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Income Convergence Or Divergence in The Aftermath of the COVID-19 Shock?

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ABSTRACT: The paper extends the work of Deaton (2021) by exploring the period of post-crisis recovery in 2021-2024. The paper documents per-capita income divergence during the period of post-shock recovery, with countries at the bottom of the income distribution falling significantly behind. Findings suggest that higher COVID-19 vaccination rates and targeted virus containment measures are associated with faster recovery in per-capita incomes in the medium term. Evidence on the effectiveness of economic support policies for reducing cross-country income inequality, including fiscal and monetary policies, is mixed especially in the case of developing countries.

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WORKING PAPERS

Income convergence or divergence in the aftermath of the COVID-19 shock?

Prepared by Mariya Brussevich, Shihui Liu, and Chris Papageorgiou[1]

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1 Introduction

As the COVID-19 pandemic unfolded, many feared that income inequality within and between countries would widen, fueled by factors ranging from unequal access to vaccines to inability to work remotely during prolonged periods of lockdowns.[1] Within some countries, evidence on the increase in income inequality due to the pandemic is beginning to emerge (Narayan et al., 2022). Across countries, Deaton (2021) shows that, contrary to the initial expectations that the pandemic would increase global income inequality in 2020, there was indeed an acceleration in convergence of global incomes, when taking each country as a unit of analysis. Whereas axiomatic statements on the negative impact of the COVID-19 crisis on cross-country inequality in 2020 were challenged by Deaton (2021) and Goldberg (2021), little is documented about the trajectory of income inequality and its determinants during the post-crisis recovery.

In this paper, we extend the work of Deaton (2021) by exploring the period of post-crisis recovery in 2021-2024, using GDP per capita projections from the World Economic Outlook (WEO) updated by the International Monetary Fund (IMF) in October, 2021. In addition to providing a more complete picture of the evolution of per-capita incomes during the post-crisis recovery period, we augment the discussion by examining the determinants of cross-country income inequality and income convergence. We rely on the concepts of σ- and β-convergence to describe the trajectory of incomes across countries. The measure of σ-convergence captures the change in standard deviation of the logarithm of per-capita GDP across countries. The measure of β-convergence is based on the regression of per-capita GDP growth on per-capita GDP level in the initial period.

WEO data on GDP per capita show that the short-lived acceleration in income convergence in the first year of the pandemic, owing to the advanced economies (AEs) initially bearing a bigger brunt of the virus, is followed by a period of divergence in cross-country incomes.[2] This pattern holds across both σ and β-convergence measures. Acceleration of convergence, however, is documented when each country is taken as a unit of analysis and no other factors describing the impact of the pandemic are accounted for. When the data are weighted by population, we find no evidence of acceleration in income convergence in 2020. Moreover, when conditional β-convergence coefficients are used as a metric, there is evidence of cross-country income divergence even in 2020.

This paper augments one of the common growth frameworks to examine growth in the context of a global pandemic. To that end, we examine the contribution of severity of the COVID-19 virus outbreaks and the associated containment measures across countries. We rely on information on the COVID-19 cases and deaths to measure the former and vaccination rates and lockdown stringency index to capture the latter. In addition, following the insights from the growth literature, we select a set of variables describing countries' pre-pandemic macroeconomic fundamentals. Since our focus is primarily on the short- and medium-term growth, we focus on variables that are likely to interact with the pandemic-specific health outcomes and policies. Given limited theoretical evidence on the factors driving income inequality during pandemics, we use several econometric techniques to measure the contribution of various variables to the observed changes in per-capita incomes: (i) two model averaging techniques, including Bayesian Model Averaging (BMA) and Weighted Average Least Squares (WALS); and (ii) a machine-learning technique—Least Absolute Shrinkage and Selection Operator (LASSO).

We find that higher COVID-19 vaccination rates and targeted virus containment measures are associated

[1]See Tatar et al. (2021) on global vaccine inequality and Brussevich et al. (2022) on inequality in amenability of remote work.

[2]Actual 2021 GDP data are yet to be officially published by the WEO for all IMF member countries at the time of writing.

with faster recovery in per-capita incomes in the post-shock recovery period. Evidence on the impact of the economic support policies, both fiscal and monetary, as well as the overall severity of the virus, measured by the COVID-19 case and death counts varies by countries' income levels. Whereas additional debt accumulation during the pandemic is associated with higher growth in AEs, low-income and developing countries (LIDCs) and emerging market (EMs) economies see the opposite effect. The results also suggest that per-capita incomes of more open economies took a bigger hit during the pandemic. For instance, openness measured by the number of international flight arrivals per million people is responsible for almost 2.5 percent lower growth in 2021, all else held constant, in Malaysia which lies at the 70th percentile of global income distribution. However, economies with a higher GDP share of service exports, including tourism services, are projected to catch up in the recovery period. These results pertain to the global sample of 103 countries and vary substantially when we disaggregate the sample by income groups. We find that higher accumulation of public debt is associated with higher growth in AEs but negatively impacts medium-term outlook of emerging market economies (EMs) and low-income and developing countries (LIDCs). In addition, conditional β-convergence results suggest that effectiveness of COVID-19 economic support policies may be lower in developing countries.

The rest of the paper proceeds as follows. Section 2 provides a brief literature review. Section 3 discusses the approaches to measuring cross-country income inequality. Section 4 lays out the estimation framework and discusses key growth correlates. Baseline regression results on σ-convergence are contained in Section 5.1 while Section 5.2 discusses heterogeneity across country groups. Robustness checks are presented in Section 5.3. Section 6 provides results on conditional β-convergence. Section 7 concludes.

2 Brief literature review

This paper contributes to the literature investigating the effect of pandemics on cross-country inequality. The two most relevant studies include the aforementioned work by Deaton (2021) as well as Levy Yeyati and Filippini (2021). The latter study quantifies the short- and medium-term costs of the COVID-19 crisis for countries depending on their income level, including the costs of output losses, fiscal stimuli, loss of human lives, and deterioration of human capital due to disruptions to schooling. The authors find that the COVID-19 pandemic has an uneven impact across income groups and is likely to exacerbate cross-country income inequality. We contribute to this analysis by using the most up-to-date WEO projections and investigating the channels driving the cross-country inequality both in the short and medium terms.

Another related strand of literature quantifies the effect of past pandemics on inequality. Furceri et al. (2021b) and Sayed and Peng (2021) use data from major pandemics and epidemics from the last century to analyze the dynamics of within-country income inequality. While Furceri et al. (2021b) find that past pandemics have led to increases in Gini coefficient, Sayed and Peng (2021) show the opposite. Thus evidence on the effect of pandemics on income inequality remains mixed. Our study focuses on the cross-country aspect of income inequality and can inform this strand of literature on the potential channels, through which the COVID-19 pandemic could drive income inequality.

Several studies use variation in workers' ability to perform work tasks remotely during lockdowns together with microsimulation approaches to examine the effect of the COVID-19 pandemic on within-country income inequality. Cugat and Narita (2020), Palomino et al. (2020), and Cirelli and Gertler (2022) show how uneven levels of amenability of remote work fuel within-country income inequality during lockdowns. These studies show that lockdowns tend to disproportionately affect low-income workers in contact-intensive sectors and thus increase income inequality. Ferreira et al. (2021) measure welfare losses due to the COVID-19 pandemic along both health and income dimensions. They find that the mortality burden is higher in richer countries since the COVID-19 virus disproportionately affects the elderly who account for a larger share of population in these countries. The poverty burden, however, is substantially larger in poorer countries when the international poverty line definition of $1.90 is used. In contrast, Ma et al. (2021) show that child mortality is likely to increase during the periods of lockdowns due to the associated contraction of economic activity. Finally, Lustig et al. (2020) examine the offsetting effect of social assistance on the pandemic-related increase in poverty in Brazil, Colombia, and Mexico. Their simulations suggest that individuals in the middle of the income distribution are more negatively affected by the pandemic due to the offsetting effect of social support programs targeting only those who are at the bottom of the income distribution. These microsimulation results provide valuable insights for selection of relevant explanatory variables for the augmented cross-country growth framework employed in this paper.

3 Measures of cross-country income inequality and convergence

3.1 σ-convergence

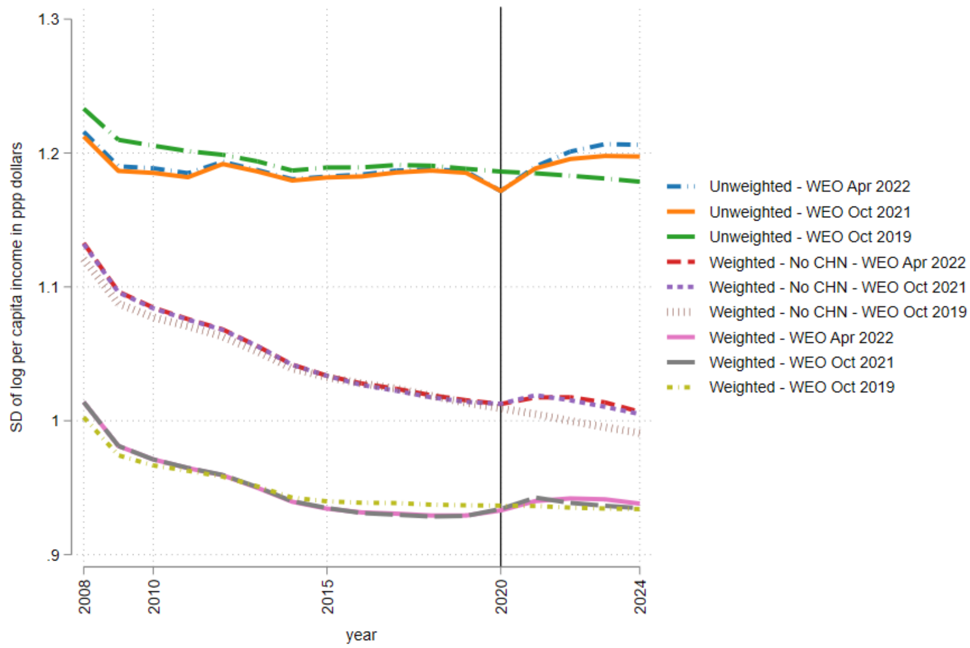
We begin our analysis by outlining the key patterns of cross-country income convergence, using σ-convergence to measure the dynamics of income inequality across countries. We extend the analysis in Deaton (2021) by using the IMF's WEO projections for 2021-2024 period.[3] To measure σ-convergence, we calculate standard deviations of the logarithm of GDP per capita using the pre-pandemic WEO projections from October 2019, October 2021 projections incorporating the effect of the pandemic, and the latest official WEO projections from April 2022. In Figure 1, we plot both unweighted and population-weighted results.

In line with Deaton (2021), Figure 1 shows that, based on the unweighted October 2021 WEO data, cross-country income inequality has declined faster in 2020 relative to the pre-pandemic projections. However, based on the post-2020 projections, we show that this episode of convergence is short-lived and, by 2021, the unweighted data suggest that world incomes diverge. Unweighted April 2022 WEO data shows that this trend is further exacerbated in large part due to the war in Ukraine. This paper, however, abstracts from the analysis of the war effects on cross-country income divergence and focuses on the October 2021 WEO projections to isolate the impact of the COVID-19 pandemic.

Moreover, when weighted by population, cross-country GDP per capita data show no acceleration in convergence in 2020 but rather faster divergence in 2021 compared to the unweighted data (Figure 1). In addition, we examine the dynamics in standard deviations in GDP per capita in a sample excluding China to account for China's population size and its relatively low COVID-19 case and death counts. The results show that presence of China in the sample has limited impact on the overall patterns of cross-country income inequality during the pandemic.

[3] Earlier versions of Deaton (2021) used σ-convergence to measure cross-country income inequality, whereas the latest version moved to the Gini coefficient. We also replicate and extend the Gini coefficient calculation shown in Appendix Figure A.1. All takeaways are consistent with those from the σ-convergence measure.

Figure 1: σ-convergence



Source: World Economic Outlook.
Note: For Oct 2021 WEO, 2021 is an estimate and from 2022 onwards are projections. For Oct 2019 WEO, 2019 is an estimate and from 2020 onwards are projections.

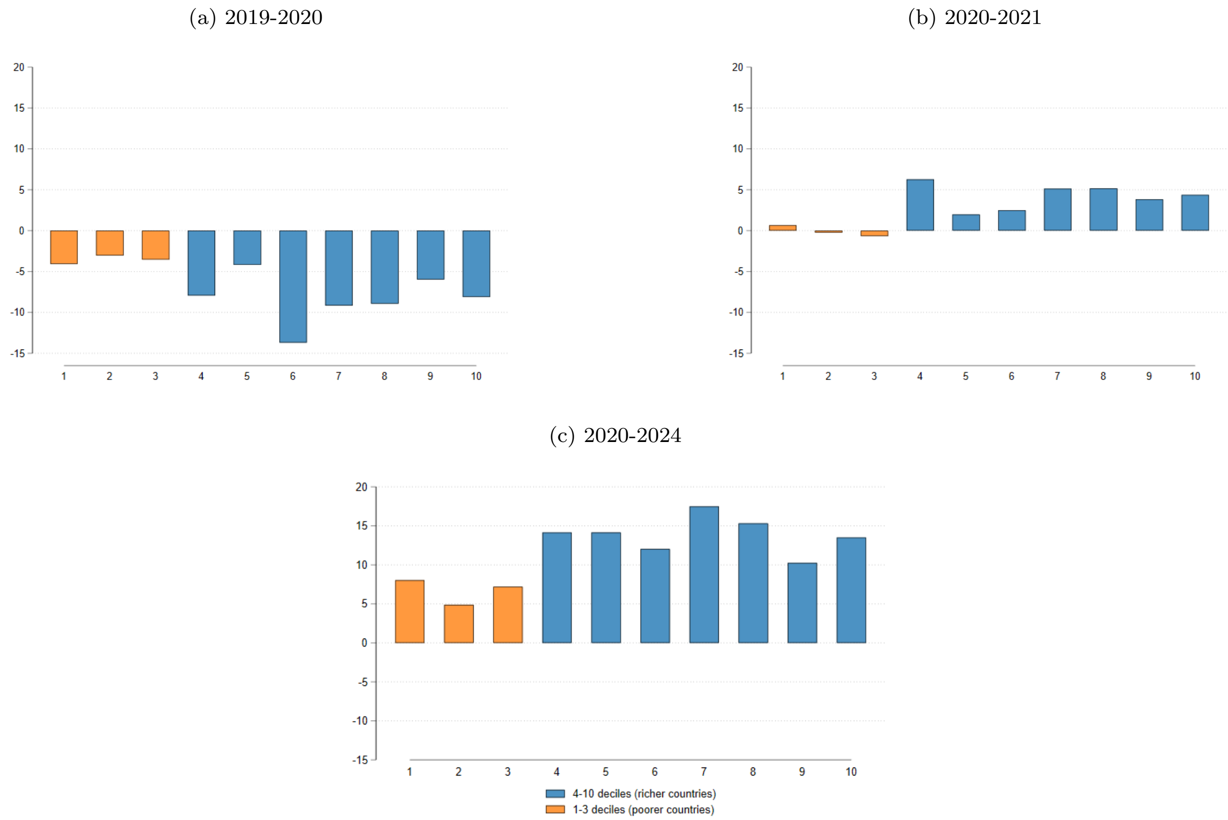
3.1.1 Which countries drive an increase in cross-country income inequality?

We further investigate which groups of countries drive an increase in cross-country income inequality after the first year of the pandemic. First, we look at the average growth in GDP per capita by income deciles. Figure 2a documents smaller income losses in the bottom three deciles of countries in 2020. This finding is consistent with the short period of acceleration in income convergence documented in Figure 1. The subsequent divergence in incomes in the post-crisis recovery period, however, is also driven by the bottom three deciles of income distribution, as evidenced by Figures 2b and 2c. In 2021, whereas most countries experience positive growth, countries in the second and third deciles, on average, see substantial income losses. In the medium term, the poorest three deciles of countries are also projected to grow at a substantially lower pace.

Figure 3a further demonstrates the role of LIDCs in the dynamics of income divergence during the pandemic. While most of the increase in variation of GDP per capita in 2020 was driven by divergent incomes within non-LIDC countries, divergence between LIDCs and non-LIDCs explains most of the rising variance in 2021. Within LIDCs, fragile and conflict-affected states (FCS) largely contribute to the deterioration of the outlook on LIDCs (Figure 3b). Divergence between FCS and the rest of the LIDCs is projected to accelerate even further in 2022, pulling the average LIDC incomes down relative to non-LIDCs. As demonstrated by Figure 3c, the effect of the pandemic is also uneven across geographic regions, with countries in Sub-Saharan Africa contributing to the acceleration of income divergence in 2021.

When dividing countries by their exporter status—commodity exporters versus diversified exporters—between-group income differences play a more prominent role in 2020 and 2022 (Figure 3d). Turbulence in

Figure 2: GDP per capita growth rates by country income decile



Source: World Economic Outlook.
Note: Deciles of countries are determined by base year 2019 for 2019-2020 calculation, and by base year 2020 for 2020-2021 and 2020-2024 calculations.

the commodity markets of 2020 and further volatility projected to dominate most of the recovery period explain weaker income growth of commodity exporters.

3.2 β-convergence

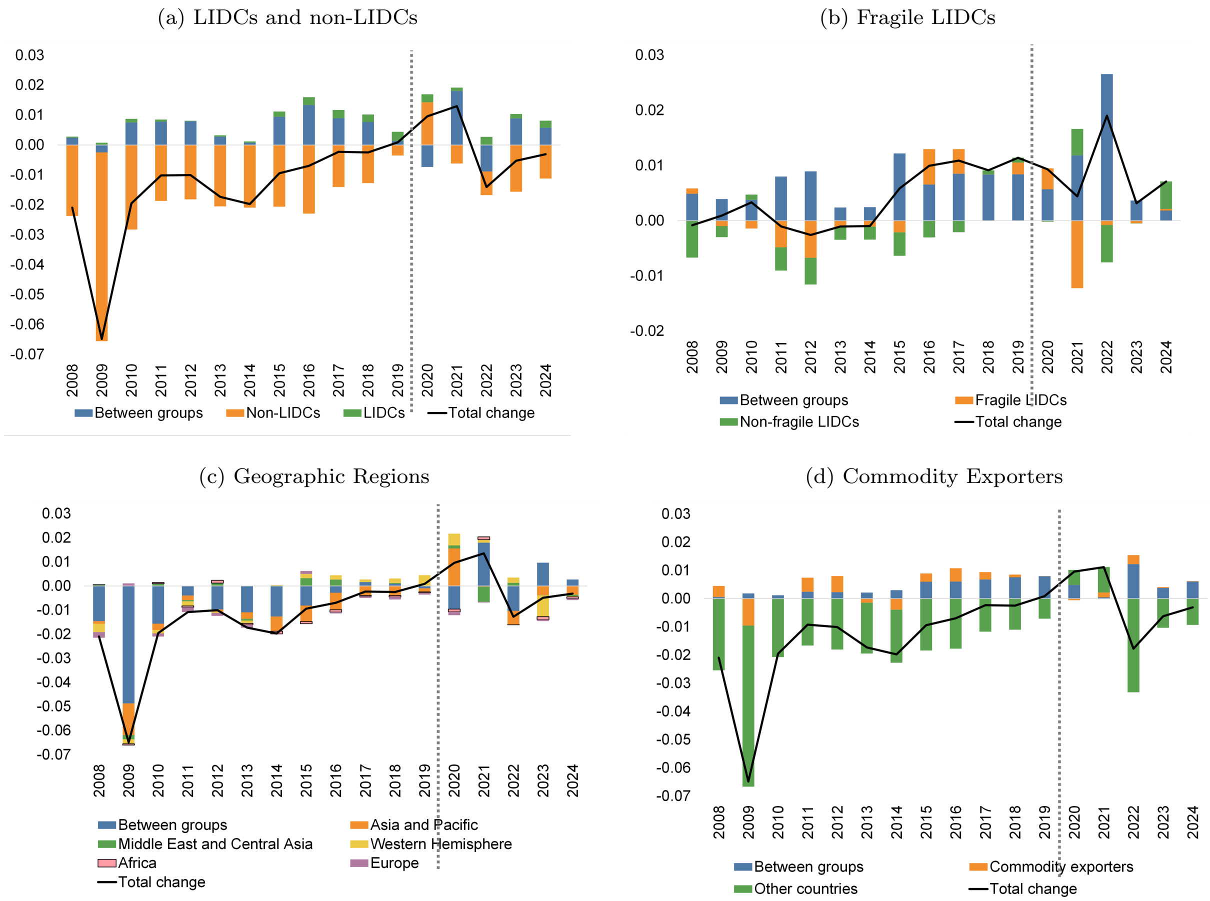
Our discussion so far has centerered around the concept of σ-convergence. In this section, we turn our attention to the concept of β-convergence. β-convergence is derived from a regression of the change in the logarithm of GDP per capita, $\Delta \log(\text{GDPpc}_{i,t})$, on the logarithm of GDP per capita in the initial period, $\log(\text{GDPpc}_{i,t-1})$ in country i:

$$\Delta \log(\text{GDPpc}_{i,t}) = \alpha_t + \beta_t \log(\text{GDPpc}_{i,t-1}) + \epsilon_{i,t}, \tag{1}$$

where $\Delta \log(\text{GDPpc}_{i,t}) = \log(\text{GDPpc}_{i,t}) - \log(\text{GDPpc}_{i,t-1})$, α_t is a constant, and $\epsilon_{i,t}$ is an error term.

A negative value of the coefficient on the initial level of GDP per capita, β_t, implies that richer countries grow slower than poorer countries, which results in cross-country income convergence. We estimate Equation 1 sequentially year by year to capture changes in the β_t coefficients over time. Most importantly, we are interested in the dynamics of the coefficients during the pandemic and in the period of projected recovery.

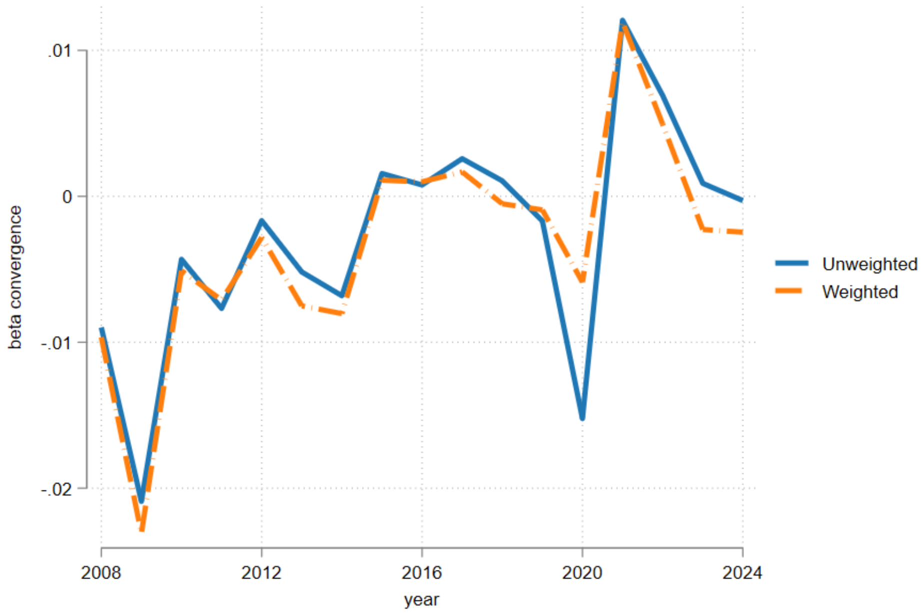
Figure 3: Within- and between-group variance decomposition of GDP per capita



Source: World Economic Outlook.
Note: Variance contribution is calculated by the sum of weighted within group variances and between group variance. For Oct 2021 WEO, 2021 is an estimate and from 2022 onwards are projections. For Oct 2019 WEO, 2019 is an estimate and from 2020 onwards are projections.

The results are contained in Figure 4 for both unweighted and population-weighted specifications. Weighted and unweighted results are fairly close in the entire period, with an exception of 2020, where unweighted coefficients suggest substantially faster convergence than the weighted results. Overall, the negative coefficients suggest a period of steady convergence, with an exception of several years of divergence following the commodity price shock of 2014 and even faster divergence in 2021 and 2022. Figure 4 also shows that during global crises, including the Global Financial Crisis (GFC) and the COVID-19 crisis, poorer countries fare relatively better but fall behind during the recovery period. Unlike the case of recovery after the GFC where convergence merely slowed, the COVID-19 shock was followed by a period of cross-country income divergence, as suggested by the positive coefficients in 2021 and 2022. These results on β-convergence are consistent with our findings on σ-convergence and provide additional evidence on the unique nature of the COVID-19 pandemic and its disproportionate impact on countries at the bottom of the income distribution.

Figure 4: Absolute β-convergence coefficients



Source: World Economic Outlook.
Note: Absolute β convergence specification: $\Delta \log(GDPpc_{i,t}) = \alpha_t + \beta_t \log(GDPpc_{i,t-1}) + \epsilon_{i,t}$. $\Delta \log(GDPpc_{i,t})$ is yoy growth in GDP per capita in all regressions. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections.

4 Estimation framework

Econometric analysis of cross-country income inequality predominantly focuses on identifying the determinants of income growth and convergence (Durlauf et al., 2005). Despite the vast number of studies on this topic, there is no unified theory on the drivers of growth and convergence. Analyzing income inequality in the pandemic context poses further challenges that are yet to be addressed in the literature. In this paper, we consider the factors contributing to the observed dynamics of income inequality across countries during the COVID-19 crisis and post-crisis recovery period. We start the discussion with key pandemic-related factors, including the severity of the health impact and corresponding containment policies. We then consider the extent of economic policies implemented in response to the pandemic-related contraction of economic activity. Finally, we examine how pre-pandemic economic fundamentals affect income changes during the pandemic. To measure the contribution of these factors to income growth, we employ several methods ranging from those commonly used in the growth literature to more novel machine-learning techniques.

The goal of the econometric exercise is to identify the growth correlates that explain differential rates of per-capita income growth in the context of the pandemic. The anticipated medium-term effect of the COVID-19 policies analyzed in the paper is already, to some extent, captured in IMF GDP projections. To that end, the paper aims to understand the role of these policies in the IMF country teams' outlook. We begin with the following baseline econometric specification:

$$\Delta \log(\text{GDPpc}_{i,t}) = \alpha_t + X_{i,t}\gamma_t + \epsilon_{i,t}, \tag{2}$$

where $\Delta \log(\text{GDPpc}_{i,t})$ is a cumulative change in the logarithm of GDP per capita. α_t is a constant. Vector

$X_{i,t}$ denotes country-specific characteristics as well as the pandemic outcomes and policies. $\epsilon_{i,t}$ is an error term.

Selection of relevant determinants comprising the vector $X_{i,t}$ is the main challenge. Model uncertainty stems not only from the lack of unified growth theory but more importantly from the absence of theoretical underpinnings behind the role of the virus and associated containment policies on per-capita income growth and cross-country convergence. To pin down the regressors explaining the variation in per-capita income growth, we consider several approaches including the Ordinary Least Squares (OLS), BMA, WALS, and LASSO. We then juxtapose the advantages and drawbacks offered by each of the methods to anchor the analysis in the rest of the paper.

While OLS serves as a straightforward starting point, it fails to address one of our main concerns—the lack of the a priori model. We thus turn to BMA, WALS, and LASSO methods which do not rely on the assumption of a single "true" model. WALS is a model averaging approach developed by Magnus et al. (2010).[4] One of the advantages of WALS is its proper treatment of ignorance about the role of auxiliary parameters. However, as pointed out by Magnus and De Luca (2016), WALS is unable to handle jointness between explanatory variables, which is likely to be a non-trivial issue in our context. While BMA imposes a Gaussian prior on the auxiliary parameters, it allows for their inter-dependence in the posterior distribution (Fernandez et al., 2001; Steel, 2020), which is a more plausible scenario in the context of growth and convergence determinants.[5] Finally, we employ LASSO developed by Tibshirani (1996), which performs well in situations with small samples relative to the number of potential regressors but also has limitations when it comes to multicollinearity (Rajaratnam et al., 2016).

4.1 COVID-19 health impact and containment policies

We begin by examining the key patterns of the virus spread and pandemic severity across countries, using counts of the COVID-19 cases and deaths from Dong et al. (2020). Figures 5a and 5b show correlations between the cumulative growth of per-capita GDP and cumulative population-weighted numbers of confirmed COVID-19 cases and deaths per million people as of October 14, 2021.[6] We show both short- and medium-term income growth rates (2019-2020, 2020-2022, and 2020-2024) to capture both the crisis period and the post-shock recovery. The unconditional correlation between growth and both cases and death counts is negative but not statistically significant in the short run. The severity of the COVID-19 virus outbreaks in the first year and a half of the pandemic (March 2020 to October 2021) appears to have a stronger negative relationship with income growth in the medium term (2020-2024).

Weak correlations between income growth and COVID-19 cases and death counts, particularly in the short run, could be driven by population weighting and poor data quality. Firstly, population weighting could be a concern in the case of India, for instance, where income growth remained relatively high despite its high number of cases and deaths. In Appendix Figures A.2a and A.2b, we address this concern by plotting the unweighted data and find that the sign of these correlations reverses relative to the weighted results. The resulting correlation coefficients are positive, suggesting that populous countries like India and China are unlikely to be driving the results. Secondly, the effect of COVID-19 deaths and cases on economic activity may vary throughout the year (Bakker and Goncalves, 2021) but our measures only capture the annual variation due to the nature of cross-country GDP data.

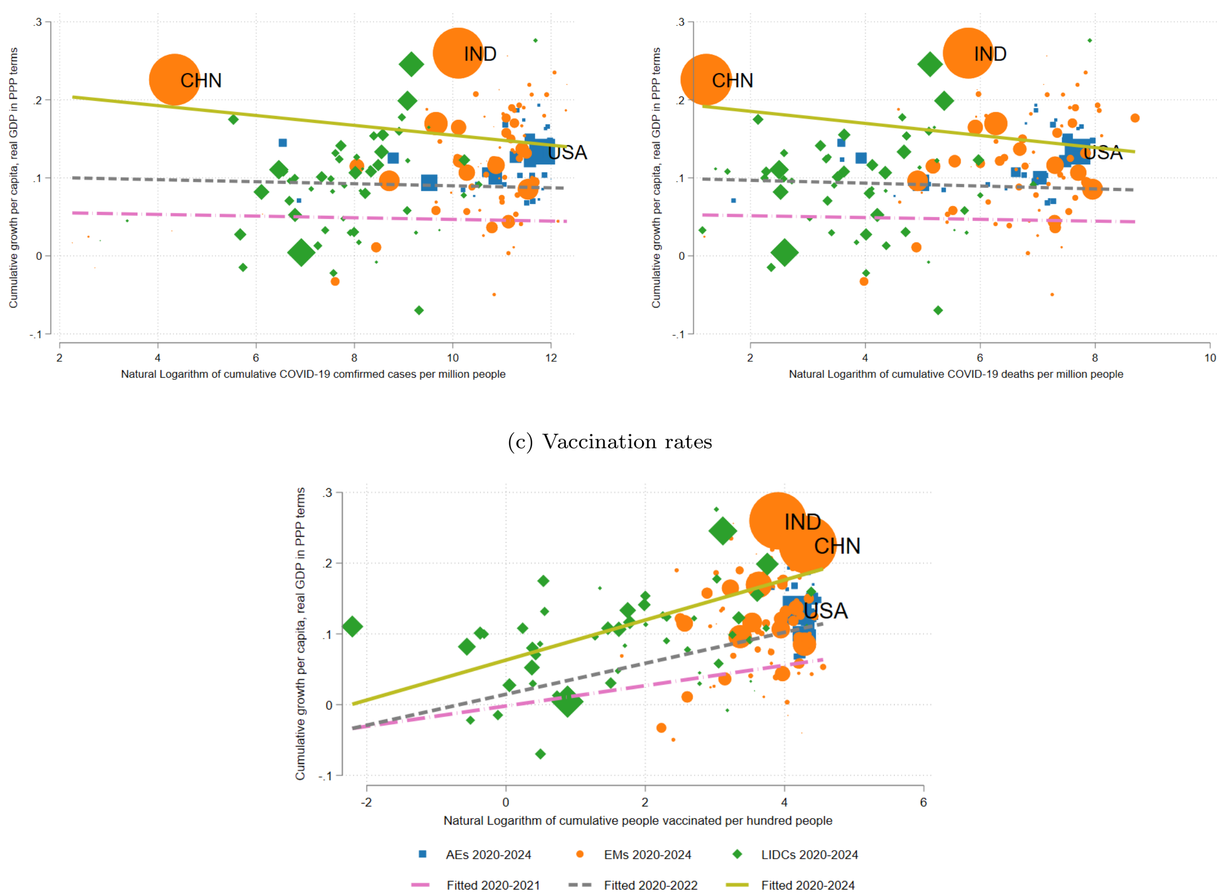
[4] Furceri et al. (2021a) use WALS as a base approach to analyze the drivers of output losses during the COVID-19 pandemic.
[5] See Eicher et al. (2011) for discussion of BMA performance in the context of growth regressions.
[6] Refer to Appendix Table A.1 variable definition and sources.

Figure 5: Growth correlates

(a) COVID-19 cases

(b) COVID-19 deaths

(c) Vaccination rates



Source: JHU CSSE COVID-19 Data, World Economic Outlook.
Note: Cumulative COVID-19 confirmed cases and deaths data is as of October 14, 2021. Cumulative people vaccinated per hundred people is the latest data available as of October 14, 2021. Growth data is based on Oct 2021 WEO. 2021 is an estimate and from 2022 onwards are projections.

Thirdly, quality of health and mortality statistics can vary substantially across countries, due to institutional limitations (Aizenman et al., 2022). We use cross-country counts of excess deaths during the pandemic calculated by The Economist (2020) as an alternative to the national statistics on the COVID-19 deaths. Appendix Figure A.2d shows the correlation between GDP per capita growth and excess deaths per million people, weighted by population. Correlations remain weakly negative similarly to the Figure 5b, where nationally reported death rates are used. These results suggest that correlations between income growth and measures of severity of the COVID-19 health impact at the country level are weak mainly due to endogeneity and less so due to data quality or data treatment issues. These outcomes are likely to largely depend on other country characteristics including pre-pandemic economic fundamentals and policies implemented by governments to contain the spread of the virus and address its economic impact.

In Figure 5c, we plot the relationship between income growth and one of the health policies aimed at containing the spread of the virus—cumulative COVID-19 vaccination rates per hundred people by October 14, 2021 from Dong et al. (2020). Unlike COVID-19 cases and deaths, vaccination rates are strongly and positively correlated with income growth, with correlation coefficients increasing over the medium term. This relationship is not sensitive to population weighting as shown in Appendix Figure A.2c. These results suggest that policies implemented by countries to contain the virus have potential to effectively offset the negative impact of the virus on growth—the hypothesis that we will test more formally in Section 5.1.

In addition to vaccination, we also consider the level of stringency of lockdown orders implemented by countries to contain the virus. We examine the relationship between income growth and lockdown stringency in Section 5.1, conditioning on case, death, and vaccination rates, as well as other country characteristics. We construct two measures of lockdown stringency, based on the data from Oxford COVID-19 Government Response Tracker (Hale et al., 2021). Firstly, we consider an average level of the lockdown stringency index from the start of the pandemic to October 14, 2021. Secondly, we are interested in examining the impact of variation in lockdown policies, which we capture by the range of lockdown stringency index values across countries. To that end, we compute differences between maximum and minimum levels of the lockdown stringency index during this period. We set the starting date for calculating the minimum lockdown stringency to May 1, 2020, since some countries were yet to impose lockdowns by the second quarter of 2020, resulting in zeros for their stringency index values. This variable allows us to capture the degree of targeting and timeliness of lockdowns. Countries with consistently high or low levels of lockdown stringency would thus have smaller a range of the corresponding index values.

4.2 Economic support policies

To measure the extent of policy support provided by governments during the pandemic, we use data from the IMF's COVID-19 Policy Tracker.[7] We first consider additional spending on health-related measures and non-health related fiscal support. Separating fiscal response by type of spending allows us to measure differential impact of these policies on short- and medium-term income growth. While health spending may be a priority when addressing an unfolding health crisis, more general economic stimulus packages may be more relevant in the medium term.

Many countries amassed unprecedented levels of public debt in an attempt to prop up the economy during the pandemic. We include a measure of accumulated new debt in percent of GDP in the baseline specification to account for its short- and medium-term impact. While new public debt accumulation due to stronger fiscal response may prevent further deterioration of incomes in the short run, there may be significant medium-term repercussions of high debt levels for growth. High levels of debt could be especially detrimental for developing countries, further limiting their fiscal space and barring them from accessing more financing on the international market.

On the monetary policy side, we consider changes in the policy rates and the size of liquidity support from central banks. We use data from the IMF's COVID-19 Policy Tracker to capture the changes in policy rate between December 2019 and September 2021 and the amount of additional liquidity in percent of GDP injected by central banks.

4.3 Pre-pandemic economic fundamentals

We consider a number of macroeconomic characteristics to control for pre-pandemic economic conditions that may have affected the ability of governments to respond to the pandemic. First, we include public debt

[7] The IMF's COVID-19 Policy Tracker can be found here.

as percent of GDP in 2019 to capture countries' ability to access finacing for pandemic response and overall availability of fiscal space.

Second, we consider several proxies of economic openness, including trade as a share of GDP and service exports as a share of GDP separately to proxy for countries' reliance on tourism receipts.[8] We use the logarithm of the total number of international flight arrivals per million people in 2019 as a proxy for country's openness to international travel and hence its susceptibility to cross-border virus transmission. We also compute growth in international flights arrivals from 2019 to 2020 to capture differential levels of stringency of border closures across countries in response to the COVID-19 spread.

Finally, we condition on the pre-pandemic level of per-capita income as well as the pre-pandemic income growth. This allows us to account for the overall impact of development in countries' ability to respond to the crisis, which is highly correlated with key Solow fundamentals and the quality of institutions (Kremer et al., 2021).

5 σ-convergence results

5.1 Baseline results

We use WEO projections from October 2021 to construct the dependent variable—change in the logarithm of GDP per capita in Equation 2. We consider two time periods of recovery after the initial COVID-19 shock: 2020-2021 (short term) and 2020-2024 (medium term). The sample, for which data on the variables described above is readily available, consists of 103 countries. We apply the aforementioned four methods—OLS, BMA, WALS, and LASSO—to examine the contribution of these variables to per-capita income growth.

Table 1 contains our baseline results. The set of selected variables is largely consistent across four econometric methods for both time periods. For OLS, we use standard cutoffs for p-values to denote the statistical significance level of a given point estimate. In the case of BMA, we rely on the posterior inclusion probabilities, setting the threshold value to 0.5 for choosing variables that plausibly explain variation in the per-capita income growth. For WALS, we use a threshold value of a corresponding t-statistic of 1 in absolute value to pinpoint the determinants of growth. For LASSO, the tuning parameter is selected using the cross-validation method. The resulting standardized coefficients on selected variables tend to be of a similar magnitude, albeit with LASSO producing consistently smaller estimates.

Evidence on the impact of severity of the pandemic on growth, measured by case and death counts, is weak. However, our results suggest that vaccination rates have a lasting and positive impact on growth. The importance of vaccination rates as a contributor to the projected income growth is captured across all four econometric approaches. Lockdown policies also tend to have a lasting positive effect on growth rates, as evidenced by the results in both short and medium terms. Interestingly, differences between minimum and maximum stringency levels of lockdowns implemented during the pandemic appear to have a stronger predictive power compared to the mean level of lockdown stringency. This result suggests that more targeted lockdowns in terms of timing and stringency level could be more effective at fighting the spread of the virus and, at the same time, put less undue burden on economic activity in the country.

Among economic policies implemented during the pandemic, there is some evidence on the positive contribution of fiscal spending and liquidity support to income growth in the recovery period. However, the results are not robust across all specifications. Particularly, BMA appears to be more conservative in selection

[8] Up-to-date data on tourism receipts are not available for many LIDCs. Thus, we use service exports as a proxy.

Table 1: Baseline regressions - weighted, base year 2020

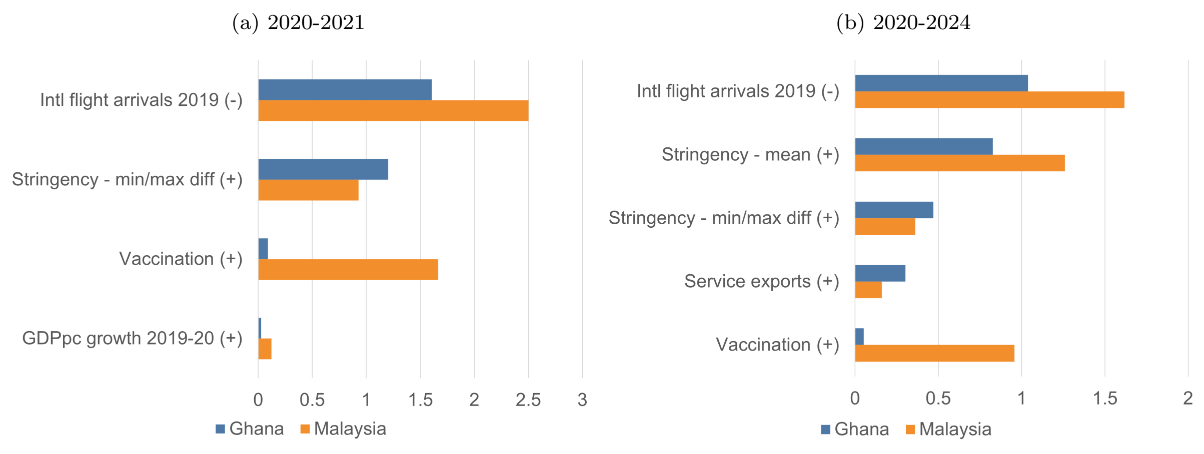
	(1) OLS 2021	(2) BMA 2021	(3) WALS 2021	(4) LASSO 2021	(5) OLS 2024	(6) BMA 2024	(7) WALS 2024	(8) LASSO 2024
Deaths	0.047	0.053	0.058		-0.052	**-0.078**	-0.064	-0.090
	(0.094)	(0.074)	(0.082)		(0.067)	(0.050)	(0.069)	
Vaccination	0.887***	**0.969**	**0.721**	0.388	0.623**	**0.526**	**0.528**	0.182
	(0.275)	(0.162)	(0.198)		(0.280)	(0.132)	(0.166)	
Confirmed cases	-0.136	0.008	-0.106		-0.091	-0.000	-0.067	
	(0.124)	(0.042)	(0.109)		(0.089)	(0.025)	(0.083)	
Stringency - mean	-0.156	0.006	0.004		0.701	**0.908**	**0.616**	0.504
	(0.612)	(0.089)	(0.342)		(0.498)	(0.311)	(0.276)	
Stringency - min/max diff	0.810**	**0.769**	**0.639**	0.248	0.484*	**0.283**	**0.365**	0.174
	(0.342)	(0.165)	(0.156)		(0.246)	(0.202)	(0.127)	
Fiscal spending - health	0.077	0.023	**0.078**		0.079	0.041	**0.056**	
	(0.088)	(0.054)	(0.068)		(0.074)	(0.064)	(0.056)	
Fiscal spending - non-health	0.127	0.053	0.081		0.257**	0.036	**0.171**	
	(0.131)	(0.100)	(0.115)		(0.111)	(0.075)	(0.099)	
Policy rate cut	0.044	0.007	0.056	0.018	-0.035	-0.001	-0.024	
	(0.079)	(0.029)	(0.059)		(0.096)	(0.013)	(0.045)	
Liquidity	0.137	0.015	0.113	0.169	-0.068	-0.008	-0.047	0.097
	(0.167)	(0.064)	(0.114)		(0.126)	(0.036)	(0.096)	
Debt	-0.227	-0.014	**-0.146**		-0.196*	-0.004	**-0.118**	
	(0.140)	(0.062)	(0.131)		(0.114)	(0.034)	(0.106)	
New debt 2020	0.176	0.039	**0.149**	0.025	-0.010	-0.001	0.015	
	(0.152)	(0.082)	(0.098)		(0.123)	(0.021)	(0.079)	
Trade	-0.083	-0.011	-0.087		-0.066	-0.016	-0.045	
	(0.110)	(0.062)	(0.127)		(0.123)	(0.063)	(0.097)	
Intl flight arrivals 2019	-1.417***	**-1.378**	**-1.097**		-1.189***	**-0.841**	**-0.931**	
	(0.521)	(0.441)	(0.415)		(0.446)	(0.287)	(0.338)	
Intl flight arrivals growth	0.140	0.027	0.075		-0.174	-0.008	**-0.152**	-0.022
	(0.194)	(0.080)	(0.124)		(0.158)	(0.046)	(0.101)	
Service exports	0.149**	0.053	**0.149**	0.094	0.163**	**0.121**	**0.139**	0.137
	(0.064)	(0.074)	(0.068)		(0.074)	(0.063)	(0.054)	
GDPpc 2019	1.987	1.079	**1.258**		0.514	0.075	0.191	
	(1.478)	(1.432)	(1.017)		(1.378)	(0.435)	(0.796)	
GDPpc growth 2019-20	-0.259	**-0.094**	**-0.196**	-0.142	-0.084	-0.008	**-0.075**	-0.060
	(0.195)	(0.105)	(0.084)		(0.132)	(0.032)	(0.067)	
Constant	-1.528	-0.834	**-0.955**		-0.369	-0.087	-0.001	
	(1.184)	(1.143)	(0.931)		(1.190)	(0.585)	(0.748)	
Observations	103	103	103	103	103	103	103	103

Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Coefficients are standardized. Countries are weighted by population. Dependent variable is cumulative per capita growth in 2020-2021 or 2020-2024. Growth data is based on Oct 2021 WEO. 2020 is an estimate and from 2021 onwards are projections. Debt, trade, fiscal spending, service exports, and liquidity variables are in % of GDP. Intl. flight arrivals in 2019 variable is logged. Lockdown stringency difference is calculated as the maximum of stringency index over entire period less the minimum of stringency index after the first peak. Confirmed cases, deaths, vaccination and stringency data are as of October 14, 2021. Standard errors are in parentheses. BMA coefficients in bold indicate the corresponding pip$\geq$ 0.5. WALS coefficients in bold indicate the corresponding t-stat$\geq$ 1 in absolute value. For OLS coefficients, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

of the relevant regressors, which could be in part due to the multicollinearity issue within and between the groups of explanatory variables. In the following sections, we adopt BMA as a preferred method, given its properties discussed above and the ease of interpretation.

Among pre-pandemic fundamentals, results on the role of pre-pandemic indebtedness are mixed, only with WALS consistently pointing to the negative impact of the public debt burden on per-capita income growth. Among openness proxies, international flight arrivals per million people appear to be a non-trivial determinant of income growth, according to all alternative specifications. Namely, more open countries experienced a particularly detrimental contraction in per-capita incomes. Higher growth in international flight arrivals during the pandemic, which may be indicative of more lax travel restrictions, have a negative impact on medium-term growth (last two columns of Table 1). However, this result is not robust across all specifications. Service exports in percent of GDP, as a proxy for tourism receipts, appear to be a strong predictor of the pace of recovery especially in the medium term. Associated coefficients suggest that economies oriented towards service exports, including tourism, face a more positive growth outlook in the recovery period. This result could signal a period of growth catch-up for tourism-oriented economies, given that these countries were disproportionately affected by the COVID-19 containment measures. In the next section, we take a closer look at tourism-dependent countries to understand the channels driving these results. Overall, the results are consistent with the patterns of divergence documented in Section 3. The coefficients on pre-pandemic per-capita income growth suggest that faster growing countries fall behind during the recovery period, resulting in cross-country income divergence.

Figure 6: Magnitude of key channels for countries in the 30th and 70th percentiles of GDP per capita distribution



Source: Flightradar24, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Each bar shows the magnitude of the corresponding variable's effect on Ghana's (representing the 30th percentile of world's GDP per capita distribution) and Malaysia's (representing the 70th percentile of world's GDP per capita distribution) per-capita GDP growth. The coefficients are from Columns 2 and 6 of Table 1. (-) and (+) denote negative and positive effects of the variables.

To gauge the magnitudes of the estimated effects, we select Ghana and Malaysia as illustrative examples. Whereas Ghana is at the 30th percentile of the cross-country income distribution, Malaysia represents the 70th percentile—the two points of interest as shown in Figures 2a-2c. In Figures 6a and 6b, we show the resulting conditional effects of the variables selected by BMA on 2020-2021 and 2020-2024 growth rates corresponding to the posterior coefficients in Columns 2 and 6 in Table 1. Given the higher rate of vaccination in Malaysia, its impact on income growth is over 1.5 percentage points higher than for Ghana in the first year of recovery and close to 0.9 percentage point higher in the medium term. At the same time, disruptions in international mobility due to the pandemic have a bigger and more lasting effect in the case of Malaysia, as captured by the international flight arrivals variable. For Malaysia, this effect translates to close to 2.5 percentage points drop in GDP per capita, holding all else constant, while for Ghana it is close to 1.6 percentage points in 2021. The effect diminishes in 2024, but still remains substantial at 1.6 percentage points for Malaysia and 1 percentage point for Ghana. on the other hand, service exports as a share of GDP prior to the pandemic have a mitigating impact on per-capita income growth in the medium term, associated with almost 0.5 percentage point higher growth in the case of Ghana and slightly lower impact in Malaysia. Finally, variation in lockdown stringency, captured by the difference between maximum and minimum levels of the corresponding index have similar effects on growth in both Malaysia and Ghana, with the latter effect estimated at 1.2 percentage points in 2021 and close to 0.5 percentage point in 2024. However, the overall impact of the average stringency of lockdowns is stronger in the case of Malaysia over the medium term at over 1.2 percentage points.

5.2 Heterogeneity by income group and exporter status

Income groups. We disaggregate the sample of countries by income group—AEs, EMs, and LIDCs—and examine heterogeneity of the COVID-19 pandemic shock and associated policies on income growth within these groups in Table 2.

We first document contrasting results on the effect of COVID-19 deaths in AEs and LIDCs. In 2021, the estimated impact of the COVID-19 death toll on growth is positive in the case of AEs and EMs, while it is negative in the case of LIDCs.[9] The same holds for AEs and LIDCs in the 2024, whereas the impact of deaths in EMs dissipates in 2024. These results suggest that, conditional on containment and economic support policies implemented during the pandemic, pandemic death toll in LIDCs is a bigger contributor to the decline in per-capita income growth. On the other hand, policies implemented in AEs appeared to be able to offset the negative impact of the COVID-19 deaths on growth. The result on the role of deaths in LIDCs, however, is moderated by the positive effect of confirmed cases, suggesting that limited capacity of local health systems to deal with the virus and contain the number of associated deaths may be more detrimental for growth in poorer countries. Higher vaccination rates are associated with higher per-capita income growth in LIDCs and EMs in the short run, and have a more lasting impact in LIDCs. In case of AEs, where variation in vaccination rates by October, 2021 was smaller than in LIDCs and EMs, we find little evidence of vaccination rates being a major contributor to variation in per-capita income growth in this income group.

We find limited evidence of the effect of economic policies on growth in developing countries. There is evidence of a negative impact of liquidity injections during the crisis for the medium-term growth of AEs, which could reflect advanced economies weaning off strong policy support and the associated slowdown in aggregate demand. Interestingly, accumulation of public debt in 2020 is associated with higher income growth in AEs in 2021 and declining growth rates in EMs and LIDCs in the medium term. As debt service moratorium expires, many LIDCs and EMs are faced with unsustainable levels of public debt in the aftermath of the crisis and limited sources of financing (IMF, 2021). This, in its turn, is projected to slow down growth and increase cross-country income inequality.

[9] Coefficients are standardized in the context of each sample divided by income group. While the coefficient on deaths in the case of LIDCs is larger in absolute value, the associated numbers of deaths are significantly smaller than in AEs and EMs.

Table 2: BMA regressions by income group - weighted, base year 2020

	(1) AEs 2021	(2) AEs 2024	(3) EMs 2021	(4) EMs 2024	(5) LIDCs 2021	(6) LIDCs 2024
Deaths	**0.236**	**0.132**	**0.133**	-0.015	**-12.177**	**-8.378**
	(0.054)	(0.034)	(0.051)	(0.047)	(3.164)	(2.239)
Vaccination	0.028	0.013	**0.795**	0.029	**0.921**	**1.300**
	(0.150)	(0.082)	(0.261)	(0.112)	(0.796)	(0.553)
Confirmed cases	-0.000	-0.000	-0.018	-0.021	**13.209**	**9.524**
	(0.019)	(0.012)	(0.055)	(0.053)	(3.560)	(2.563)
Stringency - mean	0.010	0.019	0.314	**1.426**	-0.085	**0.322**
	(0.086)	(0.079)	(0.549)	(0.420)	(0.295)	(0.365)
Stringency - min/max diff	0.010	-0.002	**0.435**	0.089	0.107	0.263
	(0.070)	(0.028)	(0.211)	(0.130)	(0.351)	(0.370)
Fiscal spending - health	0.000	-0.000	-0.076	0.000	0.045	-0.038
	(0.007)	(0.004)	(0.129)	(0.025)	(0.150)	(0.115)
Fiscal spending - non-health	0.007	0.026	-0.077	-0.033	-0.283	-0.670
	(0.038)	(0.048)	(0.165)	(0.092)	(1.050)	(1.064)
Policy rate cut	-0.090	-0.093	0.018	0.003	0.070	-0.015
	(0.207)	(0.165)	(0.048)	(0.018)	(0.160)	(0.056)
Liquidity	0.003	**-0.053**	0.028	0.006	-0.462	-0.272
	(0.024)	(0.062)	(0.072)	(0.030)	(1.007)	(0.541)
Debt	0.010	0.006	**-0.572**	-0.142	-0.292	-0.058
	(0.037)	(0.029)	(0.267)	(0.221)	(0.687)	(0.322)
New debt 2020	**0.146**	0.032	0.001	**-0.181**	-0.030	**-0.181**
	(0.126)	(0.058)	(0.086)	(0.140)	(0.126)	(0.178)
Trade	-0.002	0.006	-0.015	0.007	0.119	-0.017
	(0.030)	(0.019)	(0.061)	(0.039)	(0.288)	(0.121)
Intl flight arrivals 2019	0.003	0.071	**-1.790**	**-2.029**	0.256	0.051
	(0.189)	(0.205)	(0.409)	(0.308)	(0.767)	(0.353)
Intl flight arrivals growth	**-0.158**	**-0.097**	0.006	**-0.184**	**0.954**	**0.615**
	(0.146)	(0.109)	(0.044)	(0.141)	(0.529)	(0.273)
Service exports	**0.042**	0.008	**0.405**	**0.423**	0.006	**0.183**
	(0.031)	(0.014)	(0.074)	(0.053)	(0.063)	(0.191)
GDPpc 2019	-0.655	-0.961	1.552	**4.469**	**-2.722**	**-4.397**
	(1.576)	(1.437)	(2.040)	(1.313)	(2.457)	(1.553)
GDPpc growth 2019-20	-0.001	0.002	0.005	0.012	**-0.652**	0.001
	(0.041)	(0.022)	(0.026)	(0.035)	(0.288)	(0.055)
Constant	0.796	1.369	-0.301	**-3.503**	2.508	**4.189**
	(2.066)	(1.820)	(2.385)	(1.584)	(2.791)	(1.881)
Observations	30	30	49	49	24	24

Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.

Note: Coefficients are standardized. Countries are weighted by population. Dependent variable is cumulative per capita growth in 2020-2021 or 2020-2024. Growth data is based on Oct 2021 WEO. 2020 is an estimate and from 2021 onwards are projections. Debt, trade, fiscal spending, service exports, and liquidity variables are in % of GDP. Intl. flight arrivals in 2019 variable is logged. Lockdown stringency difference is calculated as the maximum of stringency index over entire period less the minimum of stringency index after the first peak. Confirmed cases, deaths, vaccination and stringency data are as of October 14, 2021. Standard errors are in parentheses. BMA coefficients in bold indicate the corresponding pip$\geq$ 0.5.

The posterior coefficients on proxies for openness to international travel during the pandemic suggest that more lax restrictions on international travel are associated with bigger income declines in AEs and EMs. This result does not hold for LIDCs. For all countries, however, we find a positive association between service exports and growth, suggesting that tourism-dependent countries are likely to see faster-paced recovery in the medium term.

Exporter status. In Table 3, we examine the heterogeneous impact of pandemic-related and macroeconomic variables on per- capita income growth by the country's type of primary exports. We divide countries into commodity exporters and diversified exporters and consider tourism-dependent economies separately.[10] For both diversified and commodity exporters, the extent of containment policies measured by stringency of lockdowns as well as vaccination rates are associated with higher growth. However, these containment policies pay off for commodity exporters only in the medium term. Death rates have a negative impact on income growth among diversified exporters, but matter less in the case of commodity exporters.

The effects of fiscal and monetary policies are distinct for diversified and commodity exporters. In both cases, higher levels of public debt before the pandemic tend to bring down the medium-term growth outlook. However, in the case of diversified exporters, accumulation of new debt during the pandemic tends to prop up per-capita incomes. Stronger monetary policy response through policy rate cuts has a positive effect on short-run income growth in both groups of exporters but has a more lasting impact for diversified exporters. On the other hand, liquidity injections are more effective at supporting income growth in the case of diversified exporters. Finally, the posterior coefficients on the pre-pandemic GDP per capita growth suggest higher income divergence rates among diversified exporters compared to commodity exporters.

We consider 16 tourism-dependent countries, based on their tourism receipts as a share of total exports.[11] Since there are only 16 countries in the sample, we limit the set of variables to those that were selected by BMA in previous specifications in Tables 1 and 2.

The results on the severity of the virus outbreak and associated containment policies are mixed, in part due to the small sample of countries. In the medium term, tourism-dependent economies with a history of stricter and more targeted lockdowns are likely to see an acceleration in income growth, as evidenced by sizable coefficients on stringency variables. Measures of openness—pre-pandemic number of international flight arrivals per million, arrivals growth in 2020 and service exports—suggest that countries more reliant on tourism receipts were disproportionately impacted. Finally, additional spending on health sector and ample fiscal space, as evidence by the coefficients on health spending and pre-pandemic public debt level, ameliorated further divergence in these economies in the medium term.

5.3 Robustness checks

Population weights. Population-weighted regressions allow us to examine changes in income inequality, taking global population distribution as an object of interest. When population weights are not applied, we shift our focus to countries as units of observations. The latter approach allows to consider the effectiveness of pandemic containment and economic measures from a policymaker's point of view. In addition, it allows

[10] We use standard IMF definitions for diversified and commodity exporters. If more than 50 percent of country's exports correspond to fuels and primary commodity, it is classified as a commodity exporter. Analogously, if more than 50 percent of country's exports consist of manufacturing goods, a country is classified as a diversified exporter.

[11] We include Albania, Croatia, Dominica, Dominican Republic, Fiji, Greece, Honduras, Jamaica, Mauritius, Panama, Portugal, Seychelles, Singapore, Solomon Islands, Spain, and Turkey in the list of tourism-dependent countries. Based on the latest available data from the World Bank's World Development Indicators, tourism receipts account for over 20 percent of exports in these countries in recent years.

Table 3: BMA regressions by exporter status - weighted, base year 2020

	(1) Diversified 2021	(2) Diversified 2024	(3) Commodity 2021	(4) Commodity 2024	(5) Tourism 2021	(6) Tourism 2024
Deaths	-0.044	**-0.196**	**0.193**	**0.178**	-0.126	**0.362**
	(0.088)	(0.061)	(0.035)	(0.037)	(0.201)	(0.279)
Vaccination	**0.455**	0.141	0.054	**0.349**	-0.182	-0.097
	(0.414)	(0.172)	(0.098)	(0.115)	(0.417)	(0.203)
Confirmed cases	0.000	0.005	0.001	0.003	0.062	**-0.468**
	(0.050)	(0.037)	(0.021)	(0.025)	(0.153)	(0.361)
Stringency - mean	-0.122	0.099	0.088	**0.806**	0.229	**2.364**
	(0.321)	(0.248)	(0.180)	(0.327)	(0.597)	(1.736)
Stringency - min/max diff	**0.849**	**0.357**	0.003	**0.741**	0.179	**1.498**
	(0.173)	(0.156)	(0.043)	(0.128)	(0.349)	(0.749)
Fiscal spending - health	0.003	0.002	**0.229**	0.025	0.039	**0.901**
	(0.021)	(0.015)	(0.056)	(0.072)	(0.229)	(0.732)
Liquidity	**0.171**	0.022	**-0.290**	-0.009	-0.151	-0.269
	(0.185)	(0.057)	(0.129)	(0.055)	(0.628)	(0.635)
Debt	-0.095	**-0.228**	0.011	**-0.334**	-0.011	**-0.553**
	(0.156)	(0.124)	(0.045)	(0.180)	(0.086)	(0.460)
New debt 2020	**0.455**	**0.296**	0.006	-0.018	0.109	0.052
	(0.164)	(0.126)	(0.015)	(0.039)	(0.269)	(0.175)
Intl flight arrivals 2019	**-1.785**	**-1.720**	-0.045	-0.059	-0.009	**5.183**
	(0.478)	(0.326)	(0.131)	(0.175)	(0.658)	(4.125)
Intl flight arrivals growth	0.027	-0.009	0.023	**-0.319**	0.120	**-0.386**
	(0.092)	(0.044)	(0.059)	(0.119)	(0.313)	(0.824)
Service exports	0.003	0.005	-0.001	-0.010	-0.009	**0.058**
	(0.020)	(0.021)	(0.041)	(0.063)	(0.034)	(0.045)
GDPpc 2019	**4.202**	**3.921**	**0.970**	**-1.420**	1.768	**-3.612**
	(1.963)	(1.113)	(0.438)	(0.655)	(3.029)	(4.767)
GDPpc growth 2019-20	**-0.330**	**-0.260**	**0.298**	**0.365**	0.004	**0.249**
	(0.119)	(0.067)	(0.037)	(0.060)	(0.063)	(0.382)
Fiscal spending - non-health	-0.008	0.003	**0.998**	**-0.251**		
	(0.051)	(0.036)	(0.087)	(0.164)		
Policy rate cut	**0.086**	0.058	**0.193**	0.027		
	(0.097)	(0.069)	(0.080)	(0.084)		
Trade	0.008	0.018	-0.067	**0.107**		
	(0.042)	(0.051)	(0.118)	(0.126)		
Constant	**-3.553**	**-2.060**	**-0.889**	0.005	-1.291	**-7.359**
	(1.610)	(0.887)	(0.446)	(0.518)	(3.448)	(4.177)
Observations	83	83	20	20	16	16

Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Coefficients are standardized. Countries are weighted by population. Diversified represents diversified exporters. Commodity represents commodity exporters. Tourism represents tourism-dependent countries. Dependent variable is cumulative per capita growth in 2020-2021 or 2020-2024. Growth data is based on Oct 2021 WEO. 2020 is an estimate and from 2021 onwards are projections. Debt, trade, fiscal spending, service exports, and liquidity variables are in % of GDP. Intl. flight arrivals in 2019 variable is logged. Lockdown stringency difference is calculated as the maximum of stringency index over entire period less the minimum of stringency index after the first peak. Confirmed cases, deaths, vaccination and stringency data are as of October 14, 2021. Standard errors are in parentheses. BMA coefficients in bold indicate the corresponding pip$\geq$ 0.5.

to gauge the impact of most populous countries on the average effects estimated in the baseline regression. In Columns 1 and 2 of Table 4, we thus present an additional set of BMA-derived results, where regressions are not weighted by population. Our findings suggest that many of the results in Table 1 are indeed driven by more populous countries. Namely, our BMA model no longer selects variation in stringency measures, pre-pandemic international flights arrivals as a proxy of openness, and service exports as a proxy of tourism receipts as determinants of per-capita income growth. In addition, posterior coefficients on vaccination rates are smaller both in short and medium terms, and regression results no longer suggest that their impact on growth is lasting. In sum, from a global perspective, where countries are taken as a unit of analysis, vaccination and lockdown measures appear to be the most effective tools of policy-making with substantial impact on income growth in the short run. These effects, however, dissipate over time.

Table 4: BMA Regressions - unweighted 2020 and weighted 2019

	(1) Unweighted, 2020-2021	(2) Unweighted, 2020-2024	(3) Weighted, 2019-2021	(4) Weighted, 2019-2024
Deaths	**0.133**	**0.106**	0.010	**-0.124**
	(0.047)	(0.058)	(0.064)	(0.065)
Vaccination	**0.090**	0.020	**0.932**	**0.622**
	(0.082)	(0.049)	(0.169)	(0.163)
Confirmed cases	0.004	0.017	0.005	-0.001
	(0.024)	(0.049)	(0.034)	(0.031)
Stringency - mean	0.000	0.005	-0.002	**0.868**
	(0.014)	(0.025)	(0.085)	(0.435)
Stringency - min/max diff	**0.065**	0.057	**0.745**	**0.316**
	(0.063)	(0.070)	(0.159)	(0.227)
Fiscal spending - health	0.009	0.002	0.015	0.032
	(0.031)	(0.019)	(0.043)	(0.062)
Fiscal spending - non-health	0.005	0.001	0.085	0.072
	(0.024)	(0.017)	(0.124)	(0.116)
Policy rate cut	0.014	0.002	0.006	-0.003
	(0.035)	(0.016)	(0.025)	(0.020)
Liquidity	-0.000	-0.004	0.027	-0.003
	(0.010)	(0.019)	(0.077)	(0.036)
Debt	0.001	0.001	-0.052	-0.046
	(0.016)	(0.016)	(0.103)	(0.104)
New debt 2020	0.139	-0.010	0.036	-0.001
	(0.783)	(0.102)	(0.079)	(0.025)
Trade	-0.001	0.002	-0.005	-0.016
	(0.014)	(0.018)	(0.049)	(0.071)
Intl flight arrivals 2019	0.001	0.007	**-1.311**	**-0.914**
	(0.029)	(0.031)	(0.427)	(0.348)
Intl flight arrivals growth	0.008	-0.003	0.028	-0.013
	(0.030)	(0.021)	(0.082)	(0.062)
Service exports	0.001	0.002	0.024	**0.099**
	(0.012)	(0.014)	(0.051)	(0.080)
GDPpc 2019	0.038	0.001	1.185	0.095
	(0.072)	(0.028)	(1.447)	(0.508)
GDPpc growth 2019-20	-0.002	-0.008	**0.773**	**0.306**
	(0.029)	(0.045)	(0.077)	(0.083)
Constant	-0.351	**0.550**	-0.972	0.007
	(0.534)	(0.370)	(1.152)	(0.745)
Observations	103	103	103	103

Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Coefficients are standardized. Countries are weighted by population. Dependent variable is cumulative per capita growth in 2020-2021 or 2020-2024. Growth data is based on Oct 2021 WEO. 2020 is an estimate and from 2021 onwards are projections. Debt, trade, fiscal spending, service exports, and liquidity variables are in % of GDP. Intl. flight arrivals in 2019 variable is logged. Lockdown stringency difference is calculated as the maximum of stringency index over entire period less the minimum of stringency index after the first peak. Confirmed cases, deaths, vaccination and stringency data are as of October 14, 2021. Standard errors are in parentheses. BMA coefficients in bold indicate the corresponding pip$\geq$ 0.5.

Table 5: BMA regressions - weighted, base year 2020, excl. China and India

	(1) Excl. China 2021	(2) Excl. India 2021	(3) Excl. Both 2021	(4) Excl. China 2024	(5) Excl. India 2024	(6) Excl. Both 2024
Deaths	0.038	**0.068**	**0.154**	**-0.071**	**-0.089**	0.020
	(0.073)	(0.055)	(0.064)	(0.059)	(0.053)	(0.049)
Vaccination	**0.774**	**0.567**	**0.399**	**0.524**	**0.318**	0.031
	(0.189)	(0.219)	(0.195)	(0.172)	(0.173)	(0.080)
Confirmed cases	0.020	-0.001	0.004	0.000	-0.010	0.002
	(0.064)	(0.027)	(0.030)	(0.026)	(0.038)	(0.022)
Stringency - mean	-0.007	-0.003	-0.026	**0.880**	**0.671**	0.274
	(0.091)	(0.079)	(0.124)	(0.342)	(0.362)	(0.324)
Stringency - min/max diff	**0.760**	**0.646**	**0.607**	**0.265**	0.110	0.124
	(0.165)	(0.153)	(0.144)	(0.204)	(0.152)	(0.154)
Fiscal spending - health	0.024	0.015	0.025	0.039	0.011	0.033
	(0.055)	(0.043)	(0.053)	(0.063)	(0.033)	(0.054)
Fiscal spending - non-health	0.077	0.023	0.013	0.033	0.015	0.007
	(0.116)	(0.062)	(0.048)	(0.073)	(0.050)	(0.031)
Policy rate cut	0.007	0.008	0.011	-0.001	-0.002	-0.001
	(0.027)	(0.028)	(0.033)	(0.013)	(0.016)	(0.013)
Liquidity	-0.002	**0.269**	-0.000	-0.056	0.057	-0.033
	(0.041)	(0.136)	(0.036)	(0.121)	(0.095)	(0.084)
Debt	-0.010	-0.007	0.000	-0.005	-0.048	-0.005
	(0.051)	(0.042)	(0.029)	(0.037)	(0.093)	(0.031)
New debt 2020	0.020	0.012	0.005	-0.001	-0.003	-0.009
	(0.060)	(0.045)	(0.030)	(0.021)	(0.024)	(0.035)
Trade	-0.027	-0.012	-0.006	-0.022	-0.002	0.001
	(0.095)	(0.044)	(0.032)	(0.075)	(0.022)	(0.017)
Intl flight arrivals 2019	**-1.206**	-0.123	-0.014	**-0.847**	-0.018	0.022
	(0.484)	(0.321)	(0.121)	(0.324)	(0.119)	(0.087)
Intl flight arrivals growth	0.073	0.064	0.110	-0.008	-0.006	-0.005
	(0.132)	(0.115)	(0.139)	(0.045)	(0.037)	(0.030)
Service exports	0.065	-0.001	-0.000	**0.124**	0.001	0.003
	(0.082)	(0.017)	(0.014)	(0.072)	(0.012)	(0.015)
GDPpc 2019	1.045	0.268	0.174	0.072	0.024	0.034
	(1.414)	(0.746)	(0.532)	(0.437)	(0.268)	(0.187)
GDPpc growth 2019-20	**-0.273**	-0.004	-0.027	-0.019	0.040	0.000
	(0.118)	(0.031)	(0.068)	(0.056)	(0.072)	(0.018)
Constant	-0.926	**-0.937**	**-0.815**	-0.019	-0.262	0.086
	(1.113)	(0.659)	(0.543)	(0.630)	(0.542)	(0.473)
Observations	102	102	101	102	102	101

Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Coefficients are standardized. Countries are weighted by population. Dependent variable is cumulative per capita growth in 2020-2021 or 2020-2024. Growth data is based on Oct 2021 WEO. 2020 is an estimate and from 2021 onwards are projections. Debt, trade, fiscal spending, service exports, and liquidity variables are in % of GDP. Intl. flight arrivals in 2019 variable is logged. Lockdown stringency difference is calculated as the maximum of stringency index over entire period less the minimum of stringency index after the first peak. Confirmed cases, deaths, vaccination and stringency data are as of October 14, 2021. Standard errors are in parentheses. BMA coefficients in bold indicate the corresponding pip$\geq$ 0.5.

Base year. Given the initial scale and uneven impact of the COVID-19 shock, the choice of the base year for calculating per-capita changes can have implications for how the results are interpreted. For instance, countries that were disproportionately hit by the pandemic in 2020 may experience stronger growth during the recovery period, but still lag behind their pre-pandemic level of performance compared to countries that were less impacted in the first year of the pandemic. To test this hypothesis, we set the base year to 2019 (last two columns of Table 4). Results remain similar in terms of the selected variables and magnitudes of the associated coefficients, with two exceptions. First, in the alternative specification, the role of the COVID-19 death toll is more prominent. While countries with higher death counts show higher growth in the first year of recovery, there are negative repercussions in the medium term. Second, coefficients on the pre-pandemic income growth are positive in the alternative specification, implying income convergence. This result, however, has to be taken with a grain of salt, given that the base year for both growth variables is set to 2019, yielding a stronger positive correlation between them.

Role of China and India. Our conclusions on the potential role of population weighting point to the role of large countries like China and India as drivers of the main results. Table 5 contains the results of specifications, where we exclude China, India, and both countries from our sample. Dropping China from the sample leaves the baseline posterior coefficients listed in Columns 2 and 6 of Table 1 largely unaltered, albeit smaller in magnitude. The impact of India on the short- and medium-term estimates is present for several estimates, however. While magnitudes and direction of the posterior coefficient estimates are similar to the baseline, BMA no longer deems lockdown stringency variation and openness to have long-lasting impact on income growth (Columns 5 and 6 of Table 5). On the contrary, the posterior coefficients in Columns 2 and 3 suggest that higher death toll and stronger liquidity injections are associated with higher income growth in other countries compared to India. In addition, BMA no longer attributes any explanatory power to the pre-pandemic growth variable. Overall, these results do not point to the disproportionate impact of large countries like China and India on the main conclusions. In Section 6, we further explore the contribution of India and China to β-convergence and find similar results.

Investment flows. In Columns 1 and 2 of Table 6, we include additional variables in the model: portfolio and other investments as a share of GDP in 2019 as well as direct investment. Both portfolio and direct investment flows plunged in 2020 due to uncertainty surrounding the spread of the COVID-19 virus. Thus, countries with higher reliance on investment as a driver of growth may have been disproportionately impacted. However, we find that both portfolio and direct investment flows have little explanatory power, while the rest of the results hardly change when these variables are controlled for.

Excess deaths. Finally, we address the concern about reliability of the nationally-reported data on COVID-19 deaths due to reasons ranging from weakness of statistical institutions to limitations in countries' COVID-19 testing capacity. We use the data on the estimated excess deaths from The Economist (2020) to measure the COVID-19 death toll. There is a negative correlation between countries' level of per-capita income and the discrepancy between reported and excess deaths.[12] This may bias the estimates upwards if developing countries tend to under-report the COVID-19 death counts but also face a larger deterioration of incomes. To that end, we replace the confirmed deaths variable with the excess deaths estimates in Table 6 (Columns 3 and 4) and find little support for this hypothesis. On the contrary, the coefficient on excess deaths is positive, suggesting that higher death toll is associated with faster per-capita income growth. In addition, compared to the baseline in Table 1, confirmed cases and non-health fiscal spending are selected as determinants of long-term income growth in the alternative specification. Overall, evidence on the impact of the virus on growth is ambiguous, when controlling for policies implemented to contain it and to support economic activity during the pandemic. This could stem from a double-edge sword nature of stringent lockdowns associated with lower case and death counts but more stifling impact on economic activity.

[12] Results demonstrating the positive association between estimated excess deaths and reported COVID-19 deaths are available upon request.

Table 6: BMA regressions - weighted, base year 2020, with additional variables

	(1) 2021	(2) 2024	(3) 2021	(4) 2024
Deaths	0.058	**-0.075**		
	(0.074)	(0.048)		
Excess deaths			**0.211**	**0.162**
			(0.093)	(0.084)
Vaccination	**0.974**	**0.529**	**1.033**	**0.585**
	(0.160)	(0.131)	(0.149)	(0.128)
Confirmed cases	0.008	-0.002	0.001	**-0.110**
	(0.041)	(0.026)	(0.029)	(0.108)
Stringency - mean	0.006	**0.897**	0.005	**0.746**
	(0.084)	(0.310)	(0.085)	(0.357)
Stringency - min/max diff	**0.766**	**0.261**	**0.673**	**0.240**
	(0.165)	(0.202)	(0.174)	(0.206)
Fiscal spending - health	0.022	0.050	0.023	0.032
	(0.054)	(0.070)	(0.054)	(0.060)
Fiscal spending - non-health	0.050	0.032	0.060	**0.103**
	(0.097)	(0.071)	(0.101)	(0.123)
Policy rate cut	0.007	-0.001	0.041	0.005
	(0.028)	(0.012)	(0.068)	(0.023)
Liquidity	0.013	-0.005	0.024	-0.000
	(0.059)	(0.030)	(0.075)	(0.021)
Debt	-0.012	-0.005	-0.005	-0.009
	(0.057)	(0.035)	(0.041)	(0.040)
New debt 2020	0.036	-0.002	0.070	0.002
	(0.080)	(0.021)	(0.107)	(0.024)
Trade	-0.012	-0.024	-0.001	-0.017
	(0.063)	(0.074)	(0.045)	(0.067)
Intl flight arrivals 2019	**-1.376**	**-0.831**	**-1.100**	**-0.892**
	(0.444)	(0.302)	(0.325)	(0.320)
Intl flight arrivals growth	0.026	-0.006	0.024	-0.040
	(0.079)	(0.039)	(0.073)	(0.097)
Service exports	0.060	**0.163**	0.031	**0.150**
	(0.082)	(0.074)	(0.056)	(0.054)
GDPpc 2019	1.054	0.108	0.376	0.004
	(1.434)	(0.488)	(0.921)	(0.367)
GDPpc growth 2019-20	-0.085	-0.005	-0.035	0.002
	(0.103)	(0.025)	(0.072)	(0.017)
Portfolio and other investment excl. SDR	-0.002	-0.033		
	(0.022)	(0.058)		
Direct investment	-0.005	-0.024		
	(0.026)	(0.049)		
Constant	-0.808	-0.115	-0.446	0.038
	(1.141)	(0.615)	(0.761)	(0.644)
Observations	103	103	103	103

Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.

Note: Coefficients are standardized. Countries are weighted by population. Dependent variable is cumulative per capita growth in 2020-2021 or 2020-2024. Growth data is based on Oct 2021 WEO. 2020 is an estimate and from 2021 onwards are projections. Debt, trade, fiscal spending, service exports, and liquidity variables are in % of GDP. Intl. flight arrivals in 2019 variable is logged. Lockdown stringency difference is calculated as the maximum of stringency index over entire period less the minimum of stringency index after the first peak. Confirmed cases, deaths, vaccination and stringency data are as of October 14, 2021. Standard errors are in parentheses. BMA coefficients in bold indicate the corresponding pip$\geq$ 0.5.

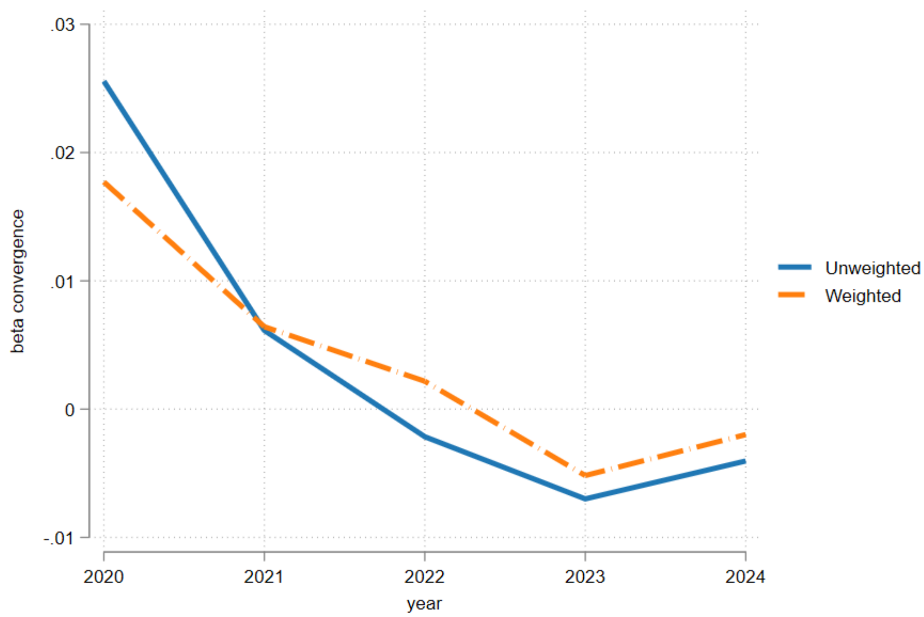
6 Conditional β-convergence

We estimate the conditional β-convergence, using the set of regressors described in Section 4. To that end, we augment Equation 1 with a vector of country-specific characteristics denoted by $X_{i,t}$:

$$\Delta \log(\text{GDPpc}_{i,t}) = \alpha_t + \beta_t^* \log(\text{GDPpc}_{i,t-1}) + X_{i,t}\lambda_t + \epsilon_{i,t}. \tag{3}$$

Coefficients β_t^* from Equation 3 are plotted in Figure 7. Contrary to the absolute beta convergence results in Figure 4, conditional coefficients imply divergence in cross-country incomes in 2020. In 2021 and 2022, consistent with the absolute results, incomes further diverge, attaining convergence only in 2023. Population weights do not appear to significantly impact the estimates.

Figure 7: Conditional β-convergence coefficients



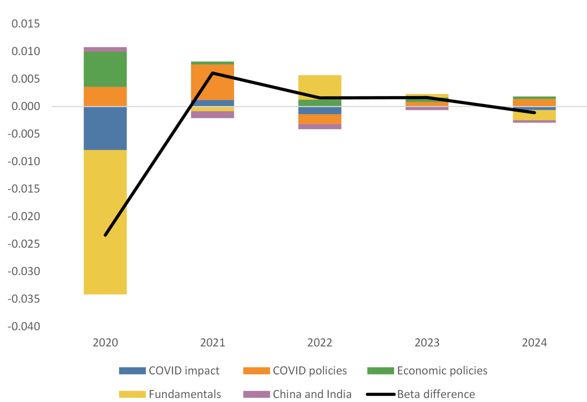
Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Conditional β convergence specification in Equation 3. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections. $X_{i,t}$ includes cumulative COVID-19 deaths per million people, vaccination rate per hundred people, cumulative confirmed COVID-19 cases per million people, mean lockdown stringency, difference in max and min stringency indices, pandemic spending on health as a share of GDP, non-health related pandemic spending, changes in policy rate, liquidity injections as a share of GDP, public debt accumulated in 2020 as a share of GDP, 2019 public debt-to-GDP ratio, 2019 trade-to-GDP ratio, international airline arrivals in 2019, growth in international arrivals in 2020, 2019 trade in services-to-GDP ratio. Square root of population is used as weights in weighted specifications. Confirmed cases, deaths, and stringency data are as of October 14, 2021. Vaccination data is the latest available as of October 14, 2021.

6.1 Decomposing the gap between absolute and conditional β-convergence coefficients

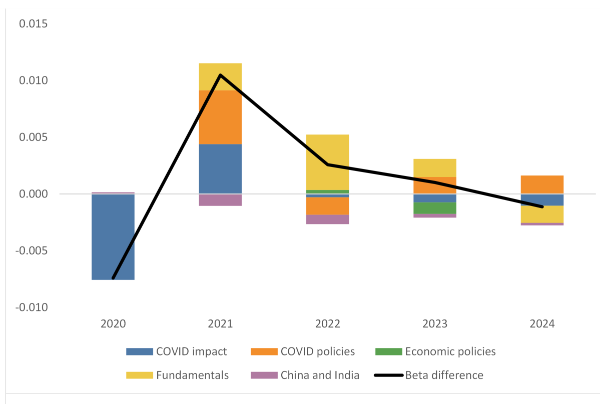
The ultimate goal of the exercise is to compare the absolute β coefficients from Equation 1 and conditional β^* from Equation 3. In the spirit of Kremer et al. (2021), we use the omitted variable formula to perform the decomposition attributing the differences in the absolute and conditional estimates to various explanatory variables. This approach allows us to account for the correlation between explanatory variables when computing the contribution of each of the variable groups to the difference. For ease of interpretation, we divide the explanatory variables in five blocks: (i) severity of the COVID-19 virus, including cumulative COVID-19 deaths and cumulative confirmed COVID-19 cases per million people; (ii) COVID-19 containment policies including vaccination rate per million people, mean lockdown stringency, and the difference between maximum and minimum levels of lockdown stringency indices; (iii) COVID-19 economic support policies including pandemic spending on health as a share of GDP, non-health related pandemic spending, changes in policy rate, liquidity injections as a share of GDP, and public debt accumulated in 2020; (iv) macroeconomic fundamentals including 2019 public debt-to-GDP ratio, 2019 trade-to-GDP ratio, pre-pandemic international flight arrivals, growth in international arrivals in 2020, and 2019 trade in services-to-GDP ratio; as well as (v) indicators for India and China.

Figure 8: Decomposition of difference between absolute and conditional β-convergence

(a) All correlates



(b) BMA-selected correlates



Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Conditional β convergence specification in Equation 1. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections. $X_{i,t}$ includes cumulative COVID-19 deaths per million people, vaccination rate per hundred people, cumulative confirmed COVID-19 cases per million people, mean lockdown stringency, difference in max and min stringency indices, pandemic spending on health as a share of GDP, non-health related pandemic spending, changes in policy rate, liquidity injections as a share of GDP, public debt accumulated in 2020 as a share of GDP, 2019 public debt-to-GDP ratio, 2019 trade-to-GDP ratio, international airline arrivals in 2019, growth in international arrivals in 2020, 2019 trade in services-to-GDP ratio. BMA-selected variable for 2020 includes deaths. BMA-selected variable for 2021 include deaths, vaccination, difference in max and min stringency indices, and international airline arrivals in 2019. BMA-selected variable for 2022 include deaths, vaccination, difference in max and min stringency indices, non-health related pandemic spending, 2019 public debt-to-GDP ratio, international airline arrivals in 2019, and 2019 trade in services-to-GDP ratio. BMA-selected variable for 2023 include deaths, vaccination, mean lockdown stringency, difference in max and min stringency indices, non-health related pandemic spending, 2019 public debt-to-GDP ratio, international airline arrivals in 2019, and 2019 trade in services-to-GDP ratio. BMA-selected variable for 2024 include deaths, vaccination, mean lockdown stringency, difference in max and min stringency indices, international airline arrivals in 2019, and 2019 trade in services-to-GDP ratio. Square root of population is used as weights in weighted specifications. Confirmed cases, deaths, and stringency data are as of October 14, 2021. Vaccination data is the latest available as of October 14, 2021.

Figure 8a shows the shares of the differences between absolute and conditional β-convergence coefficients explained by the five blocks of explanatory variables. The difference between absolute and conditional β coefficients in 2020 is the largest, since β predicts income convergence and β^* predicts divergence. We find that most of the difference between conditional and absolute β coefficients in 2020 is explained by cross-country differences in pre-pandemic economic fundamentals and severity of virus outbreaks. This result is consistent with the fact that richer countries experiencing faster spread of the virus in 2020 had a larger economic fallout in the first year of the pandemic. On the other hand, the results on the contribution of economic support and containment policies imply that, controlling for other macroeconomic fundamentals, these policies were more effective at cushioning the blow of the pandemic in richer countries. Finally, the estimated contribution of India and China to the difference in 2020 coefficients suggests that these countries fared relatively worse in the first year of the pandemic exacerbating the extent of divergence.[13]

In 2021-2023, conditional β^* coefficients are lower than their absolute counterparts. However, these differences are not statistically different from zero and both coefficients suggest divergence in 2021. In 2021, China and India's contribution to the total difference suggests that the two countries fared relatively better than an average country, reducing the extent of divergence. The rest of the difference is explained by the COVID-19 specific factors, ranging from cases and deaths to containment and economic policies. Macroeconomic fundamentals once again have a bigger explanatory power from 2022 onwards, when the difference between the absolute and conditional estimates becomes negligible.

In Figure 8b, we perform the same exercise, now limiting the number of variables in each block of regressors to those selected via the BMA method. The resulting blocks contain the following variables: (i) the impact of the COVID-19 virus, including cumulative COVID-19 deaths per million people across all years; (ii) COVID-19 containment policies including vaccination rate per million people and difference in maximum and minimum levels of lockdown stringency indices in 2021-2024; (iii) COVID-19 economic support policies including non-health related pandemic spending in 2021-2023; (iv) macroeconomic fundamentals including pre-pandemic international flight arrivals in 2021-2024, public debt-to-GDP ratio in 2022, and trade in services-to-GDP ratio in 2022-2024; as well as (v) indicators for India and China. Overall, the results are consistent with those where the entire set of variables is used. However, macroeconomic fundamentals tend to play a more prominent role in explaining the differences between absolute and conditional β-convergence coefficients in projection years.

7 Conclusion

In line with the findings in Deaton (2021), we show that the COVID-19 crisis yielded a temporary acceleration of per-capita income convergence in 2020. However, this episode of convergence was short-lived, and WEO GDP per capita projections point to income divergence during the recovery period, with countries at the bottom of the global income distribution significantly lagging behind their richer counterparts. Moreover, we show that temporary acceleration in convergence in 2020 can be mainly explained by countries closer to the top of the global income distribution facing a more severe health impact of the COVID-19 virus. Our findings suggest that well-targeted lockdown policies, stronger vaccination campaigns and economic support policies implemented in these countries, however, softened the initial blow of the virus.

We also show that effectiveness of economic support policies in containing the increase in cross-country income inequality varies by countries' income level. The effect of these policies tends to be limited for developing countries, where rapid debt accumulation during the pandemic, for instance, is not necessarily

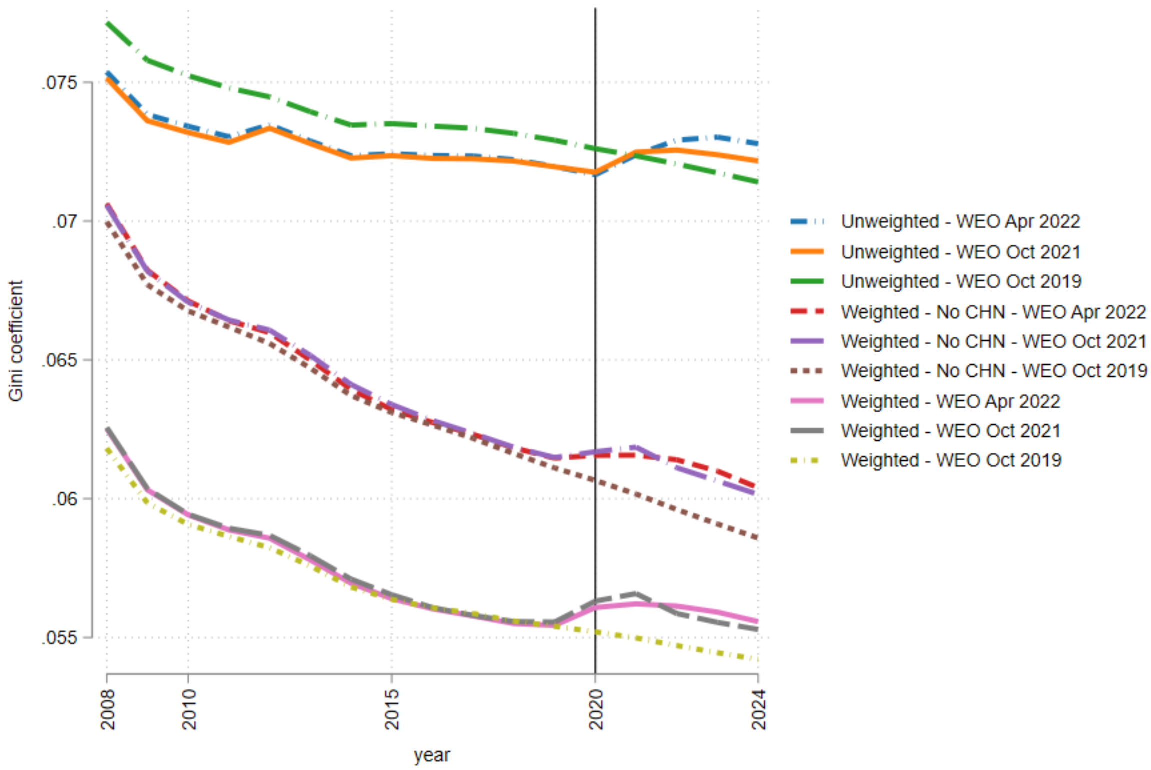
[13] In Appendix Figure A.3, we perform the decomposition exercise without weighting the data by population. While the results remain largely consistent, several discrepancies between weighted and unweighted results stand out. First, COVID-19 containment policies have more explanatory power in 2021, suggesting that these policies were less effective in the case of large countries like India and China, when it comes to the pandemic effect on incomes. The role of economic support policies in projection years, however, signals that those were less effective at preventing income divergence in the medium term.

associated with stronger income growth. More importantly, weak economic fundamentals going into the pandemic and limited policy space to implement additional support measures during the pandemic exacerbate cross-country income inequality.

Our findings suggest that vaccine equity is key to not only ending the pandemic but containing further income divergence across countries. Additional financing for vaccination and vaccine transfers to low-income countries are a priority. More broadly, our results suggest that economic policies, including accumulation of additional public debt during the pandemic to support economic activity, were more effective in AEs. Nevertheless, the burden of higher debt levels is larger and more detrimental for many developing countries' recovery. For LIDCs, in particular, international cooperation to provide debt relief is of utmost importance to prevent further income divergence.

A Additional figures and tables

Figure A.1: Gini coefficients of GDP per capita

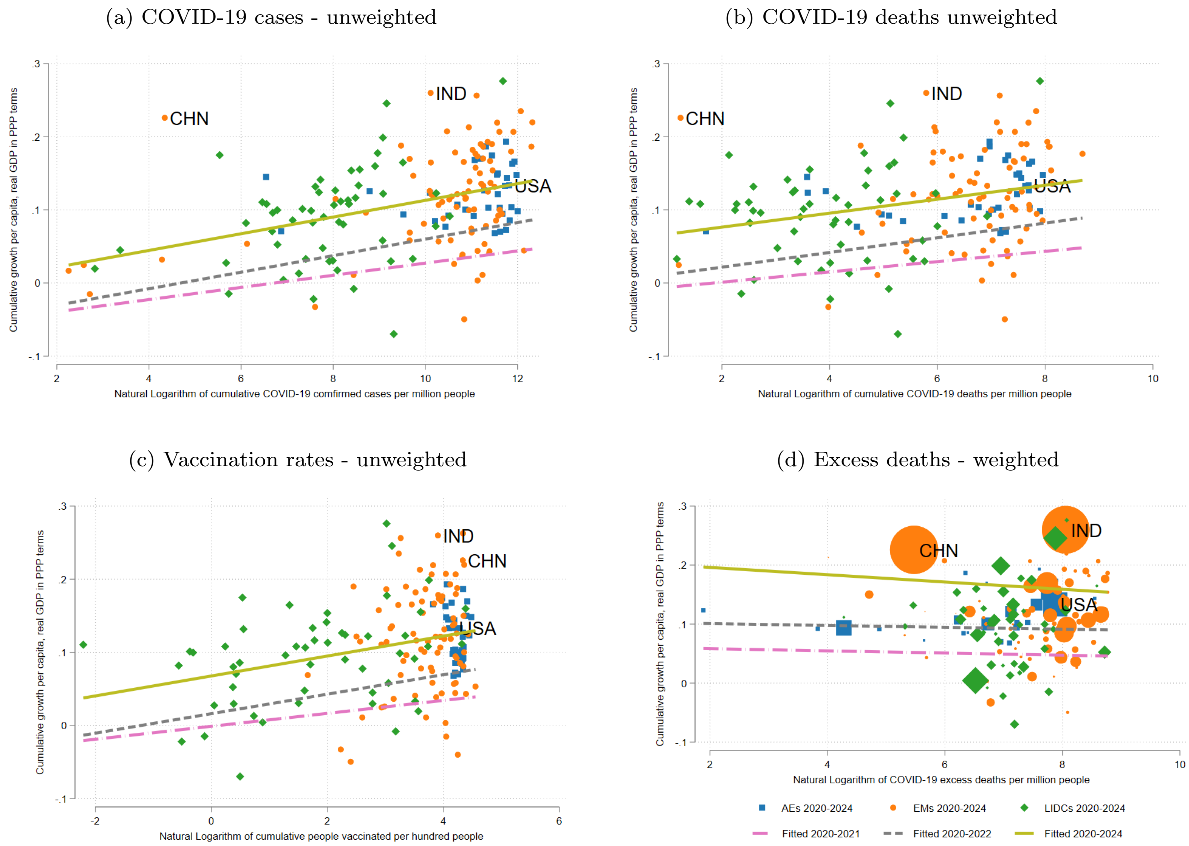


Source: World Economic Outlook.
Note: For Oct 2021 WEO, 2021 is an estimate and from 2022 onwards are projections. For Oct 2019 WEO, 2019 is an estimate and from 2020 onwards are projections.

Table A.1: Summary statistics table for variables

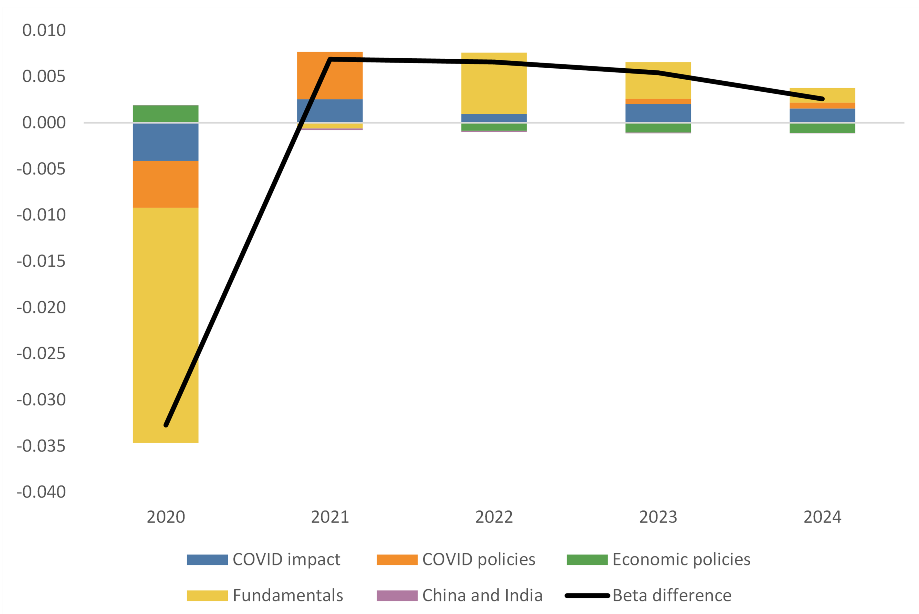
Variable	Mean	Standard diviation	Source	Definition
Vaccination	46.71	26.89	Our World in Data	COVID-19 vaccination per hundred people as of Oct 14, 2021.
Confirmed cases	59544.42	50754.28	JHU CSSE COVID-19 Data	COVID-19 confirmed cases per million people as of Oct 14, 2021.
Deaths	1047.13	1015.19	JHU CSSE COVID-19 Data	COVID-19 official reported deaths per million people as of Oct 14, 2021.
Excess deaths	1933.36	1584.74	The Economist	COVID-19 estimated excess deaths per million people as of Oct 11, 2021.
Stringency - mean	55.48	11.77	Oxford COVID-19 Government Response Tracker	Average level of index measuring stringency of COVID-19 containment policy measures between Jan 1, 2020 and Apr 7, 2022.
Stringency - min/max diff	50.00	13.63	Oxford COVID-19 Government Response Tracker	Difference between min and max level of index measuring stringency of COVID-19 containment policy measures between May 1, 2020 and Apr 7, 2022.
Debt	70.18	39.41	World Economic Outlook	General government gross debt as % of GDP in 2019.
New debt 2020	10.15	7.52	World Economic Outlook	New public debt as % of GDP accumulated in 2020.
Trade	90.23	56.05	World Bank WDI	International trade (exports + imports) as % of GDP in 2019.
Intl flight arrivals 2019	7.93	1.78	Flightradar24	Pre-pandemic international flight arrivals per million people in 2019.
Intl flight arrivals growth	-135.81	62.06	Flightradar24	Growth in international flight arrivals per million people from 2019 to 2020.
Fiscal spending - health	0.91	0.91	Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic	Additional fiscal spending on the health sector as % of GDP in 2020.
Fiscal spending - non-health	4.13	3.85	Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic	Additional fiscal spending on non-health sectors as % of GDP in 2020.
Policy rate cut	-103.98	176.68	IMF Survey of Policy Responses	Changes in policy rate as of Sep 8, 2021.
Liquidity	2.42	4.95	IMF Survey of Policy Responses	Liquidity injections as % of GDP as of Sep 8, 2021.
Service exports	12.17	19.83	World Economic Outlook	Service exports as % of GDP in 2019.
GDPpc 2019	9.64	1.10	World Economic Outlook	Real GDP per capita in 2019.
GDPpc growth 2019-20	-0.06	0.05	World Economic Outlook	Growth in real GDP pe capita 2019-2020.
External liabilities	3.45	19.61	IMF International Financial Statistics	Total external liabilities as % of GDP in 2019.
Portfolio and other investment excl. SDR	1.98	12.00	IMF International Financial Statistics	Portfolio investment and other investment excluding SDR holdings as % of GDP in 2019.
Direct investment	1.47	7.82	IMF International Financial Statistics	Foreign direct investment as % of GDP in 2019.

Figure A.2: Gross correlates robustness



Source: JHU CSSE COVID-19 Data, The Economist, World Economic Outlook.
Note: Cumulative COVID-19 confirmed cases and deaths data is as of October 14, 2021. Cumulative people vaccinated per hundred people is the latest data available as of October 14, 2021. Excess deaths data is as of October 11, 2021. Growth data is based on Oct 2021 WEO. 2021 is an estimate and from 2022 onwards are projections.

Figure A.3: Decomposition of difference between absolute and conditional β-convergence - unweighted



Source: Fiscal Monitor Database of Country Fiscal Measures in Response to the COVID-19 Pandemic, Flightradar24, IMF Survey of Policy Responses, JHU CSSE COVID-19 Data, Our World in Data, Oxford COVID-19 Government Response Tracker, World Bank, World Economic Outlook.
Note: Conditional β convergence specification in Equation 3. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections. GDP data is based on Oct 2021 WEO, with 2020 data being an estimate and from 2021 onwards are projections. $X_{i,t}$ includes cumulative COVID-19 deaths per million people, vaccination rate per hundred people, cumulative confirmed COVID-19 cases per million people, mean lockdown stringency, difference in max and min stringency indices, pandemic spending on health as a share of GDP, non-health related pandemic spending, changes in policy rate, liquidity injections as a share of GDP, public debt accumulated in 2020 as a share of GDP, 2019 public debt-to-GDP ratio, 2019 trade-to-GDP ratio, international airline arrivals in 2019, growth in international arrivals in 2020, 2019 trade in services-to-GDP ratio. Confirmed cases, deaths, and stringency data are as of October 14, 2021. Vaccination data is the latest available as of October 14, 2021.

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