The Effect of Case Detection on the Global Dynamics of Covid-19 Mortality: A Cross-Country Analysis

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This study analyzes the dynamics of Covid-19 lethality using a global sample of 137 countries for the period that ranges from January 2020 to December 2020. Using β-convergence and σ-convergence tests we find that there has been a convergence process in lethality rates and case detection rates across the globe. In a second step, we investigate if cross-country disparities growth rates of Covid-19 lethality can be explained by country differences in the rate of case detection and its evolution during the pandemic. Our results show the existence of a negative statistically significant relationship among these variables, such that the speed of approximation towards lower long-run equilibrium mortality rates appears to be driven by increasing case-detection rates.

1 Introduction

The Covid-19 pandemic has been the greatest global public health emergency since the influenza pandemic of 1918, and by February 2021 there have been 2.3 million deaths and 106 million infections worldwide. However, the effects of the pandemic have been highly asymmetric across countries and numerous studies have attempted to explain the determinants of lethality differentials by analyzing the role played by exogenous factors like climate and culture,[1] the national health-system characteristics and other social and demographic features.[2]

However, as seen in Figure (1), a remarkable feature of the cross-country distribution of Covid-19 mortality, measured by the Case Fatality Rate (CFR), is that after reaching its peak (which usually occurred 50 days after the first death record in each country) not only its average level but also its dispersion has decreased rapidly over time. In fact, by December 2020, the probability of any country experiencing CFRs in the upper extremes of the distribution decreased substantially and the estimation of the ergodic distribution reveals that the long run probability of the CFR being centered around the 1.4% threshold, in the future will be higher to that observed at the beginning of the epidemic outbreak.

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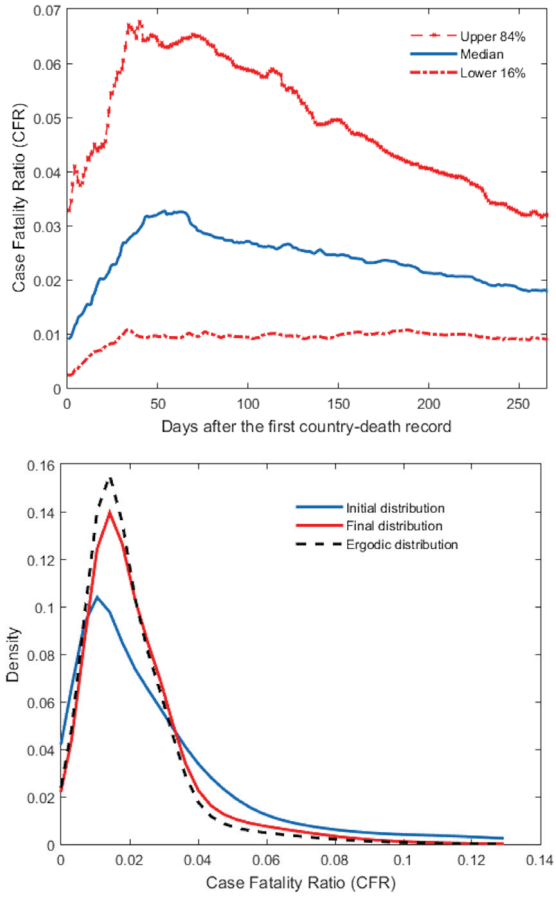


Figure 1: The dynamics of Covid-19 lethality.

These stylized facts suggest the existence of a fast convergence process in lethality rates.

Therefore, a satisfactory explanation of the evolution of global lethality dynamics cannot rely solely on socio-demographic factors or cultural traits, which are well known to be slowly varying over time. Against this background, in this study we show that the evolution of Covid-19's lethality is strongly influenced by the share of detected cases and its growth rate. The main argument for a link between case detection and convergence in lethality rates, is that countries that experienced initially high rates of lethality did so, precisely because they did not detect a large share of their cases, which artificially increased their mortality rates relative to the rest of the world.

In this regard, it should be noted that a problematic issue when analyzing early Covid-19 lethality is that CFRs may have provided an imperfect and

unreliable measure of the true lethality. There are two reasons to explain this. First, epidemic surveillance initially focused on symptomatic patients whereas milder and asymptomatic cases were unlikely to be detected leading to an overestimation of the CFR. Second, during an ongoing epidemic some of the cases already detected at time t die subsequently (i.e, at $t + h$), which bias downwards the estimate of CFR_t.[3]

Nevertheless, given that the under-ascertainment bias is likely to be the dominant because of the high share of asymptomatic carriers of the virus (the best available estimates from[4] and[5] range between the 33-40%), lethality overestimation should tend to vanish with higher detection rates. For this reason, a catch-up process in the detection of cases between countries that initially were not detecting with those that were detecting many of them, could help to explain both, (i) the decrease in the average lethality and (ii) the decrease in the dispersion of the CFR. The rest of this note is devoted to analyze this issue.

2 Data

Our research requires information about the CFR and the degree of case reporting in the various countries.

The CFR indicator used to capture the dynamics of Covid-19 lethality is calculated as $CFR_{it} = \frac{D_{it}}{C_{it}}$, where C_{it} and and D_{it} are the total cases and deaths of country i at time t, respectively. Data on these metrics were collected from the European Center of Disease Control (ECDC) website for a global sample of 137 countries between January, 2020 to December 14, 2020[1].

On the other hand, to estimate the share of reported of cases we follow Nishura et al.[3] and Russel et al.[6] who show that by combining a *best estimate* of the infection to lethality ratio (bCFR) and a delay-adjusted case fatality distribution of cases with known outcomes (dCFR), it is possible to obtain daily estimates of the under-ascertainment of cases in the official statistics. Specifically, we calculate the share of detected cases with respect the true total epidemic size as:

$$R_t = \frac{bCFR}{dCFR_t} \tag{1}$$

where *(i)* $bCFR$ denotes the best available estimates of lethality taken from large randomized sero-prevalence studies in China, Spain and South Korea, which are in the 1% - 1.7% range (we assume a Gaussian process for the $bCFR \sim N(1.25, 0.3)$ after adjusting or controlling for under-reporting) and

[1]For more detailed information on the sample composition see the Appendix.

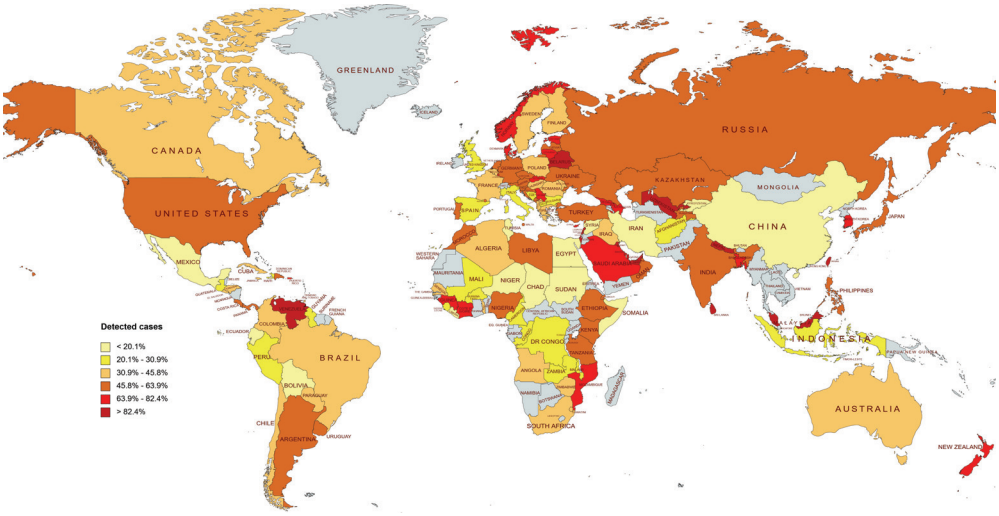


Figure 2: The geographical distribution of case detection.

(ii) $dCFR_{it} = \frac{\sum_{t=0}^{T} d_{it}}{dC_{it}}$ is the delay-adjusted case fatality ratio in t[2]. The delay-adjusted case fatality is given by the ratio of the number of daily deaths d_{it} to dC_{it}, which is a correction of the cases accounting for the proportion of them with known outcomes:

$$dC_{it} = \sum_{t=0}^{T} \sum_{s<t} c_{i,t-s} g_s \tag{2}$$

where g represents the probability density function between confirmation to death and T is last date for which data are available[3].

3 Preliminary Evidence

Figure (2) below plots the estimated median geographical distribution of the cumulative case detection in percentage across the world by December 14[4]. As observed, there are important differences between the countries with minimum values such as Sudan (7.8%), Chad (8.7%) or Mexico (10%, with those of the

[2]For example, if a country has an adjusted CFR that is higher to the (e.g. 20%), it suggests that only a fraction of cases have been detected (in this case, 1.25/ 20 = 6.25% cases have been reported approximately.

[3]g_s represents the probability that an eventually fatal case leads to death during the s-th day from the day of confirmation. We follow Russell et al.[6] by assuming a log-normal distribution with a mean delay of 13 days and standard deviation of 12.7 days.

[4]Obviously, there are countries where the uncertainty over the true detection rate is higher than others but for simplicity here we just focus on the median values across 1,000 simulations of the bCFR.

most advanced countries like Qatar (99%), Singapore (98.3%) or Israel (90.6%) who have managed to detect a large share of their infections. It is also worth mentioning than the group of medium to low level of detection we find a variety of European countries that were strongly hit by the pandemic like Spain (29.3%), Italy (25.5%) or UK (24.3%).

To complement this information, Figure (3) provides preliminary evidence on the link between the level (and growth rates) of the detection of cases and lethality. The two scatter plots suggest the existence of a negative relationship between mortality outcomes and country detection rates during the Covid-19 crisis. This means that on average, countries with higher levels of detection experienced lower CFRs and that countries that improved the most their detection of cases, were characterized by a lower mortality growth rates. Indeed, the pairwise correlation between the two variables is statistically significant ($\rho = -0.58$ and -0.28 with p-value = 0.00, respectively). Nevertheless, the information provided by Figure (3) should be treated with caution, as the observed connections may simply be a spurious correlation resulting from the omission of other variables. For this reason, we develop a more formal treatment in the next section.

4 Methods

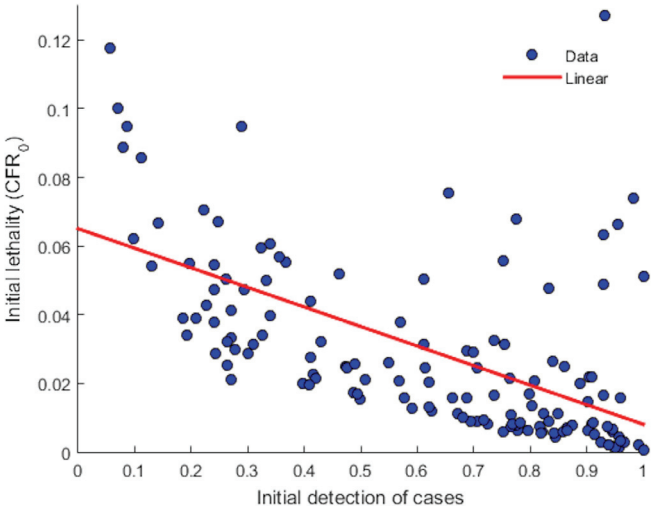
We now turn our attention to the convergence dynamics in the CFR and the detection of cases focusing on two different convergence tests.

The first one, is that of β-convergence, proposed by Barro and Sala-i-Martin.[7] The notion of β-convergence in the context of epidemic analysis, measures *the extent to which countries with higher fatality ratios (lower detection) catch up with countries with lower fatality ratios(higher detection) over time*. The hypothesis basically tests if: $Cov\left(y_{i0}, \frac{y_{iT}-y_{i0}}{T}\right) < 0$,where $\frac{y_{iT}-y_{i0}}{T}$ is the long run average growth rate of the corresponding variable and y_{i0} is the initial sample value. The initial CFR y_{i0}, is calculated as the average CFR during the time interval $[t_{p-h}(i), t_{p+h}(i)]$ where $t_p(i)$ denotes the peak date of cases during the first wave of the outbreak for country i and h is a time window used to smooth the data. We proceed in this way to minimize administrative noise and fluctuations in the data and because of a large share of cases by the time of the peak had no closed outcomes. We set h to 25 to absorb most of the probability of the delay distribution from detection to death during the first wave[5].

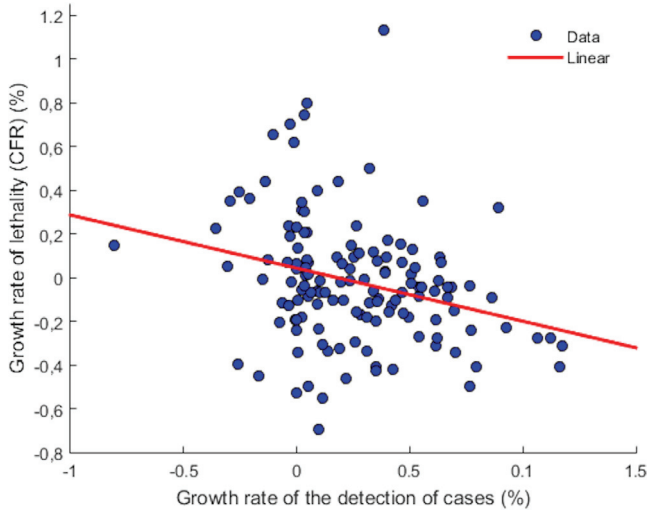
The regression model employed to test the β-convergence hypothesis is given by:

$$\frac{\Delta \ln y_{i,[0,T]}}{T} = \alpha + \beta_1 \ln y_{i,0} + \epsilon_i \tag{3}$$

[5]Note that the Log-normal (13,12.7) time-delay distribution taken from[6] implies that 95% of cases die after 33 days.



(a) Detection rate and lethality rates

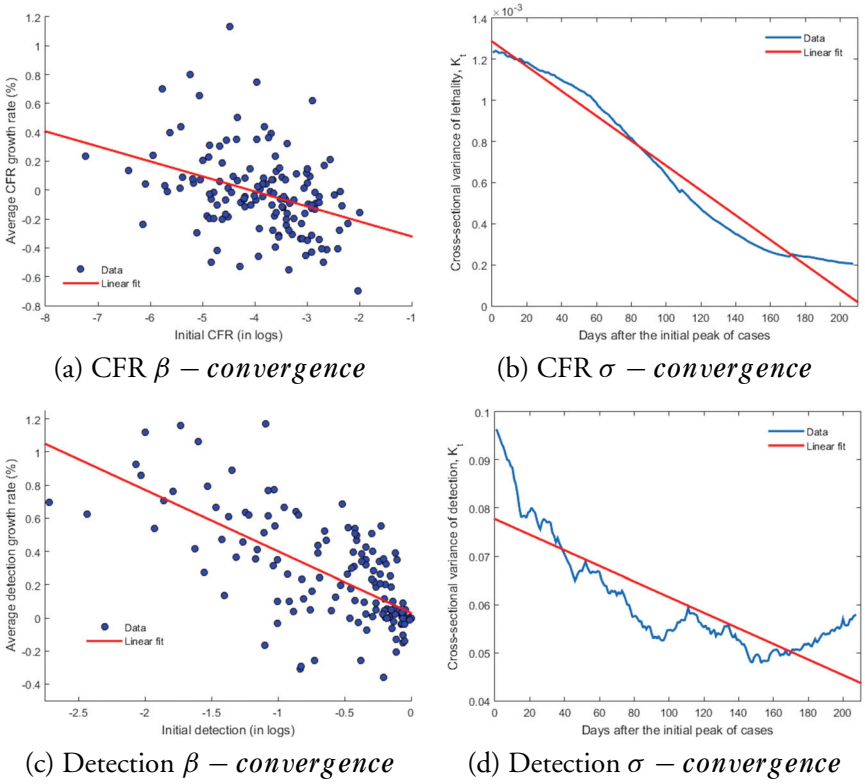


(b) Detection growth and lethality growth

Figure 3: The link between case detection and lethality.

In this context, $\phi = -\ln\left(1+\hat{\beta}_1\right)$ is the speed of convergence towards the long run values of either the CFR or the detection rate.

Other authors like Kong et al.[8] and Sul[9] consider that *true convergence* implies that cross-sectional dispersion should be decreased over time. The process of consistent decrease of variance along the cross-sectional dimension over time, has received the name of (ii) σ*-convergence* in the specialized literature. Letting $K_t = \frac{1}{n}\sum_{i=1}^{n}(y_{it}-\bar{y}_t)^2$ denote the cross-sectional variance in a panel setting,



(a) CFR $\beta - convergence$ (b) CFR $\sigma - convergence$

(c) Detection $\beta - convergence$ (d) Detection $\sigma - convergence$

Figure 4: Convergence dynamics in lethality and reporting.

testing this hypothesis is equivalent to verify if $Cov\,(K_t, t) \leq 0$. As described in[8] and,[9] the weak σ-convergence test is given by the t-statistic of the OLS estimate $\hat{\rho}(L)$ based on the Newey-West HAC estimator with lags $L = int(T^{1/3})$, from the following simple trend regression:

$$K_t^y = \alpha + \rho t + u_t \tag{4}$$

Graphical evidence on how each variable fits these notions of convergence is provided in Figure (4). On the one hand, Figure (4.a) reports the relationship between the average growth rate of the CFR and the logarithm of the CFR at the beginning of the pandemic outbreak for each country whereas Figure (4.b) plots the evolution of the cross-sectional dispersion of the CFRs across countries over time, thereby capturing the notion of σ-convergence. Figure (4.c) and (4.d) provide the same information for the share of detected cases. Importantly, both the β-convergence and σ-convergence panels presented in Figure (4) point to the same stylized fact: (i) lethality and reporting disparities across countries have

Table 1: Convergence test results.

	β-convergence			σ-convergence		
	$\hat{\beta}$	Implied ϕ	Half-life	$\hat{\rho}(L)$ Full sample	$\hat{\rho}(L)$ First half	$\hat{\rho}(L)$ Second half
CFR	0.0011	0.11%	666.30 days	-0.0000067***	-0.0000087***	-0.000005***
	(-4.47)			(-17.83)	(-5.69)	(-16.57)
Detection	-0.0036***	0.36%	191.79 days	-0.0002***	-0.0002***	-0.00005***
	(-12.77)			(-10.68)	(-3.11)	(-3.37)

Notes: Entries in columns 1-2 of this table correspond to the key statistics of the β-convergence test. The dependent variable in the β-convergence regressions is in all cases the average growth rate of the CFR during in the period that goes from $t_p(i) + h + 1$ to December 14, 2020, where $t_p(i)$ stands for the peak of new cases during the first wave and $h = 25$. Estimates of $\phi = -log(1 + \hat{\beta}_1)$. Columns 4-6 are provide the trend parameter estimates $\hat{\rho}$ of the weak σ convergence test for different windows of time after $t_p(i)$. The t-ratios, t_ρ(L) indicate whether or not y_{it} is weakly σ-converging ($t_{\hat{\rho}} < -1.65$), fluctuating ($t_{\hat{\rho}} \rightarrow^d N(0, 1)$), or diverging ($t_{\hat{\rho}} > 1.65$). * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. *** denote significant at the 1%. t-statistics computed using the HAC estimator in brackets.

narrowed over time, which has been (ii) mainly driven by a catch-up process of countries that either had either very high CFRs or very low reporting-rates, respectively.

5 Results

The results of formal statistical tests regarding the existence of convergence are provided in Table (1). The results regarding the weak σ-convergence test and the β-convergence one show that the key parameters involved in each of them are statistically significant at the 1% level and display the expected signs. The estimate absolute daily speed of convergence in lethality is the 0.18% which implies a half-life of 666 days (i.e the time span which is necessary for current disparities to be halved) whereas the 0.36% implies a half-life of 191 days. Therefore, it is possible to conclude that although at different speeds, cross-country differentials in mortality and detection have been narrowing over time, irrespective of the notion of convergence under consideration.

However, to investigate if the observed convergence dynamics of lethality are a byproduct of the evolution and the cross-country differentials in the share of detected cases, we now extend the growth model used to investigate β-convergence as follows:

$$\frac{\Delta \ln y_{i,[0,T]}}{T} = \alpha + \beta_1 \ln y_{i,0} + \beta_2 \frac{1}{T} \ln R_i + \beta_3 \frac{\Delta \ln R_{i,[0,T]}}{T} + \mathbf{X}_i \gamma + \epsilon_i \quad (5)$$

where $\frac{\Delta \ln y_{i,[0,T]}}{T}$ denotes the average growth rate of the CFR of country i during the period $[0, T]$, $\ln y_{i,0}$ is the logarithm of the initial CFR, $\ln \bar{R}_i$ is the log of average level of reporting, $\frac{\Delta \ln R_{i,[0,T]}}{T}$ is the average growth rate of the detection of

Table 2: Results

Variables	(I)	(II)	(III)	(IV)	(V)
Constant	-0.005***	-0.004***	-0.005***	-0.004**	-0.004*
	[-4.62]	[-3.73]	[-2.63]	[-2.25]	[-1.69]
Initial lethality (logs)	-0.001***	-0.001***	-0.002***	-0.001***	-0.001***
	[-4.73]	[-5.10]	[-6.07]	[-5.39]	[-3.44]
Case detection rate (logs)	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***
	[-4.92]	[-3.13]	[-3.05]	[-3.94]	[-5.15]
Growth rate of detection	-0.144**	-0.133**	-0.134**	-0.126**	-0.507**
	[-2.27]	[-2.19]	[-2.16]	[-2.33]	[-2.62]
Population density		-0.0007**	-0.0008***	-0.0005**	-0.0004***
		[-2.55]	[-2.88]	[-2.03]	[-5.19]
Population > 65 years old (in %)		-0.015***	-0.023***	-0.016**	-0.016**
		[-4.84]	[-5.37]	[-2.49]	-[2.54]
Individualism		0.001	0.001	0.001	0.0001
		[0.94]	[0.68]	[0.68]	[0.33]
Liberal democracy index			0.002***	0.003***	0.002**
			[2.67]	[3.01]	[2.41]
Epidemic policy stringency			-0.0001	-0.0001	-0.0001
			[-0.53]	[-0.85]	[-0.65]
GDP per capita				-0.00003**	-0.0001
				[-2.61]	[-0.92]
Hospital beds				-0.00004	-0.00004
				[-0.33]	[-0.03]
Initial lethality (logs) ×					-0.104**
Growth rate of detection					[-2.05]
R^2	0.195	0.338	0.506	0.508	0.706
N	137	137	137	137	137

Notes: The dependent variable is in all cases the average growth rate of the CFR of each country i during in the period that goes from $t_p(i) + h + 1$ to December 14, 2020, where $t_p(i)$ stands for the peak of new cases during the first wave and $h = 25$. *** denote significant at the 1%, ** significant at the 5% and * significant at the 10%. t-statistics computed using the HAC estimator in brackets.

cases and $\mathbf{X}$ is a matrix of control variables that may affect both the CFR and the level of reporting. In turn, ϵ_i is the disturbance term.

The choice of control variables in $\mathbf{X}$ is mainly guided by the need to account for factors which may affect both the CFR and reporting scores and, consequently, whose omission might bias the estimated effect of the level of reporting and its growth rate on registered mortality. To that end, we consider (i) the GDP per capita (at PPP), (ii) the population density, (iii) an index of liberal democracy, (iv) an index of individualism, (v) the number hospital beds per capita, (vi) a composite index reflecting the stringency of the epidemic policy and (vii) the share of population above 65 years old[6].

The results of running lethality growth regressions by progressively including our set of controls are shown in Table (2). As observed, the negative effect of

[6]For more information and descriptive statistics see Table A1 in the Appendix.

initial lethality shows the result of β-convergence is robust after controlling for other variables. After controlling for disparities in exogenous factors in X we observe a slightly faster convergence speed than that of Table (1) (0.14% vs 0.11%). Overall, the results of the regressors are in line with previous evidence in the literature: income, age and density are negatively related to the growth rate of mortality whereas liberal democracies have performed poorly when compared to other alternative forms of political organization. On the other hand, the health-policy stringency index, the hospital beds per capita and the level of individualism are not statistically significant in this context.

Turning our attention to the main goal of this study, we find a robust negative significant effect of the level of detection and its growth rate on the growth rate of mortality. In fact, the two coefficients are statistically significant at the 5% level in all the model specifications. This suggests, that the negative effect of detection and the faster the improvement in the detection of cases are relevant factors to explain why some countries have experienced lower lethality growth rates. As a further check, in Column (5) of Table (2) we report the results of a model extended with an interaction term between the initial lethality and the growth rate of detection. This interaction term allows us to compute estimates of the speed of convergence (i.e, the speed at which lethality decreases) as a function of the growth rate of case detection. $\hat{\phi}\left(\frac{\Delta \ln R_{i,[0,T]}}{T}\right)$. As observed, the effect is negative and statistically significant at the 5% level, which implies that the convergence speed increases with the growth rate of detection as shown in Figure (5).

6 Conclusions

This study analyzes the role of case detection in the global dynamics of Covid-19 mortality.

To investigate this relationship, in a first step we estimate the share of detected cases for a global sample of 137 countries for the period that goes from January 2020 to December 2020. By applying σ-convergence and β-convergence tests on the evolution of infection detection and mortality rates, we find that there has been a marked reduction in disparities across countries over time in the two variables.

Secondly, we extend the baseline growth lethality regression of the β-convergence framework including the average level of case detection and its growth rate. We find that not only higher detection rates reduce lethality growth but also that countries that increased their levels of detection over time more rapidly, have also experienced faster reductions in mortality rates during 2020.

Furthermore, we observe a statistically significant conditional relationship between initial lethality, detection growth and lethality growth, which suggests

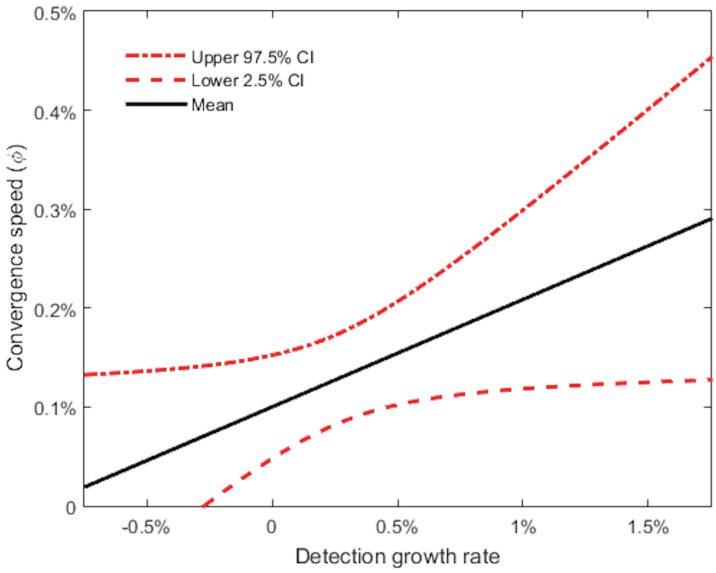


Figure 5: The link between case convergence speed and detection growth.

that the convergence dynamics of cross-country lethality disparities towards a lower long-run equilibrium mortality threshold are strongly influenced by those of the share of detected cases.

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