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Financial Resilience to Pandemics through Social Reinsurance: Application to COVID-19

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Abstract

The crisis caused by COVID-19 revealed the global unpreparedness to handle the impact of a pandemic. At the outbreak of a pandemic, time is the key variable that can save lives and reduce financial losses. In the present paper, we propose, as a risk transfer tool, a reinsurance product mainly for developing countries, based on a parametric insurance design, that can supplement a state's social insurance during a pandemic. The key feature of the proposed *social reinsurance* is a conditional payout function: the trigger provides guaranteed and immediate financing at the onset of a pandemic, while the cap links further payments to infection dynamics and the effectiveness of government measures. This two-step structure offers a win–win outcome, by delivering unconditional early support consistent with insurance principles, while at the same time incentivising proactive risk management and addressing market concerns over moral hazard. We develop the cap-curve concept as a benchmark mechanism that can be constructed from pooled early-wave infection-speed profiles across comparable countries or regions, and used to assess whether subsequent payouts remain justified. We illustrate the approach by exploring different trigger candidates and by constructing anonymised benchmark and policyholder infection-speed curves calibrated on early COVID-19 dynamics. Any numerical illustrations are intended to demonstrate contract mechanics rather than provide implementable market pricing.

Keywords: epidemic risk, moral hazard, parametric insurance, social protection, financial resilience, risk transfer.

1 Introduction

For rare catastrophic events, the people's and the governments' perceptions of risk and of risk management measures do not necessarily coincide. Pandemics have a significant impact on health systems, financial markets, manufacturing, tourism and hospitality industries, among others. Unlike other rare events, such as a tsunami or an earthquake, a pandemic can last over relatively long periods, putting severe strain on households' income through lockdown restrictions. Therefore, trust is one of the key factors that influence people's perception and

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compliance with risk management measures, see Siegrist and Zingg (2014) and Wong and Jensen (2020). As Siegrist et al. (2021) state, social trust has a severe impact on people's acceptance of government's implemented measures. A high level of social trust – that implies that information provided by the government is considered unbiased – has a positive effect on the participants' risk perceptions and vice versa.

By deciding about the necessary measures, every government has to face country-specific social trust indicators, and as stated in Kunreuther and Useem (2018), overcome the myopic "everything will be alright" bias or possibly overoptimism – see for instance Royal and Walls (2019) or Derbyshire (2022) among others – when preparing for low-probability, high-consequence events. As explained in Johnson et al. (2023), disasters of a similar severity can have entirely different effects on communities with different resilience levels. The most important task of authorities during a disaster is to make decisions that align the identified risks with appropriate risk management measures and policy responses, balancing safety, economic costs, and social impacts. However, governments' hands may be tied if strict early-stage containment measures are socially or economically infeasible due to their immediate consequences for vulnerable groups.

Low- and lower-middle-income countries are particularly exposed to this tension, as fiscal space, health-system capacity, and social protection coverage are often limited. Empirical evidence from the COVID-19 pandemic highlights how income losses, food insecurity, and constrained access to health care amplified the social costs of delayed or insufficient interventions. In many African countries, pandemic preparedness and response capacity can be shaped by reliance on external financial and technical assistance, although the extent and nature of this reliance varies substantially across the continent; see Renzaho (2020). Josephson et al. (2021) state that approximately 77% of the population in Ethiopia, Malawi, Nigeria and Uganda lost income due to COVID-19 as of early 2021. Whilst evidence from 2020 suggests that infection and mortality rates in some low-income settings were similar to, or even greater than, those in high-income countries (see, for instance, Walker et al. (2020)), health-care capacities are not directly comparable. The situation was further exacerbated by food insecurity across Uganda, Nigeria, Malawi and Ethiopia following the onset of the COVID-19 pandemic. One World Bank Blog reports that "over 70% of adults in Nigeria and Malawi are impacted by moderate or severe food insecurity, as well as 47% in Ethiopia, 42% in Burkina Faso, and 43% in Uganda" as of February 2021, see Gourlay et al. (2021). Taken together, these figures highlight the vulnerability of many low-income countries during pandemics, underscoring the urgency of rapid and reliable financial support mechanisms such as social reinsurance.

In 2017, the Pandemic Emergency Financial Facility (PEF) was launched by the World Bank and its partners to provide rapid disbursement for infectious diseases likely to cause pandemics in developing countries. Through this three-year insurance vehicle, the World Bank issued bonds sold to private investors, an investment tool that can be viewed as a form of catastrophe bond. Catastrophe bonds are securities that allow insureds to transfer risk to capital markets[1] and provide diversification opportunities for capital providers. For the PEF, the World Bank offered market-driven interest rates to compensate investors for the risk that payouts would be required in the event of a pandemic outbreak.

The PEF was widely criticised, primarily due to difficulties in accessing funding during the early stages of outbreaks and the provided margins to investors. A central structural

[1] See Bauer and Kramer (2012) for mathematical modelling of catastrophe mortality bonds.

weakness was the highly restrictive and complex triggering mechanism, which required multiple epidemiological and geographical thresholds to be met simultaneously, together with minimum time delays, before any payout could occur (Zhu, 2020; Fan and Plant, 2020; Zheng et al., 2023). As a result, support provided during the first wave of COVID-19 was widely regarded as "too little and too late" (Hodgson, 2020). Critics further argued that while investors received secure returns, affected countries were left without timely support (Fan and Plant, 2020; Zhu, 2020). Consequently, the second issuance of pandemic bonds was shelved.

These shortcomings have prompted renewed debate on how pandemic risks should be financed more effectively. Recent contributions emphasise that pandemic financing must move beyond ad hoc post-crisis aid towards pre-arranged, scalable instruments embedded within broader resilience strategies. The Center for Global Development (2024), for example, outlines a financing cycle spanning prevention, preparedness, response, and recovery. McKinsey (2022) highlights the need to combine financial protection with strengthened health systems, while the Centre for Disaster Protection (2023) points to the potential role of parametric and other innovative risk-transfer tools in closing existing protection gaps. Situating our proposal within this policy agenda, we focus on the *conceptual design* of a social reinsurance mechanism that can support timely financing and strengthen incentives for effective risk management, rather than on operational implementation or calibrated market pricing. Accordingly, we do not claim that the proposed mechanism dominates existing instruments; instead, we develop the cap-curve as a conceptual device for incentive-compatible conditionality within parametric pandemic financing, with the intended use case being a small, early-phase "bridge" tranche that provides rapid, bounded support while larger-scale public and international financing is mobilised.

Emergency cash transfers have been a key tool to provide a social and economic response to COVID-19, especially in low-income countries. In April 2020, the World Bank approved financial emergency support for developing countries to protect lives and support economic recovery. Half of the measures taken by the World Bank Group were through cash transfer targeting – as of December 2020 – 166 developing countries but other measures involved in-kind food and/or voucher schemes. Through this COVID-19 fast-track facility, the World Bank has been making available up to 160 billion US dollars from the start of the pandemic until June 2021, Gentilini et al. (2020).

In its Social Protection Spotlight Brief, the International Labour Organisation (ILO) explores the role of social protection in addressing the COVID-19 crisis, especially in developing countries, ILO (2020a). Social security is an essential component of all four main pillars established by ILO for combating the COVID-19 pandemic.[2] In collaboration with the UN agencies and the World Bank, ILO has programmed 21 million (April-December 2020) US dollars funding to respond to the COVID-19 pandemic to eliminate child labour and forced labour. The estimated total budget is 71 million US dollars for the period June 2020-June 2022 and it has been expected to increase due to an increase in funding requirements particularly in the least developed countries, ILO (2020b).

The sheer scale of financing needs during pandemics cannot be met by public budgets or international aid alone, making it necessary to involve private sector mechanisms such as

[2]Grounded on International Labour Standards, the ILO has established a four-pillar policy structure: Pillar 1: Stimulating the economy and employment; Pillar 2: Supporting enterprises, jobs, and incomes; Pillar 3: Protecting workers in the workplace; Pillar 4: Relying on social dialogue for solutions.

insurance and risk transfer. One of the traditional principles of insurance is risk pooling in the sense that the losses incurred by a few insured are spread over the entire group. Risk pooling arrangement allows to reduce the cost of insurance through risk diversification. Pandemic risks have a very low probability of occurrence but with a high severity loss. However, pandemic risks cannot be considered as catastrophe risks such as earthquakes or floods. It is a macro risk that affects large populations – in this case, the entire world – and can be pooled to some extent, with certain insurance products already available for epidemics, see for instance Assa and Boonen (2022). It is essential to have a social approach to pandemic financial preparedness and response. Then, it becomes the responsibility of the society to share the losses and of governments to minimise the damage to the economy and society safeguarding jobs and livelihoods. This situation can be compared to terrorism coverage. Similar to Kunreuther (2002), one faces three questions: 1) What factors determine whether the risk is insurable? 2) How much capital is required in order to provide protection? 3) What role can and should the private and public sectors play in providing protection?

It is, of course, an urgent need to find adequate measures to confront an ongoing pandemic, see, for example, Wu et al. (2021). However, acting in an optimal way at the beginning of a pandemic may be a game-changer. For instance, a quickly introduced hard lockdown may localise, slow down or even stop the spread of an infection.

This raises the question of how resources can be mobilised almost instantaneously. Rather than proposing an operational insurance product ready for market deployment, this paper develops and analyses a conceptual social reinsurance design intended to complement existing public and international responses during the early phase of a pandemic. The contract discussed provides short-term financial relief to governments and vulnerable populations by covering pandemic-related expenditures such as income support and social protection, thereby acting as a bridge until more comprehensive aid packages become available.

Thus, within this framework, the state is treated as the policyholder, reflecting an interaction between public and private sectors. As states already act as social insurers for their citizens, we refer to the proposed design as *social reinsurance*. Coverage against large-scale events such as global pandemics, similar to other catastrophic risks, is unlikely to be sustainable without significant government support. This support may take the form of direct public insurance or public–private partnerships (PPP). The proposed solution can fund social insurance systems or operate within a PPP structure, where private insurers cover individuals and firms to a limited extent and governments share in the underlying risk.
International organisations could act as buyers of such contracts, for example through competitive tendering. While reinsurers are not charitable organisations, the bounded-loss structure of the proposed contracts speaks to questions of insurability and capital requirements, and may align with broader objectives around responsible and impactful use of capital.[3]

This paper contributes to what is referred to in risk analysis as the “type B” pillar. It develops a conceptual method and contract design for social reinsurance aimed at mitigat-

[3]For instance, The Z Zurich Foundation (a charitable organisation founded by Zurich Insurance) has donated 1 million CHF in support of UNICEF’s vaccination campaign; The Foundation of Reinsurance Group of America has announced in April 2020 a donation of $1.5 million to help support COVID-19 relief efforts. In April 2021, the Insurance Industry Charitable Foundation (IICF) has gathered the leaders from AIG, Amwins, AXA XL, EY, Lloyd’s and The Hartford to discuss their COVID-19 relief initiatives. IICF explained that it would be “a way for the industry to help itself attract new talent while also helping others.” Some of the IICF philanthropic projects can be found, for instance, in IICF Insurance Industry Philantropic Showcase (2002).

ing the financial burden on states during the early phase of a pandemic. Section 2 reviews the key principles of insurance and parametric contracts and provides a novel discussion of the moral hazard issues specific to parametric insurance for pandemics, as well as potential mitigation mechanisms. Section 3 introduces the proposed parametric social reinsurance design, with particular emphasis on the cap-curve mechanism. Section 4 provides an illustrative application motivated by COVID-19, intended solely to demonstrate the mechanics of the design rather than to deliver a fully operational pricing framework. Section 5 concludes. In particular, we do not attempt market pricing. A market premium would generally exceed the actuarial expected value due to (i) risk loadings/markups reflecting cost of capital and ambiguity in non-diversifiable pandemic risk; (ii) the need to estimate (or bound) the probability that the policyholder trajectory breaches the cap-curve; and (iii) liquidity, transaction, data-verification, and monitoring costs. These components are necessary for operationalisation but lie beyond the scope of the present conceptual contribution.

2 Parametric Insurance and Pandemics

Parametric insurance products have been available since late 1990s and are suited for events with low probability of happening, but very costly damages, such as natural disasters (i.e. earthquakes) or any weather-related risks. In practice, parametric insurance products are mostly used in the reinsurance sector around catastrophe risks. An epidemic or a pandemic disease spread is considered a rare event with widespread impact which might destabilise state's medical, economic, financial and political systems in a country at the same time.[4]

The sudden nature and the uncontrollable aggregation of losses makes pandemics extremely difficult to insure as the huge economic losses would go beyond the capacities of any insurance company.

In the event of a pandemic, parametric insurance may be more effective than classical indemnity insurance (see for instance (Hillier, 2022)), not because total losses can be fully covered, but because its proxies (parameters) allow for rapid settlement and highly customisable triggers. This enables timely, targeted payouts even before the full extent of losses is known, providing critical early support when delays would be most costly. Such coverage is particularly valuable in pandemics, where small but immediate financing can help enforce social distancing, subsidise vulnerable households or firms, or fund urgent medical responses, while the overall scale of indemnity losses remains far beyond insurable limits.

The principle of parametric insurance is simple. Instead of indemnifying for the actual loss incurred – as in traditional insurance contracts – parametric insurance covers the probability of a predefined event happening and pays out according to a predefined scheme. In this way, the so-called parametric insurance provides fast payments for claims when predetermined parameters are met. This type of insurance helps governments to initiate a prompt recovery after a disaster as payments are made within a few days of a catastrophic event.

Contracts based on parametric insurance consist of two main elements: triggering events and the pay-out scheme. These two elements define the scope of the policy and are vital for pricing

[4]See the National Academies of Sciences, Engineering and Medicine (2006), Madhav et al. (2017) and World Health Organization (2018).

insurance parametric contracts.

The insurance pays if an event hits the defined trigger level, i.e. if pre-defined event parameters are met or exceeded. The defined trigger level is measured by an *objective* and *reliable* parameter or index – given by an independent, third party data source - that is related to an insured's exposure to risk. For example, in natural disasters, a triggering event might be a hurricane where the parameter is a pre-defined level of wind speed. All triggering events must be *fortuitous* and *quantifiable* to be able to model them. The pay-out scheme outlines the amount paid out to the insured in the case that the event reaches the trigger level.

The PEF also shares some features of the parametric insurance. In particular, the payments are predefined at the beginning of the contract and the trigger depends on factors such as infection and death rates, growth of infection rate and countries affected by the epidemic, amongst others.

Characteristics of the parametric insurance

Indemnity amount: Traditional insurance reimburses the insured for the actual losses incurred. In contrast, payments of parametric insurance are triggered by a fortuitous and quantifiable event exceeding a parametric threshold and pays out according to a predefined scheme.

Claims handling: While the assessment of actual losses with traditional insurance might be both complex and time-consuming, the pay-out of parametric insurance is instead a matter of days. Hence, the insurers' administrative burden is reduced.

Basis risk: The differences between the actual losses and the trigger creates basis risk. For example, a low-intensity earthquake might not trigger a parametric payout but still can provoke some damages and therefore some losses. Thoughtful design for triggers can limit the basis risk but cannot eliminate it.

Structure of the contract: While traditional insurance contracts typically have standardised wording, parametric insurance is a customised product with uniquely tailored index and pay-out provisions. However, the wording of the parametric insurance contracts tends to be much shorter than standard traditional policies.

Moral hazard: When a variable exceeds an agreed threshold, the agreed payment needs to be made. Consequently, parametric insurance contracts are immune from moral hazard because they are triggered based on objective and reliable measurements beyond the control of the insurer and the insured. In contrast, in non-parametric products, once covered, the insured can behave more riskily.[5]

Advantages of parametric insurance for pandemics

- A parametric insurance would provide fast payments, when the money is most needed, and help government to initiate a prompt response;
- it bridges the gap to the aid provided by international organisations;
- it provides a simple way around the uncertainty as the insurance payments are contractually agreed and do not need to be assessed first.

[5] In practice, in traditional insurance, the insurer combats moral hazard by using deductibles and/or different level of premia.

Challenges of parametric insurance for pandemics

Due to the very nature of pandemics:

- All triggers (for example, death rates and/or infection rates above a certain level for a pre-defined period) will depend on the governments' actions like lockdown, obligatory masks and social distancing, provided financial support etc. This dependence is precisely why parametric insurance for pandemics creates moral hazard, in contrast to parametric insurance for other natural hazards such as floods or droughts. As a result, designing an effective trigger is difficult. The joint trigger of the PEF, for example, was criticised as the activation criteria were very restrictive and difficult to be met simultaneously – creating a considerable obstacle for accessing the funding when it was really needed.

- The introduction of a cap to mitigate moral hazard, will require a surveillance tool as the publicly available data on dead and infected reported by countries can be contaminated (on purpose or due to reporting errors), see for instance Karlinsky and Kobak (2021). By comparing the infected/dead data from different hospitals and testing stations inside one country, using compositional functional data analysis, one can detect the outliers, see Rieser and Filzmoser (2022). What happens if there are too many or too severe outliers can be specified in the contract. Adopting a machine learning approach for outlier detection, like in Benatti (2019), can keep the costs of such a surveillance tool very low.

- Moral hazard becomes an issue as countries can manipulate the triggers in order to get the insurance. Therefore, the amount of help expected from the reinsurance product we suggest, should be smaller than the expected damage from the declaration of the state of emergency if this is not really necessary. Concerning the other triggers like the number of dead or infected – this can be monitored by outlier detection tools as suggested above.

In addition, as it is stated, for instance, in Carter (Carter, 2013, p. 4) "Not all insurance contracts are subject to the principle of indemnity; it is well accepted law that insurances covering human life (i.e. life, personal accident and sickness policies) are excluded from the principle and therefore are sometimes termed benefit policies."
As the dangers of a pandemic are life threatening indeed, a possible overcompensation by a parametric insurance can be neglected.
Note that, from now on, we will call the presented product a reinsurance contract since the parametric insurance described on this section is intended to serve as a supplement to a state's social insurance.

3 Social Reinsurance Product Description

The proposed reinsurance design based on parametric insurance principles, targets primarily to provide a quick financial payout to a country affected by an epidemic event. The state is considered a policyholder. This product is not aimed at overtaking governmental duties or enforcing specific lines of action. In particular, the latter requirement is in line with the UN's principle of non-intervention in the inner affairs of other states (UN General Assembly, 1970).

Reinsurance premia could be funded through international organisations such as the United Nations or any global reinsurance platform and/or institutional donors (e.g. Global Shield). Another alternative for developed countries can be the charge of an insurance tax on certain types of insurance.

An important aspect of a classical parametric reinsurance, as we mentioned in Section 2, is that it is immune to moral hazard, in the sense that neither the insurer nor the insured are able to influence the event. Unfortunately, in the case of epidemic reinsurance, it is impossible to separate the occurrence and development of an epidemic (for instance, death rates or infection speed rates) from the government's management of the situation. For this reason, we modify the classical parametric reinsurance and add a cap reflecting the success of government's actions like a lockdown and/or masks wearing. The main components of our reinsurance product namely the trigger and cap-curve are explained below.

The Trigger

By definition, a parametric reinsurance product requires a *trigger*, which induces an immediate payment of a predefined amount of money. In our design, we propose several triggers that might be activated in a way similar to a domino effect. In Table 1 several possible triggers and their disadvantages are listed. As a first trigger, the contract may stipulate the date when the ceding government declares the state of emergency. The first payment can be defined, for instance, as the value of a market basket per household, for the next several weeks and is then, in this way, unconditional. It is expected that this action will encourage the government in introducing lockdown measures and motivating its citizens to stay home.

A second, third, etc. trigger and thus payments might be due after certain predefined (deterministic) time intervals if the state of epidemic is not abolished, or at least controlled.

Deterministic (given the starting date) triggers have the advantage that the states introducing severe lockdown measures and therefore having low death and infection speed numbers will not be punished for tackling the situation better than expected. Using as a trigger a certain level of the death rates or the infection speed would prevent reinsurance payments in those countries. However, in order to alleviate moral hazard, we modify the pure parametric reinsurance and introduce a monitoring tool (i.e. the cap-curve) that measures the effectiveness and efficacy of government's crisis management. If the government fails to implement the necessary measures to slow the spread of an infection, the payments will be frozen and no further financial help will be provided from the reinsurance side.

The Cap-Curve

We propose to use as a basis for the *cap* the *infection speed* and will explain our concept in more details in an example (Section 4.2). The main advantage of working with the infection speed, is that it quickly reflects the effectiveness of the measures taken to fight the spread of the epidemic. In contrast, the death-related variables react with a certain delay, due to the course of disease until death, and are dependent on the treatment opportunities. Also, the infection speed is more robust than death-related variables. However, the infection speed can be more easily manipulated than, for instance, death rates, because it highly depends on the number of tests conducted. Given these pros and cons, the reinsurance company might want to choose a different basis, which better comprising its interests and those of the ceding state.

Candidate trigger	**Feasibility summary**
Declaration of the state of emergency + a certain number of dead and/or infected.	Would need to be specifically called for an epidemic.
Declaration of the state of emergency in one or several neighbouring countries.	Would need to be specifically called for an epidemic/pandemic.
A certain boundary for the official number of deaths, death rates, infection speed or fatality ratio has been exceeded.	■ Not reliable triggers. Would need control by an independent organisation, e.g. UN. ■ The minimal number of tests should be contractually stipulated. ■ States calling an early lockdown and preventing high death and infection speed numbers will be disadvantaged.
Official lockdown called + a certain number of dead and/or infected.	■ Definition of a lockdown required. ■ Manipulation possibilities for the reinsurance company and the state. ■ Political influence on the part of reinsurance company.
Outbreak size (the number of cases of infections and fatalities) + outbreak growth (increase in the number of dead and/or infected over a defined time period) + outbreak spread (the number of countries affected by the outbreak)	■ Waiting for all three parameters to be met may allow the virus to spread. ■ Not suitable for epidemics. ■ Manipulation possibilities for the reinsurance company and the state.

Table 1: Summary of candidate trigger feasibility assessment.

The reinsurance agreement described above can be compared with a lookback option on a forward contract. Some crucial quantities like the number, the time and the amount of payments will be contractually fixed as it is usually done in forward contracts. But all payments except the first one are linked to a lookback option having a predefined cap-curve as a strike. Here, we would like to emphasise that the cap-curve can be turned into a piecewise constant function or be even randomised.

4 Application to COVID-19

The outbreak of a novel coronavirus-infected pneumonia (COVID-19) was first identified in late 2019 and subsequently evolved into a global health emergency. Declared a pandemic by the World Health Organization in March 2020, the highly contagious virus rapidly spread across countries and regions, placing unprecedented strain on public health systems, economies, and social safety nets worldwide.

Every individual and every government was confronted with significant uncertainty in responding to the crisis caused by COVID-19. Governments introduced containment measures such as lockdowns and implemented economic support programmes aimed at safeguarding employment and household incomes. While these measures were often necessary from a public health perspective, they imposed substantial fiscal costs and placed additional pressure on already constrained public finances.

The organisation Oxfam has reported that, as a consequence of the economic and social disruptions associated with COVID-19, indirect effects such as food insecurity and poverty-related mortality could rival or even exceed deaths directly attributable to the virus itself Oxfam Media Briefing (2020). In many cases, financial support did not arrive with sufficient speed or at the scale required to prevent severe short-term hardship, particularly for vulnerable populations.

Insurance markets were widely criticised during the pandemic, as most standard policies—especially business interruption insurance[6] did not provide coverage for infectious diseases, or explicitly excluded pandemics. Even where coverage existed, contractual ambiguity and post-event disputes limited the effectiveness of insurance as a rapid-response financing mechanism.

The social reinsurance mechanism proposed in this paper is designed to address these shortcomings by providing rapid, rules-based financial support in the early stages of a pandemic. As a contractual risk-financing instrument rather than a discretionary transfer or charitable intervention, it aims to deliver predefined payments without ex post bargaining by the ceding state or unilateral changes to contract terms by the reinsurer. While it is clearly too late for COVID-19 itself, the widespread recognition of pandemic risk underscores the importance of developing financing mechanisms that can be activated quickly in future outbreaks. Accordingly, the following sections illustrate how early-phase epidemic data may be analysed and how a social reinsurance product could be structured using COVID-19 as a reference event. For additional discussion of early-phase COVID-19 dynamics and policy response at the country level, see for instance Şahin et al. (2020).

In the following subsections, we describe the data and methodology used to construct benchmark infection-speed cap-curve and present an illustrative example of product design motivated by the COVID-19 pandemic.

Our analysis relies exclusively on data available up to the end of March 2020. This restriction reflects the intended purpose of the proposed reinsurance product: to alleviate fiscal and social pressures during the very early stages of a pandemic, when uncertainty is high and policy responses are most constrained. Pandemic preparedness is widely characterised by a "panic and neglect" cycle, whereby attention and investment peak during crises and fade thereafter. Long before COVID-19, scientists and policy analysts had warned of insufficient

[6]Business interruption insurance covers the loss of income that a business suffers after a disaster.

investment in pandemic preparedness, see for example Center for Strategic and International Studies (2022). Consistent with this literature, we assume that responses in a future pandemic may resemble those observed in early 2020, both in terms of government interventions and behavioural reactions by individuals.

4.1 COVID-19 Data analysis and methods employed

To illustrate the proposed reinsurance design, we work with anonymised and stylised infection data reflecting the first wave of a COVID-19–type pandemic. The empirical inputs used in this section should be understood as representative early-wave infection dynamics rather than as country-specific case studies. Our objective is not to analyse or compare particular national experiences, but to demonstrate how a cap-curve can be constructed and applied within the proposed social reinsurance framework.

Conceptually, the benchmark cap-curve may be obtained as an average infection-speed profile across a group of comparable countries or regions (for example, European countries with broadly similar surveillance capacity), based on their observed or reconstructed infection rates during the early phase of a pandemic. Such an average curve provides a neutral and anonymised benchmark (reference) against which the infection dynamics of a given policyholder country, denoted hereafter as *Country X*, can be assessed. In practice, the underlying data could equally be simulated or derived from a pooled historical dataset, provided that a surveillance mechanism ensures consistency and minimum data quality standards.

While the specific empirical series used to generate the illustrative figures in this paper are drawn from publicly available COVID-19 datasets, all results are presented in anonymised form and should be interpreted as artificial benchmark and comparison curves. The precise identity of the underlying jurisdictions is not material for the design logic discussed below.

Based on the available early-wave data, we focus on infection speed as the key metric for constructing the cap-curve. Importantly, the trigger that activates the first payment (e.g. the declaration of a public health emergency) and the starting point of the cap-curve serve different purposes and need not coincide in time.

The trigger is a policy decision and is designed to enable immediate, unconditional financial support at the onset of perceived risk. By contrast, the cap-curve is a monitoring device intended to assess the subsequent evolution of the epidemic once epidemiological impact becomes observable. Accordingly, the starting point of the cap-curve can be defined as the first date on which excess mortality attributable to the pandemic exceeds a small threshold relative to historical averages (e.g. 0.1% above the average cumulative deaths over the previous five years).[7]

This anchoring ensures that the cap-curve comparison begins only once measurable epidemic effects emerge, and remains independent of the calendar date of the emergency declaration. In cases where a state of emergency is declared pre-emptively, before excess mortality is observed, [8] the first payment is still triggered immediately, while the cap-curve comparison

[7]This threshold is chosen arbitrarily for illustrative purposes. For a particular country, the threshold should be checked against normal fluctuations in excess mortality, such as those caused by flu seasons, heatwaves, or accidents. One way to do this is to compare the proposed threshold to the volatility of excess mortality, ensuring that the threshold lies above the normal noise level.

[8]It is also useful to note that using a declaration of emergency, like the contingent finance tools of the Multilateral Development Banks, allows funding to be triggered even before the first recorded case or death (as was the case for Romania, for instance).

window is activated only once the mortality threshold is crossed.

We define infection speed using the number of cumulative confirmed cases at time t, denoted by CC_t. The infection speed at time t, v_t, is defined as the ratio of newly confirmed cases to the remaining uninfected population:

$$v_t = \frac{\mathrm{CC}_t - \mathrm{CC}_{t-1}}{\mathrm{TP} - \mathrm{CC}_{t-1}},$$

where TP denotes total population size.

Two assumptions are required. First, as daily population updates are unavailable, total population is treated as fixed over the short early-wave window considered. Second, recovered individuals are assumed to be immune over the relevant horizon and are therefore excluded from the pool of susceptible individuals when computing infection speed.

Using this definition, daily infection-speed series are constructed over a fixed early-pandemic window (here, 41 days) for both the anonymised benchmark group and Country X. Figure 1 displays scatter plots of the resulting infection-speed trajectories.

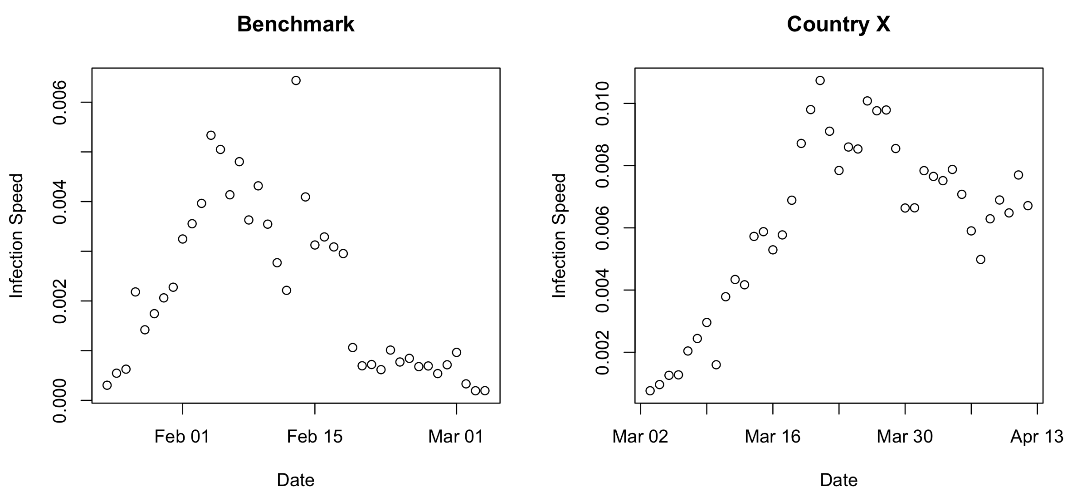

Figure 1: Infection speed (Benchmark and Country X)

For both series, infection speed follows a characteristic pattern: an initial acceleration phase followed by a gradual decline as containment measures take effect. The raw data may contain reporting artefacts, such as isolated extreme observations or excess zeros, reflecting changes in testing protocols, reporting delays, or administrative practices. These features are not representative of underlying epidemic dynamics and are therefore excluded from the construction of the cap-curve.

We employ Autoregressive Integrated Moving Average (ARIMA) models to obtain smoothed infection-speed curves for both the anonymised benchmark and Country X, with full methodological details reported in the Appendix. In this paper, ARIMA is used purely as an expository smoothing device to reduce reporting noise and short-term administrative artefacts; it is not used for forecasting. The purpose is to obtain transparent and comparable infection-speed profiles suitable for defining a cap-curve in a legally and operationally robust manner.

Importantly, the proposed reinsurance design does not depend on ARIMA specifically. Any reasonable smoothing or filtering approach that preserves the early-wave dynamics could be adopted without altering the structure of the contract. Alternative approaches demonstrated in the literature include, among others, Shaman and Karspeck (2012), Held et al. (2006), Meyer and Held (2014), Flaxman et al. (2020), Dehning et al. (2020), and Chinazzi et al. (2020).

4.2 COVID-19 example of product design

We present a numerical illustration in which a generic sovereign, denoted *Country X*, is assumed to hold a *10-year social reinsurance contract* of the type described in Section 3. The empirical infection-speed data used in this illustration are anonymised and treated as if they corresponded to the early phase of a new pandemic. The purpose of this section is not to design a contract ready for implementation, but to illustrate how the proposed trigger, payment structure, and cap-curve interact within a conditional payout framework.

We first describe the contract specifications and the simplifying assumptions used for the illustrative premium calculation. We then examine the implied payout outcomes given the observed infection-speed dynamics of Country X relative to a benchmark cap-curve.

Three contract specifications: triggers, payments, and the cap-curve

1. Triggers. The first triggering event activating the initial payment is the formal declaration of a public health emergency related to the pandemic, as discussed in Section 3. This trigger is policy-based and designed to enable rapid financial support at the onset of perceived risk.

2. Payments. Two sets of payments are included in the illustrative contract:

- The first payment, activated immediately after the emergency declaration, is defined as half of the average food expenditure per household over a 4-week period. For the numerical illustration, the stipulated amount is €220 per household, applied to an illustrative population of 20 million households.[9]

- The second payment is due eight weeks after the first payment, conditional on the evolution of infection speed. Specifically, it is paid only if the fitted infection-speed trajectory for Country X does not exceed the benchmark cap-curve over the relevant monitoring window. This second payment is defined as a monthly transfer of €500 for one month to a vulnerable subpopulation, corresponding to a stylised income-support scheme.[10]

- Note that the primary value of our proposed instrument lies in providing liquidity during the midst of a crisis, rather than serving as a funding mechanism. Accordingly, for both types of payments, we assume that the government only needs to maintain one month of cash on hand, without needing to borrow or reallocate resources during an emergency.

[9] Household counts are used here solely for numerical illustration and do not correspond to any specific country. The amount of €220 is in line with the average level of monthly means-tested benefits in the European Union in 2022.

[10] The size and targeting of this payment are illustrative and chosen to demonstrate the mechanics of the conditional payout structure.

3. Cap-curve.

The cap-curve is constructed as a benchmark infection-speed profile, which may be interpreted as an average curve derived from a group of comparable countries or regions with broadly similar surveillance capacity and reporting standards, as illustrated in Section 4.1. Its role is not to represent an "optimal" or "ideal" response, but to provide a neutral reference envelope against which the realised infection dynamics of Country X can be compared.

The contract introduces an 8-week monitoring window to assess whether containment measures are effective. During this window, continued eligibility for the second payment depends on whether Country X's infection-speed trajectory remains below the benchmark cap-curve. In this way, the cap-curve acts as a monitoring device that mitigates moral hazard without requiring the specification of additional policy-based triggers.

It is contractually necessary to specify when the comparison between Country X and the benchmark cap-curve begins. Following Section 4.1, we link this starting point to epidemiological observables rather than policy decisions. In particular, the comparison window may begin on the first date at which accumulated deaths attributable to the epidemic exceed a small threshold relative to historical averages (for example, 0.1% above the average cumulative deaths over the previous five years). This approach ensures consistency across jurisdictions and avoids dependence on the timing of emergency declarations.

Alongside triggers and payments, the cap-curve is a key input into pricing. In practice, reinsurers would need to model the probability that the infection-speed trajectory of a given country exceeds the benchmark curve. These "cutting probabilities" would depend on behavioural responses, policy compliance, and socio-economic factors, and would require extensive empirical and behavioural modelling. Such analysis lies beyond the scope of this paper. Accordingly, the pricing assumptions adopted below are deliberately simplified and used solely for illustrative purposes. However, we would like to note that the high degree of uncertainty surrounding political and behavioural responses discourages private actors from using estimated probabilities in pricing. As a result, a viable price is likely to emerge only if policy insurance is introduced, offering a cover of hard-to-quantify political risks.

Main data and assumptions

- The probability of a pandemic occurring over a 10-year horizon is derived from estimates of global pandemic risk in the literature (Madhav et al. (2017)), implying a cumulative probability of approximately 9.6% under an assumption of annual independence.
- As the example is purely illustrative, the probability that Country X's infection-speed trajectory exceeds the benchmark cap-curve, conditional on a pandemic, is assumed to be 50%.
- A zero interest rate is assumed for discounting, to simplify calculations.
- We also examine the sensitivity of results to modest shifts in the benchmark cap-curve, reflecting uncertainty in the construction of reference infection-speed profiles. In practice, such benchmarks would ideally be derived from pooled multi-country data once a pandemic has fully unfolded.

Illustrative reinsurance pricing

The calculation below reports an illustrative actuarial benchmark (expected present value under simplifying assumptions) to demonstrate the mechanics of the two-tranche contract. It should not be interpreted as a market premium: in practice, any implementable premium would incorporate a risk loading/markup for capital and ambiguity, would depend critically on the (hard-to-estimate) probability of breaching the cap-curve, and would include liquidity, transaction, and monitoring/verification costs.
The present value of the first payment amounts to

$$220 \times 20 \times 10^6 = €4{,}400\text{m}.$$

The present value of the second payment, under the assumption that half of the population is vulnerable, amounts to

$$500 \times 10 \times 10^6 = €5{,}000\text{m}.$$

In this numerical illustration, the total expected present value of covered benefits is below 0.5% of GDP for a developed country affected by a pandemic in the reference year. This is in line with other contingent financing instruments, such as Cat-DDOs, which are capped at 0.5% of countries' GDP.

The resulting net annual premium for a 10-year contract is therefore

$$0.096 \times \left(4.4 \times 10^9 + 0.5 \times 5 \times 10^9\right) = €655.5\text{m}.$$

Illustrative reinsurance payments

Upon declaration of a public health emergency, the first payment is triggered immediately. The second payment (due eight weeks after the first payment) is conditional on how the infection evolves relative to a benchmark *cap-curve*. The role of the cap-curve is to act as a simple monitoring device: if the policyholder country's infection-speed trajectory develops *worse* than the benchmark, further payments are frozen; if it develops *no worse* than the benchmark, the second payment is made.

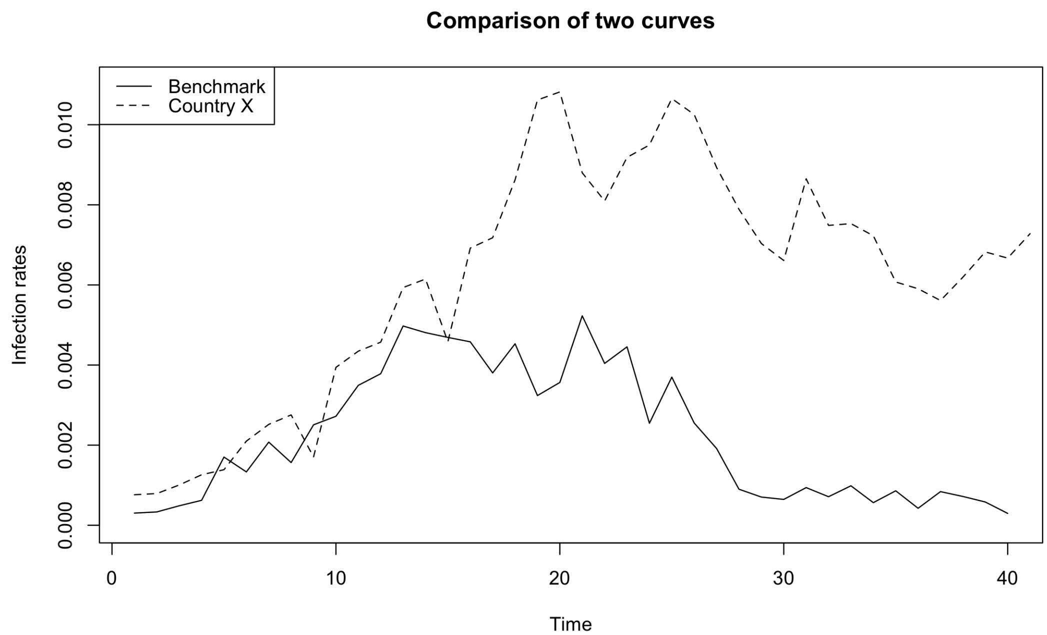

Figure 2: Benchmark cap-curve (solid) and fitted infection-speed trajectory for Country X (dashed). If Country X exceeds the cap-curve during the monitoring period between the first and second payments, the second payment is not triggered.

Figure 2 illustrates this comparison on a common scale. The solid line is the benchmark cap-curve (average infection speed curve derived from a group of countries, e.g. European countries), and the dashed line is the fitted infection-speed trajectory for the policyholder, denoted Country X. The key question is whether Country X *hits or exceeds* the cap-curve during the monitoring period. If Country X exceeds the cap-curve at any point during the monitoring period, the second tranche is not paid.

As a starting point for the comparison, we use the *first day of excess mortality* (defined in Section 4.1 as the first day when accumulated deaths attributable to the pandemic exceed a small threshold relative to historical averages). This date is used only to start the monitoring clock. Importantly, Figure 2 does *not* plot mortality; it plots infection speed. The excess-mortality definition is simply a practical way to ensure that the cap-curve comparison begins once measurable epidemic effects have emerged.

In the illustrative data shown in Figure 2, the first day of excess mortality occurs within the eight-week interval between the first and second payments. Over that interval, Country X (dashed line) lies above the benchmark cap-curve (solid line). Therefore, in this illustrative example, Country X would not receive the second payment.

More generally, the first day of excess mortality may occur after the eight-week interval or before the emergency declaration. The contract logic accommodates these cases by activating the cap-curve comparison only once the mortality threshold is crossed. If the mortality threshold is not crossed during the full eight-week interval, then the cap-curve comparison is never activated within that window, and the second payment would be made as scheduled. If the mortality threshold is crossed before the emergency declaration, the comparison begins earlier, and the second payment would be made only if Country X remains below the cap-curve throughout the relevant monitoring window.

As described in details in the Appendix, this paper uses ARIMA models to obtain smooth infection-speed curves suitable for constructing and comparing cap-curves. We deliberately rely on fitted values rather than forecasts, as forecasting under pandemic conditions is highly sensitive to interventions such as lockdowns or vaccination campaigns. The fitted models serve to reduce reporting noise and provide a transparent basis for comparison.

The numerical example presented in this section is purely illustrative and not intended to represent a product ready for implementation. Payment levels, probabilities, and pricing assumptions are chosen to demonstrate the mechanics of the cap-curve and conditional payout design, rather than to provide realistic market pricing. A practical implementation would require more sophisticated financial structuring, potentially involving capital market instruments such as parametric catastrophe bonds, as well as explicit treatment of liquidity, transaction costs, and behavioural uncertainty. These extensions lie beyond the scope of this paper, whose primary contribution is to demonstrate how cap-curves can be used to structure incentive-compatible pandemic risk financing instruments.

5 Conclusion

In recent years, in particular after the outbreak of SARS in 2002, scientists have warned about the possibility of a new pandemic. The warning stated that most of the world is unprepared for such a challenge, see for instance World Bank (2017), since pandemics create unmanageable risks for life, travel and business insurance and ultimately the entire (re)insurance industry. As predicted, on 11 March 2020, when the World Health Organization declared COVID-19 a global pandemic, governments were caught unprepared to respond effectively to the crisis caused by the spread of the coronavirus. Unfortunately, business income insurance policies do not provide cover for infectious diseases and those that do usually exclude viruses like COVID-19. In terms of financial impact, the shock to the global economy from COVID-19 has been faster and more severe than the 2008 global financial crisis and even the Great Depression. The World Bank's forecasts envision the deepest global recession since World War II, with millions of people falling into unemployment and poverty. In response, governments launched unprecedented public health and economic measures, while numerous low- and middle-income countries sought financial assistance from international financial institutions as they struggled to cope with the economic fallout of the pandemic. These experiences reinforce the need for pre-arranged and predictable financing mechanisms that can operate in the critical early stages of a pandemic, before large-scale international support is mobilised.

It should be noted that some reinsurance companies are already offering epidemic and pandemic insurance products. For instance, Munich Re's Epidemic Risk Solutions team (ERS) provides tailored epidemic and pandemic protection solutions[11]. In addition, the African Risk Capacity (ARC), a specialised agency of the African Union, offers parametric risk insurance products for outbreaks and epidemics to its member states. However, experience has shown that capacity-building and sustained engagement remain challenging, which may pose long-term risks to the effectiveness of such arrangements.

[11] `https://www.munichre.com/en/solutions/for-industry-clients/epidemic-risk-solutions.html`

In the present paper, we have proposed a social reinsurance design intended to supplement state-provided social insurance during pandemics. The product is based on parametric principles and aims to deliver rapid liquidity when it is most valuable, enabling governments to implement early containment and support measures. Rather than presenting a fully operational insurance product, the contribution of the paper lies in developing and analysing a conditional payout structure that explicitly addresses moral hazard through the introduction of a cap-curve.

Different triggers that activate pre-defined payments have different advantages and disadvantages. A key strength of parametric reinsurance is that payouts are not directly linked to reported financial losses, which reduces certain forms of moral hazard compared to indemnity-based contracts. However, in the context of pandemics, moral hazard cannot be eliminated entirely, as governments may influence reported data or policy responses. The cap-curve proposed in this paper is designed as a monitoring and incentive device, linking continued payouts to observed infection dynamics relative to a benchmark trajectory, rather than as a precise pricing or loss-coverage mechanism.

Unlike much of the actuarial literature, which focuses on insurance solutions for individuals or firms, our framework is explicitly state-centred. We emphasise that the empirical illustrations provided—based on anonymised and benchmarked infection-speed trajectories—are intended solely to demonstrate the logic and feasibility of the cap-curve mechanism, not to price a contract ready for market deployment. The data-driven construction of the cap-curve, using smoothed infection-speed measures, illustrates how conditionality can be embedded in parametric designs without relying on detailed loss assessments.

A potential concern is that countries facing structural constraints might be penalised by a cap-curve if they are unable to reduce infection rates quickly. The proposed design mitigates this risk by front-loading unconditional payments at the onset of a pandemic, ensuring that immediate resources are available to support early interventions such as lockdowns, social distancing, or emergency income support. The cap-curve applies only to subsequent tranches and is therefore intended to complement, rather than undermine, early response efforts.

Several directions for future research follow naturally from this work. First, pricing a social reinsurance contract of this type requires modelling the probability of pandemics and the likelihood that infection dynamics breach the cap-curve—quantities that are inherently difficult to estimate. In addition, any operational premium would require explicit treatment of reinsurance loadings/markups, liquidity and transaction costs, and the costs of monitoring and data verification required to support cap-curve conditionality. A second priority is a cost–benefit assessment of the product, quantifying how early, pre-arranged payouts may reduce downstream fiscal costs and welfare losses. Relatedly, administrative, monitoring, and governance costs should be incorporated into any realistic implementation framework.

Third, trigger and cap-curve designs should be stress-tested across different pathogen archetypes, since infection dynamics may vary substantially across diseases. Fourth, market feasibility and governance questions—including data validation, transparency, and audit mechanisms—require dedicated analysis to balance rapid disbursement with underwriting clarity and low moral hazard.

Overall, this paper positions the cap-curve as a conceptual innovation for pandemic risk financing. By focusing on incentive-compatible conditional payouts rather than full loss coverage or precise pricing, the framework contributes to ongoing debates on how insurance and reinsurance mechanisms can complement public and international responses to future pandemics.

Appendix

ARIMA models for the infection speed

Autoregressive Integrated Moving Average (ARIMA) models are a general class of models mainly used for forecasting time series data. Generally, ARIMA models are denoted as ARIMA(p,d,q) where p is the order of the autoregressive model (AR), d is the degree of differencing and q is the order of moving-average (MA) model. ARIMA models use differencing in order to convert a non-stationary time series into a stationary one, and then predict future values from historical data.

First, we will define an autoregressive moving average (ARMA) model of order p,q which is denoted as ARMA(p,q) with no covariates:

$$y_t = \phi_1 y_1 + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z_t,$$

where y_t represents time series data and z_t is a white noise process (i.e., zero mean and iid).

The ARMA model is combined from the AR and MA models. In this model, the impact of previous lags along with the residuals is considered for forecasting the future values of the time series.

If we write the model using backshift operators B, where $By_t = y_{t-1}$, the ARMA model is given by

$$\phi(B)y_t = \theta(B)z_t \text{ or } y_t = \frac{\theta(B)}{\phi(B)}z_t,$$

where $\phi(B)y_t = \theta(B)z_t, \quad \phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p, \quad \theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q.$

For ARIMA errors, we simply replace $\phi(B)$ with $\bigtriangledown^d \phi(B)$ where $\bigtriangledown = (1 - B)$ denotes the differencing operator. Notice that this is equivalent to differencing both y_t and x_t before fitting the model with ARMA errors. The ARIMA model is the combination of AR and MA models and differencing. Specifically the ARIMA(p,d,q) model is denoted as

$$y'_t = \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 z_{t-1} + \cdots + \theta_q z_{t-q} + z_t,$$

where p is the order of the autoregressive part, d the degree of first differencing involved and q the order of the moving average part.

We follow the steps below to build the ARIMA(p,d,q) model.

Step 1: Testing and Ensuring Stationarity

To model a time series with the Box-Jenkins approach, the series has to be stationary. According to this approach when the process is non-stationary we take the difference of the series, which is known as *differencing*, one or more times in order to achieve stationarity. As a result, this approach produces an ARIMA model. A stationary time series means a time series without trend, having a constant mean and variance over time.

We apply the appropriate differencing order (d) to make a time series stationary before we can proceed to the next step.

Step 2: Identification of p and q.

In this step, we identify the appropriate order of AR and MA processes by using the Autocorrelation function (ACF) and Partial Autocorrelation function (PACF). The ACF defines how data points in a time series are related, on average, to the preceding data points. Also, the PACF is a summary of the relationship between an observation in a time series with observations at prior time periods with the relationships of intervening observations removed. ACF and PACF can be used to check for stationarity and also to identify the order of an ARIMA model.

Step 3: Estimation

Once we have determined the parameters (p,d,q) we check whether our fitted values are in line with the real data.

Regarding the data used in this study, the first step is to examine whether the first difference of the infection-speed series for the benchmark average and Country X behaves like a sequence of random noise, as required for ARIMA modelling.

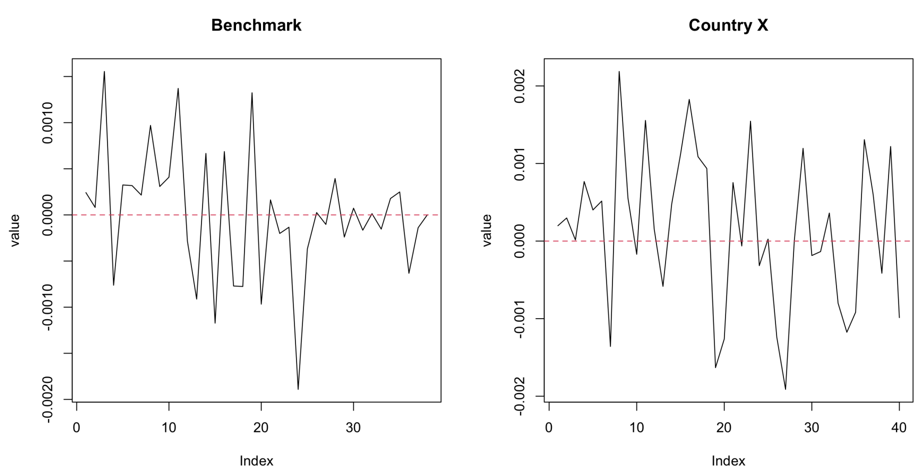

Figure 3: First difference of the infection speed for the benchmark average and Country X.

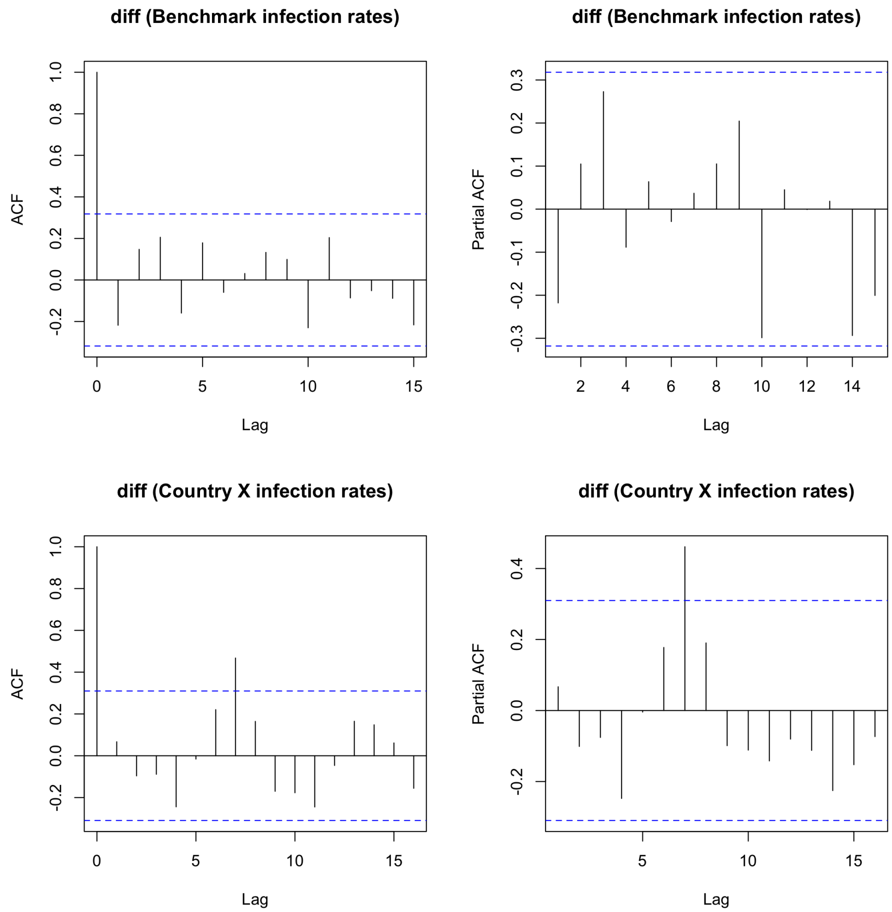

Figure 4: ACF and PACF plots for the benchmark average and Country X.

Figure 3 indicates that the differenced infection-speed series for both the benchmark and Country X are stationary. Next, we examine the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the differenced data in order to identify suitable model orders.
Figure 4 shows that, although most ACF and PACF values are small, a limited number exceed the confidence bounds. Since autocorrelation coefficients are typically used to identify moving-average (MA) orders and partial autocorrelation coefficients to identify autoregressive (AR) orders, these plots suggest that moderate ARMA orders are sufficient for modelling the benchmark series. For Country X, the ACF and PACF plots indicate a pronounced periodic component, reflected by significant values at a weekly lag.

Using the Akaike Information Criterion (AIC) for model selection, we identify an $\mathrm{ARIMA}(2, 1, 1)$ specification for the benchmark infection-speed series. For Country X, the preferred specification is an $\mathrm{ARIMA}(0, 1, 0)$ model with a seasonal autoregressive component of order $(1, 0, 0)$ at lag 7. We then conduct residual diagnostic tests to assess the adequacy of the fitted models:

- the residuals should exhibit no systematic patterns;
- there should be no structure when residuals are plotted against fitted values;

- there should be no significant residual autocorrelation.

Figure 5 presents residuals versus fitted values obtained from the estimated ARIMA models. These diagnostics are used to test the null hypothesis that residuals are independent and identically distributed (*iid*), which is a key assumption underlying ARIMA modelling. We apply a turning-point test implemented in R to assess this hypothesis. For the benchmark series, the test yields a p-value of 0.3061, so the *iid* hypothesis cannot be rejected. Figure 6 further confirms that residual ACF and PACF values remain within the confidence bounds, indicating an adequate fit.

For Country X, the turning-point test yields a p-value of 0.7048, again failing to reject the *iid* hypothesis. The residual diagnostics similarly support the suitability of the selected ARIMA specification.

Infection-speed curves for the benchmark and Country X

Finally, we plot the infection-speed curves obtained from the fitted ARIMA models for both the benchmark average and Country X. Figure 7 displays the observed and fitted values on a common scale, illustrating that the models provide a close representation of the smoothed early-wave infection dynamics.

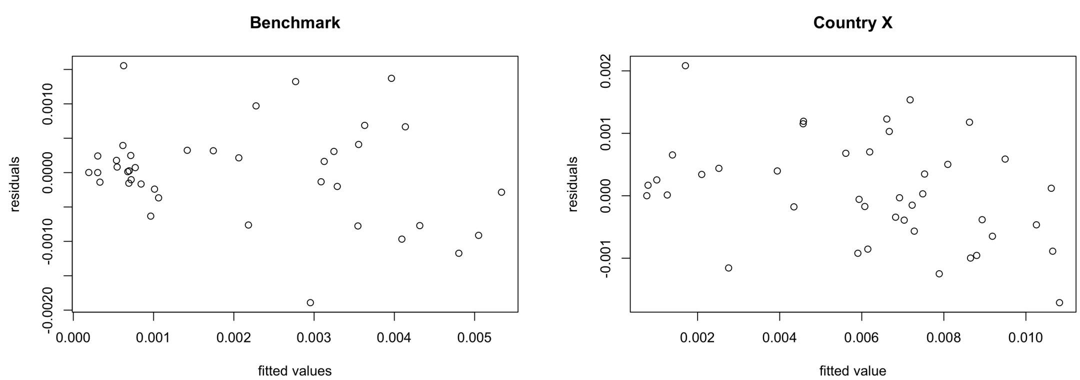

Figure 5: Residuals versus fitted values for the benchmark and Country X.

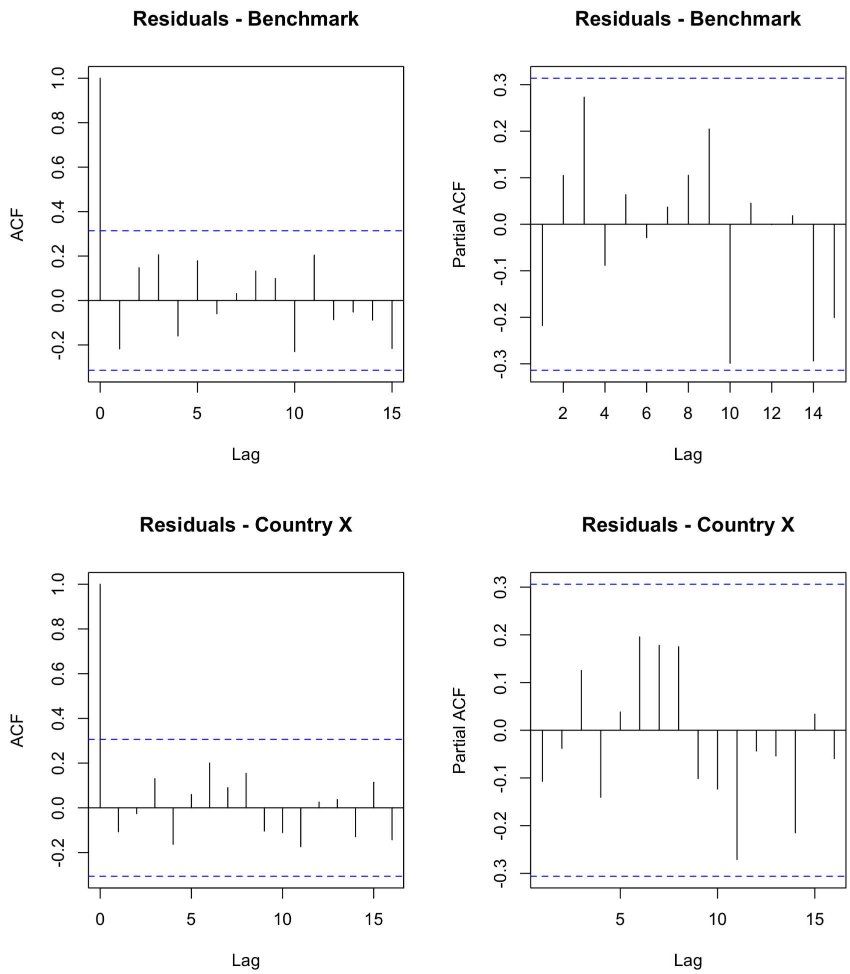

Figure 6: Residual diagnostic plots for the infection speed of the benchmark and Country X.

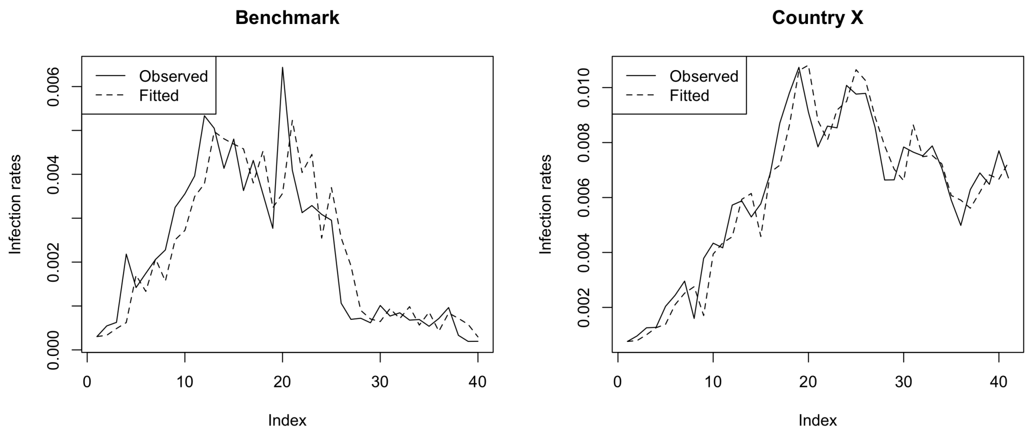

Figure 7: Observed and fitted infection-speed curves for the benchmark and Country X.

ARIMA models constructed in this way can be applied to infection-speed data from different countries or regions to assess whether infection dynamics remain within a predefined benchmark envelope. If policy measures prove insufficient and the fitted infection-speed trajectory of a given country exceeds the benchmark cap-curve, reinsurance payments would be suspended under the proposed contract design. Importantly, this mechanism operates without prescribing specific policy actions ex ante; instead, it provides incentives for timely and effective interventions by linking continued payouts to observable epidemic dynamics.

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