To test this prediction, we regress the sovereign bond yield spreads on *Count* and *Downaction* using the sovereign credit rating actions announced by S&P, Moody's and Fitch during the period January 2020 - March 2021. Our regressions utilise a large cross-country dataset of sovereign bond spreads obtained from Datastream.[25]

[24] Additionally, we check robustness of our results from the analyses of individual CRAs using mortality rates. We find that the results remain unchanged and strongly consistent with the results using infection case rates. Moreover, mortality rates are insignificant in all model specifications, thereby lend support to our argument that CRAs' sovereign rating assessments are not triggered directly by the depth of the health crisis. Full results of Eq. (2) using mortality rates are displayed in Appendix C.

[25] Merging bond spreads with our sample results in missing data points due to the scarcity of bond data. Our pooled sample is left with 2328 observations for 72 countries for whom bond yields are available.

We argue that an empirical analysis from the perspective of financial markets provides original insights to the literature. Recall that the current situation of the pandemic is different to the past episodes of market downturns which moved CRAs to the forefront of the debate. For example, one could observe accelerated rating committees during the 2010 European sovereign debt crisis when S&P reviewed all and downgraded several Euro area sovereigns in January 2012 (S&P, 2012). Although CRAs' accelerating approach provided rating users with a full view of comparable ratings, it also subjected them to criticism from regulators. Public criticism against the CRAs also emerged during the 1997 Asian currency crisis and the 2007 global financial crisis. CRAs were blamed for following rather than leading the market (i.e., upgrades in good times and downgrades in bad times) (Kaminsky and Schmukler, 2002). The pro-cyclicality of sovereign ratings exacerbates the euphoria among investors on the bond markets, thereby aggravating the market instability (Afonso et al., 2014; Reisen and Maltzan, 1999). Therefore, if the markets can identify CRAs' change of approach (from accelerating review efforts in the past to adhering to the minimum regulatory requirements during the ongoing pandemic) then sovereign rating actions will not prompt as significant adjustment in sovereign credit spreads as documented in the past crises (Baum et al., 2016; De Santis, 2014). In this respect, our empirical analysis in this section makes an original contribution to the literature.

To test our prediction, we employ the following multivariate linear regression model:

$$\Delta Spread_{i,t} = \beta_1 Count_{i,j,t} + \beta_2 Downaction_{i,j,t} + \beta_3 Downaction_{i,j,t} * CaseRates_{i,t} + \beta_4 Downaction_{i,j,t} * GovtResponse_{i,t} + \beta_5 GDP\_Outlook_{i,t} + \beta_6 CAB\_Outlook_{i,t} + \beta_7 NetLB\_Outlook_{i,t} + \beta_8 CaseRates_{i,t} + \beta_9 GovtResponse_{i,t} + \beta_{10} ShockandAwe_t + \beta_{11} Maturity_{i,t} + \beta_{12} Amount_{i,t} + \lambda Region + \theta CRA + \varepsilon_{i,j,t} \quad (3)$$

Eq. (3) is estimated for the pooled sample and for individual CRAs.[26] Note for the latter regressions the CRA dummy is removed.

[26] The literature reveals mixed results regarding the effects of individual CRA's rating news on securities' prices, whereby foreign exchange rates, bond spreads and credit default swaps (CDS) spreads react heterogeneously to the sovereign rating news from individual CRAs (e.g., Afonso et al., 2012; Alsakka and ap Gwilym, 2012; Brooks et al., 2004).

The dependent variable $\Delta Spread_{i,t}$ represents the change of sovereign bond yield spread[27] (measured in basis points) of country i in the event window [0,+1]. Date 0 is the event date when the rating action is publicly released and date +1 is the business day immediately following date 0. Our data includes US dollar denominated senior unsecured sovereign bonds whose market data is available during the examined period. Since each sovereign might have more than one bond outstanding, we select for each sovereign the bond with the largest issue volume as representative bond. The bonds' remaining maturities range from one year to 29 years.

Although we impose several data filtering rules to make sure that bond data is homogenous such as currency of denomination, seniority, coupon type, absence of embedded options, our bond spread data is heterogenous in terms of issue volume ($Amount_{i,t}$) and maturity ($Maturity_{i,t}$). Therefore, in Eq. (3), we control for these two bond specific characteristics that can affect the bond spreads.

The remaining variable descriptions follow those of Eq. (1). Finally, we include the interactions of $Downaction_{i,j,t}$ with two COVID-19 related variables including $CaseRates_{i,t}$ and $GovtResponse_{i,t}$ to capture the effects of country-specific depth of the health crisis and the government response to the crisis on the information value of sovereign rating news.

We envisage that coefficient β_1 on *Count* variable will be statistically significant with a positive sign if markets embed the CRAs' business-as-usual approach into the bond prices. Longer the time elapsed since the previous rating review (closer it is to the next rating committee), the bigger the spreads as markets adjust pricing with expectation of a forthcoming rating action.

Moreover, sovereign bond market reaction to sovereign rating news is captured by the coefficient β_2 on *Downaction*. We predict β_2 will be statistically insignificant if the CRAs' business-as-usual working mode is reflected in the sovereign credit premium (spreads). This is because the rating actions are anticipated by the markets and spreads adjust in the period leading to the actual announcement of rating changes.

[27] Spread is the yield to maturity of a sovereign bond minus the yield on a benchmark US treasury note/bond with comparable maturity with the sovereign bond of interest.

Table 6 presents the full estimation results. Pooled results are displayed in Columns (1)-(2) while individual CRA results in Columns (3)-(8). Variable *Count* is indistinguishable from zero in all model specifications. This is in line with the notion that rating actions released during the pandemic are not anticipated by the financial market participants, which is opposite to our expectation. More importantly, it implies that CRAs' disappointing reactions to the pandemic have not been fully picked up by the financial markets.

Consistent with the above finding, we obtain positive estimates on the coefficient β_2 of *Downaction* in Columns (1), (2). β_2 remains significant at 1% level and robust to the inclusion of region fixed effects. The estimation on the pooled sample reveals that, compared to the benchmark cases of no rating news, confirmations and positive rating news, *ΔSpread* increases by 71.06 basis points when a CRA releases a negative outlook. The relationship between rating actions and bond spreads is strong for S&P (Table 6, Columns (3) and (4)) and moderate for Moody's in individual CRAs sub-samples (Table 6, Columns (5) and (6)). Contrary to S&P and Moody's, Fitch's rating announcements during the pandemic do not trigger significant immediate reactions in the sovereign bond yield spreads. Our results show that the markets do not realise there has been a change of working mode among global CRAs, particularly S&P and Moody's. Their rating actions announced during the pandemic still trigger significant reactions from the markets, especially the negative actions by S&P, which resembles what happened during the European sovereign debt crisis (Alsakka and ap Gwilym, 2013; Alsakka et al., 2017).

Turning to the interactions of *Downaction* with *CaseRates* and with *GovtResponse*, we do not find any evidence that the magnitude of the market reactions to rating news varies with the spread of the virus (coefficient estimate β_3 on the interaction of *Downaction* with *CaseRates* is insignificant in all model specifications*)*. The estimates of β_4 on the interaction of *Downaction* with the government response index *GovtResponse* are negative and strongly significant at 1% level in the pooled sample and the sub-sample of S&P. It indicates that the restrictive measures put in place by governments in containing the spread of the virus have attenuating effects on the yield spreads when S&P announces a negative rating action. This result is interesting as it reveals that there is a disagreement between CRAs and the market participants regarding the counter measures imposed by governments during the pandemic. From the perspective of the market participants, restrictions measures are perceived positively. This might be because investors put more hope in a quick return to normality in countries that take prompt actions to contain the virus. This result contrasts with our previous sections which highlight the detrimental repercussion of such containing measures on sovereign creditworthiness.

In summary, our bond analysis shows that investors do not recognise the global CRAs' business-as-usual working mode during the pandemic. Accordingly, rating actions released during COVID-19 by S&P and Moody's are still treated as 'news', hence reflected in the adjustments of sovereign credit spreads. In addition, the magnitude of the yield spread changes following a release of a negative rating action vary with the governments' response to COVID-19. Despite the economic cost of governments' counter measures, the market perceives them to be a necessary step in moving a country out of the epidemic and bringing the economy back to normal.

6. Conclusion

This is the first paper that investigates the response of the three largest CRAs to the COVID-19 pandemic. We document four key empirical findings. We find that economic repercussions of the pandemic, such as a country's economic outlook and the government's response to the health crisis triggered negative sovereign rating actions, not the severity of the pandemic itself (measured by case and mortality rates). Each additional percentage point reduction in the 2020-2021 average GDP growth forecast increased the likelihood of a rating downgrade by 0.42%, and that of a negative outlook by 0.40%.

On the other hand, we find that the government's response to the pandemic has unintended consequences for sovereign creditworthiness. Specifically, more comprehensive measures to fight the pandemic such as restricting mobility and contact or mitigating public spending programmes lead to a higher likelihood of negative revisions. A one point increase in the index value increases the likelihood of a downgrade or a negative outlook by 0.03%.

Contrary to expectations, our results conclude that in the face of an unprecedented crisis, CRAs have often continued to operate in a business-as-usual mode reviewing ratings close to the dates when they would have been due to be reviewed for regulatory purposes. For each month that the preceding rating review ages, the probability of a downgrade increases by 0.14% and that of a negative outlook or watch by 0.13%. This finding has policy implications suggesting that the CRAs prefer to stick to initial committees set in advance rather than reacting in a more timely manner to the rapidly deteriorating fundamentals.

Although CRAs' hesitance in elevating rating reviews in the pandemic is disappointing from the markets' perspective, our findings show that rating users do not realise this. We document two important evidences for the market's oblivion to the CRAs' business-as-usual working mode. First, we find no evidence that sovereign credit spreads adjust as CRAs move closer to a next pre-scheduled review date. Second, actual sovereign rating announcements in the pandemic are still met with significant reactions in the sovereign credit spreads. Specifically, spreads can increase by 71 basis points in the window [0; +1] of a negative sovereign rating action in the pandemic. Amongst the CRAs, downgrades by S&P caused the largest market impact. Apart from the market oblivion to the CRAs business-as-usual mode, we find a smaller increase in yield spreads for countries actively engaged in a fight against the virus. Our finding implies that the CRAs and investors are in disagreement. CRAs were more likely to lower the rating when a government pulled the resources to stop the spread of the virus. Investors, on the other hand have rewarded decisive action by governments with lower spreads.

Declarations of interest: none.

Acknowledgments: We would like to thank anonymous referees for their comments and Thang Ngoc Dang and Lucia Murgia for their invaluable research assistance.

Author statement: **Yen Tran**: Data curation; Formal analysis; Investigation; Validation; **Huong Vu**: Conceptualization; Investigation; Methodology; Supervision; Writing – original draft; Writing - review & editing; **Patrycja Klusak:** Conceptualization; Investigation; Methodology; Project ad- ministration; Writing – original draft; Writing - review & editing; **Moritz Kraemer:** Conceptualization; Investigation; Methodology; Writing – original draft; Writing -review & editing; **Tri Hoang:** Data curation; Investigation; Visualization; Validation.

References

Acharya, V. V. and Steffen, S. (2020). The Risk of Being a Fallen Angel and the Corporate Dash for Cash in the Midst of COVID. *Review of Corporate Finance Studies,* 9, 430-471.

Afonso, A., Furceri, D. and Gomes, P. (2012). Sovereign Credit Ratings and Financial Markets Linkages: Application to European Data. *Journal of International Money and Finance*, 31, 606-638.

Afonso, A., Gomes, P. and Rother, P. (2011). Short- and Long-run Determinants of Sovereign Debt Credit Ratings. *International Journal of Finance and Economics,* 16, 1-15.

Afonso, A., Gomes, P. and Taamouti, A. (2014). Sovereign Credit Ratings, Market Volatility, and Financial Gains. *Computational Statistics and Data Analysis*, 76, 20–33.

Agren, D. (2020). Understanding Mexican Health Worker COVID-19 Deaths. Lancet, 396(0254), 807.

Akhtaruzzaman, M., Boubaker, S. and Sensoy, A. (2020). Financial Contagion During COVID–19 Crisis. *Finance Research Letters*, 101-604.

Alsakka, R. and ap Gwilym, O. (2013). Rating Agencies' Signals During the European Sovereign Debt Crisis: Market Impact and Spillovers. *Journal of Economic Behavior and Organization*, 85, 144-162.

Alsakka, R. and ap Gwilym, O. (2012). Foreign Exchange Market Reactions to Sovereign Credit News. *Journal of International Money and Finance,* 31**,** 845-864.

Alsakka, R. and ap Gwilym, O. (2010). Leads and Lags in Sovereign Credit Ratings. *Journal of Banking and Finance*, 34, 2614-2626.

Alsakka, R., ap Gwilym, O. and Vu, H. (2017). Differences of Opinion in Sovereign Credit Signals During the European Crisis. *European Journal of Finance,* 23, 859-884.

Alsakka, R., ap Gwilym, O. and Vu, N. T. (2014). The Sovereign-Bank Rating Channel and Rating Agencies' Downgrades During the European Debt Crisis. *Journal of International Money and Finance*, 49, 235-257.

Altman, E. I. and Rijken, H. A. (2004). How Rating Agencies Achieve Rating Stability. *Journal of Banking and Finance*, 28, 2679-2714.

Ashraf, B. N. (2020). Research in International Business and Finance Stock Markets' Reaction to COVID-19: Cases or Fatalities? *Research in International Business and Finance*, 54, 101249.

Azimli, A. (2020). The Impact of COVID-19 on the Degree of Dependence and Structure of Risk-Return Relationship: A Quantile Regression Approach. *Finance Research Letters*, 36, 101648.

Baig, A. S., Butt, H. A., Haroon, O. and Rizvi, S. A. R. (2020). Deaths, Panic, Lockdowns and US Equity Markets: The Case of COVID-19 Pandemic. *Finance Research Letters*, 101701.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M. and Viratyosin, T. (2020). The Unprecedented Stock Market Reaction to COVID-19. *Review of Asset Pricing Studies*, 10, 742–758.

Balajee, A. (2020). COVID-19, Fiscal Stimulus, and Credit Ratings. CAFRAL Working Paper.

Bank of England (BOE) (2011). Whither the Credit Ratings Industry? *Financial Stability Paper*, No. 9. March 2011.

Bannier, E. C., Behr, P. and Guttler, A. (2010). Rating Opaque Borrowers: Why Are Unsolicited Ratings Lower? *Review of Finance*, 14, 263–294.

Baum, C. F., Schäfer, D. and Stephan, A. (2016). Credit Rating Agency Downgrades and the Eurozone Sovereign Debt Crises. *Journal of Financial Stability*, 24, 117-131.

Becker, B. and Milbourn, T. (2011). How Did Increased Competition Affect Credit Ratings? *Journal of Financial Economics*, 101, 493–514.

Binder, C. (2020). Coronavirus Fears and Macroeconomic Expectations. *Review of Economics and Statistics*, 102, 721–730.

Borensztein, E., Cowan, K. and Valenzuela, P. (2013). Sovereign Ceiling Lite? The Impact of Sovereign Ratings on Corporate Ratings in Emerging Market Economies. *Journal of Banking and Finance*, 37, 4014–4024.

Brooks, R., Faff, R. W., Hillier, D. and Hillier, J. (2004). The National Market Impact of Sovereign Rating Changes. *Journal of Banking and Finance*, 28, 233-250.

Cantor, R. and Mann, C. (2007). Analyzing the Trade-Off Between Ratings Accuracy and Stability. *Journal of Fixed Income*, 16, 60-68.

Cepoi, C. O. (2020). Asymmetric Dependence Between Stock Market Returns and News During

COVID-19 Financial Turmoil. *Finance Research Letters*, 36, 101658.
Conlon, T. and McGee, R. (2020). Safe Haven or Risky Hazard? Bitcoin During the COVID-19 Bear Market. *Finance Research Letters*, 35, 101607.
Corbet, S., Larkin, C. and Lucey, B. (2020). The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. *Finance Research Letters,* 35, 101554.
Correia, S., Luck, S. and Verner, E. (2020). Pandemics Depress the Economy, Public Health Interventions Do Not: Evidence From the 1918 Flu. SSRN Working Paper 3561560.
De Haan, J. and Amtenbrink, F. (2012). Taming the Beast? New European Regulation for Credit Rating Agencies. Zeitschrift für Staats-und Europawissenschaften (ZSE)/Journal for Comparative Government and European Policy, 433-458.
De Santis, R. A. (2014). The Euro Area Sovereign Debt Crisis: Identifying Flight-To-Liquidity and the Spillover Mechanisms. *Journal of Empirical Finance*, 26, 150-170.
Eichenbaum, M. S., Rebelo, S. and Trabandt M. (2020). The Macroeconomics of Epidemics. NBER Working Paper 26882.
European Commission (EC) (2013). EU CRA Regulation. Regulation (EU) No 1060/2009 on Credit Rating Agencies, as Amended by Regulation (EU) No 462/2013.
Fetzer, T., Hermle, J., Hensel, L. and Roth, C. (2020). Coronavirus Perceptions and Economic Anxiety. *Review of Economics and Statistics*. Forthcoming. 1–36.
Financial Times (FT), (2015). Italy Seeks to Prosecute Sandp and Fitch Over Ratings. Oct 4, 2015.
Fitch, (2020). Sovereign Rating Criteria Master Criteria. Oct 26, 2020.
Fracassi, C., Petry, S. and Tate, G. (2016). Does Rating Analyst Subjectivity Affect Corporate Debt Pricing? *Journal of Financial Economics*, 120, 514–538.
Fulghieri, P., Strobl, G. and Xia, H. (2014). The Economics of Solicited and Unsolicited Credit Ratings. *Review of Financial Studies*, 27, 484–518.
Gibert, A. (2019). Solicited Versus Unsolicited Ratings: The Role of Selection. *Journal of Financial Management, Markets and Institutions,* 7, 1950005.
Goodell, J. W. (2020). COVID-19 and Finance : Agendas For Future Research. *Finance Research Letters*, 35, 101512.
Goodell, J. W. and Goutte, S. (2020). Co-movement of COVID-19 and Bitcoin: Evidence From Wavelet Coherence Analysis. *Finance Research Letters*, (June), 101625.
Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S. and Tatlow, H. (2021). A Global Panel Database of Pandemic Policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, 5, 529-538.
Hamilton, D. T. and Cantor, R. (2004). Rating Transition and Default Rates Conditioned on Outlooks. *Journal of Fixed Income*, 14, 54-70.
Hoang, D. P. B. and Narayan, P. K. (2020). Country Responses and the Reaction of the Stock Market to COVID-19 — a Preliminary Exposition. *Emerging Markets Finance and Trade*, 56, 2138–2150.
House of Commons (2012). Inquiry into Credit Rating Agencies. Uncorrected Transcript of Oral Evidence Taken Before the Treasury Committee. HC 1866-ii, 7 March 2012.
International Monetary Fund (IMF) (2020a). World Economic Outlook, October 2020: A Long and Difficult Ascent. Oct. 2020.
International Monetary Fund (IMF) (2020b). WEO Database, October 2020. https://www.imf.org/en/Publications/WEO/weo-database/2020/October.
Izzeldin, M., Muradoğlu, Y. G., Pappas, V. and Sivaprasad, S. (2021). The Impact of Covid-19 on G7 Stock Markets Volatility: Evidence from a ST-HAR Model. *International Review of Financial Analysis*, 74, 101671.
Ji, Q., Zhang, D. and Zhao, Y. (2020). Searching for Safe-Haven Assets During the COVID-19 Pandemic. *International Review of Financial Analysis,* 71, 101526.
Kaminsky, G. and Schmukler, S. L. (2012). Emerging Market Instability. Do Sovereign Ratings Affect Country Risk and Stock Returns? *World Bank Economic Review,* 16, 171-195.
Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P.-O. and Zúñiga, D. (2020). Corporate Bond Liquidity During the COVID-19 Crisis. NBER Working Paper 27355.
Kedia, S., Rajgopal, S. and Zhou, X. (2014). Did Going Public Impair Moody's Credit Ratings? *Journal of Financial Economics*, 114, 293–315.

Klusak, P., Alsakka, R. and Gwilym, O. A. (2017). Does the Disclosure of Unsolicited Sovereign Rating Status Affect Bank Ratings? *British Accounting Review*, 49, 194-210.
Kraemer, M. (2020). Asian Emerging Markets Must Brace for Coming Wave of Downgrades – and Debt Defaults. South China Morning Post, Oct 11, 2020.
Kraemer, N. and Gunter, E. (2020). 2019 Annual Sovereign Default and Rating Transition Study. S&P Global, May 18, 2020.
Lee, D. and Lee, J. (2020). Testing on the Move: South Korea's Rapid Response to the COVID-19 Pandemic. *Transportation Research Interdisciplinary Perspectives*, 5, 100111.
Lyócsa, Š., Baumöhl, E., Výrost, T. and Molnár, P. (2020). Fear of the Coronavirus and the Stock Markets. *Finance Research Letters*, 36, 101735.
Mnif, E., Jarboui, A. and Mouakhar, K. (2020). How the Cryptocurrency Market Has Performed During COVID 19 ? A Multifractal Analysis. *Finance Research Letters*, 36, 101647.
Moody's, (2020). Rating Symbols and Definitions. Dec 14, 2020.
Mora, N. (2006). Sovereign Credit Ratings: Guilty Beyond Reasonable Doubt? *Journal of Banking and Finance*, 30, 2041-2062.
Poon, W. P. H. (2003). Are Unsolicited Credit Ratings Biased Downward? *Journal of Banking and Financ*e, 27, 593–614.
Reisen, H. and Von Maltzan, J. (1999). Boom and Bust and Sovereign Ratings. *International Finance*, 2, 273-293.
Reuters, (2020). EU Watchdog Cautions Rating Agencies over Knee-Jerk Downgrades in Pandemic. Apr 9, 2020.
Salisu, A. A. and Vinh, X. (2020). Predicting Stock Returns in the Presence of COVID-19 Pandemic: The Role of Health News. *International Review of Financial Analysis*, 71, 101546.
Securities and Exchange Commission (SEC), (2020). Annual Report on Nationally Recognised Statistical Rating Organisations. December 2020.
Sharif, A., Aloui, C. and Yarovaya, L. (2020). COVID-19 Pandemic, Oil Prices, Stock Market, Geopolitical Risk and Policy Uncertainty Nexus in the US Economy: Fresh Evidence From the Wavelet- Based Approach. *International Review of Financial Analysis*, 70, 101496.
S&P, (2018). S&P Global Ratings Definitions. August 18, 2018.
S&P, (2017). Sovereign Rating Methodology. Dec 18, 2017.
S&P, (2014). Outlooks: The Sovereign Credit Weathervane. Year-End 2012 Update. February 4, 2014.
S&P, (2012). Standard & Poor's Takes Various Rating Actions on 16 Eurozone Sovereign Governments. Jan 13, 2012.
S&P, (2005). CreditWatch and Ratings Outlooks: Valuable Predictors of Ratings Behavior. Jun 01, 2005.
Stolper, A. (2009). Regulation of Credit Rating Agencies. *Journal of Banking and Finance*, 33, 1266-1273.
Wang, J., Lu, X., He, F. and Ma, F. (2020). Which Popular Predictor is More Useful to Forecast International Stock Markets During the Coronavirus Pandemic: VIX vs EPU? *Finance Research Letters*, 72, 101596.
Wang, L., Zhang, M. and Verousis, T. (2021). The Road to Economic Recovery: Pandemics and Innovation. *International Review of Financial Analysis*, 75, 101729.
Williams, G., Alsakka, R. and ap Gwilym, O. (2013). The Impact of Sovereign Rating Actions on Bank Ratings in Emerging Markets. *Journal of Banking and Finance*, 37, 563–577.
World Health Organisation (WHO) (2020). WHO Timeline - COVID-19. Apr 27, 2020. https://www.who.int/news/item/27-04-2020-who-timeline---covid-19
Yarovaya, L., Brzeszczynski, J., Goodell, J. W., Lucey, B. M. and Lau, C. K. (2020). Rethinking Financial Contagion: Information Transmission Mechanism During the COVID-19 Pandemic. Working Paper.
Zhang, W. and Hamori, S. (2021). Crude Oil Market and Stock Markets During the COVID-19 Pandemic: Evidence from the US, Japan, and Germany. *International Review of Financial Analysis*, 74, 101702.

Table 1 - Credit rating agencies' rating reviews from 30 Jan 2020 to 31 Mar 2021 - by IMF regions

Region	No. of Obs.	Sovereigns	Reviews/ Reviewed Sovereigns					% Neg Revisions	% Sovereigns Received Negative Revisions
			Affirmation or Positive Revisions/ Sovereigns	Negative Outlooks or Watches/ Sovereigns	Downgrades/ Sovereigns	Total Negative Revisions/ Sovereigns	Total Revisions/ Sovereigns		
PANEL I: 3 CRAS									
ED ASIA	563	15	24/9	15/10	10/5	25/11	49/13	4.44	73.33
ED EUR	502	13	56/13	12/9	1/1	13/9	69/13	2.59	69.23
LAC	853	23	39/17	25/15	36/13	61/19	100/23	7.15	82.61
ME&CA	698	19	54/16	20/13	14/6	34/14	88/18	4.87	73.68
SSA	862	29	52/23	26/19	31/17	57/25	109/28	6.61	86.21
AEs	1,693	38	158/38	23/16	7/6	30/21	188/38	1.77	55.26
Total	**5,171**	**137**	**383/116**	**121/82**	**99/48**	**220/99**	**603/133**	**4.25**	**72.26**
PANEL II: S&P									
ED ASIA	182	12	10/8	4/4	3/2	7/6	17/12	3.85	50.00
ED EUR	180	12	27/12	5/5	0/0	5/5	32/12	2.78	41.67
LAC	315	23	21/16	9/9	14/11	23/16	44/23	7.30	69.57
ME&CA	229	16	30/15	6/6	4/3	10/8	40/16	4.37	50.00
SSA	268	19	25/17	9/9	10/10	19/13	44/19	7.09	68.42
AEs	568	36	73/36	8/8	0/0	8/8	81/36	1.41	22.22
Total	**1742**	**118**	**186/104**	**41/41**	**31/26**	**72/56**	**258/118**	**4.13**	**47.46**
PANEL III: MOODY'S									
ED ASIA	210	15	6/6	5/5	3/3	8/6	14/11	3.81	40.00
ED EUR	171	13	8/8	1/1	1/1	2/2	10/10	1.17	15.38
LAC	291	22	6/6	8/8	9/7	17/13	23/16	5.84	59.09
ME&CA	249	19	8/6	6/6	4/3	10/7	18/12	4.02	36.84
SSA	333	25	9/8	11/11	10/9	21/17	30/20	6.31	68.00
AEs	525	37	20/20	2/2	1/1	3/3	23/23	0.57	8.11
Total	**1779**	**131**	**57/54**	**33/33**	**28/24**	**61/48**	**118/92**	**3.43**	**36.64**
PANEL IV: FITCH									
ED ASIA	171	11	8/6	6/6	4/3	10/7	18/11	5.85	63.64
ED EUR	151	10	21/10	6/6	0/0	6/6	27/10	3.97	60.00
LAC	247	18	12/11	8/8	13/10	21/16	33/18	8.50	88.89
ME&CA	220	16	16/11	8/8	6/5	14/11	30/16	6.36	68.75
SSA	261	19	18/13	6/6	11/8	17/14	35/19	6.51	73.68
AEs	600	38	65/35	13/13	6/6	19/18	84/38	3.17	47.37
Total	**1650**	**112**	**140/86**	**47/47**	**40/32**	**87/72**	**227/112**	**5.27**	**64.29**

Notes: This table presents summary statistics for the credit rating dataset, which includes monthly ratings including outlook and watch by S&P, Moody's and Fitch from 137 sovereigns for the period 30 Jan 2020- 31 Mar 2021. Abbreviation of regions: ED ASIA (Emerging & Developing Asia), ED EUR (Emerging & Developing Europe), LAC (Latin America & Caribbean), ME&CA (Middle East & Central Asia), SSA (Sub-Saharan Africa), and AEs (Advanced Economies).

Table 2 - Summary statistics

Variables	Units	Definitions	N	median	mean	sd	min	max
PANEL I: 3 CRAs								
Downaction	0-1-2	0 No review/Affirma/Pos review; 1 Neg outlook/watch; 2 Downgrade	5171	0.00	0.06	0.31	0.00	2.00
CAB_Outlook	% GDP	Change in IMF's Current Account Balance forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	5171	-0.19	-0.83	3.13	-14.76	5.51
NetLB_Outlook	% GDP	Change in IMF's Govt Net Lending/Borrowing forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	5171	-2.34	-2.74	2.68	-14.70	3.10
GDP_Outlook	% GDP	Change in IMF's GDP forecast (%, 2020-2021 average) from Oct 2019 to Oct 2020	5171	-2.16	-2.06	1.44	-5.40	1.76
CaseRates	1/million	COVID-19 cases per 1 million people	5171	1444.49	9087.26	16235.09	0.03	79597.33
GovtResponse	0-100	Government response to COVID-19 index	5171	58.85	55.53	16.86	0.00	89.69
Count	months	No. of months since the last rating review by three CRAs	5171	4.60	6.27	5.86	0.03	32.43
Count*	months	No. of months since the last rating review by three CRAs excluding non-rating events	603	6.07	7.81	5.73	0.17	32.43
ShockandAwe	0-1	1 March and April 2020; 0 Otherwise	5171	0.00	0.13	0.34	0.00	1.00
PANEL II: S&P								
Downaction	0-1-2	0 No review/Affirma/Pos review; 1 Neg outlook/watch; 2 Downgrade	1742	0.00	0.06	0.30	0.00	2.00
CAB_Outlook	% GDP	Change in IMF's Current Account Balance forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	1742	-0.20	-0.81	2.94	-14.76	5.30
NetLB_Outlook	% GDP	Change in IMF's Govt Net Lending/Borrowing forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	1742	-2.38	-2.78	2.68	-14.70	3.10
GDP_Outlook	% GDP	Change in IMF's GDP forecast (%, 2020-2021 average) from Oct 2019 to Oct 2020	1742	-2.25	-2.08	1.41	-5.40	1.26
CaseRates	1/million	COVID-19 cases per 1 million people	1742	1444.37	9287.55	16486.51	0.02	79597.33
GovtResponse	0-100	Government response to COVID-19 index	1742	58.85	55.86	16.57	0.00	89.69
SP_count	months	No. of months since the last rating review by S&P	1742	3.63	3.95	2.74	0.03	15.37
SP_count*	months	No. of months since the last rating review by S&P excluding non-rating events	258	6.07	5.88	2.65	0.20	15.37
ShockandAwe	0-1	1 March and April 2020; 0 Otherwise	1742	0.00	0.14	0.35	0.00	1.00

PANEL III: MOODY'S								
Downaction	0-1-2	0 No review/Affirmation/Pos review; 1 Neg outlook/watch; 2 Downgrade	1779	0.00	0.05	0.28	0.00	2.00
CAB_Outlook	% GDP	Change in IMF's Current Account Balance forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	1779	-0.20	-0.80	3.13	-14.76	6.16
NetLB_Outlook	% GDP	Change in IMF's Govt Net Lending/Borrowing forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	1779	-2.28	-2.62	2.60	-14.70	2.76
GDP_Outlook	% GDP	Change in IMF's GDP forecast (%, 2020-2021 average) from Oct 2019 to Oct 2020	1779	-2.16	-2.06	1.44	-5.80	1.76
CaseRates	1/million	COVID-19 cases per 1 million people	1779	1246.15	8379.91	15421.28	0.03	78249.83
GovtResponse	0 to 100	Government response to COVID-19 index	1779	58.07	54.82	17.06	0.00	89.69
Moody's_count	months	No. of months since the last rating review by Moody's	1779	9.20	10.56	7.59	0.03	32.43
Moody's_count*	months	No. of months since the last rating review by Moody's excluding non-rating events	118	14.53	14.79	9.00	0.83	32.43
ShockandAwe	0-1	1 March and April 2020; 0 Otherwise	1779	0.00	0.12	0.32	0.00	1.00
PANEL IV: FITCH								
Downaction	0-1-2	0 No review/Affirmation/Pos review; 1 Neg outlook/watch; 2 Downgrade	1650	0.00	0.08	0.35	0.00	2.00
CAB_Outlook	% GDP	Change in IMF's Current Account Balance forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	1650	-0.17	-0.86	3.32	-14.76	5.51
NetLB_Outlook	% GDP	Change in IMF's Govt Net Lending/Borrowing forecast (% GDP, 2020-2021 average) from Oct 2019 to Oct 2020	1650	-2.52	-2.84	2.75	-14.70	3.10
GDP_Outlook	% GDP	Change in IMF's GDP forecast (%, 2020-2021 average) from Oct 2019 to Oct 2020	1650	-2.16	-2.05	1.49	-5.80	1.76
CaseRates	1/million	COVID-19 cases per 1 million people	1650	1683.13	9626.56	16746.85	0.02	79789.67
GovtResponse	0-100	Government response to COVID-19 index	1650	59.11	55.93	16.94	0.00	89.69
Fitch_count	months	No. of months since the last rating review by Fitch	1650	3.73	4.09	2.73	0.03	12.10
Fitch_count*	months	No. of months since the last rating review by Fitch excluding non-rating events	227	6.07	6.37	2.41	0.17	12.10
ShockandAwe	0-1	1 March and April 2020; 0 Otherwise	1650	0.00	0.14	0.34	0.00	1.00

Notes: This table presents the summary statistics, abbreviations and definitions of variables used in the multivariate analysis on 137 sovereigns rated by S&P, Moody's and Fitch for the period 30 Jan 2020- 31 Mar 2021. "Obs." is the number of observations. "S.D." is the standard deviation. *CAB_Outlook, NetLB_Outlook, GDP_Outlook*, and *CaseRates* are winsorised per sub-sample at the 1st and 99th percentiles. Sources of data are explained in Section 3.1.

Table 3 - Credit rating agencies' rating reviews from 30 Jan 2020 to 31 Mar 2021 - by IMF regions

Region	N	Sov	CAB_Outlook (mean)	NetLB_Outlook (mean)	GDP_Outlook (mean)	CaseRates (mean)	GovtResponse (mean)	Count (mean)	Count* (mean)
PANEL I: 3 CRAs									
ED ASIA	563	15	-0.33	-2.04	-2.05	881.10	54.96	6.03	8.82
ED EUR	502	13	-0.28	-2.19	-1.93	13033.52	52.78	5.93	7.13
LAC	853	23	-0.93	-2.27	-2.44	10524.08	59.93	6.14	8.27
ME&CA	698	19	-2.48	-3.36	-2.39	11121.48	58.88	6.43	6.81
SSA	862	29	-0.78	-1.80	-2.09	1771.08	50.75	6.08	7.52
AEs	1693	38	-0.44	-3.61	-1.75	12808.53	55.36	6.54	8.18
Total	**5171**	**137**	**-0.83**	**-2.74**	**-2.06**	**9087.26**	**55.53**	**6.27**	**7.81**
PANEL II: S&P									
ED ASIA	182	12	-0.45	-2.19	-2.03	894.23	56.25	4.96	7.60
ED EUR	180	12	-0.36	-2.23	-1.95	12588.65	52.81	3.14	4.88
LAC	315	23	-1.17	-2.31	-2.42	10330.33	59.71	4.47	7.16
ME&CA	229	16	-2.67	-3.43	-2.34	11223.14	58.59	3.47	4.86
SSA	268	19	-0.69	-1.78	-2.19	1789.37	51.47	3.50	4.94
AEs	568	36	-0.18	-3.62	-1.79	13110.03	55.54	4.01	6.24
Total	**1742**	**118**	**-0.81**	**-2.78**	**-2.08**	**9287.55**	**55.86**	**3.95**	**5.88**
PANEL III: MOODY'S									
ED ASIA	210	15	-0.65	-1.94	-2.13	776.35	53.15	8.08	12.09
ED EUR	171	13	-0.33	-2.17	-1.96	13507.38	53.15	11.23	19.11
LAC	291	22	-0.81	-2.16	-2.45	9725.41	60.89	9.06	12.31
ME&CA	249	19	-2.24	-3.29	-2.41	10584.14	57.83	11.27	11.81
SSA	333	25	-0.45	-1.58	-1.98	1425.89	48.71	9.60	12.06
AEs	525	37	-0.55	-3.64	-1.73	12370.85	55.11	12.43	22.91
Total	**1779**	**131**	**-0.80**	**-2.62**	**-2.06**	**8379.91**	**54.82**	**10.56**	**14.79**
PANEL IV: FITCH									
ED ASIA	171	11	0.19	-1.99	-1.99	995.75	55.82	4.65	7.42
ED EUR	151	10	-0.14	-2.17	-1.87	13027.19	52.33	3.26	5.36
LAC	247	18	-0.77	-2.33	-2.49	11701.97	59.08	4.81	6.95
ME&CA	220	16	-2.55	-3.38	-2.44	11618.58	60.38	4.04	6.41
SSA	261	19	-1.27	-2.12	-2.13	2192.70	52.61	4.24	6.88
AEs	600	38	-0.59	-3.57	-1.75	12879.46	55.40	3.80	6.03
Total	**1650**	**112**	**-0.86**	**-2.84**	**-2.05**	**9626.56**	**55.93**	**4.09**	**6.37**

Notes: This table presents the summary statistics for 137 sovereigns rated by S&P, Moody's and Fitch for the period 30 Jan 2020- 31 Mar 2021 using IMF region classification. "Obs." is the number of observations. For regions and variables' definitions refer to Tables 1 and 2.

Table 4 - Pooled results

3 CRAs				Marginal effects Spec. (3) (%)		
	Spec. (1)	Spec. (2)	Spec. (3)	0	1	2
CAB_Outlook		-0.018	0.010			
		(-1.57)	(0.71)			
NetLB_Outlook		0.012	-0.036**	0.286**	-0.139**	-0.147**
		(0.82)	(-2.23)	(2.22)	(-2.20)	(-2.19)
GDP_Outlook		-0.117***	-0.103***	0.822***	-0.400***	-0.422***
		(-4.78)	(-3.89)	(3.83)	(-3.83)	(-3.61)
CaseRates	-0.000**	-0.000	-0.000			
	(-2.10)	(-1.15)	(-0.14)			
GovtResponse	0.008***	0.008***	0.007***	-0.056***	0.027***	0.029***
	(4.07)	(3.94)	(3.34)	(-3.35)	(3.20)	(3.36)
Count	0.030***	0.030***	0.033***	-0.265***	0.129***	0.136***
	(4.62)	(4.72)	(5.39)	(-5.29)	(4.75)	(5.27)
Shockandawe	0.726***	0.688***	0.748***	-8.733***	3.960***	4.773***
	(9.71)	(9.16)	(9.45)	(-7.12)	(6.59)	(6.36)
ED ASIA			0.095			
			(0.68)			
ED EUR			-0.242			
			(-1.57)			
LAC			0.269**	-2.680**	1.275**	1.405**
			(2.34)	(-2.43)	(2.44)	(2.37)
SSA			0.374***	-4.032***	1.877***	2.155***
			(3.07)	(-3.12)	(3.16)	(2.97)
AEs			-0.482***	2.662***	-1.412***	-1.251***
			(-3.80)	(3.24)	(-3.27)	(-3.06)
CRA dummies	Yes	Yes	Yes			
pseudo R-squared	0.072	0.083	0.119			
No. of Obs.	5171	5171	5171			

Note: This table reports the estimated coefficients and t-statistics in parentheses from various specifications of the ordered probit model of Eq. (1) (see Section 5.1). The credit rating dataset consists of sovereign ratings from 137 sovereigns for the period 30 Jan 2020- 31 Mar 2021. The dependent variable is *Downaction*. The variable definitions and summary statistics are presented in Table 2. We further estimate the effect of the statistically significant coefficients resulting from Spec. (3) on the probability of sovereign rating events using Marginal effects (MEs). Significant levels are: * p<0.10 ** p<0.05 *** p<0.01. Errors are estimated with Huber-White robust standard errors.

Table 5 - Individual CRA results

PANEL I	S&P			Moody's			Fitch		
	Spec. (1)	Spec. (2)	Spec. (3)	Spec. (1)	Spec. (2)	Spec. (3)	Spec. (1)	Spec. (2)	Spec. (3)
CAB_Outlook		-0.072***	-0.037		-0.009	0.022		0.021	0.038*
		(-2.98)	(-1.33)		(-0.43)	(0.87)		(1.07)	(1.78)
NetLB_Outlook		0.044*	-0.009		-0.011	-0.075**		-0.005	-0.031
		(1.68)	(-0.30)		(-0.42)	(-2.44)		(-0.22)	(-1.15)
GDP_Outlook		-0.098**	-0.083		-0.102**	-0.107**		-0.158***	-0.143***
		(-2.03)	(-1.64)		(-2.52)	(-2.45)		(-3.71)	(-3.10)
CaseRates	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000**	-0.000*	-0.000*
	(-0.54)	(-0.27)	(0.49)	(-1.36)	(-0.88)	(-0.07)	(-2.32)	(-1.94)	(-1.79)
GovtResponse	0.005	0.005	0.005	0.006	0.005	0.004	0.016***	0.016***	0.016***
	(1.43)	(1.36)	(1.19)	(1.62)	(1.47)	(0.85)	(4.26)	(4.33)	(4.29)
Count	0.082***	0.089***	0.096***	0.006	0.006	0.016**	0.133***	0.138***	0.133***
	(4.90)	(5.08)	(5.00)	(0.81)	(0.82)	(2.26)	(8.01)	(8.50)	(7.96)
ShockandAwe	0.773***	0.720***	0.792***	0.402***	0.351**	0.419***	0.929***	0.888***	0.907***
	(5.81)	(5.23)	(5.43)	(2.75)	(2.40)	(2.69)	(7.11)	(6.78)	(6.72)
ED ASIA			-0.075			0.194			-0.085
			(-0.28)			(0.82)			(-0.34)
ED EUR			-0.050			-0.428			-0.068
			(-0.18)			(-1.33)			(-0.26)
LAC			0.170			0.357*			0.158
			(0.82)			(1.78)			(0.76)
SSA			0.480**			0.495**			0.173
			(2.13)			(2.33)			(0.78)
AEs			-0.510**			-0.814***			-0.294
			(-2.04)			(-2.94)			(-1.43)
pseudo R-squared	0.091	0.116	0.151	0.024	0.034	0.103	0.164	0.181	0.192
No. of Obs.	1742	1742	1742	1779	1779	1779	1650	1650	1650
PANEL II: Marginal effects Spec. (3) (%)	**0**	**1**	**2**	**0**	**1**	**2**	**0**	**1**	**2**
GDP_Outlook				0.724**	-0.343**	-0.381**	1.209***	-0.567***	-0.642***
				(2.35)	(-2.31)	(-2.22)	(3.09)	(-3.12)	(-2.81)
GovtResponse							-0.133***	0.063***	0.071***
							(-4.21)	(3.85)	(3.89)
Count	-0.718***	0.367***	0.351***	-0.105**	0.050*	0.055**	-1.119***	0.525***	0.595***
	(-4.70)	(3.94)	(4.39)	(-2.23)	(1.96)	(2.38)	(-6.63)	(5.31)	(5.66)
AEs	2.605*	-1.445*	-1.160*	2.698**	-1.463**	-1.234**			
	(1.77)	(-1.81)	(-1.66)	(2.41)	(-2.37)	(-2.23)			

Note: This table reports the estimated coefficients and t-statistics in parentheses from various specifications of the ordered probit model of Eq. (2) for S&P, Moody, and Fitch (see Section 5.2). The credit rating dataset consists of sovereign ratings from 118, 131, 112 sovereigns rated by S&P, Moody, and Fitch, respectively, for the period 30 Jan 2020- 31 Mar 2021. The dependent variable is *Downaction*. The variable definitions and summary statistics are presented in Table 2. We further estimate the effect of the statistically significant coefficients resulting from Spec. (3) on the probability of sovereign rating events using Marginal effects (MEs). Significant levels are: * p<0.10 ** p<0.05 *** p<0.01. Errors are estimated with Huber-White robust standard errors.

Table 6 – The effects of sovereign rating actions on sovereign bond yield spreads during the pandemic

	Pooled		S&P		Moody's		Fitch	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Count	0.123	0.085	0.003	-0.003	0.005	0.005	0.003	-0.000
	(1.24)	(0.85)	(0.22)	(-0.25)	(1.49)	(1.37)	(0.43)	(-0.04)
Downaction	70.668***	71.062***	162.399***	163.953***	34.418***	33.836***	8.673	9.018
	(11.87)	(11.93)	(13.67)	(13.72)	(3.46)	(3.39)	(1.10)	(1.15)
Downaction*CaseRates	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000*	0.000	0.000
	(-0.42)	(-0.49)	(-0.15)	(-0.18)	(-1.54)	(-1.65)	(0.18)	(0.21)
Downaction*GovtResponse	-0.993***	-0.994***	-2.608***	-2.626***	-0.297*	-0.276	-0.048	-0.051
	(-9.96)	(-9.97)	(-12.50)	(-12.53)	(-1.73)	(-1.60)	(-0.38)	(-0.41)
GDP_Outlook	0.173	0.084	0.456	0.423	0.281	0.100	-0.152	-0.080
	(0.42)	(0.20)	(0.57)	(0.51)	(0.41)	(0.14)	(-0.29)	(-0.15)
CAB_Outlook	0.626***	0.390	0.648	0.507	0.563	0.271	0.788***	0.580*
	(2.88)	(1.61)	(1.54)	(1.07)	(1.52)	(0.66)	(2.83)	(1.86)
NetLB_Outlook	-0.322	-0.089	-0.724	-0.527	-0.250	-0.018	-0.142	0.092
	(-1.39)	(-0.35)	(-1.61)	(-1.06)	(-0.65)	(-0.04)	(-0.47)	(0.28)
CaseRates	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.85)	(0.64)	(0.63)	(0.53)	(0.58)	(0.66)	(0.34)	(-0.08)
GovtResponse	-0.026	-0.047	-0.019	-0.050	-0.058	-0.082	-0.006	-0.027
	(-0.63)	(-1.10)	(-0.23)	(-0.60)	(-0.83)	(-1.15)	(-0.11)	(-0.50)
ShockandAwe	-1.233	-1.246	4.031	4.112	-1.540	-1.517	-6.719***	-6.701***
	(-0.74)	(-0.75)	(1.30)	(1.32)	(-0.54)	(-0.53)	(-3.07)	(-3.08)
_cons	-2.477	-2.059	-4.419	-1.682	-0.379	-1.685	-1.626	1.136
	(-0.93)	(-0.68)	(-0.82)	(-0.28)	(-0.09)	(-0.35)	(-0.47)	(0.28)
Maturity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	No	Yes	No	Yes	No	Yes	No	Yes
CRA dummies	Yes	Yes	No	No	No	No	No	No
adjusted R-squared	0.072	0.076	0.196	0.196	0.046	0.048	0.038	0.052
No. of Obs.	2328	2328	826	826	741	741	761	761

Note: This table reports the estimated coefficients and t-statistics in parentheses from various specifications of the OLS model of Eq. (3) for the pooled sample (Column (1)-(2)) and for individual CRAs (Column (3)-(8)) (see Section 5.3). The dependent variable is sovereign bond yield spreads ($\Delta Spread$) calculated in the window [0;+1] of the sovereign rating events released in the period 30 Jan 2020 - 31 Mar 2021. The variable capturing the rating actions is *Downaction* which takes value two for downgrades, value one for negative outlook/watch and value zero for rating confirmations/positive rating changes/no rating changes. Definitions of other variables and summary statistics are presented in Table 2. Significant levels are: * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Appendices

Appendix A - Data sampling and summary statistics

Table A.1 - Rating categories and numerical conversion

Long-term foreign currency issuer rating symbol			Numerical rating	Rating grade	
S&P	Moody's	Fitch			
AAA	Aaa	AAA	22	Prime high grade	Investment grade
AA+	Aa1	AA+	21	High grade	
AA	Aa2/Aa	AA	20		
AA-	Aa3	AA-	19		
A+	A1	A+	18	Upper medium grade	
A	A2	A	17		
A-	A3	A-	16		
BBB+	Baa1	BBB+	15	Lower medium grade	
BBB	Baa2	BBB	14		
BBB-	Baa3	BBB-	13		
BB+	Ba1	BB+	12	Speculative	Non-investment grade
BB	Ba2	BB	11		
BB-	Ba3	BB-	10		
B+	B1	B+	9	Highly speculative	
B	B2	B	8		
B-	B3	B-	7		
CCC+	Caa1	CCC+	6	Substantial risks	
CCC	Caa2	CCC	5		
CCC-	Caa3	CCC-	4		
CC	Ca	CC	3	Extremely speculative	
C		C	2		
SD	D	RD/D	1	In default	

Notes: According to S&P Global Ratings (Jan 2021). 'S&P's Global Rating Definitions'. Available from: https://www.standardandpoors.com/en_US/web/guest/article/-/view/sourceId/504352; Moody's Investor Services (Jan 2021). 'Rating Symbols and Definitions'. Available from: https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_79004; Fitch Ratings (Jun 2020). 'Rating Definitions'. Available from: https://www.fitchratings.com/research/fund-asset-managers/rating-definitions-11-06-2020.

Table A.2. - List of negative rating reviews from 30th Jan 2020 to 31st Mar 2021

Entity	No. of Neg OL_W			No. of Downgrade			Entity	No. of Neg OL_W			No. of Downgrade		
	SP	Moody	Fitch	SP	Moody	Fitch		SP	Moody	Fitch	SP	Moody	Fitch
Albania							Latvia	1					
Angola		1		1	1	1	Lebanon				1	1	1
Aruba			1	1		1	Lesotho	1					
Australia	1		1				Lithuania		1				
Austria	1						Luxembourg						
Azerbaijan	1		1				Macao						
Bahamas		1			1	2	Malaysia	1		1	1		
Bahrain			1	1			Mali, Government of		1			1	
Bangladesh							Malta	1		1			
Barbados							Mauritius		1			1	
Belarus	1		1				Mexico				1	1	1
Belgium	1						Moldova						
Belize		1	2		2	3	Mongolia		1				
Benin	1	1					Morocco	1	1	1	1		
Bolivia			1	1	1	1	Mozambique						
Bosnia			1				Namibia	1	1			1	
Botswana		1	1				Netherlands						
Brazil	1		1				New Zealand			1			
Bulgaria	1	1	1				Nicaragua	1					
Burkina Faso							Niger						
Cabo Verde	1		1	1		1	Nigeria			1	1		1
Cambodia							Norway						
Cameroon	1	1				1	Oman	1	1		2	2	2
Canada				1			Pakistan		1				
Chile	1	1	1	1		1	Panama		1	1	1	1	1
China							Papua New Guinea						1
Colombia		1	1	1			Paraguay						
Congo, Democratic Republic of the			1				Peru	1					
Congo, Republic of			1			1	Philippines	1					
Costa Rica		1		1		1	Poland						
Cote d'Ivoire		1					Portugal	1		1			
Croatia	1	1					Qatar						
Cyprus	1						Republic of Fiji		1	1			
Czech Republic							Romania	1	1				
Denmark							Russia						
Dominican Republic	1		1				Rwanda		1	1			
Ecuador		1	1	3	1	1	San Marino				1		
Egypt							Saudi Arabia	1	1				

El Salvador	1	1				
Estonia			1			
Eswatini					1	
Ethiopia			1	1	1	1
Finland						
France	1	1				
Gabon		1		1		
Georgia	1		1			
Germany						
Ghana		1	1			1
Greece	1		1			
Guatemala	1	1	1	1		
Honduras						
Hong Kong				1		
Hungary			1			
Iceland	1					
India	1				1	
Indonesia			1			
Iraq	1					
Ireland						
Israel		1				
Italy				1		
Jamaica	1		1			
Japan	1		1			
Jordan	1					
Kazakhstan						
Kenya	1	1	1			1
Korea						
Kuwait	1	1	1		1	1
Kyrgyzstan		1				
Laos	1	1		1	1	
Senegal		1				
Serbia		1	1			
Seychelles				2		
Singapore						
Slovakia	1		1	1		
Slovenia		1				
Solomon Islands						
South Africa				2	2	1
Spain			1			
Sri Lanka		1		2	1	2
Suriname		1	1	2	2	1
Sweden						
Switzerland						
Taiwan						
Tajikistan						
Tanzania					1	
Thailand	1	1	1			
Togo						
Trinidad and Tobago	1				1	
Tunisia	1	1		1		
Turkey	1				1	
Uganda	1					
Ukraine	1	1				
United Arab Emirates						
United Kingdom			1	1		
United States	1					
Uruguay						
Uzbekistan			1			
Vietnam	1					
Zambia				2	1	1
Total 137 sovereigns	**49**	**45**	**46**	**40**	**28**	**31**

Notes: We collect rating history and press releases related to rating changes, outlook and credit watch revisions, as well as rating affirmations by S&P, Moody's, and Fitch during the period 30 Jan 2020 – 31 Mar 2021 from S&P's Ratings Direct, Moody's website, and Fitch Connect. The final sample encompasses 5171 observations of 137 sovereigns spanning the period from 30 Jan 2020 to 31 Mar 2021. S&P assigned 49 negative outlooks/credit watches and 40 downgrades. Moody's assigned 45 negative outlooks/ credit watches and 28 downgrades. Fitch issued 46 negative outlooks/ credit watches and 31 downgrades.

Appendix B - Pooled results (Replaced CaseRates with MortalityRates)

3 CRAs				Marginal effects Spec. (3)		
	Spec. (1)	Spec. (2)	Spec. (3)	0	1	2
CAB_Outlook		-0.041***	-0.014			
		(-2.94)	(-0.94)			
NetLB_Outlook		0.031*	-0.016			
		(1.88)	(-0.89)			
GDP_Outlook		-0.107***	-0.086***	0.659***	-0.329***	-0.330***
		(-4.25)	(-3.12)	(3.09)	(-3.06)	(-2.98)
MortalityRates	-0.000	-0.000	0.000			
	(-1.53)	(-0.44)	(0.36)			
GovtResponse	0.006**	0.005*	0.005*	-0.042*	0.021*	0.021*
	(2.14)	(1.71)	(1.87)	(-1.88)	(1.86)	(1.87)
Count	0.033***	0.034***	0.037***	-0.284***	0.141***	0.142***
	(4.74)	(4.86)	(5.53)	(-5.38)	(4.78)	(5.35)
ShockandAwe	0.858***	0.843***	0.897***	-11.435***	5.174***	6.260***
	(10.41)	(10.12)	(10.31)	(-7.25)	(6.61)	(6.35)
ED ASIA			0.103			
			(0.64)			
ED EUR			-0.132			
			(-0.81)			
LAC			0.358***	-3.211***	1.583***	1.628***
			(2.83)	(-2.98)	(2.99)	(2.85)
SSA			0.473***	-4.645***	2.239***	2.406***
			(3.66)	(-3.72)	(3.82)	(3.42)
AEs			-0.330**	1.690**	-0.919**	-0.772**
			(-2.39)	(2.15)	(-2.16)	(-2.09)
CRA dummies	Yes	Yes	Yes			
pseudo R-squared	0.0841	0.0968	0.1293			
No. of Obs.	4641	4641	4641			

Note: This table reports the estimated coefficients and t-statistics in parentheses from various specifications of the ordered probit model of Eq. (1). The credit rating dataset consists of sovereign ratings from 137 sovereigns for the period 30 Jan 2020- 31 Mar 2021. The dependent variable is *Downaction*. The variable capturing severity of the outbreak is *MortalityRates* which is the cumulative death toll as a percentage of the population. The remainder of variable definitions and summary statistics are presented in Table 2. We further estimate the effects of the statistically significant coefficients resulting from Spec. (3) on the probability of sovereign rating events using Marginal effects (MEs). Significant levels are: * p<0.10 ** p<0.05 *** p<0.01. Errors are estimated with Huber-White robust standard errors.

Appendix C - Individual CRA results (Replaced CaseRates with MortalityRates)

PANEL I		**S&P**			**Moody's**			**Fitch**	
	Spec. (1)	Spec. (2)	Spec. (3)	Spec. (1)	Spec. (2)	Spec. (3)	Spec. (1)	Spec. (2)	Spec. (3)
CAB_Outlook		-0.081***	-0.055**		-0.046*	-0.016		0.001	0.018
		(-3.43)	(-2.24)		(-1.76)	(-0.60)		(0.03)	(0.73)
NetLB_Outlook		0.056**	0.006		0.025	-0.039		0.009	-0.016
		(2.00)	(0.20)		(0.79)	(-1.09)		(0.33)	(-0.51)
GDP_Outlook		-0.087**	-0.063		-0.094**	-0.079		-0.132***	-0.117**
		(-1.99)	(-1.31)		(-2.13)	(-1.64)		(-3.08)	(-2.55)
MortalityRates	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(-0.80)	(-0.03)	(0.61)	(-0.90)	(-0.23)	(0.55)	(-1.39)	(-1.10)	(-0.94)
GovtResponse	0.002	0.002	0.003	0.004	0.003	0.004	0.015***	0.015***	0.015***
	(0.50)	(0.33)	(0.57)	(0.83)	(0.49)	(0.60)	(2.93)	(2.77)	(2.93)
Count	0.079***	0.085***	0.090***	0.011	0.011	0.020***	0.141***	0.141***	0.138***
	(4.50)	(4.67)	(4.47)	(1.51)	(1.55)	(2.81)	(7.54)	(7.75)	(7.34)
ShockandAwe	0.835***	0.846***	0.913***	0.536***	0.542***	0.618***	1.140***	1.091***	1.112***
	(5.77)	(5.72)	(5.91)	(3.25)	(3.26)	(3.56)	(7.93)	(7.56)	(7.46)
ED ASIA			0.035			0.199			-0.027
			(0.11)			(0.68)			(-0.10)
ED EUR			0.062			-0.270			0.038
			(0.21)			(-0.78)			(0.14)
LAC			0.293			0.498**			0.220
			(1.25)			(2.13)			(0.99)
SSA			0.585**			0.662***			0.275
			(2.44)			(2.90)			(1.18)
AEs			-0.379			-0.579**			-0.150
			(-1.42)			(-2.01)			(-0.67)
pseudo R-squared	0.095	0.121	0.157	0.030	0.043	0.112	0.180	0.191	0.199
No. of Obs.	1590	1590	1590	1585	1585	1585	1466	1466	1466
PANEL II Marginal effects Spec. (3) (%)	**0**	**1**	**2**	**0**	**1**	**2**	**0**	**1**	**2**
GDP_Outlook							0.965**	-0.467**	-0.498**
							(2.54)	(-2.53)	(-2.38)
GovtResponse							-0.126***	0.061***	0.065***
							(-2.92)	(2.86)	(2.71)
Count	-0.649***	0.354***	0.295***	-0.132***	0.060**	0.072***	-1.137***	0.550***	0.587***
	(-4.17)	(3.67)	(3.78)	(-2.72)	(2.25)	(2.95)	(-6.11)	(5.01)	(5.12)
AEs				1.668*	-0.891*	-0.776			
				(1.70)	(-1.67)	(-1.64)			

Note: This table reports the estimated coefficients and t-statistics in parentheses from various specifications of the ordered probit model of Eq. (2) for S&P, Moody, and Fitch. The credit rating dataset consists of sovereign ratings from 137 sovereigns for the period 30 Jan 2020- 31 Mar 2021. The dependent variable is *Downaction*. The variable capturing severity of the outbreak is *MortalityRates* which is the cumulative death toll as a percentage of the population. The remainder of variable definitions and summary statistics are presented in Table 2. We further estimate the effects of the statistically significant coefficients resulting from Spec. (3) on the probability of sovereign rating events using Marginal effects (MEs). Significant levels are: * $p<0.10$ ** $p<0.05$ *** $p<0.01$. Errors are estimated with Huber-White robust standard errors