Online Annex 2: Reversing the Trend: Enhancing Medium-Term Growth Prospects

2.1. Growth Decomposition

Production Function

The growth decomposition used in Chapter 2 is based on the following Cobb-Douglas production function:

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

where Y_t is real GDP, A_t is Total Factor Productivity (TFP), K_t is the capital stock, E_t is total employment, and α is the capital compensation share of output (0< $\alpha < 1$). Rewriting this in per-capita terms yields:

$$\frac{Y_t}{N_t} = A_t \left(\frac{K_t}{E_t}\right)^{\alpha} \frac{E_t}{N_t}$$

where N_t is the total population. Taking the natural logarithm of this expression and differencing produces the decomposition real GDP per capita growth ($x = \ln(X)$):

$$\Delta y_t - \Delta n_t = \Delta a_t + \alpha(\Delta k_t - \Delta e_t) + \Delta e_t - \Delta n_t$$

where Δa_t is the contribution to growth from TFP growth, $\alpha(\Delta k_t - \Delta e_t)$ is the contribution from growth in the capital-labor ratio (capital deepening), and $(\Delta e_t - \Delta n_t)$ is the contribution from employment per capita growth.

Decomposition of Employment per Capita Growth

Employment per capita can be written as:

$$\frac{E_t}{N_t} = \left(\frac{E_t}{LF_t}\right)\left(\frac{LF_t}{WAP_t}\right)\left(\frac{WAP_t}{N_t}\right) = ER_t LFPR_t \left(\frac{WAP_t}{N_t}\right)$$

where LF_t is the labor force, WAP_t is the working age population, and ER_t and $LFPR_t$ are the employment rate (one minus the unemployment rate) and labor force participation rate, respectively. Taking the natural logarithm of this expression and differencing produces the decomposition of employment per capita growth:

$$\Delta e_t - \Delta n_t = \Delta er_t + \Delta lfpr_t + \Delta wap_t - \Delta n_t$$

where Δer_t is the contribution to employment per capita growth from growth in the employment rate, $\Delta lfpr_t$ is the contribution from growth in the labor force participation rate, and $(\Delta wap_t - \Delta n_t)$ is the contribution from growth in the working age population per capita.

Growth Impacts from Closing Gaps

Female Labor Force Participation Rate

The labor force and working age population contains males (*m*) and females (*f*). This implies that the total labor force participation rate can be written as:

$$LFPR = \frac{LF}{WAP} = \frac{LF^m + LF^f}{WAP^m + WAP^f} = \frac{LF^m}{WAP^m}\left(\frac{WAP^m}{WAP}\right) + \frac{LF^f}{WAP^f}\left(\frac{WAP^f}{WAP}\right) = LFPR^m\sigma^m + LFPR^f\sigma^f$$

where $LFPR^m$ and $LFPR^f$ are the male and female labor force participation rates, respectively, and σ^m and σ^f are the shares of males and females in the total working age population.

Assuming there is a desired rate of female labor force participation $LFPR^{f*}$, the gap between the actual female labor force participation rate and the desired rate in period 0 is then:

$$\widehat{LFPR}^f = LFPR^{f*} - LFPR_0^f$$

All else equal, the direct effect on the total labor force participation rate from closing the female labor force participation rate gap between period 0 and period 1 is $\widehat{LFPR}^f\sigma^f$ so that new level of the total labor force participation rate is:

$$LFPR_1 = LFPR_0 + \widehat{LFPR}^f\sigma^f$$

From growth decomposition above, the direct impact on output per capita from closing the female labor force participation rate gap in percentage points is the log change in the total labor force participation rate between periods 0 and 1:

$$\Delta y_1 - \Delta n_1 = \Delta lfpr_1$$

where the average impact on growth per capita from a one percentage point change in the female labor force participation rate between periods 0 and 1 is:

$$Z_1 = \frac{\Delta y_1 - \Delta n_1}{\widehat{LFPR}^f}$$

Youth Employment/Unemployment Rate

Total employment and the labor force are made up of adult (*a*) and young *(y)* citizens. This implies that the total employment rate can be written as:

$$ER = \frac{E}{LF} = \frac{E^a + E^y}{LF^a + LF^y} = \frac{E^a}{LF^a}\left(\frac{LF^a}{LF}\right) + \frac{E^y}{LF^y}\left(\frac{LF^y}{LF}\right) = ER^a\omega^a + ER^y\omega^y$$

where ER^a and ER^y are the adult and youth employment rates, respectively, and ω^a and ω^y are the shares of adults and youth in the total labor force.

Assuming there is a desired rate of youth employment ER^{y*}, the gap between the actual youth employment rate and the desired rate in period 0 is then:

$$\widehat{ER^y} = ER^{y*} - ER_0^y$$

All else equal, the direct effect on the total employment rate from closing the youth employment gap between period 0 and period 1 is $\widehat{ER^y}\omega^y$ so that new level of the total employment rate is:

$$ER_1 = ER_0 + \widehat{ER^y}\omega^y$$

From growth decomposition above, the direct impact on output per capita from closing the youth employment rate gap in percentage points is the log change in the total employment rate between periods 0 and 1:

$$\Delta y_1 - \Delta n_1 = \Delta er_1$$

where average impact on growth per capita from a one percentage point change in the youth employment rate between periods 0 and 1 is:

$$Z_1 = \frac{\Delta y_1 - \Delta n_1}{\widehat{ER^y}}$$

Capital Deepening

Assuming there is some desired rate of capital deepening $(\Delta k - \Delta e)^*$, the gap between the actual rate of capital deepening and the desired rate in period *t* is:

$$\widehat{\Delta k_t - \Delta e_t} = (\Delta k - \Delta e)^* - (\Delta k_t - \Delta e_t)$$

From the growth decomposition above, the direct impact on output per capita growth in percentage points from closing this capital deepening gap, all else equal, is:

$$\Delta y_t - \Delta n_t = \alpha\left(\widehat{\Delta k_t - \Delta e_t}\right)$$

2.2. An Empirical Analysis of TFP Growth

This empirical analysis aims to identify and quantify the key structural drivers of Total Factor Productivity (TFP) growth in the Middle East and North Africa (MENA) and Caucasus and Central Asia (CCA) regions using an augmented TFP growth equation. The study uses a panel dataset covering 18 economies from 2000 to 2023. The variables selected for this analysis are based on their regional relevance, data availability, and a thorough review of the existing literature on TFP growth. Key structural drivers included in the analysis are macroeconomic stability, trade complexity, capital account openness, digitalization, labor and inclusion, institutional quality, financial integration, and state footprint. Annex Table 2.2. highlights the expected impacts of each factor on productivity growth as derived from economic theory and empirical evidence. Some factors, such as human capital quality and trade openness (last two rows in Annex Table 2.2.), are often cited in the literature but are omitted from our empirical regressions due to their statistical insignificance, economic interpretation, and collinearity with other factors. The selection of drivers provides a focused examination of some of the factors affecting TFP in the MENA and CCA regions, even if not exhaustive.

The vast majority of drivers in Annex Table 2.2. are expected to have a positive impact on productivity growth, except for state footprint, which has no consensus in the literature. Some studies suggest that state footprint could positively affect productivity growth by fostering legal institutions, infrastructure, and market corrections (Ghali 1999). In contrast, other empirical evidence for the region also suggests that a large government is not conducive to higher productivity growth or better economic performance (Loko and Diouf 2009).

Annex Table 2.2. Determinants of Productivity Growth in Literature

Driver	Importance	Expected Impact on Productivity Growth	Key References
Macroeconomic Stability	Provides a predictable environment for investment and consumption, fostering productivity growth. Key indicators include inflation and growth volatility.	Positive	Fischer (1993); Ramey and Ramey (1995); Barro (2013)
Trade Complexity	A diverse and sophisticated export profile integrates countries into global value chains, facilitating technology diffusion.	Positive	Grossman and Helpman (1991); Hausmann and others (2007)
Capital Account Openness	More cross-border capital flows tend to increase access to capital, technology transfer, enhance competition and diversify domestic investment sources.	Positive	Borensztein and others (1998); IMF (2018)
Digitalization	Advanced digital infrastructures enable technological innovation, streamline business processes, and improve productivity.	Positive	Brynjolfsson and Hitt (2000); Abidi and others (2022); Dabla-Norris and others (2023)
Labor and Inclusion	Improved labor quality and inclusion, particularly through female labor force participation, positively impact economic outcomes.	Positive	McGuckin and Van Ark (2005); Klasen and Lamanna (2009)
Institutional Quality	Strong institutions reduce transaction costs and enhance business environments, essential for sustained productivity growth.	Positive	Hall and Jones (1999); Acemoglu and others (2004); Acemoglu and Robinson (2015)
Financial Integration	Well-developed financial systems improve resource allocation, supporting business investment and innovation.	Positive	Levine (2005); Lane and Milesi-Ferretti (2017)
State Footprint	The extent and efficiency of government intervention can support or hinder productivity, depending on the effectiveness of interventions.	No consensus, depends on the efficiency of government intervention	Barro (1991); Ghali (1999); Dar and Khalkhali (2002); Loko and Diouf (2009)
Human Capital *	Enhance productivity by improving the skills, knowledge, and abilities of the workforce	Positive	Mankiw, Romer, and Weil (1992); Barro (2001)
Trade Openness *	Countries with greater trade openness are argued to benefit more from technology diffusion and lead to economics of scale and productivity gains	Positive	Grossman and Helpman (1991); Dollar and Kraay (2004)

Note: Human capital quality and trade openness are often cited in the literature but are omitted from our empirical regressions due to their statistical significance, economic interpretation, and collinearity with other factors.

Model Specification

This section describes the reduced-form estimation of the relationship between these factors and TFP. Specifically, Section 2.5 of the main text estimates the following baseline specification:

$$TFP\_Growth_{i,r,t} = \alpha + \sum_{k} \beta_k F_{k,i,t} + \gamma_r * \eta_t + \gamma_i + \eta_t + \epsilon_{i,t} \qquad (1)$$

$$F_{k,i,t} = \begin{cases} 1, & if\ factor\ k's\ value\ of\ F^{PC1}\ is\ above\ sample\ median\ value\ in\ t \\ & 0, otherwise \end{cases}$$

where:

- $TFP\_Growth_{i,r,t}$ is the annual growth of TFP for country i in sub-region r in year t.
- $F_{k,i,t}$ is a dummy variable for factor F^{PC1} which equals one if country i's value of factor F^{PC1} is above the median of the sample in year t.
- γ_r, γ_i, and η_t captures subregional, country, and time fixed effects, respectively.

- $\epsilon_{i,t}$ is the error term.

TFP growth data are IMF staff estimates (April 2024 *World Economic Outlook*). A summary of statistics for TFP growth by subregion are provided in Annex Table 2.3. Considering the complexity and multidimensionality of variables related to TFP determinants, Principal Components Analysis (PCA) was employed to create composite indices that effectively capture the core elements of each determinant with fewer, uncorrelated components. PCA, a dimensionality reduction technique, projects correlated variables into a reduced space defined by principal components (PCs), which are linear combinations of the original variables. This method enhances interpretability by capturing most of the variance in the data through a limited number of components, typically the top two, which compress most of the information content (Plerou and others 2002; Tsoulfidis and Athanasiadis 2022). For each driver k, the dummy variable $F_{k,i,t}$ was constructed in two steps: After the first principal component (F^{PC1}) was extracted from PCA, a cross-country median was calculated for each year. Then $F_{k,i,t}$ was assigned a value of one if country i's value of F^{PC1} is above the median.

The model is estimated using a fixed effects panel regression approach, which is augmented by Interacting subregion-specific fixed effects (γ_r) with time fixed effects (η_t) to capture subregion-specific shocks (e.g., regional economic downturns, geopolitical tensions, or commodity price fluctuations). This interaction allows us to account for unobserved heterogeneity and temporal dynamics that may vary across sub-regions, while clustering at the country level addresses potential heteroscedasticity and autocorrelation in the panel data. The results remain robust to alternative specifications, including the addition of dummies for the post-2008 Global Financial Crisis and the COVID-19 shock. Estimated results of coefficients are presented in Annex Figure 2.1.a.

Annex Table 2.3. Summary of Statistics: TFP Growth by Sub-region

Subregion	# of obs	Mean	St. dev	Min	25th Percentile	Median	75th Percentile	Max
CCA	72	2.803	5.311	-16.242	-.027	1.945	5.285	21.838
GCC	120	-2.257	4.617	-24.947	-4.723	-2.302	.732	10.852
MENA excl GCC	216	-0.161	4.086	-35.473	-1.357	0.205	1.694	13.356
Total	**408**	**-0.255**	**4.776**	**-35.473**	**-2.319**	**-0.013**	**1.974**	**21.838**

Grouping of Economic Indicators by TFP Driver

Annex Table 2.4. provides details of the economic indicators considered for each structural driver. PCA was only applied to drivers that contained non-single variable. Regression results are generally robust to alternative selections of some variables because the input data for regression are based on the dummy variables of first principal components extracted from PCA.

Annex Table 2.4. Principal Components and Economic Indicators

Driver	Description	Source
Macroeconomic Stability	Standard deviation of inflation from long-term average	National authorities, IMF
	Standard deviation of real GDP growth from long-term average	National authorities, IMF
Trade Complexity	Complexity of trade exports	Harvard CID
Capital Account Openness	Net FDI inflows (% of GDP)	World Bank WDI
Digitalization	Fixed broadband subscriptions (per 100 people)	ITU, World Bank WDI
	High-tech exports (% of manufactured exports)	World Bank WDI
Labor and Inclusion	Female labor force participation rate	ILO, World Bank WDI
Institutional Quality	Rating of impartial courts	World Bank WGI
	Rating of legal enforcement of contracts	World Bank WGI
Financial Integration	Financial market development index	IMF Financial Development Index
	Financial development index	IMF Financial Development Index
	Financial institutions index	IMF Financial Development Index

	Domestic credit to private sector (% of GDP)	World Bank WDI
	Market capitalization (% of GDP)	World Bank WDI
	Rating of credit market regulations	Fraser Institute, Economic Freedom Index
State Footprint	Rating of protection of property rights	Fraser Institute, Economic Freedom Index
	Rating of transfers and subsidies	Fraser Institute, Economic Freedom Index
	Government consumption (% GDP)	World Bank WDI
	Share of banking assets held by state-owned enterprises with government ownership higher than 50%	OECD, National Accounts
	Government effectiveness	World Bank WGI

Economic Importance

In this analysis (Figures 2.8.b and 2.9.), the approach introduced by Sterck (2019) is employed to assess the absolute economic importance of various factors. This method is particularly useful for disentangling the contributions of different explanatory variables to the variation in the dependent variable, providing a clearer understanding of their relative economic importance beyond the conventional statistical significance. The key measures include:

Effect Size (c_i)

The effect size for each variable, c_i is defined as the product of the regression coefficient β_i and a measure of statistical dispersion $d(x_i)$,where x_i denotes each TFP driver. In this study, the mean absolute deviation (MAD) is used as the measure of dispersion, because it is more robust and appropriate for dummy variables with large dispersion than standard deviation.

$$c_i = |\beta_i| * d(x_i)$$

Specifically, the mean absolute deviation, measures the average distance of observations from the mean as follows:

$$d(x_i) = \frac{1}{N} * \sum_{k} |x_{i,k} - \overline{x_i}|$$

As suggested by Sterck (2019), both standard deviation and MAD have pros and cons. While standard deviations are widely used in the literature, they are difficult to visualize and interpret because their calculation involves a nonlinear function of observations (it requires taking the square root of a sum of squares). In comparison, MAD is less commonly used but more intuitive and more robust (e.g., gives less importance to extreme values), as it is a linear function of observations on each side of the mean.

Absolute Economic Importance (α_i)

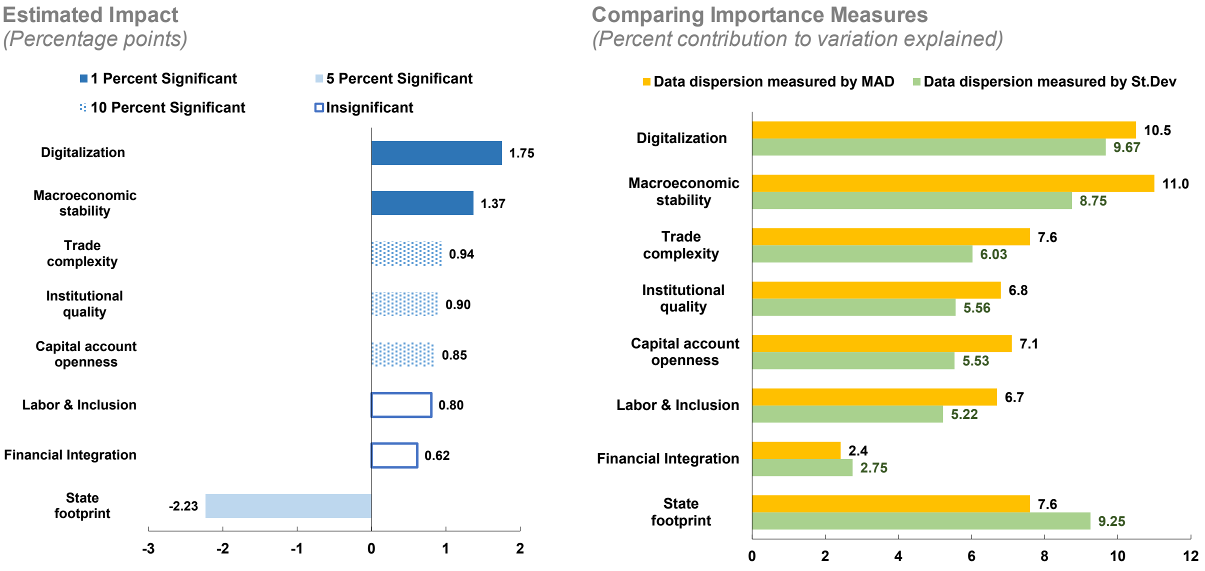
The absolute economic importance of a variable α_i is calculated as the proportion of the total effect size across observed variables and unobserved error term. This measure provides a percentage interpretation, making it easier to compare the statistical significance of different variables:

$$\alpha_i = \frac{c_i}{\sum_j c_j} = \frac{|\beta_i| * d(x_i)}{d(x_\epsilon) + \sum_j |\beta_j| * d(x_j)}$$

Following the simple error term approach suggested by Sterck (2019), the error term was assumed as one single unobserved variable with regression coefficient equals to 1 ($\beta_\epsilon = 1$). Therefore, the effective size of error term equals to its data dispersion, denoted as $d(x_{\epsilon})$ and was calculated using the same equation as other observed variables based on the MAD measure.

The absolute economic importance of all drivers is illustrated in Annex Figure 2.2.b, including statistically significant variables identified (digitalization, macroeconomic stability, trade complexity, institutional quality, capital account openness, and state footprint), as well as two insignificant variables (e.g., labor and inclusion, financial integration). This methodology not only quantifies the impact of individual factors but also compares their relative contributions in a consistent and meaningful way, ensuring that the findings remain robust. Importance estimates based on data dispersion measured by standard deviation was provided for robustness check.

Annex Figure 2.2. Results of All Drivers, 2000–23



Source: IMF staff calculations.
Note: The bars on the left represent the estimated beta coefficients of the drivers (β_i). The bars on the right show the contribution of each explanatory variable in percentage terms, following the methodology of Sterck (2019). Yellow bars are based on data dispersion measured by mean absolute deviation (MAD), while the gray bars are based on data dispersion measured by standard deviation (St.Dev). The importance metrics of eight key drivers add up to 100 percent in the chart, as the importance of residual term account for 40-47 percent for the two measures.

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