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Productivity and Efficiency Trends of Russian Firms in 2018–2023*

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Abstract

This study examines total factor productivity (TFP) growth among Russian enterprises in 2018–2023 using stochastic frontier analysis (SFA) and firm-level data from the SPARK dataset (approximately 120,000 firms across major sectors). The analysis involves estimating stochastic production functions separately for 198 narrowly defined industries. This approach accounts for firm-specific inefficiency levels, capturing shortfalls relative to industry best practises (the stochastic production frontier), thereby decomposing TFP dynamics into technological progress (frontier expansion) and changes in efficiency relative to the frontier.

Average annual TFP growth fluctuates between -2.4% and 3.9%, yielding approximately 5% cumulative growth over six years. Fluctuations during the 2020 COVID-19 pandemic and the 2022 sanctions shocks stemmed primarily from efficiency changes rather than frontier expansion: technological progress remained modest and stable. Although overall TFP growth remained positive in 2020, contact-intensive services (accommodation and food, arts and entertainment, personal services) contracted sharply; wholesale trade and transportation drove the decline in 2021 amid lasting supply chain disruptions; nearly all sectors experienced negative growth in 2022 (except manufacturing, which accelerated); and most sectors rebounded strongly in 2023, except wholesale and retail trade.

Using Rosstat input-output tables to classify industries by trade integration, the study finds that exporters were hit hardest in 2021–2022, while importers (especially in manufacturing) exhibited stable or even accelerating TFP growth, and non-traders remained stagnant.

Keywords: total factor productivity (TFP), stochastic frontier analysis

JEL Codes: D24

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Non-technical summary

This working paper analyses how productivity evolved in Russia between 2018 and 2023, a period marked by significant economic shocks. Using detailed data on firms across all major sectors of the economy, the study estimates TFP growth and its components (productivity frontier expansion, efficiency change and scale effects) at the firm level.

TFP growth decomposition distinguishes between improvements driven by adoption of new technologies and practices into the best practices in the industry (captured by the 'productivity frontier' and referred to as technological progress or frontier expansion) and changes in how efficiently a firm operates relative to these best practices (distance to the frontier, referred to as technical efficiency changes). In addition, it considers how scale of production may affect productivity (scale effects).

The study uses a four-component stochastic frontier analysis (SFA) model with a translog production function. This flexible approach additionally allows for firms heterogeneity and separates long-term structural inefficiencies from short-term fluctuations in performance.

The analysis uses data from the SPARK dataset, covering approximately 120,000 firms across all major sectors. The sample represents between 14% and 22% of total employment and revenues in the covered sectors. The firms are grouped into 198 narrowly defined industries for stochastic production function estimation separately in each narrow industry.

The study finds that average annual TFP growth fluctuated from -2.4% to 3.9%, resulting in approximately 5% of cumulative TFP growth over the six years from 2018 to 2023. This aligns with the sluggish productivity growth in previous years documented in the literature. TFP fluctuations were driven almost entirely by changes in technical efficiency (firms moving closer to or further from the productivity frontier), rather than expansion of the frontier itself. The technology progress component remained relatively constant and modest throughout the period.

The COVID-19 pandemic in 2020 had a mixed impact. While average TFP growth remained positive across the full sample, specific services sectors such as accommodation and food services (sector I), art and entertainment (sector R) and other personal services (sector S) experienced significant contractions, tied to the "contact-intensive" nature of these businesses. In 2021, TFP declined primarily due to the wholesale trade and transportation sectors, likely reflecting prolonged supply chain disruptions. In 2022, following new sanctions and structural shifts, TFP growth turned negative across almost all sectors, with manufacturing being the sole exception to show acceleration. Most sectors experienced a sharp recovery in TFP growth in 2023, except for wholesale and retail trade. However, this recovery may partly reflect more intensive use of existing resources — such as longer working hours or increased use of capital — as well as increased government spending.

Since the impact of the economic shocks in 2020 and 2022 may vary significantly based on a firm's integration into global markets, the study categorizes industries by their involvement in international trade using Rosstat input-output tables. The study reveals that exporters were hit hardest in 2021–2022 due to disrupted access to traditional markets. In contrast, importers (particularly those in manufacturing) maintained more stable or even accelerating TFP growth, while non-trading industries remained largely stagnant.

Several factors may influence the results. The dataset excludes small and medium enterprises (SMEs), which do not report data on value added, and many large sanctioned companies. This potentially introduces sample selection bias in estimates. The data does not capture variations in working hours or the intensity of capital use, meaning demand-driven "business cycle" fluctuations may be misidentified as TFP growth. Extensive government purchases in 2023 may have altered price dynamics, making value-added figures a less reliable proxy for actual output.

The study concludes that while Russian firms demonstrated notable resilience to the recent shocks, the underlying drivers of the 2023 recovery warrant scrutiny regarding long-term sustainability. Sectoral divergence suggests that while manufacturing benefited from import substitution and increased government demand, productivity decline in the trade and logistics sectors reflects the lasting costs of structural transformation. Future productivity growth will depend on the economy's capacity to foster technological progress and navigate access constraints in global capital and technology markets.

1 Introduction

The global financial crisis in 2007–2009 and the subsequent slow and uneven recovery were followed by decelerated world economic growth.[1] It strengthened temporarily in 2017–2018, but was replaced with slowdown in economic activity in 2019 amid the trade tensions between China and the United States. The downturn was then exacerbated in 2020 by the deepest recession since World War II, caused by the COVID-19 pandemic, which adversely affected global supply chains and investor confidence. The recovery in 2021 was accompanied by financial stress due to rising global debt and prolonged global value chain disruptions. That was followed by accelerated inflation in advanced economies, increased interest rates, weak global trade growth and heightened global political uncertainty in 2022–2023. The dynamics of world economic growth are represented in Figure 1.

Figure 1: GDP and labour productivity growth. World and Russia

Sources: World Bank, Rosstat.

The Russian economy experienced a short recession during the global financial crisis and a relatively quick recovery after the crisis, which was followed by renewed growth in 2010–2013. However, economic growth slowed down in 2014–2016, even turning negative in 2015, mainly due to falling oil prices and sanctions. After modest growth in 2017–2019, the economy entered the pandemic-induced recession in 2020, recovered in 2021, and fell into a new recession in 2022 provoked by sanctions, logistical challenges, and structural adjustments. The rebound in 2023 was partly driven by increased government spending and stronger domestic demand, supported by import substitution. Labour productivity follows closely these dynamics (see Figure 1).

In this study, we focus on productivity growth during the period of two recent shocks

[1] Some economists argue that the economy faced 'secular stagnation' (Summers, 2014).

(pandemic crisis and sanctions). Firm productivity reflects the ability of firms to transform inputs into outputs. Theoretically, productivity is determined by production technology and is the key determinant of economic growth. Various metrics attempt to measure it empirically. Labour productivity, defined as output per unit of labour, is usually reported by statistical agencies but it does not separate productivity growth from capital accumulation. Total factor productivity (TFP), by contrast, captures the portion of output that is not explained by traditional inputs such as labour and capital, and thus better reflects innovation, management quality, and technology adoption – the main drivers of long-run economic growth. However, TFP estimation is not straightforward, and the results may significantly depend on the method and the estimation model, which is discussed below. Nevertheless, empirical estimates of TFP can reveal heterogeneity in growth across industries or characterise the efficiency of resource allocation in the economy.

Firms within a particular industry can also differ substantially in terms of productivity: the most efficient firms define the so-called *productivity frontier*, while the gap in productivity between a given firm and the frontier, indicating its shortfall relative to best practices, is referred to as *inefficiency*.

This study investigates TFP growth among Russian firms from 2018 to 2023 using stochastic frontier analysis (SFA). This approach enables the decomposition of firm-level productivity growth into three components: expansion of the productivity frontier, changes in firm-level efficiency relative to the frontier, and scale effects. The period under consideration covers two major economic shocks — the COVID-19 pandemic in 2020 and structural changes in 2022 — providing an opportunity to assess their impact on technological progress and efficiency dynamics among Russian firms. We use a rather flexible four-component stochastic frontier model introduced by Colombi et al. (2014) with a translog production function that imposes minimal restrictions on production technology or efficiency.

Our analysis is based on a large firm-level dataset from the SPARK database[2] covering approximately 120,000 firms across all major sectors. The results show that average firm-level TFP growth slowed in 2020 and turned negative in 2021–2022, before rebounding in 2023. These movements were largely attributed to changes in efficiency, whereas the overall frontier was expanding at rather even and moderate rates. However, frontier dynamics vary significantly between sectors, accelerating in industrial production and contracting in trade.

Although average TFP growth across the observed firms was positive in 2020, TFP in services contracted over the year. The downturn in 2021 was mainly attributed to transportation and trade sectors. In 2022, TFP declined across most sectors, including mining, information and communication, transportation, trade, and services. A notable

[2] SPARK is an analytical system providing firm data created by Interfax Group.

rebound followed in 2023 in nearly all analysed sectors, except for wholesale and retail.

This paper is organized as follows. Section 2 reviews the literature. Section 3 outlines the method. Section 4 describes the data used and their preparation for analysis. Section 5 presents and discusses the results. Section 6 concludes.

2 Literature review

This paper contributes to the extensive literature on productivity. Interest in measuring productivity stems from the fact that it is widely regarded as the key driver of long-term economic growth. Firm-level estimates of TFP growth help identify which firms or sectors drive national productivity and where inefficiencies may lie. These estimates can also reveal misallocation in the economy, e.g. when resources are stuck in low-productivity firms due to distortions such as subsidies, credit misallocation, or entry barriers.[3] Hence, such estimates can provide policy recommendations, including as regards sectors or firms may require support, detect if highly regulated sectors are lagging behind in terms of TFP, identify firms or regions where productivity gains are linked to research and development, or determine whether market power suppresses productivity growth.[4] Additionally, estimating trends in TFP growth allows evaluating the impact of external shocks on firm-level productivity.

Statistical agencies typically publish labour productivity. However, while labour productivity is a common and straightforward measure, it does not separate productivity from capital accumulation. Increases in labour productivity may reflect higher capital investment or labour reallocation, rather than genuine efficiency or innovation gains. By contrast, TFP growth better captures the effects of technology, innovation and management improvements, but its estimation is a more complex task lacking a universal approach. Instead, various approaches to measuring TFP growth have been developed over time, differing in their underlying assumptions and data requirements. The choice of the method depends on the availability and structure of data and on the research question.[5] Despite methodological advances, challenges remain in accurately measuring

[3]A study by Hsieh and Klenow (2009) explores how allocative inefficiency promotes reduces aggregate TFP using Chinese and Indian microdata. Fontagné and Santoni (2015) show that resource misallocation causes more efficient firms to operate below their optimal size, thus adversely affecting overall productivity. Decker et al. (2016b) observes decline in firm turnover rate and thus in the contribution of reallocation to the aggregate productivity growth, which was significant historically.

[4]For instance, Sheng et al. (2024) find that regional monopoly may hinder the expansion of more productive firms. Baqaee and Farhi (2020) estimate that eliminating misallocation caused by large and dispersed markups would raise U.S. aggregate TFP by about 15%.

[5]Hulten (2010) gives a thorough review on growth accounting and its extensions, normally used to estimate TFP growth on aggregate data. Francis et al. (2020) provides one of the most recent reviews on firm-level TFP estimation methods. Van Biesebroeck (2007) compares multiple firm-level productivity measurement models using Monte Carlo simulations. Bournakis and Mallick (2018) evaluate several recent TFP estimation methods for UK manufacturing firms.

and explaining productivity differences across firms, particularly with respect to firm heterogeneity, economies of scale, and market power. Furthermore, TFP estimates depend significantly on the model, underlying assumptions, and parametrisation, which complicates the comparison between different estimations.[6]

Productivity trends

Recent years have witnessed a widespread slowdown in labour productivity growth across the world. In advanced economies, this slowdown reflects a long-standing downward trend that began in the 1970s[7] and intensified after the global financial crisis (GFC). As for emerging market and developing economies (EMDEs), labour productivity growth there accelerated rapidly before the GFC, but subsequently these countries experienced the 'steepest, longest, and broadest multiyear productivity slowdown' (Dieppe, 2021), affecting approximately 70 percent of these economies, with commodity exporters hit particularly hard. The slowdown was pervasive across industries, with manufacturing contributing significantly.

An extensive study on productivity trends by the World Bank, edited by Dieppe (2021), provides a comprehensive review of the evolution, sources and drivers of productivity growth until the COVID-19 pandemic. Among other things, the study highlights that, over the past decade, Russia experienced a particularly sharp slowdown in productivity growth. According to this study, the decline in Russia was largely attributed to international sanctions and falling commodity prices (notably the oil price collapse in 2014–2016), which significantly deterred investment. The study further notes that 'slowing capital accumulation accounted for most (abour three-quarters) of the slowdown in productivity growth in the post-GFC period'.[8]

The COVID-19 pandemic is expected to further exacerbate the slowdown in investment in EMDEs, particularly by dampening foreign direct investment. It can also affect economies through the erosion of human capital (due to unemployment and loss of schooling), underinvestment caused by increased uncertainty, a decline in global trade, and a retreat from global supply chains. Indeed, the pandemic triggered the deepest global recession since World War II, whereas previous milder health crises[9] were followed by lasting investment and labour productivity losses, 'mainly through their adverse effects on investment due to elevated uncertainty'. Nevertheless, the pandemic may also trigger

[6] Potential measurement errors, differences in aggregation methods, deflators, measures of output, capital and labour, and accounting for reallocation of production factors and substitution between labour, capital and intermediate consumption further complicate the comparison between estimates.

[7] 'Average annual labour productivity growth in those EU countries with sufficiently long time series has declined from 3.9% in the 1970s to 2.5% in the 1980s to 1.5% in the 1990s to 1% since the early 2000s, excluding the period of the global financial crisis' (ECB, 2021).

[8] Term 'capital' therein refers to both physical and human capital.

[9] Recent major epidemics include swine influenza (2009–2010), severe acute respiratory syndrome (2002–2003), Middle East respiratory syndrome (2012), Ebola (2014–2015), and Zika (2015–2016).

technological changes that could result in productivity gains.[10]

The effect of the COVID-19 crisis and lockdowns on productivity growth could be partially offset by national rescue policies. For instance, Konings et al. (2023) find that Belgian companies supported by rescue measures exhibited higher productivity growth in 2020 compared to non-supported firms. However, rescue policies are generally aim to support employment and help businesses survive during crises. Their effect on productivity remains ambiguous, especially in the medium and long term. On the one hand, providing loan guarantees — a policy that was widely implemented during the pandemic period — may drive faster development of small businesses and resolve information asymmetry problem.[11] On the other hand, cheap loans may prolong the lives of inefficient zombie companies, which would have left the market, and increase moral hazard by transferring default risk from banks to the government. Demmou and Franco (2021) discuss European rescue policies and their effects in more detail, concluding that higher level of public guarantee schemes is associated with lower allocative efficiency, as employment stays in low-productivity firms. As for Russia, Bessonova et al. (2022) find that loan guarantee programmes implemented during the COVID-19 crisis had a positive effect on employment and sales in subsidised companies, while their effect on productivity is statistically insignificant.

Total factor productivity

Having outlined the main productivity trends documented in the literature, we now focus on TFP. Fernald et al. (2025) find that, in the United States and the largest European economies, TFP is the main factor explaining major differences in labour productivity growth across countries and over time (1980–2019). The World Bank's study (Dieppe, 2021), however, argues that during the post-crisis productivity slowdown (2013–2018), TFP growth largely returned to its pre-crisis average levels of 0.4%, while weak investment accounted for the major share of the slowdown. The study further notes that, in EMDEs, both the deceleration in TFP growth and weaker investment contributed equally to the slowdown in labour productivity. Overall, TFP growth remains a significant contributor to labour productivity growth.

A substantial literature examines determinants of TFP growth at the firm level. These studies relate productivity differences to firm characteristics such as size, ownership structure, export status, etc.

A growing body of literature explores the distribution of productivity across firms. In particular, the existing studies identify a significant and widening performance gap

[10] For example, Muzi et al. (2023) find that more productive firms and firms with digital presence and innovation were more likely to survive the pandemic crisis, thus confirming the Schumpeterian cleansing hypothesis.

[11] Many banks either are reluctant to lend to small or young firms with a short credit history and limited financial disclosure, or offer them unfavourable loan terms due to perceived high risk.

between firms operating at the productivity frontier and those lagging behind within industries (Andrews et al., 2015; Berlingieri et al., 2017; Decker et al., 2016a). Larger and younger firms, as well as those that are part of international groups, are more likely to be at the frontier (Andrews et al., 2015). These findings support the importance of accounting for firm-specific inefficiencies and decomposing productivity growth into technological progress at the frontier and efficiency changes among other firms (catching up or falling behind).

Stochastic frontier analysis

SFA has been widely used in the empirical literature for decomposing TFP dynamics into frontier expansion and changes in efficiency, to estimate firm-specific inefficiency and identify its determinants.[12] For example, Diaz and Sánchez (2008), Pham et al. (2020) and Rawat and Sharma (2021) examine the relationship between firm size and efficiency.[13] Rawat and Sharma (2021) employ a four-component stochastic frontier model to separate persistent and transient (time-varying) inefficiency. Focusing on India's manufacturing sector over 1999–2018, they conclude that transiently inefficient firms tend to catch up, whereas persistently inefficient firms are more likely to exit the market over time. The study also finds that exporting firms show slightly higher efficiency level and higher TFP growth and that foreign ownership is also associated with improved TFP growth.

Several studies apply SFA to investigate productivity and efficiency in Russia. For example, Tleubayev et al. (2022) examine the Russian agricultural sector in 2015, analysing the relationship between subsidies, farmers' education, insurance programmes, and efficiency. Similarly, Singh et al. (2022) explore the technical efficiency of Russian firms during the COVID-19 pandemic, finding that government aid improved efficiency among firms with increasing sales but had no effect on firms experiencing a decline in sales. Both studies rely on cross-sectional survey data at the firm level.

Bessonova and Tsvetkova (2022) apply SFA to verify efficiency divergence using firm-level panel data for 2011–2016. Tsvetkova (2021) explores trends and the relationship between technical efficiency, firm size and age using firm-level data for 2013–2018. Arazmuradov et al. (2014) employ a stochastic frontier model to carry out a cross-country analysis of former Soviet Union economies based on aggregate macroeconomic data for 1995–2008, investigating the effect of foreign direct investment on technical efficiency.

[12] Compared to another common productivity frontier approach – non-parametric data envelopment analysis (DEA), SFA allows for non-balanced panels, copes better with potentially noisy firm-level data, and does not assume a unique deterministic productivity frontier. Therefore, like other parametric methods, SFA suits better for firm-level data, and DEA is therefore not considered herein.

[13] Using Spanish data for 1995–2001, Diaz and Sánchez (2008) find that smaller firms are more efficient. Pham et al. (2020) explore Vietnamese firms in 2000–2016 and find that middle-sized firms exhibit higher efficiency than smaller or larger firms. Rawat and Sharma (2021) find that persistent efficiency is higher in larger firms, while transient efficiency does not statistically significantly vary across firm sizes.

Contribution

This study measures TFP growth among Russian firms from 2018 to 2023 applying the four-component SFA model developed by Colombi et al. (2014), which allows the decomposition of firm-level productivity growth into frontier expansion, efficiency changes, and scale effects, and accounts for firm heterogeneity as well as persistent and transient inefficiencies. The model by Colombi et al. (2014) has a rather flexible structure, thus loosening parametrisation assumptions and allowing an analysis of the turbulent period under review.

The analysis covers approximately 120,000 firms over 2018–2023, grouped into around 200 narrowly defined industries, with a stochastic frontier production function estimated for each industry. The study evaluates the effects of the COVID-19 pandemic in 2020 and the 2022 crisis on the average TFP growth rate in the Russian economy overall, across specific sectors, and by trade involvement. In particular, the study reveals that exporting industries were affected most severely in 2021–2022, while importing industries demonstrated stable or even accelerating TFP growth.

These findings are subject to parametrisation assumptions and certain data limitations, which are discussed further in the paper. For instance, potential sample selection bias in 2020 and 2023 may have led to an underestimation of adverse effects in 2020 or an overstatement of TFP growth in 2023.

To the best of our knowledge, this is the first study to examine firm-level productivity and efficiency trends in Russia over the selected period using a stochastic frontier framework.

3 Method

The study employs a stochastic frontier approach to estimate firm-level TFP growth and efficiency. Stochastic production functions are estimated across a large number of narrowly defined industries, assuming a common functional form within each industry. We also provide trends in output-based labour productivity growth as a robustness check and for sample characterisation.

3.1 Stochastic frontier analysis

SFA is a parametric frontier method, introduced independently by Aigner, Lovell and Schmidt (1977) and by Meeusen and van den Broeck (1977).

The main idea is as follows. Suppose that an industry production frontier is described with production function $Y = F(K, L, t)$ that depends on capital (K) and labour (L) inputs and can evolve over time t. A specific firm i may produce below the frontier due to a degree of inefficiency u_{it}. Assume also that a firm's output is subject to random shocks v_{it}. Therefore, the output of firm i at time t is described as follows:

$$Y_{it} = F(K_{it}, L_{it}, t)e^{-u_{it}}e^{v_{it}}, \quad u_{it} \in [0, \infty), \quad v_{it} \sim \text{i.i.d. } \mathcal{N}(0, \sigma_v^2)$$

where u_{it} is the inefficiency term, and v_{it} is a random shock. Also, $\xi_{it} = e^{-u_{it}} \in (0, 1]$ is referred to as the level of efficiency for firm i at time t, corresponding to inefficiency u_{it}.

Taking the logarithm and using a translog production function with a time trend for deterministic part $F(K, L, t)$ provides:

$$\begin{aligned} \ln Y_{it} =& \beta_0 + \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_t t + \beta_{LL}(\ln L_{it})^2 + \beta_{KK}(\ln K_{it})^2 + \beta_{tt}t^2 + \\ & \beta_{KL} \ln K_{it} \ln L_{it} + \beta_{Kt} \ln K_{it} \cdot t + \beta_{Lt} \ln L_{it} \cdot t - u_{it} + v_{it} \end{aligned} \tag{1}$$

Various stochastic frontier models make different assumptions regarding the production function and the non-deterministic part, specifically the inefficiency term.[14] This study uses the four-component stochastic frontier model developed by Colombi et al. (2014) because of its flexible structure.

Four-component stochastic frontier model

Proposed by Colombi et al. (2014), Kumbhakar et al. (2014), and Tsionas and Kumbhakar (2014), the model splits the non-deterministic part — the error term — into four components, thus accounting for (1) firm heterogeneity, representing the effect of unobserved factors, (2) persistent (time-invariant) and (3) transient (time-varying) inefficiencies, representing the presence of some persistent and varying rigidities within a firm's organisation and production process, and (4) random shocks:

$$\ln Y_{it} = \ln F(K_{it}, L_{it}, t) + v_i^0 - u_i^{\text{p}} - u_{it}^{\text{tr}} + v_{it}$$

Here, $\varepsilon_{it} = v_i^0 - u_i^{\text{p}} - u_{it}^{\text{tr}} + v_{it}$ is the non-deterministic part of the equation (error term), where $v_i^0 \sim \mathcal{N}(0, \sigma_{v0}^2)$ captures latent firm heterogeneity, $u_i^{\text{p}} \sim \mathcal{N}^+(0, \sigma_{u,\text{p}}^2)$ is persistent inefficiency, $u_{it}^{\text{tr}} \sim \mathcal{N}^+(0, \sigma_{u,\text{tr}}^2)$ is transient inefficiency, and random shock is standard $v_{it} \sim \mathcal{N}(0, \sigma_v^2)$. Overall inefficiency is then

$$u_{it} = u_i^{\text{p}} + u_{it}^{\text{tr}}$$

[14] Generally, Cobb-Douglas or translog production functions are applied. We opt for a translog production function with a time trend because of its higher flexibility. Commonly used distributions for modelling the inefficiency term include half-normal, truncated normal, exponential or gamma distributions. For panel data, studies often employ the time decay model developed by Battese and Coelli (1992), but this model imposes a strict structure for the evolution of efficiency. Multiple specifications, including time-invariant and time-varying, as well as homoskedastic and heteroskedastic inefficiency, are discussed by Kumbhakar and Lovell (2003) and Kumbhakar et al. (2015).

Persistent, transient, and overall efficiency levels can be thus defined as:

$$\xi_i^{\mathrm{p}} = \exp(-u_i^{\mathrm{p}}), \quad \xi_{it}^{\mathrm{tr}} = \exp(-u_{it}^{\mathrm{tr}}), \quad \xi_{it} = \xi_i^{\mathrm{p}} \cdot \xi_{it}^{\mathrm{tr}} = \exp(-u_{it})$$

Persistent inefficiencies generally arise from long-standing factors such as obsolete equipment that has not been replaced for long periods, old buildings and road systems, and systematic behavioural failures (Filippini and Hunt, 2015). Transient inefficiencies, by contrast, are caused by short-run moral hazards such as inefficient supplier selection, suboptimal resource allocation, and trial-and-error processes in unknown situations (Colombi et al., 2017).

Colombi et al. (2014) argue that models with a single inefficiency component are likely to produce biases in efficiency estimates. They also note that persistent inefficiency might be associated with regulatory constraints. Similarly, Badunenko and Kumbhakar (2016) suggest that high values of u_i^{p} indicate non-competitive market conditions since persistently inefficient firms would exit in a competitive market. They also imply that substantial policy changes are required to improve persistent efficiency, whereas transient inefficiency is less of a concern for policymakers.

The model is estimated using maximum likelihood method under the corresponding distribution assumptions.

TFP growth

Once model (1) is estimated, TFP growth can be calculated and decomposed into three parts at the firm level (Kumbhakar and Lovell, 2003):[15]

$$\Delta TFP = \Delta TP + \Delta TE + RTS$$

1. Technological progress (expansion of the production frontier):

$$\Delta TP = \frac{\partial \ln F(K, L, t)}{\partial t} = \beta_t + 2\beta_{tt}t + \beta_{Kt} \ln K_{it} + \beta_{Lt} \ln L_{it}$$

2. Technical inefficiency change (a change in the distance to the frontier):

$$\Delta TE = -\Delta u_{it} = -(u_{i,t} - u_{i,t-1})$$

3. Return to scale term:

$$RTS = (\nu - 1)\left(\frac{\eta_K}{\nu}\Delta \ln K + \frac{\eta_L}{\nu}\Delta \ln L\right)$$

[15] The derivation is provided in Appendix D.

where ν is return to scale and η_K and η_L are capital and labour elasticities of output:

$$\eta_{K,it} = \frac{\partial \ln F(K,L,t)}{\partial \ln K} = \beta_K + 2\beta_{KK} \ln K_{it} + \beta_{KL} \ln L_{it} + \beta_{Kt} t$$

$$\eta_{L,it} = \frac{\partial \ln F(K,L,t)}{\partial \ln L} = \beta_L + 2\beta_{LL} \ln L_{it} + \beta KL \ln K_{it} + \beta_{Lt} t$$

Since we use discrete time observations, the continuous time elasticities are approximated as the mean of the corresponding two periods:

$$\eta_K \equiv \bar{\eta}_{K,it} = \frac{\eta_{K,it} + \eta_{K,it-1}}{2}, \quad \eta_L \equiv \bar{\eta}_{L,it} = \frac{\eta_{L,it} + \eta_{L,it-1}}{2}$$

$$\nu = \eta_K + \eta_L$$

For the four-component model, the efficiency component – a change in technical efficiency – is determined by the transient inefficiency component, while persistent inefficiency is constant by construction:

$$\Delta TE = -\Delta u_{it} = -\Delta u_{it}^{\text{tr}} = -(u_{i,t}^{\text{tr}} - u_{i,t-1}^{\text{tr}})$$

3.2 Labour productivity

Additionally, we calculate output-based labour productivity:

$$LP = LP^{\text{Rev}} = \frac{R}{L}$$

and value-added-based labour productivity:

$$LP^{\text{VA}} = \frac{\text{VA}}{L}$$

where R is revenues, VA is value added, and L is labour, proxied by the number of employees.[16]

Labour productivity growth is measured in logarithms:

$$\Delta \ln LP_t = \ln LP_t - \ln LP_{t-1}$$

[16] Value added dynamics may differ from revenue dynamics due to a changing share of expenses on intermediate consumption (e.g. increasing outsourcing, or acquisition of providers). Since we use value added as a measure of output for TFP estimates, value added-based labour productivity growth may suit better for comparing with TFP growth and assessing the portion of labour productivity attributable to TFP. However, this is out of scope of this study.

Additionally, hours worked, if available, would be a better representation of labour than the number of employees. For example, the labour productivity index from Rosstat, presented in Figure 1, is calculated based on value added and hours worked.

Value added-based labour productivity is used to determine leaders and laggards (subsection 5.1). Output-based labour productivity serves as a check for sample selection: calculating value added, a measure of output Y, substantially restricts the dataset, while revenues and labour are available for a much broader set of firms, including small and medium enterprises (SMEs).[17] We compare labour productivity growth in the SFA subsample and in the maximum available SPARK sample to account for potential differences between productivity trends in our sample compared to the general population of Russian firms. For reference, we also compare the results with aggregate sectoral labour productivity growth from Rosstat,[18] although its calculation relies on a different method.

4 Data

The study uses yearly firm-level panel data from SPARK for the 2017–2023.[19] The analysis is limited to the following sectors (according to the NACE classification):

- B – Mining and quarrying
- C – Manufacturing
- D – Electricity, gas, steam and air conditioning supply
- E – Water supply; sewerage, waste management and remediation activities
- G – Wholesale and retail trade; repair of motor vehicles and motorcycles
- H – Transportation and storage
- I – Accommodation and food service activities
- J – Information and communication
- M – Professional, scientific and technical activities
- N – Administrative and support service activities
- R – Arts, entertainment and recreation
- S – Other service activities

Sectors such as agriculture, construction, finance, public administration, education, and healthcare are excluded from the analysis for different reasons. Agriculture involves specific production factors (land), unobserved in our data, that contribute sufficiently to production processes. In public administration, education and medical services, value added is an imperfect proxy for multiple outputs.

The firm-level data used in the study contains the following fields: INN (a unique tax identification number), primary OKVED-2 code for a firm's core economic activity,[20]

[17] Labour data are available for 83% of firms, revenues – for 79.5% of firms, capital – for 38% of firms, while value added can only be calculated for 11% of firms. For details, see Table A4 in Appendix A.

[18] The Federal State Statistics Service of the Russia Federation.

[19] The study is limited with this period because SPARK data prior to 2017 may be inconsistent due to different data sources, and the dataset was expanding until 2017, which could affect estimates as new firms entered the sample. In addition, deflators used in the study are consistently provided since 2017.

[20] OKVED-2 stands for the Russian Economic Activities Classification System, Edition 2. The classification follows the Statistical classification of economic activities in the European Community Revision 2

fixed assets (field 1150), wage costs (field 4122), revenues (field 2110), the cost of sales (field 2120), and the number of employees.[21]

Deflation. Nominal values, provided in rubles, were deflated to 2017 rubles using several industry-specific deflators, detailed to the maximum degree possible.

Gross value added, revenues and costs in sectors B, C, D, and E were deflated using the producer price index from Rosstat, available up to five-digit OKVED-2 codes depending on the sector. In other sectors, these values were deflated with gross value added deflators,[22] available up to two-digit OKVED-2 codes.[23]

Fixed assets were deflated using sector-specific capital deflators, constructed as the ratio of average fixed assets in average current-year prices to the fixed asset value change index in constant prices, both provided by Rosstat.

Table 1 presents a summary of the deflators used.

Table 1: DEFLATORS

Variable	Sector	
	B, C, D, E	G, H, I, J, M, N, R, S
Revenues, wage costs, cost of sales	Producer price index	Gross value added deflator
Fixed assets	Constructed capital deflator	

Output, capital and labour measures. For the analysis, output (Y) is defined as real value added, calculated from real revenues, real wage costs and the real cost of sales, noting that the cost of sales includes expenses on intermediate goods and wages:

$$\begin{aligned} Y \equiv \text{real value added} &= \text{real revenues} - \text{real expenses on intermediate goods} = \\ &= \text{real revenues} - \text{real cost of sales} + \text{real wage costs} \end{aligned}$$

(NACE Rev.2) up to four-digit codes, which, in turn, closely corresponds to the International Standard Industrial Classification of All Economic Activities Revision 4 (ISIC Rev.4). Thus, two- to four-digit codes are generally the same in all the three classifications.

[21]The numbers correspond to the field codes of the financial reports. Some firms reported negative values for wage costs and the cost of sales, which seem implausible. Data checks indicate that these were likely inconsistent signs. All negative values in these fields were replaced with their absolute values.

[22]Gross value added is revenues minus intermediate consumption, but not deducting consumption of fixed capital (or depreciation charges). For detailed gross value added indices, see Rosstat website, as Unified Interdepartmental Statistical Information System (EMISS) only provides sector-level indices. The data were downloaded in November 2024, and since then, Rosstat could have updated some of them.

[23]The best practice would be to use different deflators for revenues and intermediate consumption before calculating real value added (double deflation). We use the same deflators for revenues, costs and value added (single deflation) due to deflators availability. However, different levels of inflation for final products and intermediate consumption may affect the output measure. For example, Staritsyna (2024) finds that, over 2011–2016, single deflation results in higher GDP growth in Russia, compared to double deflation.

Capital input (K) is proxied by real fixed assets,[24] labour input (L) – by the number of employees.[25] Both measures have limitations: the capital stock and the number of employees are prefixed, while the intensity of capital use and labour services (hours worked) can vary in the short term. Consequently, the analysis cannot fully capture the dynamics of capital use and labour services, which may result in procyclical TFP dynamics.

Industries. Firms in each sector are grouped into narrowly defined industries. The procedure is largely manual. The general principle is that industries should be as narrow as possible, corresponding to similar production processes, while keeping around 100 observations each year for an industry in the sample for maximum likelihood estimation. Firms that did not fit into sufficiently large groups with similar production processes or had overly general OKVED-2 codes were sometimes omitted, but omitting large shares in terms of revenues or labour was avoided.[26]

As a result of grouping, the sample includes 291 industries. Each industry corresponds to a single two-digit code or a combination of one or few three-/four-digit codes. Stochastic frontier production functions were estimated separately for each industry. Maximum likelihood estimation for the four-component model converged for 198 industries. The list of industries is provided in Table A5 in Appendix A.

Interquartile outlier removal. Outliers — firms with substantially different labour, capital or output — may have production processes different from most other firms in an industry and add noise to the data, potentially affecting estimates or preventing convergence of the SFA at the narrow-industry level. Therefore, before estimation, extreme outliers in output, capital, and labour ($\ln Y$, $\ln K$, and $\ln L$) within industry-year groups were removed using interquartile range (IQR) method.[27]

[24] Fixed assets represent well the capital stock but not the intensity of capital use. Growting demand for firm products may require higher intensity of capital use, which would lead to higher output with the same capital stock and thus increase estimated productivity without any innovation in technology.

[25] This measure is accurate as long as labour services (i.e., hours worked) are proportional to the number of employees. However, hours worked are more flexible as they can be increased with the number of employees kept unchanged. Like higher intensity of capital use, the resulting expansion of output increases estimated productivity without any innovation in technology. Aggregate sectoral data on hours worked do not account for firm heterogeneity, while firm-level data on hours worked are unavailable.

[26] Usually, firms have multiple outputs and, accordingly, multiple OKVED-2 codes. However, each firm has a primary OKVED-2 code that must correspond to its core economic activity generating most of its revenues. Since we cannot disentangle the revenues generated by each activity, the firm is attributed to an industry based on its primary OKVED-2 code. Codes can change over time, but for maximum likelihood estimation of the production function, we used fixed codes to keep firms within the same industry as much as possible. There is a potential risk that firms with a sufficiently different set of outputs and therefore different production processes can fit into the same industry and thus be assumed to have the same production function, and this risk cannot be fully resolved.

[27] This is a common approach to identifying outliers, for example, see Dallah and Sulieman (2024). The procedure is as follows. First, for each industry-year group, we calculate the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of $\ln Y$, $\ln K$, and $\ln L$, denoted p_{25} and p_{75}, respectively. The IQR is defined as the distance between them: $\text{IQR} = p_{75} - p_{25}$. Observations are retained if they lie within the range of 1.5 IQRs from the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, i.e. within $[p_{25} - 1.5 \times \text{IQR};\ p_{75} + 1.5 \times \text{IQR}]$. Observations outside this range

The final dataset used in the SFA, herein referred to as the SFA subsample, includes 120,873 firms (408,341 observations in the unbalanced panel) grouped into 198 industries, providing 274,412 firm-year TFP growth estimates over 2018–2023.[28] The sample does not cover the general population of firms in the Russian economy. In particular, the largest sanctioned companies are not included in the SPARK data, while SMEs do not report the cost of sales or wage costs, necessary for calculating value added. Subsection 5.3 provides additional representativeness checks to describe the characteristics of firms in the sample.

In order to identify clearer trends in productivity growth and reduce noise in the plotted averages, outliers in firm-level TFP growth estimates within sector-year groups were also removed using the IQR method before calculating the averages.

5 Results

Equation (1) is estimated separately for each narrowly defined industry.[29] From the equation estimation, for each firm-year observation we obtain: the predicted inefficiency term (u_{it}), its persistent and transient components (u_i^{p}, u_{it}^{tr}), capital and labour elasticities ($\eta_{K\,it}$, $\eta_{L\,it}$), and TFP growth rates (ΔTFP_{it}) with components (ΔTP_{it}, ΔTE_{it}, RTS_{it}).

Figure 2 presents cumulative average TFP growth across all narrowly defined industries for which stochastic production functions are estimated. The dynamics are highly heterogeneous. Industrial sectors are generally among the top performers with steady annual TFP growth, while the trade sector lags behind. Service sectors appear both among the leaders and among the lagging industries, especially around 2020.

The estimates of TFP growth and components, as well as labour productivity growth, are subject to considerable noise. To capture general trends, sector-year outliers in estimated ΔTFP are excluded using the IQR method. Firm-level trends are then aggregated with average growth rates.

Figure 3 presents cumulative average TFP growth across all sectors covered in the study. The dynamics are also diverse. TFP in sectors such as electricity, gas, steam and air conditioning (D), other services (S), and manufacturing (C) increases steadily, while in information and communication (J) and wholesale and retail trade (G) TFP declines after 2020.

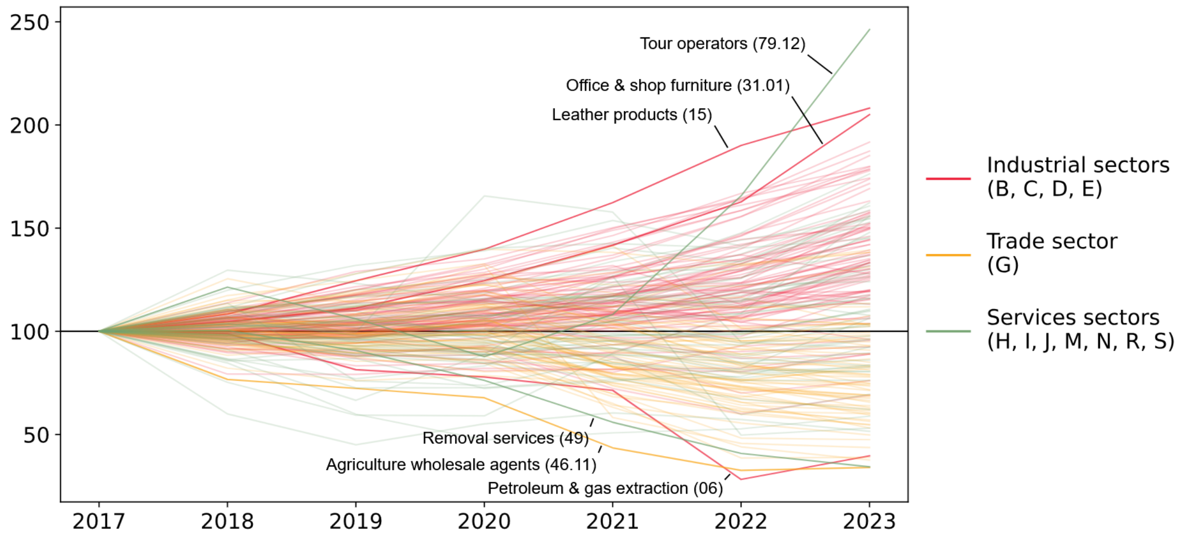
The further results are presented as follows. Subsection 5.1 outlines general trends across all industries. Subsection 5.2 groups industries by trade involvement to examine

are considered outliers and excluded. For a normal distribution, 0.7% of the distribution is outside this range.

[28] For details, see Tables A1 and A2 in Appendix A.

[29] The model is estimated in R with the `npsf` package by Badunenko et al. (2017). The procedure provides coefficient estimates for the translog production function and estimates of predicted persistent and transient efficiencies $\mathbb{E}[\xi_i^{\mathrm{p}}|\varepsilon_{it}]$ and $\mathbb{E}[\xi_{it}^{\mathrm{tr}}|\varepsilon_{it}]$.

Figure 2: Cumulative average TFP growth across all industries



At the top: Tour operator activities (code 79.12, N), Manufacture of leather and related products (code 15, C), Manufacture of office and shop furniture (code 31.01, C). *At the bottom*: Extraction of crude petroleum and natural gas (code 06, B), Agents involved in the sale of agricultural raw materials, live animals, textile raw materials and semi-finished goods (code 46.11, G), Removal services (code 49.42, H).

TFP growth separately for each group. Subsection 5.3 evaluates the representativeness of the dataset and discusses potential data limitations. Subsection 5.4 further discusses the assumptions and limitations of the study. Additionally, Appendix B provides graphs with TFP growth rates in narrowly defined industries by year, Appendix C describes sector-specific trends.

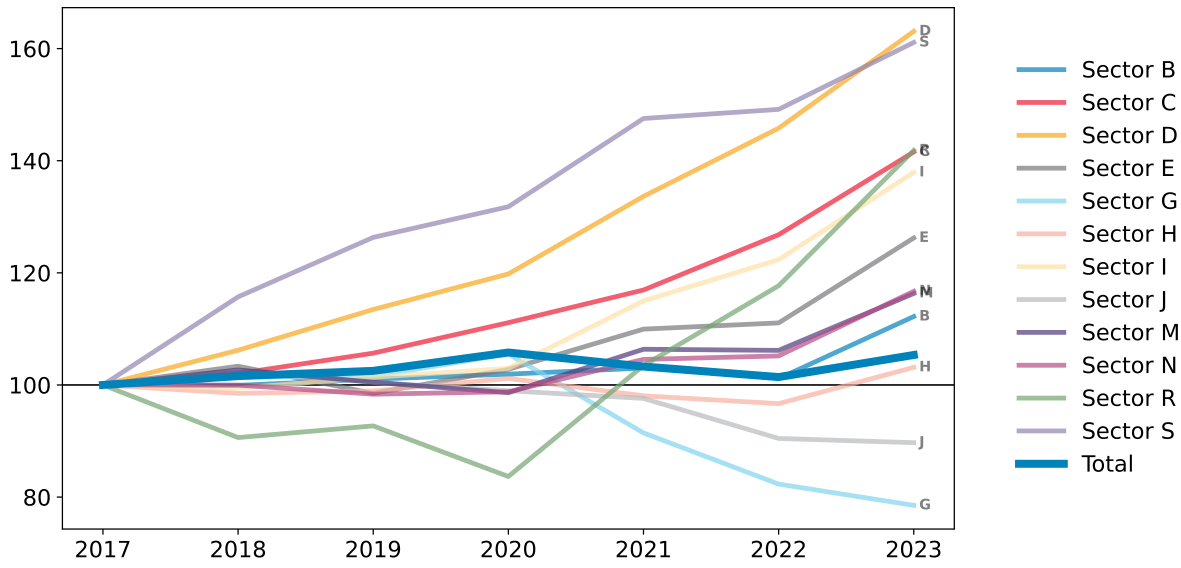
5.1 General trends

Average TFP growth and its components. Figure 4 presents average TFP growth and its components across all firms in the sample. The varying dynamics of TFP growth during the turbulent period are primarily associated with changes in technical efficiency. The technology progress component remains roughly constant and follows a monotonic trend in the estimated translog production function $F(K, L, t)$. The return-to-scale term fluctuates around zero.

The overall pattern indicates that TFP growth during 2018–2020 was followed by a decline in 2021 and 2022 and a subsequent return to initial growth rates in 2023. In 2021, the decrease in TFP was mostly accounted for by wholesale,[30] while in 2022, the decline occurred in most of the sectors.

[30] Sector G – wholesale and retail – comprises huge number of firms affecting the economy's average (for the number of observations in sectors, see Table A2, Appendix A). Appendix B shows distribution of average TFP growth rates across industries in each year. Appendix C shows TFP growth for each sector.

Figure 3: Cumulative average TFP growth across all sectors



Sector B – Mining and quarrying. Sector C – Manufacturing. Sector D – Electricity, gas, steam and air conditioning supply. Sector E – Water supply; sewerage, waste management and remediation activities. Sector G – Wholesale and retail trade; repair of motor vehicles and motorcycles. Sector H – Transportation and storage. Sector I – Accommodation and food service activities. Sector J – Information and communication. Sector M – Professional, scientific and technical activities. Sector N – Administrative and support service activities. Sector R – Arts, entertainment and recreation. Sector S – Other service activities.

Aggregate averages conceal considerable sectoral variations. In 2020, total average TFP growth was positive, whereas performance across sectors diverged. Manufacturing, trade and transportation sectors experienced accelerated TFP growth, while services sectors (specifically, sectors J, M, and R) were hit by the crisis, suffering a decrease both efficiency and TFP (Figure 5). Figure 6 provides comparison in terms of cumulative TFP growth. SMEs, not included in stochastic analysis, were also adversely affected in general by the pandemic: including SMEs in the sample substantially lowers the average rate of labour productivity growth in 2020, resulting in negative average growth rates (see Subsection 5.3).

The decline in 2021 was mostly associated with trade and transportation sectors (G and H), which can be explained by the prolonged effect of the pandemic on international trade and global supply chains.

In 2022, TFP growth declined across almost all sectors, with manufacturing (C) being the only sector demonstrating an acceleration. The trade and information and communication sectors (G and J) were affected most severely. In 2023, TFP growth rebounded in nearly all sectors, except for trade and information and communication. The list of industries boasting high productivity growth in 2023 is diverse. Industries with the highest TFP growth rates in 2023 include those supported by government purchases or subsidies[31], import substitution and growing domestic demand driven by rising real wages

[31] Manufacture of fabricated metal products, except machinery and equipment (code 25, C), landscape

Figure 4: TFP growth decomposition. Average across all industries

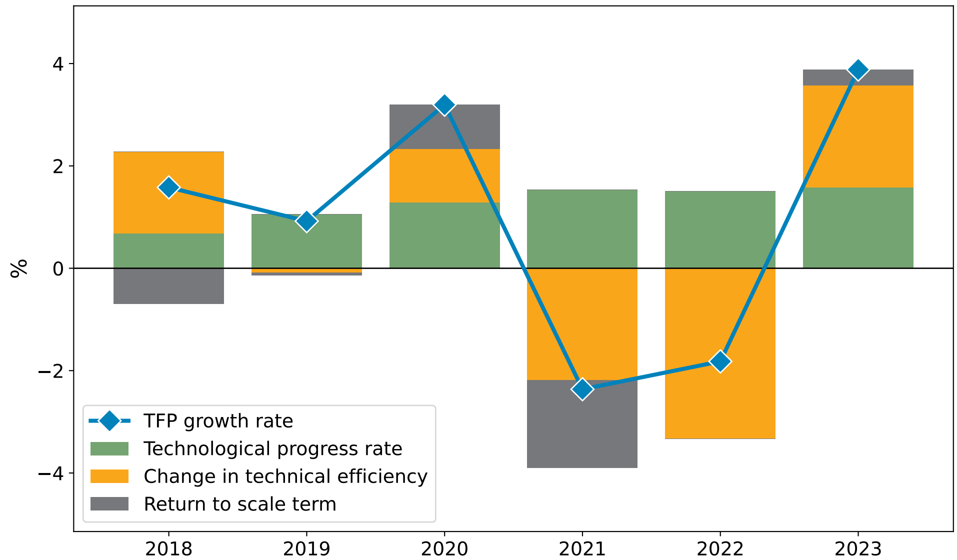
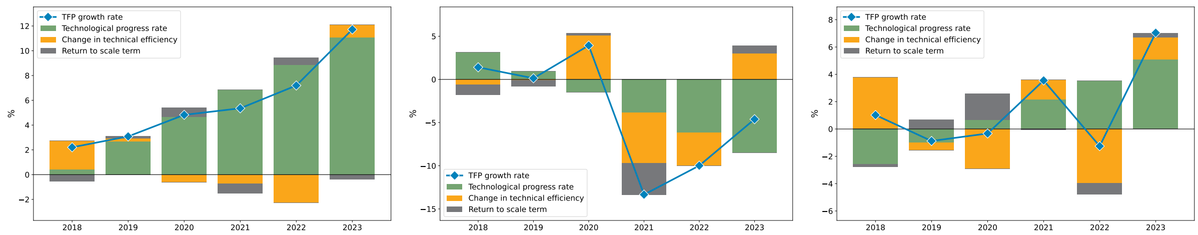


Figure 5: TFP growth in aggregated sectors



(a) Industrial sectors (B, C, D, E)

(b) Trade sector (G)

(c) Services sectors (H, I, J, M, N, R, S)

or related to construction[32], as well as related to machinery and equipment,[33] and media.[34] Additionally, they include crude petroleum and natural gas extraction (code 06, B), water collection, treatment and supply (code 36, E), materials recovery (code 38.3, E), and postal activities (code 53.1, H). Average TFP growth in each of these industries is estimated above 15%.[35]

Leaders and laggards. Figure 7 presents the average TFP growth rates of leaders

service activities (code 81.3, N).

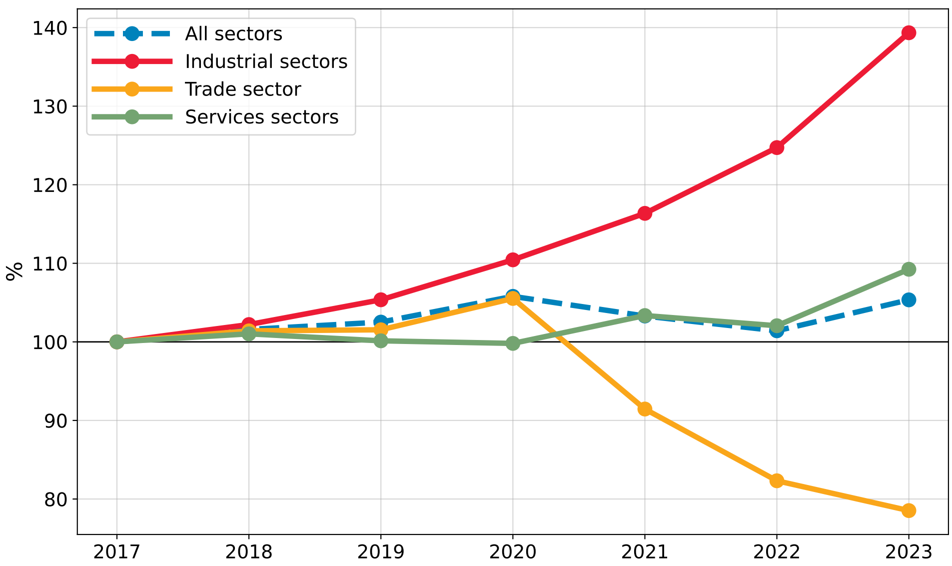
[32]Manufacture of food products (code 10, C), soft drinks, mineral waters and other bottled waters (code 11.07, C), products of wood, cork, straw and plaiting materials (code 16.2, C), furniture (code 31, C), builders' ware of plastic (code 22.23, C), restaurants and mobile food service activities (code 56.1, I), travel agency, tour operator reservation service and related activities (code 79.12, N), landscape service activities (code 81.3, N), creative, arts and entertainment activities (code 90.0, R), activities of sport clubs (code 93.12, R) and fitness facilities (code 93.13, R), amusement and recreation activities (code 93.2, R).

[33]Rubber products (code 22.1, C), batteries and accumulators (code 27.2, C) and wiring devices (code 27.3, C), bodies for motor vehicles, trailers and semi-trailers (code 29.2, C), parts and accessories for motor vehicles (code 29.3, C).

[34]Printing and reproduction of recorded media (code 18, C), motion picture, video and television programme production activities (code 59.11, J), radio broadcasting (code 60.1, J).

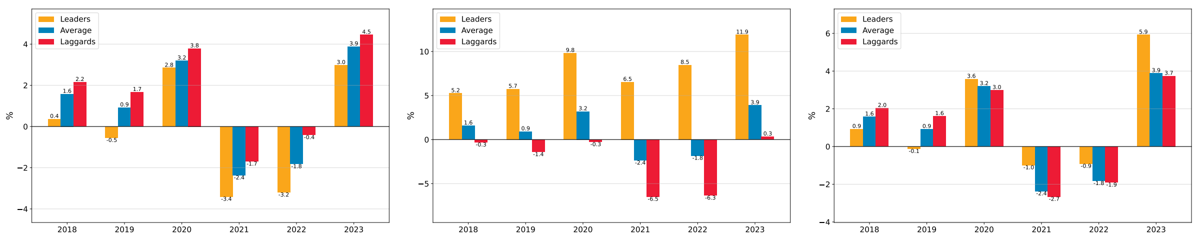
[35]For details, see Table C1 in Appendix C.

Figure 6: Cumulative TFP growth in aggregated sectors



and laggards. A firm is classified as a leader in its sector in a given year if it belongs to the top 10% of firms in terms of efficiency, and as a laggard if it is in the bottom 50% of of the distribution. The figures use three measures of efficiency: persistent efficiency, overall efficiency, and labour productivity.[36]

Figure 7: TFP growth: leaders and laggards



(a) By persistent efficiency (b) By overall efficiency (c) By labour productivity

Orange bars represent leaders, red bars – laggards, and blue bars – average TFP growth.

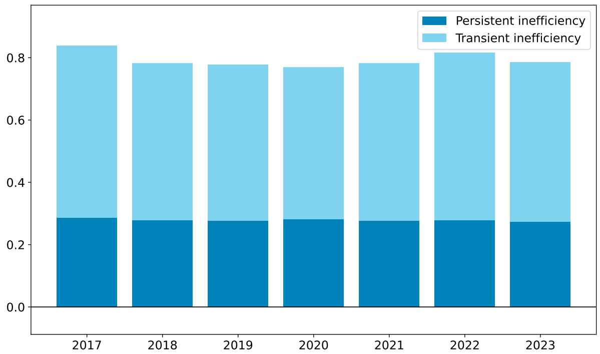
Figure 7a presents TFP growth rates for leaders and laggards, identified by persistent efficiency levels over the entire period under review, estimated from the stochastic frontier model. Therefore, leaders and laggards are fixed groups of firms. The figure shows that firms with lower persistent efficiency (laggards) exhibit slightly higher TFP growth rates than firms that are closer to the frontier (leaders). However, this apparent 'catching-up' may not necessarily indicate an actual narrowing of the productivity gap. Smaller firms that are far behind the frontier can grow faster initially but may not necessarily continue catching up over time. Exploring this issue in depth is beyond the scope of this study.[37]

[36] Value-added-based labour productivity.

[37] Additionally, estimated persistent inefficiencies are exactly zero for some industries, which makes all firms both leaders and laggards, and consequently, these industries, especially their leaders, have disproportionately higher weights in average TFP growth, due to different sizes of the groups.

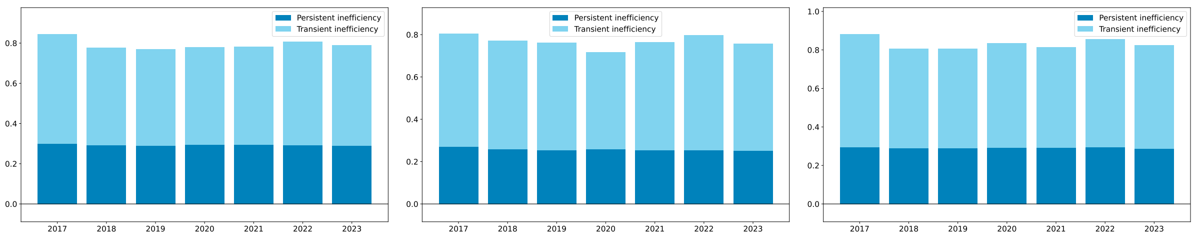
Figure 7b classifies leaders and laggards by overall efficiency, which changes over time. It shows that leaders consistently exhibit considerably higher TFP growth than laggards. However, these groups are dynamic, the same firm can be a leader in one year and a laggard in another. Higher TFP growth is typically associated with higher efficiency over the same period, as firms demonstrating stronger TFP growth often increase their efficiency and approach the frontier, while firms showing weaker TFP growth face reduction in efficiency and may fall into the group of laggards. This aligns with the observation that changes in efficiency drive TFP growth dynamics.

Figure 8: Persistent and transient inefficiencies



Dark blue: persistent inefficiency; light blue: transient inefficiency.

Figure 9: Persistent and transient inefficiencies in aggregated sectors



(a) Industrial sectors (B, C, D, E)

(b) Trade sector (G)

(c) Services sectors (H, I, J, M, N, R, S)

Dark blue: persistent inefficiency; light blue: transient inefficiency.

On average, the contribution of persistent inefficiency to overall firm inefficiency is smaller than that of transient inefficiency (Figure 8), partially due to industries with exactly zero persistent inefficiencies. The overall average inefficiency level varies around 0.8, which corresponds to the efficiency level $\xi = e^{-0.8} \approx 0.45$, suggesting that, on average, firms produce half of the output compared to the frontier. Fluctuations in aggregate averages and aggregated sectors (Figure 9) are relatively modest compared to the levels of inefficiency. Nevertheless, they make a considerable input into TFP dynamics (Figures 4, and 5).

Finally, Figure 7c defines leaders and laggards based on labour productivity in a given year. These groups also change over time. The figure shows that leaders and laggards had similar productivity growth rates, although since 2020, leaders had been demonstrating slightly higher TFP growth. This pattern reflects the partial alignment between labour productivity and TFP growth, similar to the results based on overall efficiency.

Summarising the above, this study does not reveal a decline in TFP across all industries in 2020, although TFP in services did decrease. The decline in 2021 was mostly accounted for trade and transportation, while in 2022, TFP growth decreased in almost all sectors. The subsequent rebound in 2023 also happened in many sectors, which can be partially explained by rising domestic demand, driven by government demand and import substitution. Note that TFP growth estimates can be procyclical since we cannot account for the intensity of capital use and working hours, e.g. higher output may be achieved with the same number of employees and capital stock to meet higher demand by using capital and labour more intensively.

5.2 Trade involvement and TFP growth

The trade theory argues that international trade is closely linked to productivity and can boost it through multiple channels: specialisation and reallocation of resources towards industries with a comparative advantage, economies of scale, increased competition and reallocation of resources within industries towards more productive firms, transfer of skills, and higher competition in input markets ensuring lower costs and a wider variety of intermediate goods. These ideas are supported by substantial empirical evidence. For example, Ferreira and Rossi (2003) show that trade liberalisation spurred productivity growth in Brazil. Economidou and Murshid (2008) find a positive effect of trade on TFP growth, especially from imports. Kowalski and Büge (2013) conclude that both export orientation and import penetration positively affect sectoral productivity growth, confirming a greater effect of imports on productivity. A review of empirical literature by Shu and Steinwender (2019) shows that most studies find positive effects of trade liberalisation on firm-level productivity, particularly via export opportunities and access to imported intermediates, with stronger effects in emerging economies and among larger and more productive firms.

Accordingly, industries with higher levels of exports or intermediate imports are expected to exhibit stronger productivity growth. However, these industries may have been adversely affected by the economic shocks in 2020 and 2022 due to the decline in global trade, imposed sanctions, and logistical disruptions. This subsection examines the potential effects of these developments on firm-level TFP growth depending on the degree of industry involvement in international trade.

Based on input-output tables of goods and services from Rosstat,[38] narrow industries are classified as export-oriented, import-dependent, non-trading or strongly involved in

[38] Basic input-output tables for 2021 (in Russian: Базовые таблицы «затраты-выпуск» за 2021 год).

trade (both importing and exporting).

Based on the supply table,[39] for each product, the share of imported product is defined as the ratio of a product imports to the product total supply in basic prices:

$$\text{Share of product imports} = \frac{\text{Product imports}}{\text{Total product supply}}$$

Since each industry is supplied with multiple products, an industry's share of imports is defined as the sum of the calculated shares of product imports, weighted by each product's share in the industry's total supply:

$$\text{Industry's share of imports} = \sum_{\text{products}} \frac{\text{Product imports}}{\text{Total product supply}} \cdot \frac{\text{Industry's product supply}}{\text{Industry's total supply}}$$

Industries with the share of imports exceeing the threshold of 13%[40] are classified as high-import industries.

Similarly, based on the use table,[41] for each product, the share of exported product is defined as the ratio of product exports to total product use (output) in basic prices:

$$\text{Share of product exports} = \frac{\text{Product exports}}{\text{Total product use}}$$

An industry's share of exports is the weighted sum of the shares of product exports, with the weights given by the product's share in the industry's total use:

$$\text{Industry's share of exports} = \sum_{\text{products}} \frac{\text{Product exports}}{\text{Total product use}} \cdot \frac{\text{Industry's product use}}{\text{Industry's total use}}$$

Industries with the share of exports above 6% are classified as high-export industries.

Based on these thresholds, industries are split into four groups, summarised in Table 2. Average TFP growth rates and components for these groups are given in Figures 10–12.

The results indicate that exporting industries (Figure 10) experienced declines in both efficiency and TFP during 2021–2022, which were not fully reversed in 2023. The productivity frontier also shows a downward trend over that period. These patterns align with the dynamics observed in trade, particularly wholesale, suggesting that exporting industries were affected most severely by global trade disruptions following the COVID-19 pandemic, as well as by sanctions and logistical challenges. However, excluding wholesale (Figure 10b) reverses the trend at the production frontier. Moreover, the average

[39] Supply table (in Russian: таблица ресурсов товаров и услуг) from the basic input-output tables for 2021.

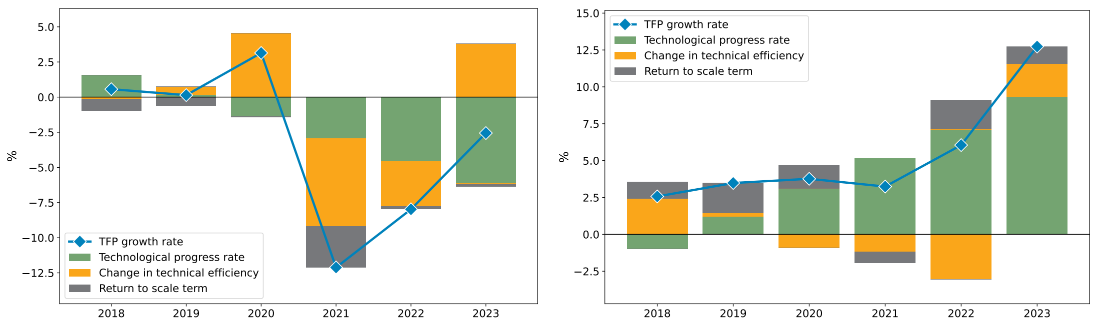
[40] The thresholds were chosen to divide industries into roughly equal groups, consistent with an intuitive classification of import-dependent and export-oriented industries in Russia.

[41] Use table at basic prices (in Russian: таблица использования товаров и услуг в основных ценах) from the basic input-output tables for 2021.

Table 2: Industry groups by involvement in international trade.

Group	Criteria	Industries
Exporting	High export, low import	Mining (oil, metals, coal), oil refining, metallurgy, flour milling, animal feed, transportation, wholesale
Importing	Low export, high import	Food, clothing, medicine, glass products, IT, architecture, film production
Importing-exporting	High export, high import	Beverages, paper, furniture production, chemical industry, metal products, jewellery
Non-trading	Low export, low import	Electricity, gas, steam, water supply, tobacco, retail, railways, insurance, accommodation, IT, media, sport and other services

Figure 10: TFP growth. Exporting industries



(a) Exporting industries

(b) Exporting industries, except wholesale

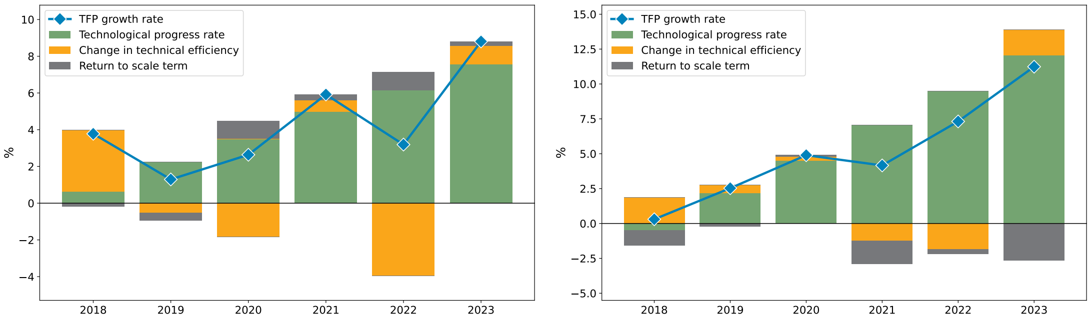
TFP growth rate in exporting industries without wholesale remains positive throughout the entire period, although inefficiency rises in 2020-2022. Therefore, the strongest negative effect is observed in wholesale, which carries substantial weight among exporting industries because it comprises a large number of firms.

For importing firms (Figure 11a), TFP increased and generally accelerated over most of the period under review, except for the slowdown in 2022 associated with efficiency decrease. Industries that both intensively export their products and import intermediaries (Figure 11b) demonstrate an even stronger and accelerating TFP growth and were comparatively less affected by the shocks in 2020 and 2022, although their efficiency still declined in 2022.

Non-trading industries (Figure 12) exhibit fluctuations around modest positive productivity growth rates over the period under review. Their efficiency declined in 2019, 2020, and 2022, which is reflected in TFP growth, particularly in 2022.

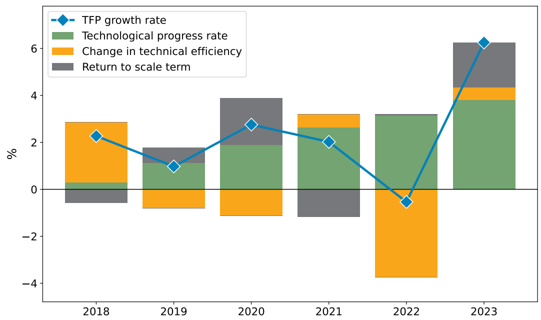
Overall, the pandemic in 2020 had mixed or moderate effects on productivity. Ex-

Figure 11: TFP Growth. Importing and importing-exporting industries



(a) Importing industries (b) Importing-exporting industries

Figure 12: TFP Growth. Non-trading industries



porting industries, especially wholesale, were most negatively affected in terms of TFP growth in 2021–2022. Non-trading industries also faced a decrease in TFP in 2022. Indeed, all groups show a negative change in efficiency. Nevertheless, importing and exporting-importing industries experienced a mild slowdown in TFP growth rather than a decline. All groups demonstrate improved efficiency and accelerating TFP growth in 2023.

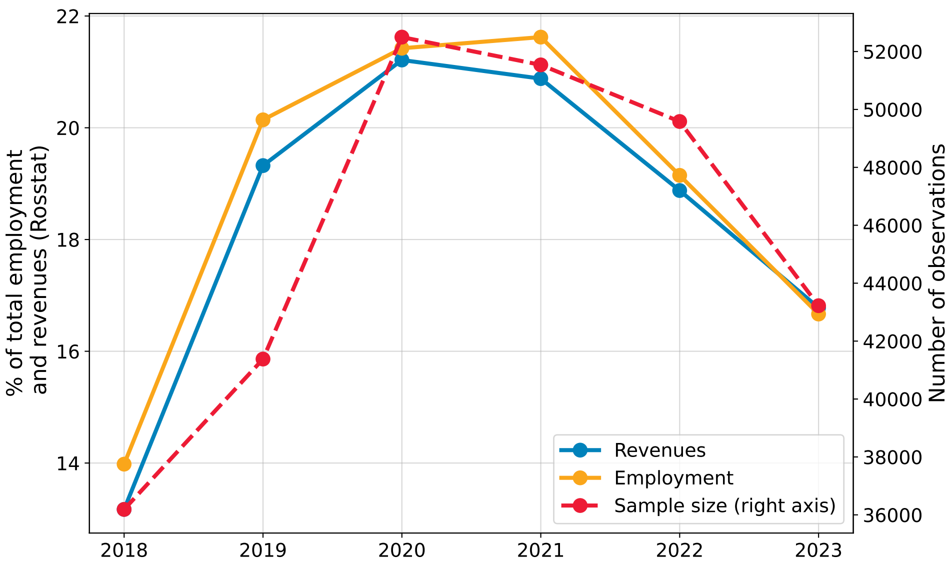
5.3 Representativeness checks

The dataset used for the SFA does not cover the entire Russian economy. In particular, large sanctioned companies are not included in the SPARK database, and SMEs do not report data (namely, cost of sales and expenses on wages) to calculate their value added. Additionally, some records are incomplete, contain missing or inconsistent data, or lack sufficiently detailed industry codes, and were therefore excluded from the analysis. This subsection assesses the coverage of the dataset and evaluates how well it represents the Russian economy.[42]

The resulting panel dataset is rather unbalanced, partly due to firms turnover and partly due to non-reporting. Figure 13 illustrates characteristics of the sample. It shows the number of estimated TFP growth observations (dashed red line, right axis), which

[42] Appendix C provides the results of similar checks on sector-level.

Figure 13: Sample characteristics



varies from approximately 36,000 to 52,000. The sample size increases from 2018 to 2020, remains relatively stable between 2020 and 2022, and then declines in 2023.[43] The figure also presents the percentage of employment and revenues covered by the analysis relative to the Rosstat data on total employment and total revenues for the corresponding sectors. Both metrics range between 14% and 22%, mirroring the sample size trends: increasing from 2018 to 2020 and declining in 2022–2023.

Additionally, to assess whether productivity growth rate in the SFA subsample is consistent with the full SPARK sample and Rosstat data, we examine labour productivity trends. Labour productivity measures output per employee, where output can be defined either as revenue (output-based labour productivity) or as value added (value-added based labour productivity). Since calculating value added significantly limits the sample,[44] we use output-based labour productivity in this analysis.

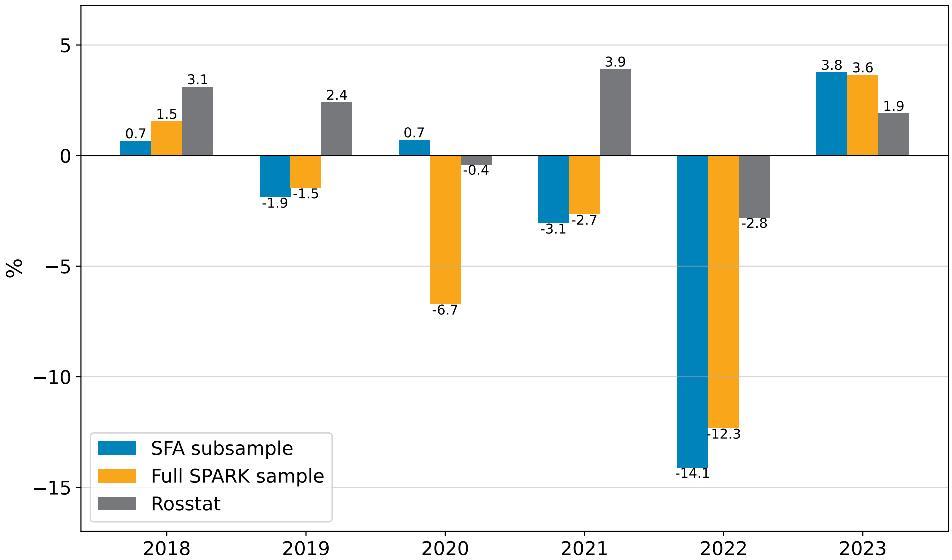
Labour productivity growth rates in the full SPARK sample, which includes SMEs, is overall close to labour productivity growth in the SFA subsample, with a notable exception in 2020 (Figure 14). During the pandemic, the SFA subsample does not demonstrate a fall in labour productivity, while the full SPARK sample does. Therefore, the SFA results for 2020 can be partly attributed to the sample selection, i.e. TFP growth for firms included in the SFA subsample may be less pronounced compared to the overall economy. Labour productivity in all other years is closely aligned between the two samples, suggesting the absence of additional sample-selection bias in the estimates.

Figure 14 also provides Rosstat's labour productivity growth index for reference, while

[43] Table A2 in Appendix A also provides sample size along with sector-year number of TFP growth estimates.

[44] Labour data are available for 83% of firms, revenues –for 79.5% of firms, while value added can only be calculated for 11% of firms (see Table A4 in Appendix A).

Figure 14: LABOUR PRODUCTIVITY GROWTH



the alignment with our estimates is moderate due to differences in both data and methods.[45] Nevertheless, the discrepancy between labour productivity growth in the sample and in Rosstat data can provide guidance regarding the potential contribution of accounting for working hours and of including large firms not covered by the SPARK dataset. For example, Figure 14 suggests that including large companies in the sample could mitigate the observed decline in average productivity in 2021.

The SFA subsample covers roughly 4% of observations in SPARK data and about 5% of firms. Nevertheless, it accounts for over 30% of labour and revenues in SPARK.[46] In terms of mean, median and presented percentiles, firms in the SFA subsample have notably higher levels of labour, capital and revenues, as well as output-based labour productivity compared to the full SPARK data, indicating that the subsample primarily represents medium-sized and large enterprises with higher labour productivity levels.

In summary, the SFA subsample covers approximately 15–20% of employment and revenues in the economy. It does not include large sanctioned companies not disclosing their financial statements and SMEs. Irregular reporting may introduce some bias in the productivity estimates, particularly in 2018–2019 and 2023. Nevertheless, the comparison

[45]Regarding data, a different scope of sectors and the absence of large firms in our dataset can account for a significant portion of labour productivity change in the economy and, accordingly, potential differences in the estimates. As for the method, we define labour productivity in terms of revenues and the number of employees at the firm level and calculate aggregate values as simple averages not accounting for firm sizes. Rosstat defines labour productivity in terms of value added and hours worked at the aggregate level.

For example, Rosstat reporting a mild decline in labour productivity in 2020 may indicate that the change in average labour productivity in the SPARK sample attributes a higher weight to SMEs, or does not account well for a reduction in working hours due to shutdowns, or that sectors out of scope of our study (such as agriculture) account for labour productivity stabilisation, or may involve any combination of these factors.

[46]For more details, see Tables A3 and A4 in Appendix A.

of the labour productivity trends suggests that the analysis largely captures the overall dynamics, except for the decrease in productivity growth in 2020.

5.4 Discussion

Several assumptions and limitations related to the results and their interpretation should be noted.

First, the study estimates firm-level TFP growth rates. As a result, the reported TFP trends do not capture aggregate productivity changes driven by firm entry and exit (turnover) or by labour reallocation from less productive towards more productive firms.

Second, the parametric model relies on assumptions regarding the form of the production function with two production factors and the distribution of inefficiency. Although the study attempts to relax these assumptions by incorporating a second-order time trend into the translog production function and by adopting a flexible inefficiency specification following Colombi et al. (2014), these assumptions cannot be fully eliminated. In addition, we assume that firms classified within the same industry according to their primary OKVED2 code share a common production function.

Third, value added, which is used here as a measure of output, is an appropriate proxy under the assumption of competitive markets, i.e. when revenues are not substantially influenced by market power. Otherwise, increases in value added may reflect rising markups rather than genuine productivity growth. This concern is partially mitigated by the absence of large firms in the SPARK dataset.

Fourth, the number of employees and fixed assets, used as measures of labour and capital respectively, do not capture variations in working hours or the intensity of capital use. Consequently, the increases in output driven by longer working hours or higher capital utilisation would be attributed to TFP growth. As a result, the estimated productivity growth rates may partly reflect demand-driven fluctuations (business cycles). For example, the decline in labour productivity in the SPARK sample over 2020 (Figure 14) partly reflects the decrease in working hours per employee.

Fifth, the dataset does not cover the entire economy. In particular, it underrepresents small firms and large sanctioned companies. This sample composition may support the assumptions of similar production processes and competitive behaviour for the firms included in the sample. At the same time, sample selection may introduce bias in the estimated TFP dynamics if firms in the sample differ systematically from the broader population. For example, the comparison of labour productivity in Subsection 5.3 indicates that productivity growth among small firms during the pandemic was affected more adversely compared to firms included in the SFA subsample. Additionally, Rosstat's labour productivity index suggests that having large companies in the sample and accounting for reallocation effects and variations in hours worked could yield higher estimated productivity growth rates in 2018–2019 and 2021–2022. In this case, large companies, which contribute significantly to aggregate productivity, could offset the decline observed in 2021 and mitigate the contraction in 2022.

Additionally, the data are a strongly unbalanced panel with varying coverage of the economy over time, which may reflect missing or erroneous observations. The removal of outliers, implemented to improve the robustness of the parametric estimation and to clarify graphical trends, may also exclude firms that contributed substantially to productivity changes.

Finally, TFP growth estimates are better suited to capture technological and management improvements over longer panels. The relatively short panel examined in this study spans a particularly turbulent period for the Russian economy, including two major shocks. As a result, the estimated TFP growth may largely reflect procyclical dynamics rather than long-run productivity trends.

6 Conclusion

In this paper, we use a four-component stochastic frontier model (Colombi et al., 2014) on the firm-level panel data for Russia covering multiple sectors to estimate TFP growth and its decomposition at the firm level. This framework allows us to examine the trends of the productivity distribution over time and, in particular, to analyse productivity dynamics associated with major economic shocks in 2020 and 2022.

The estimated mean TFP growth rates do not exhibit a pronounced trend over the period under review. Although TFP growth displays substantial variation across the years, cumulative TFP growth from 2018 to 2023 is approximately 5%, which is consistent with sluggish productivity growth in previous years documented in the literature (Section 2).

The data do not provide strong evidence of an immediate broad impact of the COVID-19 pandemic on TFP in 2020. With the exception of the services and accommodation sectors (J, M, R, and S), the initial decline in TFP was either small or not observed. However, the economy-wide average efficiency and TFP decreased in 2021, primarily due to exporting industries, particularly wholesale trade and transportation (G and H), while services sectors were recovering. That decline can be partly attributed to the prolonged effects of the pandemic, including disruptions in global supply chains and segmentation of international trade. It may also reflect sample selection bias, since output-based labour productivity declined in 2020 in the broader SPARK dataset and in Rosstat data, but not in the subsample used for the SFA.

Efficiency decreased further in 2022, contributing to the corresponding drop in TFP growth across much of the economy. This trend, however, reversed in 2023.

TFP growth in 2023 should be interpreted with caution, as several factors may affect the reliability of the estimates. First, the data do not capture working hours or the intensity of capital use. Thus, the observed rebound may partly reflect increased revenues from rising domestic demand, driven by government purchases and import substitution, rather than genuine productivity gains. A limited capacity to accumulate new capital or expand employment may result in higher capital utilisation and longer working hours, captured in the estimated TFP growth despite the absence of technological shifts or other factors of a long-term increase in the supply side. Second, extensive government purchases may distort market prices, making value added a less reliable proxy for output. Consequently, the observed TFP growth may not be sustainable and could decline once these temporary effects of intensified use of inputs or price distortions dissipate. Finally, the reduced sample size in 2023 may introduce selection bias, affecting the robustness of the estimates.

Examining TFP dynamics by trade involvement reveals that exporting industries were affected particularly hard in 2021–2023, while TFP in non-trading industries remained largely stagnant, and importing industries generally exhibited faster TFP growth. However, firm-level trends within industries are heterogeneous, and identifying exporters and importers at the firm level could yield different results.

Overall, this study provides one of the first comprehensive analyses of firm-level TFP growth in Russia during the recent period of significant economic turbulence. By distinguishing between frontier expansion and efficiency dynamics, it sheds light on the sources of observed TFP trends. Providing a rather descriptive analysis, it lays the groundwork for future research that could extend it by further exploring the effects of specific sanctions on productivity growth, comparing sector- and firm-specific resilience in terms of productivity, or linking TFP dynamics to labour market outcomes, or industrial and innovation policies.

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Appendix

A Data description

Table A1 summarises the number of observations in the SPARK dataset, in the subsample used for SFA, and the corresponding number of estimated firm-level TFP growth rates. The table highlights that a substantial share of observations could not be used due to missing data, particularly for calculating value added. Consequently, the analysis is conducted on a limited sample of firms.

Table A2 reports the number of firm-year TFP growth rate estimates obtained for each sector.

Tables A3 and A4 provide detailed statistics on the observations (Table A3) and firms (Table A4) included in the SFA, namely the tables show the percentage of labour, capital, and revenues relative to the full SPARK sample and their statistics on the SPARK sample and the SFA subsample.

Table A5 presents the list of industries for which production functions are estimated and TFP growth rates are computed. Industry names follow the NACE Rev. 2 classification up to 4-digit level. For more detailed 5-digit industries, names correspond to their respective 4-digit NACE Rev. 2 categories and are denoted by an asterisk (*).

Table A1: Observations

Description	Observations	Firms	Industries
Total number	9,818,859	2,395,758	291
In sectors of interest	9,818,859	2,395,758	291
where Revenues are defined	7,817,407	1,935,958	291
where $\ln L$ is defined	8,010,209	2,044,195	291
where $\ln K$ is defined	3,330,485	860,660	291
where $\ln Y$ is defined	871,787	265,954	291
where $\ln Y$, $\ln K$, $\ln L$ are defined	544,783	162,718	289
and industry is defined	485,504	143,450	289
IQR outliers excluded	472,197	140,096	289
SFA four-component converged	408,341	120,873	198
ΔTFP estimates	274,412	85,603	198

Most of the records were excluded as they did not allow obtaining value added, a measure of output. Additionally, around 20,000 firms were dropped because they could not be assigned to a sufficiently narrow industry. Some industries (codes 39, 58.2, 94.91+94.92, and 94.99) were excluded as well, as they contained fewer than 15 observations over the six-year period under review.

Table A2: Number of TFP growth estimates

Sector	2018	2019	2020	2021	2022	2023	Total
B	825	985	1,343	1,351	1,344	1,170	7,018
C	10,386	12,142	15,748	15,525	13,912	11,718	79,431
D	685	790	938	934	893	739	4 979
E	782	873	1,150	1,157	1,142	941	6,045
G	13,935	15,894	20,194	19,833	19,704	17,347	106,907
H	2,453	2,723	3,333	3,204	3,224	2,935	17,872
I	767	834	992	857	880	800	5,130
J	1,808	2,034	2,540	2,618	2,566	2,401	13,967
M	3,417	3,896	4,857	4,704	4,492	3,994	25,360
N	898	942	1,078	1,057	1,118	935	6,028
R	128	156	179	159	176	137	935
S	104	111	146	140	133	106	740
Total	36,188	41,380	52,498	51,539	49,584	43,223	274,412

Table A3: Share of observations covered by the SFA

Variable	Sample	Obs	Share obs	Share	Mean	p10	Median	p90
Labour	SFA	408,341	4%	35%	91.68	3.00	26.00	215.00
number of employees	SPARK	8,010,213	82%	100%	13.46	1.00	2.00	19.00
Capital	SFA	408,341	4%	12%	114.44	0.13	5.83	162.37
real fixed assets	SPARK	3,613,841	37%	100%	105.62	0.01	0.83	22.48
Output	SFA	408,341	4%	30%	193.54	3.31	50.93	438.25
real value added	SPARK	911,293	9%	100%	287.87	0.34	16.07	316.74
Revenues	SFA	408 341	4%	24%	692.47	9.77	167.02	1 604.15
real revenues	SPARK	7,817,407	80%	100%	149.48	0.17	7.11	107.58
LP^{VA}	SFA	408,341	4%	55%	5.54	0.36	1.62	8.47
Labour productivity w.r.t. value added	SPARK	774,298	8%	100%	5.30	0.23	1.31	7.70
LP^{Rev}	SFA	407,254	4%	14%	26.39	0.92	5.03	41.24
Labour productivity w.r.t. revenues	SPARK	6,691,938	68%	100%	11.67	0.29	2.35	18.11

SFA in column *Sample* represents the subsample where the SFA model converged. SPARK in column *Sample* stands for the maximum available sample in the initial SPARK dataset where the corresponding variable is fulfilled. *Obs* stands for the number of observations. *Share obs* stands for the share of observations in the corresponding sample relative to the total number of observations in the original dataset (9,818,859). *Share* stands for the share of the summed value for the corresponding sample relative to the sum in the SPARK sample. *Mean*, *p10*, *Median*, and *p90* stand for mean, 10% percentile, median, and 90% percentile values, respectively. Statistics for Capital, Output, Revenues and Labour productivity are measured in millions of rubles of 2017. Only the sectors of interest are considered.

Table A4: Share of firms covered by the SFA

Variable	Sample	Firms	Share firms	Share	Mean	p10	Median	p90
Labour	SFA	115,925	5%	34%	69.85	2.00	17.00	153.57
number of employees	SPARK	2,044,197	85%	100%	11.67	1.00	1.75	13.57
Capital	SFA	115,925	5%	15%	97.69	0.12	4.11	110.39
real fixed assets	SPARK	897,403	37%	100%	82.78	0.01	0.75	16.43
Output	SFA	115,925	5%	34%	152.98	2.60	35.19	317.74
real value added	SPARK	273,184	11%	100%	192.76	0.27	9.27	189.05
Revenue	SFA	115,925	5%	29%	573.85	7.94	115.99	1 216.09
real revenues	SPARK	1,935,958	81%	100%	117.86	0.19	6.62	90.30
P_L^{VA}	SFA	115,925	5%	54%	6.14	0.38	1.70	8.82
Labour productivity w.r.t. value added	SPARK	243,310	10%	100%	5.46	0.21	1.28	7.61
P_L^{Rev}	SFA	115,666	5%	14%	30.40	0.98	5.52	45.41
Labour productivity w.r.t. revenues	SPARK	1,715,957	72%	100%	15.09	0.31	2.64	21.55

The data are provided for firms, and therefore the observations were grouped into means (with respect to Labour, Capital, Revenues and Labour productivity) to represent a firm. SFA in column *Sample* represents the subsample of firms where the SFA model converged. SPARK in column *Sample* stands for the maximum available sample in the initial SPARK dataset where the corresponding variable is fulfilled at least in one period for a firm. *Firms* stands for the number of firms. *Share firms* stands for the share of firms included in the corresponding sample relative to the total number of firms in the original dataset (2 395 758). *Share* stands for the share of the summed value for the corresponding sample relative to the sum in the SPARK sample. *Mean*, *p10*, *Median*, and *p90* stand for mean, 10% percentile, median, and 90% percentile values, respectively. Statistics for Capital, Output, Revenues and Labour productivity are measured in millions of rubles of 2017. Only sectors of interest are considered.

Table A5: List of industries

Code	**Industry name**
05	Mining of coal and lignite
06	Extraction of crude petroleum and natural gas
07	Mining of metal ores
08.11	Quarrying of ornamental and building stone, limestone, gypsum, chalk and slate
08.12	Operation of gravel and sand pits; mining of clays and kaolin
09	Mining support service activities
10.1	Processing and preserving of meat and production of meat products

Continued on next page

Table A5 continued

Code	**Industry name**
10.2	Processing and preserving of fish, crustaceans and molluscs
10.3	Processing and preserving of fruit and vegetables
10.5	Manufacture of dairy products
10.6	Manufacture of grain mill products, starches and starch products
10.7	Manufacture of bakery and farinaceous products
10.81+10.82	Manufacture of sugar + Manufacture of cocoa, chocolate and sugar confectionery
10.9	Manufacture of prepared animal feeds
11.07	Manufacture of soft drinks; production of mineral waters and other bottled waters
12	Manufacture of tobacco products
13.95	Manufacture of non-wovens and articles made from non-wovens, except apparel
14.12	Manufacture of workwear
15	Manufacture of leather and related products
16.10	Sawmilling and planing of wood
16.21+16.22 +16.24+16.29	Manufacture of veneer sheets and wood-based panels + Manufacture of assembled parquet floors + Manufacture of wooden containers + Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials
16.23	Manufacture of other builders' carpentry and joinery
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19.2	Manufacture of refined petroleum products
20.1	Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms
20.2+20.5+20.6	Manufacture of pesticides and other agrochemical products + Manufacture of other chemical products + Manufacture of man-made fibres
20.3	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
20.4	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations

Continued on next page

Table A5 continued

Code	Industry name
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22.1	Manufacture of rubber products
22.21	Manufacture of plastic plates, sheets, tubes and profiles
22.22	Manufacture of plastic packing goods
22.23	Manufacture of builders' ware of plastic
22.29	Manufacture of other plastic products
23.1	Manufacture of glass and glass products
23.2+23.3+23.4+23.5	Manufacture of refractory products + Manufacture of clay building materials + Manufacture of other porcelain and ceramic products + Manufacture of cement, lime and plaster
23.61	Manufacture of concrete products for construction purposes
23.63	Manufacture of ready-mixed concrete
23.7	Cutting, shaping and finishing of stone
23.9	Manufacture of abrasive products and non-metallic mineral products n.e.c.
24.1+24.2+24.3	Manufacture of basic iron and steel and of ferro-alloys + Manufacture of tubes, pipes, hollow profiles and related fittings, of steel + Manufacture of other products of first processing of steel
24.4+24.5	Manufacture of basic precious and other non-ferrous metals + Casting of metals
25.11	Manufacture of metal structures and parts of structures
25.12	Manufacture of doors and windows of metal
25.2+25.3+25.4+25.5	Manufacture of tanks, reservoirs and containers of metal + Manufacture of steam generators, except central heating hot water boilers + Manufacture of weapons and ammunition + Forging, pressing, stamping and roll-forming of metal; powder metallurgy
25.61	Treatment and coating of metals
25.62	Machining
25.7+25.9	Manufacture of cutlery, tools and general hardware + Manufacture of other fabricated metal products
26.2+26.3	Manufacture of computers and peripheral equipment + Manufacture of communication equipment

Continued on next page

Table A5 continued

Code	Industry name
26.4+26.6+26.7+26.8	Manufacture of consumer electronics + Manufacture of irradiation, electromedical and electrotherapeutic equipment + Manufacture of optical instruments and photographic equipment + Manufacture of magnetic and optical media
26.5	Manufacture of instruments and appliances for measuring, testing and navigation; watches and clocks
27.11	Manufacture of electric motors, generators and transformers
27.12	Manufacture of electricity distribution and control apparatus
27.2+27.3	Manufacture of batteries and accumulators + Manufacture of wiring and wiring devices
27.4+27.5	Manufacture of electric lighting equipment + Manufacture of domestic appliances
27.9	Manufacture of other electrical equipment
28.1	Manufacture of general — purpose machinery
28.21+28.22+28.23 +28.24+28.29	Manufacture of ovens, furnaces and furnace burners + Manufacture of lifting and handling equipment + Manufacture of office machinery and equipment (except computers and peripheral equipment) + Manufacture of power-driven hand tools + Manufacture of other general-purpose machinery n.e.c.
28.3+28.4	Manufacture of agricultural and forestry machinery + Manufacture of metal forming machinery and machine tools
28.9	Manufacture of other special-purpose machinery
29.1	Manufacture of motor vehicles
29.2+29.3	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers + Manufacture of parts and accessories for motor vehicles
30	Manufacture of other transport equipment
31.01	Manufacture of office and shop furniture
31.02+31.03	Manufacture of kitchen furniture + Manufacture of mattresses
32.1	Manufacture of jewellery, bijouterie and related articles
32.2+32.3+32.4+32.5	Manufacture of musical instruments + Manufacture of sports goods + Manufacture of games and toys + Manufacture of medical and dental instruments and supplies

Continued on next page

Table A5 continued

Code	Industry name
32.9	Manufacturing n.e.c.
33.11+33.15 +33.16+33.19	Repair of fabricated metal products + Repair and maintenance of ships and boats + Repair and maintenance of aircraft and spacecraft + Repair of other equipment
33.12	Repair of machinery
33.13	Repair of electronic and optical equipment
33.2	Installation of industrial machinery and equipment
35.12	Transmission of electricity
35.30.1	Steam and air conditioning supply*
35.30.2+35.30.3 +35.30.4+35.30.5	Steam and air conditioning supply*
36	Water collection, treatment and supply
37	Sewerage
38.1+38.2	Waste collection + Waste treatment and disposal
38.3	Materials recovery
45.1	Sale of motor vehicles
45.20.1	Maintenance and repair of motor vehicles*
45.20.2+45.20.3	Maintenance and repair of motor vehicles*
45.31	Wholesale trade of motor vehicle parts and accessories
45.32	Retail trade of motor vehicle parts and accessories
45.4	Sale, maintenance and repair of motorcycles and related parts and accessories
46.11	Agents involved in the sale of agricultural raw materials, live animals, textile raw materials and semi-finished goods
46.12	Agents involved in the sale of fuels, ores, metals and industrial chemicals
46.14	Agents involved in the sale of machinery, industrial equipment, ships and aircraft
46.15	Agents involved in the sale of furniture, household goods, hardware and ironmongery
46.17	Agents involved in the sale of food, beverages and tobacco
46.18	Agents specialised in the sale of other particular products
46.19	Agents involved in the sale of a variety of goods
46.21	Wholesale of grain, unmanufactured tobacco, seeds and animal feeds

Continued on next page

Table A5 continued

Code	**Industry name**
46.22+46.23+46.24	Wholesale of flowers and plants + Wholesale of live animals + Wholesale of hides, skins and leather
46.31	Wholesale of fruit and vegetables
46.33	Wholesale of dairy products, eggs and edible oils and fats
46.34	Wholesale of beverages
46.35	Wholesale of tobacco products
46.36	Wholesale of sugar and chocolate and sugar confectionery
46.37	Wholesale of coffee, tea, cocoa and spices
46.38	Wholesale of other food, including fish, crustaceans and molluscs
46.39	Non-specialised wholesale of food, beverages and tobacco
46.41	Wholesale of textiles
46.42	Wholesale of clothing and footwear
46.43	Wholesale of electrical household appliances
46.44	Wholesale of china and glassware and cleaning materials
46.45	Wholesale of perfume and cosmetics
46.46	Wholesale of pharmaceutical goods
46.47	Wholesale of furniture, carpets and lighting equipment
46.49	Wholesale of other household goods
46.5	Wholesale of information and communication equipment
46.61	Wholesale of agricultural machinery, equipment and supplies
46.62	Wholesale of machine tools
46.63	Wholesale of mining, construction and civil engineering machinery
46.64+46.65	Wholesale of machinery for the textile industry and of sewing and knitting machines + Wholesale of office furniture
46.66	Wholesale of other office machinery and equipment
46.69.1+46.69.2+46.69.3	Wholesale of other machinery and equipment*
46.69.4+46.69.5	Wholesale of other machinery and equipment*
46.69.7+46.69.8+46.69.9	Wholesale of other machinery and equipment*
46.71	Wholesale of solid, liquid and gaseous fuels and related products
46.72	Wholesale of metals and metal ores

Continued on next page

Table A5 continued

Code	Industry name
46.73.2+46.73.5 +46.73.7+46.73.8	Dispensing chemist in specialised stores*
46.73.4	46.73.4 Dispensing chemist in specialised stores*
46.73.6	Dispensing chemist in specialised stores*
46.74	Wholesale of hardware, plumbing and heating equipment and supplies
46.75	Wholesale of chemical products
46.76	Wholesale of other intermediate products
46.77	Wholesale of waste and scrap
46.9	Non-specialised wholesale trade
47.11	Retail sale in non-specialised stores with food, beverages or tobacco predominating
47.19	Other retail sale in non-specialised stores
47.23+47.26	Retail sale of fish, crustaceans and molluscs in specialised stores + Retail sale of tobacco products in specialised stores
47.25	Retail sale of beverages in specialised stores
47.3	Retail sale of automotive fuel in specialised stores
47.4	Retail sale of information and communication equipment in specialised stores
47.51+47.53+47.54	Retail sale of textiles in specialised stores + Retail sale of carpets, rugs, wall and floor coverings in specialised stores + Retail sale of electrical household appliances in specialised stores
47.52	Retail sale of hardware, paints and glass in specialised stores
47.59	Retail sale of furniture, lighting equipment and other household articles in specialised stores
47.71	Retail sale of clothing in specialised stores
47.73	Dispensing chemist in specialised stores
47.74	Retail sale of medical and orthopaedic goods in specialised stores
47.75	Retail sale of cosmetic and toilet articles in specialised stores
47.77	Retail sale of watches and jewellery in specialised stores
47.91	Retail sale via mail order houses or via Internet
49.2	Freight rail transport
49.41.2+49.41.3	Freight transport by road*

Continued on next page

Table A5 continued

Code	**Industry name**
49.42	Removal services
50.1+50.2	Sea and coastal passenger water transport + Sea and coastal freight water transport
50.3+50.4	Inland passenger water transport + Inland freight water transport
52.1	Warehousing and storage
52.21	Service activities incidental to land transportation
52.23	Service activities incidental to air transportation
52.24	Cargo handling
52.29	Other transportation support activities
53.1	Postal activities under universal service obligation
56.10	Restaurants and mobile food service activities
56.2	Event catering and other food service activities
59.11	Motion picture, video and television programme production activities
60.1	Radio broadcasting
61.1	Wired telecommunications activities
62.01	Computer programming activities
62.09	Other information technology and computer service activities
63.1	Data processing, hosting and related activities; web portals
63.9	Other information service activities
70.1	Activities of head offices
70.2	Management consultancy activities
71.11	Architectural activities
71.12.1	Renting and leasing of trucks*
71.12.2	Renting and leasing of trucks*
71.12.3	Renting and leasing of trucks*
71.12.4+71.12.5 +71.12.6+71.12.7	Renting and leasing of trucks*
71.2	Technical testing and analysis
72.11+72.2	Research and experimental development on biotechnology + Research and experimental development on social sciences and humanities
72.19	Other research and experimental development on natural sciences and engineering

Continued on next page

Table A5 continued

Code	Industry name
73.1	Advertising
73.2	Market research and public opinion polling
74.1	Specialised design activities
74.9	Other professional, scientific and technical activities n.e.c.
77.32	Renting and leasing of construction and civil engineering machinery and equipment
77.39.1	Renting and leasing of other machinery, equipment and tangible goods n.e.c.*
77.4	Leasing of intellectual property and similar products, except copyrighted works
78.2	Temporary employment agency activities
79.12	Tour operator activities
80.1	Private security activities
81.1	Combined facilities support activities
81.21	General cleaning of buildings
81.22	Other building and industrial cleaning activities
81.3	Landscape service activities
82.1+82.2	Office administrative and support activities + Activities of call centres
82.92	Packaging activities
90.02+90.03+90.04	Support activities to performing arts + Artistic creation + Operation of arts facilities
91.02+91.03+91.04	Museums activities + Operation of historical sites and buildings and similar visitor attractions + Botanical and zoological gardens and nature reserves activities
93.12+93.13	Activities of sport clubs + Fitness facilities
93.2	Amusement and recreation activities
94.11	Activities of business and employers membership organisations
96.01	Washing and (dry-)cleaning of textile and fur products
96.03	Funeral and related activities

Names of detailed 5-digit industries correspond to their respective 4-digit NACE Rev. 2 categories and are denoted by an asterisk (*).

B TFP growth rates in industries by year

Figure B1: TFP growth in 2018

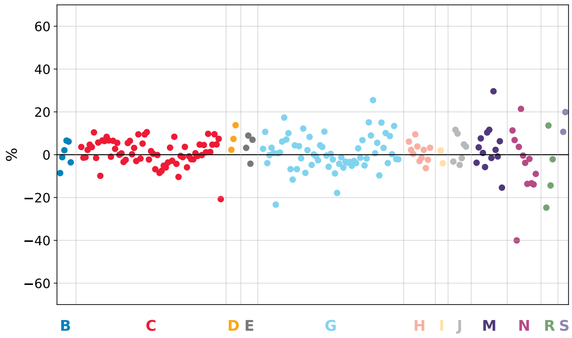


Figure B2: TFP growth in 2019

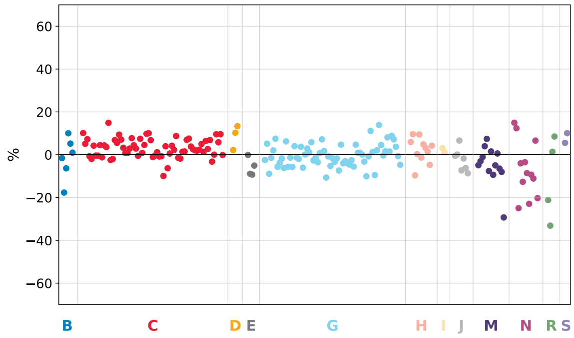


Figure B3: TFP growth in 2020

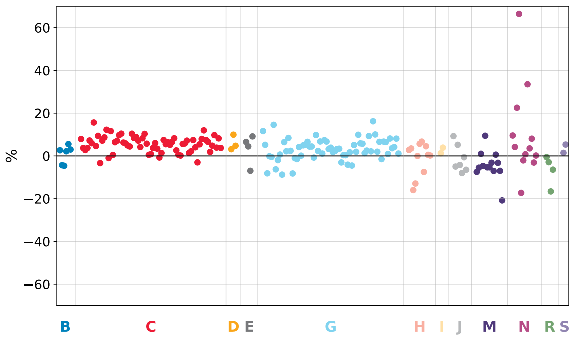


Figure B4: TFP growth in 2021

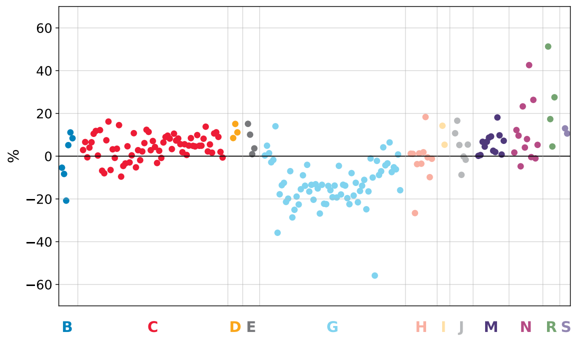


Figure B5: TFP growth in 2022

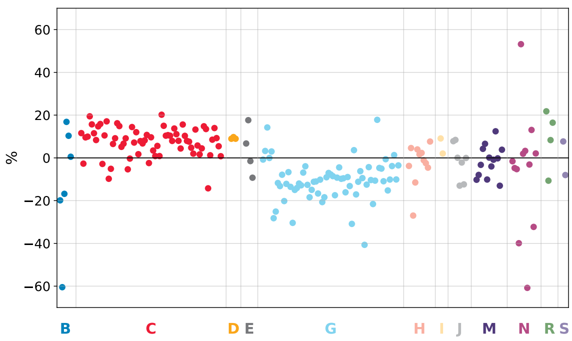
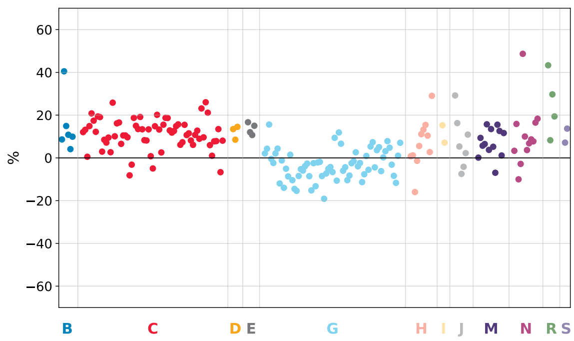


Figure B6: TFP growth in 2023



Sector B – Mining and quarrying. Sector C – Manufacturing. Sector D – Electricity, gas, steam and air conditioning supply. Sector E – Water supply; sewerage, waste management and remediation activities. Sector G – Wholesale and retail trade; repair of motor vehicles and motorcycles. Sector H – Transportation and storage. Sector I – Accommodation and food service activities. Sector J – Information and communication. Sector M – Professional, scientific and technical activities. Sector N – Administrative and support service activities. Sector R – Arts, entertainment and recreation. Sector S – Other service activities.

C Sectoral TFP growth estimates

Figures C1–C12 present productivity growth rates and sample description for each sector. The figures have the same structure: (a) provides trends for average TFP growth and its components as in Figure 4 in the main body of the paper; (b) compares labour productivity growth in the SFA sample and the full SPARK sample, which includes SMEs, and aggregate labour productivity growth measured by Rosstat, except for sectors R and S, for which Rosstat does not provide labour productivity growth index; (c) contains the TFP growth rates of laggards and leaders defined by the persistent efficiency level as in Figure 7a; and (d) characterises the sample, in the same way as in Subsection 5.3, with the percentage of total employment and revenues relative to Rosstat data[47] covered by SFA (left axis) and the number of observations in the sample (right axis). The estimated TFP growth rates vary significantly across sectors.

Mining and quarrying (sector B, Figure C1) showed a decrease in TFP over 2022, followed by its sharp rise in 2023, and stable or close-to-zero growth rates in all other years of the period under review.

Manufacturing (sector C, Figure C2) showed accelerating firm-level TFP growth, with only a mild slowdown in 2021, while average technical efficiency declined in 2021–2022. The return to scale term was close to zero. The acceleration in TFP growth was mainly driven by frontier expansion, which is identified based on the time trend in the deterministic part of the estimated production function. However, firm-level output-based labour productivity growth does not follow the trend: the rate was low in 2019 and turned negative in 2020 and 2022.[48]

In **electricity, gas, steam and air conditioning supply (sector D, Figure C3)**, TFP growth was rather strong, although slowing in 2020 and 2022, and accelerated in 2021 and 2023. The average growth trend is aligned with labour productivity growth at the firm and aggregate levels.

Water supply; sewerage, waste management and remediation activities (sector E, Figure C4) demonstrated uneven dynamics in productivity growth (a decline in 2019 and a slowdown in 2022), despite an upward trend in technological progress. To some degree, the decline in 2019 can be artificial as many firms were added to the sample in 2019 (Figure C4d).

Trade (sector G, Figure C5) was the most adversely affected sector in 2021–2022 in terms of TFP growth. TFP in the sector continued to decline in 2023. This must have determined the negative trend in technological progress from the deterministic part of the productivity function, but it was also associated with the fall in efficiency in

[47] Employment is compared to total employment in a given sector (Rosstat data). Revenues are compared to total revenues generated by a sector (Rosstat data).

[48] Note that revenues can decline, while value added remains stable. Value added-based labour productivity on the SFA sample does not decrease in 2019–2020.

2021–2022. Wholesale was the main contributor to the decrease in 2021–2022, while retail demonstrated stabler productivity dynamics.

It is worth noting that marketplaces are underrepresented in the dataset due to missing employment data. Since they are large and growing companies that adopt new technologies and novel retail practices, and are increasing their market share, their exclusion from the analysis may lead to an underestimation of productivity growth in the trade sector. This bias may be particularly relevant given that the shocks analysed may have had a positive effect on marketplaces relative to other firms, while rising logistics costs since 2022 have affected all firms.

In **transportation and storage (sector H, Figure C6)**, according to SFA estimates, TFP growth was uneven but overall close to zero over the period under review. However, the output-base labour productivity growth in the SFA subsample is negative across 2018–2022, falling sharply in 2020 and 2022. The fall in labour productivity in 2020 is not reflected in TFP growth estimates based on SFA. Decline in efficiency and TFP was observed in 2021–2022, followed by their rebound in 2023.

Accommodation and food service activities (sector I, Figure C7) was arguably the most negatively affected sector in 2020 in terms of labour productivity, along with **arts, entertainment and recreation** (sector R, Figure C11). However, the SFA suggests that TFP growth did not fall in 2020: although efficiency declined, that was offset by a positive trend in technological progress and the return to scale term. Note also that falling average revenues and value added in the sector were accompanied by decrease in labour and capital; and the sample size varies significantly around 2020.

Information and communication (sector J, Figure C8) experienced a fall in TFP in 2022, while demonstrating close-to-zero negative growth rates in all other years. Labour productivity declined in both 2020 and 2022.

Professional, scientific and technical activities (sector M, Figure C9) demonstrate zigzag growth in both TFP and labour productivity, with a decline in 2019–2020 and 2022 and acceleration in 2021 and 2023. Similar dynamics are observed in **administrative and support service activities (sector N, Figure C10)**.

In **arts, entertainment and recreation (sector R, Figure C11)**, similar to accommodation and food service activities, TFP declined in 2020 and increased afterwards. Labour productivity plunged, while TFP growth demonstrated milder decline due to reduced capital in 2020.

Other service activities (sector S, Figure C12), which include non-for-profit organisations and personal services, have demonstrated declining but still positive average TFP growth rates throughout the period under review, with TFP growth being lower in 2020 and 2022. However, the SFA sample does not capture the fall in labour productivity in 2020 that is observed in the SPARK sample, which comprise SMEs (Figure C12b).

Summarising the sectoral trends, in 2020, manufacturing, trade, and transportation

Table C1: INDUSTRIES WITH HIGHEST AVERAGE TFP GROWTH IN 2023

Sector	Industry code	Industry name	TFP growth, %
B	06	Extraction of crude petroleum and natural gas	25.6
C	10	Manufacture of food products	17.8
C	11.07	Manufacture of soft drinks; production of mineral waters and other bottled waters	18.1
C	16.2	Manufacture of products of wood, cork, straw and plaiting materials	18.7
C	18	Printing and reproduction of recorded media	15.9
C	22.1	Manufacture of rubber products	16.4
C	22.23	Manufacture of builders' ware of plastic	18.0
C	25	Manufacture of fabricated metal products, except machinery and equipment	17.2
C	27.2, 27.3	Manufacture of batteries and accumulators Manufacture of wiring and wiring devices	15.5
C	29.2, 29.3	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers Manufacture of parts and accessories for motor vehicles	16.5
C	31	Manufacture of furniture	21.5
E	36	Water collection, treatment and supply	16.2
E	38.3	Materials recovery	15.5
H	53.1	Postal activities under universal service obligation	18.4
I	56.10	Restaurants and mobile food service activities	15.1
J	59.11	Motion picture, video and television programme production activities	19.8
J	60.1	Radio broadcasting	16.0
N	79.12	Tour operator activities	15.2
N	81.3	Landscape service activities	28.9
R	90.0	Creative, arts and entertainment activities	27.6
R	93.12, 93.13	Activities of sport clubs; Fitness facilities	24.3
R	93.2	Amusement and recreation activities	19.0

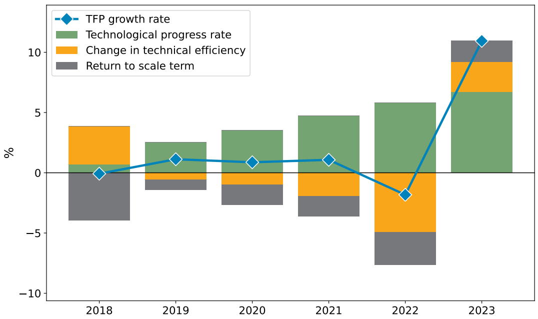
(C, G, and H) were the only sectors demonstrating accelerating TFP growth, while other sectors faced a slowdown in TFP growth, and services sectors (J, L, M, and R) recorded negative rates. In 2022, TFP growth rates decreased in almost all sectors, with manufacturing (C) being the only sector boasting a rise. Trade (G), and information and communication (J) were affected particularly hard in 2022, which entailed a significant fall in their TFP. In 2023, TFP bounced back in all sectors, except for trade (G) and information and communication (J).

Table C1 lists the industries that were the main drivers of TFP growth in 2023. Their average TFP increased by over 15%. For the most part, these industries are supported by government purchases or subsidies, import substitution, or growing domestic demand, driven by rising real wages, or related to construction, boosted by an extensive programme of preferential mortgages.

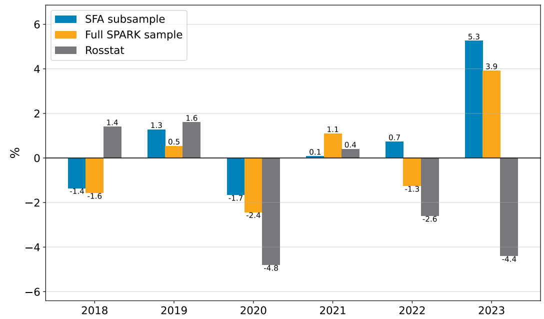
Defined by persistent inefficiency, leaders and laggards show rather close productivity growth rates. However, laggards often record slightly higher TFP growth than leaders.

The sample characteristics also vary across sectors. The sample size mostly rises from 2018 to 2020, remaining stable from 2020 to 2022, and then falls in 2023. The percentage of employment covered varies significantly between the sectors, ranging from about 2% in sectors R and S to around 20% in sectors D, G, I, and J and higher in sectors B, C, and E. The revenue share dynamics are similar, ranging from 2–5% in sectors R and S to around 20% in sectors C, G, I, J, and M and up to 40% in sector E, but are more volatile over time. Both revenue and labour percentages are mostly consistent with the sample size dynamics. The average labour productivity growth rates on the full SPARK dataset and the SFA sample are rather consistent, except for sectors C, H, and S, in which labour productivity dynamics on the SFA sample do not capture the decline in 2020, evident on the full SPARK data.

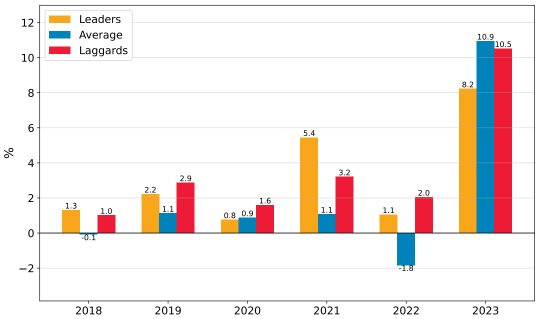
Figure C1: TFP growth. Sector B – Mining and quarrying



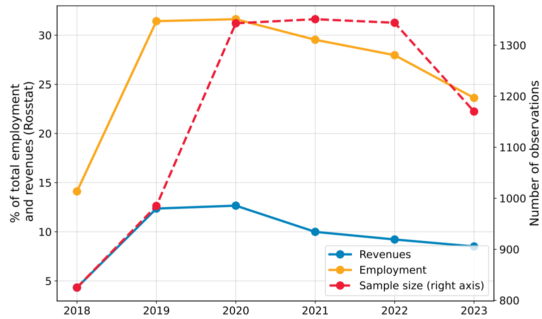
(a) TFP growth decomposition



(b) Labour productivity growth

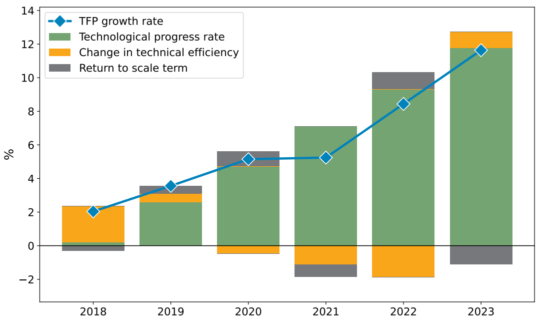


(c) Leaders and laggards

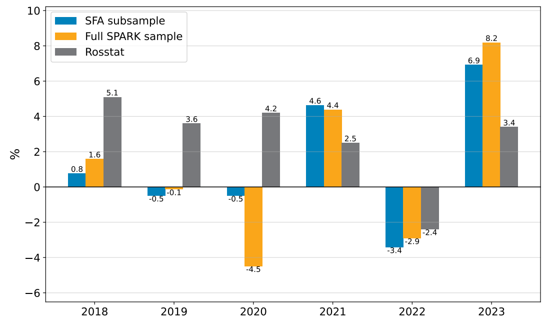


(d) Sample characteristics

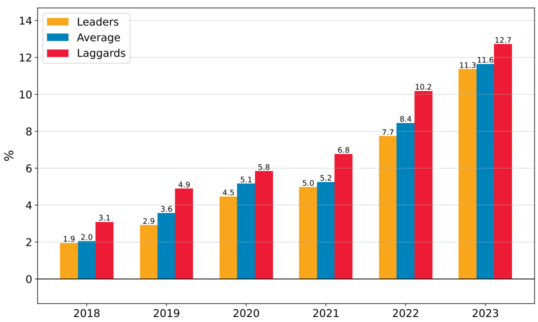
Figure C2: TFP growth. Sector C – Manufacturing



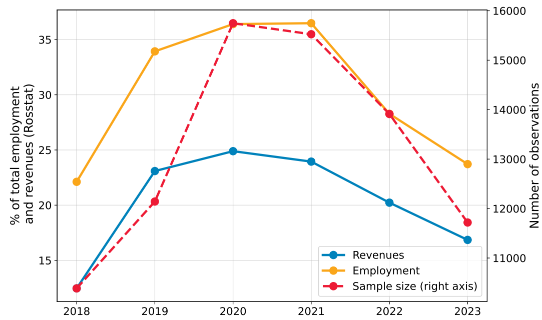
(a) TFP growth decomposition



(b) Labour productivity growth

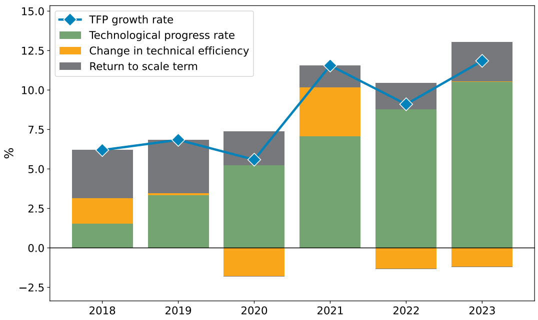


(c) Leaders and laggards

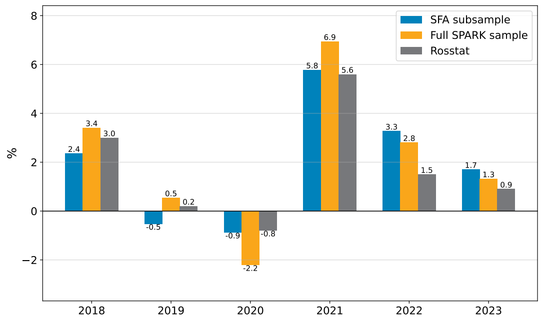


(d) Sample characteristics

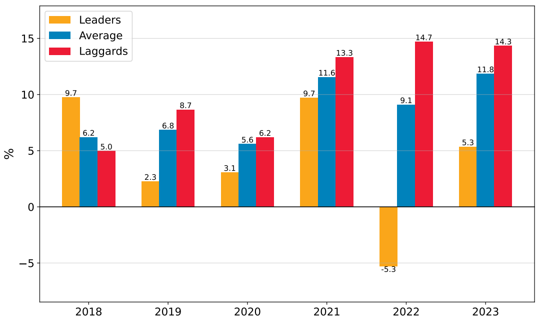
Figure C3: TFP growth. Sector D – Electricity, gas, steam and air conditioning supply



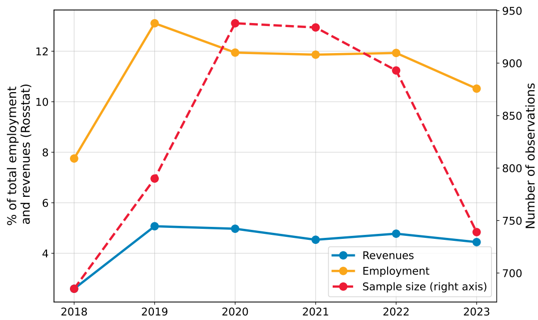
(a) TFP growth decomposition



(b) Labour productivity growth

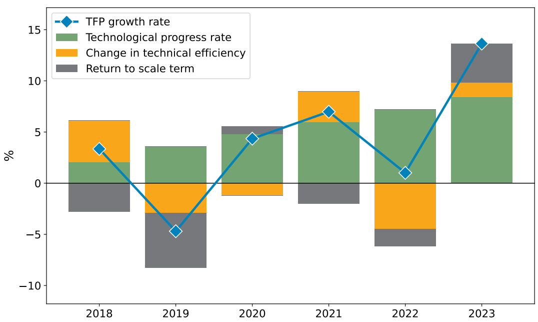


(c) Leaders and laggards

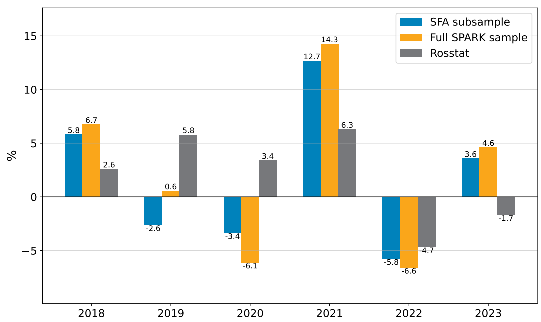


(d) Sample characteristics

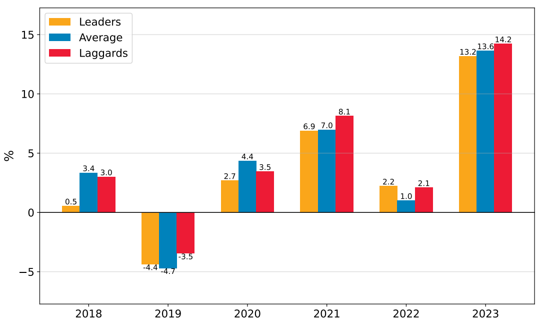
Figure C4: TFP growth. Sector E – Water supply; sewerage, waste management and remediation activities



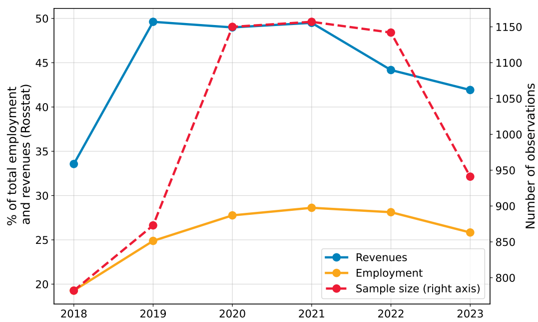
(a) TFP growth decomposition



(b) Labour productivity growth

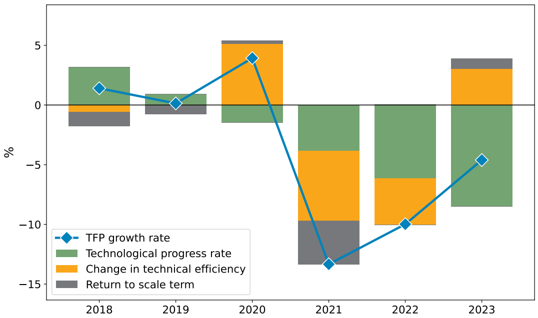


(c) Leaders and laggards

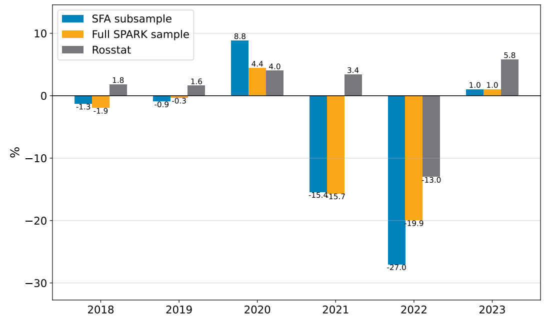


(d) Sample characteristics

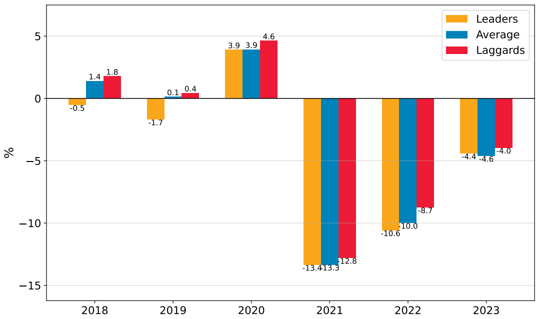
Figure C5: TFP growth. Sector G – Wholesale and retail trade; repair and selling of motor vehicles and motorcycles



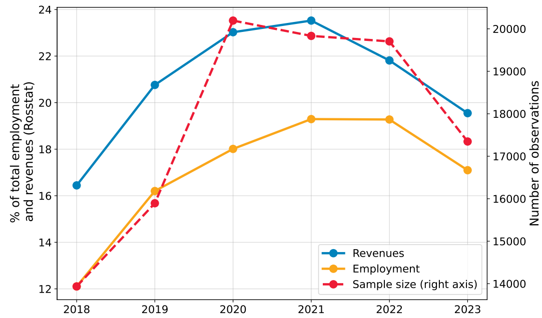
(a) TFP growth decomposition



(b) Labour productivity growth

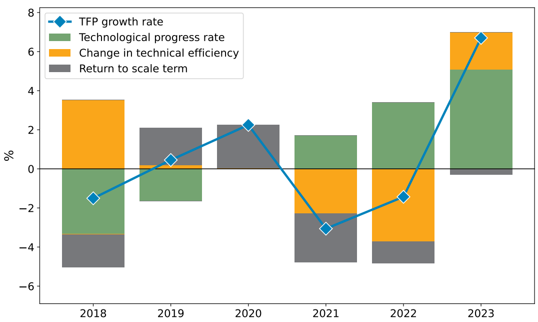


(c) Leaders and laggards

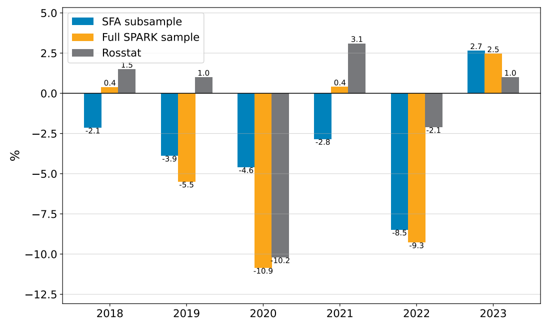


(d) Sample characteristics

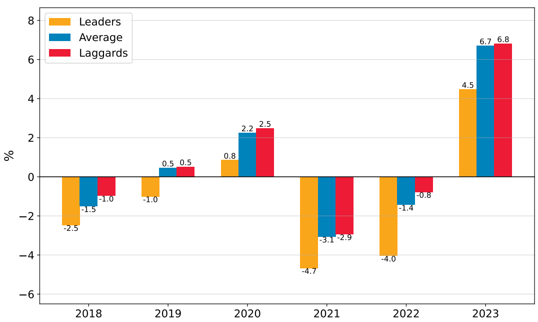
Figure C6: TFP growth. Sector H – Transportation and storage



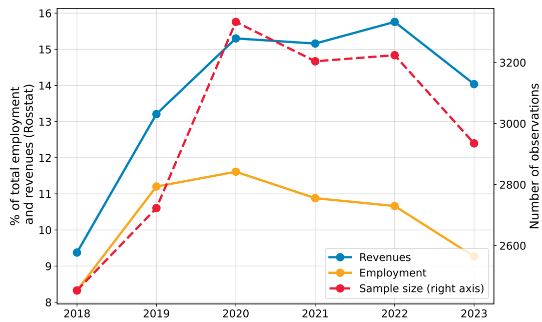
(a) TFP growth decomposition



(b) Labour productivity growth

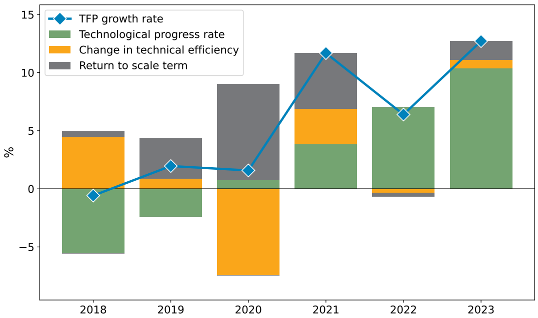


(c) Leaders and laggards

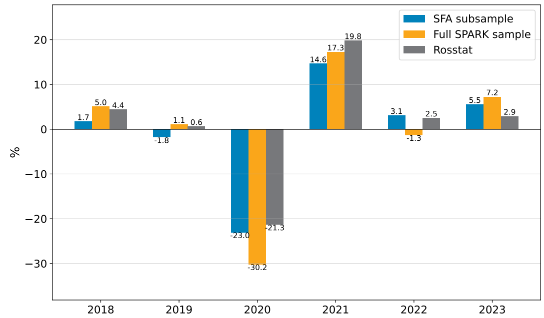


(d) Sample characteristics

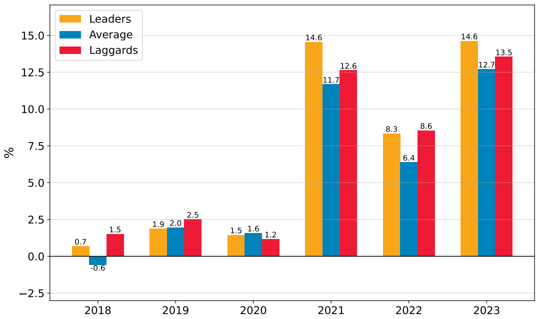
Figure C7: TFP growth. Sector I – Accommodation and food service activities



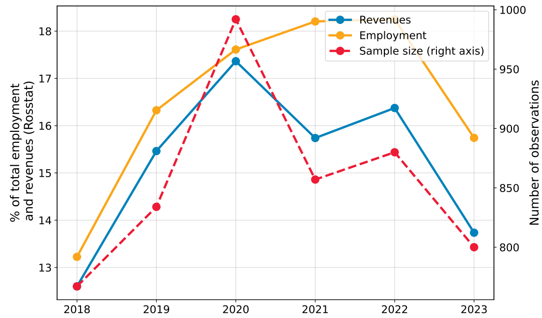
(a) TFP growth decomposition



(b) Labour productivity growth

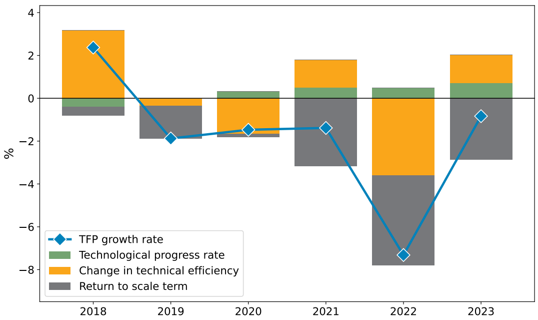


(c) Leaders and laggards

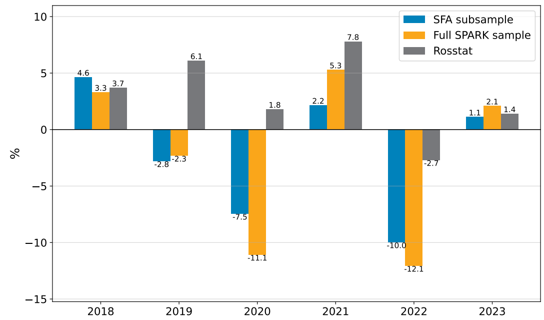


(d) Sample characteristics

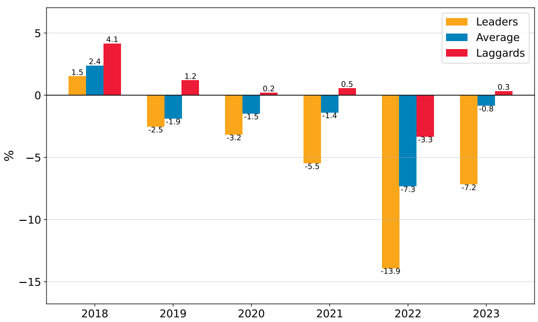
Figure C8: TFP growth. Sector J – Information and communication



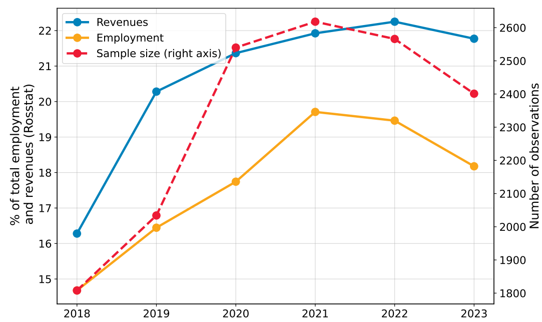
(a) TFP growth decomposition



(b) Labour productivity growth

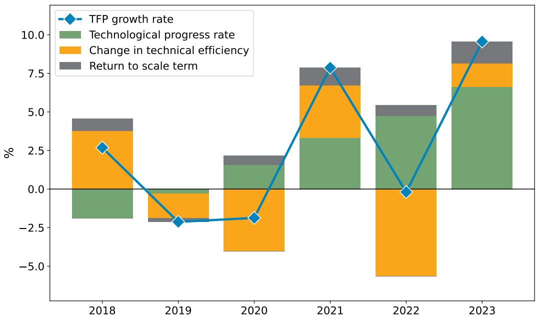


(c) Leaders and laggards

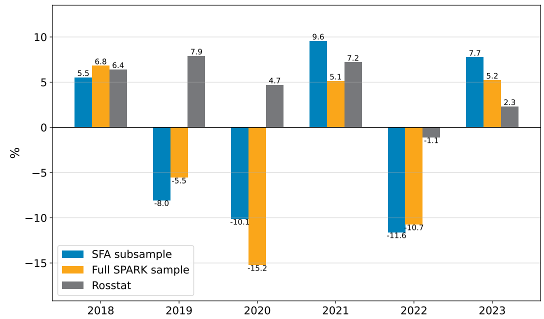


(d) Sample characteristics

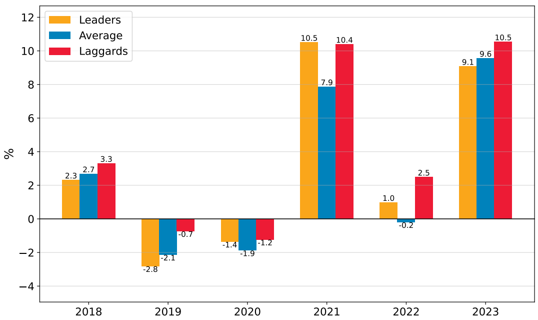
Figure C9: TFP growth. Sector M – Professional, scientific and technical activities



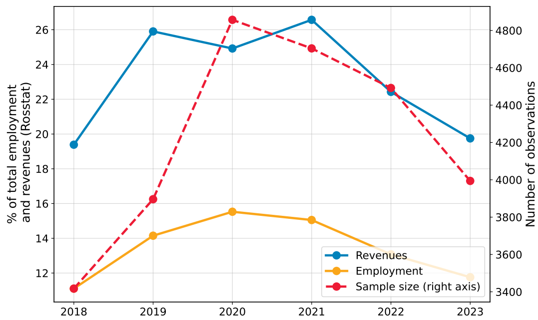
(a) TFP growth decomposition



(b) Labour productivity growth

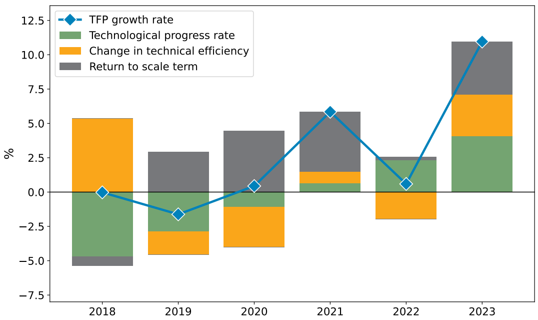


(c) Leaders and laggards

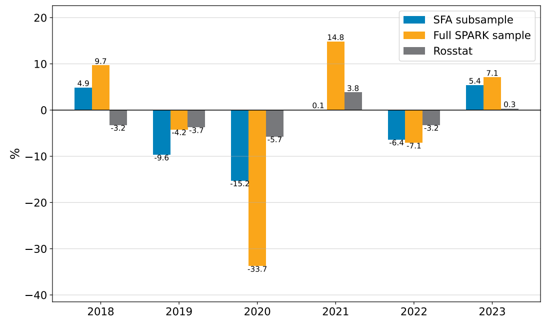


(d) Sample characteristics

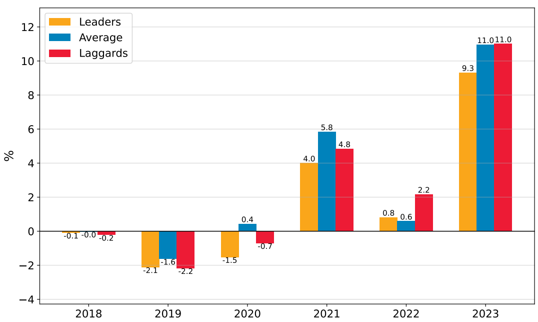
Figure C10: TFP growth. Sector N – Administrative and support service activities



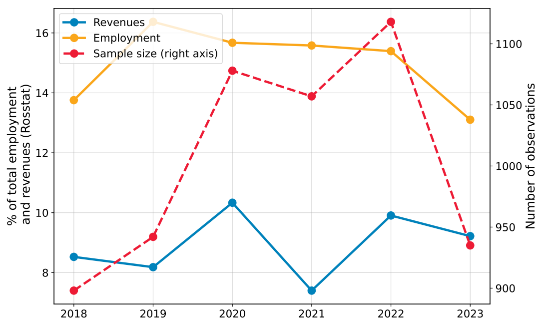
(a) TFP growth decomposition



(b) Labour productivity growth

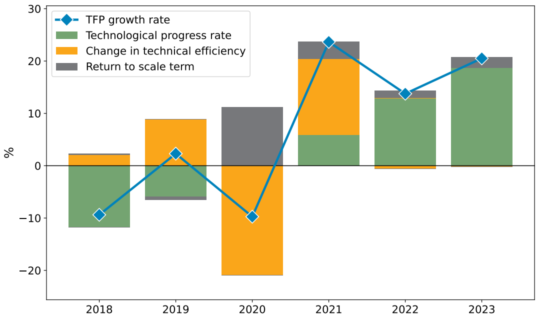


(c) Leaders and laggards

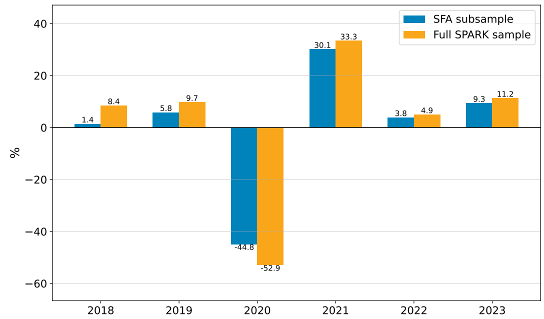


(d) Sample characteristics

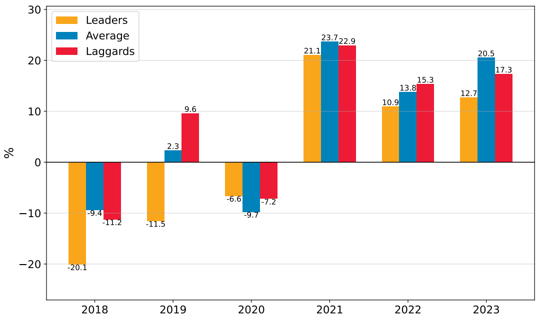
Figure C11: TFP growth. Sector R – Arts, entertainment and recreation



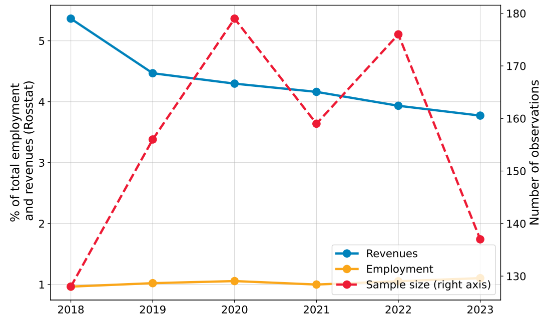
(a) TFP growth decomposition



(b) Labour productivity growth

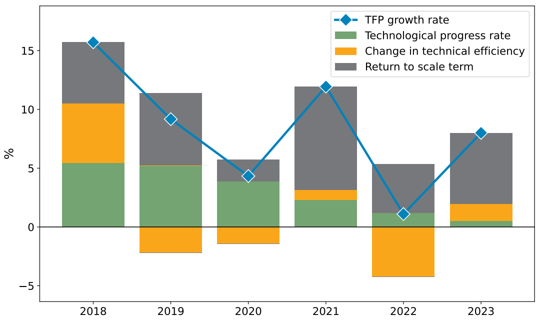


(c) Leaders and laggards

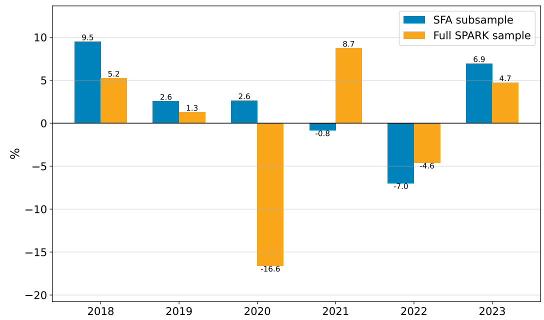


(d) Sample characteristics

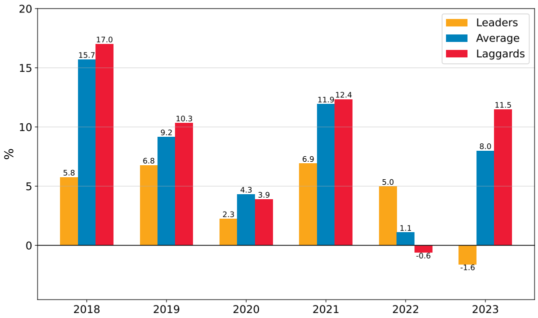
Figure C12: TFP growth. Sector S – Other service activities



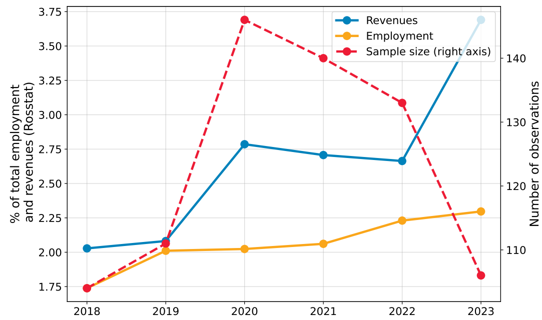
(a) TFP growth decomposition



(b) Labour productivity growth



(c) Leaders and laggards



(d) Sample characteristics

D TFP components derivation

This appendix presents the derivation of the TFP growth decomposition and its underlying assumptions, summarizing Chapter 8.2.1 from *Stochastic Frontier Analysis* by Kumbhakar and Lovell (2003).

TFP growth is defined as the rate of changes in output excluding the rate of changes in inputs (weighted by respective expenditure shares),[49] i.e.

$$T\dot{F}P = \frac{d\ln Y}{dt} - \frac{rK}{rK+wL}\frac{d\ln K}{dt} - \frac{wL}{rK+wL}\frac{d\ln L}{dt}$$

where r is the market rental price of capital K, and w is the market price of labour L.

$$\ln Y = \ln F(K,L,t) - u$$

$$\Rightarrow \quad \frac{d\ln Y}{dt} = \frac{\partial \ln F(K,L,t)}{\partial t} + \frac{\partial \ln F(K,L,t)}{\partial \ln K}\frac{d\ln K}{dt} + \frac{\partial \ln F(K,L,t)}{\partial \ln L}\frac{d\ln L}{dt} - \frac{\partial u}{\partial t}$$

Denote

$$\eta_K = \frac{\partial \ln F(K,L,t)}{\partial \ln K}, \quad \eta_L = \frac{\partial \ln F(K,L,t)}{\partial \ln L}, \quad \nu = \eta_K + \eta_L$$

η_K is capital elasticity of output, η_L is labour elasticity of output, and ν is the scale elasticity.

Substitute into TFP growth:

$$\begin{aligned}
T\dot{F}P &= \frac{\partial \ln F(K,L,t)}{\partial t} + \left(\eta_K - \frac{rK}{rK+wL}\right)\frac{d\ln K}{dt} + \left(\eta_L - \frac{wL}{rK+wL}\right)\frac{d\ln L}{dt} - \frac{\partial u}{\partial t} = \\
&= \frac{\partial \ln F(K,L,t)}{\partial t} + \left(\eta_K - \frac{\eta_K}{\nu} + \frac{\eta_K}{\nu} - \frac{rK}{rK+wL}\right)\frac{d\ln K}{dt} + \\
&\quad + \left(\eta_L - \frac{\eta_L}{\nu} + \frac{\eta_L}{\nu} - \frac{wL}{rK+wL}\right)\frac{d\ln L}{dt} - \frac{\partial u}{\partial t} = \\
&= \frac{\partial \ln F(K,L,t)}{\partial t} + (\nu-1)\frac{\eta_K}{\nu}\frac{d\ln K}{dt} + \left(\frac{\eta_K}{\nu} - \frac{rK}{rK+wL}\right)\frac{d\ln K}{dt} + \\
&\quad + (\nu-1)\frac{\eta_L}{\nu}\frac{d\ln L}{dt} + \left(\frac{\eta_L}{\nu} - \frac{wL}{rK+wL}\right)\frac{d\ln L}{dt} - \frac{\partial u}{\partial t} = \\
&= \underbrace{\frac{\partial \ln F(K,L,t)}{\partial t}}_{\dot{TP}} + \underbrace{(\nu-1)\left(\frac{\eta_K}{\nu}\frac{d\ln K}{dt} + \frac{\eta_L}{\nu}\frac{d\ln L}{dt}\right)}_{RTS} + \\
&\quad + \underbrace{\left(\frac{\eta_K}{\nu} - \frac{rK}{rK+wL}\right)\frac{d\ln K}{dt} + \left(\frac{\eta_L}{\nu} - \frac{wL}{rK+wL}\right)\frac{d\ln L}{dt}}_{T\dot{A}E} \underbrace{- \frac{\partial u}{\partial t}}_{\dot{TE}}
\end{aligned}$$

[49] In growth accounting, TFP growth is commonly defined with elasticities as weights (e.g. Hulten, 2010). The two definitions are equivalent under the assuptions of the constant return to scale and competitive markets.

Thus, TFP growth is split into the following components:

1. Technological progress
$$\dot{TP} = \frac{\partial F(K,L,t)}{\partial t}$$

2. Technical inefficiency
$$\dot{TE} = -\frac{\partial u}{\partial t}$$

3. Return to scale term
$$RTS = (\nu - 1)\left(\frac{\eta_K}{\nu}\frac{d\ln K}{dt} + \frac{\eta_L}{\nu}\frac{d\ln L}{dt}\right)$$

4. Allocative inefficiency component
$$T\dot{A}E = \left(\frac{\eta_K}{\nu} - \frac{rK}{rK+wL}\right)\frac{d\ln K}{dt} + \left(\frac{\eta_L}{\nu} - \frac{wL}{rK+wL}\right)\frac{d\ln L}{dt}$$

Allocative efficiency (with competitive capital and labour markets) implies

$$\frac{r}{p} = \frac{dY}{dK} = \frac{dF(K,L,t)}{dK}e^{-u} = F_K(K,L,t)e^{-u}, \quad \frac{w}{p} = \frac{dY}{dL} = \frac{dF(K,L,t)}{dL}e^{-u} = F_L(K,L,t)e^{-u},$$

by definition, elasticities are

$$\eta_K = \frac{F_K(K,L,t)K}{F(K,L,t)}, \quad \eta_L = \frac{F_L(K,L,t)L}{F(K,L,t)}$$

$$\Rightarrow \quad \begin{aligned} \frac{\eta_K}{\nu} &= \frac{F_K(K,L,t)K}{F_K(K,L,t)K + F_L(K,L,t)L} = \frac{rK}{rK+wL}, \\ \frac{\eta_L}{\nu} &= \frac{F_L(K,L,t)L}{F_K(K,L,t)K + F_L(K,L,t)L} = \frac{wL}{rK+wL} \end{aligned}$$

Since prices of inputs are not available in the data, we cannot calculate the allocative inefficiency component and therefore omit it, implicitly assuming that allocative efficiency holds: $T\dot{A}E \equiv 0$.