CHAPTER 3

SLOWDOWN IN GLOBAL MEDIUM-TERM GROWTH: WHAT WILL IT TAKE TO TURN THE TIDE?

Online Annexes

Online Annexes 3.1–3.3 of the April 2024 World Economic Outlook lay out the data sources, sample coverage, variable definitions and methodologies used in the main chapter. The Online Annex follows the structure of the Chapter. The Chapter draws on a variety of datasets which are described in detail in what follows.

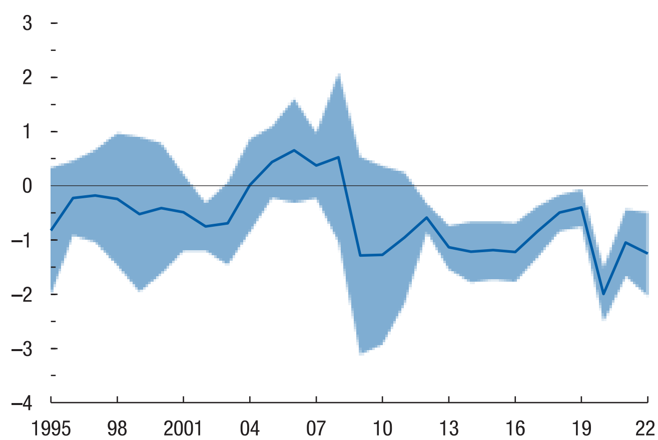
Online Annex 3.1. Insights from Medium-Term Forecasts

Online Annex Figure 3.1.1 traces the difference between the medium-term growth forecasts and actual realizations. This is based on a vintage-by-vintage cross-country regression $e_{i,t} = \alpha_t + \varepsilon_{i,t}$, where $e_{i,t}$ is the forecast error for country i in year t defined as the difference between actual growth in year t and the medium-term growth projection for the same year (made five years prior). To smooth year-to-year fluctuations in actual growth, the chapter uses an end-of-period three-year moving average. Online Annex Figure 3.1.1 presents the estimate of α_t along with the 95 percent confidence interval.

Online Annex Figure 3.1.2 assesses whether the medium-term growth forecasts are aligned with the projections for potential growth. It is based on a vintage-by-vintage cross-country regression $z_{i,t} = \alpha_t + \varepsilon_{i,t}$, where $z_{i,t}$ is the difference between the medium-term growth forecast and the respective forecast of potential growth for country i in year t. The results show that the difference is statistically insignificant except for periods after major crises. For instance, output growth forecasts were projected to be higher than that of potential growth over the medium term after the GFC. This reflected deep

Online Annex Figure 3.1.1. Five-Year-Ahead Forecasts versus Actual Realizations

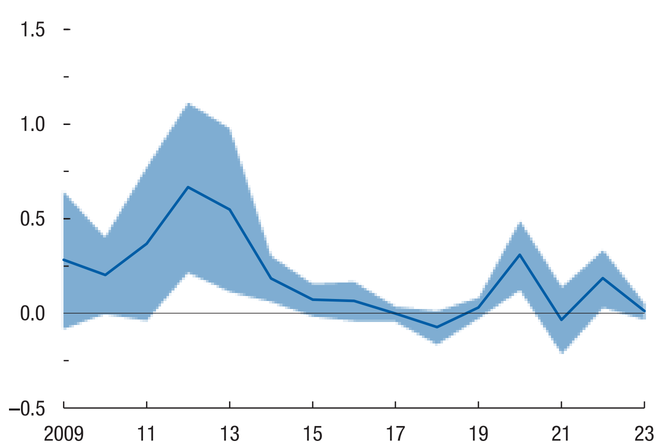
(Difference, percentage points)



Source: IMF staff calculations.
Note: The years on the horizontal axis refer to the year for which a forecast is made, using the April WEO for respective years. For example, the 2022 forecast is based on the April 2017 WEO. Shaded area represents the 95 percent confidence interval. WEO = *World Economic Outlook*.

Online Annex Figure 3.1.2. Five-Year-Ahead Forecasts versus Potential Growth Projections

(Difference, percentage points)



Source: IMF staff calculations.
Note: The years on the horizontal axis refer to the year of the April *World Economic Outlook* in which the five-year-ahead forecast is made. Shaded area represents the 95 percent confidence interval.

scarring in advanced economies with output running significantly below potential, with the projection of faster catching up over the medium term to close the output gap. This was also the case for emerging markets and developing economies in the aftermath of the pandemic shock in 2020.

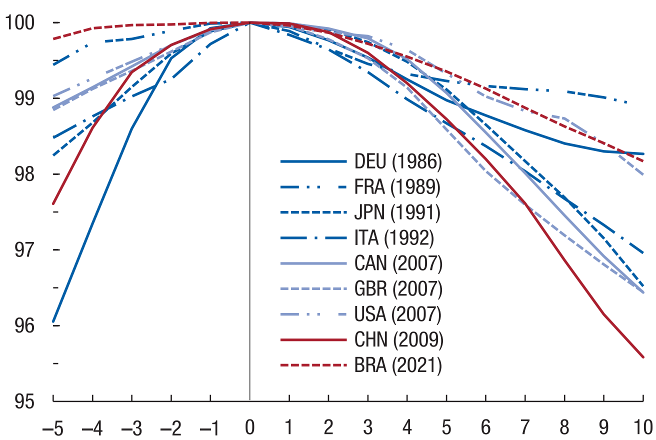
Online Annex 3.2. Additional Figures, Data Sources and Technical Details for the section "How Did We Get Here?"

Labor Inputs

Shrinking Share of the Working-Age Population

Online Annex Figure 3.2.1 identifies the timing of demographic turning points for the world's largest economies. In a demographic transition, as fertility rates decline and as the population ages, the share of the working-age population in the total population starts to shrink eventually. A demographic turning point is identified as the year—recorded in parentheses next to the country names—in which this share peaks before it starts to decline due to an aging population, marking a shift from a demographic dividend to potentially a demographic drag on growth. This is shown as point 0 on the horizontal axis, which economies have hit at different points in time. The time period around the GFC is noteworthy as it coincided with some of the world's largest economies—namely the US, UK, Canada and China—witnessing this turning point.

Online Annex Figure 3.2.1. Demographic Turning Points: Shrinking Working-Age Population Share
(Share of working-age population in total population, peak year = 100)



Sources: United Nations, World Population Prospects; and IMF staff calculations.
Note: Working-age population is defined as population aged 15 to 64. For India and South Africa, the peak year is 2032 and 2043, respectively. Data labels in the legend use International Organization for Standardization (ISO) country codes.

Shift-Share Analysis of Labor Force Participation Rates

Figure 3.6 in the main text uses shift-share analysis to tease out the impact of aging on labor force participation (LFP) rates.[1] For country i in year t, the gender-specific LFP rate, LFP_{it}^{g}, can be rewritten as the participation rates of workers in age group a and gender g, weighted by their share in the male or female population:

[1] Throughout, the Chapter uses the International Labour Organization (ILO) modelled estimates series, which provides labor market statistics that are comparable across counties. The modelled estimates series—ILOEST database—includes both nationally-reported data and imputed data when observations are missing.

$$LFP_{i,t}^{g} = \sum_{a=1}^{n} s_{i,t}^{a,g} LFP_{i,t}^{a,g}$$

where the age group a correspond to ages 15–24, 25–54, 55–64, and 65 and above, and $s_{i,t}^{a,g}$ denotes the respective population shares. The change in the LFP between 2008 and 2021 for gender g, denoted by $\Delta LFP_{i,t}^{g}$, can be written as:

$$\Delta LFP_{i,t}^{g} \equiv LFP_{i,t}^{g} - LFP_{i,0}^{g} = \sum_{a=1}^{n} LFP_{i,t}^{a,g}\, s_{i,t}^{a,g} - \sum_{a=1}^{n} LFP_{i,0}^{a,g}\, s_{i,0}^{a,g}$$

$$= \underbrace{\sum_{a=1}^{n} \left(LFP_{i,t}^{a,g} - LFP_{i,0}^{a,g}\right) s_{i,t}^{a,g}}_{Change\ in\ participation\ rates} + \underbrace{\sum_{a=1}^{n} \left(s_{i,t}^{a,g} - s_{i,0}^{a,g}\right) LFP_{i,0}^{a,g}}_{Demographic\ effect}.$$

The first term attributes the change in the LFP rate to changes in participation for different age groups, assuming constant population shares. The second term captures the population aging effect due to changing population shares, assuming LFP rates are held constant at its 2008 level.

Online Annex Table 3.2.1. Labor Market Policies Regression Data Sources

Indicator	Sources
Output Gap	IMF, WEO database
Trade Openness	IMF, WEO database
Service/Industry Employment Ratio	World Bank, World Development Indicators database
Urbanization Rate	World Bank, World Development Indicators database
Population by Education (secondary, tertiary)	Barro-Lee Educational Attainment data set
Labor Tax Wedge	OECD, Tax database
Unemployment Benefits	OECD, Benefits and Wages: Statistics
Spending on Labor Market Programs	OECD, Social Expenditure database
Union Density	OECD, Employment database
Coordination of Wage Setting	OECD/AIAS database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS)
Spending on Early Childhood Education and Care	OECD, Social Expenditure database
Share of Part-time Employment	OECD, Employment database
Length of Maternity Leave	OECD, Family database
Retirement Age	International Social Security Association, Social Security Programs throughout the World
Public Pension Spending	OECD, Social Expenditure database
Public Spending on Incapacity	OECD, Social Expenditure database

Source: IMF staff compilation.

Labor Force Participation and the Role of Policies

Figure 3.7 in the main text uses estimates from a reduced-form regression where LFP for specific groups of workers are related to cyclical, structural and policy variables that may affect the decision to supply labor (see Chapter 2 of the April 2018 WEO). The regression equation takes the form:

$$LFP_{i,t}^{g} = \beta^{g} Cycle_{i,t} + \gamma^{g} X_{i,t} + \delta^{g} Z_{i,t}^{g} + \alpha_{i}^{g} + \alpha_{t}^{g} + \varepsilon_{i,t}^{g},$$

Online Annex Table 3.2.2. Policies and Labor Force Participation Rates

	Youth Ages 15–24	Prime-Age Men Ages 25–54	Prime-Age Women Ages 25–54	Close-to-Retirement Workers Ages 55–64	Older Workers Ages 65+
	(1)	(2)	(3)	(4)	(5)
Output Gap (Lagged)	0.122	–0.0619**	0.0109	0.0337	0.0701**
	(0.103)	(0.0228)	(0.0662)	(0.0914)	(0.0238)
Trade Openness (Lagged)	–0.0316	0.00514	0.0116	–0.000912	–0.0603***
	(0.0248)	(0.00617)	(0.0113)	(0.0174)	(0.0110)
Service/Industry Employment Ratio (Lagged)	–0.00526	0.000005	0.0223***	–0.00477	0.0129***
	(0.00936)	(0.00206)	(0.00334)	(0.00582)	(0.00164)
Urbanization Rate (Lagged)	0.00509	0.0230	0.0930*	0.159	–0.0755*
	(0.123)	(0.0280)	(0.0492)	(0.0979)	(0.0409)
Secondary Education (All gender, ages 15–24)	0.0622**				
	(0.0242)				
Tertiary Education (All gender, ages 15–24)	0.0109				
	(0.0382)				
Secondary Education (Male, ages 25–54)		–0.0310			
		(0.0179)			
Tertiary Education (Male, ages 25–54)		–0.0108			
		(0.0147)			
Secondary Education (Female, ages 25–54)			0.121***		
			(0.0253)		
Tertiary Education (Female, ages 25–54)			0.0432		
			(0.0342)		
Secondary Education (All gender, ages 55–64)				0.126	–0.0891***
				(0.110)	(0.0199)
Tertiary Education (All gender, ages 55–64)				–0.177*	–0.160***
				(0.0887)	(0.0228)
Labor Tax Wedge	–0.0632	–0.0978***	0.0197	0.0206	–0.0577
	(0.0816)	(0.0286)	(0.0486)	(0.0837)	(0.0400)
Unemployment Benefits	0.00680	–0.0174***	–0.0512***	0.00197	0.00785
	(0.0156)	(0.00535)	(0.0151)	(0.0413)	(0.00644)
Spending on Labor Market Programs	0.227	–0.306	0.774*	1.358**	0.0650
	(0.729)	(0.195)	(0.363)	(0.505)	(0.211)
Union Density	–0.0574	–0.104***	0.358***	–0.346***	0.0432
	(0.135)	(0.0334)	(0.0812)	(0.113)	(0.0470)
Coordination of Wage Setting	1.514**	0.375**	0.837***	0.866***	–0.0272
	(0.635)	(0.128)	(0.238)	(0.225)	(0.129)
Spending on Early Childhood Education and			4.310***		
			(0.646)		
Share of Part-Time Employment			0.302**		
			(0.103)		
Length of Maternity Leave			–0.00042		
			(0.00834)		
Retirement Age				0.735***	0.432***
				(0.204)	(0.0560)
Public Pension Spending				–1.598***	–1.102***
				(0.313)	(0.0962)
Public Spending on Incapacity				0.638	0.630***
				(0.617)	(0.195)
Observations	487	394	363	379	379
Within R^2	0.30	0.30	0.65	0.77	0.65

Source: IMF staff calculations.

Note: Standard errors are shown in parenthesis. *, ** and *** indicate that coefficients are statistically different from 0 at the 10 percent, 5 percent, and 1 percent levels, respectively.

Where $LFP_{i,t}^{g}$ denotes the participation rate of worker group g in country i in year t. $Cycle_{i,t}$ is the cyclical position of the economy captured by the output gap. $X_{i,t}$ represents structural variables such as trade openness, the share of employment in the services sector, urbanization rates, in addition to educational attributes such as the share of the population with secondary and tertiary education. $Z_{i,t}^{g}$ includes the set of policies and institutions (some of which are specific to group g), that may affect the decision to participate in the labor force. α_{i}^{g} and α_{t}^{g} are country and year fixed effects. Some of the variables are included in the specification with a one-year lag to mitigate potential endogeneity. The regression is run for five distinct groups: young workers (15–24); prime-age men (25–54); prime-age women (25–54), close-to-retirement workers (55-64); and older workers (65+). Online Annex Table 3.2.2 presents the regression results from the cross-country panel regression and representative policies for different groups that have been used to construct Figure 3.7 in the main text.

The variables included in the analysis are listed in Online Annex Table 3.2.1, along with the data sources, and described next. Estimates of the output gap are taken from the most recent vintage of WEO database. For the structural variables, trade openness is defined as $(X + M)/GDP$, where X and M respectively denote total exports and imports of goods and services, and the urbanization rate is the share of the urban population in the total population in a given year. Educational attainment is from the Barro-Lee database (Barro and Lee 2013; Barro and Lee 2015) and is measured as the share of the population within a specific age-gender group with the highest level of education reported as primary, secondary, or tertiary.

For the policy variable, the following data sources are used:

- Labor tax wedge is the ratio between the average tax paid by a single-earner family (one parent at 100 percent of average earnings with two children) and the corresponding total labor cost for the employer.
- Unemployment benefits refer to the net replacement rate, which is the ratio of net household income during a selected month of the unemployment spell to the net household income before the job loss.
- Public expenditure on active labor market programs is calculated as active labor market program spending per unemployed person in percent of GDP per capita.
- Union density is measured as net union membership as a proportion of wage earners in employment.
- Coordination of wage setting is an index published by the Amsterdam Institute for Advanced Labour Studies Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts. The index runs from 1 to 5 with higher values indicating more centralized wage bargaining arrangements.
- Policies that may help prime-age women (25–54) participate in the labor force include public spending on early childhood education and care as a percent of GDP; maternity leave defined as the total number of weeks of job-protected maternity leave available to mothers; and the proportion of employees with a part-time contract to total employees.

- Retirement incentives are proxied by the statutory retirement age and by the generosity of pension plans. The latter, which may affect decisions for early retirement, is captured by old-age and incapacity spending as a percent of GDP.

The sample of advanced economies includes Australia, Austria, Belgium, Canada, Denmark, Estonia, Finland, France, Germany, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Slovak Republic, Slovenia, Spain, Switzerland, United Kingdom, and the United States. The sample of emerging markets includes Chile, Hungary, and Poland.

Aggregate Business Investment

Business investment and fiscal shocks data

In OECD economies, aggregate business investment is the gross fixed capital formation for non-financial corporations deflated using the WEO private investment deflator. The sample is restricted to 21 OECD economies for which the narrative fiscal shocks from Devries and others (2011) are available. These fiscal shocks are fiscal policy changes primarily intended to reduce budget deficits but unrelated to business cycle fluctuations. The sample runs from the late 1970s to 2021—assuming zero-fiscal shock in 2020-21—and includes 16 advanced economies (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Portugal, Spain, Sweden, United Kingdom, United States) and 5 emerging markets and developing economies (Brazil, Chile, Colombia, Costa Rica, Mexico).

Online Annex Table 3.2.3. Investment-Output Growth Instrumental Variable Regression

Dependant Variable: Investment Growth $\Delta \ln I_{i,t}$		
Definition of $Y_{i,t}$	GDP	*C* + *X*
$\Delta \ln Y_{i,t}^{IV}$ (*IV*: Fiscal Shocks)	1.985**	2.878**
	(0.851)	(1.441)
$\Delta \ln I_{i,t-1}$	0.018	0.006
	(0.090)	(0.098)
Country FE	Yes	Yes
Year FE	Yes	Yes
Number of Observations	499	488
Adjusted R^2	0.668	0.537
First-Stage *F*-Statistic	16.446	10.832
p-Value of *F*-Statistic	< 0.0001	0.0011

Sources: Organisation for Economic Co-operation and Development; and IMF staff calculations.
Note: Regression includes country and year fixed effects. Heteroscedasticity-robust standard errors are in parentheses. Fiscal shocks are changes in fiscal policy primarily intended to reduce the budget deficit (Devries and others 2011). *C* = total (private and government) consumption; *X* = exports. *, ** and *** indicate that coefficients are statistically different from 0 at the 10 percent, 5 percent, and 1 percent levels, respectively.

Investment growth-output growth regression

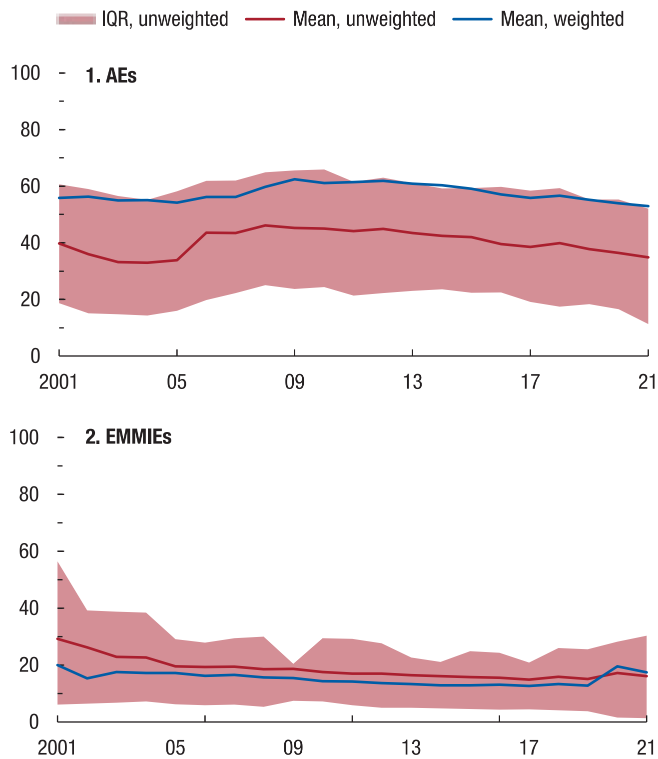
The estimation results are obtained from a two-stage instrumental variable regression (Chapter 4 of the April 2015 WEO). Using the narrative fiscal shocks (Devries and others 2011), the first stage builds an instrument for real GDP growth denoted by $\Delta \ln Y_{i,t}^{IV}$. The second stage estimates the following equation:

$$\Delta \ln I_{i,t} = \beta \Delta \ln Y_{i,t}^{IV} + \rho \Delta \ln I_{i,t-1} + a_i + \tau_t + \varepsilon_{i,t},$$

where $\Delta \ln I_{i,t}$ is the change in (log) real business investment in country *i* in year *t*; and $\Delta \ln Y_{i,t}^{IV}$ is the change in (log) real GDP, instrumented using fiscal narrative shocks; $\Delta \ln I_{i,t-1}$ is the lagged value of the investment term which reflects potential persistence in capital formation given that investment projects can span many years; α_i and τ_t are country and time fixed effects; $\varepsilon_{i,t}$ is the error term. The Online Annex Table 3.2.3 reports the first-stage relevance test results which suggest that the narrative fiscal shocks have explanatory power for real GDP growth (column 1). The first-stage *F*-statistic on the excluded instrument has a *p*-value below 0.1 percent and is above 15, suggesting that the narrative fiscal shocks have explanatory power for output growth. The second stage results suggest that the investment-output growth elasticity is statistically significant and close to 2. Consistent results are obtained when the growth rate of total demand (consumption plus export) is used instead of GDP growth as an alternative measure of aggregate demand (column 2).[2]

Online Annex Figure 3.2.2. Representativeness of Investment Data from Worldscope

(Percent of total investment by non-financial corporations)



Sources: Organisation for Economic Co-operation and Development (OECD); Thomson Reuters Worldscope; and IMF staff calculations.
Note: The representativeness is computed as the aggregate investment from Thomson Reuters Worldscope over the aggregate gross fixed capital formation from OECD. The numerator is computed by summing firm-level total investment at the country-year level; the denominator is the nominal gross fixed capital formation at the country-year level. The blue lines are the weighted average ratio for AEs and EMMIEs, using October 2023 GDP in purchasing power parity in international dollar weights. The red lines are the simple average ratios for AEs and EMMIEs. The red areas denote the interquartile range of the ratios for AEs and EMMIEs. AEs= advanced economies; EMMIEs = emerging market and middle-income economies.

Firm-level Investment Analysis

Representativeness of Thomson Reuters Worldscope Investment Relative to OECD Non-Financial Business Investment Data.

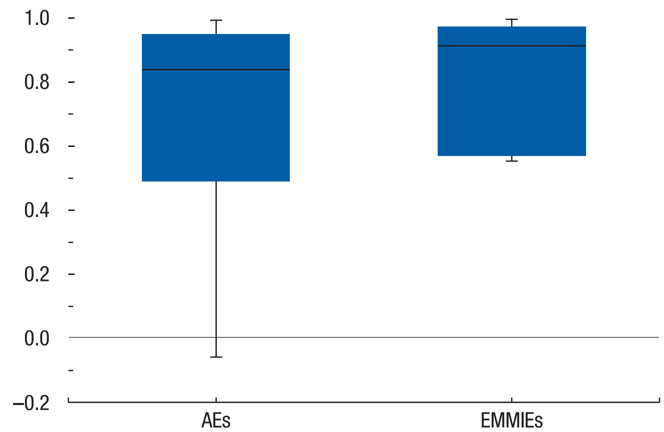
Firm-level data come from Thomson Reuters Worldscope. Firm-level data on total (tangible and intangible) investment is aggregated up to the country-year level (for details on the construction of total investment at the firm level see next subsection). Finance, insurance and

[2] The first-stage regression results are $\Delta \ln GDP_{i,t} = -0.661^{***} FiscalShock + 0.063^{***} \Delta \ln I_{i,t-1} + \alpha_i + \lambda_t + u_t$ and $\Delta \ln(C+X)_{i,t} = -0.514^{***} FiscalShock + 0.046^{**} \Delta \ln I_{i,t-1} + \alpha_i + \lambda_t + u_t$, respectively. At least two instrumental variables are needed to run the overidentification restrictions tests. When the regressions are estimated using both fiscal shocks and lagged fiscal shocks as instruments, the *p*-values of the Hansen *J*-statistics exceed 10 percent, indicating that the narrative fiscal shock instruments are valid. The investment-growth regressions also reflect the business confidence channel, as low output growth may depress firms' sales and hold back business investment.

real estate, and government agencies are excluded from the analysis. A 95% winsorization is applied on the variables used for the construction of total investment.

The sample of advanced economies in the analysis includes Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, Iceland, Ireland, Israel, Italy, Japan, Korea, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States. Among them, Hong Kong SAR, Iceland, and Singapore are not used in the comparison with OECD fixed capital formation.

Online Annex Figure 3.2.3. Representativeness of Investment Data from Worldscope
(Correlation coefficient)



Sources: Organisation for Economic Co-operation and Development (OECD); Thomson Reuters Worldscope; and IMF staff calculations.
Note: This figure shows the correlation between the aggregate country-level investment in Worldscope and the country-level investment in OECD non-financial corporations sector. The black lines in the bars represent the median, the bars the interquartile range, and the whiskers the data points within 1.5 times the interquartile range from the 25th or 75th percentile across economies in the group. Boxes exclude outlier points. The outliers are Czech Republic, Hungary, and Russia. AEs = advanced economies; EMMIEs = emerging market and middle-income economies.

The sample of emerging market economies in the analysis includes Brazil, Chile, China, Colombia, Hungary, India, Malaysia, Mexico, Poland, Russia, South Africa, Thailand, Türkiye. Among them, India, Malaysia, and Thailand are not used in the comparison with OECD fixed capital formation.

Online Annex Figures 3.2.2 and 3.2.3 show that the aggregated firm-level investment data represent around half of the total business investment in advanced economies, with a correlation between the two series of over 0.8 for the majority of the advanced economies in our sample. For emerging markets, the aggregated firm-level investments represent up to 30 percent of business investment compared to the aggregate OECD series, with a correlation reaching more than 0.8 for half of the emerging markets in the sample.

Construction of Net Investment Rates in Thomson Reuters Worldscope

The mismeasurement of intangible capital has been considered a key explanation behind the observed decline in investment rates, particularly in advanced economies. For instance, Crouzet and Eberly (2019) show that properly accounting for intangible capital can explain 30 to 60 percent of the decline in investment in the United States from 2000.

To address the problem of mismeasuring intangible capital, the analysis follows Peters and Taylor (2017) and defines the net investment rate for firm *i* in year *t* as

$$\frac{Net\ Total\ Investment_{it}}{Total\ K_{it-1}} = \frac{Net\ Tangible\ Investment_{it} + Intangible\ Investment_{it}}{Tangible\ K_{it-1} + Intangible\ K_{it-1}}.$$

Net Tangible Investment is constructed using the measure for tangible capital expenditure in Worldscope subtracting depreciation.

Following Peters and Taylor (2017), intangible investment for firm *i* in year *t* is constructed as $Intangible\ Investment_{it} = R\&D_{it} + 0.3\ SGA_{it}$, with $R\&D$ being the annual spending on research and development, and SGA referring to annual selling, general and administrative expenses. Intangible capital, instead, is constructed as follows:

$$Intangible\ K_{it} = Intangible\ Assets_{it} + Knowledge\ K_{it} + Organizational\ K_{it},$$

with $Intangible\ Assets_{it}$ referring to the book value of a firm's patents, leasehold improvements and trademarks; $Knowledge\ K_{it}$ and $Organizational\ K_{it}$ constructed following Peters and Taylor 2017, as

$$Knowledge\ K_{it} = (1 - \delta_{knowledgeK})Knowledge\ K_{it-1} + R\&D_{it},$$

$$Organizational\ K_{it} = (1 - \delta_{organizationalK})\ Organizational\ K_{it-1} + \mathrm{SGA}_{it},$$

with depreciation rates $\delta_{knowledgeK} = 0.15$ and $\delta_{organizationalK} = 0.2$.

Descriptive Statistics from Thomson Reuters Worldscope

Online Annex Table 3.2.4 presents the descriptive statistics of investment variables and its determinants in the regression over the sample period 2000-2021. All variables are winsorized at the 5^{th} and 95^{th} percentile.

Online Annex Table 3.2.4. Descriptive Statistics

Variable	Median	Mean	Standard Deviation
Gross Tangible Investment Ratio	6.35	9.66	10.43
Intangible Investment Ratio	8.44	10.88	10.66
Total Net Investment Ratio	10.39	14.04	15.54
Tobin's *q*	1.16	1.48	0.93
Leverage	23.28	25.11	17.39
Cost of Debt	4.36	6.87	9.49
Profit Margin	4.95	–1.39	35.52
Cash Stock over Total Assets	10.57	13.70	12.74

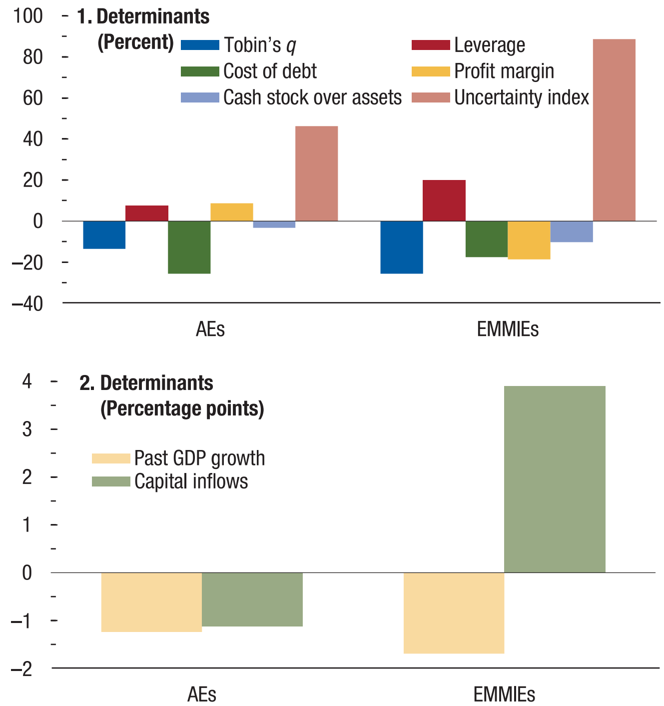
Sources: Thomson Reuters Worldscope; and IMF staff calculations.

Investment Regression

Online Annex Table 3.2.5 relates net investment rate with selected firm- and macro-level determinants of investment. The results should be interpreted as follows: (i) for Tobin's q—a firm's market value relative to its cost of capital, a 1 unit increase leads to a 4.03 percentage points increase in the net investment rate in advanced economies (column 1), and a 3.57 percentage points increase in emerging markets (column 2). Post-2008 this increase is reduced to 2.9 percentage points in advanced economies, and 3.15 percentage points in emerging markets; (ii) for the (log) of the uncertainty index, a 1 percent increase in the uncertainty index leads approximately to a 5.82 basis points decline in investment rates; (iii) for the other coefficient estimates denoted by β, a 1 percentage point increase in the regressor leads to a $(100 \times \beta)$ basis points increase in the net investment rate.

The regression also detects whether firms changed their responsiveness to these determinants after 2008. Results show a marked reduction in the sensitivity of investment rates to Tobin's q, profit margins, and accumulated cash after 2008, especially in advanced economies. This is in line with growing research linking these weakened investment relationships to the rise of large firms and decrease in business competition.[3] Moreover, in emerging markets, firms have become more responsive to leverage and the cost of debt, consistent with evidence highlighting the rising vulnerabilities of corporate investment resulting from increased corporate debt, as featured in the Chapter 2 of the April 2021 *Global Financial Stability Report* (GFSR) and Chapter 2 of the April 2022 WEO.[4]

Online Annex Figure 3.2.4. Post-2008 Changes in Investment Rate Determinants



Sources: Ahir, Bloom, and Furceri 2022; Thomson Reuters Worldscope; and IMF staff calculations.
Note: The figure computes the difference between the post- and pre-2008 levels of the investment determinants listed in the legends. Values are in percent of the average pre-2008 levels in panel 1, while variables in panel 2 are expressed in percentage point difference. For AEs, pre-2008 averages are computed over 2000–08. For EMMIEs, pre-2008 refers to 2006–08. For the firm-level determinants listed in panel 1, the post-pre 2008 difference is computed at the firm level and then aggregated at the country level using as weights the relative capital share of each firm. Averages for AEs and EMMIEs are computed using GDP in purchasing power parity in international dollar weights. AEs = advanced economies; EMMIEs = emerging market and middle-income economies; Tobin's *q* = the ratio of the market value to the book value of a firm's assets.

Evolution of key investment determinants over time

Online Annex Figure 3.2.4 summarizes post-2008 relative to pre-2008 averages of the firm- and macro-level determinants of investment rates included in the regression equation in Online Annex Table 3.2.5. For the firm-level determinants listed in the left panel, the post-pre 2008 difference is computed at the firm-level and then aggregated at the country level using as weights the relative capital share of each firm. Averages for advanced and emerging economies are computed using GDP PPP weights. As clearly stands out from the Figure, Tobin's q, Cost of Debt, Cash Stock over Assets and Past GDP Growth declined post-2008 in both advanced and emerging markets. Leverage and the country-level Uncertainty Index increased in both advanced and emerging markets. Profit margins increased in

[3] Gutiérrez and Philippon (2017) show that underinvestment relative to Tobin's q is mostly explained by decreased competition. More recently, Gormsen and Huber (2023) confirmed that higher market power firms display a weaker relationship between Tobin's q and investment rates. Relatedly, Dao and Maggi (2018) show that firms that save more than invest, and so accumulate cash, tend to be larger and more profitable.

[4] Alter and Elekdag (2020) and Chapter 2 of the April 2021 *Global Financial Stability Report* (GFSR) showed that exceptionally loose global monetary conditions after the global financial crisis led to a sharp increase in corporate leverage in emerging markets. Alter and Elekdag (2020) showed that leverage in emerging markets grew disproportionally for firms that were either less profitable or less solvent. This resulted in stronger investment vulnerabilities in response to adverse growth shocks including the COVID-19 pandemic shock (Chapter 2 of the April 2021 GFSR, and Chapter 2 of the April 2022 WEO).

advanced economies but decreased in emerging markets. Capital inflows over GDP decreased in advanced economies after 2008; conversely, they increased in emerging markets.

Online Annex Table 3.2.5. Firm-level Evidence: Investment Rate Determinants

Dependent Variable: Net Investment Rate	AEs	EMMIEs
Tobin's q (t - 1)	0.0403***	0.0357***
	(0.0011)	(0.0021)
Leverage (t - 1)	–0.1059***	–0.0757***
	(0.0051)	(0.0112)
Cost Debt (t - 1)	–0.0303***	–0.0277**
	(0.0071)	(0.0140)
Profit Margin (t - 1)	0.0137***	0.0719***
	(0.0033)	(0.0076)
Cash Stock over Assets (t - 1)	0.2673***	0.3345***
	(0.0081)	(0.0193)
Post - 2008 X Tobin's q (t - 1)	–0.0113***	–0.0042**
	(0.0012)	(0.0021)
Post - 2008 X Leverage (t - 1)	–0.0019	–0.1030***
	(0.0051)	(0.0115)
Post - 2008 X Cost of Debt (t - 1)	–0.0009	–0.0757***
	(0.0083)	(0.0159)
Post - 2008 X Profit Margin (t - 1)	–0.0087**	–0.0414***
	(0.0035)	(0.0081)
Post - 2008 X Cash Stock over Assets (t - 1)	–0.0994***	–0.0504**
	(0.0082)	(0.0198)
GDP Growth (t - 1)	0.0885***	0.0140
	(0.0195)	(0.0272)
GDP Growth (t - 2)	0.0551***	0.1890***
	(0.0197)	(0.0297)
GDP Growth (t - 3)	0.1294***	0.2538***
	(0.0204)	(0.0294)
Uncertainty Index	–0.0582***	0.0022
	(0.0058)	(0.0103)
Capital Inflow over GDP	0.0242	0.1981***
	(0.0153)	(0.0277)
Observations	214458	90301
Adjusted R^2	0.4985	0.338

Sources: Ahir, Bloom, and Furceri 2022; Thomson Reuters Worldscope; and IMF staff calculations.
Note: Regression includes firms and year fixed effects. Standard errors are clustered at the firm level and shown in parenthesis. *, ** and *** indicate that coefficients are statistically different from 0 at the 10 percent, 5 percent, and 1 percent levels, respectively. AEs= advanced economies; EMMIEs = emerging market and middle-income economies.

Resource Misallocation

Data Sample

The analysis in this section covers a sample of 20 economies (Austria, Belgium, Bulgaria, China, Czechia, Estonia, France, Germany, Italy, Japan, Korea, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Switzerland, and the USA) in the period 2000-19. It uses data on firm-level value-added, capital stocks and employment from Orbis, covering 19 broad economic sectors (Agriculture, Mining, Food, Textiles, Wood Products, Petroleum Products, Chemical Products, Plastics, Basic Metals, Electronics, Machinery, Transport Equipment, Other Manufacturing, Construction, Retail, Hospitality, Information Services, Finance and Real Estate, and Professional Services). These sectors span the whole economy, excluding only non-market sectors (Utilities, Public Administration, Education, and Arts). The country sample was selected to ensure a consistent coverage of the included countries' total and sectoral economic activity over time. For these countries, the total value of firm sales reported in Orbis consistently exceeds 60 percent of the value of total gross output reported by the OECD. The one exception is the United States, for which Orbis firm data consistently covers only listed firms accounting for about 30 percent of total output.

Measuring Allocative Efficiency at the Sector Level

Under the assumptions of Hsieh and Klenow (2009):

$$\widehat{TFPQ}_{csit} \propto \frac{VA_{csit}^{\frac{\sigma}{\sigma-1}}}{K_{csit}^{\alpha_s} L_{csit}^{1-\alpha_s}}, \qquad \widehat{MRPK}_{csit} \propto \frac{VA_{csit}}{K_{csit}}, \qquad \widehat{MRPL}_{csit} \propto \frac{VA_{csit}}{L_{csit}},$$

where VA_{csit}, K_{csit}, L_{csit} are respectively the value added, capital stock and employment of a firm i operating in sector s of country c in year t; and $\widehat{TFPQ}_{csit}$, $\widehat{MRPK}_{csit}$ and $\widehat{MRPL}_{csit}$ are respectively measures of the firm's real productivity (TFPQ), marginal revenue product of capital (MRPK) and marginal revenue product of labor (MRPL). The parameters σ and α_s respectively denote the elasticity of substitution between the outputs of different firms, and the capital share in sector s. For the 20 economies listed above, $\widehat{TFPQ}_{csit}$, $\widehat{MRPK}_{csit}$ and $\widehat{MRPL}_{csit}$ are computed for the period 2000-19 at the sector level using data on value added, capital stocks and employment from Orbis, imposing $\sigma = 3$, and setting α_s equal to 1 minus the average U.S. labor share in sector s during this period from EU-KLEMs data.[5]

Detecting and Correcting for Additive Measurement Error

$\widehat{TFPQ}_{csit}$, $\widehat{MRPK}_{csit}$ and $\widehat{MRPL}_{csit}$ could be measured with error, either because the underlying data is reported with error or because the underlying assumptions about production technologies and market structure are mis-specified. Bils and others (2017) show that if (a part of) this error is additive, it can be detected by running a regression of the form:[6]

$$\begin{aligned}\Delta \ln VA_{csit} = {} & \Phi_{cs} \Delta \ln \widehat{TFPR}_{csit} + \Psi_{cs} \Delta \ln K_{csit}^{\alpha_s} L_{csit}^{1-\alpha_s} \\ & - \Psi_{cs}(1-\lambda_{cs}) \ln \widehat{TFPR}_{csit} \times \Delta \ln K_{csit}^{\alpha_s} L_{csit}^{1-\alpha_s} + D_{cs} + \xi_{csit},\end{aligned}$$

where D_{cs} is a country-sector fixed effect, and ξ_{csit} is a mean-zero error. If $\hat{\lambda}_{cs} = 1$, there is no

[5] The Orbis data is cleaned following the steps described Kalemli-Ozcan and others (2015). Only those countries are selected into the sample for which the total shares of firms reporting in Orbis cover a sufficiently large share of the value of gross output reported for the country in OECD TiVA, and this coverage is consistent over the 2000-19 period and balanced across 19 broad sectors. This delivers the above-described sample of 20 economies. The assumption $\sigma = 3$ is conservatively chosen at the low end of values used in the literature, since lower values of σ imply lower measured misallocation for given data.

[6] Bils and others (2017) is the pre-published working paper version of Bils and others (2021), which is cited throughout the main text. It contains additional methodological details on which the analysis described here draws.

additive measurement error; if $\hat{\lambda}_{cs} = 0$, the measures or productivity and marginal products are pure noise.

Online Annex Table 3.2.6. Strength of Additive Measurement Error for Selected Countries and Country Groups, by Period and Sector Type

		United States	China	AEs Median	EMMIEs Median	Sample Median
Goods	2000–09	0.837	0.812	0.738	0.833	0.757
		(0.014)	(0.005)	(0.010)	(0.005)	(0.008)
	2010–19	0.898	0.728	0.767	0.797	0.768
		(0.017)	(0.011)	(0.006)	(0.004)	(0.006)
Services	2000–09	0.945	0.884	0.820	0.884	0.834
		(0.012)	(0.017)	(0.007)	(0.005)	(0.005)
	2010–19	0.772	0.835	0.772	0.835	0.782
		(0.016)	(0.009)	(0.004)	(0.003)	(0.003)

Source: IMF staff calculations.

Note: Table shows estimates of λ_{cs} from the regression described in the text for selected countries and country groups, by period and by sector type. Regressions are estimated by country and sector group, for the two periods 2000–09 and 2010–19. Standard errors are in parentheses.

Online Annex Table 3.2.6 shows $\hat{\lambda}_{cs}$ for selected countries, and its median for different country groups in the sample. The estimates suggest that additive measurement error is present, but small, with $\hat{\lambda}_{cs}$ consistently closer to 1 than to 0. Moreover, while there are small differences between periods, countries and sector types, there is no systematic evidence that additive measurement plays a bigger role for some distinctive subset of the sample. In particular, productivity and marginal products computed for service sectors appear to be less prone to additive measurement error than their counterparts computed for goods sectors.

Under additional assumptions about the distribution of the measurement error, Bils and others (2017) show that the values of $\hat{\lambda}_{cs}$ described above can be used to compute the "true" values of productivity and MRPs from their measured counterparts as follows:

$$\ln TFPQ_{csit} = E\left[\hat{\lambda}_{cs} \ln \widehat{TFPQ}_{csit}\right], \qquad ln\, MRPK_{csit} = E\left[\hat{\lambda}_{cs}\, ln\, \widehat{MRPK}_{csit}\right],$$

$$\ln MRPL_{csit} = E\left[\hat{\lambda}_{cs} \ln \widehat{MRPL}_{csit}\right],$$

where variables without "hats" represent the value of "hatted" variables net of additive measurement error. These are then used to compute firms' total revenue factor productivities:

$$TFPR_{csit} = MRPK_{csit}^{\alpha_s} MRPL_{csit}^{1-\alpha_s}, \;\; \overline{TFPR}_{cst} = \overline{MRPK}_{cst}^{\alpha_s} \overline{MRPL}_{cst}^{1-\alpha_s},$$

where $TFPR_{csit}$ is the total revenue factor productivity of firm i in sector s; $\overline{TFPR}_{cst}$ is the average total revenue productivity in the sector; and $\overline{MRPK}_{cst}$ and $\overline{MRPL}_{cst}$ are respectively the revenue-weighted harmonic means of firms' MRPKs and MRPLs in the sector. Following Hsieh and Klenow (2009), allocative efficiency in country c, sector s and year t is then

$$AL_{cst} \equiv \left[\sum_i \frac{\left(TFPQ_{csit} \frac{\overline{TFPR}_{cst}}{TFPR_{csit}} \right)^{\sigma-1}}{\sum_i TFPQ_{csit}^{\sigma-1}} \right]^{\frac{1}{\sigma-1}}.$$

Note that $AL_{cst} \in [0,1]$, and that $1 - AL_{cst}$ measures the share of the sector's potential TFP lost due to misallocation.

Aggregate TFP Impact of Changes in Allocative Efficiency

Aggregate TFP in country c and year t can be written as:

$$\ln TFP_{ct} \equiv \ln TFP_{ct}^{*} + \sum_{s} \theta_{cst} \ln AL_{cst} ,$$

where TFP_{ct}^{*} is the "ideal" TFP that would prevail in the absence of misallocation, and θ_{cst} is the share of sector s in country-c GDP.[7] Sector GDP shares for the 20 sample economies are taken from EU-KLEMS where possible, and from OECD-TiVA otherwise.

It follows that the growth of aggregate TFP can be decomposed as follows:

$$\Delta \ln TFP_{ct} \equiv \Delta \ln TFP_{ct}^{*} + \Delta \ln AL_{ct} , \qquad \Delta \ln AL_{ct} \equiv \Delta \sum_{s} \theta_{cst} \ln AL_{cst} .$$

The term $\Delta \ln TFP_{ct}^{*}$ captures the growth in TFP due to innovation in firms' productivities and entry of new product varieties. The term $\Delta \ln AL_{ct}$ captures the TFP impact of changes in allocative efficiency. The distribution of the average of this second term for the 2000-19 period across the 20 sample economies is described in Figure 3.11 in the main text.

The TFP impact of changes in allocative efficiency can be decomposed further using a shift-share approach:

$$\Delta \ln AL_{ct} \equiv \sum_{s} (\Delta \theta_{cst}) \ln AL_{cst} + \sum_{s} \theta_{cst-1} (\Delta \ln AL_{cst}),$$

where the first term captures the impact on aggregate allocative efficiency of changes in sector's GDP shares (i.e. the composition of economic activity), and the second term captures changes in within-sector allocative efficiency (holding sector shares constant). This decomposition is shown for select economies and country groups from the sample in in Figure 3.12a in the main text. Finally, Figure 3.12b in the main text shows the distribution, for goods-producing and service-producing sectors, of the TFP loss due to misallocation in 2019, computed as $1 - AL_{cst}$.

Firm-Level Evidence of Adjustment Frictions

A number of possible adjustment frictions – including labor-market imperfections, credit constraints and limited managerial scope – imply that it may take firms some time to attract additional resources after a positive shock. In this case, firms should see a temporary increase in their "misallocation wedge". The misallocation wedge roughly corresponds to the measured gap between the firm's actual capital and labor allocation and the capital and labor it should ideally be employing.

[7] This expression captures the TFP impact of misallocation of capital and labor between firms within sectors, but not of misallocation of capital and labor between sectors. Computing between-sector misallocation for a subset of the 20 sample economies using data from EU-KLEMS, it is found to be one order of magnitude smaller than within-sector, between-sector misallocation. For this reason, the analysis focuses on the latter dimension of misallocation.

Online Annex Table 3.2.7. The Dynamics of Misallocation Wedges at Firm Level, 2000–19

Dependent Variable Log Change in Misallocation Wedge	(1)	(2)	(3)	(4)
Log Change in TFPQ		0.727 (0.000)***		0.703 (0.000)***
Log Initial Misallocation Wedge			–0.595 (0.000)***	–0.066 (0.000)***
R^2	0.160	0.940	0.410	0.940
Number of Observations	34,399,920	34,399,920	34,399,920	34,399,920

Source: IMF staff calculations.

Note: The dependent variable is the log year-on-year change in firms' measured misallocation wedge. The main regressor is the log year-on-year change in firms' real productivity (TFPQ). Regressions are estimated at firm level for the period 2000–19. All regressions include firm and country-sectoryear fixed effects. Standard errors clustered at the firm level are in parentheses. *, ** and *** indicate that coefficients are statistically different from 0 at the 10 percent, 5 percent, and 1 percent levels, respectively.

Online Annex Table 3.2.7 shows coefficient estimates ($\hat{\gamma}_1$ and $\hat{\gamma}_2$) and goodness of fit from the firm-level regression designed to test this hypothesis.

$$\Delta\ln\left(\frac{TFPR_{csit}}{\overline{TFPR}_{cst}}\right) = \gamma_1\,\Delta\ln TFPQ_{csit} + \gamma_2\ln\left(\frac{TFPR_{csit}}{\overline{TFPR}_{cst}}\right) + \delta_i + \delta_{cst} + \zeta_{csit},$$

where Δ denotes the change of a variable between years t and $t+1$; δ_i and δ_{cst} are respectively a firm and a country-sector-year fixed effect; and ζ_{csit} is a mean-zero error. $TFPR_{csit}/\overline{TFPR}_{cst}$ can be interpreted as the misallocation wedge of a firm i operating in country c and sector s in year t. If firms are subject to temporary adjustment frictions, their misallocation wedge should rise if their productivity grows relatively fast ($\gamma_1>0$). However, absent further shocks the wedge should shrink back from its elevated level ($\gamma_2 < 0$).

As can be seen from Columns (2) and (4), firms whose TFPQ grows relatively fast do indeed tend to see an increase in their misallocation wedge on impact. Furthermore, Columns (3) and (4) confirm that the change in firms' misallocation wedges also depends negatively on their initial level. These estimates are consistent with firms only being able to attract additional capital and labor gradually after receiving a one-time boost to their relative productivity. The regression output suggests that this process is rather slow. The estimates in column (4) imply that it takes about $\ln 0.5\,/\,\ln(1+\hat{\gamma}_2) \approx 11$ years on average for a firm's misallocation wedge to return half-way to its initial value, following a one-time shock.[8] This finding is very robust across different countries and country groups. However, there is some evidence that U.S. misallocation wedges rise less in response to firm productivity shocks, and revert faster.[9]

[8] We can also use the results in Column (4) of Table 3.2.7 to obtain firms' structural misallocation wedge, defined as the wedge absent shocks ($\Delta\ln TFPQ_{csit} = 0$; ζ_{csit}). This yields $\ln\left(\frac{TFPR_{csi}}{\overline{TFPR}_{cs}}\right) = -(\delta_i + \delta_{cst})/\gamma_2$. We compute this for all firms in the regression sample, and aggregate across sectors and countries, using appropriate weights, to find that – for our sample as a whole – about 37 percent of overall misallocation is due to transitory factors, and 63 percent is structural.

[9] However, since the coverage of U.S. firms in Orbis is less complete than for other sample countries, and restricted to listed firms only, these differences are at best indicative.

A corollary of the findings described above is that a sector should experience a transitory increase in misallocation if, over some period, the TFPQ of some firms in the sector grows more rapidly than that of others, leading to an increased dispersion of real productivities. The next subsection presents evidence that confirms this logic.

Sector-Level Evidence of Adjustment Frictions

Table 3.2.8. Accounting for Sector-Level Changes in Allocative Efficiency, 2000–19

Dependent Variable Log Change in Allocative Efficiency	(1)	(2)	(3)	(4)
Log Change in Productivity Dispersion		–0.470 (0.128)***		–0.365 (0.105)***
Log Initial Allocative Efficiency			–0.611 (0.051)***	–0.516 (0.080)***
R^2	0.100	0.340	0.430	0.570
Number of Observations	586	586	586	586

Source: IMF staff calculations.
Note: The dependent variable is the log change in the allocative efficiency component of TFP over a ten-year period. The main regressors is the log change in the dispersion of firms' real productivity (TFPQ) over the same period. Regressions are estimated at country-sector level for the two periods 2000–09 and 2010–19. All regressions include country and sector fixed effects. Standard errors clustered at the country-sector level are in parentheses. *, ** and *** indicate that coefficients are statistically different from 0 at the 10 percent, 5 percent, and 1 percent levels, respectively.

Online Annex Table 3.2.8 shows coefficient estimates ($\hat{\beta}_1$ and $\hat{\beta}_2$) and goodness of fit from the sector-level regression

$$\Delta_{t+9,t}\ln AL_{cst} = \beta_1\,\Delta_{t+9,t}\ln PD_{cst} + \beta_2\ln AL_{cst} + \delta_c + \delta_s + \zeta_{cst},$$

where $\Delta_{t+9,t}\ln AL_{ct}$ is the log change in sector-level allocative efficiency between year t and $t+9$; $\Delta_{t+9,t}\ln PD_{ct}$ is the log change in the dispersion of firm TFPQs in the same period;[10] δ_c and δ_s are respectively a country and sector fixed effect; and ζ_{cst} is a mean-zero error. The regression is estimated pooling the ten-year changes for two periods, 2000-9 and 2010-19.

Columns (2) and (4) in the table document that an increase in a sector's dispersion of firm productivities is accompanied by a contemporaneous decline in the sector's allocative efficiency. Columns (3) and (4) show that the change in a sector's allocative efficiency over a given period is also negatively related to the initial extent of the inefficiency. This implies that, following a decline in a sector's allocative efficiency due to a shock to the firm productivity distribution, allocative efficiency tends to recover. Both these findings are consistent with the firm-level evidence presented in the previous subsection.

The regression implies that in the long run, in the absence of shocks, AL_{cst} converges to

$$\lim_{t\to\infty}\ln AL_{cst} \equiv \ln AL_{cs} = -\frac{\hat{\delta}_c + \hat{\delta}_s}{\hat{\beta}_2}.$$

Long-run allocative efficiency in country c and sector s can thus be thought of as reflecting sector-inherent characteristics (captured by $-\hat{\delta}_s/\hat{\beta}_2$) and the country's economic and

[10] As in Bils and others (2021), PD_{cst} is computed for each sector as the ratio of the power mean of firm TFPQs (with $\sigma = 3$) to the geometric mean of TFPQs.

institutional environment (captured by $-\hat{\delta}_c/\hat{\beta}_2$). Figure 3.14 in the main text plots the country component of long-run structural allocative efficiency, $-\hat{\delta}_c/\hat{\beta}_2$, estimated from the regression above against measures of the institutional and policy environment, averaged for the regression period. Using the definition of long-run structural allocative efficiency, note that in the absence of shocks:

$$\Delta_{t+9,t}\ln AL_{cst} = \hat{\beta}_2(\ln AL_{cst} - \ln AL_{cs}),$$

so $9 \times \ln 0.5 / \ln\left(1 + \hat{\beta}_2\right)$ measures the approximate half-life in years of a deviation of allocative efficiency from its long-run fundamental. The estimates in column (4) of Online Annex Table 3.2.8 imply a half-life of 9 years, a similar order of magnitude as the 11-year half-life of the firm-level misallocation wedge documented in the previous subsection.

Online Annex 3.3. Assumptions and Calculations for Medium-term Projections

This online annex describes the methodology used to project trend LFP rate, potential employment growth, growth rates of TFP and capital in the medium-term (year 2030).

Projecting potential employment growth in the medium term

To forecast labor supply, this section uses a cohort-based analysis to first estimate the trend LFP rates for different age and gender groups in 83 economies, accounting for all determinants of labor supply that are specific to each age-gender (life cycle effects) and birth-year (cohort effects).

Specifically, following a similar cohort-based model approach as in Chapter 3 of the April 2015 WEO and Chapter 2 of the April 2018 WEO, LFP rates for each age (a) and gender (g) group in year t is estimated according to the following specification:

$$\log LFPR_t^{a,g} = \alpha^{a,g} + \frac{1}{n^a}\sum_{b=1932}^{2006} \beta_b^g I_{b(=t-a),t}^g + \gamma^{a,g} cycle_t + \lambda^{a,g} X_t^{a,g} + \varepsilon_t^{a,g}.$$

Using the LFP data from ILO for four age groups (15 to 24, 25 to 54, 55 to 64, and 65 above) for the period of 1995-2021, the above specification is estimated for each of the 83 countries. The group-specific labor participation rates have four determinants: age-gender-specific constant ($\alpha^{a,g}$) that captures life-cycle pattern of labor supply, which could differ between men and women; unobserved birth-cohort effects ($I_{b,t}^g$); impacts of business cycles $(cycle_t)$ measured by HP-filtered output gap, and structural factors ($X_t^{a,g}$). Linear and quadratic deterministic time trends are also included in the regressions to control for historical trends.

The birth-cohort-specific factors capture all factors associated with a particular birth year (such as social norms and preferences towards education, work, marriage and children) that could have a lasting effect on labor participation throughout the life cycle. These cohort effects are captured by a fixed effect ($I_{b(=t-a),t}^g$) for each birth-year cohort b. The analysis includes cohorts born between 1932 and 2006, grouping individuals born in five-year intervals into cohorts starting from the initial year. Then the cohort coefficient is divided by number of cohorts included in an age group n^a.

Structural factors can impact the trend participation rate of particular age groups, and include life expectancy, fertility, education attainment, and education enrollment. For women of prime working age, participation in the workforce is negatively correlated with the fertility rate. Among working-age women, there is a positive correlation between participation and years of schooling (with data from Barro and Lee 2021 September update). For young adults, workforce participation is positively linked to the percentage of secondary education completed. Furthermore, as life expectancy rises, individuals nearing the official retirement age are more likely to participate in the workforce.

Using the LFP data from ILO for four age groups (15 to 24, 25 to 54, 55 to 64, and 65 above) for the period of 1995-2023, the above specification is estimated for each of the 35 advanced economies and 48 emerging market and developing economies. For each country, there are four equations (four age groups) jointly estimated for each gender with constraints that the cohort coefficients are the same across equations.

To predict medium-term participation rates for each age and gender group, the exercise assumes no cyclical gap, constant time trends over the medium term, and uses the projected structural factors from the UN Population and Development Database. It allows for the natural progression of existing cohorts through their life cycles, and assumes the participation profile of new cohorts entering the labor force will mirror those of the most recently observed cohort. These predictions by individual groups are then aggregated up to obtain the country-level labor participation rates based on the projected population share of each group. Lastly, the projected growth rate in LFP rate by 2030, along with the expected growth of population (aged 15 above), is used to estimate the medium-term potential employment growth, assuming stable employment rates in the medium-term.

Constructing the Baseline Scenario for Global Medium-Term Growth

This section describes the chapter's approach to predict medium-term global growth. Different from the WEO projection which is bottom-up approach, this chapter adopts a top-down approach.

Starting with growth decomposition $\Delta \ln Y_t = \Delta \ln TFP_t + (1-\alpha)\Delta \ln L_t + \alpha \Delta \ln K_t$, the previous section explains how growth for the labor component is forecasted, this section focuses on capital component and TFP.

- *Capital growth projection*. The growth rate of the capital stock can be broken down into contributions from both public and private investment rates, expressed as $\Delta \ln K_t = s\frac{\Delta K^{pub}}{K^{pub}} + (1-s)\frac{\Delta K^{priv}}{K^{priv}}$, where s is the share of public capital stock in the total capital stock and $\frac{\Delta \mathrm{K}}{K} = \frac{I}{K} - \delta$, which corresponds to the net investment rate (after depreciation). The chapter uses the projected investment rates from WEO for the medium term. This projection is typically based on the medium-term budget projections provided by country authorities, making it a reliable source for this component.

  To forecast the private investment rate, the chapter first estimates the output growth elasticity of the private investment rate using an accelerator model-based approach. This requires regressing the net private investment rates against the GDP growth rate, using the narrative fiscal shocks (see Online Annex Section 3.2) as an instrumental variable, and controlling for both country-specific and time-specific fixed effects. The estimated investment-growth elasticity ($\hat{\beta}$) is then used to determine the net private investment rate for a given GDP growth rate, according to

$$\frac{{NI_{2030}}^{priv}}{K_{2029}^{priv}} = \hat{\beta}(\Delta \ln Y_{2030} - \Delta \ln Y_{t0}) + \frac{{NI_{t0}}^{priv}}{K_{t0}^{priv}}. \quad (1)$$

The pre-pandemic five-year (2015-19) averages are used for initial values of global output growth and net private investment rate in the above equation.

- *TFP growth projection.* As presented in Online Annex 3.2, TFP growth can be generally decomposed into two parts—the change in efficient TFP ($\Delta \ln TFP_t^*$) and the change in allocative efficiency ($\Delta \ln AL_t$): $\Delta \ln TFP_t \equiv \Delta \ln TFP_t^* + \Delta \ln AL_t$.

  The projection for the change in allocative efficiency in 2030 is based on the analysis of sector-level allocative efficiency performed in Online Annex 3.2. In particular, given the estimates in Online Annex Table 3.2.8, the change in allocative efficiency over the next decade for any country c can be projected using $E\left[\Delta_{t+9,t} \ln AL_{ct}\right] = \sum_s \theta_{cst}\left[\hat{\beta}_2 \ln AL_{cst} + \hat{\delta}_c + \hat{\delta}_s\right]$, given only an initial extent of sector-level misallocation in t and assuming no further shocks to the firm distribution and constant sector shares. Countries' 2019 sector-level misallocation is used as the initial value, allowing for some "depreciation" of misallocation between 2019 and 2024. We aggregate the resulting projection across the 20 sample countries used in the misallocation analysis, using PPP GDP weights to arrive at $E[\Delta \ln AL_t] = \frac{1}{9}\sum_c \omega_c E\left[\Delta_{t+9,t} \ln AL_{ct}\right]$.

  The growth rate of the efficient TFP is assumed to continue its historical downward trend. By combining these two factors, the expected TFP growth in the medium term is estimated to be around 0.9 percent.

- *Global output growth projection.* Global GDP growth in 2030 is then projected based on the following equation:

  $\Delta \ln Y_{2030} = \Delta \ln TFP_{2030} + (1-\alpha)\Delta \ln L_{2030} + \alpha \left[s \frac{{NI_{2030}}^{pub}}{K_{2029}^{pub}} + (1-s) \frac{{NI_{2030}}^{priv}}{K_{2029}^{priv}} \right]$ and the above equation (1), where $\Delta \ln TFP_{2030} = 0.9$, $\Delta \ln L_t = 0.32, \alpha = 0.487, s = 0.27, \frac{{NI_{2030}}^{pub}}{K_{2029}^{pub}} = 0.3$, and $\hat{\beta} = 0.85, \Delta \log Y_{t0} = 3.41, \frac{{NI_{t0}}^{priv}}{K_{t0}^{priv}} = 4.24$. Solving the equation for $\Delta \ln Y_{2030}$ implies global growth will likely to be 2.77 percent.

Scenario Analyses

This section describes the estimation method in the chapter's scenario analyses.

- *Policies to increase LFP.* Using the regression coefficients in Table 3.2.2, this scenario computes the impact on aggregate LFP if all countries converged on the best policies, defined as the 25th percentile of the distribution of the policy variables. This impacts aggregate LFP in economies in the sample differentially with a median increase of 3.2 percentage points. It is assumed that all countries (the 29 economies in the policy regression sample as well as the remaining 111 economies) will see their aggregate participation rate increase by 3.2 percentage points.

- *A migration boost to labor supply in advanced economies*. This scenario assumes additional migrant worker flows coupled with better labor market integration that translates to a 1 percent increase in advanced economies' labor force in 2030, which adds about 5.5 million workers. To put this increase into context, pre-pandemic (2015-19) migration flows in Australia, Canada, EU, UK, and the US ranged from 0.6 to 2.2 percent of their respective labor forces, on average. The year 2022 saw a strong rebound in migration flows after the pandemic shock, which constituted an additional 1 percent of the labor force in Canada and the UK relative to the pre-pandemic average. This would increase labor supply by (1 - Unemp) * 5.5 million workers, where Unemp is the structural unemployment rate proxied by the average unemployment rate over the period 2015-19. Absent enhanced frameworks for labor market integration, migrant workers could face worse labor market outcomes. Assuming a higher structural unemployment rate for migrants (Amo-Agyei 2020, Table 4) and assuming the pay gap between migrants and native-born workers accounting to 16.1 percent (Amo-Agyei 2020, Figure 17) represents productivity differentials, the total impact on effective labor supply in AEs could amount to (1 - UnempMig) * 5.5 million workers * (1 - 0.161), where UnempMig is unemployment rate for migrant workers. In this case, the impact would be a more modest increase in global growth of 15 basis points.

- *Structural reforms for improving allocative efficiency*. Taking the correlations in Figure 3.14 in the main text at face value, a closing of high-misallocation countries' policy gap with the U.S. by 1 percent would be expected to improve their structural allocative efficiency by approximately 1 percent. Looking at the distribution of decadal changes in countries' realizations of the structural policy indices between 1988 and 2018, a 15-percent closing of the structural policy gap with the U.S. is uncommon (approximately in the top 10 percent of the distribution) but appears empirically plausible. The corresponding improvement in TFP is computed for the sample of 20 economies from the misallocation analysis, and used to extrapolate the global boost to TFP growth if high-misallocation countries were to achieve a 15-percent policy-gap reduction over the next decade.

- *Improved talent allocation in emerging market and developing economies*. Hsieh and others (2019) estimate that 20 percent of growth in income per worker over the past 50 years in the U.S. resulted from the improved allocation of talent; that is, 0.4 percent of growth per year. Suppose talent allocations in emerging market and developing economies would follow the same trend as in the United States. Given the share of these economies in global economy, this translates into a global growth boost of about 0.25 percentage point per year.

- *Legacy of high public debt*. The exercise is based on a FSGM-based simulation. Specifically, three scenarios are considered: (1) Larger transfers to households between 2015 and 2025 which increase public debt to GDP ratio by 15 percentage points in advanced economies and 10 percentage points in emerging economies. These increase in debt level over the medium term reflects the calculated difference in public debt to GDP ratio in the latest WEO compared to the Jan-2019 vintage of WEO projections). From 2025 and onward, public deficit stays at the same high level and debt does not stabilize; (2) In addition to (1), a full debt stabilization occurs over 2025-2030 via a reduction in transfers to cover larger interest payments; (3) In addition to (1), a full debt stabilization occurs over 2025-2030 via a reduction in public investment.

- *Geoeconomic fragmentation.* This scenario is based on simulations using the Global Integrated Monetary and Fiscal (GIMF) model, building on exercises first performed for Chapter 3 of the October 2023 *Regional Economic Outlook: Asia and Pacific*. These exercises have been updated to fine-tune the country configuration and coverage (see Online Annex for Chapter 4 for details). The range of impacts reflects two different scenarios with respect to the extent of fragmentation. In the limited fragmentation scenario, there is some friend-shoring by a U.S.-led and a China-led bloc of countries, reducing their imports from the other bloc by 5-10 percentage points across different types of goods. In the more extensive fragmentation scenario, there is re-shoring by all countries and regions, reducing their imports from the rest of the world by 1-3 percentage points across different types of goods.

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