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Determinants of Productivity-enhancing Structural Change and the Role of the Business Environment

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Bureau for Employers Activities (ACT/EMP)
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Foreword

Productivity is the most important driver of long-term economic growth and standards of living. As nations and regions navigate the complexities of economic development, the underlying mechanisms of structural change become a primary focus. The various trajectories of different regions raise pressing questions about the determinants of productivity-enhancing structural changes.

Our exploration into this landscape seeks to understand the influence of the business environment on these changes. With Asia demonstrating remarkable growth and other regions like Latin America, Sub-Sharan Africa, and Middle East and North Africa facing challenges, it’s essential to grasp the specific factors that drive these disparate outcomes. Our investigation delves deep into the interplay of labour reallocation, sectoral advancements, and the vital role of market efficiency.

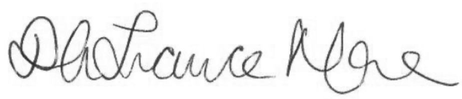
Utilizing extensive data from 1990 to 2018 and applying rigorous analytical methodologies, this report illuminates the intricate relationship between the business environment and productivity growth. Our findings spotlight the East Asia region’s achievements, driven significantly by a business environment that prioritizes market efficiency. This research underscores the power of market efficiency as a determinant in guiding regions toward productivity-enhancing structural shifts.

While previous studies have approached these topics from various angles, our empirical exploration offers fresh insights, emphasizing the importance of strategic policy decisions. It highlights the need for innovative initiatives, especially in sectors grappling with stagnation, and the creation of a business environment that promotes competition and adaptability.

I owe a debt of gratitude to the collective dedication that brought this report to fruition. Samuel Asfaha and José Luis Viveros Añorve of ILO-ACT/EMP have not only guided the research but also provided valuable technical inputs throughout its progression. Our appreciation extends to Hernan Viscarra Andrade for his exhaustive literature review and empirical analysis. Ekkehard Ernst’s and Nikolai Rogovsky’ s keen analytical comments have enriched our study, and Ward Rinehart’s editorial finesse has been invaluable in improving the clarity and coherence of this report.

To our ILO constituents, this report is presented with the hope that it serves as both an informational resource and a stimulus for action. We believe it offers critical perspectives on productivity and the business environment, and we hope it fosters meaningful discussions and inspires effective strategies. Our collective goal remains clear: to promote conditions that enhance productivity and ultimately improve standards of living for everyone.

Deborah France-Massin



Director
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Executive Summary

Productivity is fundamentally intertwined with long-term economic growth and the enhancement of living standards. At its core, it reflects how efficiently an economy allocates and utilizes its resources—such as labour, capital, and materials—in production processes. Over the years, evidence has continually pointed towards the positive impact of a conducive business environment on structural changes that amplify productivity. When economies are characterized by stable macroeconomic conditions, transparent regulations, accessible financing, robust infrastructure, and strong institutions, they invariably cultivate grounds for businesses to innovate, expand, and streamline operations.

Between 1990 and 2019, different regions demonstrated varied trends in Total Factor Productivity (TFP) growth. Regions such as Latin America, Africa, and the Middle East experienced negative TFP growth, with Latin America leading the decline. In stark contrast, Asia manifested a positive TFP trajectory, especially noteworthy given global economic conditions. Diving deeper into labour composition reveals that while Latin America, Africa, and the Middle East predominantly hinge on labour-intensive industries, Asia, and particularly the East Asia (EA) region, has showcased significant growth in labour productivity. This growth in the EA region notably exceeds that of regions such as Latin America and Africa.

The aftermath of the 2009-2010 financial crisis unveiled a universal decline in capital intensity across regions. A subsequent shift-share analysis from 1990 to 2018 exhibited a clear move from agriculture to services in almost all regions. However, this transition was not consistently towards sectors with increased productivity.

> Our study accentuates the pivotal role the business environment plays in influencing structural change.

From 1996 to 2018, when dissecting the business environment, the EA region emerged as the frontrunner, boasting the most favourable business conditions. In contrast, Sub-Saharan Africa (SSA) faced challenges, trailing behind other regions. A pivotal revelation from this period was the discernible gap in market efficiency between the EA region and other regions. This gap was closely mirrored in disparities in labour productivity growth, hinting at a profound relationship between the two.

Intriguingly, market efficiency, which encapsulates facets like the ease of doing business, financial evolution, and labour market agility, seems to be a primary driver for structural transformation. This is most pronounced in the EA region. Our research findings align with several existing studies, underscoring the significant connection between market efficiency and productivity growth.

In conclusion, our study accentuates the pivotal role the business environment plays in influencing structural change. While a shift from agriculture to services is universally evident, Asia, especially the EA region, stands out for its productivity growth in both manufacturing and services. With market efficiency being a defining factor that differentiates the EA from other regions, future policies must focus on honing this aspect. This includes streamlining business processes, bolstering financial institutions, and encouraging healthy competition. Such measures will not only enhance productivity but will also pave the way for sustainable economic growth.

Introduction

Introduction

Productivity is a key driver of sustained economic growth and long-term improvement in standards of living (Easterly and Levine 2001, Caselli 2005). It reflects the economy's efficiency in the allocation and use of resources (that is, labour, human and physical capital, and materials) in the production process.

Increasing interest in understanding the sources of economic growth, structural change and productivity has generated a vast amount of theoretical and empirical literature over the last decades.[1] The first wave of studies relied on aggregate, cross-country data to understand determinants of economic growth, as conducted by Barro (1991), Easterly and Levine (1997, 2001) and Loayza and Servén (2010), among others.

The analysis of productivity goes back to Solow (1956), who developed a theoretical model in which changes in physical capital, labour and total factor productivity (TFP) determine economic growth rates. One of the main shortcomings of this model is that TFP is assumed to be exogeneous, which implies that firms are not able to improve it. Later studies tried to internalize the factors of production that explain productivity growth. For example, Romer (1987, 1990) and Grossman and Helpman (1991a) included research and development as a proxy for technological advance; Lucas (1998) explored how the accumulation of human capital drives productivity and long-run growth. Barro and Sala-i-Martin (1992) analysed how tax-financed public goods complement private capital to foster long-run growth, while Acemoglu, Johnson and Robinson (2001, 2004) argue that political and economic institutions are key to economic growth.

The availability of micro-level data at the sectoral and firm levels allowed research to focus on resources reallocation and structural transformation, as explored by Lewis (1954), Foster, Haltiwanger and Krizan (2001), Restuccia and Rogerson (2008), Hsieh and Klenow (2009) and McMillan and Rodrik (2011). For Lewis (1954), Kuznets (1957) and Chenery (1960), economic growth required a "structural transformation" that shifted resources from less to more productive sectors of the economy. McMillan and Rodrik (2011) contend that labour productivity depends on the interaction of "within-sector, or fundamentals" and "between-sector, or structural change" components.

However, it is important to recognize that structural change does not always result in productivity growth. In the case of Africa, as noted by Diao, McMillan, and Rodrik (2017), the continent experienced growth-increasing structural change until 2010. It is nonetheless crucial to consider that this structural transformation was accompanied by a decline in labour productivity growth in the more modern sectors of the economy.

Similarly, in Latin America, there has been a reallocation of labour from high-productivity sectors to low-productivity sectors, which has contributed to a weak negative structural change in labour productivity growth, with the exception of agriculture.

By the same token, Duernecker, and Sanchez-Martinez (2021) argue that structural change in the European Union has exerted a negative effect on productivity growth. They contend that the process of sector transformation has been characterized by labour transition toward the tertiary sector (mostly stagnant services), which has had a negative impact on long-term aggregate productivity growth across the region's economies.

On the other hand, within-sector productivity, which is a crucial contributor to overall productivity growth, can be hindered by several barriers, including stagnant technological innovation (Acemoglu, Aghion, & Zilibotti, 2006), a shortage of skilled human capital (Bloom & Van Reenen, 2010), restrictive regulatory barriers (Djankov, McLiesh, & Ramalho, 2006), and limited access to finance and robust infrastructure (Rajan & Zingales, 1998). These obstacles, in combination, can significantly stifle efficiency and growth.

1 See Woo, Parker and Sachs (1997); Ben-David and Papell (1998) and Easterly (2001).

However, a favourable business environment can be a significant catalyst for productivity-enhancing structural change (Acemoglu & Dell, 2010). Such an environment—characterized by stable economic conditions, clear regulations, easy access to finance, good infrastructure, and strong institutions—enables businesses to innovate, grow, and operate efficiently. It nurtures competitive markets and entrepreneurial spirit, promotes the adoption of technology and skills development, and helps mitigate risks and reduce costs. Therefore, fostering a conducive business environment is essential for driving productivity growth and economic transformation.

Our analysis is focused on understanding how business environment variables influence productivity growth. The hypothesis motivating this study is that a business-enabling environment has a significant effect on productivity growth.

In this context, our analysis is focused on understanding how business environment variables influence productivity growth. The hypothesis motivating this study is that a business-enabling environment has a significant effect on productivity growth. Thus, this paper aims to answer the following research questions:

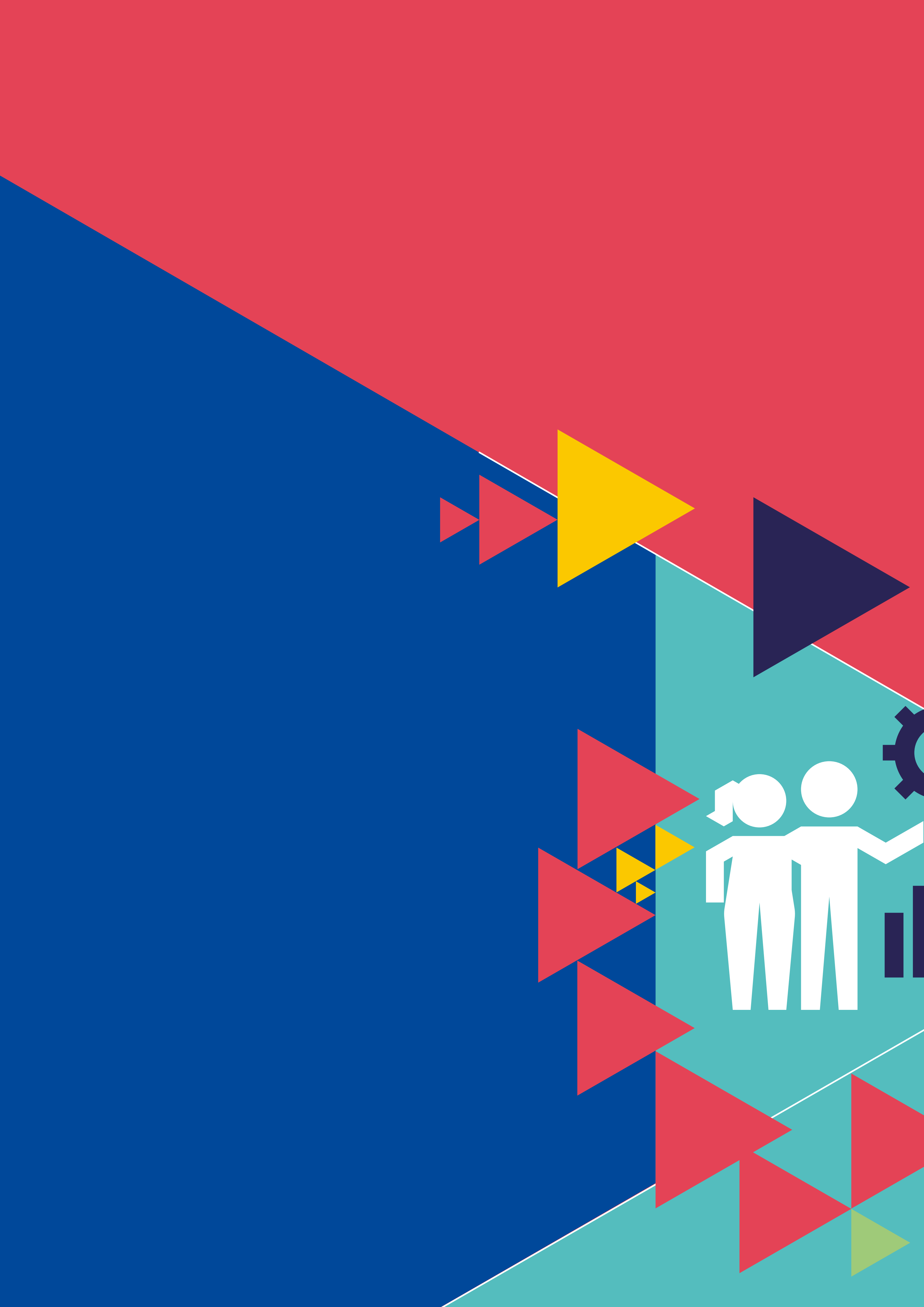
- Does the national business environment influence within-sector and between-sector productivity growth?
- Does it have an impact on the reallocation of factors, such as labour and capital, from low- to high-productivity economic activities?
- If so, what business environment factors matter most?

Section 1 of this paper reviews the literature on divergence and drivers of productivity changes, using decomposition techniques such as the shift–share analysis and applications of the neoclassical framework that decompose labour productivity growth into multi-factor, labour composition and capital intensity. Other methods are explored, as well, such as the structural decomposition of TFP growth into growth of value added, labour and capital requirements. In addition, this section includes a review of empirical literature that focus on determining how the business environment affects productivity trends at the firm level and the main drivers that could explain such changes.

Section 2 is divided in two parts. The first part includes a descriptive analysis of productivity growth trends and business environment variables for selected economies in the period of analysis. The second part analyses productivity growth components using the shift–share analysis proposed by McMillan and Rodrik (2011) and the neoclassical growth model as applied by the Bureau of Labour Statistics (BLS) of the United States of America. We argue that these methods are complimentary and provide a more comprehensive picture of the components of labour productivity growth.

In Section 3 we propose an econometric model to explore the relationship between business environment and within-sector and between-sector productivity growth, using a large panel dataset on the cross-section (N) and time-series (T) dimensions. In the analysis we address possible sources of bias that might arise in asymptotic large panels, such as nonstationarity, cointegration, heterogeneous coefficients across groups, dynamic panels and omitted common effects, among others.

Finally, Section 4 presents the main conclusions and recommendations of the study along with suggestions for policymakers to promote and foster productivity growth.



Chapter 1

"Productivity growth is determined by a wide range of factors, some of which lie within an enterprise's sphere of influence (internal factors), while others are external [...]."

▶ **International Labour Organization,** 2021

1. Review of the literature

▶ 1.1 Business obstacles and productivity

Productivity growth depends on various factors and needs to be addressed as a multi-dimension problem and at different levels. According to the International Labour Organization,[2] *"Productivity growth is determined by a wide range of factors, some of which lie within an enterprise's sphere of influence (internal factors), while others are external. The latter include a conducive business environment, the structure of the industry in which enterprises operate and compete, and foreign markets that may affect input prices."*

The business environment specifically is a complex mix of policy, legal, institutional and regulatory conditions that affect business performance. A poor business environment constrains productivity and returns on investment and, thus, the economic viability of enterprises, which in turn affects the quality and quantity of job creation.[3] The literature shows that, in contrast, good business environments contribute significantly to sales, TFP and profitability at the firm level, which, in turn, contributes to aggregate productivity.

Farole et al. (2017) explore the relationship between the business environment and firm outcomes in four European countries – Italy, Poland, Romania and Spain. The authors conducted an ordinary least squares (OLS) regression to determine the association between business environment and firm performance measured as five 3-year averages of sales growth, employment growth, investment rate growth, productivity growth and returns on assets (ROA). They found a strong and significant association. The explanatory variables were calculated using the subnational doing business indicators produced by the World Bank, and regional market competition was proxied by the Herfindahl–Hirschman Index. The results indicate that firms operating in regions with better business environments perform better in employment, sales growth and profitability. Moreover, the study finds that being located in a lagging region aggravated the effect of a poor business environment on firm performance.

2 See ILO 2021, page 10.
3 See Gogokhia and Berulava (2021), Glodowska (2017), Lopez-Acevedo (2017), Farole et al. (2017), Dollar, Hallward-Driemeier and Mengistae (2005), and Hallward-Driemeier (2005).

Kim and Loayza (2019) assess the effects of innovation, education, market efficiency, infrastructure and institutions on TFP for the period 1985–2014.[4] The results show that market efficiency and education are the main contributors to the variance in TFP growth. In addition, the authors decompose TFP growth to assess the contribution of each predictor to TFP growth variance using the dominance analysis proposed by Budescu (1993). The authors model the TFP growth rate as a function of a time-lagged overall index that comprises business environment across economies and a time-lagged TFP level with country- and time-effects and White–uber robust standard errors.[5] The authors applied a time lag of five years to reduce the likelihood of endogeneity as reverse causation. As a robustness check, the authors ran different regression without country effects and with random country effects and with different time lags. In addition, the authors decompose the variance of the TFP growth rate by each subcomponent index, using the "dominance analysis"[6] and controlling for initial TFP level and time effects at the country level.

The European Bank for Reconstruction and Development et al. (2016) found that political instability, corruption, unreliable electricity supply and inadequate access to finance are associated with a negative effect, mainly on smaller firms, on labour productivity growth and sales. Similarly, the International Monetary Fund (IMF) (2019) suggests that political instability, corruption, lack of access to finance, and unreliable electricity supply played a significant role in the lack of employment growth in 2009–2012 in the five countries studied – Egypt, Jordan, Lebanon, Morocco and Tunisia.

▶ 1.2 Productivity growth determinants

As Syverson (2011) pointed out, "the discovery of ubiquitous, large and persistent productivity differences has shaped research agendas in a number of fields". Macroeconomic studies have focused on the neoclassical framework, but with the emergence of micro data at the sectoral and firm levels, the research agenda has shifted to examining the sources of divergence in productivity growth within sectors or between sectors.

In the neoclassical framework, originally proposed by Solow (1956), growth depends on the incentives to save, accumulate physical and human capital, and innovate. The dual-economy approach, initially formalized by Lewis (1954), proposes that productivity growth takes place in the modern sector. Thus, economy-wide growth depends on the rate at which resources (for example, labour) migrate from less to more productive sectors.

These two approaches offer complementary perspectives on economic growth. The neoclassical model focuses on understanding the factors that affect within-sector productivity, while the dual-economy model focuses on the flows of resources among sectors – that is, structural transformation.

1.2.1 Shift–share analysis – dual economy

Based on the dual-economy approach, the shift–share method decomposes labour productivity growth into within-industry and inter-industry productivity differences. The theoretical model proposes that the movement of labour from traditional to modern economic activities – structural change – increases labour productivity and expands income.[7]

4 The TFP was provided by the Penn World Table (PWT) 9.0. For robustness checks the authors used the TFP data from the World Development Indicators. The explanatory variables were constructed as indices formed by several indicators from World Bank World Development Indicators (WDI) databases using factor analysis/principal component analysis (FA/PCA) dimensionality reduction techniques.

5 The OLS model included fixed effects for: country, year and sector; firm controls include: (log) age, (log) size, (log) total assets, assets per employee; and financial leverage.

6 See Menard and Grömping (2007).

7 The first theoretical framework was initially proposed by Lewis in 1954 and was then expanded by Ranis and Fei in 1964. In this framework economic growth depends on the rate at which resources such as labour can move from the traditional to the modern sector, where innovation and productivity growth take place (McMillan and Rodrik, 2011).

Growth in labour productivity depends on the interaction of "within-sector" and "between-sector" components. The former determines changes in productivity due to the flow of resources from traditional to modern activities, while the latter focus on the accumulation of skills and the quality of institutions' capabilities (for example, governance, rules of law and the business environment) to generate sustained productivity growth (McMillan, Rodrik and Sepulveda 2017).[8]

The literature on shift–share productivity shows that developing economies are characterized by large productivity gaps between sectors, gaps larger than in advanced economies. The typology of growth patterns and outcomes shows that structural change on its own can foster growth, but, without improvements in the fundamentals, growth eventually declines or remains episodic. According to McMillan, Rodrik and Sepulveda (2017), changes in productivity driven only by changes in the "within" effect are costly, time-consuming and associated with slow growth. Changes in within-sector productivity require broad investments in human capital and in strengthening institutions and infrastructure, among other changes, and take time to translate into productivity growth.

The McMillan et al. 2011 find that recent growth accelerations were based on either rapid within-sector labour productivity growth (for example, Latin America) or growth-increasing structural change (for example, Africa) but rarely at the same time. The authors found notable disparities in labour productivity between Latin America, Africa, and Asia since 1990, attributable primarily to the differing patterns of structural change in these regions. In Asia, there was a marked trend of labour reallocation from sectors with lower productivity to those with higher productivity. Conversely, in both Latin America and Africa, the labour force trended towards sectors with lower productivity. Interestingly, the researchers posit that structural change can potentially inhibit growth, particularly in nations where exports are significantly composed of natural resources.

In most of the studies analysed, the "within" effect has an overall stronger effect than the reallocation effect. For example, Isaksson (2010) concludes that productivity growth in most economies is explained by the "within" component rather than by the structural transformation component. Ocampo et al. (2009) argue that the gap in aggregate labour productivity growth between Asia and Latin America is explained mainly by the "within" component. Kucera and Roncolato (2012) find evidence of a greater contribution of the "within" component than of the reallocation effects in most regions except Asia, where the reallocation effect on productivity has been strong.

Timmer and de Vries (2009) find that the "within" effect, rather than the "between" component, better explains the divergence between regions in ten countries in Latin America and nine countries in Asia from 1950 to 2005. Conversely, Ferreira and Silva (2014) find that economies in Latin America experienced productivity growth until the mid-1970s due to a shift from agriculture to services and manufacturing (structural change). However, post-1970s, productivity growth declined significantly, possibly due to a slowdown in labour productivity in the services sector during the 1980s and 1990s, contributing largely to the region's economic stagnation.

1.2.2 Neoclassical framework

The other approach – the neoclassical framework – has its roots in Solow's neoclassical growth model (1956), in which growth depends on the incentives to save, accumulate physical and human capital, and innovate. Labour productivity growth also can be decomposed into multifactor productivity growth (MFP), which accounts for the contributions of capital intensity and labour composition, as follows:

The MFP represents the portion of output growth that is accounted for by technological advances, streamlining of industrial organization and other factors that are not related to the growth of capital and labour inputs. The contribution of capital[9] reflects businesses' process of deciding between hiring more workers and purchasing more or higher-quality equipment, or of substituting equipment for workers

8 For more references see Acemoglu and Dell (2010) and Glaeser et al. (2004).

9 The contribution of capital intensity is defined as the capital-weighted change in the capital–labour ratio. It is measured as capital's share of current dollar costs multiplied by the growth in capital services per labour hour. In cases in which firms increase their usage of capital relative to labour, or where capital costs rise relative to labour costs, there will be an increase in the contribution of capital intensity to labour productivity growth.

or vice versa. The contribution of labour composition[10] reflects shifts in the level of skills and experience of the workforce.

The neoclassical model in general relies on several assumptions: markets are perfectly competitive; returns to scale are constant; labour and capital are assumed to be completely mobile, with a single wage rate across sectors; market structure is competitive; and enterprises allocate their resources to maximize benefits.

1.2.3 TFP decomposition

Foster-McGregor and Verspagen (2017) decompose TFP growth into changes in factor requirements, changes in the value-added content of output and changes in the structure and composition of intermediate and final demand. Their study used the World Input–Output Database (WIOD) for a sample of 40 economies during the period 1995–2009, building on work conducted by Dietzenbacher, Hoen and Los (2000).

The authors move away from the traditional shift–share method and instead use a structural decomposition method based on the approach of Chenery, Shishido and Watanabe (1962); Feldman, McClain and Palmer (1987); Wolff (1985); and Dietzenbacher, Hoen and Los (2000). According to Foster-McGregor and Verspagen (2017), this approach acknowledges industry interdependence both within and across economies and the productivity effects of these interactions, which are captured through the input–output linkages exhibited in the WIOD.

The decomposition sums up year-by-year real TFP growth and year-by-year real changes in the components of TFP growth calculated using previous year price data. The growth in real TFP $\hat{g}_t^{\phi}$ is expressed as follows:

$$v\hat{g}_t^{\phi} = ln\frac{\phi_t^{t-1}}{\phi_t^{t-1}} = ln\frac{v_t^{t-1}}{v_{t-1}^{t-1}} - \bar{\alpha}_t ln\frac{l_t}{l_{t-1}} - \bar{\beta}_t ln\frac{k_t}{k_{t-1}}$$

where v_t^{t-1} is the value added in period t using previous year (t-1) prices. The factor inputs labour (l) and capital (K) are taken from socioeconomic accounts and expressed in real terms. The labour share α is the share of labour compensation in value added, and the capital share β is calculated as a residual $\beta = 1 - \alpha$. Finally, $\bar{\alpha}_t = \frac{1}{2}(\alpha_{t-1} + \alpha_t)$ and $\bar{\beta}_t = \frac{1}{2}(\beta_{t-1} + \beta_t)$ which are time-varying.

1.2.4 Multi-sector general equilibrium models

In the literature we identified different approaches to understand increases in productivity and expansion of income. Several studies use multi-sector general equilibrium models to analyse productivity changes due to supply factors: market frictions, changes in demand preferences, business cycles and changes in long-term growth.

These models use theoretical approaches to analyse productivity changes due to demand and/or supply factors. As summarized by Lief van Neuss (2019), the main channels of structural change in these models are: aggregate real income, relative sectoral prices (technology-driven structural transformation), and sectorial linkages and comparative advantages from trade.[11]

McMillan, Rodrik, and Sepulveda's 2017 study aimed to understand the patterns and drivers of structural transformation in economies. They argued that structural change is influenced not only by overall productivity growth but also by within-sector productivity variation. By analysing firm-level data, they found significant disparities in productivity within sectors, even during periods of structural transformation. Their research emphasized the importance of addressing the heterogeneity

10 The contribution of labour composition is defined as the labour-weighted change in a measure – labour composition. It is computed as labour's share of current dollar costs multiplied by labour composition.

11 See also the work of Acemoglu and Guerrieri (2008), Alvarez-Cuadrado, Long and Poschke (2017), Herrendorf, Rogerson and Valentinyi (2013), Kongsamut, Rebelo and Xie (2001), Ngai and Pissarides (2007) and Matsuyama (2009).

of productivity within sectors when designing policies to promote economic development. The study highlighted the need to focus on improving the productivity of specific firms within sectors to foster overall structural transformation and enhance economic performance.

In their subsequent study published in 2019, Diao, McMillan, and Rodrik built upon the research conducted by McMillan, Rodrik, and Sepulveda (2017) to further investigate the dynamics of structural transformation and productivity growth. Their research aimed to deepen our understanding of the underlying mechanisms driving these processes. The study revealed that not only does within-sector productivity variation play a significant role in structural transformation, but it is also influenced by various factors such as market frictions, technological progress, and firm-level capabilities. By examining these factors and their interplay, Diao, McMillan, and Rodrik provided valuable insights into the complexities of structural change and offered guidance on how policies can effectively promote productivity growth and foster sustainable economic development. This research highlighted the need for a comprehensive approach that addresses both aggregate and within-sector productivity dynamics to achieve successful structural transformation and enhance overall economic performance.

Herrendorf, Rogerson and Valentinyi (2013) estimated the contribution of structural change to economy-wide productivity growth. They stressed the role of human capital in determining both within- and across-sector productivity growth and how market failures and the extent to which externalities, public goods, market power or other factors associated with inefficient equilibrium outcomes shape the process of structural change.

For Ngai and Pissarides (2007), as technological growth rates differ between sectors, relative prices associated with differences in productivity drive labour reallocation. This pushes resources, such as labour, from sectors with high productivity growth rates to those with low productivity growth rates.

Matsuyama (2009) emphasized the crucial role of comparative advantage in the process of resource reallocation, which arises as a result of the dynamic impact of international trade on the relative productivity and growth of different sectors. According to Matsuyama, as countries engage in international trade, sectors with a comparative advantage experience a positive feedback loop. This means that increased trade in these sectors leads to productivity gains, which further enhances the sector's competitiveness and growth. As a result, resources, such as labour and capital, tend to be reallocated from less productive sectors to those with a comparative advantage.

In their influential study published in 2010, Duarte and Restuccia conducted a comprehensive analysis of the relationship between protectionism, regulation, trade openness, and productivity growth in different countries. Their research shed light on the crucial role these factors play in determining the economic performance of nations.

One of the key findings of their study was the negative impact of sectoral protectionism on productivity growth. They observed that when certain industries are shielded from international competition through protective measures such as tariffs or subsidies, it often leads to a lack of incentive for domestic firms to innovate and improve their productivity. As a result, these protected sectors tend to become less efficient and less competitive over time.

Acemoglu and Guerrieri (2008) stated that the continuous increase in the ratio of capital to labour causes a reduction in the price of capital-intensive goods, which drives resources away from the sector that is more intensive in capital. According to Alvarez-Cuadrado, Long, and Poschke (2017), structural change could also arise from differences among sectors in the elasticity of substitution between labour and capital. Thus, highly elastic sectors can become more capital-intensive when labour cost increases or when capital becomes more abundant.

Chapter 2

2. Methodological approach

▶ 2.1 Decomposition of productivity growth

There are several ways proposed in the literature to decompose productivity.[12] For this section, we use a simple approach to describe the within-sector and structural transformation effects on changes in labour productivity.

Equation (1) describes a change in economy-wide labour productivity in a given period of (t-k, t):

$$(1) \quad P_t - P_{t-k} = \Delta P_t = \sum_{i=1}^{n} \theta_{i,t}\ p_{i,t} - \sum_{i=1}^{n} p_{i,t-k} \Delta\theta_{i,t-k}$$

where P_t and $P_{t\text{-}k}$ are aggregate labour productivity at time t and time t-k, respectively; $P_{i,t}$ and $P_{i,t\text{-}k}$ are sector i's labour productivity at t and t-k; $\theta_{i,t} = \frac{L_i^t}{L_t}$ and $\theta_{i,t-k} = \frac{L_i^{t-k}}{L_{t-k}}$ are share of labour (L) employed in sector i at t and t-k; and t > k; where k refers to the number of years. $\Delta P_t = P_t - P_{t-k}$ and $\Delta\theta_{i,t} = \theta_t - \theta_{t-k}$

Rearranged, equation (1) can be expressed in two ways:

$$(2) \quad \Delta P_t = \sum_{i=1}^{n} \theta_{i,t-k}\ \Delta p_{i,t} + \sum_{i=1}^{n} p_{i,t} \Delta\theta_{i,t}$$

In equation 2 the "within" term is weighted by labour shares at the beginning of the period, and the weights in the "between" term are sectors' labour productivity at the end of the period. Following McMillan and Rodrik (2011), we selected equation 1 for the analysis in this paper.

The first component of equation 1 measures the effect of a change in productivity in sector i $(\Delta p_{i,t})$ weighted by its share in labour in the initial period $(\theta_{i,t-k})$. This is also called the "intra-industry" or "within-sector" factor. The second component is called the "inter-industry" or "between-sector"; it captures the effect of a change in the labour share hired by sector i in time t $(\Delta\theta_{i,t})$, weighted by the productivity of the sector in the final period $(p_{i,t})$. When labour moves from a low productivity sector to a high productivity one, the sign of the second term is positive, which means that it contributes positively to the productivity growth of the aggregate economy.[13]

The "inter-industry" term in equation (2) could be further decomposed into static and dynamic components of structural change, as shown in de Vries, Timmer and de Vries (2015). For simplicity, and following the recommendations of McMillan and Rodrik (2011), we did not decompose the second term into the static and dynamic components. They argue that:

> **First, structural change by definition is a dynamic concept. And second, the third term alone is difficult to interpret when, for example, reductions in the employment share are accompanied by increases in productivity. This is because the term becomes negative, seemingly acting as a**

12 See Rodrik (2013) and McMillan, Rodrik and Verduzco-Gallo (2014).

13 In equation (3) $\Delta P_t = \sum_{i=1}^{n} \theta_{i,t}\ \Delta p_{i,t} + \sum_{i=1}^{n} p_{i,t-k} \Delta\theta_{i,t}$, the weights are the opposite; the "within" term uses end-point weights, while the "between" term uses start-point weights. The selection of weights might affect the magnitude of growth in both the "within" and "between" components of the growth decomposition. For further discussion see Annex 1.

drag on productivity, when in fact it could be viewed as a positive development in such sectors as agriculture.

The choices related to the growth decomposition exercise are whether we calculate changes just in a given period (for example, over one or ten years), as shown in equation (2), or we compute their annual growth rates. Moreover, the method to annualize growth rates and the choice between using annual data or period endpoint could influence the magnitude of labour productivity growth rates within sector and from structural change.[14] For the descriptive analysis we explored changes in both the entire period (1990–2018) and annual changes, while the empirical analysis uses the annual rates.

To complement the descriptive analysis, we explored an alternative for the labour productivity decomposition (measured by output per hour worked), following the work conducted by the Bureau of Labor Statistics (BLS) of the United States of America. The components are capital deepening, measured as the amount of capital per hour worked; labour composition, which measures changes in the quality of labour; and multifactor productivity.

Labour productivity growth = multifactor productivity growth + contribution of capital intensity + contribution of labour composition[15]

The contribution of capital intensity is defined as:

$$w_k[\left(ln\frac{K_t}{K_{t-1}}\right) - (ln\frac{L_t}{L_{t-1}})$$

where w_k is the k-year average cost share of capital, and K_t and L_t are capital services and labour hours at a given time t.

The contribution of labour composition is defined as labour's share of current dollar costs multiplied by labour composition. This measure reflects shifts in the level of skills and experience of the workforce.

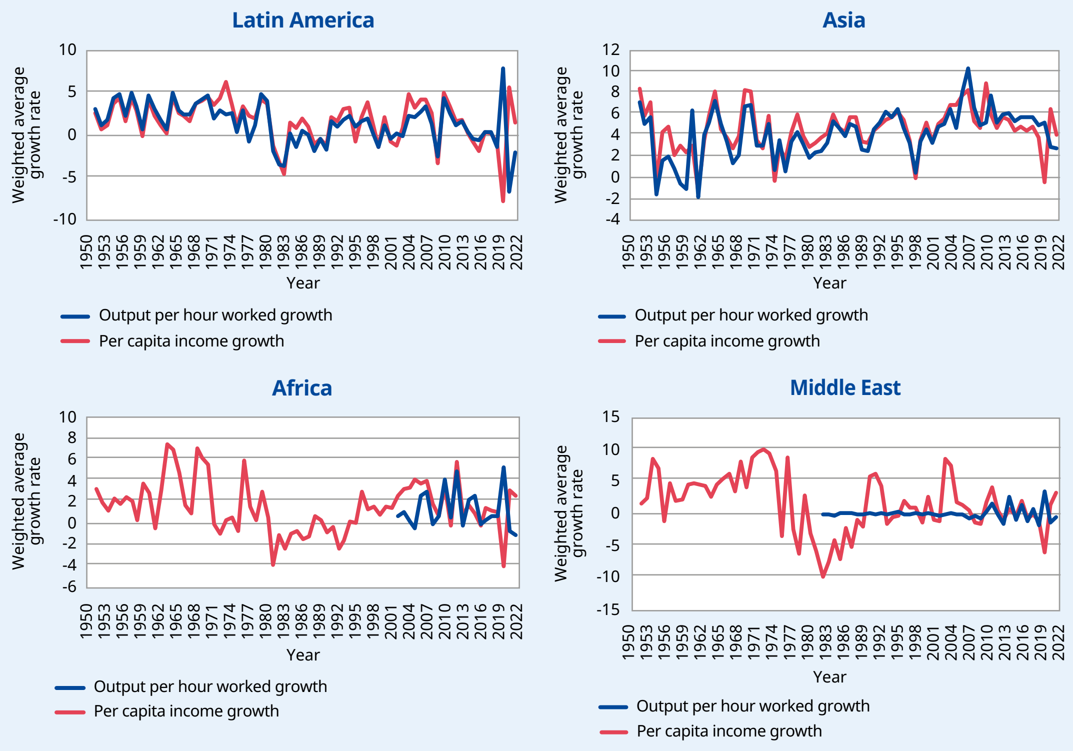
14 In addition, we need to select the method to calculate growth rates. Depending on data availability, we could calculate growth rates over an entire period and then annualize the series to obtain an average annual growth rate as in McMillan and Rodrik (2011) and de Vries, Timmer and de Vries (2015). Otherwise, we could use time series to calculate annual growth rates.
15 For more references see: https://www.bls.gov/opub/mlr/2021/article/the-us-productivity-slowdown-the-economy-wide-and-industry-level-analysis.htm; https://www.bls.gov/productivity/technical-notes/; and https://www.bls.gov/productivity/technical-notes/changes-in-composition-of-labor-total-factor-productivity-2014.pdf.

Chapter 3

3. Descriptive analysis

This section starts by analysing labour productivity and growth in gross domestic product (GDP) per capita and its main contributors (TFP, labour and capital contribution) from 1950 to 2020 and how they track during this period, comparing trends across groups of economies.

▶ Figure 1. GDP per capita growth and productivity growth, four regions, 1950–2022

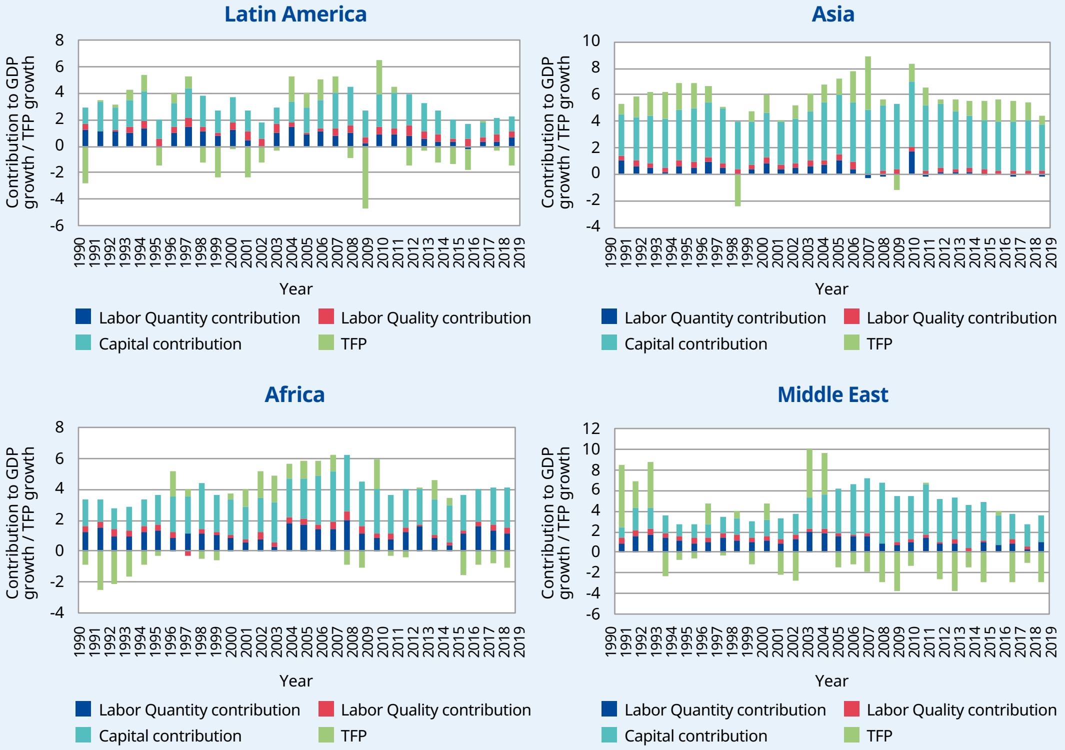


Source: The Conference Board, 1950–2022.

Figure 1 shows weighted average growth in GDP per capita and labour productivity from 1950 to 2022. The correlation between GDP and labour productivity growth is strong. The lines practically overlap with each other every year, which suggests that economic growth depended heavily on productivity gains. Of all the regions, Asia alone showed positive labour productivity growth in every year since 1960, and the region had the largest average productivity growth (around 5 per cent). The other regions experienced episodes of positive and negative growth, with an average productivity growth of approximately 2 per cent.[16]

16 Country productivity statistics are detailed in Annex 3.

▶ Figure 2. Labour, capital and TFP contribution to GDP growth, weighted average for four regions, 1990–2019



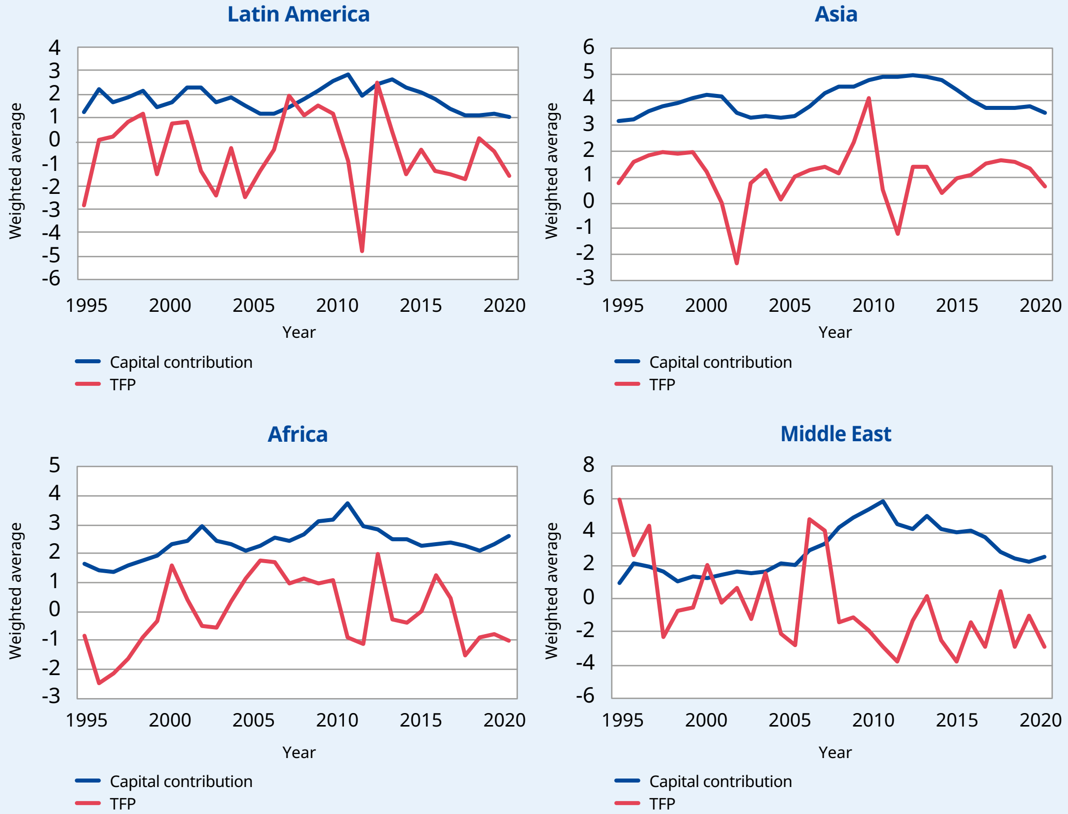
Source: The Conference Board, 1990–2019.

Figure 2 shows the contributions to GDP growth made by TFP, capital intensity and labour composition (quantity and quality). We can see that negative TFP growth was the source of the slowdown in GDP growth in Latin America, Africa, and the Middle East. In fact, Latin America exhibited the largest negative TFP contribution (-1.2 per cent), followed by MENA (-0.73 per cent) and Africa (-0.33 per cent). Only Asia, in contrast, exhibited a positive TFP contribution (0.30 per cent). The investigation of the sources or causes of TFP growth is outside the scope of this study and might require a country-by-country approach. TFP growth cannot be measured on its own; it can be calculated only as an unexplained residual after subtracting all measurable inputs to production (labour and capital).

The contributions of labour composition to GDP growth are much larger in Latin America, Africa and the Middle East than in Asia. This means that the former relies more than Asian economies on labour-intensive industries such as agriculture and/or low-productivity services. In fact, the contribution of labour composition in Asia explains less than 5% of the economic growth since 2011, while, in the other regions, it explains almost half of GDP growth.

Figure 3 shows a slowdown in the contribution of capital intensity in all regions since 2009–2010 that coincides with the Great Financial Crisis. The contributions of capital intensity in LATAM, Africa and the Middle East were around 2 per cent, while in Asia it was around 4 per cent.

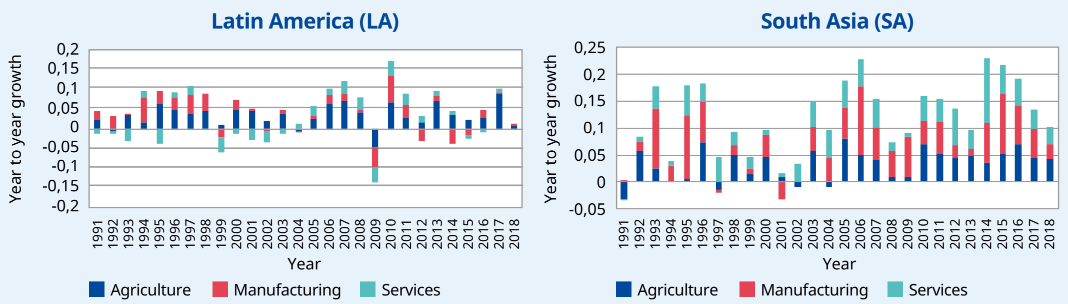
▶ Figure 3. Capital contribution and TFP trend in four regions, 1990–2019, weighted average

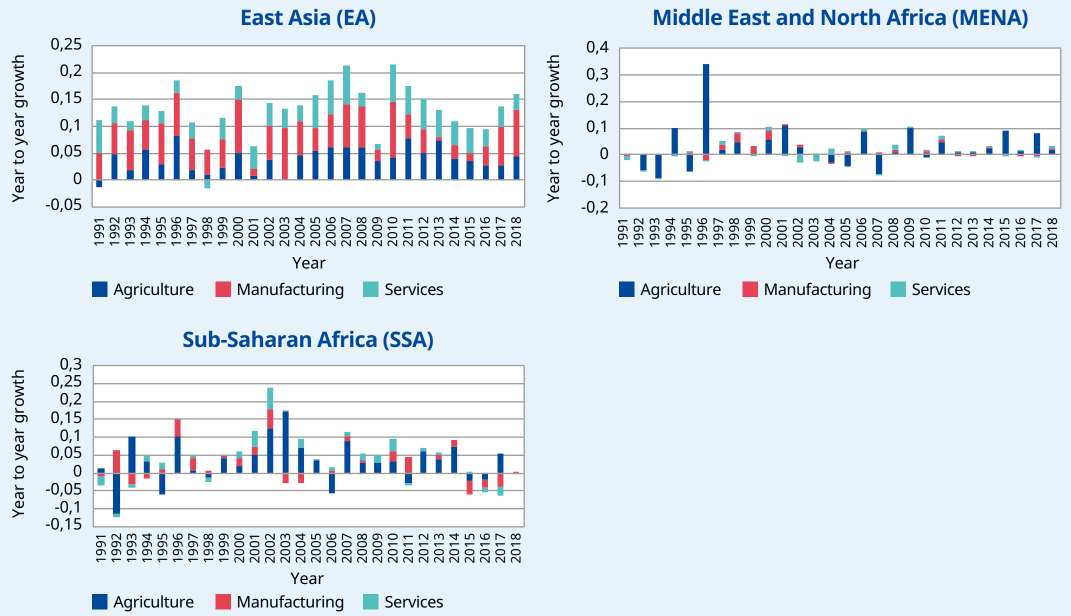


Source: The Conference Board, 1950–2022.

Figure 4 shows year-to-year growth in labour productivity from 1990 to 2018 in five regions. The East Asia (EA) region had the largest labour productivity growth (4.8 per cent over the period) followed by South Asia (3.8 per cent). In Asia overall the countries with the largest growth in labour productivity were China (8.1 per cent) and Myanmar (7.3 per cent). Latin America (LA) and Africa exhibited more erratic patterns, with episodes of positive and negative growth.

▶ Figure 4. Labour productivity growth by sector in five regions, 1990–2019, weighted averages





Source: GGDC/UNU-WIDER. The Economic Transformation Database 2021.

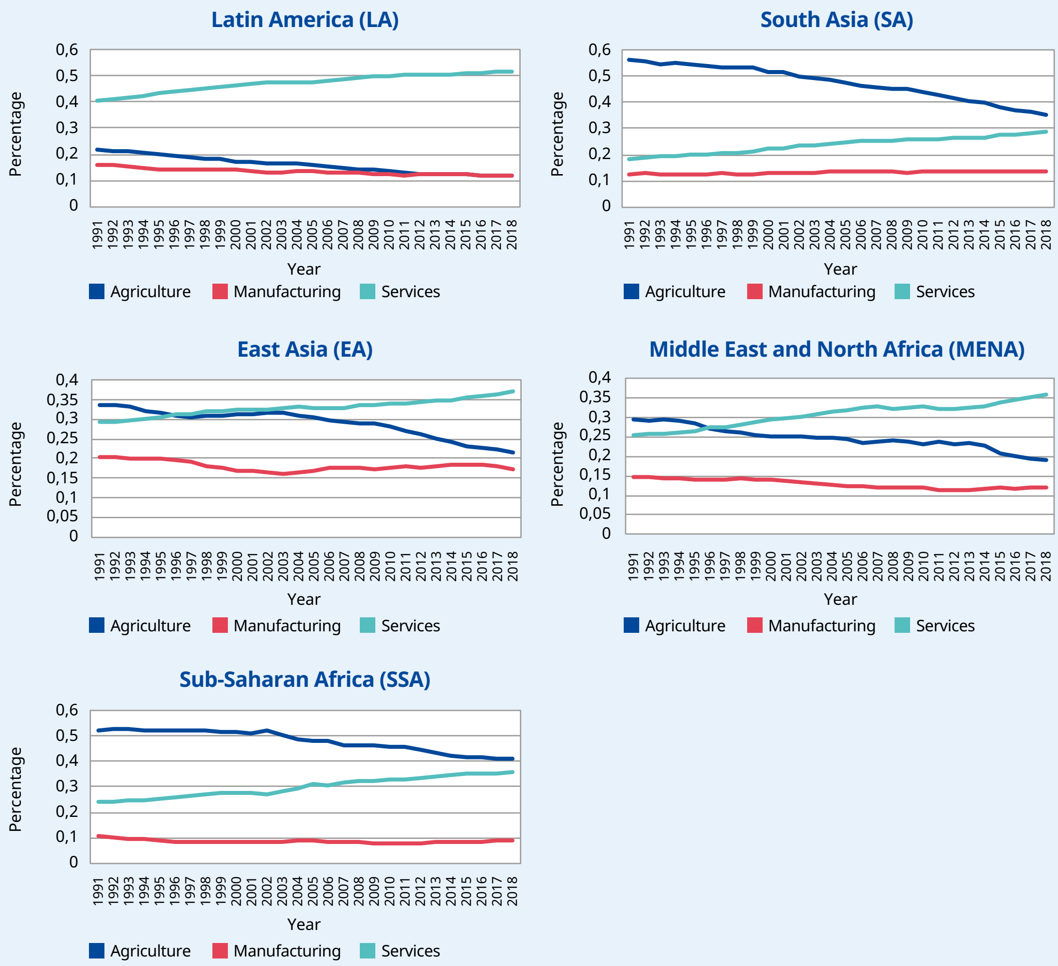
Average productivity growth in Asia exceeded that in LA by 2.5 percentage points and that in Africa by 1.5 percentage points. In 2008–2009 all regions exhibited a decline in productivity growth due to the Great Financial Crisis. However, the Asian economies have been able to return to annual average productivity growth of over 4 per cent, while, in LA, MENA and SSA, productivity growth has been around 2 per cent annually, with periods of negative productivity growth after 2010.

In Asia the labour productivity growth takes place mainly in the manufacturing and service sectors, while in MENA, SSA and LA, improvements in the agriculture sector explain productivity growth. In fact, after 2015 these regions exhibited a negative productivity growth rate in manufacturing and services productivity.

▶ 3.1 Shift–share analysis

This section describes the pace of structural change in the sample economies over the period 1990–2018. For this analysis we used the Groningen Growth and Development Center (GGDC) database (Timmer, de Vries and de Vries 2016 and de Vries et al. 2021), which includes sectoral gross value added at constant 2015 prices (millions of local currency) and the number of persons employed (thousands) for the period 1990–2018 for 51 countries and 12 sectors. The countries include 21 in Africa, 21 in Asia and 9 in LA. The value added at 2015 prices was converted to dollars using the 2015 purchasing power parity exchange rate provided by the World Bank. Labour productivity was computed by dividing each sector’s value added by the corresponding level of sectoral employment.

▶ Figure 5. Labour share by sector in five regions, 1990–2018, weighted averages



Source: GGDC/UNU-WIDER The Economic Transformation Database 2021.

In general, labour has reallocated from agriculture to services across all regions (Figure 5). In LA, MENA and SSA, labour has transitioned from agriculture (with a positive within-productivity contribution) toward the service sector, which exhibits declining productivity growth. Mallick (2015) contend that, due to globalization, labour has moved from the agricultural sector toward industrial and service activities, but our findings suggest that the transition has been mainly towards services.

Several empirical studies have found that a transition from agriculture to non-agricultural sectors might lead to stronger productivity growth (Jaumotte and Spatafora 2007 and Poirson 2000). However, there is evidence that contradicts those findings and supports our findings. Diao, McMillan and Rodrik (2017) contend that in Africa structural transformation came accompanied by declining labour productivity growth in the more modern sectors of the economy, while in Latin America structural change has been weak and has made a negative contribution to overall productivity (except in agriculture).

Similarly, Duernecker, and Sanchez-Martinez (2021) provide evidence of labour reallocation toward stagnant services in the European Union, with a negative impact on long-term aggregate productivity growth across all economies.

▶ **Figure 6. Decomposition of labour productivity, by region, 1990–2018**

Source: GGDC/UNU-WIDER The Economic Transformation Database 2021.

Figure 6 shows that, in LA, SSA and EA, recent aggregate productivity growth has been based on within-sector productivity contributions. Asia (mainly EA) has experienced productivity-enhancing structural change over the period 1990–2018, with an average productivity growth of 3.6 per cent. In LA, SSA and MENA, labour has reallocated toward low-productivity service sectors, which has not contributed much to average productivity growth in those regions (1.5 per cent). In fact, MENA exhibits productivity-reducing structural change from 1990 to 2018.

McMillan and Rodrik (2011) found similar results for the period 1990–2005, with MENA, SSA and LA exhibiting productivity-reducing structural change. The authors argue that the productivity growth gap between Asia and other regions might be explained by structural change patterns rather than by changes in within-productivity. Diao, McMillan and Rodrik (2017) found that recent growth accelerations were based on within-sector labour productivity growth in Latin America and structural change in Africa. In Africa structural change came at the expense of declining labour productivity growth in non-agricultural sectors, as also shown in figure 4.

The Inter-American Development Bank (IDB) found that, between 1950 and 1975, LA experienced rapid labour productivity growth (around 4 per year), and roughly half of that was due to structural change. The debt crisis in the region between 1975 and 1990 was accompanied by negative productivity growth.

After 1990 the region returned to growth but with little gain in productivity, which might be explained by labour mobility toward low productivity service sectors, which seems to have been the trend until 2018.

The Africa and LA regions exhibit a competitive advantage in the export of primary products and face low incentives in a globalized economy to diversify its productive matrix toward modern sectors. In contrast, Asia is well endowed with labour resources and exhibits an advantage in labour mobility toward more productive sectors. McMillan and Rodrik (2011) suggest that globalization has boosted specialization in sectors that have a competitive advantage, thus disincentivizing diversification and displacing workers toward less productive sectors.

▶ 3.2 Empirical analysis

> The main hypothesis of this analysis is that growth-enhancing structural changes take place in countries where the business environment is conducive to enterprise development.

This section conducts an econometric analysis to explore the effects of business environment factors on the structural component of labour productivity growth. The main hypothesis of this analysis is that growth-enhancing structural changes take place in countries where the business environment is conducive to enterprise development.

The structural component was calculated using data from the Groningen Growth and Development Centre (GGDC) Economic Transformation Database, which reports on 51 developed and developing countries in Africa, Asia and Latin America over a period of 29 years (1990–2018). The sectors included for the analysis are:[17] agriculture, mining, manufacturing, utilities, construction, trade services, business services, financial services, real estate, government services and other services.[18]

The business environment data were obtained from the World Bank Development Indicators (WDI), the World Governance Dataset,[19] the World Bank Education Statistics,[20] the Patent Cooperation Treaty Dataset, the IMF Financial Development Index, the Global Competitiveness Index, the World Bank Doing Business,[21] the ILOSTAT Database and the Penn World Table version 10.0 1950–2019.[22] The total number of observations used for the empirical analysis is 1428 for a period that ranges between 1991 and 2018 (28 years) and covering 51 countries.

17 According to the International Standard Industrial Classification Rev4, agriculture, forestry and fishing (agriculture); mining and quarrying (mining); manufacturing; electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities (utilities); construction, wholesale and retail trade, repair of motor vehicles and motorcycles, accommodation and food service activities (trade services); information and communication, professional scientific and technical activities, administrative and support service activities (business services); financial and insurance activities (financial services); real estate activities; public administration and defense, compulsory social security, education, human health and social work activities (government services); and arts, entertainment and recreation, other service activities of households as employers, undifferentiated goods-and-services-producing activities of households for own use, activities of extraterritorial organization and bodies (other services).

18 See Annex 2 for a list of the countries included in the model specification.

19 www.govindicators.org

20 https://databank.worldbank.org/source/education-statistics-%5e-all-indicators

21 http://www.doingbusiness.org/

22 The dataset of PWT 10.0 is available at http:// www.ggdc.net/pwt.

3.2.1 Definitions of variables

The *dependent variable* used in the model is the year-by-year growth in the contribution of structural transformation to labour productivity, using shift–share analysis to consider real changes observed in the dataset. The labour productivity by sector used to construct the structural transformation component was calculated as the output divided by the number of workers.

Other choices could be considered for the dependent variable, such as calculating changes in a given period (for example, over 10 years) or computing annualized growth rates.[23] The first of these options leads to loss of information, since years are omitted from the analysis and, therefore, the variability of the indicator is reduced. However, the argument for this option is based on the fact that structural transformations are generated in the medium term. The latter option involves annualizing the variation by taking two ad-hoc points in time and using the compound annual growth rate formula. This option incurs no loss of information and smooths the variability of the data.

A vast literature focuses on analysis of the effects of technology diffusion and openness to trade on productivity growth (Grossman and Helpman 1991b, Barro, Sala-i-Martin 1997, and Edwards 1998). Recently, research has become interested the effects on productivity growth of complementary factors, such as market efficiency, infrastructure, business regulations and flexibility of labour markets, among others (Chang et al. 2009 and Kim and Loayza 2019).

In line with these newer efforts, this study focuses on the association between structural change and the business environment. Following the work of Kim and Loayza (2019), we constructed five dimensions, the purpose of which is to comprehensively capture the business environment of each country: innovation, education, market efficiency, infrastructure and institutions. The dimensions were constructed by the aggregation of several indicators using factor analysis and then normalized to the range from zero (worst) to 1 (best).

The *innovation dimension* was constructed using research and development expenditure as a percentage of GDP; the ratio of number of resident and non-resident patents to total population; the ratio of number of scientific and technical journal articles to total population; business value-added share with respect to total value added across all sectors; and information and communication’s share of technological capital.

Education levels are linked to productivity growth.[24] The *education dimension* was characterized using the human capital index, completed secondary education; completed tertiary education; government expenditure on education as a percentage of GDP; and labour quality’s contribution to GDP.

The *market efficiency dimension* was disaggregated into three sub-indices: output, financial and labour markets. The output sub-index includes the costs of startup, time to prepare taxes, time to enforce contracts, time to register property, time to start a business and time to resolve insolvency.

The financial sub-index includes risk premium lending, value-added financial services, access to financial institutions, financial market depth, financial market access, and the financial institutional access indices developed by the IMF for the Financial Development Index Database.[25]

The labour market sub-index includes flexible wage, hiring and firing regulations; redundancy costs; labour taxes; labour share (share of total labour compensation in GDP); quantity contribution of labour input to GDP; and the proportion of female workers[26] with respect to the total wage and salaried workforce. Labour mobility toward more productive sectors can be influenced by the ease of entry and exit to these industries as well as the flexibility of labour markets (Ciccone and Papaioannou 2008). Entry barriers and rigid employment conditions (for example, firing costs are too high) slow down the

23 For example, McMillan and Rodrik (2011) use structural transformation annualized in percentage terms for the period 1990–2005. Kim and Loayza (2019) use annualized TFP growth over t-5 and t to determine the relationship with a composite index of business environment variables. In the latter the authors ended up with a panel of 98 countries over five years. See: https://stats.mom.gov.sg/SL/Pages/Annualised-Percentage-Growth-Concepts-and-Definitions.aspx.

24 In general, a more educated workforce will be able to adapt more easily to new business models, processes and industries; see Schultz (1975) and Romer (1990).

25 https://data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B

26 The evidence on female participation in the workforce and productivity gains is mixed. McGuckin and Van Ark (2005) find that female participation in the workforce may lead to lower productivity when the new entrants are older women, while De Jong and Tsiachristas (2008) argue for the opposite effect when female workers can adapt to innovations.

transition to more productive sectors and incentivizes the use of capital (for example, upgrading plant and equipment) and the use of technology rather than hiring new workers.

The *infrastructure dimension* includes access to electricity (percentage of population), fixed telephone subscriptions (per 100 people), access to water (percentage of population), access to sanitation (percentage of population), access to internet (percentage of population), mobile cellular subscriptions (per 100 people) and density of rail lines calculated as rail lines in km with respect to surface area.

The *institutional dimension* includes the following World Bank Governance Indices: control of corruption (the extent to which public power is exercised for personal gain), government effectiveness (the quality of public services and policy formulation and implementation), political stability (the absence of politically motivated conflict), regulatory quality, rule of law, and voice and accountability (citizens' participation in selecting their government and freedom of expression).[27]

Finally, we included other controls that are commonly used in the literature: trade openness, growth of foreign direct investment (FDI), growth of GDP per capita, manufacturing and agriculture shares of value-added and growth of gross fixed capital.[28]

3.2.2 Data analysis and treatment of variables

To ensure comparability across countries, the variables were expressed in relative terms (for example, as percentage of GDP, population or, in some cases, land area); appropriate transformations were performed to deal with outliers and non-normal distributions; and several imputation methods were conducted to deal with missing values.

First, we conducted an exploratory and descriptive examination of the variables considered for the model specification. Second, we explored the distribution of each variable to spot outlier observations. After examining the variables' distribution using box, quantile plots and interquartile ranges (see Annex 4), we decided to winsorize variables with outliers using 5 and 95 percentiles.

Third, we imputed some of the variables using a mix of linear interpolation and median value replacement. For a country indicator that has data for more than 10 of 30 years (1991-2020), we project a linear trend over years to impute missing values. For a country indicator with less than ten years of data, we replace missing values with a median value corresponding to the country's income and regional group by year. The average percentage of missing values before imputation is 35.0%. After imputation the average percentage of missing values dropped to 18.8% of total observations.[29]

27 The World Bank Doing Business scores regarding the ease of firms to start a business, trade across borders, register property and obtain credit, among others, are used to capture the subdimension of output market efficiency. The International Monetary Fund (IMF) Financial Development Index is included as an indicator of financial market efficiency.

28 Neoclassical trade theory predicts that opening domestic markets to international markets leads to increases in productivity. In theory FDI inflows might improve productivity through the entrance of foreign firms, which generally exhibit higher productivity rates than local firms, and through the investment of capital and spill-over effects of modern technologies, production processes, business models and management practices, among others, into the local markets. However, research suggest that the overall impact of FDI on productivity depends on other factors, such as the level of human development (Borensztein, De Gregorio and Lee 1998) and the strength of financial markets (Alfaro et al. 2003), among other factors.

29 See Annex 5 for statistics describing missing values.

▶ Figure 7. Business environment and productivity in five regions, 1996–2018

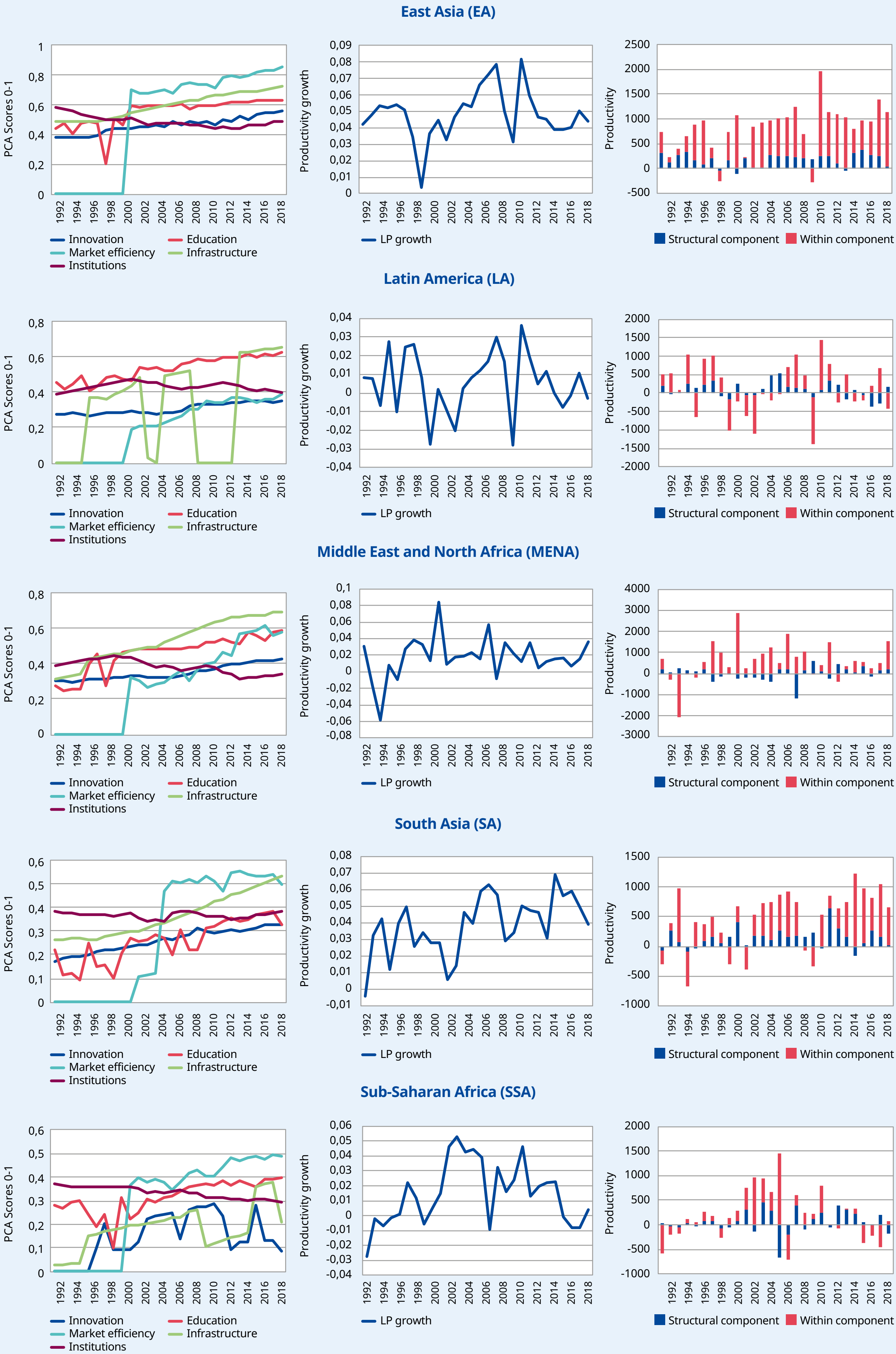


Figure 7 shows the evolution of the business environment dimensions (innovation, education, market efficiency, infrastructure and institutions) along with labour productivity growth and its decomposition for each region. In general, *innovation* and *institutions* are the dimensions with the worst performance, while infrastructure has improved most during the period of analysis. Figure 7 shows that East Asia (EA) is the region with the best business environment while SSA exhibits the worst business environment across all regions. The largest gap among all business environment dimensions between EA and the rest of regions is *market efficiency*. The market efficiency score has been at around 0.8 for EA and below 0.6 for the rest of the regions. This gap coincides with the one in labour productivity growth, which might suggest a moderate or strong correlation between the two measures.

3.2.3 Econometric approach

Based on the literature review, our model specification argues that the structural transformation component of growth is positively associated with the business environment, as controlled by sectoral composition, macroeconomic factors, time and country fixed effects.

> Our model specification argues that the structural transformation component of growth is positively associated with the business environment, as controlled by sectoral composition, macroeconomic factors, time and country fixed effects.

The literature suggests that the selection of dynamic panel data estimators depends on its asymptotic properties, which are related to the magnitudes of N and T.[30] For example, in the case for N=1, the traditional approach is to estimate autoregressive distributed lag models and/or cointegrating relationships from a single time series. For N>1 the Seemingly Unrelated Regression Equation (SURE) procedure is often used in the literature, but it is possible only when N is reasonably small relative to T; otherwise it is not feasible. In the presence of a non-zero error covariate due to omitted common effects, the analyst might include cross-sectional means of the included regressors and additional covariates in the model. Different approaches might be considered in the presence of heterogeneous coefficients across groups, dynamic panels and cointegration, among other issues that might violate classical assumptions.

Most research studies have employed techniques for static panel datasets, assuming dynamic effects of the structural transformation. For the coefficient estimation, the authors have relied on fixed effects models and in some cases Generalized Method of Momentum (GMM) estimators, assuming no cross-section dependence and homogenous coefficients across units (Mallick 2015) and using instruments for the lagged dependent variable and predetermined and endogenous regressors.

For small T panels, the estimation approach usually relies on fixed or random effects estimators or a combination of fixed-effect and instrumental variables estimators such as in the GMM proposed by Arellano and Bond (1991) for dynamic panels with endogenous lagged dependent variables.[31]

In our case we constructed a data panel of 51 countries and 28 years, which could be considered a "large T, large N" panel. For the specification model, we did not have prior knowledge of dynamic or static dependencies, and so we decided to start with an Autoregressive Distributed Lag (ARDL) Model (1,1), given that social and economic processes are dependent on the past. Our assumptions are backed by the Wooldridge test for serial correlation in panel-data models, suggesting the presence of first-order

30 N refers to the number of cross-section units and T, to the length of the time series.

31 The GMM for panel data analysis was proposed by Arellano and Bond (1991) and further developed by Blundell and Bond (1998). The Arellano-Bover/Blundell-Bond estimator augments Arellano-Bond by making an additional assumption that the first differences of instrument variables are uncorrelated with the fixed effects.

autocorrelation (Prob> F=0.32). Alternative models with more or fewer lags were estimated to assess the influence on the results, including static panel model ARDL (p,q) with p and q to show possible biased estimates due to few lags or reduction of efficiency and power due to many lags (Chudik et al. 2016).

The model specification follows the decision-making framework proposed by Thombs (2022) for large N, large T panel data models. The first step is to define the ARDL(p,q) or Error Correction Model (ECM)(p,q) specification based on theory to guide the modelling approach.

The Levin–Lin–Chu (LLC) (Levin, Lin and Chu 2002) unit root test analysis null hypothesis was rejected in favour of stationary panels. Thus, we are more confident that the dataset does not contain unit roots.

The analysis started with the following specification:

$$(1)\ STC_{it} = \beta_{0i} + \beta_{1i} STC_{it-1} + \beta_{2i} X_{it} + \beta_{3i} X_{it-1} + \gamma_i \bar{\upsilon}_t + \varepsilon_{it}$$

where STC_{it} refers to the structural transformation growth for country i in time t; $STC_{it\text{-}1}$ is the lagged dependent variable; X_{it} is the vector of the business environment dimensions, and other sectoral and macroeconomic variables included as controls. $X_{it\text{-}1}$ is the vector of lagged regressors. $\bar{\upsilon}_t$ is a vector with the cross-section averages of the dependent and independent covariates, and ε_{it} is the error term.

The second step is to assess the presence of heterogeneity coefficients in the model using the test proposed by Blomquist and Westerlund (2013) (see also Pesaran and Yamagata 2008). The results show that the model exhibits heterogenous coefficient slopes (Delta: -8.7; p-value=0.00), and so, to avoid inconsistent and biased results, we use a mean group estimator instead of alternatives such as a 1-way fixed effects estimator. In large N and T panel datasets, the estimations obtained by the fixed effects and even GMM models with instruments are inconsistent due to the presence of slope heterogeneity and cross-sectional dependence (Pesaran and Smith 1995, Pesaran 2006, 2015).[32]

Third, we conducted the Pesaran (2015) test for weak cross-sectional dependence. The null hypothesis of weakly cross-sectional dependent errors was rejected (CD=12.2, p-value=0.00) in favour of strong cross-sectional dependence.[33] Thus, the data are likely to exhibit strong cross-sectional dependence. Hence, we need an estimator that accounts for a) cross section dependence and b) heterogenous slopes.[34]

Pesaran, Shin, and Smith (1999) propose two techniques to estimate nonstationary dynamic panels with heterogeneity across groups: the mean-group (MG) and the pooled mean-group estimators. The former estimates N time-series regressions, which averages the coefficients, whereas the latter relies on a combination of pooling and averaging coefficients using maximum likelihood estimation. To account for the common correlated effects (CCE), Pesaran (2006) proposes an approximation of the linear combinations of the unobserved factors by cross-sectional averages of observables and then running standard panel regressions augmented with these cross-sectional averages.[35] For dynamic panels Chudik and Pesaran (2015a and 2015b) propose an extension of the CCE including lagged dependent variables in the model for consistent estimation.

However, to avoid two issues, we did not use the CCE estimator. The first issue is the bias correction needed to ensure valid inferences asymptotically (incidental parameters' bias), which in many scenarios cannot be fully eliminated, causing substantial size distortions in finite samples (Westerlund and Urbain 2015, Juodis, Karabiyik, and Westerlund 2021). The second issue is related to the loss of degrees of

32 According to Chudik and Pesaran (2015a), "the presence of some form of cross-sectional correlation of errors in panel data applications in economics is likely to be the rule rather than the exception."
33 The sources of cross-correlation errors are multiple, such as omitted common and spatial effects that can produce misleading inference and inconsistent estimators (for example, when the source of cross-sectional dependence is correlated with regressors) even when applying conventional panel estimators such as fixed and random effects.
34 See Annex 6 for a detailed explanation of the residual multifactor approach.
35 There are two methods for dealing with cross-sectional dependence: the spatial econometric and the residual multifactor approaches. The former assumes that the cross-sectional correlation is explained by location and distance among units and the latter assumes that cross-sectional dependence can be modelled by a small number of unobserved common factors. For our purposes we used the residual multifactor approach because the spatial econometric approach does not allow for slope heterogeneity across units and requires a priori knowledge of the weight matrix. See Annex 2 for a more detailed discussion of the residual multifactor approach. For Stata commands see Ditzen (2018).

freedom due to the large number of regressors and the length of the temporal dimension, mainly in Dynamic CCE (DCCE) estimations with T around 30. For these cases Monte Carlo Simulations conducted by Thombs (2022) suggest that the use of fixed effects is preferable to DCCE even in the presence of high slope heterogeneity.

As an alternative, Norkute et al. (2021) and Cui et al. (2020) propose a two-stage general instrumental variables approach (2SIV) for weakly exogenous and/or endogenous variables where the common factors are projected using PCA rather than cross-sectional averages, as proposed in the CCE, which does not require bias correction and does not severely affect the number of degrees of freedom. Moreover, the estimation is valid for models with homogeneous or heterogenous slope coefficients and accommodates estimation of unbalanced panels.

First, we explored 2SIV approach (with homogeneous slope coefficients) between business environment and macroeconomic variables. The p-value of the Hansen test statistic suggests that the overidentifying restrictions are valid (Chi: 23.3; p-value: 0.98). The output shows that 43% of the total variance of the composite error term is explained by common factors. The results indicate the preferability of the 2SIV mean group model specification because failing to control for commons shocks is likely to severely bias the estimations.

Chapter

4

4. Results

Table 1 shows the results of four different specifications. The first is the fixed effects model; the second is common correlated pooled second stage instrumental variable specification (2SIV); the third is the common correlated mean group 2SIV; and the last is similar to the third but with second lags of the business environment covariates, which in some cases are statistically significant.[36]

▶ Table 1. Main results of the dynamic model

Variable	Fixed effects (1)	2SIV Pooled ARDL (1,1) (2)	2SIV Mean group ARDL (1,1) (3)	2SIV Mean group ARDL (1,1) (4)
Lagged dependent variable	0.112	1.140**	2.763	3.314
	–0.234	–0.569	–4.295	–4.602
Innovation	–56.74	–117.2	21.42	
	–56.17	–129.5	–31.51	
L.innovation	–109.1	–69.56	–2.307	–15.91
	–108.3	–144.1	–7.69	–11.07
Education	–7.656	26.01	79.06***	74.9
	–28.6	–25.04	–27.08	–51.61
L.education	–21.44	–9.253	0.783	4.996
	–19.85	–33.23	–56.93	–18.65
Market efficiency	12.51	–93.41**	42.78	54.03**
	–14.15	–39.71	–71.71	–22.27
L.market efficiency	–58.29	–187.7***	14.12	–2.128
	–60.65	–36.06	–25.92	–16.81
Infrastructure	–23.75	18.9	95.31	114.9
	–20.63	–33.69	–71.89	–129.6
L.infrastructure	–15.31	–21.39	42.58	0.232
	–25.1	–29.59	–29.76	–7.726
Institutions	33.74	60.37*	–27.18	5.091
	–20.64	–36.66	–29.11	–14.45
L.institutions	95.97	123.5***	19.97	60.84
	–75.49	–25.61	–24.75	–46.53
Trade growth	–58.62	–112.9***	1.785	–15.34
	–43.53	–35.88	–38.97	–18.97
L.trade growth	–48.55	–9.378	–2.558	34.45
	–60.2	–39.1	–30.99	–35.21

36 For robustness we also estimated our results assuming static panel results; see Annex 7.

Variable	Fixed effects (1)	2SIV Pooled ARDL (1,1) (2)	2SIV Mean group ARDL (1,1) (3)	2SIV Mean group ARDL (1,1) (4)
Foreign Direct Investment growth (FDI_gr)	−0.0111	−1.003	−7.487	−8.903
	−0.131	−0.619	−9.207	−8.437
L.FDI_gr	−0.177	−0.104	−0.398	7.124
	−0.26	−0.758	−6.687	−9.515
Gross Fixed Capital growth (GFC)	76.35	161.0***	196.8*	65.84**
	−90.75	−53.73	−108.7	−25.97
L.GFC growth	−23.86	−40.12	31.95	20.19
	−30.82	−38.97	−30.89	−20.22
Gross Domestic Product (GDP) per capita growth	325.3	327.4**	−17.49	
	−326.4	−163.7	−17.49	
L.GDP per capita growth	177.6	330.0*	−28.82	
	−155.9	−199.2	−28.82	
Agriculture value added (va) share	−100	−1,125		
	−206.1	−967.7		
L.agriculture value added share	722	1,718**		
	−457.2	−728.9		
L2.innovation				−29.61*
				−16.73
L2.education				30.46*
				−17.16
L2.market efficiency				−35.96
				−44.52
L2.infrastructure				51.74**
				−20.47
L2.institutions				83.53
				−65.18
L2.trade growth				−15.95
				−48.83
Constant	−105.4	−92.24	−11.22	−43.8
	−82.95	−71.31	−15.77	−45.23
Observations	409	266	266	266

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.
Abbreviations: ARDL = Autoregressive distributed lag; L = Lagged, L2=Lagged minus two periods.

After correcting for heterogenous coefficient slopes and common cross estimators, specification (4) shows that market efficiency, infrastructure and education, as well as gross fixed capital, affect positively and significantly while education and infrastructure growth exhibit delayed effects (second lag) of these covariates exhibit a negative effect on structural transformation.[37] Interestingly, growth in innovation seems to exhibit a negative sign, which suggests that these might support the within-sector contribution to labour productivity growth rather than STC.

Finally, gross fixed capital growth is positive in all specifications, which supports the theory that investment is key for structural change growth. There are various studies that highlight the importance of gross fixed investment to labour productivity growth and economic growth in both developing and developed economies (Demurger 2001, Wei 2000).[38]

Finally, we tested for possible endogenous variables, which means that errors are correlated with the dependent variables and lead to biased and inconsistent estimates. The 2SIV-MG specification controls for time and country regressors but does not for endogenous regressors. To assess the presence of possible endogenous regressors, we use the Hausman endogeneity test after the fixed effects-2SLS (FE2SLS) estimator, assuming the second lags of the regressors are exogenous.[39]

The preliminary results suggest that the variables might not exhibit endogeneity problems, but the literature suggests that reverse causal effects might be present in the model specification. Therefore, we decided to use the lags of the covariates as instruments, assuming they are not correlated with the error term and are strongly correlated with the endogenous variable.[40]

Based on the previous analysis, we decided to estimate the 2SIV model with the second lag of the regressors as instruments as a starting point. We conducted alternative analyses with different lags, but the inclusion of further lags of the covariates (three to five) magnified the weak identification problem, and the inclusion of the first lag of the covariates increased the probability of overidentification. Thus, we remained with our first choice of using the second lag of the covariates as instruments.

The use of lags as instrumental variables does not allow proper ways to test the seriousness of the endogeneity problem or to test the appropriateness of the proposed solution.[41] However, several studies have used this approach to control for endogeneity. For example, Mallick (2015) conducted a dynamic panel GMM model using 1-year lag for all endogenous and exogenous specifications to assess the effects of globalization (measured as the growth of FDI and trade) on labour productivity growth. Kim and Loayza (2019) used the 5-year lagged TFP level and time effects to estimate the effects of business environment variables on TFP growth. Table 2 presents the results of this model specification.

▶ Table 2. Main results of the dynamic model with endogenous covariates

Variable	2SIV-MG static (5)	2SIV-MG dynamic (6)
L.between total growth		1.119
		–2.776
L2.innovation	–19.33	–43.46
	–47.67	–41.6
L2.education	342.7	8.24
	–354.8	–57.97
L2.market efficiency	74.87**	89.45***

37 The results of the dynamic specification accounting for heterogenous slopes and cross-sectional correlation (model 4 and 5) show the bias of not accounting for regressors' slopes' heterogeneity and cross-sectional dependence.
38 In addition, we estimated a static model that assumes that the coefficient of the lagged dependent variable is not significant. The results show that market efficiency and infrastructure (levels and the first lag) are positively associated with STC. The education dimension remains with the same sign, but this time is non-significant (see Annex 7).
39 Different number of lags were considered to be possible instruments. The first lag did not pass the overidentification test.
40 The preferred method is to use instrumental variables. However, the FE2SLS Stata routine does not allow the inclusion of instrumental variables.
41 The results should be taken with caution, as we know that the selection of weak instruments leads to bias, inefficiency and compromised tests.

Variable	2SIV-MG static (5)	2SIV-MG dynamic (6)
	–36	–31.08
L2.infrastructure	–81.36	–43.99
	–84.34	–78.42
L2.institutions	–72.63	–17.32
	–100.5	–53.7
L2.trade growth	–95.53	–128.1
	–254.1	–147
L2.Foreign Direct Investment growth	29.23	5.891
	–25.36	–13.54
L2.Gross Foxed Capital Growth	165.5	50.7
	–150.4	–37.94
L2.Gross Domestic Product per capita growth	139.9	144
	–122	–133.9
L2.Agriculture value added share	505.5**	459.3***
	–198.1	–155.1
Constant	–77.05**	–40.14**
	–35.3	–17.28
Observations	266	266

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Abbreviations: ARDL = Autoregressive distributed lag; L =Lagged, L2=Lagged minus two periods.

In these model specification, education and infrastructure became non-significant, but market efficiency remained significant at a 99 per cent level of confidence. In fact, market efficiency was the only dimensions that remained positive and significant across different specifications. Thus, we assume with more confidence that market efficiency might have a positive and significant effect on structural change. Market efficiency is a dimension that summarizes the ease of doing business, financial development and labour market flexibility of each country.

Our findings are supported by several studies that contend that market efficiency or its components are key factors for productivity growth. For example, Jerzmanowski (2007) contends that inefficiency in the allocation of capital is associated with low income levels in 80 countries from 1960 to 1995; Bergoeing, Loayza, and Piguillem (2016) suggest that regulatory barriers to market entry and exit of firms account for 26 to 60 per cent of the income gap between the United States of America and 107 developing economies. Rajan and Zingales (1998) contend that financial development facilitates economic growth, which is strongly correlated with productivity growth (as shown in figure 1), while Beck, Levine, and Loayza (2000) argue that financial development is positively associated with TFP. Finally, with respect to labour markets, Bartelsman, Gautier, and De Wind (2016) argue that rigid employment regulations deter efficient labour reallocation across sectors.

Conclusions

Conclusions

This study contributes to the existing literature by assessing the effect of the business environment on structural change. The study uses shift-share decomposition to assess the contributions of within- and between-sector productivity to labour productivity growth from 1990 through 2018 and a dynamic panel data model specification to assess the effect of the business environment on structural change.

The study shows that labour productivity growth is higher in Asian economies than in LA, SSA and MENA. This is a consequence of labour reallocation in Asia from low-productivity to high-productivity activities. Labour shares by sector show a reallocation from agriculture toward services in all regions, while manufacturing has remained practically at the same levels. As suggested by Diao, McMillan and Rodrik (2017), LA and SSA have exhibited productivity-diminishing structural changes, with SSA showing negative labour productivity growth in non-agricultural sectors.

Our results show that structural change has played an important role in EA, has had a negligible role in LA and SSA and has contributed negatively to labour productivity growth in MENA from 1980 through 2018. The most important component of labour productivity growth has been within-sector productivity changes for all region in the period of analysis. For LA, SSA and MENA, productivity gains are explained by within-productivity changes in agriculture, which is the sector where these economies tend to exhibit competitive advantage and a sluggish and sometimes negative productivity growth in manufacturing and services. Meanwhile, Asia (both SA and EA) shows productivity growth in both manufacturing and services sectors in the period of analysis.

Moreover, our results show that EA is the region with best business environment conditions. The largest gap between EA and the rest of the regions is *market efficiency* among all business environment dimensions. This coincides with the gap observed in labour productivity growth. The relationship between market efficiency and labour productivity gaps between EA and the rest of the regions observed in the descriptive analysis is supported in the empirical analysis.

The effect of the business environment on structural change is analysed by using a dynamic panel data model specification for all the sample data. Our results suggest that market efficiency (ease of doing business, financial development and labour market flexibility of each country) might be a significant factor in explaining the surge of structural change during the period in the EA region.

As suggested by Duernecker and Sanchez-Martinez (2021), policies should focus on the promotion of productivity-enhancing technological innovation, especially in the most sluggish service sectors, where most of the reallocation of labour is happening. These policies should be accompanied by policy measures to improve overall market efficiency, for example, by facilitating the creation and operation of businesses, reducing the costs of trade, promoting flexible labour markets that allow free flow of resources across sectors, strengthening financial institutions and implementing or improving regulations that enhance competition and innovation.

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Annexes

▶ Annex 1. The shift–share decomposition method of MacMillan and Rodrik (2011)

Shift-share analysis within a dual-economy framework dissects labour productivity growth into within-sector and inter-sector variations. This approach suggests that the transition of labour from traditional to modern sectors enhances productivity and income. It relies on the interplay between within-sector and between-sector factors, where the former reflects resource shifts and the latter involves skill accumulation and institutional quality for sustained productivity growth (McMillan, Rodrik, and Sepulveda, 2017).

The within-sector first factor element measures the effect of a change in productivity in sector i (ΔP_t) weighted by its share in labour in the initial period $(\theta_{i,t-1})$. This is also called the "intra-industry" or "within-sector" factor. The second component factor captures the effect of a change in the labour share hired by sector i in time t $(\Delta\theta_{i,t})$, weighted by the productivity of the sector in the final period $(p_{i,t})$. This is also known as the "inter-industry" or "between-sector" component, since it captures the contribution associated with shifts of labour among sectors.

$$\textbf{Eq. 1:}\ \Delta P_t = \sum_{i=1}^{n} \theta_{i,t-1}\ \Delta p_{i,t} + \sum_{i=1}^{n} p_{i,t}\Delta\theta_{i,t}$$

Criticisms: One of the criticisms of this method has been that it increases the importance of the "within" component due to the base period used.

Variation 1: This variation weights the "within" component with the final period $(\theta_{i,t}\ \Delta p_{i,t})$, and the reallocation component $(p_{i,t-1}\Delta\theta_{i,t})$, with the base period. This might result in an overstated contribution of the reallocation component.

$$\textbf{Eq. 2:}\ \Delta P_{it} = \sum_{i=1}^{n} \theta_{i,t}\ \Delta p_{i,t} + \sum_{i=1}^{n} p_{i,t-1}\Delta\theta_{i,t}$$

Variation 2: A third method uses the average of the period as the weight for both components, the within $(\sum_{i=1}^{n} \bar{\theta}_i\ \Delta p_{i,t})$ and the between $(\sum_{i=1}^{n} \bar{p}_i\Delta\theta_{i,t})$ component. However, this approach only partially captures the process of structural transformation.

$$\textbf{Eq. 3:}\ \Delta P_{it} = \sum_{i=1}^{n} \bar{\theta}_i\ \Delta p_{i,t} + \sum_{i=1}^{n} \bar{p}_i\Delta\theta_{i,t}$$

***Variation 3** (Timmer and De Vries 2013):* This decomposition formula modifies the second component and includes a third one, which is commonly named the dynamic effect (or Fagerberg's dynamic effect). The first component of the formula represents the "within" component $(\theta_{i,t-1}\ \Delta p_{i,t})$. However, the second component of the formula presented in equation 1 is broken down into two components. Timmer and de Vries (2013) call the second component the static reallocation effect $(p_{i,t-1}\Delta\theta_{i,t})$ and the third one the dynamic reallocation effect $(\Delta p_{i,t}\Delta\theta_{i,t})$. The static reallocation term captures the labour reallocation to sectors with different productivity levels. Meanwhile, the dynamic reallocation term measures the contribution of the reallocation of workers to sectors with dissimilar productivity trends. Thus, the term is positive when sectors in which productivity is growing increase their labour shares or when sectors in which productivity is decreasing reduce their shares. The term is negative when they move in the opposite directions.

$$\textbf{Eq. 4: } \Delta P_{it} = \sum_{i=1}^{n} \theta_{i,t-1} \ \Delta p_{i,t} + \sum_{i=1}^{n} p_{i,t-1} \Delta\theta_{i,t} + \sum_{i=1}^{n} \Delta p_{i,t} \Delta\theta_{i,t}$$

Differentiating the dynamic from the static reallocation effect is relevant, given the fact that sectorial productivity levels and growth rates are usually negatively correlated. **Therefore, for the purpose of the analysis, this paper will present results from equation 4.**

This paper uses as the dependent variable the structural transformation, which comes from the sum of the static and dynamic reallocation components calculated in equation 4 of section 2 ($\sum_{i=1}^{n} p_{i,t-1}\Delta\theta_{i,t} + \sum_{i=1}^{n} \Delta p_{i,t}\Delta\theta_{i,t}$).

A positive component represents a growth-enhancing type of structural transformation, which implies that over the analysed period employment increased in sectors in which labour productivity is higher or is growing faster, contributing positively to the productivity growth of the overall economy. A positive sign could also indicate that the employment share shrank in the sectors in which labour productivity is lower or declining, which might also contribute positively to aggregate productivity growth.

The selection of weights might affect the indicated magnitude of growth in both the "within" and "between" components of the growth decomposition.

Assuming $\Delta P_t ! = 0$ and $\Delta\theta_{i,t} ! = 0$ for a given sector, there are four possibilities: a) $\Delta P_t > 0 \,\&\, \Delta\theta_{i,t} < 0$; b) $\Delta P_t > 0 \,\&\, \Delta\theta_{i,t} > 0$; c) $\Delta P_t < 0 \,\&\, \Delta\theta_{i,t} > 0$; and d) $\Delta P_t < 0 \,\&\, \Delta\theta_{i,t} < 0$. Under these different possibilities, the choice of weights affects the magnitudes of the two components at the sector level:

Case (a) $\Delta P_t > 0 \,\&\, \Delta\theta_{i,t} < 0$. This is common in the agricultural sector of developing countries, where the within-sector productivity growth is positive and structural change is negative. Since $\theta_{i,t-k} \ \Delta p_{i,t} > \theta_{i,t} \ \Delta p_{i,t}$ and $|\theta_{i,t} \ \Delta p_{i,t}| > |\theta_{i,t} \ \Delta p_{i,t-k}|$ compared with equation 3, equation 2 could overstate the contribution of sector i's within-sector productivity growth and overstate the negative contribution of this sector to structural change.

Case (b) $\Delta P_t > 0 \,\&\, \Delta\theta_{i,t} > 0$. This is seen among East Asian countries in the manufacturing sector. $\theta_{i,t-k} \ \Delta p_{i,t} < \theta_{i,t} \ \Delta p_{i,t}$ and $\theta_{i,t} \ \Delta p_{i,t} > \theta_{i,t} \ \Delta p_{i,t-k}$. Compared with equation A3, A2 might understate the contribution of sector i's (manufacturing) "within" sector productivity growth and overstate the contribution of this sector to structural change.

Case (c) $\Delta P_t < 0 \,\&\, \Delta\theta_{i.t} > 0$. The literature has reported this in the case of non-agricultural sectors in African countries. $\Delta p_{i,t} < 0$ and $|\theta_{i,t-k} \ \Delta p_{i,t}| < |\theta_{i,t} \ \Delta p_{i,t}|$ but $\theta_{i,t} \ \Delta p_{i,t} < \theta_{i,t} \ \Delta p_{i,t-k}$, which implies that eq. 2 could understate both the negative contribution of sector I to within-sector productivity changes and its positive contribution from structural change in comparison with eq. 3.

Case (d) $\Delta P_t < \Delta P_{t-k} \,\&\, \theta_{i,t} < \theta_{i,t-k}$, as seen in Hong Kong for the construction sector for the period 1990–2010 in the GGDC data. Both $\Delta p_{i,t} < 0$ and $|\theta_{i,t-k} \ \Delta p_{i,t}| > |\theta_{i,t} \ \Delta p_{i,t}|$ and $|\Delta\theta_{i,t} \ p_{i,t}| < |\Delta\theta_{i,t} \ p_{i,t-k}|$. In comparison with eq. A3, eq. A2 could overstate sector i's negative contribution within-sector and understate the negative contribution to structural change.

▶ Annex 2. UNU–WIDER Economic Transformation Database (ETD)

The ETD includes data for:

- 51 developing economies: 21 in Africa, 9 in Latin America and 21 in Asia;
- two sectors of the total economy, following the ISIC rev. 4 industry classification;
- nominal value added, in local currency;
- real value added, in local currency (2015 prices);
- persons engaged;
- time series with annual data from 1990 to 2018.

Employment is defined as all persons engaged, ages 15 years and older, including all paid employees, the self-employed and family workers. The preferred age boundary is 15 years, since, typically, the contribution of children to production is small. Ideally, labour input should be measured in hours worked. However, insofar as they are available, the data are irregular, and information on hours worked typically covers only the formal sector.

Countries included		
Africa	**Asia**	**Latin America**
Botswana	Bangladesh	Argentina
Burkina Faso	Cambodia	Bolivia
Cameroon	China	Brazil
Egypt	Hong Kong, China	Chile
Ethiopia	India	Colombia
Ghana	Indonesia	Costa Rica
Kenya	Israel	Ecuador
Lesotho	Japan	Mexico
Malawi	Korea (Rep. of)	Peru
Mauritius	Lao PDR	
Morocco	Malaysia	
Mozambique	Myanmar	
Namibia	Nepal	
Nigeria	Pakistan	
Rwanda	Philippines	
Senegal	Singapore	
South Africa	Sri Lanka	
Tanzania	Chinese Taipei	
Tunisia	Thailand	
Uganda	Turkey	
Zambia	Viet Nam	

▶ Annex 3. Country productivity statistics

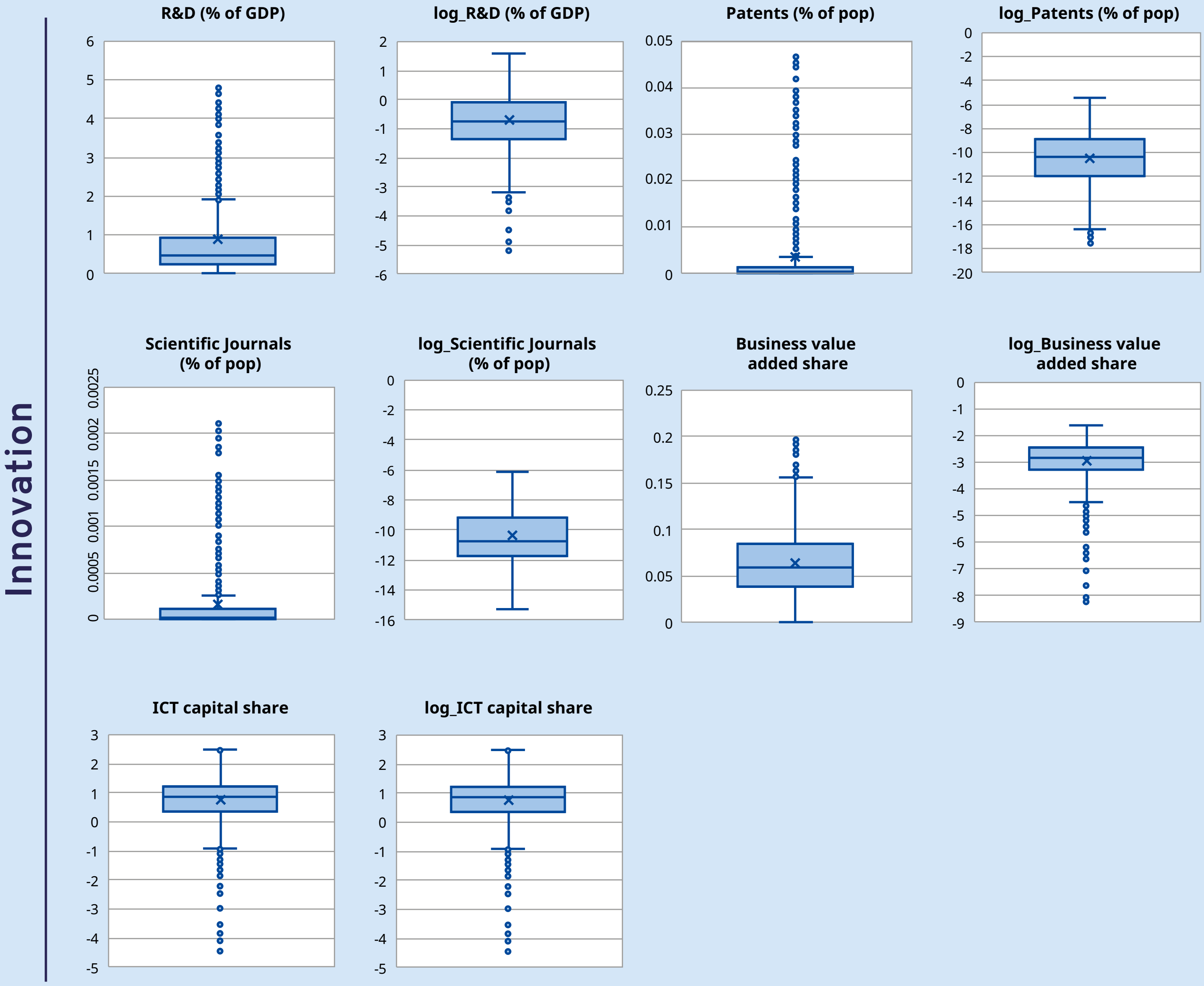
Country	Region	Agriculture Productivity PPP at constant 2015 prices (US$)	Manufacturing	Services	Total	Compound annual growth rate (%)
China	East Asia	8 089	41 195	30 200	27 541	8.12
Myanmar	East Asia	5 773	24 933	14 497	12 223	7.30
India	South and Central Asia	6 906	23 267	21 438	16 158	4.72
Viet Nam	East Asia	5 082	11 528	12 974	11 216	4.13
Lao PDR	East Asia	2 988	30 578	38 077	12 718	4.12
Bangladesh	South Asia	3 509	13 779	13 394	10 220	3.88
Nepal	South Asia	2 510	4 084	11 835	5 129	3.67
Ethiopia	Sub-Saharan Africa	1 982	2 285	6 796	3 834	3.47
Sri Lanka	South Asia	9 752	29 508	41 924	31 087	3.45
Mozambique	Sub-Saharan Africa	1 154	14 493	6 914	3 228	3.43
Korea, Rep.	East Asia	28 316	125 111	53 315	72 080	3.41
Cambodia	East Asia	3 339	10 546	10 106	7 028	3.36
Rwanda	Sub-Saharan Africa	2 031	7 136	6 988	4 397	3.30
Lesotho	Sub-Saharan Africa	2 086	19 769	11 790	13 845	3.18
Mauritius	Sub-Saharan Africa	21 064	34 564	44 965	41 007	3.16
Tanzania	Sub-Saharan Africa	2 482	17 400	9 057	6 200	3.10
Burkina Faso	Sub-Saharan Africa	2 399	5 172	3 720	4 946	3.08
Thailand	East Asia	8 655	51 619	38 796	32 226	2.99
Singapore	East Asia	10 448	223 909	123 442	133 765	2.75
Ghana	Sub-Saharan Africa	7 577	9 635	12 291	13 543	2.74
Uganda	Sub-Saharan Africa	1 922	9 368	9 375	5 169	2.70
Morocco	Middle East & North Africa	9 367	33 285	19 127	21 688	2.58
Malaysia	East Asia	40 702	78 292	51 931	57 089	2.50
Indonesia	East Asia	10 299	35 146	21 517	23 219	2.45
Philippines	East Asia	7 455	46 645	19 696	20 834	2.40
Zambia	Sub-Saharan Africa	769	17 217	14 999	10 504	2.36
Hong Kong SAR, China	East Asia	38 995	43 441	142 228	110 639	2.29
Chile	Latin America	33 943	95 178	42 258	49 407	2.20
Türkiye	Central Asia	27 309	73 641	77 208	70 800	2.07
Tunisia	Middle East & North Africa	32 996	29 137	46 695	33 134	2.03
Peru	Latin America	8 946	40 180	17 934	21 446	1.85
Bolivia	Latin America	6 288	18 619	11 063	13 343	1.84

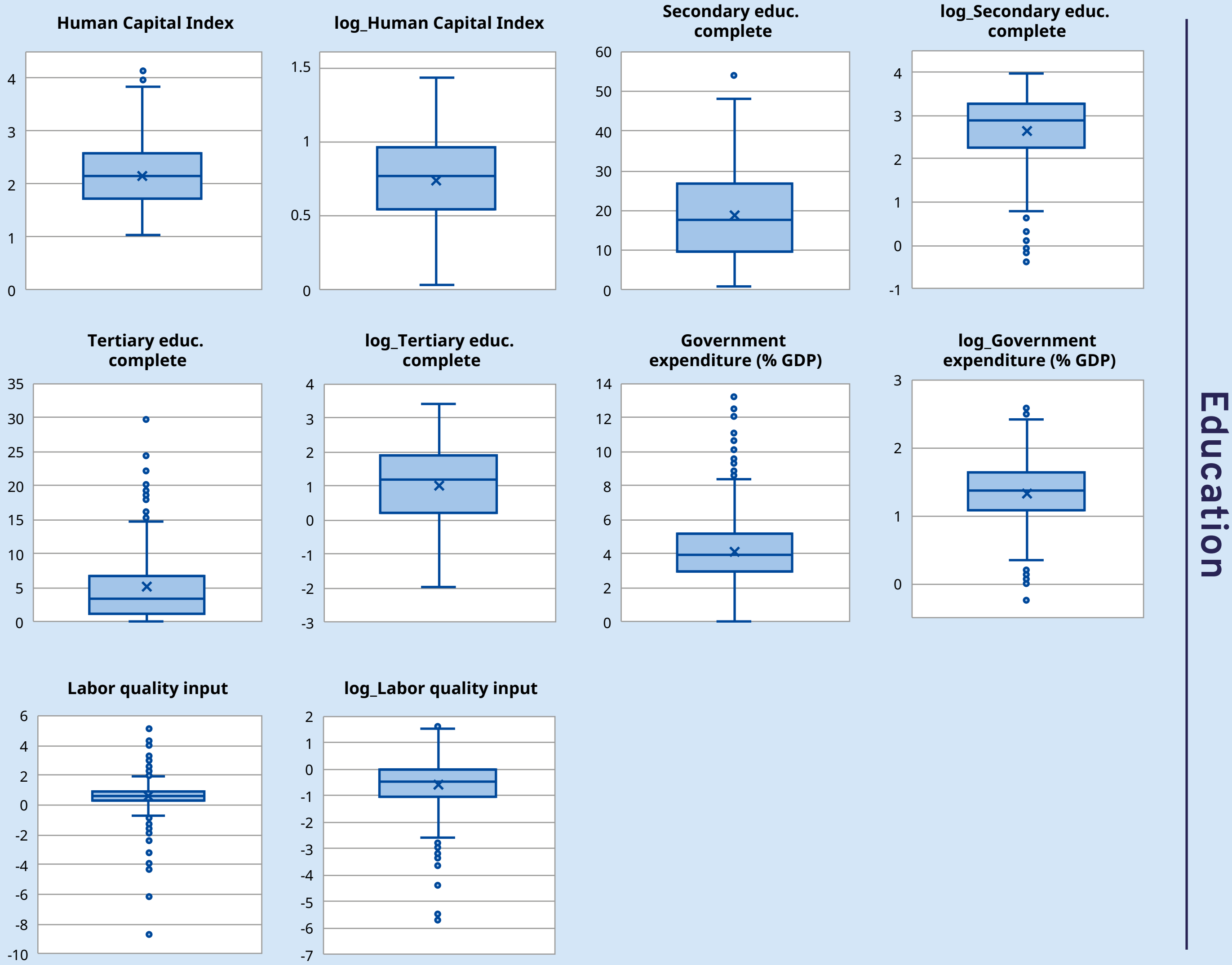
Country	Region	Agriculture Productivity PPP at constant 2015 prices (US$)	Manufacturing	Services	Total	Compound annual growth rate (%)
Egypt	Middle East & North Africa	23 642	58 850	42 707	46 256	1.77
Malawi	Sub-Saharan Africa	1 526	7 983	5 451	3 338	1.75
Nigeria	Sub-Saharan Africa	6 706	17 639	16 732	13 751	1.48
Namibia	Sub-Saharan Africa	10 167	58 888	20 376	33 403	1.45
Costa Rica	Latin America	12 998	39 201	33 596	37 386	1.42
Pakistan	South Asia	9 283	13 129	23 415	15 584	1.33
Botswana	Sub-Saharan Africa	2 408	55 665	48 562	32 822	1.32
Colombia	Latin America	10 306	35 943	18 034	28 364	0.84
Argentina	Latin America	75 684	185 532	52 824	67 180	0.83
South Africa	Sub-Saharan Africa	5 131	48 730	32 918	34 261	0.73
Japan	East Asia	19 764	112 568	68 208	78 935	0.66
Senegal	Sub-Saharan Africa	5 166	11 447	5 385	7 464	0.63
Israel	Middle East & North Africa	48 561	95 508	62 668	69 100	0.63
Brazil	Latin America	15 325	32 452	21 348	27 985	0.24
Mexico	Latin America	11 413	45 540	38 211	41 921	0.23
Cameroon	Sub-Saharan Africa	2 789	16 044	13 132	9 102	0.21
Ecuador	Latin America	8 895	30 723	15 833	20 759	–0.25
Kenya	Sub-Saharan Africa	6 395	5 796	8 839	8 928	–0.54

▶ Annex 4. Transformation of variables

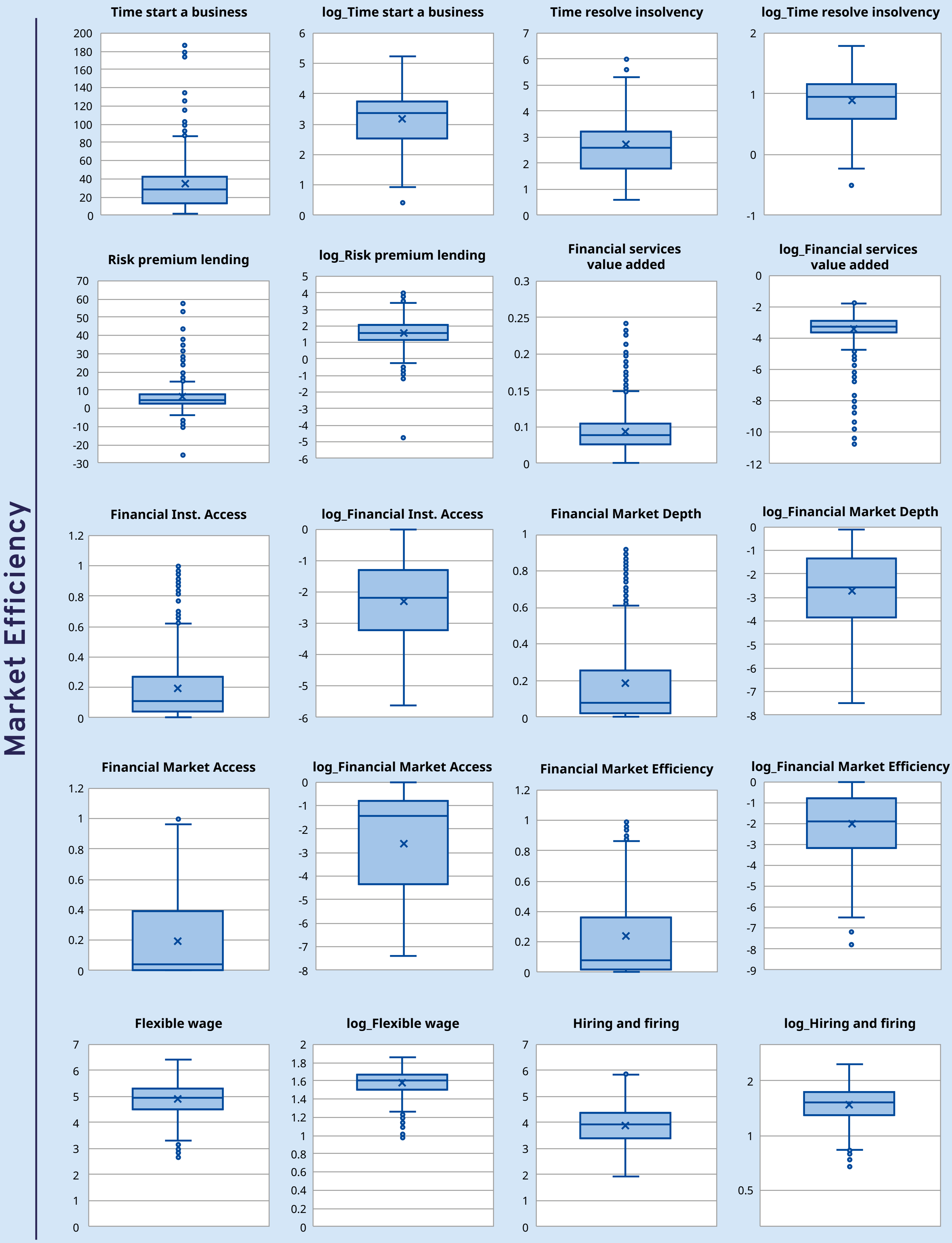
As part of the analysis, we obtained the distribution of all the variables in the combined dataset to assess the presence of outliers and deviations from normal distributions. First, we created box plots for each variable, which provide insights into their distribution, central tendency, and variability. The box in the plot represents the interquartile range (IQR), which contains the middle 50% of the data. The line inside the box represents the median (50th percentile) of the data. The whiskers extend from the box to the minimum and maximum values within a defined range, often determined by a specified number of standard deviations or other criteria. Data points outside the whiskers are considered potential outliers and are displayed individually.

▶ Figures Annex 4



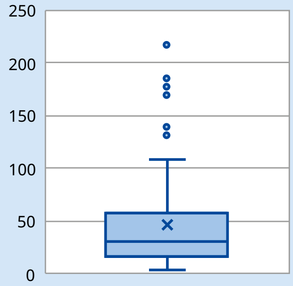

Human Capital Index
log_Human Capital Index
Secondary educ. complete
log_Secondary educ. complete
Tertiary educ. complete
log_Tertiary educ. complete
Government expenditure (% GDP)
log_Government expenditure (% GDP)
Labor quality input
log_Labor quality input
Education


Cost startup proc.
log_Cost startup proc.
Time prepare taxes
log_Time prepare taxes
Time enforce a contract
log_Time enforce a contract
Time registry a property
log_Time registry a property
Market Efficiency

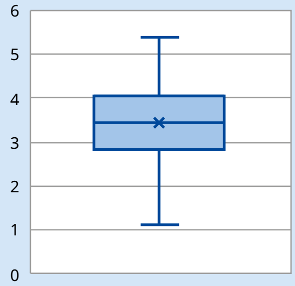

Market Efficiency
Time start a business
log_Time start a business
Time resolve insolvency
log_Time resolve insolvency
Risk premium lending
log_Risk premium lending
Financial services value added
log_Financial services value added
Financial Inst. Access
log_Financial Inst. Access
Financial Market Depth
log_Financial Market Depth
Financial Market Access
log_Financial Market Access
Financial Market Efficiency
log_Financial Market Efficiency
Flexible wage
log_Flexible wage
Hiring and firing
log_Hiring and firing

Market Efficiency

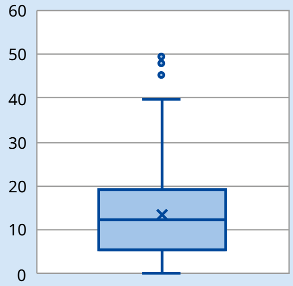
Redundancy costs



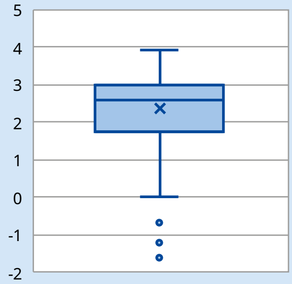
log_Redundancy costs



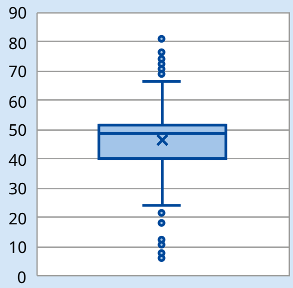
Labor tax



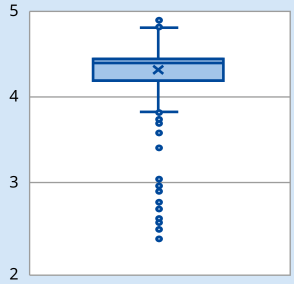
log_Labor tax



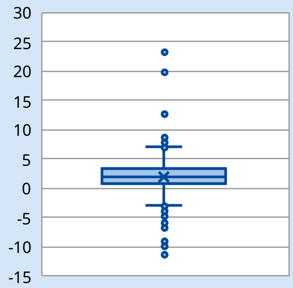
Labor share



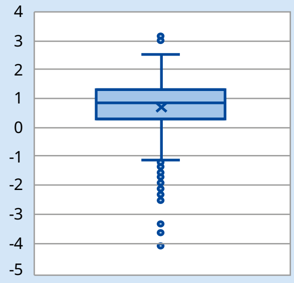
log_Labor share



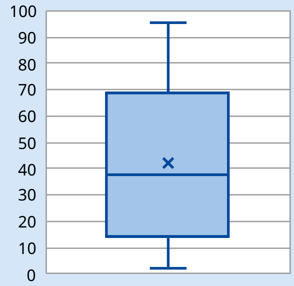
Labor input



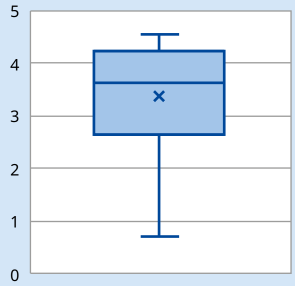
log_Labor input



Prop. women workers

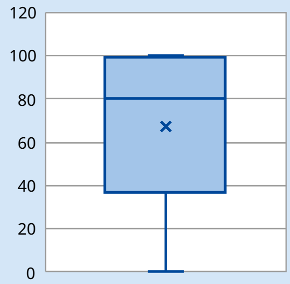


log_Prop. women workers

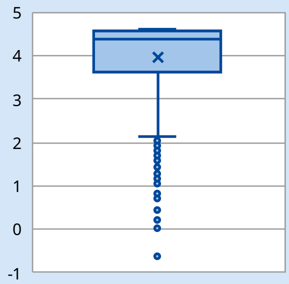


Infrastructure

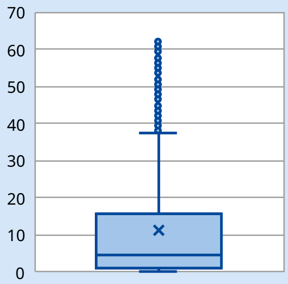
Access to electricity



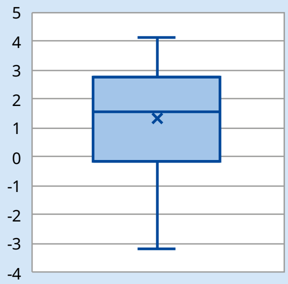
log_Access to electricity



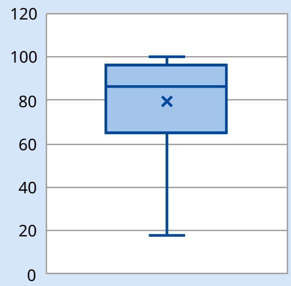
Phone subscriptions



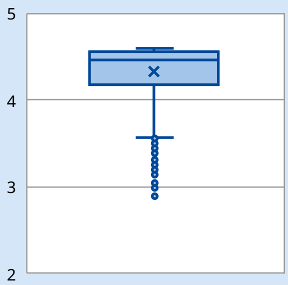
log_Phone subscriptions



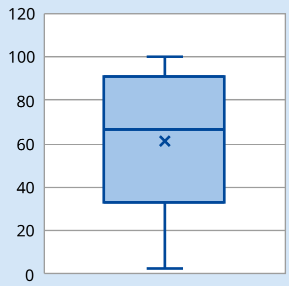
Access to water



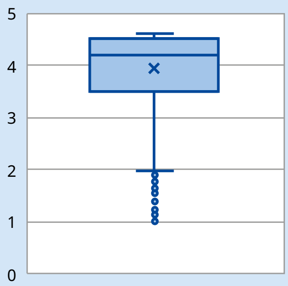
log_Access to water



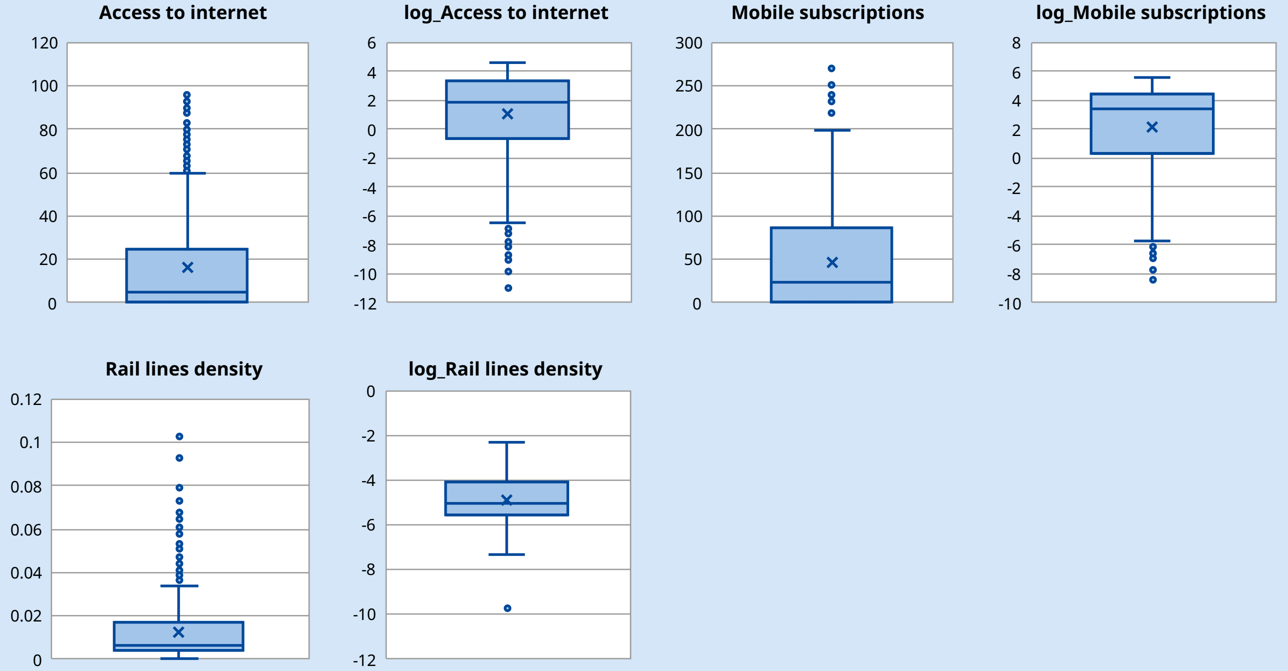
Access to sanitation



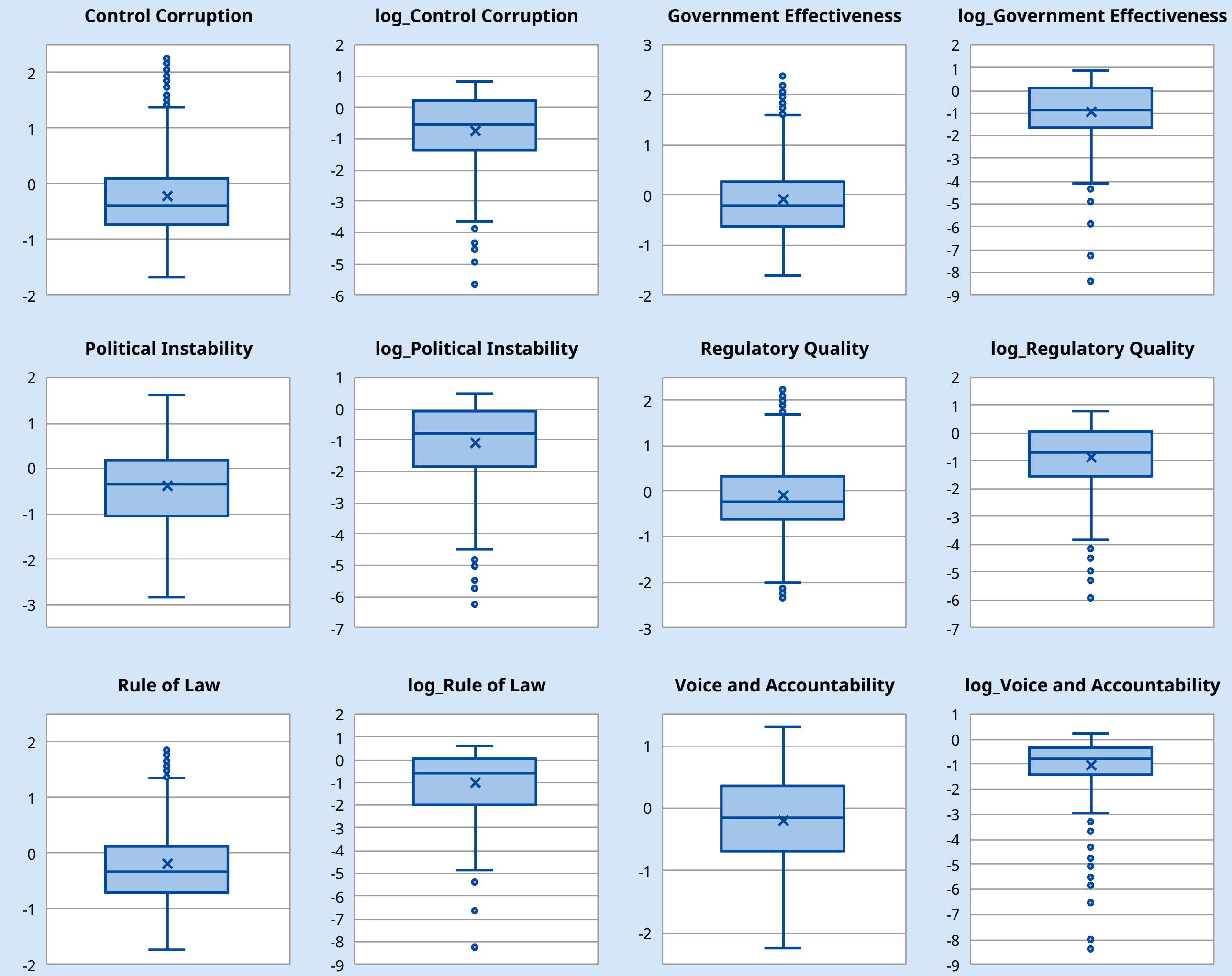
log_Access to sanitation



Infrastructure



Institutions



▶ Annex 5. Analysis of missing values

The first table shows the total number of observations, the number of missing values and the percent of missing values before applying any method to deal with missing values.

Variables	Missing	Total	Percent missing
Research and development as % of GDP (log)	859	1 428	60.15
Patents as a % of GDP (log)	433	1 428	30.32
Scientific journals (log)	497	1 428	34.8
Business value-added share	0	1 428	0
ICT capital share (log)	84	1 428	5.88
Human Capital Index (log)	0	1 428	0
Secondary education, completed	1240	1 428	86.83
Tertiary education, completed (log)	1240	1 428	86.83
Government expenditure as % of GDP (log)	658	1 428	46.08
Labour quality input (log)	192	1 428	13.45
Cost of startup procedure (log)	728	1 428	50.98
Time to prepare taxes (log)	807	1 428	56.51
Time to enforce a contract	728	1 428	50.98
Time to register a property (log)	767	1 428	53.71
Time to start a business (log)	728	1 428	50.98
Time to resolve insolvency (log)	744	1 428	52.1
Risk premium lending (log)	808	1 428	56.58
Finance services value-added share	0	1 428	0
Financial institutional access (log)	279	1 428	19.54
Financial markets depth index (log)	280	1 428	19.61
Financial markets access index (log)	541	1 428	37.89
Financial markets efficiency index (log)	517	1 428	36.2
Wage flexibility	940	1 428	65.83
Hiring and firing	940	1 428	65.83
Redundancy costs	950	1 428	66.53
Labour tax	807	1 428	56.51
Labour share	84	1 428	5.88
Labour quantity input (log)	285	1 428	19.96
Proportion of female workers	28	1 428	1.96
Access to electricity	181	1 428	12.68
Fixed telephone subscription	30	1 428	2.1
Access to water (% of population)	482	1 428	33.75
Access to sanitation (% of population)	481	1 428	33.68
Access to internet (% of population – log)	194	1 428	13.59
Mobile subscriptions (log)	122	1 428	8.54

Variables	Missing	Total	Percent missing
Rail line density (log)	865	1 428	60.57
Control of corruption index	408	1 428	28.57
Government effectiveness index	408	1 428	28.57
Political instability index	408	1 428	28.57
Regulatory quality index	408	1 428	28.57
Rule of law index	408	1 428	28.57
Voice and accountability index	408	1 428	28.57

Before running the regression methods, we applied several methods explained in the document to impute the missing values, when possible, without affecting the variables' distribution. The table below shows the reduction percentage of missing values for each variable.

Variable	Missing	Total	Per cent missing	Reduction in percentage points after interpolation
Research and development as % of GDP (log)	767	1 428	53.71	–6.44
Patents as a % of GDP (log)	386	1 428	27.03	–3.29
Scientific journals (log)	56	1 428	3.92	–30.88
Business value-added share	0	1 428	0	0
ICT capital share (log)	84	1 428	5.88	0
Human capital index (log)	0	1 428	0	0
Secondary education, completed	1240	1 428	86.83	0
Tertiary education, completed (log)	1240	1 428	86.83	0
Government expenditure as % of GDP (log)	529	1 428	37.04	–9.04
Labour quality input (log)	95	1 428	6.65	–6.8
Cost of startup procedure (log)	728	1 428	50.98	0
Time to prepare taxes (log)	807	1 428	56.51	0
Time to enforce a contract	728	1 428	50.98	0
Time to register a property (log)	767	1 428	53.71	0
Time to start a business (log)	728	1 428	50.98	0
Time to resolve insolvency (log)	744	1 428	52.1	0
Risk premium lending (log)	757	1 428	53.01	–3.57
Finance services value-added share	0	1 428	0	0
Financial institutional access (log)	84	1 428	5.88	–13.66
Financial markets depth index (log)	84	1 428	5.88	–13.73
Financial markets access index (log)	392	1 428	27.45	–10.44
Financial markets efficiency index (log)	364	1 428	25.49	–10.71
Wage flexibility	940	1 428	65.83	0
Hiring and firing	940	1 428	65.83	0
Redundancy costs	950	1 428	66.53	0

Variable	Missing	Total	Per cent missing	Reduction in percentage points after interpolation
Labour tax	807	1 428	56.51	0
Labour share	84	1 428	5.88	0
Labour quantity input (log)	134	1 428	9.38	–10.58
Proportion of female workers	28	1 428	1.96	0
Access to electricity	28	1 428	1.96	–10.72
Fixed telephone subscription	28	1 428	1.96	–0.14
Access to water (% of population)	50	1 428	3.5	–30.25
Access to sanitation (% of population)	49	1 428	3.43	–30.25
Access to internet (% of population – log)	28	1 428	1.96	–11.63
Mobile subscriptions (log)	28	1 428	1.96	–6.58
Rail line density (log)	785	1 428	54.97	–5.6
Control of corruption index	0	1 428	0	–28.57
Government effectiveness index	0	1 428	0	–28.57
Political instability index	0	1 428	0	–28.57
Regulatory quality index	0	1 428	0	–28.57
Rule of law index	0	1 428	0	–28.57
Voice and accountability index	0	1 428	0	–28.57

The following table shows a comparison between the original dataset and the final dataset after imputing the missing values. To compare the distribution of each variable we used the mean and standard deviation before and after imputation.

Variable	Original dataset			Final dataset		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Research and development as % of GDP (log)	569	–0.67	1.06	1.037	–0.89	1.03
Patents as % of GDP (log)	995	–10.38	2.33	1.384	–10.78	2.41
Scientific journals (log)	931	–10.35	1.72	1.41	–10.59	1.99
Business value-added share	1 428	0.06	0.03	1.428	0.06	0.03
ICT capital share (log)	1 344	0.79	0.65	1.4	0.79	0.64
Human capital index (log)	1428	0.74	0.27	1.428	0.74	0.27
Secondary education, completed	188	18.55	11.18	1.428	23.32	12.61
Tertiary education, completed (log)	188	1.02	1.23	1.428	1.33	1.19
Government expenditure as % of GDP (log)	770	1.34	0.38	1.329	1.31	0.36
Labour quality input (log)	1 236	–0.54	0.70	1.4	–0.52	0.71
Cost of startup procedure (log)	700	2.96	1.28	786	2.92	1.26
Time to prepare taxes (log)	621	5.60	0.53	1.428	5.94	0.61
Time to enforce a contract	700	655.14	279.97	786	644.33	274.52
Time to register a property (log)	661	3.65	0.86	738	3.62	0.84
Time to start a business (log)	700	3.20	0.79	786	3.21	0.80

Variable	Original dataset			Final dataset		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Time to resolve insolvency (log)	684	0.91	0.45	786	0.92	0.47
Risk premium lending (log)	620	1.59	0.76	1.246	1.53	0.80
Finance services value-added share	1 428	0.04	0.02	1.428	0.04	0.02
Financial institutional access (log)	1 149	–2.29	1.20	1.416	–2.13	1.21
Financial markets depth index (log)	1 148	–2.69	1.64	1.416	–2.54	1.65
Financial markets access index (log)	887	–2.62	2.15	1.348	–2.99	2.23
Financial markets efficiency index (log)	911	–1.96	1.37	1.376	–2.07	1.37
Wage flexibility	488	4.94	0.61	1.428	5.44	0.57
Hiring and firing	488	3.90	0.71	1.428	4.53	0.73
Redundancy costs	478	3.46	0.86	1.428	4.29	0.80
Labour tax	621	13.20	9.24	1.428	18.36	9.31
Labour share	1 344	47.16	9.23	1.4	46.95	9.11
Labour quantity input (log)	1 143	0.73	0.73	1.395	0.71	0.74
Proportion of female workers	1 143	41.94	28.40	1.428	42.75	28.71
Access to electricity	1 247	67.28	33.35	1.428	66.57	33.86
Fixed telephone subscription	1 398	1.33	1.66	1.428	1.38	1.68
Access to water (% of population)	946	80.19	18.42	1.401	77.90	19.78
Access to sanitation (% of population)	947	61.82	29.42	1.401	58.48	30.81
Access to internet (% of population – log)	124	1.16	2.65	1.428	0.46	3.31
Mobile subscriptions (log)	1 306	2.22	2.79	1.428	1.78	3.26
Rail line density (log)	563	–4.89	0.97	1.139	–4.99	0.97
Control of corruption index	1 020	–0.21	0.72	1.428	–0.20	0.74
Government effectiveness index	1 020	–0.07	0.71	1.428	–0.08	0.71
Political instability index	1 020	–0.36	0.82	1.428	–0.34	0.87
Regulatory quality index	1 020	–0.06	0.71	1.428	–0.06	0.70
Rule of law index	1 020	–0.17	0.70	1.428	–0.16	0.71
Voice and accountability index	1 020	–0.18	0.71	1.428	–0.18	0.72

▶ Annex 6. Residual multifactor approach

The residual multifactor approach can be defined as follows:

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + \mu_{it}$$

where d_t is a n x 1 vector of observed common effects; x_{it} is a k x 1 vector of unobserved individual-specific regressors on the *ith* cross-section unit at time t, and disturbances μ_{it} have the following common factor structure:

$$\mu_{it} = \gamma_{i1} f_{1t} + \gamma_{i2} f_{2t} + \dots + \gamma_{im} f_{mt} + e_{it} = \gamma_i' f_t + e_{it}$$

where $f_t = (f_{1t}, f_{2t} + \cdots + f_{mt})'$ is an m-dimensional vector of unobservable common factors and $\gamma_t = (\gamma_{1t}, \gamma_{2t} + \cdots + \gamma_{mt})'$ is the m x 1 vector of factor loadings. The number of factors, m, is assumed to be fixed relative to N (m<N); the idiosyncratic errors e_{it} could be cross-sectionally weakly dependent, and the factor loadings γ_i could be either random or fixed unknown coefficients.

The specification allows us to distinguish between homogeneous coefficients $\beta_i = \beta$ for all i and the heterogenous cases where β_i are random draws from a given distribution and β is estimated as $\mathrm{E}(\beta_i)$. When the regressors X_{it} are strictly exogeneous and the deviations $v_i = \beta_i - \beta$ are distributed independently, the mean coefficients β can be consistently estimated using pooled or mean group estimation procedures. For weakly exogeneous regressors and/or deviations correlated with the regressors / errors, only mean group estimation will be consistent.

Under slope heterogeneity the CCE approach assumes that β_i follow the random coefficient model:

$$\beta_i = \beta + v_i$$

where v_i are distributed independently of e_{jt}, X_{jt} and d_t for all i, j and t. To account for possible correlation between unobservable factors and the regressors, the following specification is proposed:

$$x_{it} = A_i' d_t + \Upsilon_i' f_{it} + v_{it}$$

where A_i and Υ_i are n x k and m x k factor loading matrices with fixed components v_{it} is the idiosyncratic component of x_{it} distributed independently of the common effects f_t and errors e_{jt}, for all i, j, t and t'. But v_{it} is allowed to be serially correlated and cross-sectionally weakly correlated. When the parameters of interest are the cross-sectional means of the slope coefficients β, we can consider two alternative estimators, the CCE mean group (CCEMG) estimator and the CCE pooled (CCEP) estimator.

The CCEMG is a simple average of the estimators of the individual slope coefficients:

$$\widehat{\beta ccemg} = N^{-1} \sum_{i=1}^{N} \widehat{\beta cce, \imath}$$

The cross-sectional error dependence becomes much more complicated to model once the assumption of strict exogeneity is relaxed (e.g., a model with lagged dependent variables and unobserved common factors (possibly correlated with the regressors).

$$y_{it} = \gamma_{it} y_{i,t-1} + \beta_i' x_{it} + \mu_{it}$$
$$\mu_{it} = \gamma_i' f_t + e_{it}$$

Chudik and Pesaran (2015b) proposed an extension of the CCE approach to dynamic panels with heterogeneous coefficients and weakly exogeneous regressors to account for the consequences of including lagged dependent variables in the model.[1]

▶ Annex 7. Static panel results

Variable	Fixed effects	2SIV-pooled	2SIV-MG
Innovation	–60.43	–43.97	0.383
	–62.79	–39.61	–32.27
L.innovation	–109.7	–37.15	–25.44
	–109.4	–47.99	–17.45
Education	–8.229	37.86	29.1
	–28.92	–25.45	–45.75
L.education	–22.02	29.71	22.94
	–19.92	–20.02	–41.86
mkt_eff	9.804	–117.2***	80.43**
	–11.58	–30.03	–34.55
L.mkt_eff	–57.23	–157.4***	–30.81
	–58.4	–27	–22.52
infrastruct	–23.06	–0.096	71.47**
	–19.24	–17.43	–27.79
L.infrastruct	–15.98	–26.71	116.4**
	–25.36	–33.33	–56.74
institutions	33.98	70.33***	50.76
	–20.96	–24.6	–60.42
L.institutions	95.1	107.2***	107.3
	–73.79	–18.68	–107.3
trade_gr	–58.11	–116.9***	32.24
	–42.52	–33.76	–28.54
L.trade_gr	–47.86	–5.972	9.986
	–58.99	–27.98	–54.66

1 The original method proposed by Pesaran (2006) is robust to cross section dependence, unit roots in factors and sole heterogeneity, but it did not conver the case where the panel includes a lagged dependent variable and/or weakly exogenous variables as regressors. See Chudik and Pesaran (2015b).

Variable	Fixed effects	2SIV-pooled	2SIV-MG
FDI_gr	–0.00871	–1.043**	–11.1
	–0.13	–0.497	–9.629
L.FDI_gr	–0.173	–0.357	–33.29
	–0.253	–0.681	–26.08
gfk_gr	75.15	147.1***	193.2
	–88.48	–45.91	–148.1
L.gfk_gr	–23.74	–26.19	–40.34
	–30.78	–33.63	–44.09
gdp_pc_gr	324.1	303.5**	
	–323.5	–151	
L.gdp_pc_gr	180.8	374.4*	
	–161.5	–194.2	
agric_va_share	–107.6	–1,060	–0.000127
	–201.2	–872.9	–0.000127
L.agric_va_share	723.5	1,644**	
	–459.3	–696	
Constant	–104.6	–96.95	–18.84
	–81.05	–68.36	–14.34
Observations	409	266	266

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

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