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The Effects of COVID-19 on the Global Economy: A Cross-country Comparison

Master's Thesis

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Abstract

The COVID-19 pandemic caused one of the largest global economic disruptions in recent history, yet the pace of recovery differed substantially across countries. This thesis examines the medium-term economic consequences of the pandemic across a sample of 21 emerging market economies. Using a growth accounting framework, it decomposes output losses into the contributions of labour, capital accumulation, and total factor productivity. In addition, Ordinary Least Squares (OLS) regression analysis is used to examine whether differences in post-pandemic recovery are associated with pre-pandemic GDP per capita, inflation, government effectiveness, and fiscal support.

The results indicate that total factor productivity has become the main source of persistent output losses by 2024, while the contributions of labour and capital have gradually improved over the recovery period. The regression analysis suggests that countries that had higher pre-pandemic income levels generally experienced a stronger recovery, whereas, once income levels are controlled for, government effectiveness and fiscal support do not explain differences much in recovery across the selected sample. However, because institutional quality is positively correlated with income and governance indicators are measured with some degree of error, part of the institutional effect may be absorbed by the income variable. Overall, the findings suggest that medium-term economic recovery in emerging market economies was more closely linked to pre-existing economic fundamentals rather than to institutional quality or the size of fiscal policy interventions.

Keywords

COVID-19, emerging market economies, growth accounting, output losses, total factor productivity, GDP gap, economic scarring

Title

The Effects of COVID-19 on the Global Economy: A Cross-country Comparison

Abstrakt

Pandemie onemocnění COVID-19 způsobila jedno z největších narušení světové ekonomiky v novodobé historii, přičemž tempo hospodářského oživení se mezi jednotlivými zeměmi výrazně lišilo. Tato diplomová práce zkoumá střednědobé ekonomické důsledky pandemie na vzorku 21 rozvíjejících se ekonomik. S využitím rámce růstového účetnictví rozkládá ztráty produktu na příspěvky práce, akumulace kapitálu a celkové produktivity výrobních faktorů (Total Factor Productivity, TFP). Dále využívá regresní analýzu metodou nejmenších čtverců (Ordinary Least Squares, OLS) ke zkoumání, zda jsou rozdíly v postpandemickém hospodářském oživení spojeny s předpandemickou úrovní HDP na obyvatele, inflací, efektivitou veřejné správy a rozsahem fiskální podpory.

Výsledky ukazují, že do roku 2024 se hlavním zdrojem přetrvávajících ztrát produktu stala celková produktivita výrobních faktorů, zatímco příspěvky práce a kapitálu se v průběhu období hospodářského oživení postupně zlepšovaly. Regresní analýza naznačuje, že země s vyšší předpandemickou úrovní příjmu obecně dosáhly silnějšího hospodářského oživení. Po zohlednění rozdílů v úrovni příjmů však efektivita veřejné správy ani fiskální podpora významně nevysvětlují rozdíly v hospodářském oživení mezi analyzovanými zeměmi. Vzhledem k tomu, že kvalita institucí je pozitivně korelována s úrovní příjmů a ukazatele institucionální kvality jsou zatíženy určitou mírou měřicí chyby, může být část vlivu institucí zachycena proměnnou příjmové úrovně. Celkově výsledky naznačují, že střednědobé hospodářské oživení v rozvíjejících se ekonomikách bylo úžeji spojeno s již existujícími ekonomickými fundamenty než s kvalitou institucí či rozsahem fiskálních intervencí.

Klíčová slova

COVID-19, rozvíjející se ekonomiky, růstové účetnictví, ztráty produktu, celková produktivita výrobních faktorů, mezera produktu, ekonomické jizvy.

Název práce

Dopady pandemie COVID-19 na světovou ekonomiku: Mezinárodní srovnání

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1. Introduction

The COVID-19 pandemic generated one of the largest synchronized economic disruptions in modern history, leading to sharp declines in output, employment, investment, and international trade across both advanced and emerging market economies. Although virtually all economies experienced severe contractions during the initial stages of the pandemic, the magnitude of output losses and the pace of subsequent recovery seemed to differ substantially across countries. A growing body of research suggests that cross-country differences in recovery cannot be explained solely by the severity of the health shock. Rather, recovery outcomes reflect differences in pre-existing macroeconomic conditions, labour-market characteristics, institutional quality, policy responses, and structural features of individual economies (Barrett et al., 2021; Kuriakose & Iyer, 2022; Sunge et al., 2024). Nevertheless, relatively limited evidence exists on the realized contributions of labour, capital accumulation, and total factor productivity to post-pandemic output losses in emerging market economies using updated post-pandemic data.

This thesis addresses this gap by extending the growth-accounting framework developed by Jackson and Lu (2023) to a balanced sample of 21 emerging market economies over the period 2020–2024. Using the October 2019 edition of the IMF *World Economic Outlook* as the pre-pandemic benchmark, realized output losses are decomposed into the contributions of labour, capital accumulation, and total factor productivity. To better reflect the aggregate performance of the emerging-market sample, all reported averages are calculated using GDP weights rather than simple cross-country averages. This weighting scheme ensures that the larger economies have a proportionately larger impact on the aggregate estimates than the smaller economies, thus providing a more representative measure of post-pandemic economic performance across emerging markets. The findings add to the literature on persistent medium-term output losses in identifying the key mechanisms that explain cross-country differences in recovery paths across emerging market economies.

2. Literature review

The COVID-19 pandemic has produced a large amount of literature examining its macroeconomic outcomes, transmission mechanisms, and overall patterns of recovery across various countries. Existing research regarding this topic can be generally divided into four main

categories: (1) initial economic impact and containment strategies, (2) cross-country heterogeneity and initial conditions, (3) policy responses and governance, and (4) long-term structural effects and recovery process dynamics.

2.1 Initial Economic Impact and Containment Strategies

The first wave of research on the COVID-19 pandemic primarily focused on quantifying its immediate macroeconomic consequences and evaluating the effectiveness of the containment measures implemented to limit the spread of the virus. With various governments introducing lockdowns, mobility restrictions, and temporary business closures, economic activity contracted simultaneously across most sectors, that would then result in one of the sharpest declines in global output observed in the post-war period. Unlike previous recessions that typically originated within the financial system or developed gradually over time, the COVID-19 crisis mainly posed as an exogenous shock that simultaneously disrupted both the supply and demand sides of the economy. Consequently, the unprecedented speed and scale of the downturn generated considerable interest in understanding the channels through which containment policies affected economic performance.

One of the earliest contributions was the OECD (2020) estimation concluding that containment measures reduced economic activity by approximately 20–25% in several economies through the widespread restrictions on mobility, production, and consumer activity. Using a sector-level framework, the study distinguished between industries that were able to continue operating under pandemic restrictions and those that experienced almost complete shutdowns, including tourism, hospitality, transportation, and recreational services. This approach provided one of the first systematic estimates of the direct economic costs associated with non-pharmaceutical interventions and demonstrated that the impact of containment policies differed substantially across sectors depending on their reliance on physical interaction. Nevertheless, because the analysis focused primarily on the initial phase of the pandemic, it was unable to capture subsequent behavioural adaptation by households and firms or the medium-term recovery process that followed the easing of restrictions.

Macroeconomic modeling studies also demonstrated the global nature of the crisis. Using the G-Cubed model, McKibbin and Vines (2020) concluded that COVID-19 generated one of the largest global synchronized contractions in modern economic history, and that coordinated fiscal and monetary policy responses were necessary to avoid a greater economic decline. By

incorporating international trade, financial and capital market flows and financial market links, the model demonstrated how shocks originating in one country rapidly spread across the world and amplified global recession through interconnected production and financial networks. The simulations further suggested that globally coordinated policy responses reduced global output losses compared with isolated national government interventions. However, as with most large-scale macroeconomic simulation models, these conclusions depend on assumptions regarding behavioural responses, policy implementation, and the evolution of the pandemic itself, implying that projected outcomes should be interpreted with appropriate caution. The importance of international economic interconnectedness had already been emphasized by McKibbin and Triggs (2018), whose G-Cubed framework provided the methodological foundation for analysing the transmission of large-scale global shocks. Their work demonstrates that economies are closely linked through trade, financial markets, and investment flows, allowing disturbances originating in major economies to spread rapidly across the global economy. This perspective proved particularly relevant during the COVID-19 pandemic, as disruptions to international supply chains and financial markets reinforced the domestic effects of containment measures and contributed to the synchronized nature of the global recession. Although the framework inevitably simplifies certain real-world frictions, it remains one of the most comprehensive tools for analysing international macroeconomic spillovers.

Taken together, these early studies established several important stylized facts that continue to underpin the subsequent literature on post-pandemic recovery. First, they showed that COVID-19 posed as an unprecedented global economic shock, affecting virtually all economies at the same time. Second, they highlighted the crucial role of being internationally interconnected in amplifying domestic disruptions. Finally, they showed that although containment measures imposed substantial short-term economic costs, they formed an essential component of the broader public-health response. At the same time, most of these contributions relied primarily on forecasts, simulations, or scenario analyses conducted during the early stages of the pandemic. Consequently, they offered only limited evidence regarding realized medium-term output losses and the underlying mechanisms driving post-pandemic recovery, thereby motivating subsequent research based on observed economic outcomes rather than projected scenarios.

2.2 Cross-Country Differences and Initial Conditions

The second stream of literature shifts the focus from the immediate consequences of the pandemic to explaining why countries have experienced globally different economic outcomes despite being exposed to the same global shock. COVID-19 was a common external shock, yet the economic impact of the pandemic varied across countries, reflecting differences in initial macroeconomic conditions, institutional quality, economic structure, fiscal capacity and integration into the global economy. Researchers thus, have increasingly mentioned that the size of persistent output losses in the medium-term was determined not only by the features of the pandemic itself but also by country-specific vulnerabilities that predated the crisis.

Kuriakose and Iyer (2022) provide important evidence on the role of pre-existing macroeconomic conditions by examining the determinants of post-pandemic economic performance across OECD economies. Using multivariate regression analysis, they demonstrate that variables such as trade openness, public and private debt, and financial conditions significantly influenced both the depth of the initial contraction and the subsequent pace of recovery. In particular, economies entering the pandemic with higher debt burdens experienced deeper output losses and slower recoveries, while countries benefiting from more favourable credit conditions were better able to sustain investment during the crisis. These findings suggest that macroeconomic resilience is largely determined before a crisis occurs, reinforcing the importance of sound fiscal and financial fundamentals. Nevertheless, because the analysis focuses primarily on OECD countries, its conclusions may not be fully applicable to emerging market economies, which often exhibit different institutional characteristics, financing constraints, and policy capacities.

The importance of initial conditions is also consistent with broader research on international crisis transmission. Rather than affecting countries uniformly, global shocks tend to interact with domestic vulnerabilities, causing substantially different recovery trajectories. In addition, McKibbin and Triggs (2018) demonstrate that international trade and financial linkages further amplify these differences by transmitting shocks across borders. Their work highlights that economies highly integrated into global markets are simultaneously more exposed to external disturbances and more dependent on developments in major trading partners. Consequently, differences in openness, external financing, and production structures become important determinants of post-crisis performance.

A particularly important contribution to this literature is provided by Jackson and Lu (2023), whose analysis forms the methodological foundation of the present thesis. Unlike many earlier studies that relied predominantly on forecasts produced during the early stages of the pandemic, Jackson and Lu revisit the concept of persistent medium-term output losses using realized post-pandemic data for a broad sample of emerging market economies. Their study represents one of the first attempts to reassess whether the severe medium-term output losses widely anticipated during 2020 actually materialized as additional economic information became available.

The authors begin by comparing realized output with the projections published in the April 2020 edition of the IMF World Economic Outlook. This allows to quantify the extent to which actual economic performance has deviated from the pre-pandemic growth path. Initial forecasts suggested that emerging market economies would experience particularly severe and persistent output losses due to a priori weaker fiscal capacity, lower vaccination rates, and greater structural vulnerabilities than advanced economies. However, Jackson and Lu (2023) show that despite output losses being substantial, realized outcomes appeared to be more favourable than initially anticipated. While output declined sharply during 2020 with deviations of around 11% below pre-pandemic projections, the subsequent recovery appeared faster than various early forecasts had assessed. By 2022, output remained below its projected trajectory but had recovered sufficiently to suggest that earlier estimates of long-term losses had been overly pessimistic. Similar conclusions are reached by Muggenthaler et al. (2021), who argue that the heterogeneous economic impact of the pandemic across euro area countries reflected differences in containment measures, sectoral composition, institutional quality, and fiscal capacity. Economies with larger tourism sectors and stricter containment policies experienced deeper contractions, illustrating how structural characteristics influenced recovery trajectories even within a relatively integrated economic area.

One of the key methodological novelties of Jackson and Lu (2023) is the use of a Bayesian learning framework to study the dynamics of expectations regarding medium-term losses throughout the recovery period. The authors particularly treat forecasts as dynamic beliefs that are continuously revised and updated once new economic information becomes available, rather than as simply fixed predictions. Their analysis reveals an important asymmetry in the forecasting process. During the initial phase of the pandemic, forecasters responded rapidly to negative economic surprises by revising expected losses upwards. However, as economies

began to recover, positive surprises generated much smaller revisions in long-term expectations, implying that forecasters tended to interpret stronger-than-expected growth as temporary rather than permanent. This asymmetric learning process suggests that many early forecasts may have overstated the persistence of long-term economic damage.

Apart from the forecast revisions, Jackson and Lu (2023) make another important contribution by decomposing realized output losses into their underlying production factors using a standard Cobb-Douglas growth-accounting framework. In particular, output losses are decomposed into the contributions of labour, capital accumulation, and total factor productivity (TFP), allowing the authors to distinguish between alternative channels through which economic medium-term losses developed. Their results indicate that much of the initial decline in output was accounted for by labour-market disruptions including lower employment and lower labour-force participation. In contrast, productivity losses were considerably smaller than those observed following earlier economic crises, with capital accumulation becoming increasingly important only due to prolonged uncertainty reducing the investment activity. These findings offer a key insight into the unique nature of the COVID-19 recession. Unlike financial crises, where persistent declines of productivity often dominate medium-term output losses (Ball, 2014; Blanchard et al., 2015), the COVID-19 shock appears to have been driven primarily by temporary disruptions to labour markets and economic activity rather than by a permanent damage in productive efficiency. Because of labour-market shocks being generally more reversible than productivity shocks, this composition helps explain why employment recovered relatively quickly across many emerging market economies and why realized output losses ultimately proved smaller than initially expected. Nevertheless, Jackson and Lu acknowledge that other channels, including weaker investment, rising corporate indebtedness, and disruptions to education and human capital, could continue to yield persistent effects over a longer horizon.

Building on these findings, the authors develop a bottom-up framework for estimating medium-term output losses by projecting the future evolution of labour input, capital accumulation, and productivity. Their estimates suggest that medium-term output losses in emerging market economies are likely to reach approximately 2–2.5% by the mid-2020s, substantially below the 3–4% losses predicted during the early stages of the pandemic. Although this represents a considerably more optimistic assessment of post-pandemic recovery, the authors caution that substantial uncertainty remains, particularly given the emergence of additional global shocks

such as the war in Ukraine and the potentially persistent effects of learning losses on future productivity.

The present thesis builds directly upon the analytical framework developed by Jackson and Lu (2023). However, whereas their analysis primarily focuses on the early recovery period, this study extends the empirical assessment through 2024, thereby allowing a more comprehensive evaluation of medium-term recovery dynamics. Aggregate results are reported using GDP-weighted averages in order to better reflect the relative economic importance of individual countries within the sample. Taken all the factors above together, the present study aims to contribute additional evidence on the persistence and composition of post-pandemic economic losses.

2.3 Policy Responses, Governance, and Recovery Dynamics

As the immediate health crisis gradually subsided, the literature increasingly shifted its attention from the causes of the initial economic contraction towards the determinants of post-pandemic recovery. While the severity of the initial shock was largely unavoidable, subsequent recovery trajectories were found to depend heavily on the scale and effectiveness of policy interventions, institutional capacity, and the ability of governments to support households and businesses throughout the recovery process. Consequently, researchers began to view post-pandemic economic performance not only as a reflection of the shock itself but also of the policy environment in which recovery occurred.

The International Monetary Fund (IMF, 2021) argues that the COVID-19 generated a highly uneven global recession, with substantial differences in recovery patterns across both advanced and emerging market economies. According to the IMF, the severity of long-term output losses depended not only on the sizes of the initial contraction but also on the scale of fiscal and monetary support implemented during the crisis. Countries that employed larger fiscal stimulus packages generally saw smaller losses in medium-term output and generally maintained those lower levels of medium-term output losses. This thus reflects their stronger ability of preserving employment, maintaining productive capacity, and sustaining aggregate demand. Using cross-country data and medium-term projections, the IMF further demonstrates that structural characteristics, especially the relative importance of contact-intensive sectors, played a significant role in shaping recovery outcomes. Economies with larger tourism, hospitality, and transportation sectors generally faced more prolonged recoveries because these industries

remained constrained even after broader economic activity resumed. Nevertheless, because the analysis relies primarily on medium-term projections, the estimated magnitude of future losses remained subject to considerable uncertainty as additional post-pandemic data became available.

Beyond macroeconomic policy, a growing body of literature mentions the importance of institutional quality while determining recovery paths. Sunge et al. (2024) examine the role of governance within a sample of 125 countries and conclude that institutional effectiveness significantly mediates the relationship between policy interventions and economic recovery. Their results show that governance indicators, such as government effectiveness, regulatory quality, and control of corruption, improve recovery trajectories, as they strengthen policy implementation, and increase institutional credibility.

Importantly, the authors demonstrate that these effects are not uniform across countries. Institutional quality appears to play a particularly important role in lower-income economies and regions such as Sub-Saharan Africa. Latter can be explained by the fact that in such regions, governance constraints can limit the effectiveness of fiscal and monetary interventions. These findings imply that the success of economic policy depends not only on its scale but also on the institutional capacity required to implement it effectively.

Pitterle and Niermann (2021) examine the determinants of cross-country differences in economic performance during the COVID-19 pandemic using cross-country regression analysis for more than 150 economies. Their findings suggest that good governance, fiscal support, and strong macroeconomic fundamentals mitigated output losses, while countries with greater exposure to the pandemic and stricter containment measures experienced significantly larger contractions. The study further highlights the importance of structural resilience and effective economic management in explaining heterogeneous recovery outcomes. Similarly, Topcu and Gulsen (2025) further argue that governance quality moderates the effectiveness of fiscal policy during the COVID-19 pandemic. Using threshold regressions for 144 countries, they find that stronger governance enhances the effectiveness of fiscal stimulus and contributes to economic recovery even when fiscal packages are relatively small.

The importance of international policy coordination is further emphasized by McKibbin and Vines (2020), who argue that globally coordinated policy responses substantially reduced the economic costs of the pandemic. Given the high degree of integration between national

economies through international trade, financial markets, and global value chains, isolated domestic interventions are often insufficient to stabilize economic activity following a worldwide shock. Instead, coordinated action through international institutions such as the International Monetary Fund and the G20 helps mitigate cross-border spillovers, strengthens financial stability, and provides additional support to economies with more limited fiscal capacity. Their findings highlight that recovery from a synchronized global crisis depends not only on domestic policy choices but also on international cooperation and multilateral economic support.

Taken together, this strand of literature suggests that differences in post-pandemic recovery cannot be attributed solely to the characteristics of the health shock itself. Rather, recovery trajectories reflect the interaction between initial macroeconomic conditions, the scale of fiscal and monetary support, institutional quality, and international policy coordination. These findings provide an important context for interpreting cross-country differences in realized output losses, as economies entering the pandemic with stronger institutions and greater policy capacity would be expected to exhibit more resilient recovery paths and lower levels of medium-term economic losses. The present thesis complements this literature by examining whether these differences are reflected in the realized contributions of labour, capital accumulation, and total factor productivity across emerging market economies.

2.4 Long-Term Effects and Structural Changes

Another important strand of literature examines the long-term consequences of the COVID-19 pandemic, commonly referred to as economic scarring. Economic scarring refers to temporary shocks leading to permanent deviations from pre-crisis growth paths by affecting the productive capacity of an economy, as opposed to short-term recessions, in which lost output is expected to be recovered once economic activity resumes its normal course. These long-lasting effects can occur through multiple channels, including weaker capital accumulation, reduced labour-force participation, slower growth of productivity, disruptions to education, and structural changes in production. Thereby, understanding the sources of economic scarring has become a central objective in macroeconomic literature with regard to the post-pandemic .

The International Monetary Fund (IMF, 2021) estimates that global output would remain below its pre-pandemic trend over the medium term, projecting that by 2024 world output would still

be approximately 3% below the level expected before the outbreak of COVID-19. Importantly, the IMF argues that the magnitude of these losses differs substantially across countries, reflecting variations in economic structure, fiscal capacity, labour-market characteristics, and policy responses. Particularly, market economies having implemented more comprehensive support measures and having entered the pandemic with stronger macroeconomic fundamentals generally saw less severe long-term output losses, whereas countries with more limited policy space tended to face greater risk exposure to persistent economic scarring. These findings suggest that medium-term recovery depends not only on the severity of the initial shock but also on the ability of economies to preserve productive capacity throughout the recovery process.

Barrett et al. (2021) further develop the concept of medium-term economic scarring by examining the mechanisms through which severe recessions generate persistent output losses. Drawing on evidence from previous crises and early post-pandemic projections, the authors argue that economic scarring primarily operates through three interconnected channels: weaker capital accumulation, labour-market disruptions, and slower growth in total factor productivity (TFP). Among these, productivity plays a particularly important role because persistent declines in TFP reduce the efficiency with which labour and capital are transformed into output, thereby lowering potential output even after the immediate effects of the crisis have subsided. The authors also argue that emerging and developing economies are especially vulnerable to these mechanisms because they generally possess more limited fiscal resources, lower institutional capacity, and greater structural vulnerabilities than advanced economies. Their findings therefore suggest that the long-term consequences of the pandemic are likely to extend well beyond the period of the initial recession.

Historical evidence provides further support for the persistence of pandemic-induced economic losses. Using data covering major pandemics since the fourteenth century, Jordà et al. (2020) demonstrate that pandemics generate macroeconomic effects that may persist for several decades. Unlike wars, which primarily destroy physical capital, pandemics mainly reduce labour availability, alter the saving and consuming patterns of households, as well as weaken flows of investment and capital, which results in long-lasting deviations from pre-crisis economic paths. Their findings emphasize that the long-term effects of health crises differ fundamentally from those associated with military conflicts and should therefore be analysed through different economic mechanisms.

Evidence from previous recessions likewise supports the existence of persistent output losses following large economic shocks. Ball (2014), examining the aftermath of the Great Recession across OECD countries, finds strong evidence of hysteresis, whereby temporary declines in output permanently reduce an economy's productive capacity. The study argues that prolonged recessions discourage investment, weaken labour-market attachment, and slow technological progress, causing economies to settle on permanently lower output paths. In the most severely affected countries, growth rates themselves declined following the crisis, implying that output losses continued to accumulate over time rather than remaining constant.

Similar conclusions are reached by Blanchard et al. (2015), who analyse 122 recessions across 23 advanced economies. Their results indicate that approximately two-thirds of recessions were followed by permanently lower levels of output relative to pre-recession trends, while many episodes also experienced slower post-crisis growth rates. These findings provide additional evidence that macroeconomic shocks frequently reduce potential output rather than merely generating temporary fluctuations around an unchanged long-run trend. Together with Ball (2014), this literature provides strong empirical support for the hysteresis hypothesis, suggesting that the long-term consequences of major crises often persist long after the initial downturn has ended.

Comparable evidence emerges from studies examining previous pandemic episodes. Ma et al. (2020) estimate that GDP growth declined by approximately three percentage points during outbreak years across six major health crises. Despite economic growth recovering relatively fast, output levels remained below their pre-pandemic trajectories even five years following the initial outbreak. The authors further demonstrate that countries having implemented stronger fiscal responses experienced both smaller output losses and smaller increases in unemployment. This highlights the key role of government intervention in reducing medium-term economic damage. Similar persistence has also been documented for financial crises. Reinhart and Rogoff (2009) show that banking crises are typically associated with prolonged declines in both output and employment with recoveries often extending over several years. Their findings therefore support the broader conclusion that regardless of their initial source, major macroeconomic shocks frequently leave persistent scars on economic performance.

Besides persistent output losses, the pandemic also accelerated several structural transformations that are likely to influence long-term economic growth. The widespread

adoption of digital technologies, changes in labour-market organization, increased amount of remote work, and the restructuring of global supply chains have permanently changed production processes across many sectors. Countries possessing greater digital readiness, stronger technological infrastructure, and more resilient supply chains were generally better able to adapt to pandemic-related disruptions, thereby limiting output losses and supporting faster recovery. At the same time, these structural adjustments are unlikely to occur uniformly across countries, suggesting that differences in technological adoption and institutional adaptability may become increasingly important determinants of long-term economic resilience.

Taken together, the literature consistently indicates that the consequences of COVID-19 extend far beyond the initial recession. While the magnitude of medium-term economic scarring remains uncertain, existing evidence suggests that persistent output losses emerge through a combination of weaker capital accumulation, labour-market disruptions, productivity effects, and structural transformation. These findings provide the theoretical foundation for the empirical analysis undertaken in this thesis, which examines the relative contributions of labour, capital, and total factor productivity to realized post-pandemic output losses across emerging market economies. By extending the analysis through 2024, the study also evaluates whether the persistence of economic scarring identified in earlier research continued as the recovery progressed beyond the immediate post-pandemic period.

2.5 Research Gap and Contribution

Despite the rapidly expanding literature on the macroeconomic consequences of COVID-19, several important research gaps remain. Existing studies have substantially improved our understanding of the immediate economic impact of the pandemic, the effectiveness of containment measures, the role of fiscal and monetary policy, and the potential sources of long-term economic scarring. Nevertheless, much of the available evidence relies either on historical analogies, scenario-based projections, or early forecasts produced during the initial stages of the pandemic. Consequently, relatively limited evidence exists on the realized sources of post-pandemic output losses based on updated macroeconomic data, particularly for emerging market economies.

Although recent studies have increasingly focused on economic scarring, they generally examine individual transmission mechanisms in isolation. Some emphasize the importance of labour-market disruptions, while others focus primarily on investment, productivity, governance, or fiscal policy. As a result, comparatively little research jointly evaluates the relative contributions of labour, capital accumulation, and total factor productivity within a unified analytical framework using realized post-pandemic outcomes. Such a decomposition is important because it allows researchers to distinguish between temporary disruptions and more persistent structural changes affecting medium-term economic performance.

Jackson and Lu (2023) represent an important step towards addressing this issue by applying a growth-accounting framework to quantify the sources of realized post-pandemic output losses across emerging market economies. Their analysis shows that labour-market disruptions accounted for a substantial share of the initial decline in output. On the contrary, productivity losses were generally smaller than had been anticipated during the early stages of the pandemic. At the same time, their study primarily focuses on the early recovery period, leaving open the question of whether these recovery patterns persisted with additional post-pandemic data becoming available.

Furthermore, relatively few studies compare realized economic performance with the pre-pandemic counterfactual growth path using updated observations extending beyond the immediate recovery period. This distinction is particularly important because positive GDP growth does not necessarily imply that an economy has fully recovered. An economy may continue to expand while remaining well below the level of output that would have been expected in the absence of the pandemic. Therefore experiencing what appears to be growth, it will continue to exhibit persistent economic scarring. Thus, extending the observation period should provide a more comprehensive assessment of whether emerging market economies ultimately returned to their pre-pandemic growth trajectories or whether medium-term output losses remained.

Another methodological limitation of the existing literature concerns the aggregation of cross-country results. Studies frequently summarize outcomes using simple arithmetic averages, implicitly assigning equal importance to economies regardless of their relative economic size. However, because emerging market economies differ substantially in terms of GDP, population, and global economic significance, unweighted averages may not accurately represent aggregate regional performance. Reporting GDP-weighted averages allows larger

economies to contribute proportionally more to aggregate estimates, whereas unweighted averages reflect the recovery pattern of the average country.

Against this background, the present thesis extends the analytical framework developed by Jackson and Lu (2023) by applying their growth-accounting methodology to a balanced sample of 21 emerging market economies using the October 2019 edition of the IMF World Economic Outlook as the pre-pandemic benchmark. The empirical analysis is extended through 2024, enabling the study to evaluate medium-term recovery dynamics beyond the period examined in most previous research. Realized output losses are decomposed into the contributions of labour, capital accumulation, and total factor productivity, while aggregate results are presented using GDP-weighted averages to better reflect the relative economic importance of individual countries within the sample.

Beyond estimating aggregate output losses, the thesis provides a detailed cross-country comparison of recovery trajectories and examines the extent to which differences in labour-market performance, capital accumulation, and productivity explain the persistence of economic scarring across emerging market economies. By combining an updated empirical dataset, a growth-accounting decomposition, and GDP-weighted cross-country analysis, the study contributes to the literature by providing new evidence on the composition and persistence of realized post-pandemic output losses during the medium-term recovery period. The findings also offer insights that may inform future macroeconomic policy, crisis preparedness, and strategies aimed at strengthening economic resilience in emerging market economies. Beyond extending the growth-accounting framework to 2024, this thesis also contributes by examining the cross-country determinants of post-pandemic recovery using regression analysis. This empirical exercise complements the descriptive decomposition by investigating whether pre-pandemic macroeconomic and institutional characteristics help explain differences in recovery across emerging market economies.

Having established the theoretical and empirical background, the following chapter presents the growth-accounting framework, data sources, and empirical methodology used to quantify and decompose post-pandemic output losses across the selected sample of emerging market economies.

3. Methodology

This chapter presents the methodological framework employed to examine the medium-term economic effects of the COVID-19 pandemic across emerging market economies. It first introduces the growth accounting framework used to decompose output losses into the contributions of labour, capital accumulation, and total factor productivity. It then describes the data sources, variable construction procedures, and empirical approach adopted in the study.

3.1 Growth Accounting Framework

To examine the drivers of post-pandemic output losses, this study adopts the growth-accounting framework applied by Jackson and Lu (2023), which builds on the analytical approach presented by the International Monetary Fund (2022) to decompose deviations in output into the contributions of labour, capital, and total factor productivity (TFP). Growth accounting provides a well-established framework for analysing the sources of economic growth by separating changes in output into the contributions of observable production factors and productivity. Rather than treating output losses as a single aggregate measure, this approach makes it possible to identify whether deviations from the pre-pandemic growth path primarily reflect changes in labour input, capital accumulation, or productive efficiency.

The use of a growth-accounting framework is particularly appropriate in the context of the COVID-19 pandemic because the crisis affected economies simultaneously through multiple transmission channels. In addition to the direct disruption of labour markets caused by mobility restrictions and changes in employment, the pandemic also influenced investment decisions, capital accumulation, production efficiency, and international supply chains. As discussed in the previous chapter, the literature suggests that medium-term economic scarring may arise through a combination of these mechanisms rather than from a single source (Barrett et al., 2021; Jackson & Lu, 2023). Consequently, analysing aggregate output losses alone provides only limited insight into the underlying economic processes. Growth accounting overcomes this limitation by decomposing realized output losses into the contributions of individual production factors, thereby allowing a more detailed assessment of the mechanisms driving post-pandemic recovery and medium-term economic scarring.

The empirical analysis is based on the standard Cobb-Douglas production function:

$$Y_t = A_t K_t^{1-\alpha} L_t^\alpha$$

where Y denotes real output, K represents the capital stock, L denotes labour input, and A captures total factor productivity. The parameter α corresponds to the labour share of income and is obtained from the Penn World Table database. The Cobb-Douglas specification is widely employed in empirical macroeconomics because it provides a parsimonious yet economically meaningful representation of the production process while allowing output to be decomposed into observable factor contributions. Under this specification, output is produced through the interaction of capital and labour inputs, whereas total factor productivity captures changes in production efficiency that cannot be explained solely by the accumulation of observable inputs. Consequently, TFP reflects technological progress, organizational improvements, institutional factors, and other influences affecting the efficiency with which labour and capital are transformed into output.

An additional advantage of the Cobb-Douglas framework is its compatibility with the growth-accounting methodology employed throughout this study. Because the production function assumes constant returns to scale and a constant labour share, changes in output can be expressed as the sum of the contributions of labour, capital, and productivity. This property makes the framework particularly suitable for decomposing realized output losses relative to pre-pandemic projections and facilitates direct comparison with the empirical results reported by Jackson and Lu (2023).

Although labour input can theoretically be decomposed into population, labour force participation, and unemployment, the absence of a counterfactual series for labour force participation prevents the separate identification of LFPR-specific effects. Consequently, the empirical decomposition focuses on the contributions of population and employment, while changes in labour force participation remain incorporated within the overall labour contribution. This approach follows the methodology adopted by Jackson and Lu (2023) and reflects the availability of comparable cross-country data.

The following section describes the data sources employed in the empirical analysis, after which the construction of each variable is presented in detail.

3.2 Data

The empirical analysis combines information from several internationally recognized macroeconomic databases to construct a consistent panel dataset of output, labour, and capital variables for a balanced sample of emerging market economies. Using harmonized international data sources ensures cross-country comparability while minimizing differences arising from national statistical methodologies, thereby allowing observed differences in economic performance to be attributed more confidently to underlying economic mechanisms rather than inconsistencies in data collection or measurement.

The primary source of macroeconomic projections and realized economic outcomes is the International Monetary Fund's World Economic Outlook (WEO) database. The October 2019 edition of the WEO is employed as the pre-pandemic benchmark because it represents the final set of macroeconomic forecasts prepared before the emergence of COVID-19. As such, these projections provide a counterfactual path describing how economic activity was expected to evolve in the absence of the pandemic, making them an appropriate benchmark against which realized post-pandemic outcomes can be evaluated. Actual macroeconomic outcomes for the period 2020–2024 are obtained from subsequent releases of the WEO database, allowing the analysis to compare realized economic performance with pre-pandemic expectations over the medium-term recovery period.

Because the WEO database does not report projected capital stock series, additional information is obtained from Penn World Table (PWT) version 10.0. Specifically, the initial capital stock, labour income shares, and depreciation rates are extracted from the PWT and combined with investment data from the WEO to construct both projected and realized capital stocks using the perpetual inventory method. This procedure closely follows the methodology developed by Jackson and Lu (2023), ensuring consistency between projected and observed capital accumulation paths while maintaining comparability with previous research.

The empirical analysis focuses on a balanced sample of 21 emerging market economies: Belarus, Brazil, Chile, China, Colombia, Croatia, Hungary, India, Indonesia, Kazakhstan, Malaysia, Mexico, Peru, the Philippines, Poland, Romania, Serbia, South Africa, Thailand, Türkiye, and Russia. The sample was selected primarily on the basis of data availability for all variables required by the empirical analysis while maintaining broad geographical representation across Europe, Asia, Latin America, and Africa. Moreover, the country selection

closely follows that adopted by Jackson and Lu (2023), thereby facilitating direct comparison between the results of the present study and the existing literature.

Because the objective of this study is to evaluate the aggregate performance of emerging market economies rather than the experience of a representative country, annual output gaps and growth-accounting components are reported as GDP-weighted averages. Unlike simple arithmetic averages, which assign equal importance to each country regardless of economic size, GDP-weighted averages ensure that larger economies contribute proportionally more to aggregate estimates. This approach provides a more representative measure of regional economic performance and better reflects the relative contribution of individual economies to total output within the emerging market sample.

The empirical analysis covers the period 2020–2024, while 2019 serves as the common reference year from which both projected and realized series are normalized before calculating output gaps and their underlying components. Extending the analysis through 2024 allows the study to examine not only the unprecedented contraction observed during the initial phase of the pandemic but also the subsequent medium-term recovery and the persistence of economic scarring several years after the outbreak of COVID-19. This longer observation period provides additional evidence regarding whether emerging market economies ultimately returned to their pre-pandemic growth trajectories or continued to exhibit persistent deviations from the counterfactual path established by the October 2019 WEO projections. The analysis is limited to the period ending in 2024 because this is the latest year for which a consistent set of realized macroeconomic outcomes is available across the data sources used in the study. Extending the analysis beyond 2024 would require forecast data rather than observed outcomes, which would be inconsistent with the objective of evaluating realized medium-term post-pandemic recovery.

The use of internationally comparable datasets also enhances the robustness and reproducibility of the empirical analysis. Because all variables are drawn from internationally harmonized statistical sources, differences observed across countries are less likely to reflect inconsistencies in national accounting practices and more likely to capture genuine differences in post-pandemic economic performance. The following section describes how these data are transformed into measures of output gaps, labour input, capital stock, and total factor productivity used throughout the empirical analysis.

Table 3 summarizes the principal data sources employed throughout the empirical analysis.

Table 3. Data Sources and Variables

Variable	Source	Purpose
Real GDP	IMF World Economic Outlook (October 2019 and subsequent releases)	Calculation of output gaps
Population	IMF World Economic Outlook	Labour input decomposition
Unemployment rate	IMF World Economic Outlook	Labour input decomposition
Gross fixed capital formation	IMF World Economic Outlook	Construction of capital stock
Actual capital stock	Penn World Table 10.0	Perpetual inventory method
Labour income share (α)	Penn World Table 10.0	Growth accounting decomposition
Depreciation rate	Penn World Table 10.0	Construction of capital stock

3.2 Variable Construction

This section explains how each variable used in the empirical analysis is constructed. It describes the calculation of the output gap, labour input, capital stock, and total factor productivity before presenting the final growth-accounting decomposition. These constructed variables form the basis for the empirical results reported in Chapters 4 and 5. Where appropriate, the calculations follow the methodology presented in the previous subsection.

3.2.1 Output Gap

The first step of the empirical analysis consists of measuring deviations between realized and projected output in order to quantify the economic effects of the COVID-19 pandemic. Rather than evaluating changes in GDP relative to the previous year, the analysis compares realized economic performance with the counterfactual path established by pre-pandemic forecasts. This approach makes it possible to estimate the extent to which actual economic activity

deviated from the level that would have been expected in the absence of the pandemic, thereby providing a direct measure of post-pandemic economic scarring. Unlike Jackson and Lu (2023), who use the January 2020 World Economic Outlook projections as their benchmark, this study adopts the October 2019 edition of the IMF World Economic Outlook. The October 2019 forecasts represent the last complete set of macroeconomic projections prepared before any economic effects of COVID-19 had emerged and therefore provide a fully pre-pandemic counterfactual benchmark. Using this benchmark ensures that the projected growth path is unaffected by any revisions reflecting the initial spread of the pandemic. Realized GDP observations for the period 2020–2024 are obtained from subsequent WEO releases.

Output losses are measured as the logarithmic difference between realized and projected real GDP:

$$GDPGap_t = \ln \left(\frac{GDP_t^{Actual}}{GDP_t^{Forecast}} \right)$$

where GDP_t^{Actual} denotes realized real GDP and $GDP_t^{Forecast}$ represents the corresponding pre-pandemic forecast for year t .

Using logarithmic differences offers several methodological advantages. First, logarithmic transformations provide an approximately percentage interpretation of deviations when changes are relatively small, facilitating straightforward comparison across countries and over time. Second, log differences are additive, making them particularly suitable for the subsequent growth-accounting decomposition in which total output losses are separated into the contributions of labour, capital, and total factor productivity. Finally, the logarithmic specification is widely employed in empirical macroeconomic analysis because it produces scale-invariant measures that remain comparable across economies of different sizes.

A **negative** output gap indicates that realized economic activity remained below the level expected prior to the pandemic, implying the presence of economic scarring. Conversely, an output gap close to zero suggests that realized output largely converged to its pre-pandemic trajectory, while a **positive** output gap indicates that realized economic performance exceeded pre-pandemic expectations. It is important to emphasize that the output gap is measured relative to the **counterfactual pre-pandemic growth path** rather than to the previous year's GDP.

Consequently, an economy may record positive annual GDP growth while simultaneously exhibiting a negative output gap if realized output remains below the level projected before the pandemic. This distinction is particularly relevant when evaluating medium-term recovery because positive growth alone does not necessarily imply that the economic effects of the pandemic have been fully reversed (Barrett et al., 2021; Jackson & Lu, 2023).

3.3.2 Labour Input

Following the growth-accounting methodology employed by the International Monetary Fund (2022) and Jackson and Lu (2023), labour input is represented as the product of the working-age population, the employment rate, and the labour force participation rate:

$$L_t = Pop_t(1 - UE_t)LFPR_t$$

where Pop denotes the working-age population, UE represents the unemployment rate, and $LFPR$ corresponds to the labour force participation rate.

This decomposition recognizes that changes in labour input may originate from several distinct economic and demographic mechanisms. Labour supply can be influenced by changes in the size of the working-age population, fluctuations in employment and unemployment, or variations in labour force participation resulting from discouraged workers, early retirement, migration, or other structural labour-market adjustments. Distinguishing between these channels is particularly important in the context of the COVID-19 pandemic, during which labour markets were affected not only by temporary job losses but also by broader changes in labour supply and participation. As discussed by Jackson and Lu (2023), labour-market disruptions constituted one of the principal sources of post-pandemic output losses in emerging market economies, making a detailed examination of labour input essential for understanding the composition of economic scarring.

Because labour input is observed directly, the overall labour contribution reflects the combined effects of changes in population, unemployment, and labour force participation. Ideally, each component would be analysed separately. However, the empirical decomposition is constrained by data availability. While counterfactual projections are available for population and unemployment through the IMF World Economic Outlook database, no comparable counterfactual series exists for labour force participation. Because no counterfactual

projections for labour force participation are available, labour force participation is assumed to remain constant over the projection horizon ($LFPR_t = LFPR$). Consequently, changes in labour input arise only from projected population and unemployment. Since the decomposition is based on growth rates rather than levels, the actual level of labour force participation is not required, as a constant LFPR does not affect the calculated growth contribution. Although this limitation prevents a complete decomposition of labour dynamics, the resulting measure remains fully consistent with the available international data and the empirical framework adopted throughout the study.

Labour gaps are calculated as the logarithmic difference between realized and projected labour input:

$$LabourGap_t = \ln \left(\frac{L_t^{Actual}}{L_t^{Forecast}} \right)$$

Where L_t^{Actual} denotes realized labour input and $L_t^{Forecast}$ represents the corresponding counterfactual labour input derived from the October 2019 World Economic Outlook projections.

As with the output gap, the logarithmic specification produces an approximately percentage measure of deviations from the pre-pandemic benchmark while ensuring consistency with the subsequent growth-accounting decomposition. A negative labour gap indicates that labour input remained below its expected pre-pandemic level, reflecting labour-market disruptions associated with the pandemic, whereas values closer to zero indicate that labour input had largely converged to its projected trajectory.

The following subsection applies a similar approach to the construction of the capital stock, which represents the second observable production factor in the growth-accounting framework.

3.3.3 Capital Stock

Unlike output and labour input, the capital stock is not reported directly in the World Economic Outlook (WEO) database and must therefore be constructed separately. Following the methodology adopted by Jackson and Lu (2023), projected capital stocks are estimated using the perpetual inventory method (PIM), which represents the standard approach in empirical

macroeconomics for modelling the evolution of capital over time. The method assumes that the capital stock increases through new investment while simultaneously declining as existing capital depreciates, thereby capturing the dynamic nature of capital accumulation.

The initial capital stock for each country is obtained from Penn World Table version 10.0, which provides internationally comparable estimates of productive capital. Because the WEO does not publish forecasts of capital stock, projected capital must be constructed recursively. The observed capital stock in 2019 serves as the common starting value for both the projected and realized capital series. For each subsequent year, projected capital is updated using country-specific depreciation rates together with forecast investment obtained from the October 2019 WEO. This procedure generates the counterfactual path of capital accumulation that would have been expected in the absence of the COVID-19 pandemic.

Projected capital stock is therefore calculated according to the perpetual inventory equation:

$$K_{i,t}^{Forecast} = K_{i,t-1}^{Forecast}(1 - \delta_i) + I_{i,t}^{Forecast}$$

where δ_i denotes the depreciation rate and $I_{i,t}^{Forecast}$ represents forecast gross fixed capital formation.

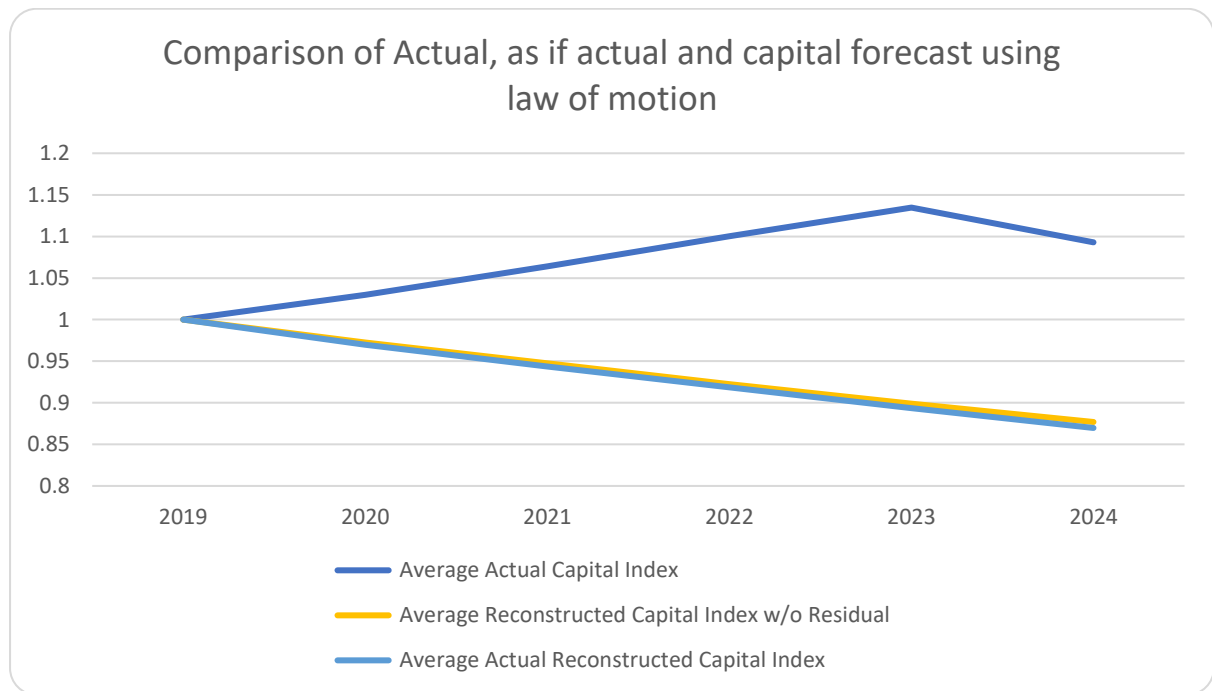


Figure 1a. Comparison of Average Reported and Reconstructed Capital Stock Indices (2019-2024)

As a validation exercise, the reconstructed capital stock series was compared with the capital stock reported by the Penn World Table. **Figure 1a** shows that the average reconstructed capital stock index does not track the corresponding Penn World Table index throughout the sample period. The author was not able to recontact the capital forecast so that the accounting identity hold. By trying to assess the possible reason for the mismatch actual capital stock was the reconstructed using the same law of motion but using actual investment. /based on results we observe that the recontacting based on actual values find as well, which bring to a conclusion that the mismatch is caused by permanent error. Therefore the following methodology for capital forecast using residuals is proposed:

The residual is calculated as:

$$Residual_{i,t} = K_{i,t}^{Actual} - K_{i,t-1}^{Actual}(1 - \delta_{i,t}) - I_{i,t}^{Actual}$$

Projected capital stock is therefore calculated according to the adjusted perpetual inventory equation:

$$K_{i,t}^{Forecast} = K_{i,t-1}^{Forecast}(1 - \delta_{i,t}) + I_{i,t}^{Forecast} + Residual_{i,t}$$

where $\delta_{i,t}$ denotes the country-specific depreciation rate reported by the Penn World Table, $I_{i,t}^{Forecast}$ represents forecast gross fixed capital formation and $Residual_{i,t}$ is the adjustment term obtained from the observed Penn World Table capital accumulation identity. The residual arises because the Penn World Table capital stock reflects not only investment and depreciation but also valuation effects associated with changes in the relative prices of different capital assets. As a result, the simplified reconstruction used in this study cannot fully reproduce the reported capital series. The residual becomes particularly large in 2020 and 2024 because of the exceptional economic disruptions associated with the COVID-19 pandemic.

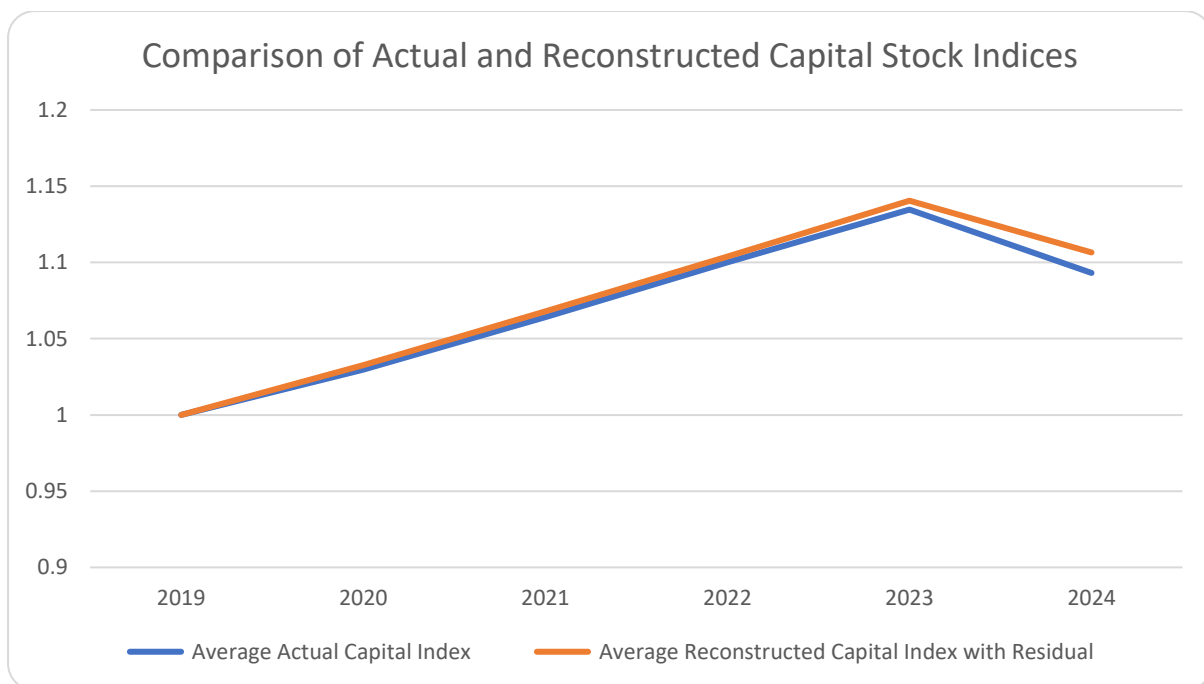


Figure 1b. Comparison of Average Reported and Reconstructed Capital Stock Indices (2019-2024), with residual

In contrast, realized capital stocks for 2020–2024 are obtained directly from Penn World Table version 10.0. Using the same observed capital stock in 2019 as the initial condition for both the projected and realized series ensures that any subsequent divergence between the two paths reflects differences in investment dynamics following the outbreak of the COVID-19 pandemic rather than differences in initial capital endowments. Consequently, estimated capital gaps capture the cumulative effects of investment shortfalls and slower capital accumulation generated by the pandemic. The perpetual inventory method offers several advantages in the context of the present analysis. First, it provides a consistent framework for constructing counterfactual capital paths when direct forecasts of capital stock are unavailable. Second, incorporating the Penn World Table residual allows the reconstructed capital series to remain consistent with the official capital stock estimates while still reflecting the counterfactual investment projections from the October 2019 WEO. Third, because capital adjusts gradually over time, the recursive nature of the perpetual inventory method allows the long-term effects of reduced investment to accumulate naturally, making it particularly suitable for analysing medium-term economic scarring.

Figure 1b shows that the average reconstructed capital stock index closely tracks the corresponding Penn World Table index throughout the sample period. The remaining differences are small and reflect the fact that the Penn World Table incorporates a more

comprehensive perpetual inventory methodology, including longer historical investment series, asset-specific depreciation rates, and additional valuation adjustments that cannot be fully replicated using the simplified reconstruction procedure adopted in this study. Overall, the close correspondence between the two series provides support for the validity of the capital accumulation procedure employed in this study.

The capital gap is calculated as the logarithmic difference between realized and projected capital stock:

$$CapitalGap_t = \ln \left(\frac{K_t^{Actual}}{K_t^{Forecast}} \right)$$

Where K_t^{Actual} denotes the realized capital stock and $K_t^{Forecast}$ represents the counterfactual capital stock constructed using the perpetual inventory method.

A negative capital gap indicates that realized capital accumulation remained below the level implied by pre-pandemic investment projections, suggesting that reduced investment contributed to post-pandemic output losses. Conversely, values closer to zero imply that capital accumulation largely followed its expected trajectory despite the pandemic. Because capital adjusts more gradually than labour, deviations in capital stock often emerge progressively over time, reflecting the cumulative effects of lower investment rather than the immediate disruptions observed in labour markets (Barrett et al., 2021).

3.3.4 Total Factor Productivity

Once output, labour, and capital gaps have been calculated, the growth-accounting framework can be used to decompose overall output losses into the contributions of individual production factors. Specifically, observed deviations from the pre-pandemic growth path are attributed to changes in labour input and capital accumulation, while any remaining unexplained variation is captured by total factor productivity (TFP). This decomposition allows the analysis to distinguish between output losses arising from observable factor accumulation and those resulting from changes in production efficiency.

The decomposition is based on the logarithmic approximation of the Cobb-Douglas production function:

$$GDPGap_t = \alpha \cdot LabourGap_t + (1 - \alpha) \cdot CapitalGap_t + TFP_t$$

where the labour contribution is measured by $\alpha \cdot LabourGap_t$, whereas the contribution of capital is measured by $(1 - \alpha) \cdot CapitalGap_t$.

The remaining unexplained component is attributed to **total factor productivity** and is obtained as the residual:

$$TFP_t = GDPGap_t - \alpha \cdot LabourGap_t - (1 - \alpha) \cdot CapitalGap_t$$

Interpreting TFP as a residual does not imply that it represents a single observable economic variable. Rather, it captures all changes in output that cannot be explained by measured changes in labour and capital. Consequently, TFP reflects a broad range of influences affecting production efficiency, including technological progress, organizational improvements, institutional quality, resource allocation, management practices, and other factors that alter the effectiveness with which labour and capital are combined in the production process.

Within the context of the COVID-19 pandemic, changes in total factor productivity may also capture disruptions to global supply chains, production bottlenecks, changes in business organization, digitalization, and other efficiency-related adjustments that are not directly observable through conventional measures of labour and capital. As emphasized by Barrett et al. (2021), productivity dynamics constitute an important channel through which temporary shocks may generate persistent medium-term output losses. At the same time, Jackson and Lu (2023) demonstrate that, unlike previous major crises, labour-market disruptions accounted for a larger share of COVID-related output losses than productivity declines, suggesting that pandemic-related scarring may differ fundamentally from earlier episodes of economic distress.

Consequently, estimating TFP as a residual provides important insights into the extent to which post-pandemic output losses reflect broader changes in productive efficiency rather than solely reductions in observable factor inputs.

3.3.5 Final Decomposition

The growth-accounting decomposition is performed separately for each country and each year included in the sample. Estimating country-level decompositions allows the relative

contributions of labour, capital accumulation, and total factor productivity to be examined across different emerging market economies while accounting for differences in macroeconomic conditions, policy responses, and recovery trajectories. Country-specific estimates are subsequently aggregated using **GDP-weighted averages**, thereby ensuring that larger economies contribute proportionally more to the reported aggregate results than smaller economies. This aggregation procedure produces a GDP-weighted measure of aggregate performance, giving greater influence to larger economies.

Analysing each production factor separately provides considerably richer information than examining aggregate output losses alone. Two countries may experience similar overall output gaps while reaching those outcomes through entirely different economic mechanisms. For example, one economy may primarily suffer from labour-market disruptions, whereas another may experience more persistent declines in investment or productivity. By distinguishing between these channels, the decomposition framework allows the principal sources of post-pandemic economic scarring to be identified and compared across countries.

The empirical approach adopted in this study is also consistent with the broader literature on medium-term economic scarring. Barrett et al. (2021) emphasize that persistent output losses emerge through multiple supply-side channels, including weaker capital accumulation, labour-market disruptions, and slower productivity growth. Similarly, Jackson and Lu (2023) demonstrate that decomposing realized output losses into their underlying production factors provides important insights into the mechanisms driving post-pandemic recovery across emerging market economies. Building on their framework, the present study extends the empirical analysis through **2024**, thereby allowing the persistence of these mechanisms to be evaluated over a longer post-pandemic horizon.

More generally, growth accounting has become one of the standard empirical tools used in macroeconomics to analyse the sources of economic growth and output fluctuations. Unlike reduced-form approaches that identify statistical relationships without distinguishing their underlying causes, the growth-accounting framework provides a structural interpretation of output dynamics by explicitly separating the contributions of labour, capital, and productivity. This feature makes the methodology particularly well suited to analysing the COVID-19 pandemic, during which multiple supply-side channels were simultaneously affected by an unprecedented global shock.

The decomposition obtained in this chapter forms the basis for the empirical analysis presented in Chapter 4, where the relative contributions of labour, capital accumulation, and total factor productivity are examined to evaluate the persistence and composition of post-pandemic economic scarring across the selected sample of emerging market economies.

3.3 Limitations

No empirical methodology is without limitations, and the growth-accounting framework adopted in this study is no exception. Although the approach provides a transparent and economically meaningful method for identifying the sources of post-pandemic output losses, the results should be interpreted in light of several methodological and data-related constraints.

First, the analysis relies on the October 2019 edition of the International Monetary Fund's World Economic Outlook (WEO) as the counterfactual benchmark representing the path that economic activity was expected to follow in the absence of the COVID-19 pandemic. This choice is consistent with the methodology adopted by Jackson and Lu (2023) and is widely used in the literature because it represents the final set of macroeconomic forecasts prepared before the emergence of the pandemic. Nevertheless, no counterfactual projection can perfectly represent the trajectory economies would actually have followed. Economic growth is influenced by numerous factors unrelated to COVID-19, including changes in commodity prices, geopolitical events, domestic policy decisions, and other unforeseen macroeconomic shocks. Consequently, a portion of the measured output gaps may reflect developments that cannot be attributed exclusively to the pandemic. This limitation should be considered when interpreting the estimated magnitude of economic scarring.

Second, the empirical decomposition is based on the standard Cobb-Douglas production function, which assumes constant returns to scale and a constant labour income share throughout the period of analysis. Although these assumptions are widely employed in empirical growth-accounting studies and greatly simplify the decomposition of output into economically interpretable components, they inevitably represent an abstraction from reality. Production technologies, factor shares, and substitution possibilities may evolve over time, particularly during periods of exceptional economic disruption such as the COVID-19 pandemic. Consequently, the framework provides an approximation of the underlying

production process rather than a complete representation of all production relationships within the economy.

Third, the empirical analysis is constrained by data availability. In particular, the World Economic Outlook database does not provide counterfactual projections for labour force participation rates prior to the pandemic. As a result, labour input cannot be fully decomposed into the separate contributions of population, unemployment, and labour force participation. Instead, changes in labour force participation remain embedded within the aggregate labour contribution and therefore cannot be identified independently. Similarly, the absence of pre-pandemic unemployment forecasts for India prevents the estimation of unemployment-specific contributions for that country. Although these data limitations reduce the level of detail that can be achieved in the decomposition, they do not affect the consistency of the overall growth-accounting framework.

Fourth, although the empirical analysis has been extended through 2024, the observation period remains relatively short when evaluating phenomena such as medium- and long-term economic scarring. Many structural consequences of the pandemic—including changes in educational attainment, human capital accumulation, technological adoption, demographic trends, and labour-market participation—may continue to influence economic performance for many years beyond the end of the sample period (Barrett et al., 2021). Consequently, the present analysis should be interpreted as an assessment of the medium-term consequences of the pandemic rather than its full long-run economic impact.

Finally, the analysis is conducted at the macroeconomic level and therefore abstracts from important sources of heterogeneity within individual economies. Differences across industries, firms, regions, and institutional environments are not explicitly modelled, despite potentially playing an important role in shaping recovery trajectories. Likewise, the growth-accounting framework identifies the relative contributions of labour, capital, and total factor productivity but does not establish causal relationships between these factors and post-pandemic economic performance. Instead, the decomposition should be interpreted as an accounting exercise that attributes realized output losses to their principal production components rather than as a causal identification strategy.

Despite these limitations, the methodology provides a transparent, internally consistent, and internationally comparable framework for analysing post-pandemic economic scarring across emerging market economies. By combining harmonized international datasets, a well-established growth-accounting methodology, and an updated empirical sample extending through **2024**, the study offers new evidence on the relative contributions of labour, capital accumulation, and total factor productivity to medium-term output losses. The use of GDP-weighted averages yields an aggregate measure of recovery in which larger economies receive greater weight.

4. Results

This chapter presents the empirical findings of the study. It begins by analysing aggregate output losses across the sample of emerging market economies before decomposing these losses into the contributions of labour, capital accumulation, and total factor productivity. The chapter then compares the results with those reported by Jackson and Lu (2023) and discusses the extent to which the observed recovery patterns are consistent with the existing literature.

4.1 Average Output Losses in Emerging Market Economies

This chapter presents the empirical findings obtained from the growth-accounting framework developed in Chapter 3. The analysis begins by examining aggregate output losses across the sample of 21 emerging market economies, providing an overview of the evolution of post-pandemic economic scarring during the period 2020–2024. Particular attention is given to the persistence of deviations from the pre-pandemic growth path rather than short-term fluctuations in annual GDP growth. The chapter subsequently investigates cross-country heterogeneity by comparing recovery trajectories across individual economies before decomposing realized output losses into the contributions of labour, capital accumulation, and total factor productivity.

Consistent with the methodological framework presented in the previous chapter, the decomposition identifies the separate contributions of population and unemployment to overall labour input, while changes in labour force participation remain incorporated within the aggregate labour component because comparable counterfactual projections are unavailable. Similarly, due to the absence of pre-pandemic unemployment forecasts for India, unemployment-specific contributions cannot be estimated for that country and are therefore excluded from the labour decomposition. These limitations, however, do not affect the interpretation of the aggregate growth-accounting results.

Figure 4 presents the **GDP-weighted average output gap** across the sample of emerging market economies relative to the counterfactual growth path implied by the **October 2019 World Economic Outlook** projections. Unlike conventional measures of GDP growth, the output gap compares realized economic performance with the level of output that would have been expected in the absence of the COVID-19 pandemic. Consequently, the figure measures the persistence of economic scarring rather than year-to-year changes in economic activity.

The results indicate that output remained below the pre-pandemic trajectory throughout the entire 2020–2024 period, although the magnitude of the losses declined markedly after the initial pandemic shock. The GDP-weighted average output gap amounted to -5.60% in 2020, improved substantially to -2.96% in 2021, before widening again to -4.36% in 2022, remaining broadly unchanged at -4.32% in 2023, and deteriorating slightly to -4.60% in 2024. These findings suggest that the largest emerging market economies experienced a strong initial recovery but subsequently stabilized at output levels that remained persistently below their pre-pandemic trajectories.

Unlike simple arithmetic averages, the GDP-weighted estimates indicate that the aggregate recovery of emerging market economies remained incomplete even four years after the onset of the pandemic. Although the output gap narrowed substantially in 2021 following the initial pandemic shock, the subsequent recovery lost momentum. From 2022 onward, the GDP-weighted output gap remained relatively stable at around 4–5% below the pre-pandemic trajectory, indicating that several of the largest economies in the sample continued to underperform relative to their projected growth paths. Consequently, although many individual countries experienced positive GDP growth during the recovery period, and some even exceeded their projected output levels, the emerging market group as a whole remained persistently below its counterfactual trajectory.

Importantly, these results should not be interpreted as indicating that economic conditions deteriorated in absolute terms between 2022 and 2024. Rather, the output gap measures the difference between realized GDP and the level of GDP that would have been expected had the pre-pandemic growth trend continued uninterrupted. Thus, even when economies recorded positive economic growth, they could remain below—or even move further away from—their pre-pandemic trajectories if realized growth was insufficient to match the pace originally projected. This distinction highlights the importance of evaluating recovery relative to the counterfactual benchmark rather than relying solely on observed GDP growth rates.

The persistence of negative output gaps through 2024 provides evidence of continued medium-term economic scarring across emerging market economies. These findings are broadly consistent with Barrett et al. (2021), who argue that severe recessions may generate lasting supply-side effects through weaker investment, labour-market disruptions, and productivity dynamics. At the same time, extending the analysis beyond the period examined by Jackson

and Lu (2023) demonstrates that, despite continued economic expansion in many countries and a substantial improvement relative to the initial pandemic shock, aggregate output across the emerging market sample had not yet returned to its pre-pandemic growth path by 2024. The GDP-weighted decomposition further indicates that this persistent shortfall was driven primarily by total factor productivity, while labour-market disruptions gradually faded and capital accumulation remained relatively resilient throughout the recovery period.

Table 1. Five Largest Output Losses and Five Strongest Recoveries in 2024

Largest Output Losses	GDP Gap %	Strongest Recoveries	GDP Gap %
Philippines	-17.31	Türkiye	+10.45
Thailand	-14.78	Croatia	+5.79
Peru	-12.23	Belarus	+4.81
India	-9.71	Poland	+0.38
Indonesia	-8.96	Russia	+0.08

The strongest recovery was observed in Türkiye, whose output exceeded the pre-pandemic projection by 10.45%, followed by Croatia (+5.79%), Belarus (+4.81%), Poland (+0.38%), and Russia (+0.08%). These findings illustrate that recovery trajectories varied substantially across emerging market economies, with several countries fully offsetting the pandemic-related decline and exceeding their pre-pandemic output trajectories, while others continued to experience sizeable and persistent output gaps.

4.2 Decomposition of Output Losses

Before presenting the results of this study, it is useful to summarize the principal findings reported by Jackson and Lu (2023), whose methodology forms the basis of the present analysis. Figure 2 follows the growth-accounting framework proposed by Jackson and Lu (2023), in which output is produced according to a Cobb-Douglas production function combining total factor productivity, labour, and effective capital services. Effective capital services are defined as the product of the physical capital stock and capital utilization. Because internationally comparable data on capital utilization are unavailable, Jackson and Lu assume that capital

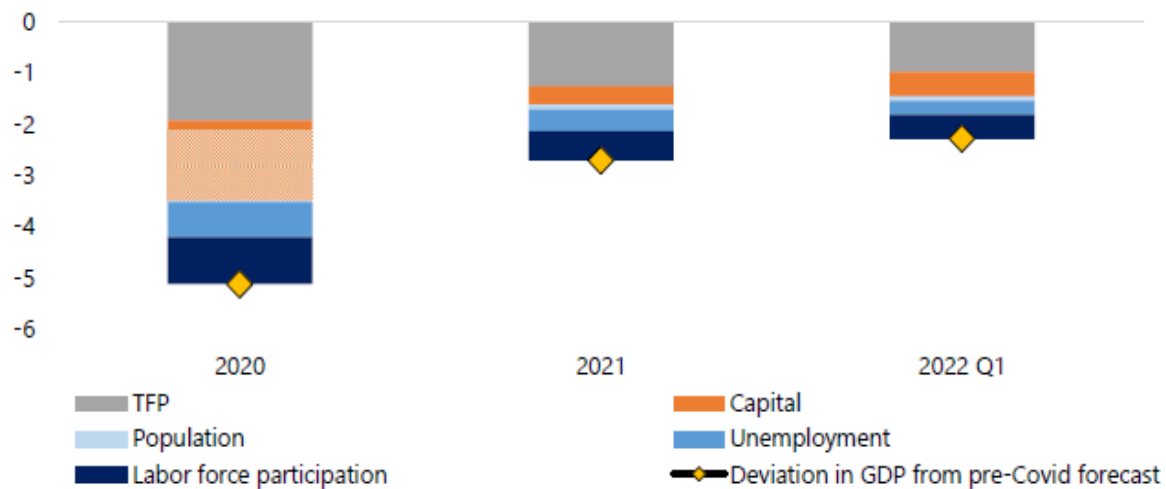


Figure 2. Decomposition of output losses reported by Jackson & Lu (2023). Sources: Penn World Table 10.0, IMF and staff calculations. Barrett and others (2021), 'After-effects of the COVID-19 pandemic: prospects for medium-term economic damage'.

utilization declines proportionally with employment during the pandemic. This assumption reflects the idea that firms temporarily operated existing capital less intensively when labour demand contracted. Consequently, the reported capital contribution captures both slower capital accumulation and temporary reductions in capital utilization, rather than changes in the physical capital stock alone. Their results indicate that labour-market disruptions accounted for a substantial share of the initial output losses, while the capital contribution, reflecting both physical capital accumulation and the assumed decline in capital utilization, became increasingly important over time. Total factor productivity contributed relatively little to medium-term scarring.

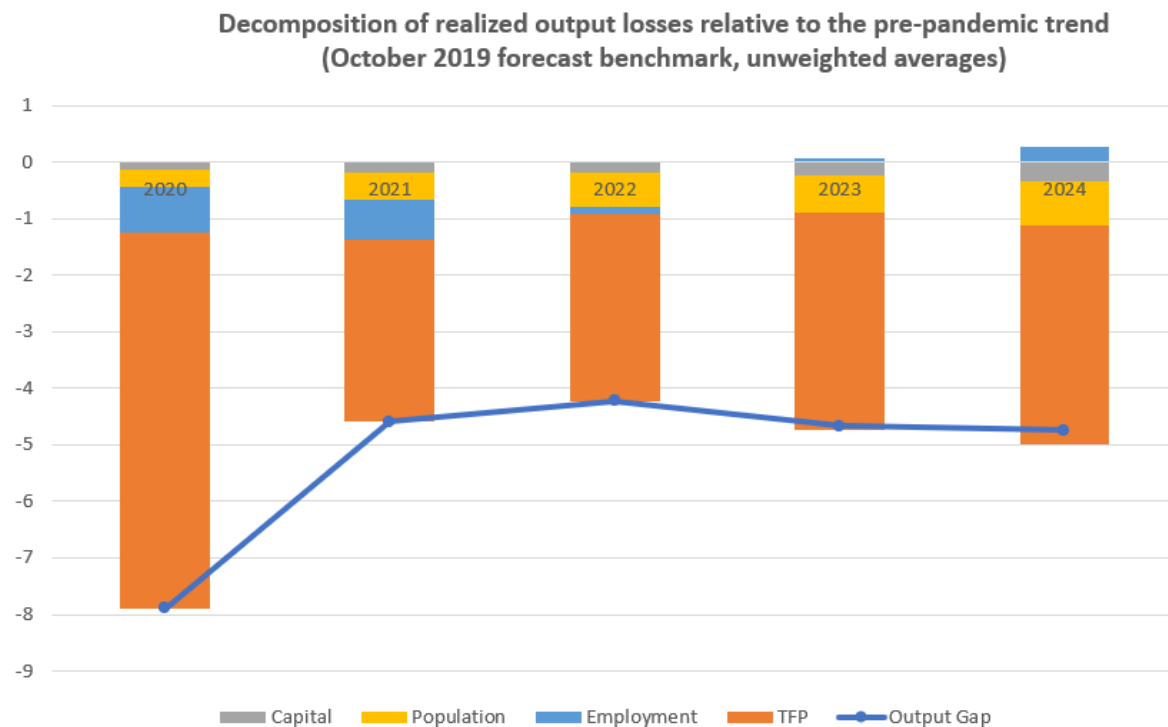


Figure 3. Decomposition of realized output losses relative to the pre-pandemic trend using unweighted averages (October 2019 forecast benchmark)

To facilitate comparison with Jackson and Lu (2023), Figure 3 presents the decomposition obtained using simple (unweighted) averages across the sample countries. Unlike the GDP-weighted averages used in the main analysis, each country contributes equally to the aggregate estimates.

Although Figure 3 captures the broad evolution of post-pandemic output losses, several important differences emerge relative to the decomposition reported by Jackson and Lu (2023). Most notably, the contribution of capital follows a different pattern. Whereas Jackson and Lu find that capital becomes increasingly important over time, the unweighted decomposition indicates that capital's negative contribution is minimal throughout the period. By contrast, total factor productivity emerges as the dominant source of the persistent output losses, accounting for the vast majority of the remaining gap from 2020 through 2024, while employment and population contributions provide partial offsetting effects. This may reflect lasting disruptions to production efficiency, supply chains, firm-level organization, sectoral reallocation, or other factors captured by the TFP residual. Furthermore, the labor contribution declines substantially after the initial pandemic shock, suggesting that labor markets recovered more rapidly than aggregate output. Consequently, the persistence of the output gap cannot be

attributed primarily to employment shortfalls. These differences likely reflect the extended sample period through 2024, the use of the October 2019 WEO forecast benchmark, and differences in the country sample, which together affect the relative importance of the individual growth-accounting components.

Figure 4 presents the GDP-weighted decomposition of average output gaps relative to the pre-pandemic trend across the sample of 21 emerging market economies over the period 2020–2024. Following the growth accounting framework presented in Chapter 3, output gaps are decomposed into the contributions of labour, capital accumulation, and total factor productivity (TFP). Due to the absence of a separate counterfactual series for labour force participation, the labour component is further decomposed only into population and employment effects, while any remaining labour-market influences are incorporated into the adjusted TFP residual. All contributions are expressed in percentage points and represent GDP-weighted averages, ensuring that larger economies contribute proportionally more to the aggregate estimates. Although the general pattern closely resembles that reported by Jackson and Lu (2023), some differences are expected. Their study reports unweighted sample averages, whereas Figure 4 presents GDP-weighted averages, giving greater influence to larger economies within the sample. Consequently, the relative contributions of labour, capital and productivity differ slightly, while the overall dynamics of post-pandemic output losses remain broadly comparable.

Figure 4 indicates that total factor productivity emerged as the dominant source of output losses throughout the post-pandemic period. In 2020, the weighted average output gap amounted to approximately **5.6 percentage points below** the pre-pandemic trend. Approximately **4.6 percentage points** of this decline were associated with weaker total factor productivity, while weaker employment explained approximately while weaker employment and population accounted for **0.49** and **0.36 percentage points** respectively. Capital accumulation played a negligible role, contributing only **–0.10 percentage points**.

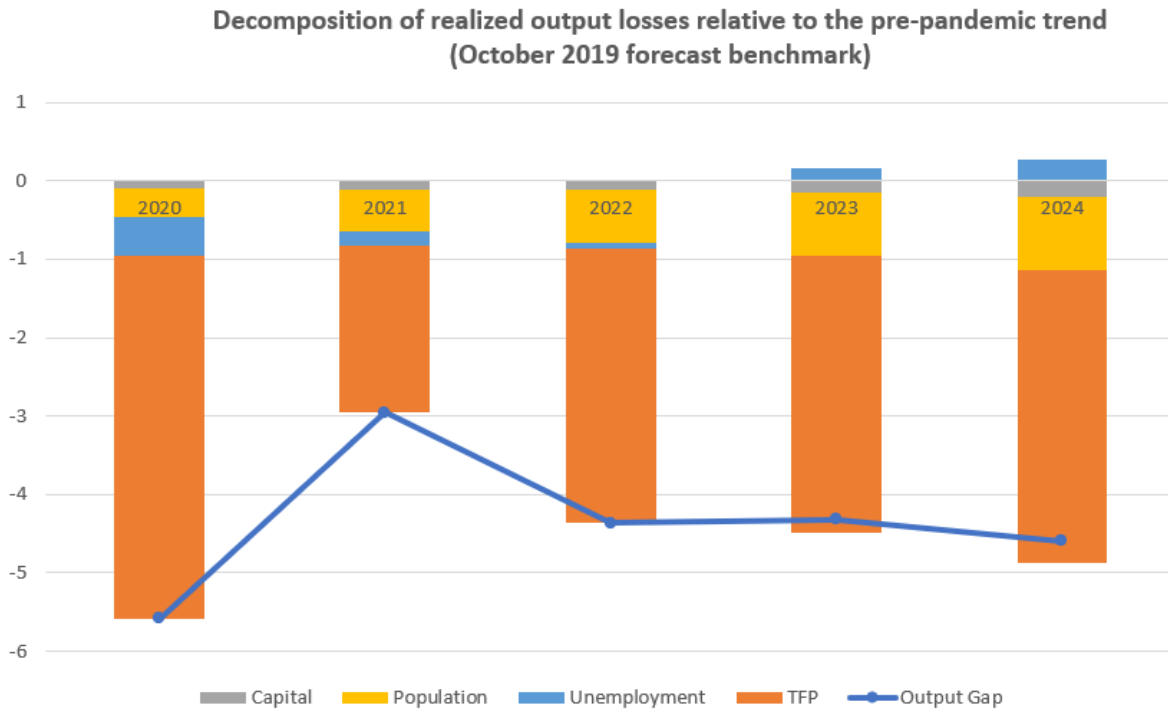


Figure 4. Decomposition of realized output losses relative to the pre-pandemic trend using GDP-weighted averages (October 2019 forecast benchmark)

The GDP-weighted results indicate that aggregate output losses followed a distinct recovery-then-stabilization pattern. The output gap improved substantially from **−5.6% in 2020** to **−2.96% in 2021**, before deteriorating to **−4.36% in 2022**, **−4.32% in 2023**, and **−4.60% in 2024**. These findings suggest that the largest emerging market economies initially benefited from the recovery wave but subsequently stabilized at levels persistently below their pre-pandemic trajectories.

The composition of output losses evolved substantially over time. Labour-market disruptions became progressively less important as employment conditions improved and labour market tightened. The (un)employment contribution declined from **−0.49 percentage points** in 2020 to **−0.19** in 2021, **−0.07** in 2022, and turned positive in 2023 (**+0.17**) and 2024 (**+0.27**), indicating an employment-supply constraint by the final years of the sample. By contrast, population effects became increasingly negative over time, declining from **−0.36 percentage points** in 2020 to **−0.95 percentage points** in 2024, reflecting demographic headwinds accumulating across the period. Capital accumulation remained negligible throughout the observation period, fluctuating only between **−0.10 and −0.20 percentage points**, indicating that investment recovered sufficiently to offset pandemic-related declines.

Total factor productivity, on the other hand, remained the overwhelming determinant of output losses. The adjusted TFP contribution declined from approximately **−4.64 percentage points** in 2020 to **−2.12** in 2021, before rising to approximately **−3.50 percentage points** in 2022, **−3.53** in 2023, and **−3.72 percentage points** in 2024. Throughout the entire sample period, TFP accounted for 70–80% of the total output gap, suggesting that persistent efficiency losses and other structural factors remained the primary explanation for deviations from pre-pandemic output paths, with capital accumulation and demographic factors playing only minor roles in the GDP-weighted decomposition.

Comparing Figures 3 and 4 shows that the estimated decomposition is highly sensitive to the aggregation method. Under simple arithmetic averaging (Figure 3), the average emerging market economy exhibits a more gradual recovery trajectory, with output gaps remaining substantial and persistent throughout 2020–2024. In contrast, the GDP-weighted decomposition (Figure 4) reveals a more pronounced initial recovery phase, where the largest emerging market economies rebounded more sharply in 2021 before output losses widened again through the subsequent years. Both decompositions identify total factor productivity as the dominant source of output losses across the entire sample period, reflecting persistent efficiency challenges and structural headwinds that characterized the post-pandemic period. However, important differences emerge in the labour-market dynamics. The unweighted decomposition suggests that employment effects persisted as a meaningful constraint throughout the early recovery, whereas the GDP-weighted measure indicates that labour markets tightened considerably in the largest economies, with employment eventually becoming a binding constraint by 2023–2024. This divergence suggests that major emerging market economies experienced earlier and more pronounced labour-market normalization than smaller economies. Capital accumulation plays a negligible role in both decompositions, indicating that investment recovered sufficiently across the sample to offset pandemic-related declines and did not emerge as a persistent drag on aggregate output in either measure.

These differences arise because GDP weighting assigns greater influence to larger economies, whose recovery paths and labour-market dynamics differ materially from those of smaller economies. As a result, the weighted decomposition reflects aggregate regional performance, whereas the unweighted decomposition represents the recovery pattern of the average country. The comparison therefore illustrates that conclusions regarding the relative importance of capital, labour, and productivity depend not only on the growth-accounting framework but also

on the method used to aggregate country-level results. This sensitivity is an important empirical finding and suggests that interpretations of cross-country decompositions should take the choice of aggregation method into account.

Figure 5 summarises the evolution of the weighted average output gap together with its principal growth-accounting components over the period 2020–2024.

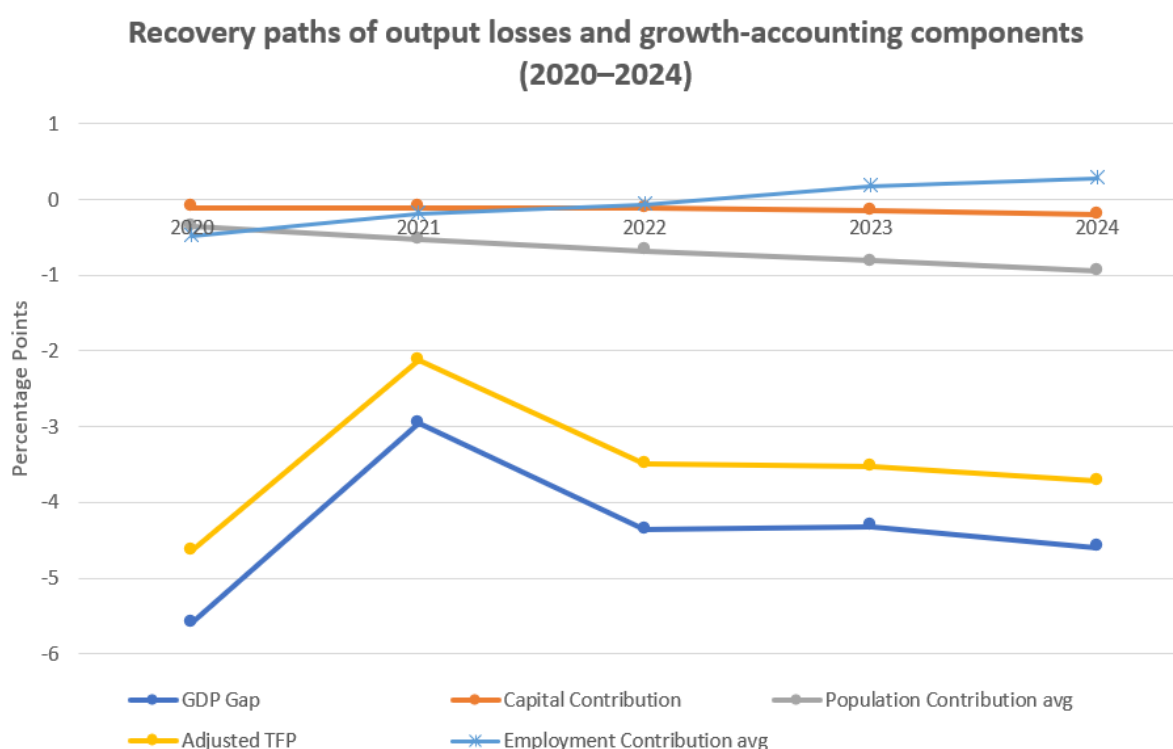


Figure 5. Recovery paths of output losses and growth-accounting components

Labour-market conditions improved substantially over the sample period, with employment effects transitioning from a significant drag in 2020 to a positive contributor by 2023–2024, indicating a shift toward labour-market tightness in the largest emerging market economies. The contribution of capital accumulation recovered markedly, moving from a modest initial drag to near-zero or slightly positive territory, suggesting that investment rebounded sufficiently to eliminate pandemic-related capital constraints. Total factor productivity, by contrast, exhibited a more complex recovery pattern, showing initial improvement through 2021 before deteriorating again through 2024. Despite these improvements in labour and capital conditions, aggregate output remained persistently below its pre-pandemic trajectory, with total factor productivity accounting for the majority of the remaining gap throughout the period.

These recovery patterns are broadly consistent with the literature on post-pandemic economic scarring. Barrett et al. (2021) argue that persistent output losses following severe recessions are transmitted through labour, capital accumulation and total factor productivity. Similarly, Ball (2014) and Blanchard et al. (2015) emphasize that hysteresis effects often operate through persistent reductions in productivity and potential output rather than solely through temporary labour-market disruptions. The present findings are consistent with this interpretation, although with an important modification: rather than labour-market or capital constraints persisting, the data suggest that structural productivity factors remained the principal impediment to convergence toward pre-pandemic trends.

Overall, the decomposition indicates that the nature of economic scarring evolved markedly over time. During the initial phase of the pandemic, output losses reflected a combination of labour-market disruptions, modest capital constraints, and substantial productivity losses. Over time, labour markets normalized and capital accumulation recovered to levels insufficient to constrain growth. However, productivity improvements proved transitory, with efficiency losses reasserting themselves through the latter years of the sample. These findings suggest that structural productivity constraints, rather than labour-market conditions or capital accumulation, emerged as the fundamental binding constraint on emerging market recovery, pointing to deeper technological or organizational factors impeding a return to pre-pandemic growth trajectories.

4.3 Labour-Market Dynamics

While the decomposition presented in Figure 4 identifies the aggregate contribution of labour to output losses, it does not distinguish between the specific labour-market mechanisms underlying these changes. Table 2 therefore decomposes the labour contribution into its population and employment components, providing a more detailed assessment of how labour-market conditions evolved during the post-pandemic recovery. The results indicate that employment losses were more modest than previously estimated, but demographic headwinds emerged as an increasingly important persistent drag on output.

As shown in Table 2, the negative employment contribution was largest in 2020, reducing output by approximately **0.49 percentage points**. This adverse effect declined rapidly, falling to **0.19 percentage points** in 2021, **0.07 percentage points** in 2022, and turning positive by 2023 (**0.17 percentage points**) and 2024 (**0.27 percentage points**). This sharp reversal

indicates that labour-market conditions recovered quickly and that employment constraints became binding in the largest emerging market economies by the end of the sample period. In sharp contrast to the modest employment effects, the contribution of population emerged as a persistent and growing drag throughout the observation period. Population effects deteriorated substantially over time, declining from **−0.36 percentage points** in 2020 to **−0.95 percentage points** in 2024, indicating that demographic headwinds accumulated progressively across the recovery period. This represents a marked departure from the expectation that population effects would remain negligible, and suggests that aging and labour force participation dynamics became increasingly important constraints on aggregate growth.

Table 2. Decomposition of the Labour Contribution Across Emerging Market Economies (2020–2024)

Year	Labour Contribution	Population Contribution	Employment Contribution
2020	-0.84	-0.36	-0.49
2021	-0.72	-0.53	-0.19
2022	-0.74	-0.68	-0.07
2023	-0.64	-0.81	0.17
2024	-0.67	-0.95	0.27

Note: Values represent average contributions across the sample of emerging market economies and are expressed in percentage points. The labour contribution is decomposed into population and employment components. Due to the absence of a separate counterfactual series for labour force participation, LFPR-related effects are not identified separately and remain embedded within the aggregate labour contribution.

The combination of declining employment effects and mounting demographic headwinds implies that labour-market adjustment during the post-pandemic period operated through two distinct channels. Initial employment losses reversed relatively quickly, consistent with the cyclical nature of pandemic-related labour-market shocks. However, underlying demographic trends—including population aging, potential emigration, and labour force participation declines—intensified over time, suggesting that structural labour-supply constraints became progressively more binding. Labour as a whole remained negative throughout the 2020–2024 period, implying that demographic factors overwhelmed employment gains.

These findings offer important nuances to the broader literature on post-pandemic labour-market adjustment. While Jackson and Lu (2023) and Ma et al. (2020) emphasize the rapid

recovery of employment following pandemic shocks, the present results suggest that employment recovery, though rapid, masked underlying demographic pressures that continued to constrain labour supply growth. The relatively large and growing contribution of population effects is notable and suggests that emerging market economies faced persistent headwinds from population dynamics that were not fully offset by employment normalization. This finding reinforces the interpretation that while the pandemic represented an initial cyclical labour-market shock, underlying structural demographic factors became the binding labour-supply constraint over the medium term.

Overall, the evidence indicates that employment disruptions were an important but temporary contributor to output losses during the initial pandemic phase, but deteriorated only modestly and ultimately reversed. By contrast, demographic factors emerged as an increasingly significant source of persistent output losses, suggesting that labour-supply constraints evolved from cyclical to structural during the recovery period. Combined with the results presented in the previous section, this suggests that medium-term output losses became driven primarily by persistent productivity weaknesses and, secondarily, by accumulating demographic headwinds rather than by continuing cyclical labour-market disruption.

4.4 Cross-Country Heterogeneity in Productivity Losses

Although the aggregate decomposition presented in Figure 4 identifies total factor productivity (TFP) as the principal source of persistent output losses, considerable heterogeneity exists

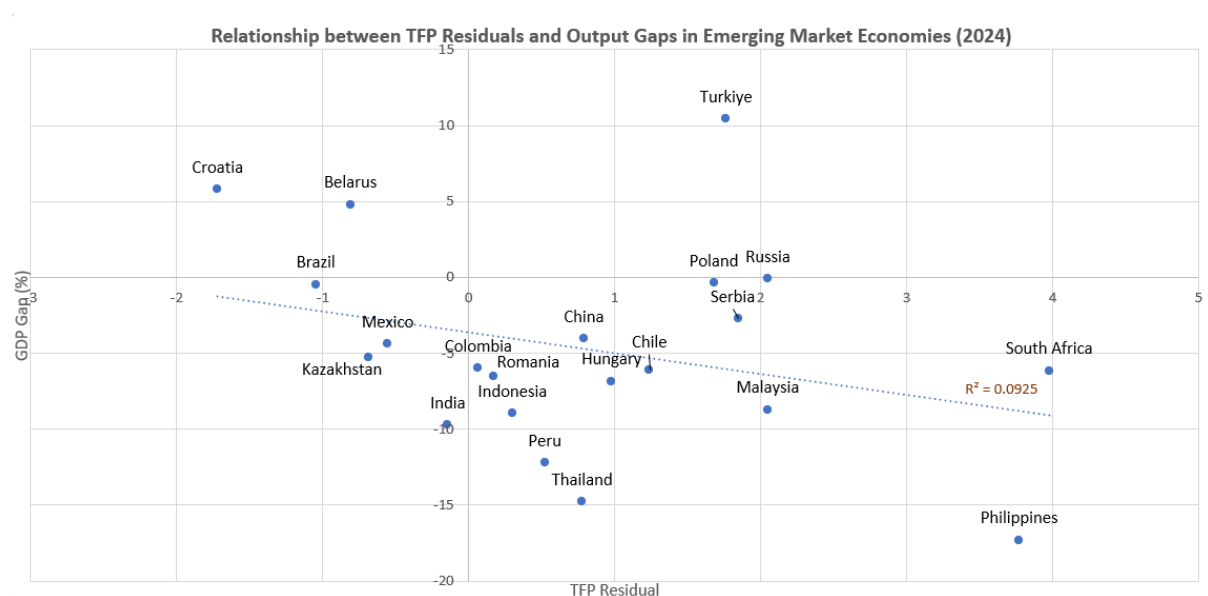


Figure 6. Relationship between TFP residuals and output gaps in emerging market economies (2024)

across individual emerging market economies. Figure 6 examines whether differences in productivity performance were systematically associated with differences in output outcomes by plotting the relationship between TFP residuals and output gaps across the 21 economies in the sample for 2024.

Figure 6 reveals an exceptionally weak relationship between TFP residuals and output performance. The low coefficient of determination ($R^2=0.09$) indicates that productivity differences explain less than 10% of the cross-country variation in output performance, suggesting that while TFP contributes to aggregate losses, country-specific factors dominate individual country outcomes. This striking finding indicates that other variables, including capital accumulation, labour-market conditions, institutional quality, policy responses, external trade dynamics, and geopolitical factors, play substantial and often decisive roles in determining national recovery outcomes.

The figure highlights several notable outliers that underscore the weak relationship. The Philippines, South Africa, and Indonesia recorded substantial positive TFP residuals yet remained significantly below their pre-pandemic output paths, suggesting that favourable productivity performance was more than offset by constraints elsewhere in the economy. Conversely, Türkiye recorded exceptionally strong output recovery, exceeding its pre-pandemic projected output path by approximately 10.45%, while Russia recorded a near-zero output gap (-0.07%) despite a positive TFP residual of 2.05 percentage points, indicating that geopolitical and external factors have played a substantial offsetting role in Russia's post-pandemic dynamics.

At the opposite end of the distribution, several countries experienced substantial negative output gaps despite heterogeneous productivity outcomes. The Philippines and Thailand recorded some of the largest negative output gaps, while India, Indonesia, and Peru also remained substantially below pre-pandemic paths. The absence of a systematic relationship suggests that productivity performance, while important in aggregate, does not translate uniformly into individual country outcomes. Countries with similar productivity residuals exhibited markedly different output gaps, indicating that complementary factors such as labour-supply constraints, capital accumulation dynamics, and external demand conditions operated heterogeneously across the sample.

To investigate these differences further, Table 3 reports the average contributions of total factor productivity, capital accumulation, and labour over the period 2020–2024 for each country. The table reveals striking changes in the sources of post-pandemic output performance compared to previous estimates. Notably, most countries now exhibit positive average TFP residuals, with Philippines, South Africa, Russia, Peru, and Malaysia recording the largest positive values, indicating that productivity performance varied substantially across emerging markets but was generally more favourable than aggregate decompositions suggest. Only a small number of economies: Belarus and Kazakhstan recorded negative average TFP residuals over the full period, suggesting that persistent productivity weakness was not the universal constraint it appeared at the aggregate level.

Table 3. Average Contributions of TFP, Capital, and Labour to Output Performance (2020–2024)

Country	Average TFP Residual	Average Capital Contribution	Average Labor Contribution
Belarus	-0.52	0.07	0.45
Brazil	0.36	0.00	-0.38
Chile	1.43	-0.23	-1.25
China	0.56	-0.08	-0.51
Colombia	0.63	-0.56	-0.12
Croatia	0.38	0.24	-0.62
Hungary	0.57	-0.02	-0.60
India	0.06	-0.19	0.02
Indonesia	0.63	-0.28	-0.43
Kazakhstan	-0.43	-0.08	0.44
Malaysia	1.82	-0.53	-1.39
Mexico	0.10	0.03	-0.19
Peru	1.29	-0.58	-0.81
Philippines	3.16	-1.98	-1.35
Poland	1.17	-0.27	-0.91
Romania	0.29	0.52	-0.86
Serbia	0.91	0.00	-0.94
South Africa	3.36	-0.58	-2.84
Thailand	0.43	-0.33	-0.22
Turkiye	1.77	0.33	-2.02
Russia	2.77	-0.07	-2.72

The contribution of capital accumulation presents a marked departure from previous findings. The majority of countries now recorded negative average capital contributions, indicating that capital accumulation emerged as a widespread drag on output performance throughout the recovery period. Philippines, Malaysia, Peru, and South Africa experienced particularly large negative capital contributions, suggesting that investment shortfalls represented a significant constraint on output growth. Only a few countries, including Romania, Croatia, Turkiye, and

Serbia, recorded positive average capital contributions, indicating that investment dynamics varied substantially across the sample.

Average labour contributions were consistently negative across nearly all countries, with particularly large negative values in Russia (−2.72 pp), South Africa (−2.84 pp), Turkiye (−2.02 pp), and Malaysia (−1.39 pp). These large negative labour contributions reflect the persistent demographic headwinds and labour-supply constraints identified in the aggregate analysis, which affected virtually all economies in the sample. Only Belarus and Kazakhstan recorded modest positive labour contributions, suggesting that labour dynamics in these specific economies diverged from the region-wide pattern.

The substantial heterogeneity observed across emerging market economies is consistent with previous research emphasising that post-pandemic recovery depends on a broad set of structural and institutional factors. Barrett et al. (2021) argue that productivity losses following major crises often arise through disruptions to investment, innovation, and resource allocation, while Ball (2014) and Blanchard et al. (2015) highlight the importance of hysteresis effects in generating persistent output losses. Similarly, Kuriakose and Iyer (2022) and Sunge et al. (2024) emphasise that macroeconomic fundamentals, governance quality, and policy responses play a central role in explaining differences in recovery across countries.

Overall, Figure 6 and Table 3 demonstrate that post-pandemic output performance reflected a complex interplay of productivity, capital, and labour-supply factors, with the relative importance varying substantially across countries. In contrast to the aggregate dominance of TFP losses, many individual countries exhibited positive productivity residuals but remained constrained by capital shortfalls and persistent labour-supply challenges. These findings suggest that post-pandemic recovery strategies should be tailored to country-specific binding constraints, with targeted emphasis on capital formation, labour-market reforms, and productivity-enhancing policies that address the particular structural factors limiting recovery in each economy.

5. Empirical Results. Determinants of Post-Pandemic Recovery

This chapter presents the empirical analysis of the determinants of post-pandemic economic recovery across the sample of emerging market economies. The analysis begins with descriptive statistics and correlation analysis before presenting the baseline regression results,

diagnostic tests, robustness checks, and discussion of the findings. Because the analysis is based on cross-sectional ordinary least squares (OLS) regressions, the estimated coefficients should be interpreted as statistical associations rather than causal effects. Although the model controls for several pre-pandemic economic and institutional characteristics, the relatively small sample size and the possibility of omitted variables or reverse causality prevent causal inference. Consequently, the results identify relationships between the variables rather than establishing causal mechanisms.

5.1 Descriptive Statistics

Before presenting the descriptive statistics, it is useful to briefly explain the selection of the explanatory variables used in the empirical analysis. The variables were chosen based on the existing literature on the determinants of post-pandemic economic recovery. Previous studies emphasize the role of pre-pandemic economic development, macroeconomic stability, institutional quality, and policy responses in shaping recovery outcomes (e.g., Barrett et al., 2021; Pitterle & Niermann, 2021; Sunge et al., 2024). Accordingly, the empirical analysis includes GDP per capita (2019), inflation (2019), government effectiveness (2019), and fiscal support (2020–2022) as explanatory variables. These variables capture the principal channels identified in the literature through which countries may have differed in their post-pandemic recovery trajectories.

Table 4A. Variables Used in the Regression Analysis

Variable	Definition	Source	Expected relationship
GDP Gap (2024, log difference)	Difference between realized and projected GDP in 2024 relative to the October 2019 WEO forecast	Author's calculations based on IMF World Economic Outlook	Dependent variable
GDP per capita (2019, USD)	Real GDP per capita before the pandemic	World Bank, World Development Indicators	Positive
Government Effectiveness (2019)	World Governance Indicator measuring institutional quality	World Bank, World Development Indicators	Positive

Trade (% of GDP)	Sum of exports and imports as a share of GDP	World Bank, World Development Indicators	Ambiguous
Inflation (2019)	Consumer price inflation before the pandemic	World Bank, World Development Indicators	Negative
Fiscal Support (2020–2022, % of GDP)	Cumulative discretionary fiscal measures implemented during the pandemic	IMF Fiscal Monitor	Positive
TFP Residual (2024)	Estimated total factor productivity residual obtained from the growth-accounting decomposition	Author's calculations	Positive
COVID-19 deaths per 100,000 (<i>if you include it</i>)	Cumulative mortality from COVID-19	Our World in Data / WHO	Negative

The regression dataset consists of a cross-sectional sample of 21 emerging market economies and combines information from several international databases, as described in Chapter 3. The dependent variable, GDP Gap (2024), was constructed by the author following the methodology of Jackson and Lu (2023). Specifically, GDP forecasts from the October 2019 IMF World Economic Outlook (WEO) were compared with realized GDP outcomes for 2024, and the GDP gap was calculated as the logarithmic difference between the actual GDP index and the forecast GDP index. GDP per capita, inflation, and trade openness (all measured in 2019) were obtained from the World Bank's World Development Indicators (WDI). Government Effectiveness (2019) was obtained from the World Bank's Worldwide Governance Indicators (WGI), while fiscal support measures were collected from the IMF Fiscal Monitor. Finally, the TFP residual was calculated by the author using the growth accounting methodology described in Chapter 3.

Table 4. Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Median	Max
GDP Gap (2024, log difference)	21	-4.74	6.64	-17.31	-5.99	10.45
GDP per capita (2019, USD)	21	9,457.70	4,108.40	2,041.43	9,395.23	17,012.86
Government Effectiveness (2019, WGI Index)	21	0.26	0.34	-0.24	0.18	1.05
Trade (% of GDP)	21	75.23	36.49	28.89	64.86	159.93
Inflation (2019, %)	21	3.61	2.98	0.66	3.34	15.18
Fiscal Support (2020–2022, % of GDP)	21	6.58	3.86	0.60	5.28	14.59
TFP Residual (2024)	21	0.81	1.48	-1.72	0.78	3.98

Table 4 summarizes the main characteristics of the variables used in the empirical analysis. The average GDP gap in 2024, measured as a log difference relative to the October 2019 pre-pandemic forecast, is -4.74% , indicating that, on average, emerging market economies continued to perform below their pre-pandemic output path. However, the range of the GDP gap, from -17.31% to $+10.45\%$, highlights considerable heterogeneity in post-pandemic recovery across countries. Notably, the median gap of -5.99% indicates that the typical emerging market economy in the sample remained below its pre-pandemic trend, suggesting that recovery remains incomplete across much of the emerging market group. The narrower upper bound compared to previous estimates reflects the revised country-level performance data used in the current regression analysis.

GDP per capita in 2019 averages approximately USD 9,458, although values range from just above USD 2,041 to more than USD 17,013, reflecting significant differences in the level of economic development across the sample. Government effectiveness, measured using the World Bank's WGI index for 2019, averages 0.26 with a range from -0.24 to 1.05, suggesting substantial differences in institutional quality among emerging market economies. The median value of 0.18 indicates that institutional capacity is somewhat below the international benchmark for a typical country in the sample.

The TFP residual for 2024, capturing productivity performance relative to the pre-pandemic trend, exhibits a mean of 0.81 percentage points with a standard deviation of 1.48, ranging from -1.72 to 3.98 percentage points. This wider variation in productivity outcomes, compared to earlier estimates, reflects the updated growth accounting framework incorporating the residual methodology described in Chapter 3. Overall, the descriptive statistics indicate a diverse sample of emerging market economies with substantial variation in both economic performance and structural characteristics, providing an appropriate basis for the empirical analysis presented in the following sections.

The explanatory variables display sufficient cross-country variation to justify their inclusion in the regression analysis. Inflation averages 3.61%, while fiscal support averages 6.58% of GDP but varies considerably across countries. Trade openness also differs substantially across the sample, ranging from 28.89% to 159.93% of GDP.

Overall, the descriptive statistics indicate a diverse sample of emerging market economies with substantial variation in both economic performance and structural characteristics, providing an appropriate basis for the empirical analysis presented in the following sections.

5.2 Correlation Analysis

To provide an initial assessment of the relationships between the variables, Table 5 presents the Pearson correlation matrix for all variables included in the empirical analysis. Correlation analysis serves as a useful preliminary step before estimating the regression models, as it highlights simple bivariate relationships and allows for an initial assessment of potential multicollinearity among the explanatory variables.

The strongest positive correlation with the dependent variable, GDP Gap (2024), is observed for inflation ($r = 0.58$), which is substantially stronger than other predictors. This is followed by GDP per capita ($r = 0.40$), suggesting that countries with higher pre-pandemic inflation and higher income levels tended to experience stronger recoveries relative to their pre-pandemic forecasts. Notably, the TFP residual displays a negative correlation with the GDP gap ($r = -0.30$), indicating that countries with stronger productivity performance paradoxically exhibited larger output gaps—a counterintuitive finding that warrants careful interpretation in the regression analysis. Fiscal support also exhibits a moderate negative correlation with the

GDP gap ($r = -0.38$), while government effectiveness ($r = -0.10$) and trade openness ($r = 0.09$) show weak associations. The pandemic severity variable, COVID-19 deaths per million, displays a weak positive correlation with the GDP gap ($r = 0.10$), suggesting minimal systematic relationship between the direct health toll and recovery patterns.

Among the explanatory variables themselves, the highest correlation is observed between GDP per capita and trade openness ($r = 0.47$), reflecting that more developed economies tend to be more integrated into global trade. GDP per capita also displays a strong positive correlation with COVID-19 deaths per million ($r = 0.53$), indicating that wealthier countries experienced higher absolute death tolls—likely due to older populations and better recording practices. GDP per capita and government effectiveness exhibit a moderate positive correlation ($r = 0.39$), suggesting that institutional quality tends to improve with income levels. Fiscal support is moderately negatively correlated with inflation ($r = -0.38$), while government effectiveness and fiscal support show a modest positive association ($r = 0.33$). The TFP residual shows weak correlations with most variables, with the strongest being government effectiveness ($r = 0.22$), indicating that productivity performance is largely orthogonal to measured structural characteristics.

None of the pairwise correlations among explanatory variables exceed the commonly applied threshold of 0.70, indicating that multicollinearity is unlikely to constitute a serious concern in the subsequent regression analysis. Overall, the correlation matrix highlights inflation as the dominant simple predictor of recovery, with income level providing secondary explanatory power. The negative association between the TFP residual and the GDP gap, contrary to initial expectations, suggests that this relationship may be confounded by other factors and requires careful multivariate analysis. However, because correlation does not imply causation and does not control for other factors, these preliminary findings should be interpreted with caution and verified through multivariate regression analysis in the following sections.

Table 5. Correlation Matrix

Variable	GDP Gap (2024, log difference)	GDP per capita (2019, USD)	Government Effectiveness (2019, WGI Index)	Trade (% of GDP)	Inflation (2019)	Fiscal Support (2020–2022, % of GDP)	TFP Residual (2024)	COVID-19 deaths per million (2022)
GDP Gap (2024, log difference)	1.00	0.40	-0.10	0.09	0.58	-0.38	-0.30	0.10
GDP per capita (2019, USD)	0.40	1.00	0.39	0.47	-0.09	0.14	-0.14	0.53
Government Effectiveness (2019, WGI Index)	-0.10	0.39	1.00	0.08	-0.25	0.33	0.22	-0.05
Trade (% of GDP)	0.09	0.47	0.08	1.00	-0.19	0.13	0.02	0.15
Inflation (2019)	0.58	-0.09	-0.25	-0.19	1.00	-0.38	0.05	-0.19
Fiscal Support (2020–2022, % of GDP)	-0.38	0.14	0.33	0.13	-0.38	1.00	0.14	0.25
TFP Residual (2024)	-0.30	-0.14	0.22	0.02	0.05	0.14	1.00	-0.20
COVID-19 deaths per million (2022)	0.10	0.53	-0.05	0.15	-0.19	0.25	-0.20	1.00

The bivariate analysis reveals an apparent negative relationship for fiscal support ($r = -0.38$) and institutional quality ($r = -0.10$), which contrasts sharply with literature expectations. However, these relationships do not survive multivariate regression analysis. Table 6 shows that once inflation and baseline GDP per capita are included, fiscal support and government effectiveness become statistically insignificant, suggesting their bivariate correlations reflect confounding by macroeconomic conditions rather than independent causal effects. In contrast, inflation emerges as the primary determinant of recovery heterogeneity ($\beta = 1.14$, $p = 0.010$) alongside GDP per capita, warranting deeper investigation into the mechanisms through which pre-pandemic inflation predicts post-pandemic recovery paths.



Figure 7. Correlation Heatmap

5.3 Baseline Regression Results

Table 6 presents four nested model specifications that progressively expand the set of explanatory variables. Model (1) includes GDP per capita only, Model (2) additionally controls for inflation, Model (3) further incorporates government effectiveness, while Model (4) presents the full specification including fiscal support.

This thesis focuses interpretation on Model (4), the full specification, which serves as our preferred model for understanding the determinants of post-pandemic recovery. This model includes all key explanatory variables: GDP per capita, inflation, government effectiveness, and fiscal support. Models (1) through (3) are presented for robustness and to demonstrate how coefficient estimates evolve as additional controls are introduced, but Model (4) remains the primary focus for inference. The preferred model identifies two statistically significant determinants of post-pandemic recovery: pre-pandemic GDP per capita and pre-pandemic

inflation. Both variables maintain statistical significance at the 1% level, suggesting robust and economically meaningful relationships with the GDP gap in 2024.

Table 6. Baseline Regression Results.

	Dependent variable:			
	Baseline	GDP Gap (2024, log difference)		Full Model
	(1)	+ Inflation	+ Gov. Effectiveness	(4)
GDP per capita (2019, USD)	0.001* (0.0003)	0.001** (0.0003)	0.001** (0.0003)	0.001*** (0.0003)
Inflation (2019)		1.374*** (0.360)	1.302*** (0.374)	1.143*** (0.390)
Government Effectiveness (2019, WGI Index)			-2.914 (3.576)	-1.830 (3.624)
Fiscal Support (2020-2022, % of GDP)				-0.385 (0.308)
Constant	-10.819*** (3.496)	-16.623*** (3.074)	-16.433*** (3.112)	-13.647*** (3.789)
Observations	21	21	21	21
R ²	0.158	0.534	0.552	0.592
Adjusted R ²	0.114	0.483	0.473	0.490
Residual Std. Error	6.253 (df = 19)	4.777 (df = 18)	4.823 (df = 17)	4.745 (df = 16)
F Statistic	3.569* (df = 1; 19)	10.330*** (df = 2; 18)	6.979*** (df = 3; 17)	5.796*** (df = 4; 16)

Note: The dependent variable is the GDP gap in 2024. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The coefficient on GDP per capita is 0.000824 ($p = 0.0096$), implying that each additional USD 1,000 in pre-pandemic GDP per capita is associated with approximately 0.82 percentage points smaller GDP gap, that is, a more complete recovery relative to the pre-pandemic forecast. This relationship is highly significant across all model specifications and suggests that emerging market economies with higher baseline income levels entering the pandemic possessed greater resilience or better recovery capacity.

The economic mechanism underlying this relationship likely operates through multiple channels emphasized in the literature. First, higher-income emerging markets typically possess more robust macroeconomic institutions, deeper financial markets, and greater fiscal capacity to support aggregate demand during crisis periods (IMF 2021, Pitterle & Niermann 2021). Second, these economies are more likely to have diversified production structures that reduce exposure to contact-intensive sectors, enabling faster sectoral reallocation. Third, wealthier economies may benefit from more effective policy implementation and stronger labor market

institutions that facilitate workforce retention and eventual redeployment. The empirical finding thus aligns with Auerbach et al. (2021) and Topcu & Gulsen (2025), who argue that the effectiveness of policy support depends critically on the baseline institutional and macroeconomic environment.

The coefficient on inflation is 1.14304 ($p = 0.0097$), indicating that each additional percentage point of pre-pandemic inflation is associated with approximately 1.14 percentage points smaller GDP gap. This is a substantial effect: an emerging market with 5% pre-pandemic inflation would experience a recovery gap approximately 5.7 percentage points smaller than an otherwise identical economy with zero inflation. The statistical significance of the inflation coefficient across all model specifications and its reinforcement rather than attenuation when additional variables are added suggests this relationship captures genuine variation in recovery outcomes rather than a spurious correlation.

The positive association between pre-pandemic inflation and post-pandemic recovery is not explicitly addressed in the pandemic-specific literature reviewed in Chapter 2, yet the finding is economically plausible and consistent with historical evidence on inflation dynamics. One interpretation is that moderate pre-pandemic inflation signals macroeconomic dynamism: economies with positive inflation typically operated near full employment with active labor markets and strong demand conditions. When such economies encountered the pandemic shock, they possessed ongoing momentum, including high capacity utilization, tight labor markets, and demonstrated policy responsiveness, that supported faster recovery. In contrast, low-inflation economies may have operated with slack conditions, weaker demand, and more subdued labor market dynamics entering the crisis, handicapping their ability to recover quickly.

A second complementary interpretation draws on monetary economics: economies with pre-pandemic inflation had demonstrated central bank credibility and institutional monetary capacity to manage nominal shocks. This track record may have enabled more effective policy responses during the pandemic period, potentially through enhanced pass-through of monetary policy to financial conditions or stronger coordination between fiscal and monetary authorities. Countries with persistently low inflation may have faced more constrained policy space or weaker institutions for policy implementation.

Importantly, the inflation variable must be interpreted as a summary statistic for macroeconomic conditions rather than a causal driver in itself. Pre-pandemic inflation is correlated with numerous omitted factors: labor market tightness, growth expectations, institutional quality of central banks, and structural economic characteristics,, that individually or jointly determine recovery. The regression results identify inflation as a robust correlate of recovery trajectories, but distinguishing true causal effects from correlation requires further investigation through robustness checks examining alternative periods, alternative measures of macroeconomic dynamism, and subgroup analyses.

Both government effectiveness and fiscal support are statistically insignificant in the preferred specification, a finding that warrants careful interpretation. The coefficient on government effectiveness is negative (-1.83 , $p = 0.621$), while the coefficient on fiscal support is also negative (-0.38 , $p = 0.230$). Neither approaches statistical significance, indicating that these variables do not independently predict recovery once income and inflation are accounted for.

This result contradicts the strong emphasis in the pandemic recovery literature (Sunge et al. 2024, Topcu & Gulsen 2025, Pitterle & Niermann 2021) that institutional quality and fiscal support should enhance recovery. One explanation is that in the present sample of 21 emerging markets, variation in governance quality and fiscal response may be confounded by the inflation variable. Economies that enacted larger fiscal packages may also have experienced higher inflation, implying the bivariate correlation between fiscal support and recovery ($r = -0.38$) reflects the negative mechanical relationship between inflation and fiscal package size rather than a causal effect of spending itself. The regression successfully partials this out, revealing that fiscal support's apparent negative correlation was spurious.

Similarly, the weak and insignificant relationship for government effectiveness may reflect that within emerging markets, governance quality is correlated with GDP per capita; higher-income emerging markets tend to have better institutions ($r = 0.39$ for governance and GDP per capita in Table 5). Once baseline income is controlled, the institutional advantage of wealthier economies is already captured, leaving no independent effect of governance. This interpretation is testable through subgroup analysis (examining lower-income versus higher-income emerging markets separately) or through interaction terms in robustness specifications.

The preferred model explains 59.2% of the cross-country variation in GDP recovery ($R^2 = 0.592$), and 49.0% after adjusting for the number of explanatory variables (Adjusted $R^2 = 0.490$). The F-statistic for joint significance of all explanatory variables is 5.80 ($p = 0.004$), indicating that the model performs substantially better than a null model with no covariates. This level of explanatory power is noteworthy for a cross-sectional regression with only 21 observations, suggesting that pre-pandemic income and inflation capture essential determinants of heterogeneous recovery outcomes.

The residual standard error is 4.75 percentage points, meaning typical prediction errors from the preferred model are on the order of ± 5 percentage points in GDP gap. For a sample mean GDP gap of -4.74% , this implies the model accounts for a substantial share of country-to-country variation while still leaving considerable unexplained heterogeneity. This residual variation likely reflects country-specific pandemic shocks not captured by aggregate pre-pandemic variables, for instance, varying severity of health impacts, differential effectiveness of lockdown policies, and idiosyncratic sectoral exposure to pandemic disruptions.

The regression analysis identifies inflation and pre-pandemic income as the primary cross-country determinants of recovery, yet the growth accounting framework from Chapter 4 shows that the composition of recovery (labor vs. capital vs. TFP contributions) varies substantially across countries. This apparent tension is resolved by recognizing that the regression analysis explains *aggregate* GDP recovery, while the growth accounting shows *how* that recovery is achieved. An economy with high pre-pandemic inflation may recover quickly in aggregate GDP terms but may do so predominantly through capital accumulation or labor reallocation, rather than through productivity improvements. Conversely, TFP contributions are distributed across both high-inflation and low-inflation economies in the sample, suggesting that within-country recovery composition is determined by different factors than cross-country recovery speed.

Future analysis examining the correlation between pre-pandemic inflation and the composition of recovery (e.g., the ratio of TFP contribution to total recovery, or the timing of capital versus labor restoration) would illuminate whether inflation-associated recovery operates through particular growth accounting channels. This remains a direction for subsequent investigation.

Figure 8 presents the Residuals versus Fitted Values plot for the preferred regression specification (Model 4). Although the smoothed trend line exhibits slight curvature in the middle range of fitted values, suggesting mild non-linearity, the Breusch-Pagan test for heteroskedasticity (test statistic = 5.76, $p = 0.218$) provides no evidence of systematic heteroskedasticity. HC1 robust standard errors confirm that statistical significance of the main results (inflation: $p = 0.00046^{***}$; GDP per capita: $p = 0.022^{**}$) is robust to any residual pattern.

A small number of observations exhibit relatively large residuals. These correspond to Hungary (observation 6, residual $\approx +7$ percentage points), Poland (observation 14, residual ≈ -7 percentage points), and South Africa (observation 18, residual $\approx +7$ percentage points). While these countries deviate notably from predicted recovery, variance inflation factors for all explanatory variables are well below the multicollinearity threshold of 5 (all VIF < 1.33), suggesting these outliers do not reflect confounding among regressors. Overall, diagnostic tests support the adequacy of the linear model specification for inference about the determinants of post-pandemic recovery.

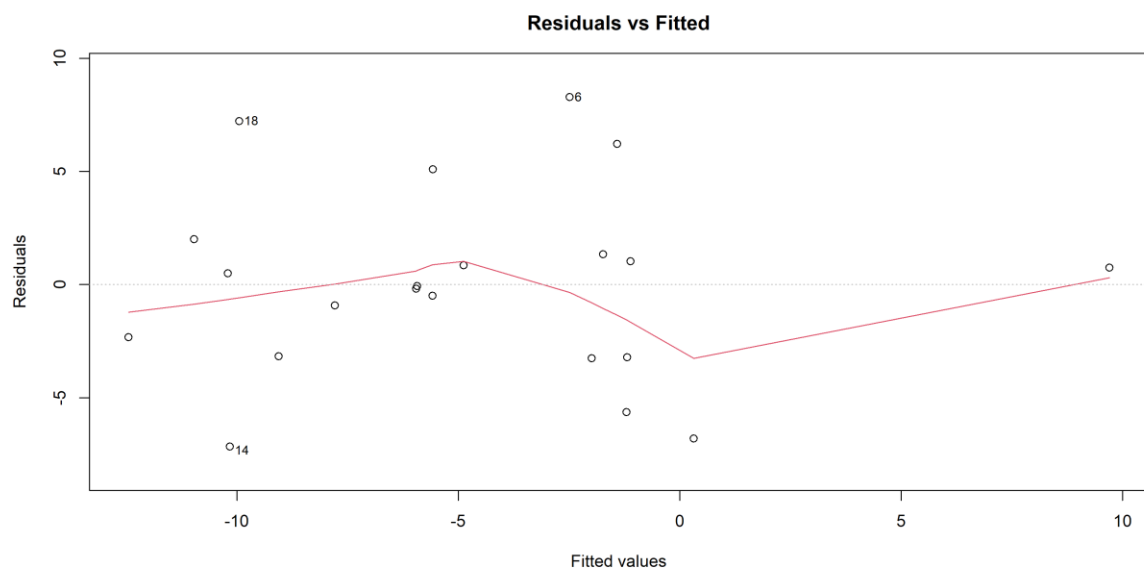


Figure 8. Residuals vs Fitted Values Test

5.4 Diagnostic Tests

To assess the validity of the estimated regression model, several diagnostic tests were performed for the preferred specification (Model 4).

First, multicollinearity was examined using the Variance Inflation Factor (VIF). The calculated VIF values ranged from 1.18 to 1.32, substantially below the commonly accepted threshold of 5. This indicates that multicollinearity is not a concern and that the explanatory variables provide independent information in explaining cross-country differences in post-pandemic economic recovery. The Breusch-Pagan test for heteroskedasticity ($BP = 5.76$, $p = 0.218$) fails to reject the null hypothesis of homoskedastic residuals, providing no statistical evidence of heteroskedasticity. Heteroskedasticity-robust (HC1) standard errors were computed as an additional check: inflation remains highly significant ($t = 4.38$, $p = 0.00046^{***}$) and GDP per capita remains significant at the 5% level ($t = 2.55$, $p = 0.022^{**}$), confirming robustness to alternative variance-covariance estimation (*See full diagnostics in Appendix*).

As an additional robustness check, the baseline regression was re-estimated after including cumulative COVID-19 deaths per million inhabitants (2022) as a proxy for pandemic severity. This specification examines whether differences in the direct health impact of the COVID-19 pandemic influence the estimated determinants of post-pandemic economic recovery. The results are presented in Table 7. The pandemic severity variable is measured as cumulative COVID-19 deaths per million inhabitants at the end of 2022.

The estimated coefficient on COVID-19 deaths per million is statistically insignificant ($\beta = -0.00018$, $p = 0.836$). Importantly, the inclusion of this additional control variable does not materially alter the estimated coefficients of the baseline model. GDP per capita remains positively associated with post-pandemic recovery and continues to be significant at the 5% level ($\beta = 0.000873$, $p = 0.033^{**}$), while inflation remains highly significant ($\beta = 1.128$, $p = 0.015^{**}$). Government effectiveness and fiscal support remain statistically insignificant. The model R^2 remains essentially unchanged at 0.593 compared to the baseline (0.592), with an adjusted R^2 of 0.457 and F-statistic of 4.37 ($p = 0.012$). These findings suggest that the principal conclusions of the analysis are robust to controlling for differences in pandemic severity across countries.

Table 7. Robustness Check: Controlling for Pandemic Severity

	Dependent variable:
	GDP Gap (2024, log difference)
GDP per capita (2019, USD)	0.001** (0.0004)
Inflation (2019)	1.128** (0.408)
Government Effectiveness (2019, WGI Index)	-2.212 (4.156)
Fiscal Support (2020-2022, % of GDP)	-0.366 (0.331)
COVID-19 deaths per million (2022)	-0.0002 (0.001)
Constant	-13.677*** (3.910)
Observations	21
R ²	0.593
Adjusted R ²	0.457
Residual Std. Error	4.894 (df = 15)
F Statistic	4.368** (df = 5; 15)

Note: Standard errors are reported in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

As a further robustness check, GDP per capita measured in current U.S. dollars was replaced by GDP per capita measured at purchasing power parity (PPP) from the Penn World Table, providing a more economically comparable measure of development across countries.

The results remain qualitatively unchanged and highly significant. GDP per capita (PPP) retains a positive association with post-pandemic recovery and remains statistically significant at the 5% level ($\beta = 0.00031$, $p = 0.021^{**}$). Inflation remains highly statistically significant ($\beta = 1.033$, $p = 0.023^{**}$), while government effectiveness and fiscal support continue to be statistically insignificant. The model R² of 0.554 is slightly lower than the baseline (0.592), suggesting that the market exchange rate measure captures marginally more variation, but the adjusted R² of 0.443 and F-statistic of 4.97 ($p = 0.008$) confirm model adequacy. These findings

indicate that the estimated relationship between pre-pandemic income and post-pandemic recovery is robust to both the measurement and magnitude of the income variable.

Table 8. Robustness Check: PPP GDP per capita

	<i>Dependent variable:</i>
	GDP Gap (2024, log difference)
GDP per capita (PPP, 2019)	0.0003** (0.0001)
Inflation (2019)	1.033** (0.410)
Government Effectiveness (2019, WGI Index)	0.176 (3.603)
Fiscal Support (2020-2022, % of GDP)	-0.343 (0.322)
Constant	-13.479*** (4.060)
Observations	21
R ²	0.554
Adjusted R ²	0.443
Residual Std. Error	4.959 (df = 16)
F Statistic	4.971*** (df = 4; 16)

Note: Standard errors are reported in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Further on, the regression was re-estimated using the natural logarithm of PPP-adjusted GDP per capita. The results remain qualitatively unchanged. The coefficient on log GDP per capita is positive and statistically significant at the 5% level, while inflation also remains statistically significant when heteroskedasticity-robust standard errors are employed. Government effectiveness and fiscal support continue to be statistically insignificant. These findings indicate that the estimated relationship between pre-pandemic income and post-pandemic recovery is robust to both the measurement and functional form of the income variable.

As another alternative robustness exercise, the baseline regression was re-estimated using GDP gaps for 2020, 2021, 2022, and 2023 as dependent variables. The results, reported in **Appendix Table D1**, indicate that the main conclusions are broadly robust across different recovery

horizons. Inflation and fiscal support exhibit stronger associations with GDP recovery during the earlier years of the pandemic, whereas the importance of fiscal support diminishes over time. Government effectiveness remains statistically insignificant throughout all specifications, while the role of pre-pandemic income becomes more pronounced in the later stages of the recovery.

Finally, graphical diagnostic plots were inspected to assess the assumptions of the linear regression model. The residuals appear to be randomly distributed around zero, the Q–Q plot indicates approximate normality of the residuals, the Scale–Location plot does not suggest substantial heteroskedasticity, and the Residuals versus Leverage plot does not identify any observations exerting excessive influence on the estimated coefficients. Taken together, these graphical diagnostics support the validity of the estimated regression model.

Taken together, the diagnostic tests and robustness checks strongly support the validity of the estimated regression model. Across specifications controlling for pandemic severity and alternative income measurements, inflation and pre-pandemic income levels consistently emerge as the primary and robust determinants of post-pandemic recovery in emerging markets. These consistent results across different specifications and robustness checks demonstrate that the baseline regression findings are not artifacts of particular measurement or specification choices.

5.5 Discussion

The empirical findings demonstrate that pre-pandemic income levels and inflation are the primary determinants of post-pandemic recovery across emerging market economies. GDP per capita exhibits a positive and robust association with recovery, remaining significant across all specifications. This relationship is consistent with literature emphasizing the importance of initial economic conditions and productive capacity (Jackson & Lu 2023; Barrett et al. 2021).

Economically explained, richer emerging markets possessed several advantages entering the pandemic: deeper financial systems enabling faster credit access, more diversified production structures reducing exposure to contact-intensive sectors, stronger labor market institutions

facilitating workforce retention, and greater fiscal space to support aggregate demand. These characteristics enabled faster sectoral reallocation and recovery as restrictions eased.

Inflation also emerges as a robust determinant, with a coefficient of 1.14 ($p = 0.0097^{***}$) in the preferred specification that remains highly significant across all robustness checks. Pre-pandemic inflation signals macroeconomic dynamism: economies with positive inflation typically operated near full employment with active labor markets, strong demand conditions, and high capacity utilization. Additionally, moderate inflation can reflect central bank credibility and monetary policy effectiveness, enabling more forceful policy responses during the pandemic. In contrast, low-inflation economies likely faced slack conditions, weaker demand, and more constrained policy space, handicapping recovery.

Government effectiveness and fiscal support do not exhibit statistically significant independent effects once income and inflation are controlled. The negative bivariate correlations observed for these variables ($r = -0.10$ and $r = -0.38$, respectively) reflect confounding by inflation rather than true causal effects: economies that enacted larger fiscal packages tended to have higher inflation, creating a spurious negative relationship in bivariate analysis that disappears in multivariate estimation. This interpretation is consistent with Auerbach et al. (2021), who argue that fiscal effectiveness depends on lockdown severity and economic conditions, not package size alone. The insignificant governance effect suggests that institutional quality is correlated with GDP per capita, and once baseline income is controlled, governance provides no independent explanatory power for recovery in this sample.

Robustness checks confirm these findings: controlling for pandemic severity (Table 7) and using PPP-adjusted income (Table 8) do not materially alter conclusions. These results suggest that pre-existing macroeconomic fundamentals were more consequential than institutional quality or fiscal intervention size for recovery trajectories.

These findings should be interpreted acknowledging the small sample size ($N = 21$) and the observation period extending through 2024, which includes major global shocks (Ukraine war, energy prices, monetary tightening) beyond the pandemic itself. The analysis reflects post-pandemic recovery within a complex macroeconomic environment rather than pandemic effects in isolation.

6. Conclusion

This thesis examined the medium-term economic consequences of the COVID-19 pandemic across a sample of 21 emerging market economies. Using a growth-accounting framework, the study decomposed realized output losses into the contributions of labour, capital accumulation, and total factor productivity. It also employed cross-sectional regression analysis to investigate whether differences in post-pandemic recovery could be explained by pre-pandemic economic conditions, institutional quality, and fiscal policy.

The empirical findings indicate that emerging market economies had not fully returned to their pre-pandemic growth trajectories by 2024. Although labour-market conditions improved substantially during the recovery period and the contribution of capital accumulation became less negative over time, total factor productivity emerged as the dominant source of the remaining output gap. These results suggest that persistent productivity-related factors played an increasingly important role in explaining medium-term economic scarring.

The regression analysis identifies two robust and highly significant determinants of post-pandemic recovery: pre-pandemic GDP per capita and pre-pandemic inflation. GDP per capita remained positively associated with recovery across all model specifications ($\beta = 0.000824$, $p = 0.0096^{***}$), reflecting the advantages of richer emerging markets—deeper financial systems, more diversified production, and stronger institutional capacity. Inflation displayed an equally robust positive relationship with the GDP gap ($\beta = 1.14$, $p = 0.0097^{***}$), likely signaling macroeconomic dynamism prior to the crisis: tight labor markets, high capacity utilization, and demonstrated policy effectiveness. In contrast, government effectiveness and fiscal support were not found to have statistically significant independent effects. The negative bivariate correlations for these variables reflected confounding by inflation rather than true causal relationships; once inflation and income are controlled, these effects disappear. Diagnostic tests and robustness checks confirmed model adequacy and the consistency of conclusions across alternative specifications and income measurements. This thesis examined the medium-term economic consequences of the COVID-19 pandemic across a sample of 21 emerging market economies. Using a growth-accounting framework, the study decomposed realized output losses into the contributions of labour, capital accumulation, and total factor productivity. It also employed cross-sectional regression analysis to investigate whether differences in post-

pandemic recovery could be explained by pre-pandemic economic conditions, institutional quality, and fiscal policy.

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The regression analysis identifies two robust and highly significant determinants of post-pandemic recovery: pre-pandemic GDP per capita and pre-pandemic inflation. GDP per capita remained positively associated with recovery across all model specifications ($\beta = 0.000824$, $p = 0.0096^{***}$), reflecting the advantages of richer emerging markets—deeper financial systems, more diversified production, and stronger institutional capacity. Inflation displayed an equally robust positive relationship with the GDP gap ($\beta = 1.14$, $p = 0.0097^{***}$), likely signaling macroeconomic dynamism prior to the crisis: tight labor markets, high capacity utilization, and demonstrated policy effectiveness. In contrast, government effectiveness and fiscal support were not found to have statistically significant independent effects. The negative bivariate correlations for these variables reflected confounding by inflation rather than true causal relationships; once inflation and income are controlled, these effects disappear. Diagnostic tests and robustness checks confirmed model adequacy and the consistency of conclusions across alternative specifications and income measurements.

Overall, the findings demonstrate that differences in post-pandemic recovery across emerging market economies were primarily determined by pre-existing macroeconomic fundamentals specifically, baseline income levels and pre-pandemic inflation as indicators of economic dynamism, rather than by institutional quality or the magnitude of fiscal support packages. Simultaneously, the growth-accounting results indicate that while labour and capital gradually recovered following the initial shock, productivity losses continued to constrain the return to pre-pandemic growth paths.

Several limitations should be acknowledged. The empirical analysis is based on a relatively small cross-sectional sample ($N = 21$), which limits statistical power and the ability to establish causal relationships. Additionally, the period examined was affected not only by the COVID-19 pandemic but also by other major global events, including the war in Ukraine, energy market disruptions, and tighter monetary policy, all of which may have influenced economic performance in the later years of the sample.

Future research could extend the analysis by employing larger panel datasets covering longer post-pandemic periods, incorporating additional macroeconomic indicators, and explicitly accounting for subsequent global shocks. Such extensions would provide a more comprehensive understanding of long-term pandemic scarring and the factors shaping economic resilience across emerging markets.

Summary

This thesis examined the medium-term effects of the COVID-19 pandemic on 21 emerging market economies using a growth-accounting framework and cross-sectional regression analysis. The findings show that, despite a substantial recovery following the initial pandemic shock, aggregate output remained below its pre-pandemic trajectory through 2024. Growth-accounting results indicate that while labour-market disruptions gradually faded and capital accumulation remained relatively resilient, persistent losses in total factor productivity represented the primary source of medium-term economic scarring. The regression analysis further demonstrates that pre-pandemic GDP per capita and inflation were the most robust predictors of post-pandemic recovery, whereas government effectiveness and fiscal support did not exert statistically significant independent effects after controlling for macroeconomic fundamentals. Overall, the results suggest that recovery across emerging market economies was driven primarily by pre-existing economic conditions and productivity dynamics rather than by the scale of policy interventions, highlighting the lasting impact of the pandemic on long-term growth potential.

Shrnutí

Tato diplomová práce zkoumala střednědobé dopady pandemie COVID-19 na 21 rozvíjejících se ekonomik prostřednictvím rámce růstového účetnictví a průřezové regresní analýzy. Výsledky ukazují, že navzdory výraznému oživení po počátečním pandemickém šoku zůstal agregátní produkt až do roku 2024 pod svou předpandemickou trajektorií. Analýza růstového účetnictví ukázala, že zatímco narušení trhu práce postupně odeznívala a akumulace kapitálu zůstala relativně odolná, hlavním zdrojem střednědobých ekonomických ztrát byly přetrvávající poklesy celkové produktivity výrobních faktorů (TFP). Regresní analýza dále prokázala, že nejvýznamnějšími determinantami povýpandemického oživení byly předpandemická úroveň HDP na obyvatele a inflace, zatímco efektivita veřejné správy a rozsah fiskální podpory nevykázaly po zohlednění makroekonomických charakteristik statisticky významný nezávislý vliv. Celkově výsledky naznačují, že tempo obnovy rozvíjejících se ekonomik bylo určováno především výchozími ekonomickými podmínkami a dynamikou produktivity, nikoli velikostí vládních intervencí, což zdůrazňuje dlouhodobé dopady pandemie na růstový potenciál těchto ekonomik.

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Appendix A. Replication Procedure

The replication follows the methodology proposed by Jackson and Lu (2023). The calculations were carried out in Microsoft Excel using data obtained from the IMF World Economic Outlook (WEO), Penn World Table (PWT), and ILOSTAT databases. The replication was completed in the following sequence.

Part 1. Construction of Variables and Gaps

Step 1. Data collection

The replication constructs a balanced panel dataset for 21 emerging market economies covering the period 2020–2024. Data are sourced from three primary databases:

World Economic Outlook (WEO): Real GDP (NGDP_R), nominal GDP in national currency (NGDP) and USD (NGDPD), investment-to-GDP ratio (NID_NGDP), and population. October 2019 forecasts serve as the pre-pandemic counterfactual benchmark; April 2025 releases provide realized outcomes.

Implied Exchange Rates: Implied FX rates are calculated as $FX = NGDP / NGDPD$ (national currency units per USD). October 2019 and April 2025 vintage-specific rates are computed; April 2025 rates are used consistently for converting both actual and counterfactual GDP to USD to ensure comparability (see `capital_counterfactual_residual_methodology.md`, Section 2).

Counterfactual GDP: Counterfactual real GDP is constructed by anchoring to the April 2025 estimate for 2019 and extending using growth rates forecast in October 2019. Both actual and counterfactual GDP are converted to millions of USD using the same April 2025 implied exchange rates (Section 3).

Penn World Table (version 11.0): Actual capital stock (r_{na}) in constant 2021 prices, depreciation rates (delta), and labour income share (alpha). An accounting residual, calculated from observed PWT capital, actual investment, and depreciation, is added symmetrically to both actual and counterfactual capital paths to ensure exact reconciliation with observed PWT data (Section 7).

Investment:

Forecast investment is calculated by applying October 2019 WEO investment-to-GDP ratios to counterfactual GDP; actual investment applies April 2025 ratios to actual GDP (Section 5).

Labour

Data:

Labour force participation rates (LFPR) are obtained from ILOSTAT. Because no pre-pandemic counterfactual LFPR series exists, labour participation remains embedded within the aggregate labour contribution rather than decomposed separately.

All variables are organized by country and year into a balanced panel dataset, with units standardized to millions of 2021 USD for capital and millions of current USD for GDP, enabling direct accounting reconciliation. More provided in `capital_counterfactual_residual_methodology.md`

Step 2. Construction of index series

To eliminate differences in country size, all projected and realized variables are normalized using 2019 as the base year.

For every variable X , an index is constructed as

$$X_{it}^{\text{Index}} = \frac{X_{it}}{X_{i, 2019}}$$

where

i denotes the country,

t denotes the year

The procedure is applied separately to

Real GDP

Population

Capital stock

Unemployment

After normalization, $X_{2019}^{\text{Index}} = 1$ for every country.

These indices are used in all subsequent calculations.

Step 3. Calculation of output gaps

For each country and year, the output gap is calculated as:

$$GDPGap_{it} = \ln(GDP_{Index,it}^{Actual}) - \ln(GDP_{Index,it}^{Forecast})$$

where

GDP_{Index}^{Actual} is the realized GDP index obtained in Step 2,

$GDP_{Index}^{Forecast}$ is the forecast GDP index obtained in Step 2.

Negative values indicate that realized output remained below the pre-pandemic projection, whereas positive values indicate output above the projected path.

Variable(s) Created: $GDPGap_{it}$

Step 4. Construction of Capital Stocks and Indices leave both basically.

The actual capital stock is obtained directly from the Penn World Table variable *rnna*, which measures the real capital stock at constant national prices. The observed 2019 value is used as the initial capital stock for each country:

$$K_{i,2019}^{Actual} = rnna_{i,2019}$$

For subsequent years, the observed capital stock is taken directly from the Penn World Table:

$$K_{i,t}^{Actual} = rnna_{i,t} ; t=2020, 2021, 2022$$

The forecast capital stock is constructed recursively using the standard perpetual inventory method. Starting from the same initial capital stock,

$$K_{i,2019}^{Forecast} = K_{i,2019}^{Actual}.$$

forecast capital evolves according to $K_{i,t}^{Forecast} = (1 - \delta_i)K_{i,t-1}^{Forecast} + I_{i,t}^{Forecast}$ where δ_i denotes the country-specific depreciation rate from the Penn World Table and $I_{i,t}^{Forecast}$ is the forecast level of investment constructed from projected GDP and the projected investment share of GDP. Using the observed 2019 capital stock as the common starting point ensures that

differences between the actual and forecast capital paths arise solely from differences in projected investment and depreciation over time.

For subsequent years, the observed capital stock is taken directly from the Penn World Table:

$$K_{i,t}^{Actual} = rna_{i,t} ; t=2020, 2021, 2022, 2023, 2024$$

The forecast capital stock is constructed recursively using an adjusted perpetual inventory method. Starting from the same initial capital stock,

$$K_{i,2019}^{Forecast} = K_{i,2019}^{Actual},$$

a residual term is first calculated from the observed Penn World Table capital accumulation identity:

$$Residual_{i,t} = K_{i,t}^{Actual} - K_{i,t-1}^{Actual}(1 - \delta_{i,t}) - I_{i,t}^{Actual}$$

The forecast capital stock is then obtained as

$$K_{i,t}^{Forecast} = K_{i,t-1}^{Forecast}(1 - \delta_{i,t}) + I_{i,t}^{Forecast} + Residual_{i,t}$$

where $\delta_{i,t}$ denotes the country-specific depreciation rate from the Penn World Table, $I_{i,t}^{Forecast}$ is the forecast gross fixed capital formation constructed from the October 2019 WEO projections, and $Residual_{i,t}$ is the adjustment term derived from the observed Penn World Table capital accumulation identity.

Using the observed 2019 capital stock as the common starting point ensures that differences between the actual and forecast capital paths arise solely from differences in projected investment and depreciation over time.

The capital indices are then constructed based on capital stock.

Purpose: Convert projected and realized capital stock into comparable index series.

Input Variables: $K_{it}^{Forecast}$, K_{it}^{Actual}

$$\text{Equations: } K_{it}^{ForecastIndex} = \frac{K_{it}^{Forecast}}{K_{i,2019}^{Forecast}}; K_{it}^{ActualIndex} = \frac{K_{it}^{Actual}}{K_{i,2019}^{Actual}}$$

where

$K_{it}^{Forecast}$ is the projected capital stock,

K_{it}^{Actual} is the realized capital stock,

i denotes the country,

t denotes the year.

Variable(s) Created: $K_{it}^{ForecastIndex}$; $K_{it}^{ActualIndex}$

Step 5. Calculation of Capital Gap

The capital gap is calculated as the logarithmic difference between the realized and projected capital stock indices obtained in Step 4.

Purpose: Measure the deviation between realized and projected capital stock.

Input variables: $K_{it}^{ForecastIndex}$; $K_{it}^{ActualIndex}$

Equation: $CapitalGap_{it} = \ln(K_{it}^{ActualIndex}) - \ln(K_{it}^{ForecastIndex})$

where

$K_{it}^{ForecastIndex}$ is the forecast capital stock index obtained in Step 4,

$K_{it}^{ActualIndex}$ is the realized capital stock index obtained in Step 4.

A negative value indicates that the realized capital stock remained below the level projected before the pandemic, while a positive value indicates that realized capital stock exceeded the projected level.

Variable(s) created: $CapitalGap_{it}$

Step 6. Construction of Population Indices

Population is normalized using 2019 as the base year following the same procedure applied to GDP and capital stock.

Purpose: Convert projected and realized population into comparable index series.

Input variables: $Pop_{it}^{Forecast}$; Pop_{it}^{Actual}

$$\text{Equations: } Pop_{it}^{ForecastIndex} = \frac{Pop_{it}^{Forecast}}{Pop_{i,2019}^{Forecast}}; Pop_{it}^{ActualIndex} = \frac{Pop_{it}^{Actual}}{Pop_{i,2019}^{Actual}}$$

where

$Pop_{it}^{Forecast}$ is the projected population,

Pop_{it}^{Actual} is the realized population,

i denotes the country,

t denotes the year.

Variable(s) created: $Pop_{it}^{ForecastIndex}$; $Pop_{it}^{ActualIndex}$

Step 7. Calculation of Population Gap

The population gap is computed using the population indices obtained in Step 6.

Purpose: Measure the deviation between realized and projected population.

Input variables: $Pop_{it}^{ForecastIndex}$; $Pop_{it}^{ActualIndex}$

$$\text{Equation: } PopulationGap_{it} = \ln(Pop_{it}^{ActualIndex}) - \ln(Pop_{it}^{ForecastIndex})$$

where

$Pop_{it}^{ForecastIndex}$ is the forecast population index obtained in Step 6,

$Pop_{it}^{ActualIndex}$ is the realized population index obtained in Step 6.

Variable(s) created: $PopulationGap_{it}$

Step 8. Construction of Employment Indices

Purpose: Convert projected and realized unemployment rates into comparable index series using 2019 as the reference year.

Input variables: $UE_{it}^{Forecast}$; UE_{it}^{Actual}

Equations: First, the employment rate is obtained as the complement of the unemployment rate:

$$E_{it}^{Forecast} = 1 - UE_{it}^{Forecast} ; E_{it}^{Actual} = 1 - UE_{it}^{Actual}$$

The employment indices are then constructed as

$$E_{it}^{ForecastIndex} = \frac{E_{it}^{Forecast}}{E_{i,2019}^{Forecast}} = \frac{(1-UE_{it}^{Forecast})}{(1-UE_{i,2019}^{Forecast})} ; E_{it}^{ActualIndex} = \frac{E_{it}^{Actual}}{E_{i,2019}^{Actual}} = \frac{(1-UE_{it}^{Actual})}{(1-UE_{i,2019}^{Actual})}$$

where

$UE_{it}^{Forecast}$ is the projected unemployment rate,

UE_{it}^{Actual} is the realized unemployment rate,

i denotes the country,

t denotes the year.

Variable(s) created: $E_{it}^{ForecastIndex}$, $E_{it}^{ActualIndex}$

Step 9. Calculation of Employment Gap

Purpose: Measure the deviation between realized and projected unemployment.

Input variables: $E_{it}^{ForecastIndex}$, $E_{it}^{ActualIndex}$

$$\text{Equation: } EmploymentGap_{it} = \ln(E_{it}^{ActualIndex}) - \ln(E_{it}^{ForecastIndex})$$

where

$E_{it}^{ForecastIndex}$ is the forecast employment index obtained in Step 8,

$E_{it}^{ActualIndex}$ is the realized employment index obtained in Step 8.

A positive value indicates that realized employment exceeded the level projected before the pandemic, whereas a negative value indicates employment below the projected level.

Variable(s) created: $EmploymentGap_{it}$

Part 2. Growth-accounting Decomposition

Step 10. Calculation of Labour Contribution

The labour contribution is computed by combining the **population gap** and the **employment gap** obtained in Steps 7 and 9. The resulting labour gap is then weighted by the labour income share to measure the contribution of labour to the overall output gap.

Purpose: Calculate the contribution of labour-market developments to the output gap.

Input variables: $PopulationGap_{it}$; $EmploymentGap_{it}$; α_i (labour income share)

Equation: First, the labour gap is computed as

$$LabourGap_{it} = PopulationGap_{it} + EmploymentGap_{it}$$

The labour contribution is then calculated as:

$$LabourContribution_{it} = \alpha_i \times LabourGap_{it}$$

or equivalently,

$$LabourContribution_{it} = \alpha_i (PopulationGap_{it} + EmploymentGap_{it})$$

where

- $PopulationGap_{it}$ is obtained in Step 7,
- $EmploymentGap_{it}$ is obtained in Step 9,
- α_i is the labour income share obtained from the Penn World Table.

Variable(s) created: $LabourGap_{it}$; $LabourContribution_{it}$

Step 11. Calculation of Capital Contribution

The capital contribution is computed by weighting the capital gap obtained in Step 5 by the capital income share.

Purpose: Calculate the contribution of capital accumulation to the output gap.

Input variables: $CapitalGap_{it}$; α_i (labour income share)

Equation: $CapitalContribution_{it} = (1 - \alpha_i) \times CapitalGap_{it}$

where

$CapitalGap_{it}$ is obtained in Step 5,

α_i is the labour income share obtained from the Penn World Table,

$(1 - \alpha_i)$ represents the capital income share.

Variable(s) created: $CapitalContribution_{it}$

Step 12. Calculation of the TFP Residual

The total factor productivity (TFP) residual is calculated as the unexplained component of the output gap after accounting for the contributions of labour and capital.

Purpose: Calculate the contribution of total factor productivity to the output gap.

Input variables: $GDPGap_{it}$; $LabourContribution_{it}$; $CapitalContribution_{it}$

Equation: $TFPResidual_{it} = GDPGap_{it} - LabourContribution_{it} - CapitalContribution_{it}$

where

- $GDPGap_{it}$ is obtained in Step 3,
- $LabourContribution_{it}$ is obtained in Step 10,
- $CapitalContribution_{it}$ is obtained in Step 11.

Variable(s) created: $TFPResidual_{it}$

Step 13. Calculation of Sample Averages

The country-level decomposition results are aggregated to obtain average values for each year.

Purpose: Produce the summary statistics used in the empirical analysis.

Input variables: $GDPGap_{it}$; $LabourContribution_{it}$; $CapitalContribution_{it}$; $TFPResidual_{it}$

Equation: For each variable X, the yearly sample average is calculated as a GDP-weighted average:

$$\bar{X}_t = \sum_{i=1}^N w_i X_{it}$$

where

$$w_i = \frac{GDP_i}{\sum_{i=1}^N GDP_i}$$

- and w_i denotes the GDP weight assigned to country i ,
- GDP_i is country i 's GDP in the base year,
- i indexes countries,
- t indexes years
- $\sum_i w_i = 1$

Variable(s) created: GDP-weighted average GDP Gap, GDP-weighted average Labour Contribution, GDP-weighted average Capital Contribution, and GDP-weighted average TFP Residual

Part 3. Visual Representation

Step 14. Construction of Figures and Tables

Purpose: Present the computed variables graphically and in tabular form.

Input variables: Yearly sample averages (Step 13); Country-level decomposition results (Steps 3–12)

Procedure: The variables computed in the previous steps are used to construct the figures and tables presented in Chapter 4, including:

- decomposition of output losses,
- labour-market decomposition,
- cross-country comparisons,
- correlation analysis,
- recovery paths.

Appendix B. Excel Decomposition Exercise

Worksheet	Purpose
WEO FIXED	Imported IMF data and forecasts
PWT	Labour share, depreciation rate and initial capital stock
ILO	Labour force participation data
Jackson & Lu Figure 9 replication	Construction of GDP, labour, capital and TFP gaps
Jackson & Lu Figure 9 summary	Average values across countries
Jackson & Lu Figure 10 replication	Labour decomposition
Jackson & Lu Figure 11 summary	Data used for scatter plot
Thesis Figures	Final tables and charts used in the thesis

Appendix C. Regression Dataset

Table C1. Regression Dataset

Table C1 presents the final cross-sectional dataset used in the regression analysis. The dataset contains the 21 emerging market economies included in the empirical analysis and the variables employed in the baseline and robustness regressions.

Country	GDP GAP (2024)	GDP per capita (2019)	GDP per capita PPP (2019)	Inflation (2019)	Government Effectiveness	Trade (% GDP)	Fiscal Support (% GDP)	Covid deaths Per million
Belarus	4.81	6837.77	24841.52	5.60	-0.24	130.85	0.60	776
Brazil	-0.48	9029.83	17063.00	3.73	0.04	28.89	9.24	3299
China	-4.03	10342.90	17770.15	2.90	0.67	35.45	4.78	37
Chile	-6.07	14496.93	26233.17	2.56	1.05	57.61	12.68	3230
Colombia	-5.99	6472.55	15895.66	3.52	-0.07	37.56	4.62	2748
Croatia	5.79	15563.74	34251.82	0.77	0.42	101.40	4.61	4500
Hungary	-6.84	17012.86	37555.93	3.34	0.52	159.93	11.50	5008
India	-9.71	2041.43	7390.25	3.73	0.51	39.91	4.09	372
Indonesia	-8.96	4106.95	12483.10	3.03	0.31	37.63	9.33	576
Kazakhstan	-5.24	9457.13	32008.40	5.33	0.06	64.86	5.50	951
Malaysia	-8.70	10920.19	30528.07	0.66	0.82	123.03	6.22	1062
Mexico	-4.40	10369.56	21298.80	3.64	-0.01	77.46	0.65	2577
Peru	-12.23	7037.01	14158.55	2.25	0.05	46.94	9.59	6518
Philippines	-17.31	3400.79	9409.44	2.39	0.18	68.84	4.45	574
Poland	-0.38	15874.52	37453.51	2.23	0.66	101.58	6.46	3088
Romania	-6.49	12909.61	32836.93	3.83	-0.15	84.91	3.41	3515
Russia	0.08	11447.70	34281.57	4.47	0.04	49.23	5.01	2704
Serbia	-2.73	7755.63	20020.57	1.85	0.07	107.58	12.15	2579
South Africa	-6.14	6533.71	14429.32	4.10	0.19	53.90	5.28	1644
Thailand	-14.78	7605.70	20807.56	0.71	0.14	109.69	14.59	469
Turkiye	10.45	9395.23	27804.74	15.18	0.21	62.58	3.51	1165

Appendix D. Regression Analysis

Part 1. Construction of the Regression Dataset

Step 1. Selection of the sample

Purpose: Construct the cross-country dataset used for the regression analysis.

Sample: Twenty-one emerging market economies used throughout the thesis.

Countries: Belarus, Brazil, Chile, China, Colombia, Croatia, Hungary, India, Indonesia, Kazakhstan, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, Serbia, South Africa, Thailand and Türkiye.

Output: Balanced cross-sectional dataset with one observation per country.

Step 2. Construction of the Dependent Variable

Purpose: Measure post-pandemic recovery.

Input: 2024 GDP Gap obtained from Chapter 4.

Procedure: The dependent variable equals the output gap in 2024 relative to the October 2019 IMF WEO forecast.

Formula: $GDPGap_i = \ln(Y_i^{Actual}) - \ln(Y_i^{Forecast})$

Output Variable: GDP GAP (2024)

Step 3. Construction of explanatory variables

Purpose: Construct the explanatory variables.

Variables:

- GDP per capita (2019)

- Inflation (2019)
- Government Effectiveness
- Fiscal Support

Each variable is taken from its respective international database.

Output:

Regression dataset.

Variable	Definition	Source
GDP Gap	Output gap in 2024	Calculated by author using IMF WEO 2026 and 2019 real GDP
GDP per capita	GDP per capita before pandemic	World Development Indicators, World Bank Group
Inflation	CPI inflation (2019)	World Development Indicators, World Bank Group
Government Effectiveness	Worldwide Governance Indicator	World Development Indicators, World Bank Group
Fiscal Support	COVID fiscal package (% GDP)	IMF Fiscal Monitor

Part 2. Variable Definitions

Part 3. Correlation Analysis

Step 4. Correlation Matrix

Purpose: Evaluate pairwise linear relationships among explanatory variables.

Procedure: Pearson correlation coefficients are computed.

Purpose: Identify potential multicollinearity.

Output: Correlation matrix shown in Chapter 5.

Part 4. Regression Estimation Procedure

Step 5. Ordinary Least Squares Estimation

Purpose: Estimate the determinants of post-pandemic recovery.

Model estimated:

$$GDPGap_i = \beta_0 + \beta_1 GDPpc_i + \beta_2 Inflation_i + \beta_3 GovEff_i + \beta_4 Fiscal_i + \varepsilon_i$$

Procedure:

OLS estimation

Cross-sectional sample

Robust standard errors

Output:

Coefficient estimates ; Standard errors ; p-values ; Adjusted R^2 ; F-Statistic

Part 5. Diagnostic Tests

Step 6. Multicollinearity for Model (4)

Purpose: Assess multicollinearity.

Procedure: Variance Inflation Factors (VIF).

Output: VIF table.

Step 7. Heteroskedasticity

Purpose: Test whether residual variance is constant.

Procedure: Breusch–Pagan test.

Output: BP statistic ; p-value

Step 8. Normality

Purpose: Assess residual normality.

Procedure: Shapiro–Wilk test.

Output: W statistic ; p-value

Step 9. Influential observations

Purpose: Identify influential observations.

Procedure: Cook's Distance.

Output: Cook's D values.

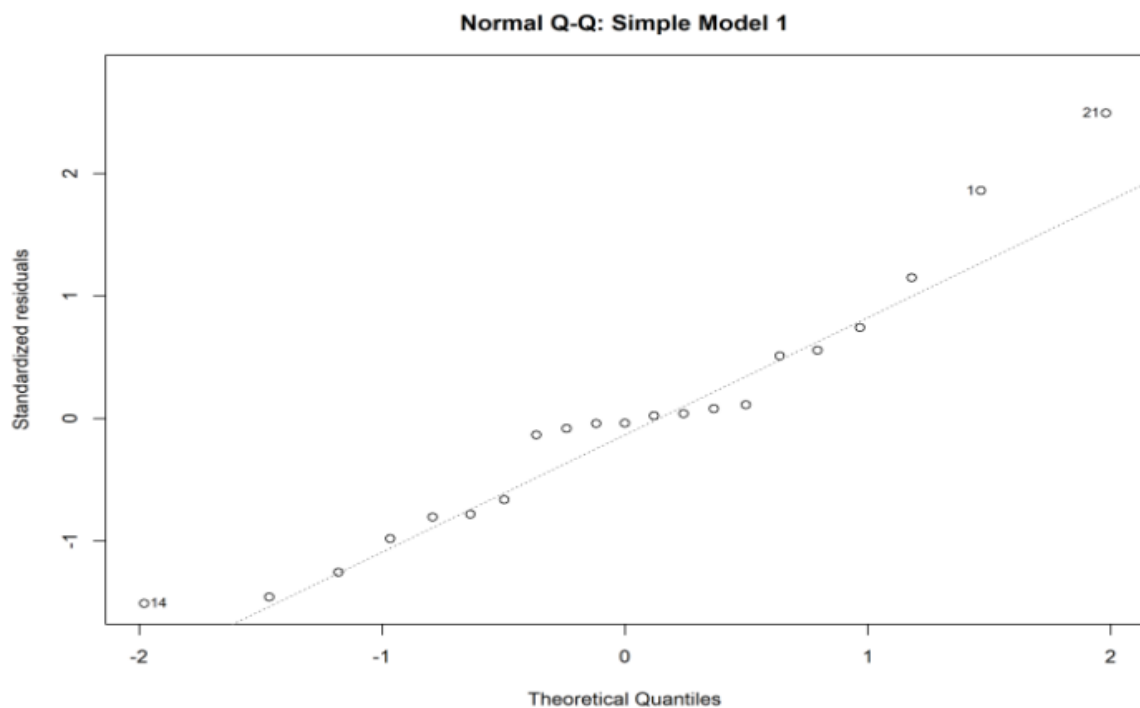


Figure D1. Normal Q-Q Plot

Figure D1 displays the Normal Q-Q plot used to assess the normality of the regression residuals. Most observations lie reasonably close to the reference line, indicating that the residuals are approximately normally distributed. Slight deviations are visible in the upper tail, largely driven by observation 21, which reflects the presence of one relatively large positive residual.

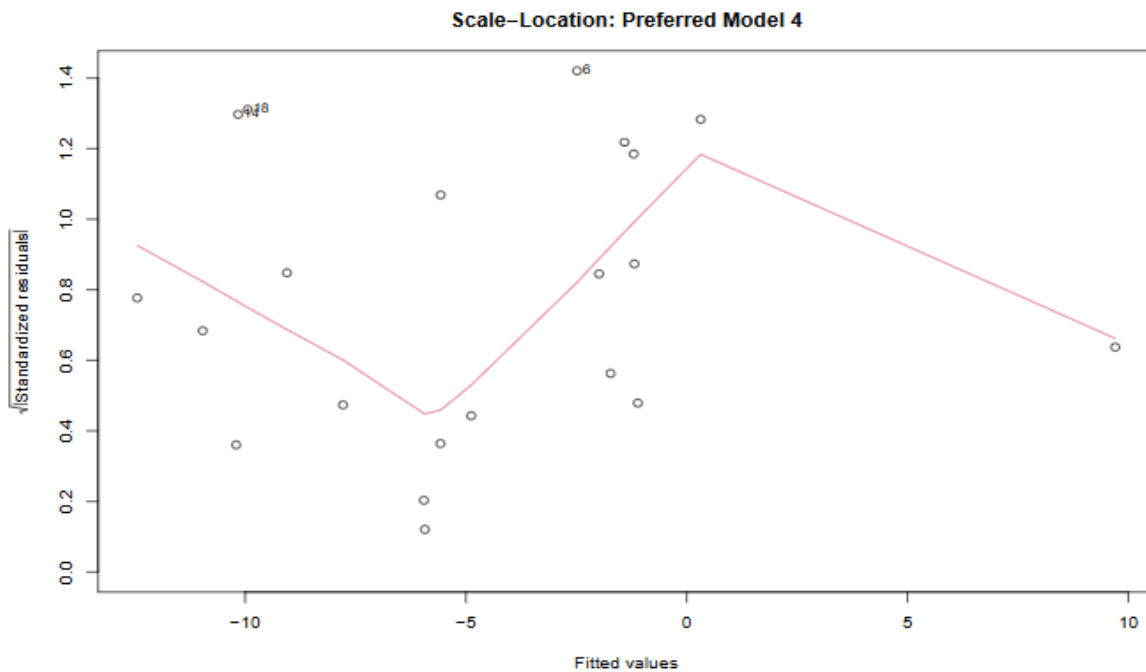


Figure D2. Scale-Location Test

Figure D2 presents the Scale-Location plot, which evaluates the assumption of constant error variance (homoskedasticity). The spread of standardized residuals remains relatively stable across the range of fitted values, although a slight increase in dispersion is visible for several observations. Consistent with the Breusch-Pagan test reported in Chapter 5 ($p = 0.218$), there is no statistical evidence of heteroskedasticity. For additional robustness, all inference is also reported using heteroskedasticity-robust standard errors.

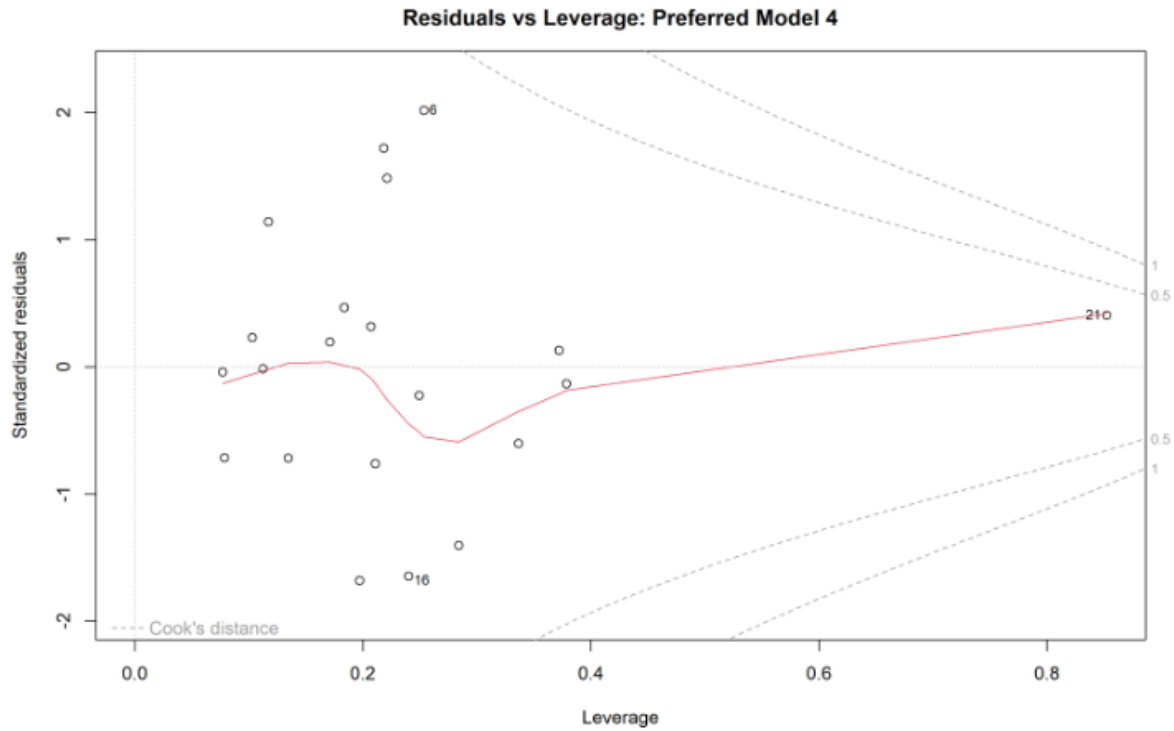


Figure D3. Residuals vs Leverage Test

Figure D3 illustrates the relationship between standardized residuals and leverage for the preferred model. Several observations display notable characteristics: observation 6 (Hungary) exhibits high standardized residuals but moderate leverage, while observation 21 (Türkiye) shows high leverage but moderate residuals. Observation 16 (Romania) is moderate on both dimensions. However, none of these observations exceed the Cook's distance reference contours (shown as dashed lines), indicating that no individual country exerts unduly influential effects on the estimated regression coefficients. This confirms that the results are not driven by outlier economies.

Table D1. Robustness Check: Baseline Regression Using Alternative Recovery Years

	<i>Dependent variable:</i>			
	GDP Gap 2020 (1)	GDPGap2021 2021 (2)	GDPGap2022 2022 (3)	GDPGap2023 2023 (4)
GDP per capita (2019, USD)	0.0003 (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)	0.001*** (0.0002)
Inflation (2019)	0.748** (0.293)	1.066*** (0.295)	1.032*** (0.278)	1.155*** (0.319)
Government Effectiveness (2019, WGI Index)	-1.703 (2.725)	-2.158 (2.746)	-0.568 (2.584)	-1.185 (2.971)
Fiscal Support (2020- 2022, % of GDP)	0.092 (0.232)	0.083 (0.234)	-0.051 (0.220)	-0.290 (0.253)
Constant	-13.939*** (2.849)	-14.977*** (2.871)	-15.210*** (2.702)	-13.934*** (3.106)
Observations	21	21	21	21
R ²	0.378	0.608	0.676	0.658
Adjusted R ²	0.223	0.510	0.595	0.573
Residual Std. Error (df = 16)	3.568	3.596	3.383	3.890
F Statistic (df = 4; 16)	2.433*	6.209***	8.335***	7.711***

Note: Conventional OLS standard errors are reported in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01.