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Linking Covid-19 epidemic and emerging market OAS:

Evidence using dynamic copulas and Pareto distributions [1]

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Abstract

This paper investigates the dependence of the Option-Adjusted Spread (OAS) for several ICE BofA Emerging Markets Corporate Plus Indexes to the outbreaks of the Covid-19 viral pandemics between March 1, 2020, and April 30, 2021. We investigate whether the number of new cases, the reproduction rate, death rate and stringency policies have resulted in an increase/decrease in the spreads. We study the bivariate distributions of epidemiological indicators and spreads to investigate their concordance using dynamic copula analysis and estimate the Kendall rank-correlation coefficient. We also investigate the effect of the epidemiological variables on the extreme values of the spreads by fitting a tail index derived from a Pareto type I distribution. We highlight the existence of correlations, robust to the type of copulas used (Clayton or Gumbel). Moreover, we show that the epidemiological variables explain well the extreme values of the spreads.

Keywords: Covid-19, corporate spreads, pandemics, emerging economies.

JEL CODES: F37; G15; I12

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1.- Introduction

The aim of this paper is to investigate a recognized, but never tested formally, hypothesis of a sensitivity of emerging markets corporate spreads to epidemiological indicators of coronavirus pandemic. Indeed, without studying the effect of epidemiological variables per se, the literature is usually interested in the impact of Covid-19 through its effects on the decisions of financial actors. Some authors are interested in the consequences of the crisis health context on the investors' choices regarding the fears they may have had about the evolution of the fundamentals of companies (liquidity, cash flows, lower returns and stock prices, higher volatility, safe heaven effects, spillovers, etc.). Alternatively, some researchers consider that the epidemic has generated uncertainty, which they capture by means of aggregate indicators, such as the World Pandemic Uncertainty index, WPUI, proposed by Ahir et al., 2018, whose effects on spreads, volatility and returns are analyzed (see also Baker et al., 2020, Narayan and Phan, 2020).

Detailed correlation studies at a daily frequency are rare. However, the kinetics of infectious diseases can only be adequately captured at this frequency. Moreover, the non-academic press suggests that investors are sensitive to high-frequency epidemic signals. For example, in its November 2020 Business news, Reuters noted that U.S. junk bond spreads narrowed on optimism about Pfizer's COVID-19 vaccine[4]. Shear et al (2021), study the impact of investors' attention to the Covid-19 pandemic using daily data of the Google search volume on the word "coronavirus". They find that investors' enhanced attention to coronavirus resulted into negative returns.

Our paper formally studies the dependence of the Option-Adjusted Spread (OAS) for several ICE BofA Emerging Markets Corporate Plus Indexes to the outbreaks of the Covid-19 viral pandemics between March 1, 2020, and April 30, 2021. While an extensive literature has already been devoted to the Covid-19 consequences on the advanced economies' debt markets (both sovereign and corporate), little has been written on emerging countries' corporate debt markets in times of Covid-19, despite the increasing weight of emerging countries' corporate debt in investors' portfolios over the recent years. We investigate the relationships between the spreads

[4] See Kate Duguid (https://www.reuters.com/article/us-usa-credit-idUKKBN27P26W)

and several indicators of the severity of the coronavirus crisis (including governments' public health interventions during the pandemic).

To do this, we favor an approach based on finance epidemiology. The background idea of this burgeoning field of research is that, in times of severe infection diseases, corporates' financial conditions are better monitored by inserting epidemiological indicators and frameworks into investors' decision models. Several fields of analysis are concerned. Firstly, from a statistical point of view, the aim is to highlight the existence of correlations or concordances between financial variables and epidemiological variables. Second, in the field of public health, the study of the links between biological and financial systems allows authorities to better target public health policies in response to disease threats, particularly the risks posed to the stability of financial markets. For example, much of the literature attributes the lull in the corporate markets from April 2020 onwards - after a liquidity crisis in February and March 2020 caused by the epidemic context - to the Fed's corporate bond purchase programs (see literature review below). But we cannot exclude that investors were also sensitive to the mitigation policies implemented by governments around the world at the same time. Third, on the theoretical level, it is possible to link finance epidemiology and behavioral finance, by studying how investors process epidemiological signals (see Philipson, 2000).

Our paper proposes an empirical contribution to the existing literature. We investigate whether epidemiological indicators were correlated with spreads during the coronavirus crisis. More specifically, we study the role of the following variables: the number of new cases, the reproduction rate, mortality rate and stringency policies (restrictions on movements and businesses, attainment policies).

To the best of our knowledge, this is the first paper analyzing the impact of the coronavirus crisis on emerging market corporate credit risks during the first wave of the epidemics. One paper which is tied to ours, in its objective, is that of Haroon and Rizvi (2021), although the empirical framework used is very different. Using financial data, the authors study the effects on returns and volatility of MSCI indices of 23 emerging countries of changes in indicators tracking the flattening epidemic curves (increasing/decreasing trend in the number of confirmed coronavirus cases, or in the number of deaths). They use a linear regression model and find that flattening the epidemic curve was a factor in reducing the risk of illiquidity in the markets.

We propose a different empirical methodology based on several observations. First, both our spread series and epidemiological indicator series have non-Gaussian distributions (they are asymmetric and heavy-tailed). This may raise difficulties when trying to measure their correlation in a standard linear framework, using classical regression methods. We investigate the co-dependence between the spreads and the epidemiological variables using a dynamic copula model to derive a general concordance coefficient, i.e. Kendall's τ. An advantage is to exploit the information on the degree of correlation between their marginal distributions in a non-Gaussian framework. Second, we show evidence of non-linear relationships, with threshold effects, between spreads and their epidemiological determinants. Third, we focus on the largest spreads and show how the inclusion of epidemiological variables explains the tail indexes of their conditional distribution by a type I Pareto distribution. In other words, the pandemic variables played a role in the fact that, during the acute phases of the covid epidemic, the spreads have reached high levels. We find evidence of the existence of strong correlations between the epidemic variables and spreads, robust to the type of copulas used (Clayton or Gumbel). Moreover, we show that the number of new cases explains well the extreme values of the spreads by a power law typical of a heavy-tailed distribution.

The remainder of the paper is structured as follows. Section 2 presents a brief review of the recent literature that has attempted to investigate the influence of Covid-19 on corporate spreads. Section 3 presents some distributional characteristics of our data that suggest strong deviations from Gaussian distributions. Section 4 contains the analysis based on copulas, and Pareto Law tail indexes. Finally, Section 5 concludes the paper.

2.- A brief literature review on Covid-19 and corporate spreads

The recent literature has paid little attention to the corporate debt markets of emerging countries. On the contrary, much of the work has focused on advanced economies, specifically the United States, to study the effects of the health crisis on corporate bond markets, or corporate credit markets. Unlike the Great Financial Crisis (GFC) of 2007-2009, the epidemic crisis seems to have affected sovereign spreads less but resulted in a liquidity crisis in the corporate credit markets. Its spread was halted by rapid intervention by monetary authorities. The effect on sovereign bonds has been documented in a few recent papers (e.g. Ortmans and Tripier, 2021, Zaremba et al., 2021). Regarding the effects on corporate spreads, the literature describes either the liquidity crisis that it caused in the credit markets or the rescue effect of central bank interventions, notably by the Fed.

Aramonte and Avalos (2020) study the spread of cross-business spreads on corporate funding markets. They highlight the role of i/ the increase in corporate downgrades by rating agencies in the sectors most exposed to the health crisis (hotels, energy, retail, entertainment, hospitality, air transportation), and ii/ the effect on the cash flow of firms borrowing through leveraged loans. The authors show that Global corporate credit markets came to a sudden halt, in March 2020, which implied a sharp contraction of issuance. The median spread-to-benchmark accordingly doubled for new issues between January and April 2020.

Zozlowski et al (2021) compare the evolution of corporate bond spreads on primary and secondary corporate credit facilities in the United States during the GFC and the Covid-19 crisis since February 2020. By calibrating a theoretical model of a firm capital structure on micro data, they interpret the GFC as a persistent shock on firms' liquidity, while the COVID-19 crisis acted as a temporary cash-flow shock. They observe that, unlike the financial crisis, credit spreads quickly started to revert trend during the pandemic episode. The authors explain these differences by the very quick reaction of the monetary authorities, barely three weeks after the beginning of the crisis, who triggered the Primary and Secondary Market Corporate Credit Facilities program on March 23, 2020 (whereas the first round of quantitative easing Term Asset-Backed Securities Loan Facility (TALF) was triggered six months after the beginning of the GFC). Liang (2020) finds the same conclusion. She shows that investment-grade corporate bond markets have dysfunctioned since March 2020 (liquidity mismatch phenomenon and huge increase in the demand for liquidity by holders of corporate bonds as concerns about the virus began to escalate). Using diff-in-diff analyses and structural estimations, Gislchrist et al. (2020) and Kargar et al. (2021) show that the second market corporate credit facility (SMCCF) program reduced trade costs and bid-ask spreads and avoided a large-scale crisis. Bordo and Duca (2020) show that by reactivating its commercial paper funding facility and its corporate bond program, the Fed acted in the same way as during the GFC by intervening as lender of last resort. The increase in the central bank's balance sheet was the counterpart of the return of spreads to pre-Covid crisis levels.

Regarding the effects of the Covid-19 crisis on the corporate debt of emerging countries, academic work is scarce. Non-academic Professional journals report on a massive buyback of emerging country corporate debt by yield-seeking investors, starting in the second quarter of 2020. Flows to domestic emerging markets in Asia increased as early as November 2020 and have continued since then. Among the reasons, the success of vaccination and health measures that have reawakened investors' appetite. Conversely, in Latin America, investors have been more cautious, because of the greater spread of the epidemic in this region[5].

The few formalized academic works on the topic show that the acute phase of the first wave of the epidemic in the first quarter of 2020 led to a worsening of emerging market debt liquidity that was illustrated by round-trip transaction costs and larger bid-ask spreads (see Gubareva, 2021). Using a panel of 17,000 firms in 73 emerging and developing countries, Feyen et al. (2020) show that a Covid shock that reduces earnings and receivables by 30 percent has the effect of increasing firms' debt by 28 percentage points and jeopardizes firms' ability to cover their short-term liabilities and interest expenses in MENA countries, South Asia. This contributes to widening spreads when these companies seek to refinance during a pandemic.

Our paper contributes to the empirical literature by proposing new statistical analysis frameworks to highlight some key epidemiological determinants of the Option-Adjusted Spread (OAS) for several ICE BofA Emerging Markets Corporate Plus Indexes.

[5] See the article by Tom Arnold (https://www.reuters.com/article/us-markets-emerging-corpbonds-graphic-idUSKBN2830JX)

3.- Data and distributional characteristics of the variables of interest: corporate OAS and epidemiological variables

3.1.- Distributional characteristics of corporate OAS

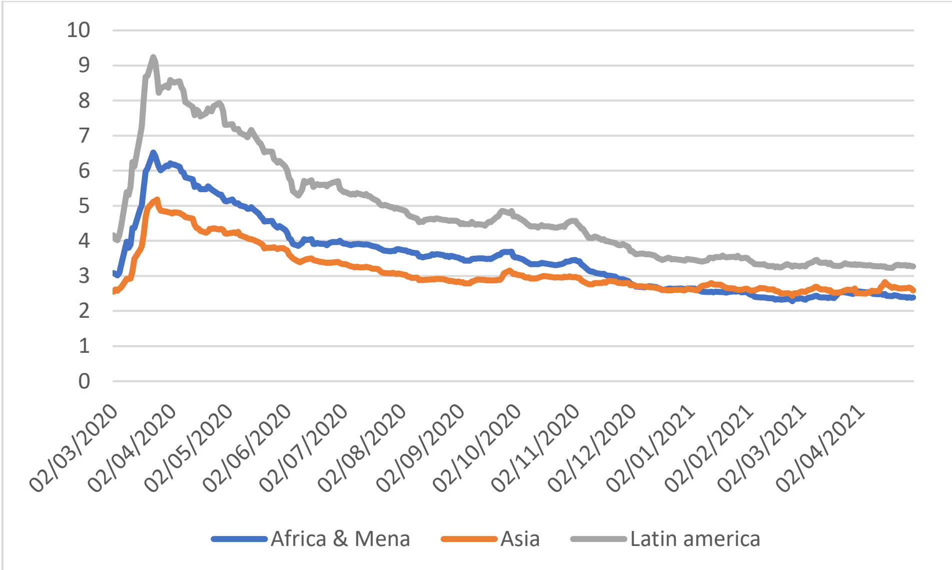
We consider a measure of credit risk, i.e. z-spreads minus option costs that are used to correct for mispricing in option embedded corporate securities. More specifically, our data consists of daily data on the Option-Adjusted Spread (OAS) for the ICE BofA emerging markets Corporate Plus Index (Latin America, Asia, Africa & Mena). The spread is defined as the difference between a weighted average of the constituents bond's OAS and a spot Treasury curve. The data are retrieved from FRED, Federal Reserve Bank of St. Louis, over the period from between March 1, 2020, and April 30, 2021.

Our choice of OAS series is motivated by several considerations. First, they can be considered as a measure of the cost of financing by corporates and therefore as a good predictor of increasing or decreasing profitability of investments in times of pandemics. Second, in standard theoretical frameworks of the valuation of embedded options (for instance, Black-Derman-Toy, 1990, Black-Karasinski, 1991), differences between the theoretical and market prices are due to financial risks, such as liquidity risks. However, cash flows have suffered from large-scale health shocks that were substantive enough to induce changes in the term structure of interest rates and to influence the epidemic risk perception of the issuers and holders of callable, putable and convertible corporate bonds.

The spread curves in Figure 1 show that, after widening during the first major wave of the pandemic in March 2021, spreads have steadily decreased since then in Africa & MENA, Latin America, and Asia. The figure also shows that spreads have been systematically higher in the Americas region than in the other two regions, and that corporates in Asian countries have benefited from lower spreads than those in the Africa & MENA region throughout the period.

Figure 1

ICE BofA US emerging markets liquid corporate plus index option-adjusted spreads



Source: FRED database (Federal Reserve Economic Data, St. Louis Fed)

Figure 2 shows the distributions of the spreads for each of the regions (histogram and estimated density using an Epanechnikov kernel). As can be seen, they are non-Gaussian, and all have a long tail spread to the right (heavy-tailed distributions). This suggests the presence of extreme values during the period under investigation.

3.1.1.- Some theoretical backgrounds

In the sequel, we show that 3 parametric distributions can be fitted to the OAS: log-normal, Weibull and Gamma. Before this, we briefly motivate these choices by presenting some theoretical backgrounds to the modelling of price bonds and interest rate options in mathematical finance literature.

Option pricing and log-normal distribution: the standard approach in the literature

To motivate the log-normal distribution, we can consider the standard framework proposed in the Black-Derman-Toy approach and generalized by Blackman-Karasinski. The dynamics of short rates is described by a stochastic differential equation:

$$d(ln\, r_t) = \left\{\mu(t) + \frac{\dot{\sigma}(t)}{\sigma(t)}\ln(r_t)\right\}dt + \sigma(t)dW_t,\ \ r(0) = r_0, \qquad (1)$$

where

r_t is short-term interest rate at time t,

$\mu(t)$ is the value of the underlying asset at option expiry,

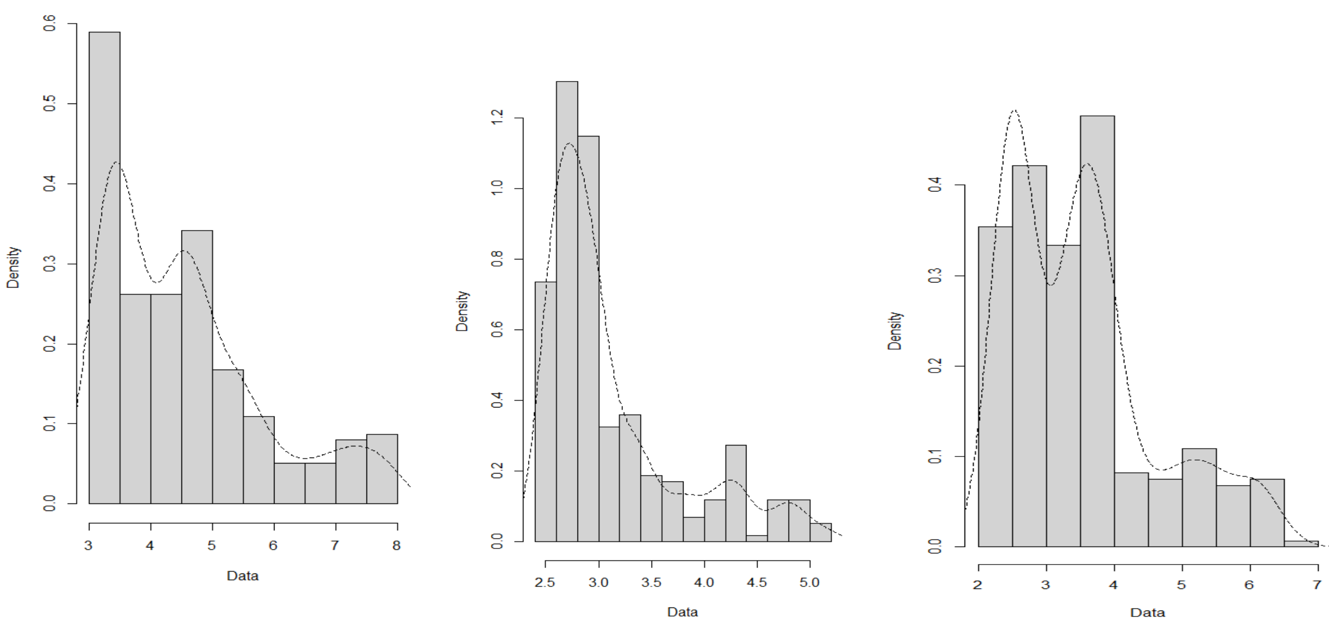
$\sigma(t)$ is short rate volatility,

$\{W_t, t \geq 0\}$ is a geometric Brownian motion.

Figure 2

Empirical distributions of OAS using Epanechnikov kernel

(from left to right, Latin America, Asia, Africa & MENA)



Equation (1) implies:

$$\frac{\sigma(t)\,du_t - d\sigma(t)u_t}{\sigma(t)^2} = \frac{\mu(t)}{\sigma(t)}dt + dW_t\,, u_t = \ln(r_t). \tag{2}$$

Using the quotient rule, and integration for u_t, we obtain the following soution

$$u_t = \frac{u_0}{\sigma(0)}\,\sigma(t) + \sigma(t)\int_0^t \frac{\mu(s)}{\sigma(s)}\,ds + \sigma(t)W_t\,. \tag{3}$$

If $\sigma(t)W_t$ is gaussian with mean 0 and variance σ_t^2/t (which implies that u_t is Gaussian), then $r_t =$ exp (u_t) is log-normal and has

$$E[r_t] = (r_0)^{\sigma(t)/\sigma(0)}\exp\left[\sigma(t)\int_0^t \frac{\mu(s)}{\sigma(s)}ds\right] exp\left[\sigma(t)^2\ \frac{t}{2}\right], \tag{3a}$$

$$V[r_t] = (r_0)^{2\sigma(t)/\sigma(0)}\exp\left[2\sigma(t)\int_0^t \frac{\mu(s)}{\sigma(s)}ds\right] exp\left[\sigma(t)^2\ t\right]\left[\exp\left(\sigma(t)^2\ t\right) - 1\right]. \tag{3b}$$

In this case, an explicit formula of the short-term rate is

$$r_t = (r_0)^{\sigma(t)/\sigma(0)}\exp\left[\sigma(t)\int_0^t \frac{\mu(s)}{\sigma(s)}ds\right] exp[\sigma(t)W_t], \tag{4}$$

Option pricing and Weibull diffusion processes: example

The standard models based on log-normal distributions have, at least, one caveat. They do not capture the skewness in the distribution of the underlying prices, which may cause some biases in the valuation of call and put options. One solution could be to adjust the log-normal distribution with a corrective skewness term in the equation that governs the dynamics of short rate and spreads. For instance, a simple way of introducing a Weibull diffusion process for the short rate is through the following equation:

$$dr_t = \left[\left(\frac{\alpha}{t}\right) - \beta t^{\alpha}\right] r_t\ d_t + \sigma\ r_t\ dW_t, \tag{5a}$$

or

$$d\ln(r_t) = \mu(t)\ \ d_t + \sigma\ dW_t\,,\ \ \mu(t) = \left(\frac{\alpha}{t}\right) - \beta t^{\alpha} \tag{5b}$$

Equation (5a) tells us how fast the mean-reverting dynamics of the short rate is, depending on the values of the coefficients α and β of the drift term. Since $\mu(t)r_t$ and $\sigma\ r_t$ are Borel measurable and satisfy the uniform Lipschitz and growth conditions, there exist a unique solution to Equation

(5a) and the probability density function (pdf) can bederived using Fokker-Planck and Kolmorogov equations.

If W_t is a Wiener process, and if $P\left(r_{t_1} = r_1\right) = 1$, the first-order moment of the short-rate random variable is a function proportional to a bi-parameter Weibull density function:

$$E[r_t] = \frac{r_1\, exp\left(\frac{\beta}{\alpha+1} t_1^{\alpha+1}\right)}{t_1^{\alpha}}\; t_1^{\alpha}\; exp\left(\frac{-\beta}{\alpha+1} t^{\alpha+1}\right) = k\; t_1^{\alpha}\; exp\left(\frac{-\beta}{\alpha+1} t^{\alpha+1}\right) \tag{6a}$$

For the derivation of pdf of Weibull diffusion processes, the reader can refer to Bahij et al. (2016). Equation (5a) can be used to see which values of α and β are compatible with the distribution of short rates and spreads derived for the existing theoretical one-factor models in the literature.

An alternative solution is to use some distributions with natural skewness like the Weibull distribution and to provide a modified Black-Scholes formula using the method of equivalent martingale measures to obtain a risk-neutral valuation of call and put options (see, among others, Savickas, 2002, Alentorn and Markose, 2011).

Option pricing and Gamma distribution

Equation (1) can be extended to allow more flexible representations of tails in the distributions of short rate and spreads. As seen in figure 2, the tails can range from moderately heavy to very heavy, including hyperbolic laws. The Gamma distribution is a good candidate to capture the heaviness in the distribution of rates and spreads. Theoretical models in the literature consider jump diffusion models, by adding a third component to the standard stochastic differential equations of option price models. A jump diffusion process driven by a Gamma process is written:

$$dr_t = \mu(r_t;\theta)dt + \sigma(r_t;\theta)\; dW_t + dL_t \tag{7}$$

where θ is a vector of parameters, $\{W_t,\ t \geq 0\}$ is a geometric Brownian motion, $\{L_t,\ t \geq 0\}$ is a Gamma processes starting at $L(0) = L_0$ with the density function

$$f_t(x) = \frac{\beta^{\alpha t} x^{\alpha t-1} \exp{(-\beta x)}}{\Gamma(\alpha t)}, x \geq 0, \tag{8}$$

At time t. α and β are positive constants, and $\Gamma(\mathrm{x})$ is the Gamma function. It is usually assumed that the processes W_t and L_t are independent.

Such models are type of Lévy-driven jump-diffusion models and are widely used in the literature for the modelling of the short rate, call and put options, and asset price dynamics (see, among others, Eberlein et al., 2013, James et al., 2017, Kawai and Takeuchi, 2010).

3.1.2.- Fitting log-normal, Weibull and Gamma distributions to OAS data

Given the facts that there are some theoretical reasons why short rate – and their spreads – can follow several types of distributions, we now fit some of them to the OAS data. We do not want to estimate a given stochastic differential model (SDE) since there are many theoretical models in the literature that could be compatible with the same distribution. We simply fit the observed spread to the 3 parametric distributions mentioned above, i.e. log-normal, Weibull and Gamma. We estimate two-parameters densities for these laws:

Log-normal distribution:

$$f(x) = \frac{1}{\sigma x\sqrt{2\pi}} exp\left\{-\frac{(lnx-\mu)^2}{2\sigma^2}\right\},\ x \in (0, +\infty),\ \mu \in (-\infty, +\infty), \sigma > 0, \qquad (9a)$$

where μ is location parameter and σ is scale parameter.

Weibull distribution:

$$f(x) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} exp\left\{-\left(\frac{x}{\lambda}\right)^k\right\},\ x \in [0, +\infty),\ k > 0, \lambda > 0, \qquad (9b)$$

where k is shape parameter and λ is scale parameter.

Gamma distribution:

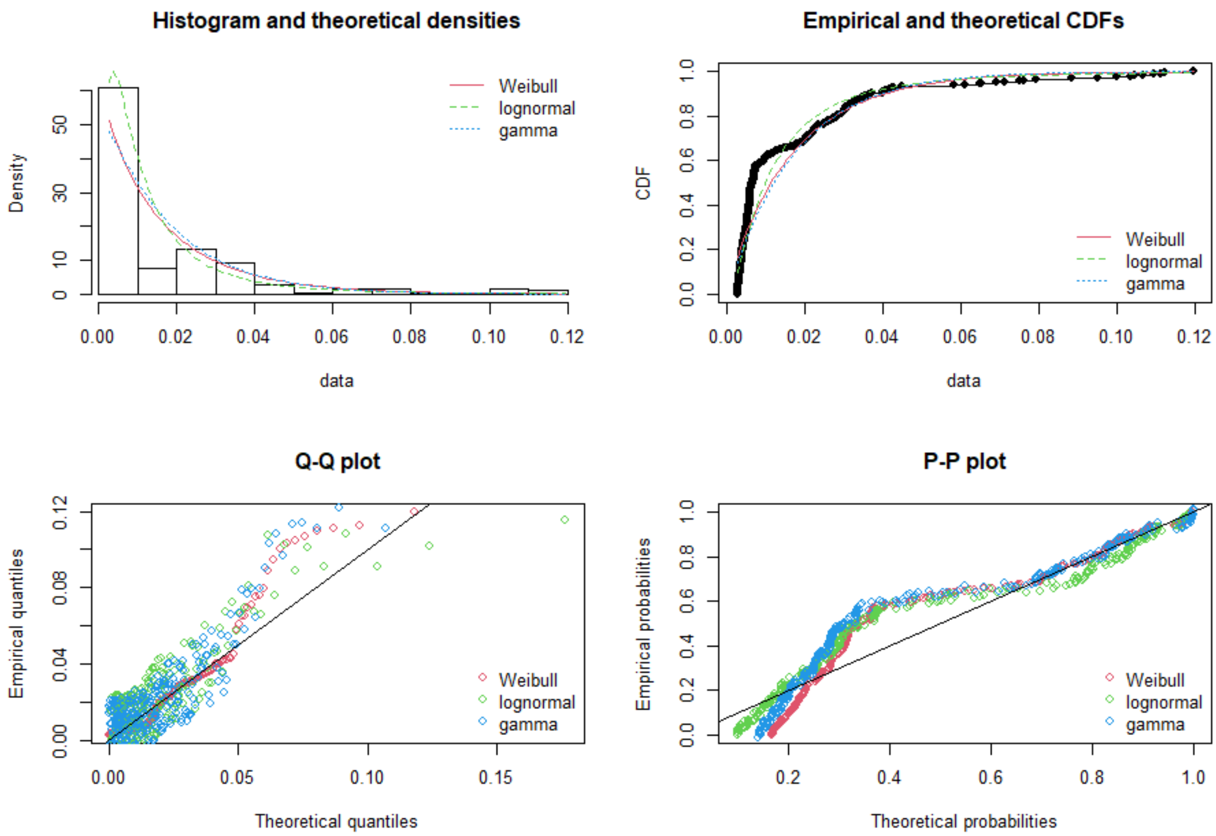
$$f(x) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} exp\left\{-\frac{x}{\theta}\right\},\ x \in (0, +\infty),\ k > 0, \theta > 0, \qquad (9c)$$

where k is shape parameter, θ is scale parameter and Γ is the Gamma function.

For the Gumbel and Gamma distributions, maximum likelihood is used. For the log-normal distribution minimum variance unbiased estimator is used.

Figure 3

Fitting Weibull, log-normal and gamma distribution to the OAS (Africa and MENA)



For illustrative purposes, Figure 3 shows the fitted densities for the Africa & MENA region. For the other two regions, see the Figures in Appendix A. All three distributions fit the histogram of observed values well, when a certain threshold is exceeded (see also the P-P plot). Comparing the three regions, the log-normal distribution most often provides a better fit than the other two.

Table 1 shows the parameter estimates of the three distributions. The parameter k of the Weibull distribution is sometimes interpreted as a "failure rate parameter". Since the estimated value of parameter k is greater than 1, the "failure" here describes a difficulty for spreads to fall rapidly after having increased at the beginning of the epidemic phase. Indeed, as shown in Figure 1, the dynamics of the decrease in spreads is hyperbolic. A rapid return to the level observed before the Covid-19 crisis would have involved k≤1 (exponential or sub-exponential decay).

The estimation of the log-normal distribution parameters confirms that on average corporate spreads were lower in the Asia region and less volatile than in the Latin America and Africa & MENA regions. The estimation of the Gamma distribution suggests the following hierarchy between the spreads of the different regions when interest rates started to rise at the beginning of the epidemic crisis (the months of March and April 2020, corresponding to the highest values of spreads). Asia had the smallest increases, while in the Asia and Africa & MENA regions, more extreme values in the spread dynamics were observed. Indeed, the pdf of Gamma distribution is steeper for higher values of the inverse scale (1/k) (or lower values of k) and has heavier tails when (1/k) decreases. In Table 1, we have k=8.65, 3.46, 3.26 (respectively for Asia, Africa & MENA, and Latin America.

Table 1

Estimates of the parameters of log-normal, Weibull and Gamma distributions for spreads

Distribution	Parameters	Asia	Latin America	Africa & MENA
Log-normal	Location	1.12 (0.01)	1.47 (0.015)	1.21 (0.01)
	Scale	0.18 (0.007)	0.25 (0.01)	0.28 (0.01)
Weibull	Shape	4.58 (0.18)	3.69 (0.16)	3.42 (0.14)
	Scale	3.39 (0.04)	5.01 (0.08)	3.90 (0.07)
Gamma	Shape	27.05 (2.22)	14.81 (1.24)	12.17 (0.98)
	Inverse scale	8.65 (0.72)	3.26 (0.28)	3.46 (0.28)

Note: the numbers between brackets are the standard errors of the estimated parameters. All the coefficients are statistically significant, at least at 10% level of confidence. For the Gumbel and Gamma distributions, maximum likelihood is used. For the log-normal distribution minimum variance unbiased estimator is used.

3.2.- Epidemiological variables

Which indicator is the best basis for inference in epidemic data is still controversial in the epidemic literature. It would be possible to estimate the reproduction rate by estimating contact interval distribution, i.e. time from the onset of infectiousness to infectious contact (this approach is typical to papers focusing on survival analysis of epidemics). The spreading behavior of Covid-19 is analyzed here using the following variables which are commonly used in the epidemiological literature (data being collected on the Our world in data site (source: https://ourworldindata.org) and Humanitarian Data Exchange (source: https://data.humdata.org/event/covid-19:

- Daily new confirmed cases vs cumulative cases,
- Confirmed deaths per million vs GDP per-capita,
- Reproduction rate,
- government response stringency index.

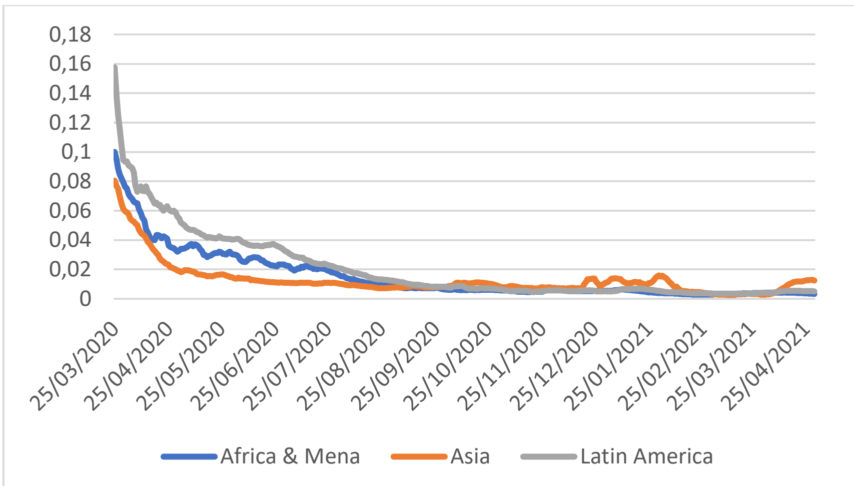
These data are taken for the three regions Asia, Latin and Central America and Africa & MENA.

As shown in Figure 4, the number of new cases versus cumulative cases has been steadily decreasing. The same is true for the reproduction rate in the Africa & Mena and Latin America regions (Figure 5). During the year 2020 and the first half of 2021, although all countries of the world were affected, the epicenter of the pandemic was the industrialized countries of North America and Europe. It is possible that the flattening epidemic curve in emerging countries has led investors to underestimate the health risk, especially in Asia. On the other hand, the higher level of spreads in Latin America could be explained by the fact that investors felt that the disease was more serious in this region, because of the higher number of confirmed deaths versus GDP per capita in the Latin American subcontinent (see Figure 6).

It is difficult, a priori, to say whether epidemiological factors have a high likelihood, or on the contrary a low likelihood, of being correlated with spreads. Indeed, on the one hand, it is possible that the dynamics of spreads were not correlated with those of epidemic factors. In the case of Asia, this could be explained, for example, by the announced strategy of eradicating the virus in this region (the so-called "zero-covid" strategy), while elsewhere in the world governments have opted instead for mitigation policies to simply reduce reproduction rates and contamination. For the other two regions, one explanation would be that reproduction rates remained stable from November 2021 and did not exceed the threshold of 1 (see Figure 5). Finally, a common explanation for all continents could be that epidemic control measures were strong from the beginning (school closures, travel restrictions, social distancing measures, border closures).

Figure 4

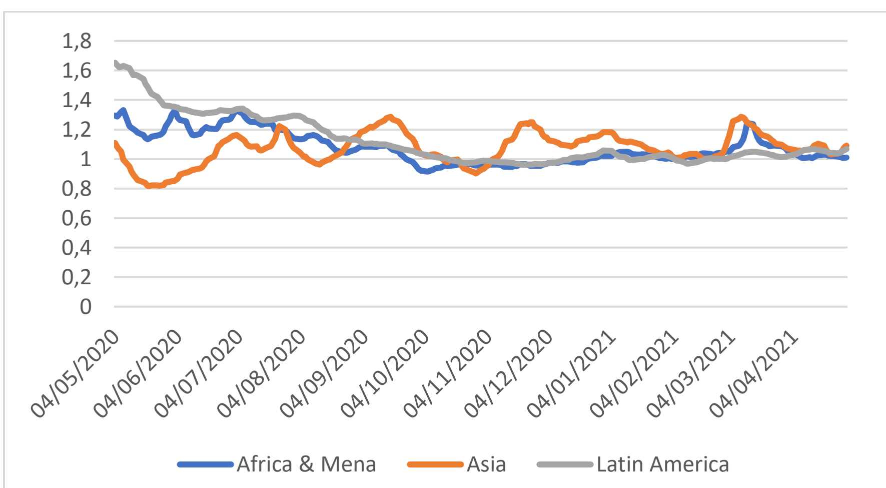
New cases versus cumulative cases



Source: Oxford Data base Our world in Data.

Figure 5

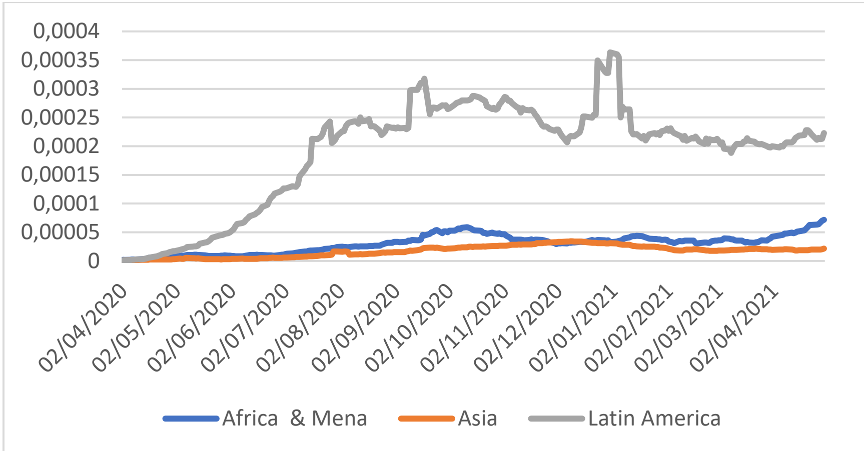
Covid-19 reproduction rate



Source: Oxford Data base Our world in Data.

Figure 6

Confirmed deaths versus GDP per capita: Covid-19



Source: Oxford Data base Our world in Data.

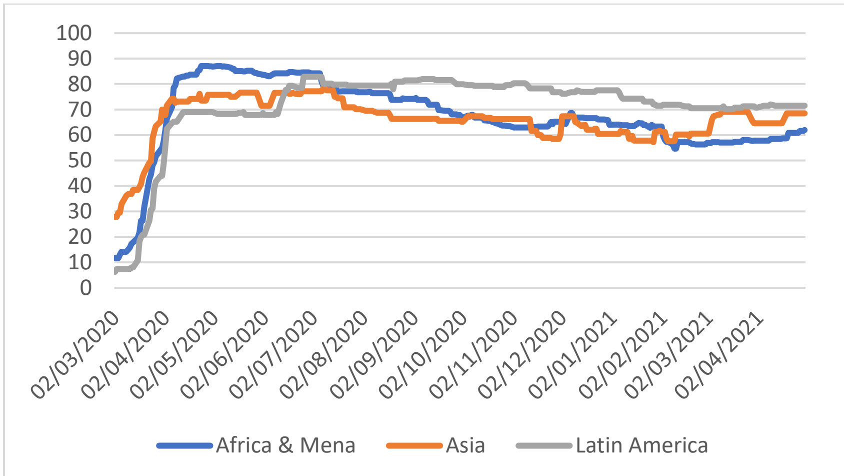
Figure 7 shows the stringency index, which is an indicator of the severity of the restriction measures implemented on a scale of 0 to 100 (100 being the highest level of severity). As can be seen, governmental responses have been quick and strong (as of April 2021, the index is at least 60 in each of the regions studied).

On the other hand, it is possible to think that, on the contrary, epidemiological factors have influenced the perception of health risk by investors and that this has been reflected in spreads. For example, the previous figures show parallel developments between spreads and the continuous decline in the new cases ratio. Similarly, the strict nature of the control measures may have sent a signal to the markets, encouraging investors to keep emerging countries' corporate debts in their portfolios. Moreover, the direction of the correlation (positive or negative) is not determined a priori. Indeed, it could be negative in the case of flight-to-safety behaviors (if the crisis is perceived by investors as being more serious in other regions), or conversely positive.

As with the spreads, none of the four epidemiological variables has a Gaussian distribution. We also estimate the parameters of Weibull, log-normal and Gamma distributions for these variables and for each region. To avoid cluttering the paper with graphs, we do not report the resulting figures (they are available on request from the authors). Instead, we report the estimated parameters in Table 2.

Figure 7

Stringency index



Source: Oxford Data base Our world in Data.

If we first look at the news confirmed cases, we can see that the shape parameter of the Weibull distribution is of the same order of magnitude in the three regions, which suggests a daily propagation speed of the coronavirus at a similar rate during the first epidemic wave (period under investigation). Indeed, the shape parameter captures here the spreading speed, i.e. the occurrence of new cases within population. The scale parameter captures the spreading speed of the disease since the first infection, i.e. how fast the new cases are progressing in relation to the total days. Again, the values are identical from one region to another. The Gamma distribution gives a different measure of the spread of the epidemic. Indeed, its parameters provide information on the probability of remaining infectious. Lower values of k (shape parameter) and larger values of θ - or equivalently lower values of 1/θ (inverse scale parameter) - in Equation (9c) indicate a steeper increase in prevalence and a shorter duration epidemic. The data in Table 2 suggest that Asia had a lower prevalence of infection than the other two regions, but that the first epidemic wave was longer. Epidemiological studies often find, at least for the first quarter of the year 2020, that the number of new confirmed cases are distributed, in advanced countries and in

China, as a log-normal law. We find the same result here for emerging countries. Indeed, the estimated parameters of the log-normal distribution are all statistically significant. This distribution is interesting because it gives an idea of the decline of the epidemic after the peak of the number of new cases. The more the tail of the distribution is spread to the right, the longer it takes for the epidemic to die out. In Table 2, the parameter estimates suggest that the average number of new cases was roughly the same in all regions during the first wave of the epidemic, but that in the Asian region, infections faded more rapidly on average (shape parameter lower than in Latin America and Africa & MENA).

The estimates for the confirmed deaths variable show a higher variance in the case of the Latin America region (see the estimate of the scale parameter for the Weibull and log-normal distributions, which is much higher than in the other two regions, and a smaller inverse scale for the Gamma distribution). The estimates obtained for the reproduction rates do not suggest significant differences in behavior between countries. The distributions for the stringency index are interesting because the parameter values provide indications of the regenerative capacity of public health policies, or in other words of "fatigue" in the implementation of policies aimed at slowing the spread of the virus. In the case of Africa, it can be observed that the shape parameters in the Weibull and Gamma distributions are much lower than those of the other two regions, and that the scale parameter of the log-normal distribution is higher, suggesting greater variability in the dynamics of the variable and the fact that the cumulative distribution function of this variable is more "curved" than those of the Latin American and Asian regions.

4.- Which epidemiological variables are correlated with corporate OAS?

4.1.- Rank-correlation through a dynamic copula analysis

We previously observed that the distributions of both corporate OAS and epidemiological variables are non- Gaussian and that they are heavy-tailed. We therefore consider tail dependence in the data through a dynamic copula analysis. Our framework is the following.

Table 2

Estimates of the parameters of log-normal, Weibull and Gamma distributions for epidemiological variables

			Asia	Latin America	Africa & MENA
New confirmed cases vs cumulative cases	Weibull	Shape Scale	1.24 (0.04) 0.014 (0.0007)	1.07 (0.05) 0.017 (0.001)	0.95 (0.04) 0.01 (0.001)
	Gamma	Shape Inversed scale	1.95 (0.15) 144.5 (12.63)	1.26 (0.09) 76.04 (7.11)	1.05 (0.07) 60.070 (5.60)
	Log-normal	Location Shape	-45.8 (0.04) 0.67 (0.027)	-4.54 (0.05) 0.91 (0.038)	-4.60 (0.06) 0.98 (0.04)
Confirmed deaths versus GDP per capita	Weibull	Shape Scale	1.58 (0.07) 2.16 (0.08)	2.17 (0.13) 27.27 (0.63)	1.62 (0.075) 4.32 (0.16)
	Gamma	Shape Inversed scale	2.05 (0.16) 1.05 (0.09)	4.14 (0.34) 0.17 (0.01)	1.94 (0.15) 0.49 (0.04)
	Log-normal	Location Shape	0.40 (0.05) 0.85 (0.03)	3.07 (0.036) 0.603 (0.025)	1.08 (0.05) 0.94 (0.04)
Reproduction rate	Weibull	Shape Scale	6.19 (0.24) 1.15 (0.01)	6.35 (0.25) 1.16 (0.01)	3.95 (0.14) 1.19 (0.02)
	Gamma	Shape Inversed scale	48.94 (4.03) 45.03 (3.73)	57.51 (4.89) 52.52 (4.48)	33.96 (2.78) 30.90 (2.55)
	Log-normal	Location Shape	0.07 (0.008) 0.14 (0.005)	0.08 (0.007) 0.13 (0.005)	0.079 (0.009) 0.16 (0.006)
Government stringency index	Weibull	Shape Scale	12.90 (0.55) 69.29 (0.33)	18.62 (0.87) 76.77 (0.26)	6.54 (0.28) 70.60 (0.67)
	Gamma	Shape Inversed scale	160.63 (13.27) 2.40 (0.199)	287.88 (24.53) 3.85 (0.33)	43.46 (3.57) 0.66 (0.054)
	Log-normal	Location Shape	4.19 (0.004) 0.078 (0.003)	4.31 (0.003) 0.06 (0.002)	4.18 (0.008) 0.15 (0.006)

Note: the numbers between brackets are the standard errors of the estimated parameters. All the coefficients are statistically significant, at least at 10% level of confidence. For the Gumbel and Gamma distributions, maximum likelihood is used. For the log-normal distribution minimum variance unbiased estimator is used.

We estimate a Patton model to find the time-varying values of a rank correlation coefficient, i.e. a bivariate Kendall's τ dynamic process that account for lower and upper tail dependence:

$$\tau_t(\theta_t) = F\left(\alpha + \beta\tau_{t-1}(\theta_{t-1}) + \gamma \sum_{j=1}^{m} \frac{|u_{t-j}-v_{t-j}|}{m}\right), \tag{10}$$

where $F(x) = [1 + \exp(-x)]^{-1}$, (u_t, v_t) are scalar defined in $(0,1)$ at time t. α, β and γ are estimated using the maximum likelihood estimator. m is an arbitrary window length, which is chosen here to be equal to 10. Therefore, $\sum_{j=1}^{m} \frac{|u_{t-j}-v_{t-j}|}{m}$ measures how close the last 10 observations were to being perfectly dependent.

We consider two models of copulas, i.e. Clayton and Gumbel, and the marginals are assumed to follow Gamma distributions. We therefore consider the following copulas:

for Clayton

$$C_{cl}(u, v, \theta) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta}, \qquad if\ \theta > 0, \tag{11a}$$

$$C_{cl}(u, v, \theta) = \max\left[\left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta}, 0\right], \ if -1 \leq \theta < 0, \tag{11b}$$

$$C_{cl}(u, v, \theta) = C_{cl}(u, v, 1), \qquad if\ \theta = 0. \tag{11c}$$

for Gumbel

$$C_{gu}(u, v, \theta) = exp\left[-\left\{(-\log u)^{\theta} + (-\log v)^{\theta}\right\}^{1/\theta}\right], \ if\ \theta > 1, \tag{12a}$$

$$C_{cl}(u, v, \theta) = C_{cl}(u, v, 1), \qquad if\ \theta = 1. \tag{12b}$$

Kendall's τ rank-correlation coefficient can be expressed as a function of θ:

$$\tau(\theta) = 4\int_0^1\int_0^1 C(u, v, \theta)\, c(u, v, \theta)\, du\, dv - 1 = 4E[C(u, v, \theta)]. \tag{13}$$

$c(u, v, \theta)$ is the pdf of the copula, i.e the second derivative of the distribution function $C(u, v, \theta)$ with respect to u and v.

Figures B1a through B3b, in Appendix B, show the estimation of θ and we compute the corresponding value of Kendall's τ (which is a rank correlation coefficient). In Table 3, we order the epidemiological variables according to their rank correlation, from the most to the least significant.

In each region, the epidemiological variable that seems to evolve most in conjunction with OSA is the new confirmed cases, while most often the variables reproduction rate and confirmed deaths do not seem to be correlated with spreads. Government stringency has a higher correlation with spreads in Africa than in the other two regions. In many cases, we observe a high variation of the parameter θ across time. Such changes could be explained by the presence of nonlinear relationships between corporate OAS and the epidemiological variables.

Figures C1 to C3, in Appendix C, suggest the existence of such nonlinear relationships. The curves are obtained using a non-parametric LOWESS (locally weighted locally smoothing) adjustment. For example, the relationship between OAS and new confirmed cases is represented by an inverted U-shaped curve. If the ratio of new cases to cumulative cases is below a threshold, spreads increase with the number of new cases. But beyond this threshold, we observe a saturation effect, i.e. spreads continue to increase but at a lower rate. This phenomenon can be explained by the kinetics of the propagation of Covid-19 which is identical to that of many viral disease epidemics (S-Shaped). At the start of an epidemic wave, the disease spreads at an exponential rate until the epidemic curve reaches an inflection point, at which the number of newly infected persons increases more and more slowly until a plateau is reached. This plateau generally marks the beginning of the epidemic's decline phase. The thresholds in the graphs correspond to the periods of these inflection points on the Covid-A9 epidemic curves of the different regions.

4.2.- Epidemiological variables are strong determinants of the right tail index of corporate OAS distribution function

4.2.1.- Fitting Pareto laws

The graphs in Appendix C also show a difficulty in adjusting the curves to the points that are far from the "center" of the graph, which can be called "outliers», and which correspond to the highest spreads. These points probably follow different laws than the other points on the chart (extreme value laws). We have seen, for example, that Weibull-type laws can be used to describe our variables. The theory of extreme values teaches us that to study the behavior of values beyond a certain threshold, we can find laws whose one of the parameters describes the heaviness of the tail. Under certain conditions, the laws of excess above a certain threshold converge to Pareto laws. We show in the following paragraphs that considering epidemiological variables significantly improves the fitness of type I Pareto laws applied to OAS series.

Table 3

Ranking of the epidemiological variables according to their rank-correlation with OAS

	Latin America	**Africa**	**Asia**
		Clayton copula	
1	New confirmed cases ($\tau = 0.75$)	New confirmed cases ($\tau = 0.73$)	New confirmed cases ($0.37 \leq \tau \leq 0.47$)
2	Confirmed deaths ($0.28 \leq \tau \leq 0.5$)	Government stringency ($\tau = 0.66$)	Government stringency ($0.13 \leq \tau \leq 0.35$)
3	Reproduction rate ($0.23 \leq \tau \leq 0.35$)	Reproduction rate ($0.09 \leq \tau \leq 0.28$)	Reproduction rate ($\tau = 0$)
4	Government stringency ($0.13 \leq \tau \leq 0.31$)	Confirmed deaths ($\tau = 0$)	Confirmed deaths ($\tau = 0$)
		Gumbel copula	
1	New confirmed cases ($\tau = 0.75$)	New confirmed cases ($\tau = 0.75$)	New confirmed cases ($0.52 \leq \tau \leq 0.55$)
2	Reproduction rate ($0.37 \leq \tau \leq 0.5$)	Government stringency ($\tau = 0.65$)	Government stringency ($0.31 \leq \tau \leq 0.35$)
3	Government stringency ($\tau = 0$)	Reproduction rate ($\tau = 0$)	Reproduction rate ($\tau = 0$)
4	Confirmed deaths ($\tau = 0$)	Confirmed deaths ($\tau = 0$)	Confirmed deaths ($\tau = 0$)

An unconditional power-law probability density function is written as follows:

$$P(y_t) = \begin{cases} C y_t^{-\alpha}, & y_t \geq y^{min} \\ 0, & y_t < y^{min} \end{cases}, \quad C = \frac{\alpha - 1}{(y^{min})^{1-\alpha}}. \tag{14}$$

C is a normalizing constant and α is a scaling – or shape – parameter describing a tail index. Typical values for a Pareto law are usually found for $\alpha < 3$ for which the mean exists but the variance and higher-order moments are not finite. y^{min} is the value beyond which spreads belong to a Pareto distribution. The m-th order moment is given by

$$< y^m \geq \int_{y^{min}}^{\infty} y^m p(y) dy = \frac{\alpha - 1}{\alpha - 1 - m} y^{min}, \tag{15}$$

which is well-defined for $m < \alpha - 1$. α is usually estimated by considering a log-log rank size regression:

$$\log\left(t - \frac{1}{2}\right) = a - b\log(\tilde{y}_t) + \varepsilon_t,\ y_t \geq y^{min}, \quad (16)$$

where t is the rank of the observations and $\tilde{y}_t$ denotes the value of the observations ranked in decreasing order. We augment this regression with the epidemiological variables (in a vector $\boldsymbol{X}_t$):

$$\log\left(t - \frac{1}{2}\right) = a - b\log(\tilde{y}_t) + \boldsymbol{\theta}'\widetilde{\boldsymbol{X}}_t + \varepsilon_t,\ y_t \geq y^{min}, \quad (17)$$

y^{min} is chosen as the 75th percentile of the OAS series. $\widetilde{\boldsymbol{X}}_t$ means that the values of epidemiological variables are ordered according to the ranked values of OAS. A Wald test can be used to test the significance of the epidemiological variables and to see whether their inclusion in the regression changes the estimate of the parameter b (tail index).

Tables 4a through 4c contain the estimates and Figures 8a through 8c show plots of the rank of observations versus the spreads. The slope of this relationship corresponds to the tail index. As can be seen, by considering the epidemiological variables, the fit of the predicted values to the observed values is significantly better. The estimate of the parameter b decreases when epidemiological variables are introduced, and it varies between 0.2 and 1.4. These variables therefore provide a crucial understanding of the tail behavior of corporate OAS, i.e. they explain the frequency of large rises in the spreads. Over the period under investigation, sudden and large rises of corporate OAS above a threshold can be considered as giving rise to a fat-right tail situation. Given the values of the estimated coefficient b, no moments exist because the condition $m < \alpha - 1$ is always violated. This sheds some doubts on the use of stable laws when we search to model – and predict - corporate spreads during times of viral epidemic diseases like Covid-19.

Table 4a

Estimates of Pareto equation. Latin American countries.

Without epidemiological variables				
Independent Variables	*Estimate*	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	2.567***	0.17072	15.04	<2e-16
Tail index (b)	2.25***	0.09033	-24.91	<2e-16
R^2	0.92			
With epidemiologial variables				
Intercept	**-0.687****	**0.324**	**-2.117**	**0.039**
Tail index (b)	0.244*	0.134	-1.819	0.075
New cases vs cumulative cases	-5.788**	1.747	-3.313	0.002
Confirm death vs GDP per capita	0.015***	0.001	8.953	1.00e-11
Reproduction rate	-0.580***	0.114	-5.087	6.26e-06
Stringency index	0.004***	0.001	4.032	0.000
R^2	0.99			

*Note: *,**,***: statistically significant coefficient at respectively 10%, 5% and 1% level of confidence*

Table 4b

Estimates of Pareto equation. Asian countries.

Without epidemiological variables				
Independent Variables	*Estimate*	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	3,269***	0,1907	17,15	<2e-16
Tail index (b)	3,691***	0.1354	-27,26	<2e-16
R^2	0,9128			
With epidemiological variables				
Intercept	**-0,232**	**0,3563**	**-0,652**	**0,5168**
Tail index (b)	1,050***	0,2441	-4,304	5,6e-05
New cases vs cumulative cases	-19,691***	2,045032	-9,629	2,9e-14
Confirm death vs GDP per capita	0,0758**	0,0368	2,059	0,0433
Reproduction rate	0,4632***	0,1006	4,602	1,91e-05
Stringency index	-0,0026	0,0030	-0,873	0,386
R^2	0,9876			

*Note: *,**,***: statistically significant coefficient at respectively 10%, 5% and 1% level of confidence.*

Table 4c

Estimates of Pareto equation. Africa & MENA countries.

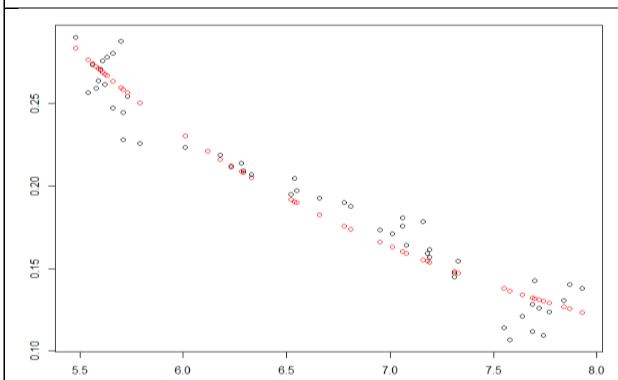
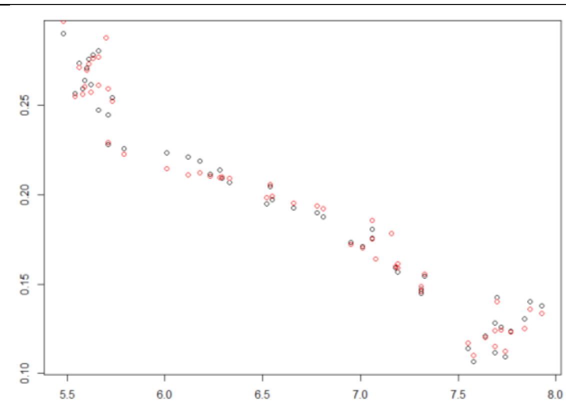
Without epidemiological variables				
Independent Variables	*Estimate*	*Std. Error*	*t value*	*Pr(>|t|)*
Intercept	2.9294***	0.3433	8.534	1.71e-12
Tail index (b)	3.0595***	0.2132	-14.353	<2e-16
R^2	0.7401			
With epidemiological variables				
Intercept	-0.483**	0.222	-2.174	0.033
Tail index (b)	1.396***	0.180	-7.755	6.65e-11
New cases vs cumulative cases	-13.051***	1.513	-8.626	1.79e-12
Confirm death vs GDP per capita	0.132***	0.027	4.937	5.54e-06
Reproduction rate	0.392***	0.067	5.803	1.95e-07
Stringency index	0.009***	0.002	3.422	0.001
R^2	0.98			

*Note: *,**,***: statistically significant coefficient at respectively 10%, 5% and 1% level of confidence.*

Figure 8a

Pareto regression log-log plot: Rank (y-axis) versus corporate OAS (x-axis)

Latin America

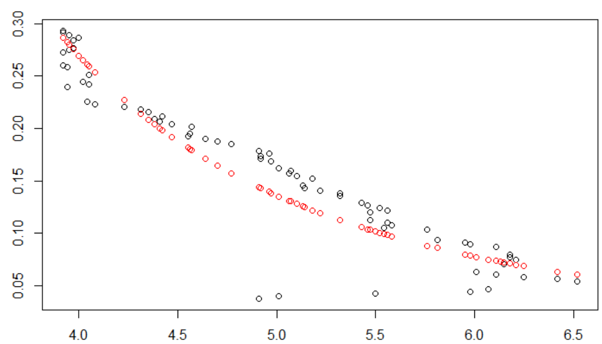
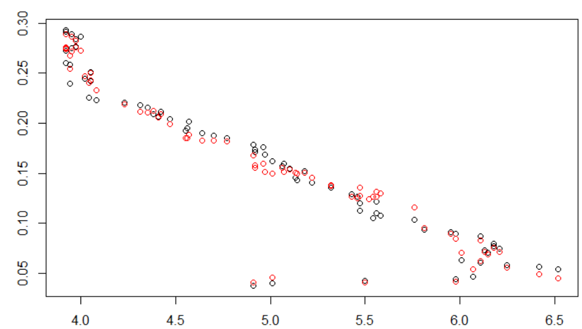
Without epidemiological variables	With epidemiological variables
	

Note: Red= fitted data. Black = raw data

Figure 8b

Pareto regression log-log plot: Rank (y-axis) versus corporate OAS (x-axis)

Africa & MENA

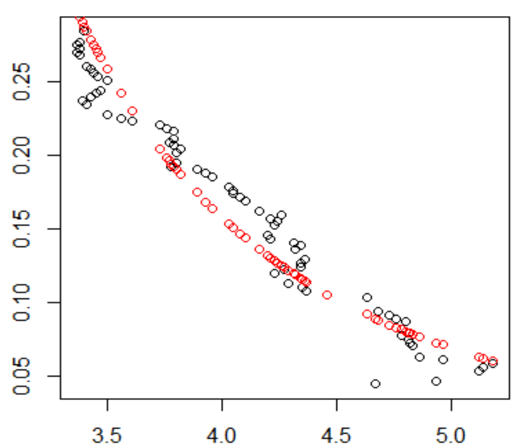
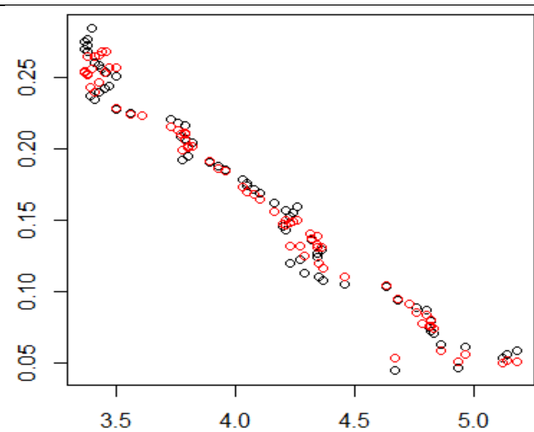
Without epidemiological variables	With epidemiological variables
	

Note: Red= fitted data. Black = raw data

Figure 8c

Pareto regression log-log plot: Rank (y-axis) versus corporate OAS (x-axis)

Asia

Without epidemiological variables	With epidemiological variables
	

Note: Red= fitted data. Black = raw data

4.2.2.- Implications for the underlying dynamics of the short rate

The estimates of the parameters of a Pareto distribution for values of spreads greater than a given threshold can be used to identify the parameters of the theoretical models that are supposed to govern the dynamics of the short interest rate for extreme values. To show this, let us consider the example of the Black-Derman-Toy model (BDT).

The Pareto distribution for the ranked spreads also applies to the ranked short rate above a threshold value, say $\bar{r}$. Let us consider the process of the short rate ranked by increasing values $\{\tilde{r}_t,\ \tilde{r}_t \geq\ \bar{r}\}$. Define $f(r)$ the invariant steady state probability density function of this process. Then, the following theorem holds:

Theorem 1. If $\{\tilde{r}_t,\ \tilde{r}_t \geq\ \bar{r}\}$ is governed by the stochastic differential equation (SDE) as in the BDT model, then $f(r)$ can be defined by the following power law function

$$f(\tilde{r}) = \begin{cases} C\tilde{r}^{-\alpha}, & \tilde{r} \geq \bar{r} \\ 0, & \tilde{r} < \bar{r} \end{cases}, \quad \alpha = 2[1 - \mu/\sigma^2],\ C\ is\ a\ constant. \tag{18}$$

Proof

Consider the following BDT stochastic differential equation, in the vicinity of the steady state distribution function of the ranked short rate:

$$d\tilde{r}(t) = \Omega_1(\tilde{r})dt + \Omega_2^{\frac{1}{2}}(\tilde{r})dW_t,\ \Omega_1(\tilde{r}) =\ \mu\,\tilde{r},\ \Omega_2(\tilde{r}) = \sigma^2 r^2 dW_t.$$

From the statistical theory of positive Lebesgue measures, we know that a general formula of the asymptotic pdf corresponding to the above equation is given by using $m(\tilde{r})$ the speed density function:

$$f(\tilde{r}) =\ \lambda_0 m(\tilde{r}), \qquad m(\tilde{r}) = \frac{exp(2\,J(\tilde{r}))}{\Omega_2(\tilde{r})},\ J(\tilde{r}) = \int_{\bar{r}}^{\tilde{r}} \frac{\Omega_1(u)}{\Omega_2(u)}\,du$$

where λ_0 is a normalizing constant. We compute

$$
\begin{aligned}
\lambda_0 m(\tilde{r}) &= \frac{\lambda_0}{\sigma^2 r^2} exp\left[2\int_{\bar{r}}^{\tilde{r}} \frac{\mu\, u}{\sigma^2\, u^2} du\right] \\
&= \frac{\lambda_0}{\sigma^2 r^2} exp\left[2\frac{\mu}{\sigma^2}\ln\left(\frac{\tilde{r}}{\bar{r}}\right)\right] \\
&= \frac{\lambda_0}{\sigma^2}(\bar{r})^{-2}\left(\frac{\tilde{r}}{\bar{r}}\right)^{-2\left(1-\frac{\mu}{\sigma^2}\right)}
\end{aligned}
$$

Finally, we have

$$f(\tilde{r}) = C(\tilde{r})^{-\alpha},\ \ C = \frac{\lambda_0}{\sigma^2}(\bar{r})^{\alpha-2}, \alpha = 2[1-\mu/\sigma^2],\ \tilde{r} \geq \bar{r}.$$

This corresponds to a power law pdf, like in Equation 14, with $\alpha = 2[1-\mu/\sigma^2]$. We then calculate the normalizing constant λ_0 such that $\int_{\bar{r}}^{+\infty} f(u)du = 1$. We obtain $\lambda_0 = -\bar{r}(2\mu - \sigma^2)$.

■

Once α and C are estimated as in the previous section, their estimates can serve as identification conditions to find the threshold value $\bar{r}$ above which the process $\{\tilde{r}_t,\ \tilde{r}_t \geq\ \bar{r}\}$ converges to a steady state distribution described by a power-law function. Define $\hat{\alpha}$ and $\hat{C}$ as the estimate of the tail index coefficient and intercept in the log-log rank regression (Equations 16 or 17). Then, we define the following system of two equations:

$$\begin{cases} \hat{\alpha} = 2[1-\mu/\sigma^2], \\ \hat{C} = \frac{-\bar{r}(2\mu-\sigma^2)}{\sigma^2}(\bar{r})^{\hat{\alpha}-2}. \end{cases} \tag{19}$$

There is an infinite number of values for μ and σ^2 that satisfy this sytem, but only one value for $\bar{r}$ which is obtained by eliminating either μ or σ^2 when solving the system by substitution.

5.- Conclusion

The results of our paper show that epidemiological variables related to the first wave of the Covid-19 crisis from March 2020 to April 2021 had an influence on corporate OAS in emerging countries. Thus, information about the spread of the epidemic became part of the informational set of investors in emerging market corporate debt. Variables such as the number of new cases, reproduction rates, mortality rates or containment policies may explain why spreads become higher during the acute phases of the crisis, but more importantly why their future evolution is impossible to predict. This is highlighted by the non-existence of moments for the Pareto law that we have estimated.

In prioritizing the variables, the one that changes most in conjunction with RSA is the number of new cases, and the variable that appears to change most independently of the spreads is the mortality rate. Our statistical analysis opposes the idea that investors are primarily sensitive to the fundamental variables of companies in deciding to buy their debt. Global variables, notably epidemiological ones, influence their decisions. Our study has at least one implication. While the epidemic is not yet over, the succession of several epidemic waves in the future could make the evolution of spreads unpredictable.

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Appendix A. – Fitting Weibull, log-normal and Gamma distributions to OAS

Figure A1. Asia

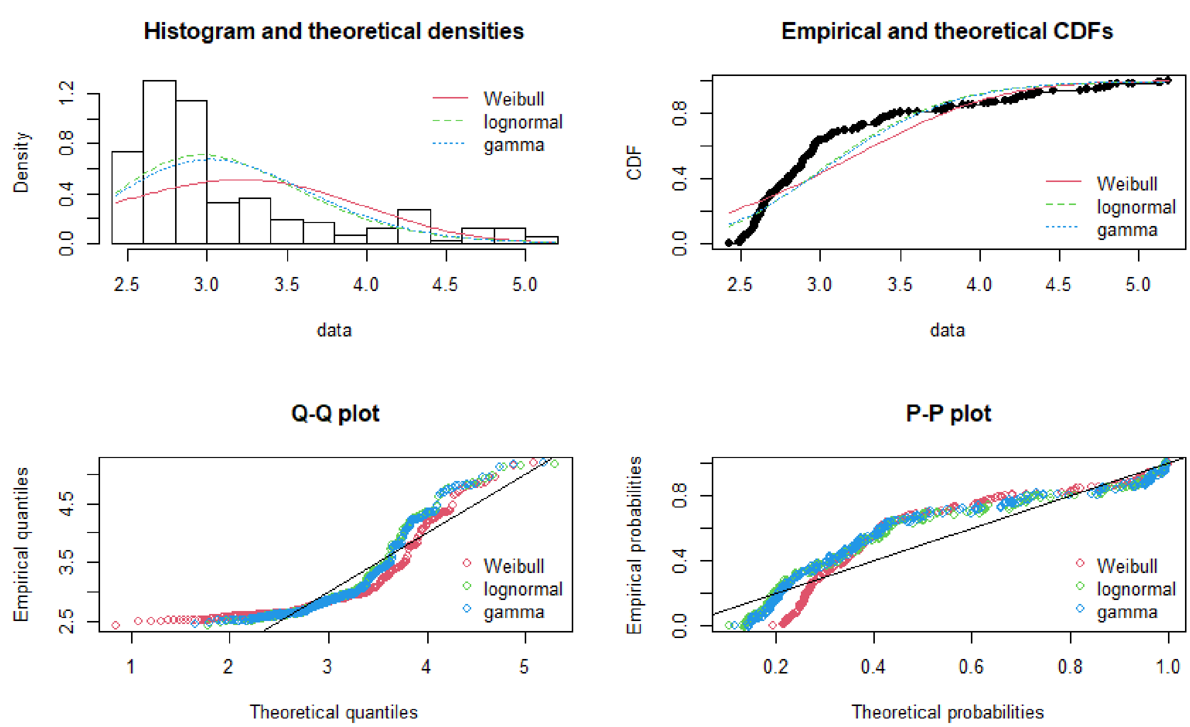
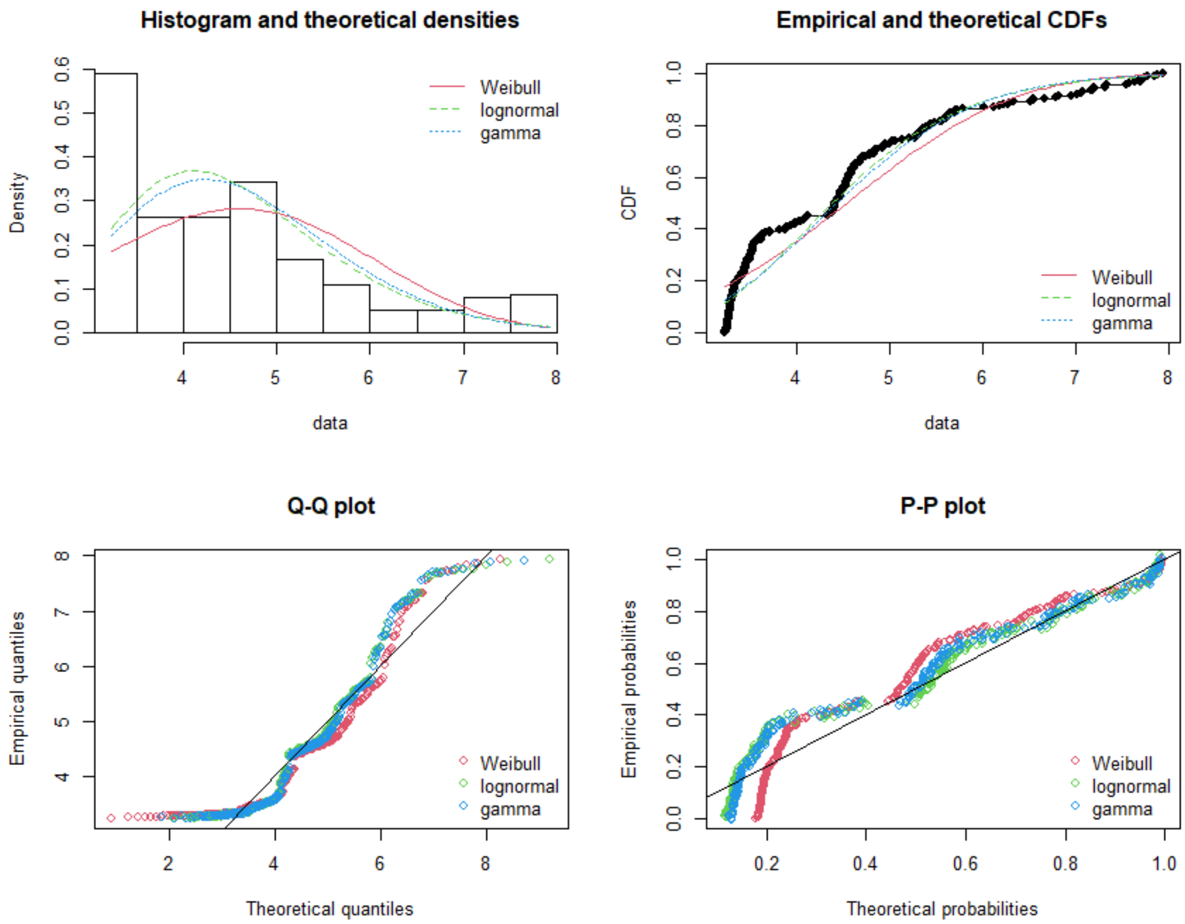


Figure A2. Latin America



Appendix B. – Graphs of time-varying copulas

Figure B1a

Time-varying θ with Clayton Copula: Latin America

x-axis : observations, y-axis : θ

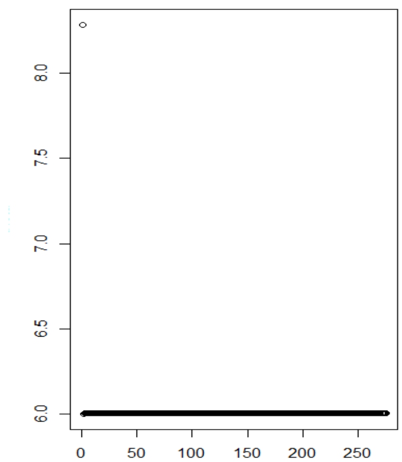
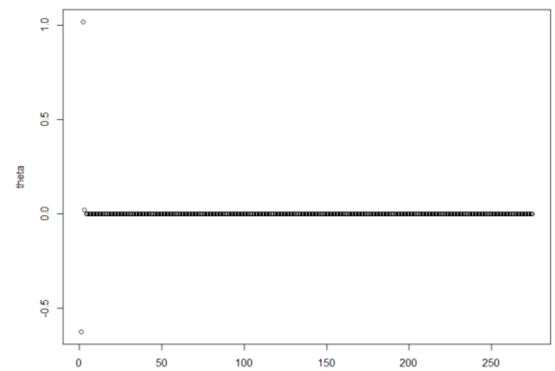
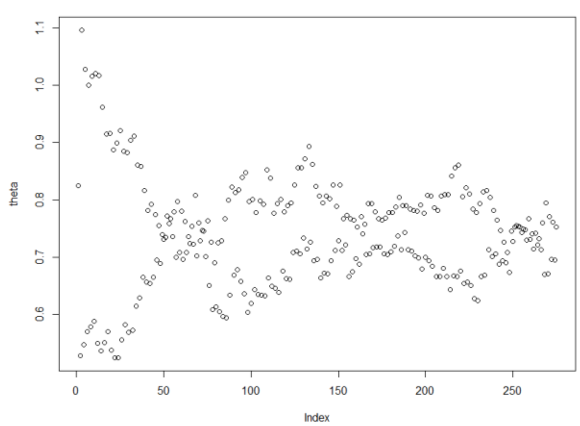
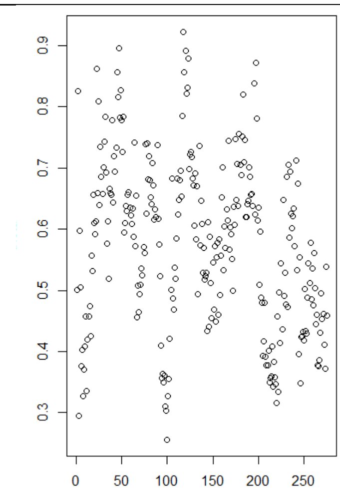
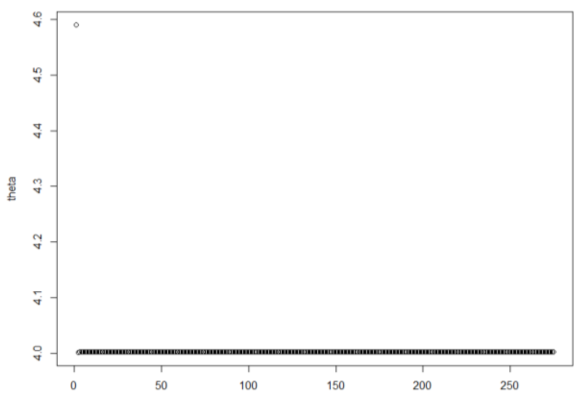
New confirmed cases ($\tau = 0.75$)	Confirmed deaths ($0.28 \leq \tau \leq 0.5$)
	
Reproduction rate ($0.23 \leq \tau \leq 0.35$)	Government stringency ($0.13 \leq \tau \leq 0.31$)
	

Figure B1b

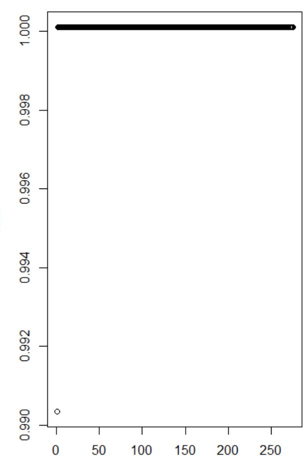
Time-varying θ with Gumbel Copula: Latin America

x-axis: observations, y-axis : θ

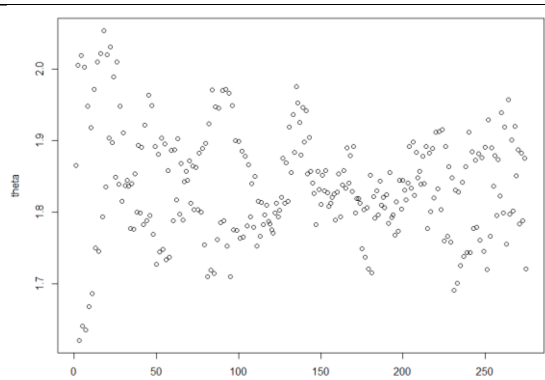
New confirmed cases ($\tau = 0.75$)



Confirmed deaths ($\tau = 0$)



Reproduction rate ($0.37 \leq \tau \leq 0.5$)



Government stringency ($0.16 \leq \tau \leq 0.5$)

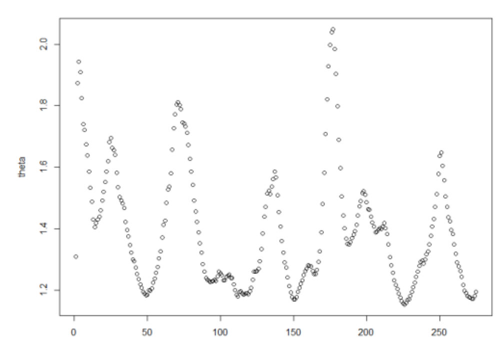


Figure B2a

Time-varying θ with Clayton Copula: Africa & MENA

x-axis: observations, y-axis : θ

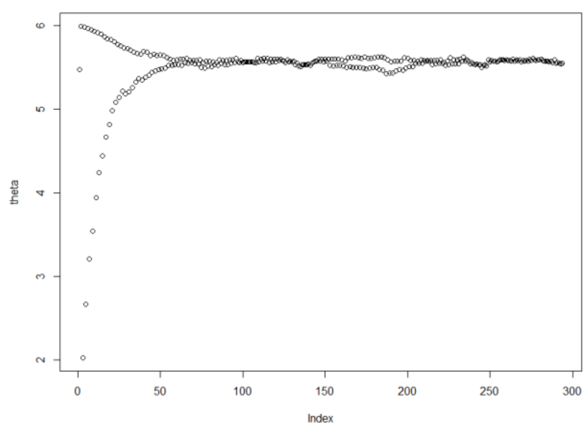
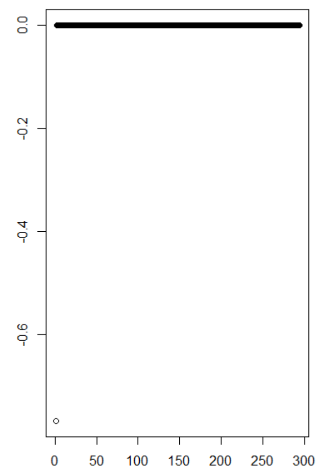
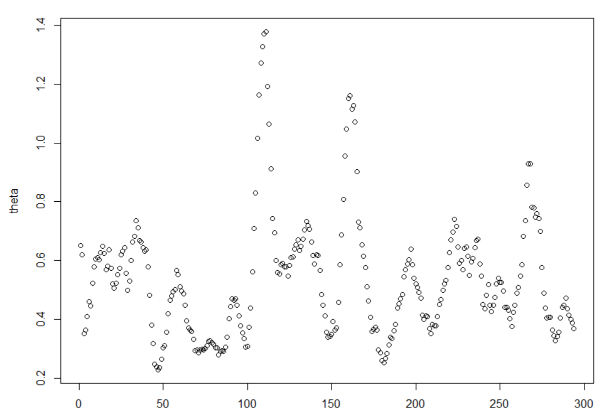
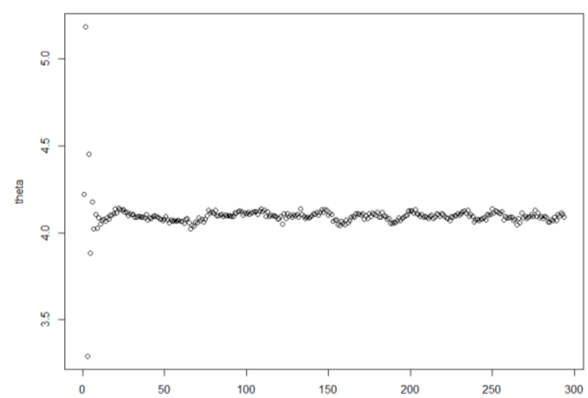
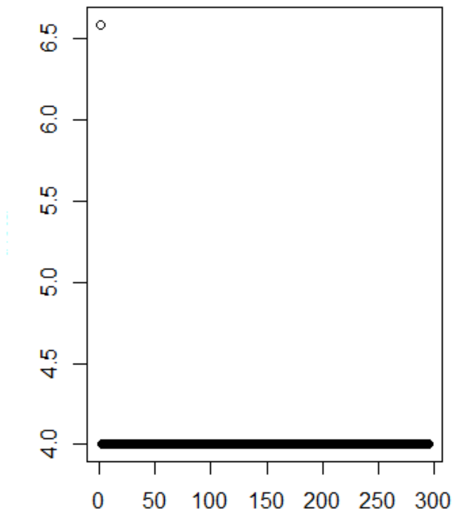
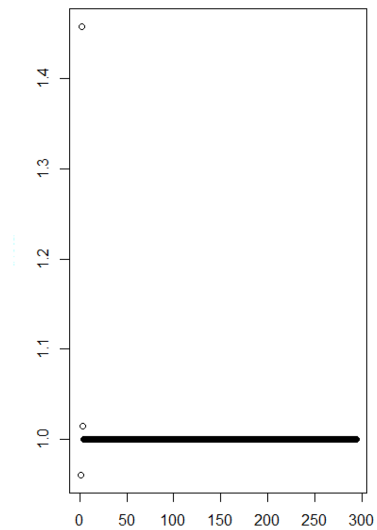
New confirmed cases ($\tau = 0.73$)	Confirmed deaths (average $\tau = 0$)
	
Reproduction rate ($0.09 \leq \tau \leq 0.28$)	Government stringency ($\tau = 0.66$)
	

Figure B2b

Time-varying θ with Gumbel Copula: Africa & MENA

x-axis: observations, y-axis : θ

<table>
<tr><td>New confirmed cases ($\tau = 0.75$)</td><td>Confirmed deaths ($\tau = 0$)</td></tr>
<tr><td>
</td><td>
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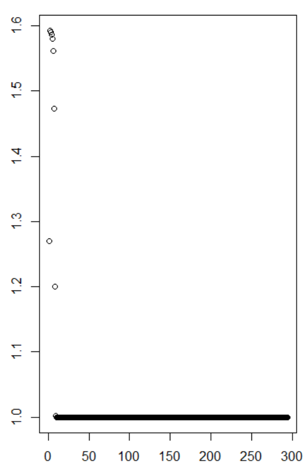
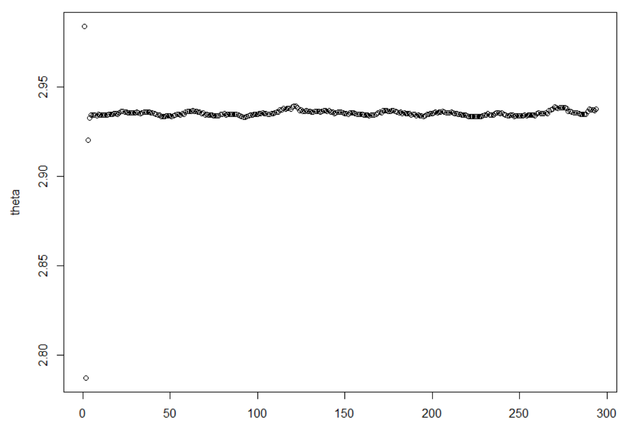
<tr><td>
</td><td>
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Figure B3a

Time-varying θ with Clayton Copula: Asia

x-axis: observations, y-axis : θ

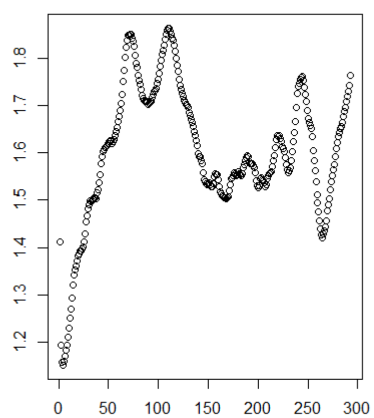
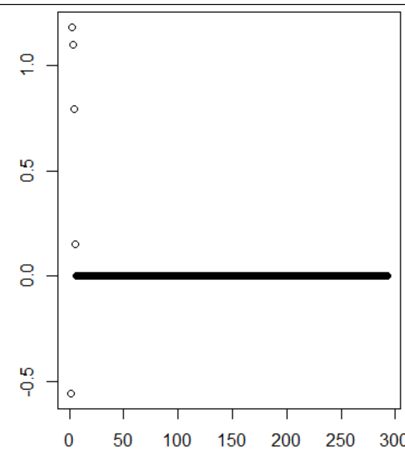
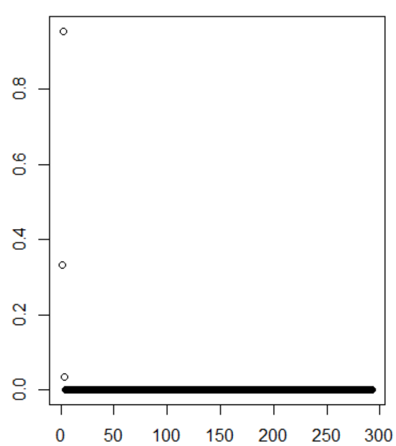
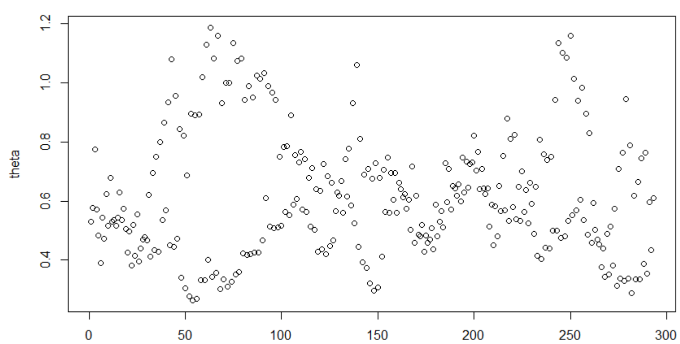
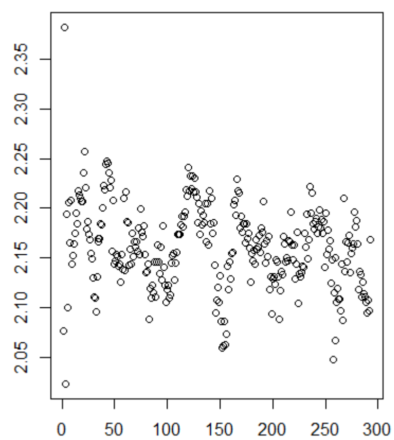
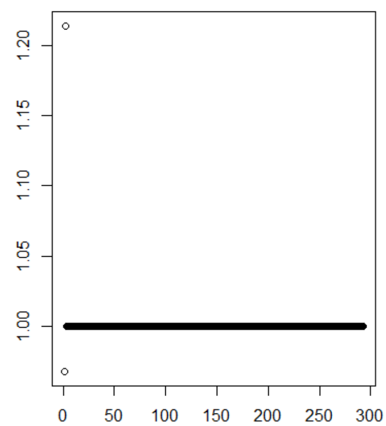
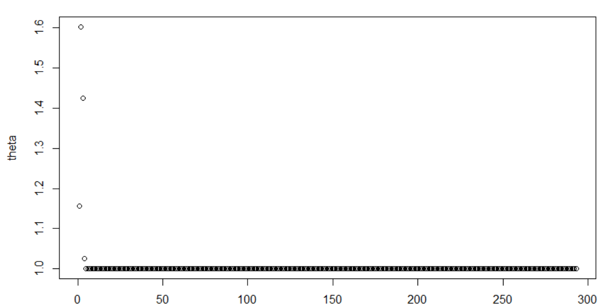
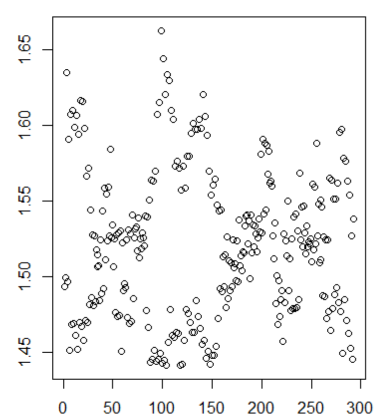
New confirmed cases ($0.37 \leq \tau \leq 0.47$)	Confirmed deaths (average $\tau = 0$)
	
Reproduction rate ($\tau = 0$)	Government stringency ($0.13 \leq \tau \leq 0.35$)
	

Figure B3b

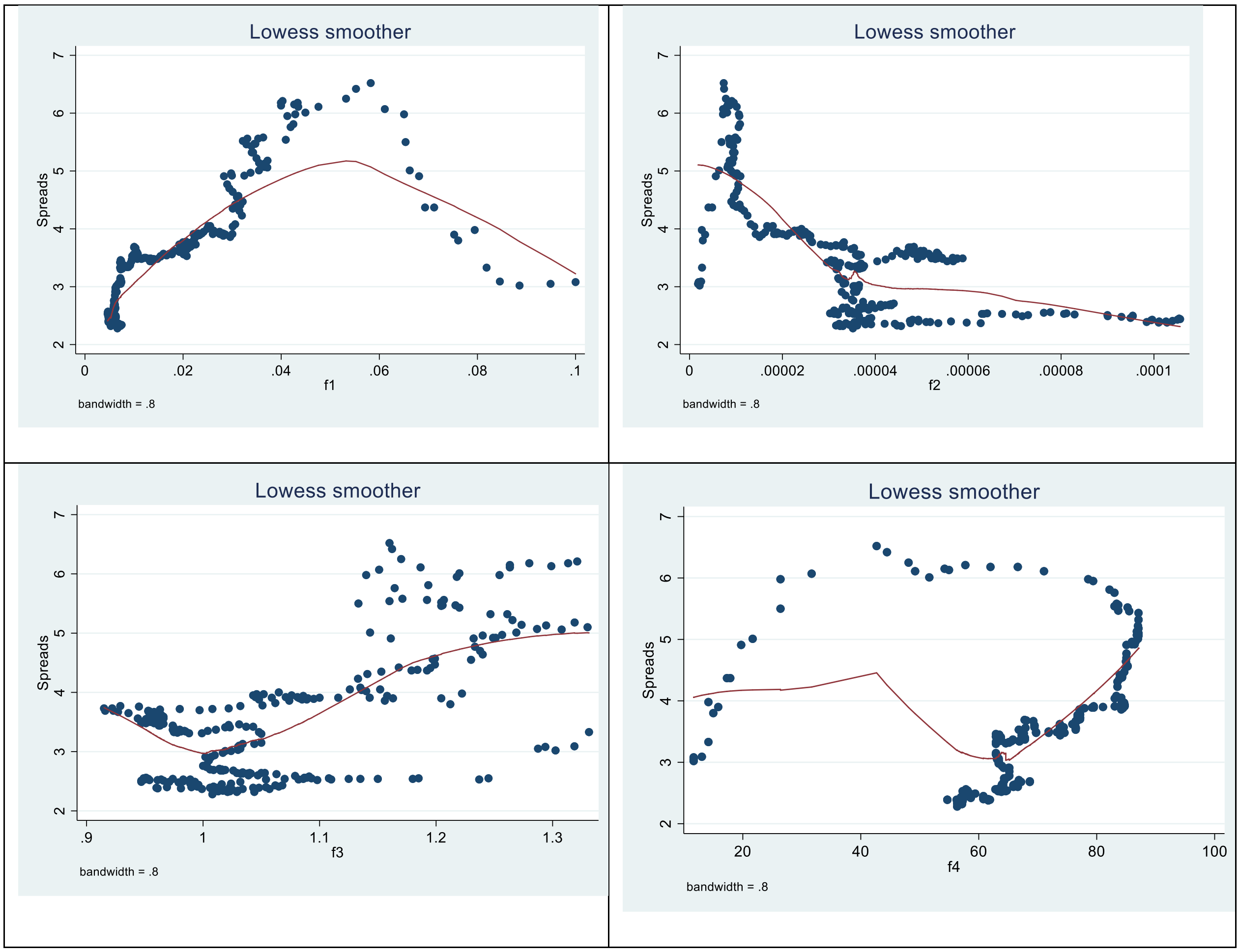
Time-varying θ with Gumbel Copula: Asia

x-axis: observations, y-axis : θ

New confirmed cases ($0.52 \leq \tau \leq 0.55$)	Confirmed deaths ($\tau = 0$)
	
Reproduction rate ($\tau = 0$)	Government stringency ($0.31 \leq \tau \leq 0.35$)
	

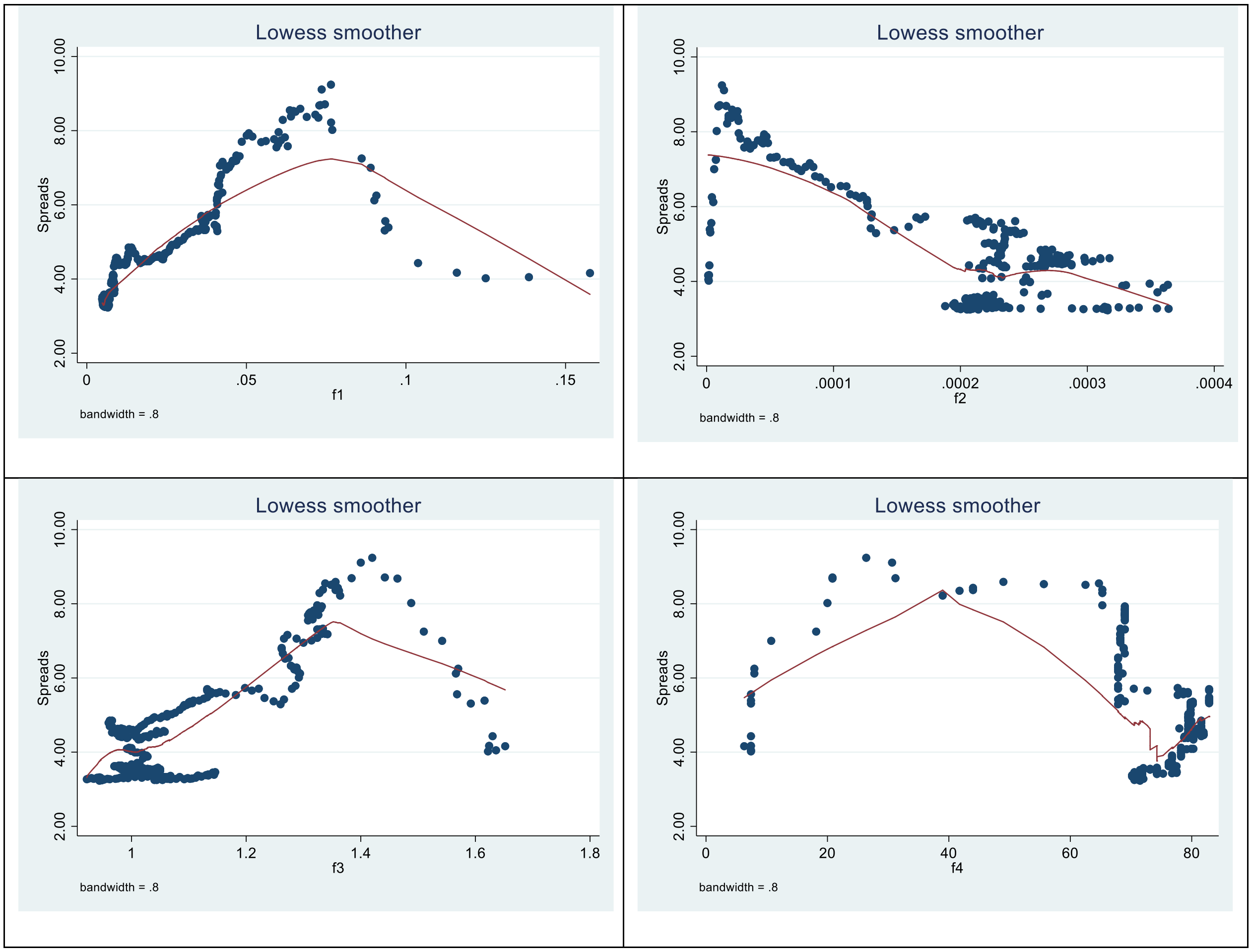
Appendix C. – Evidence of nonlinear relationships

Figure C1. Lowess smoother Spreads versus epidemic indicators (Africa & MENA)



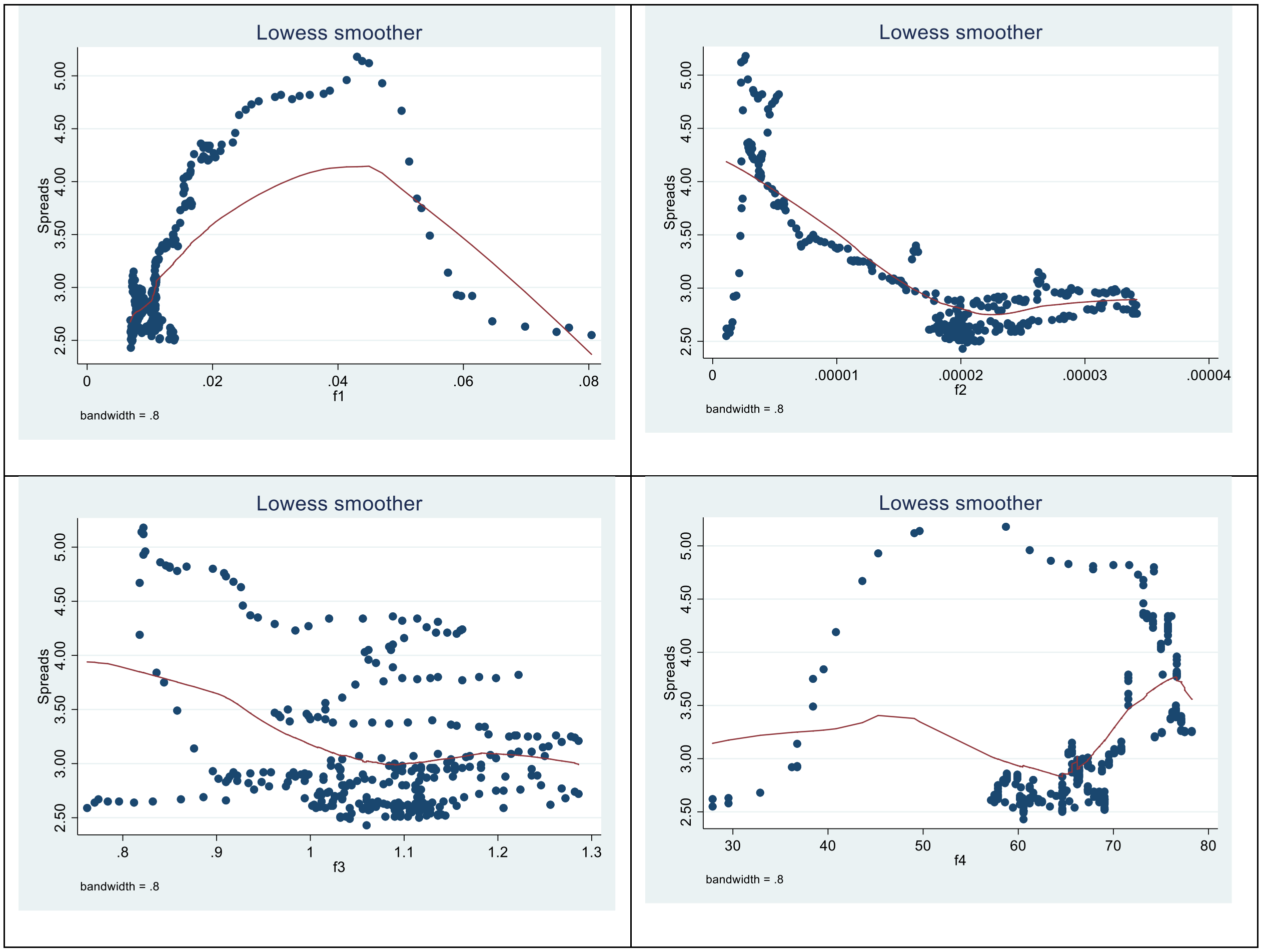
Note. f1: daily new confirmed cases vs cumulative cases. f2: Confirmed deaths per million vs GDP per capita. f3: reproduction rate. f4: government response stringency index.

Figure C2. Lowess smoother Spreads versus epidemic indicators (Latin America)



Note. f1: daily new confirmed cases vs cumulative cases. f2: Confirmed deaths per million vs GDP per capita. f3: reproduction rate. f4: government response stringency index.

Figure C3. Lowess smoother Spreads versus epidemic indicators (Asia)



Note. f1: daily new confirmed cases vs cumulative cases. f2: Confirmed deaths per million vs GDP per capita. f3: reproduction rate. f4: government response stringency index.