

Productivity Growth and Its Determinants

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Abstract: This study analyzes labor productivity, capital productivity, and total factor productivity at the sectoral level. The findings show that productivity growth in Mongolia has declined in recent years, with substantial differences across sectors. A detailed analysis of productivity in the mining sector, which has the greatest impact on economic growth, shows that the policy and regulatory environment, together with infrastructure and development investment directed toward the sector, exerts the most important influence. In addition, a stochastic frontier analysis based on microdata from coal-exporting companies shows that technological efficiency has made the main contribution to productivity growth over time.

JEL classification: D24, E22, E24

Keywords: Labor productivity, capital productivity, total factor productivity, economic sectors, principal component analysis, stochastic frontier analysis

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1. Introduction

Productivity measures the efficiency with which inputs such as labor, capital, and technology are transformed into output. Sustained productivity growth is a key factor in increasing real economic growth over the long term, enhancing the competitiveness of enterprises, raising individual incomes, and improving living standards and quality of life. However, many sources note that the challenges facing the global economy in recent years, including financial crises, pandemics, geopolitical tensions, and volatility in commodity prices, have slowed productivity growth across countries (World Bank 2021; Asian Development Bank 2020).

This study analyzes productivity in Mongolia at both the economy-wide and sectoral levels. Examining productivity at the economy-wide level provides information on the overall efficiency of the economy. Meanwhile, analyzing productivity across sectors is important for identifying differences in sectoral input sensitivities, technological resources and capacities, as well as labor market and policy-regulatory environments. Going forward, based on this information, it will be possible to identify potential directions for increasing sectoral productivity, allocate resources efficiently, and provide policymakers with the information necessary for optimal policy decisions. By improving the efficiency of low-productivity sectors, a foundation can be established for balanced and inclusive economic growth. Since an in-depth analysis covering economic sectors has not previously been conducted using Mongolia's quantitative data, this study makes a valuable contribution to productivity research.

Sectoral productivity is investigated by decomposing it into capital, labor, and total factor productivity components. While this study aims for broad coverage, data constraints necessitated a focused efficiency analysis exclusively within the mining sector. Consequently, the stochastic frontier analysis is restricted to this sector, serving as a pilot for future multi-sectoral productivity research. In Mongolia, the mining sector is not only of leading importance, but also faces an urgent need to optimize its efficiency and productivity due to limited resources, fluctuations in commodity prices, rising operating costs, and negative environmental impacts.

In terms of methodology, the analysis is conducted using traditional growth accounting methods, principal component analysis, and stochastic frontier analysis, based on macro- and micro-level statistical data covering the period 2004–2023.

The findings show that productivity growth in Mongolia has declined in recent years. These declines differ considerably across sectors of economic activity, with labor productivity being low in agriculture, education, and health, while capital productivity and total factor productivity are lowest in construction, electricity, and water supply. The sectors with the highest productivity growth are mining, real estate, finance and insurance, and professional scientific activities. These sectors make greater use of machinery, equipment, digital services, new technologies, and software. Over the past two decades, capital productivity has emerged as the primary driver of economic growth, despite experiencing a gradual decline during this period; labor productivity growth has remained positive but weak; and the contribution of total factor productivity (TFP) has been low but has shown an increasing trend, excluding periods of crisis and the pandemic.

Granular analysis of the mining sector indicates that productivity gains were positively correlated with surges in foreign direct investment, whereas a significant contraction occurred during the global pandemic. The policy and regulatory measures implemented in the sector, infrastructure investment, and the steady growth of technological efficiency have had a positive effect on productivity. However, rising prices of raw materials and inputs, including intermediate goods, wages, energy, and diesel, have reduced returns to scale, thereby exerting downward pressure on productivity.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the existing productivity literature, followed by a detailed explanation of the research methodologies in Section 3. The subsequent chapters describe the quantitative dataset (Section 4) and discuss the empirical results derived from the analysis (Section 5). Finally, Section 6 summarizes the findings and offers targeted policy recommendations.

2. Literature review

Recent studies by international organizations emphasize that productivity growth has slowed and remained below long-term averages due to economic and financial crises, pandemics, geopolitical fragmentation, and volatility in commodity prices (World Bank 2021; Asian Development Bank 2020). For example, labor productivity growth in advanced economies averaged 0.8 percent during 2013–2018, which was half the average recorded before the 2008 global financial crisis. This trend was observed in approximately 90 percent of advanced economies. In developing countries, by contrast, labor productivity growth peaked at 6.6 percent in 2007, but slowed after the financial crisis, declining to 3.5 percent in 2018, a pattern observed in more than 60 percent of developing economies (World Bank 2021). According to international organizations, Mongolia's labor productivity has been gradually increasing, but it remains below the levels observed in comparable countries (World Bank 2020a; Asian Development Bank 2020).

In addition to labor productivity, international studies place considerable emphasis on total factor productivity (TFP). In the years following the financial crisis, TFP growth also slowed globally and tended to make only a small or even negative contribution to economic growth (World Bank 2021). Recent studies likewise show that TFP growth has slowed in Mongolia. For example, the World Bank's 2020 report highlights that the negative contribution of TFP to Mongolia's economic growth over the past decade reflects the low productivity of natural resource-based growth (World Bank 2020b). Similarly, an analysis by Khulan and Bilguunzul (2024), using Mongolian quantitative data for 1986–2021, concludes that the contribution of TFP to economic growth has remained weak since 2010. The slowdown in productivity growth and its negative effect on economic growth are associated with the weak development and adoption of new technologies.

Studies on productivity in Mongolia show that capital made the main contribution to economic growth before the transition to a market economy, whereas total factor productivity became the main contributor after the transition (Cheng 2003; Altantsetseg 2018; Asian Development Bank 2020). However, over the past decade, the contribution of TFP has weakened, while the

contribution of capital productivity has increased again, as shown in the studies of the World Bank (2020a) and Khulan and Bilguunzul (2024).

A substantial body of international research has examined the causes of declining productivity growth and identified the factors affecting productivity (Diouf & Loko 2009; McGuckin & van Ark 2005; Poirson 2000). For example, Diouf and Loko (2009) used principal component analysis on panel data from Maghreb countries¹ to examine how average wages, inflation, government size, trade openness, and education levels affect TFP growth. Their findings show that reforms such as attracting foreign direct investment, optimizing the size of government, and reallocating resources from low-productivity sectors to high-productivity sectors accelerate TFP growth. In Mongolia, Munkhbayar (2018) used principal component analysis and a vector autoregressive model to analyze the determinants of productivity growth and showed that infrastructure, education, market efficiency, and innovation are the main drivers of productivity in Mongolia. However, the study concluded that the institutional environment does not exert a significant effect.

There are relatively few sector-level productivity studies based on Mongolia's quantitative data. Enerelt (2013) examined productivity in the agricultural sector using stochastic frontier analysis, while Khulan and Bilguunzul (2024) studied productivity in the energy sector. Internationally, it is common practice to analyze productivity in key sectors of the economy, such as industry, agriculture, and mining, using firm-level microdata. For example, Hosseinzadeh et al. (2016) studied productivity in Australia's mining sector, Kang and Kim (2018) examined productivity in China's industrial sector, Asgari (2019) analyzed productivity in Iran's industrial sector, and Battese and Coelli (1992) studied productivity in India's agricultural sector, particularly among rice farmers. The most commonly used methods in these studies are data envelopment analysis and stochastic frontier analysis. These methodologies have the advantage of allowing a more detailed examination of the causes of productivity growth and of measuring productivity separately from statistical noise. In summary, findings for Australia's mining sector suggest that technical and allocative efficiency are key factors in improving productivity (Ahmad 2023; Hosseinzadeh et al. 2016). In addition, Kang and Kim (2018) used a translog production model in China's industrial sector to decompose TFP into four main components: technological, technical, allocative, and scale efficiency. Their results conclude that technical efficiency positively affected TFP growth and accounted for the majority of growth, whereas scale efficiency negatively affected productivity growth.

¹ The countries of Morocco, Algeria, Tunisia, and the Sahel region are collectively referred to as the Maghreb countries.

3. Methodology

3.1 Measuring Productivity

Suppose that Mongolia's aggregate output is represented by the following traditional Cobb–Douglas production function.

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

Here, Y_t denotes real GDP, L_t denotes labor input measured by the number of employed persons, K_t denotes capital input measured by the stock of physical capital. A_t represents total factor productivity (TFP), which is defined as the residual of the Cobb–Douglas function. The stock of physical capital is defined by Equation (2), following the traditional capital accumulation framework employed in Black (2002) and Cheng (2003).

$$K_{t+1} = I_t + (1 - \delta)K_t \quad (2)$$

Here, I_t denotes real investment, δ represents the capital depreciation rate. Several studies suggest that a capital depreciation rate of 6 percent is appropriate for Mongolia (Cheng 2003; Altantsetseg 2018). When the depreciation rate is estimated separately for each economic sector, it is found to vary across sectors, with an average of 6.68 percent across all sectors, which is used in Equation (2).

Following Cheng (2003), the capital factor sensitivity coefficient (α) is estimated by dividing both sides of Equation (1) by L_t , taking logarithms, and then differencing the transformed values. The parameters of the transformed Equation (3) are subsequently estimated using the ordinary least squares (OLS) method.

$$\Delta \ln(y_t) = \mu + \alpha \Delta \ln(k_t) + \varepsilon_t \quad (3)$$

Here, $y_t = \frac{Y_t}{L_t}$ and $k_t = \frac{K_t}{L_t}$, denote output and capital per unit of labor, respectively, μ represents the average growth rate of total factor productivity (TFP), and ε_t is the error term of the model. Based on sectoral quantitative data, the parameters are estimated separately for each sector.

Although the concept of productivity is often defined in international studies in terms of total factor productivity (TFP), labor productivity and capital productivity are measured as output per unit of labor or capital ($\frac{Y_t}{L_t}$, $\frac{Y_t}{K_t}$), and their respective contributions to economic growth are subsequently calculated.

3.2 Principal component analysis

We use principal component analysis (PCA) to identify the factors affecting total factor productivity (TFP) in the mining sector. This method is a mathematical technique that reduces the dimensionality of the data by combining the common information contained in a large number of correlated variables and transforming them into a smaller number of new, mutually uncorrelated

variables. Each newly generated variable (component) is interpreted based on the contributions of the original variables. This method is implemented using a total of 10 variables grouped into 5 categories that are likely to affect TFP.

Specifically, foreign direct investment is used to represent the group of variables capturing technological progress that affects TFP; a dummy variable for changes in the policy and regulatory environment is used to represent the regulatory environment; labor force indicators are represented by real wages and the share of employees with higher education; infrastructure-related factors are represented by budgetary investment expenditure, air temperature, dummy variables for the COVID period, and changes in global oil prices, which constitute a major infrastructure-related cost; and demand-side market factors are represented by mining sector export volumes and average global economic growth. These variables are used in the principal component analysis.

3.3 Stochastic Frontier Analysis

Although productivity and efficiency are distinct concepts, the level of efficiency has a significant effect on productivity. Defining productivity as the residual of the Cobb–Douglas function implicitly relies on the assumptions of perfectly competitive markets, constant returns to scale, and firms operating at identical levels of technical efficiency (Kang & Kim 2018). These are highly restrictive assumptions in real markets, where firms operate at different levels of technical efficiency.

Therefore, a more detailed analysis is conducted to determine whether productivity growth is driven by changes in efficiency or reflects the nature of temporary shocks. This analysis is carried out using stochastic frontier analysis, based on firm-level microdata from large companies that are representative of the sector.

Following Battese and Coelli (1992), consider a panel model with a stochastic production function. This model is applied to an unbalanced panel dataset of N firms observed over T periods, assuming that firm-specific effects vary over time.

$$Q_{it} = f(x_{it}; \beta) \exp(V_{it} - U_{it}) \quad (4)$$

Here, Q_{it} denotes the level of output of firm i at time t ; x_{it} is a $1 \times k$ vector of production inputs; and $f(x_{it}; \beta)$ represents the functional form of the production function depending on x_{it} — where β is a $(k \times 1)$ vector of unknown parameters. The random error term V_{it} is assumed to follow a normal distribution $N(0, \delta_v^2)$ and is independent of U_{it} .

The term U_{it} which captures technical inefficiency, is a non-negative random variable following a truncated normal distribution $N(\mu_{it}, \delta^2)$ and varies over time.

$$U_{it} = \eta_{it} U_i = \{\exp[-\eta(t - T)]\} U_i \quad t \in T_i \quad i = 1, 2, \dots, N. \quad (5)$$

Here, η is an unknown scalar parameter, and when $\eta > 0$, the technical efficiency of firms improves over time. From Equations (4) and (5), the technical efficiency of firm i at time t is defined as:

$$TE_t \equiv E[\exp(-\eta_t U_i)] \quad \text{here, } \eta_t = \exp[-\eta(t - T)] \quad (6)$$

The parameters of the frontier model and technical efficiency are estimated simultaneously using the maximum likelihood (ML) method. The variance parameters of the ML function are defined as $\delta_S^2 = \delta_v^2 + \delta^2$ and $0 \leq \gamma = \frac{\delta^2}{\delta_S^2} \leq 1$, which makes it possible to identify the proportion of the total error variance attributable to technical inefficiency. In this study, two alternative production functions—Cobb–Douglas and translog—are selected as appropriate specifications for Equation (4) to evaluate the productivity of 20 companies operating in the coal market. In this study, two alternative production functions—Cobb–Douglas and translog—are selected as appropriate specifications for Equation (4) to evaluate the productivity of 20 companies operating in the coal market.

Cobb–Douglas production function:

For the following three-input Cobb–Douglas production function, logarithms are taken to obtain a linearized specification. Parameter estimation and efficiency analysis are then conducted using the maximum likelihood method with the FRONTIER 2 computer program developed by Coelli (1992).

$$\ln Q_{it} = \beta_0 + \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_M \ln M_{it} + \varepsilon_{it} \quad (7)$$

Here, L_{it}, K_{it}, M_{it} represent, respectively, the wage expenditure, accumulated capital, and intermediate input costs (such as inventories, operating expenses, fuel, and transportation costs) of firm i at time t . Output Q_{it} is approximated by the company's sales (export) revenue.

Translog production function:

As specified in Kang and Kim (2018), the translog production function makes it possible to decompose total factor productivity into four components. These are technological change (TC), technical efficiency change (TEC), returns to scale efficiency (RTSE), and allocative efficiency (AE), all of which are calculated based on the estimated parameters of the production function in Equation (8).

The translog production function is specified as:

$$\begin{aligned} \ln Y_{it} = & \alpha_0^i + \alpha_L^i \ln L_{it} + \alpha_K^i \ln K_{it} + \alpha_M^i \ln M_{it} + \alpha_A^i A_i \\ & + \frac{1}{2} \beta_{LL}^i (\ln L_{it})^2 + \frac{1}{2} \beta_{KK}^i (\ln K_{it})^2 + \frac{1}{2} \beta_{MM}^i (\ln M_{it})^2 + \frac{1}{2} \beta_{AA}^i (\ln A_{it})^2 \\ & + \beta_{LK}^i \ln L_{it} \cdot \ln K_{it} + \beta_{LM}^i \ln L_{it} \cdot \ln M_{it} + \beta_{LA}^i \ln L_{it} \cdot A_i \end{aligned}$$

$$+ \beta_{KM}^i \ln K_{it} \cdot \ln M_{it} + \beta_{KA}^i \ln K_{it} \cdot A_i + \beta_{MA}^i \ln M_{it} \cdot A_i - u + \epsilon \quad (8)$$

Here, A_i denotes the time trend, and the parameters are estimated using the maximum likelihood (ML) method.

The changes in technological and technical efficiency are obtained from the following equations:

$$TC_{it} = \widehat{\alpha}_A^t + \widehat{\beta}_{AA}^t A_{ti} + \widehat{\beta}_{LA}^t \ln L_{it} + \widehat{\beta}_{KA}^t \ln K_{it} + \widehat{\beta}_{MA}^t \ln M_{it} \quad (9)$$

$$TEC_{it} = -\frac{\theta u}{\theta t} \quad (10)$$

Returns to scale efficiency:

$$RTSE_{it} = (RTS - 1) \sum_j \lambda_j \dot{x}_j \quad (11)$$

where $RTS = \zeta_L^{it} + \zeta_K^{it} + \zeta_M^{it}$ is the sum of the input elasticities. Here, $\dot{x}_j$ denotes the change in input j , and $\lambda_j = \frac{\zeta_j}{RTS}$ is the marginal product share of input j . The input elasticities are calculated as:

$$\begin{aligned} \zeta_L^{it} &= \widehat{\alpha}_L^t + \widehat{\beta}_{LL}^t \ln L_{it} + \widehat{\beta}_{LK}^t \ln K_{it} + \widehat{\beta}_{LM}^t \ln M_{it} + \widehat{\beta}_{LA}^t A_i \\ \zeta_K^{it} &= \widehat{\alpha}_K^t + \widehat{\beta}_{KK}^t \ln K_{it} + \widehat{\beta}_{LK}^t \ln L_{it} + \widehat{\beta}_{KM}^t \ln M_{it} + \widehat{\beta}_{KA}^t A_i \\ \zeta_M^{it} &= \widehat{\alpha}_M^t + \widehat{\beta}_{MM}^t \ln M_{it} + \widehat{\beta}_{LM}^t \ln L_{it} + \widehat{\beta}_{KM}^t \ln K_{it} + \widehat{\beta}_{MA}^t A_i \end{aligned}$$

Allocative efficiency is calculated as:

$$AE_{it} = \sum_j (\lambda_j - S_j^a) \dot{x}_j \quad (12)$$

where $S_j^a = \frac{w_j x_j}{C}$ is the share of input j in total cost, and total cost is defined as $C = \sum_j w_j x_j$ that is, the sum of the products of inputs and their corresponding prices (w_j). From this, total factor productivity growth can be defined as:

$$TFP_{it} = TC_{it} + TEC_{it} + RTSE_{it} + AE_{it}$$

4. Data

The empirical analysis utilizes a constructed time-series dataset spanning 2004–2023, encompassing variables such as real GDP, gross fixed capital formation, the number of employed persons, and human capital. To ensure intertemporal comparability, nominal figures sourced from the National Statistics Office (NSO) were deflated into real terms using the implicit GDP deflator. Gross fixed capital formation is constructed in accordance with Equation (2) by reducing the previous year's capital stock by the depreciation rate and adding the investment flow of the current

year. The initial capital stock at the beginning of the sample period is approximated by the sum of private sector, government, and PPP capital reported by the International Monetary Fund (IMF). The number of employed persons is obtained by sector from NSO data, while human capital is calculated using the findings of Batchuluun and Dalkhjav (2014), who estimate that the level of education in Mongolia increases by an average of 0.12 years per year.

For the mining sector, time-series data covering 2000–2023 are constructed, comprising ten variables categorized into five primary determinants of productivity: technological progress, the regulatory environment, labor force conditions, infrastructure, and the market environment. These variables are sourced from the Bank of Mongolia’s external sector statistics, the NSO, and budget data from the Ministry of Finance.

The in-depth analysis of the mining sector utilizes annual financial reports, cash flow statements, and comprehensive income statements from the 20 largest enterprises ranked by coal export revenue over the period 2013–2023. Specifically, labor input is operationalized as the aggregate of personnel expenses, including wages, salaries, incentive payments, and social insurance contributions. Capital stock is proxied by the closing balance of non-current assets, while intermediate inputs are derived by subtracting total labor costs from aggregate operating expenses. Finally, output is measured by sales revenue as reported in the comprehensive income statements.

5. Empirical Results

5.1 Overview of economy-wide and sectoral productivity

Using the traditional growth accounting methodology, the dynamics of capital productivity, labor productivity, and total factor productivity were analyzed for Mongolia as a whole based on data for 2004–2023, and for 19 sectors based on data for 2010–2023. In doing so, capital accumulation was estimated for both the aggregate economy and each sector of economic activity in accordance with Equation (2), with sector-specific depreciation rates calculated separately for each sector. The aggregate depreciation rate of capital for the overall economy was estimated at 6.7 percent, which is close to the depreciation rates used in other comparable studies (Cheng 2003; Altantsetseg 2018). By sector, the highest capital depreciation rates were observed in mining at 9.3 percent and agriculture at 8.6 percent, while the lowest were in public administration at 4.1 percent and real estate at 5 percent (see Appendix 1 for details). In addition, the output sensitivities with respect to labor and capital were estimated for both the aggregate economy and each sector (see Appendix 2 for the results). For aggregate output, the sensitivity with respect to capital was estimated at 0.6, while the sensitivity with respect to labor input was 0.4. Across sectors, however, these sensitivities were estimated to vary considerably. In particular, the sectors with the highest capital sensitivity were real estate, construction, information and communication, mining, and transportation and storage, whereas the sectors with the highest labor input sensitivity were professional and scientific activities, agriculture, and finance and insurance.

Labor productivity

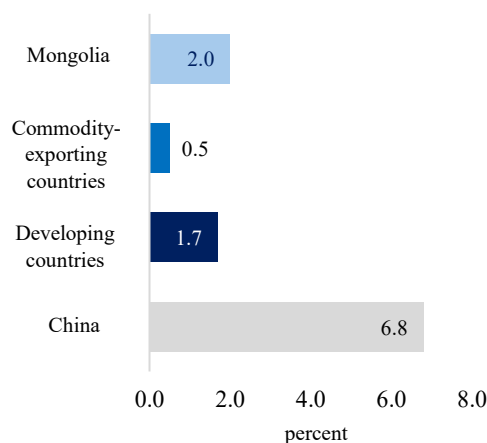
Mongolia's labor productivity, measured as the level of real output per unit of labor input, reached 2.2 in 2023, representing a twofold increase compared with its 2004 level (Chart 1). The growth of labor productivity has been highly volatile, and, excluding the sharp increase observed in 2019, the growth rate has shown a declining trend in recent years. While the average annual growth rate was 6 percent during 2004–2014, it declined to an average of 2 percent over the past 10 years. This remains high compared with the average of commodity-exporting and other developing countries, although it is lower than that of China (Chart 2) (World Bank 2020a).

Chart 1. Dynamics of labor productivity, 2004–2023



Source: Authors' calculations.

Chart 2. Average annual labor productivity growth across countries, 2013–2018, percent



Source: World Bank (2020a).

By sector (Chart 3), labor productivity is highest in mining and in finance and insurance, while it is lowest in agriculture, education, health, and service sectors such as arts. The high level of output per unit of labor in mining, finance, and insurance is associated with their high capital intensity and the strong adoption of technological progress. For example, in the mining sector, the use of various types of machinery and equipment results in high output per worker, while in finance and insurance, digital services and software increase labor productivity (Fleming & Measham 2015; McKinsey 2016). By contrast, sectors such as agriculture, health, education, and the arts tend to exhibit low labor productivity because they are highly labor-intensive, receive relatively low capital investment, and face greater difficulties in measuring output. This finding is also consistent with the results of other studies (Gollin et al. 2013).

For Mongolia, results-based budgeting has been introduced and implemented since 2021 with the aim of improving output measurement and productivity in the education and health sectors. Going forward, there is scope to increase productivity in these labor-intensive sectors by developing human resources through collaboration among the government, private institutions, universities, and vocational training schools to prepare personnel in line with market demand, raise educational attainment, and provide specialization in the required skills. In addition, the number of employed persons has declined in agriculture, while showing little growth in the health and education sectors

(Appendix 4). This suggests the need to examine and support, through policy measures, the possibility of setting differentiated minimum wages and wage growth across sectors in order to reduce constraints on intersectoral labor mobility and retain experienced personnel.

Chart 3. Labor productivity by sector

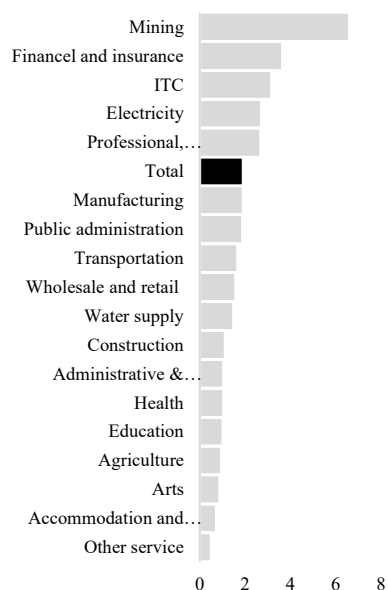


Chart 4. Capital productivity by sector

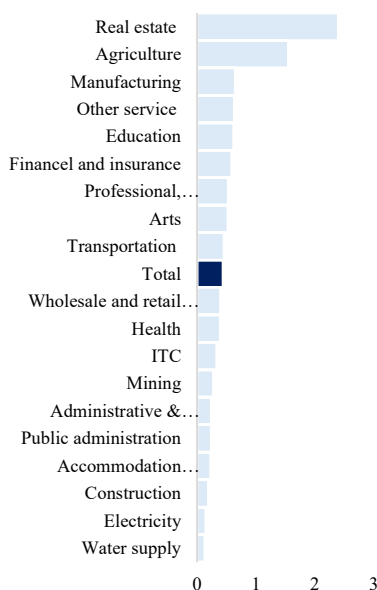
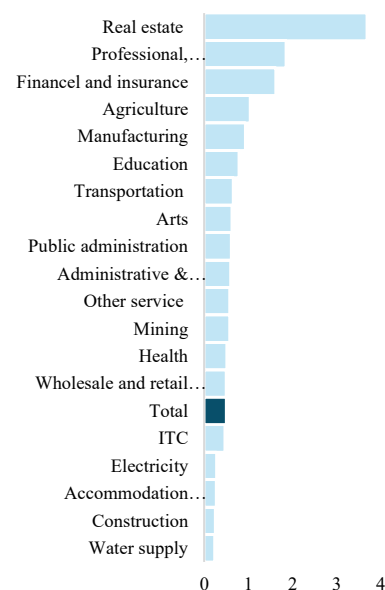


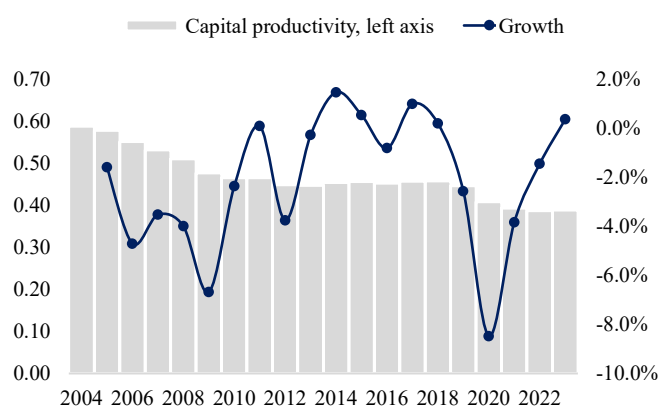
Chart 5. Total factor productivity by sector



Source: Authors' calculations.

Capital productivity

Chart 6. Dynamics of capital productivity, 2004–2023



Source: Authors' calculations.

five-year period (2013–2018). Although capital productivity declined sharply during the pandemic years, a recovery trend has been observed since 2023.

By sector, as of 2023, output per unit of capital is highest in real estate, agriculture, and manufacturing, while it is lowest in construction, electricity, and water supply (Chart 4). In the real estate sector, although direct investment is relatively limited, the rapid expansion of rental and real

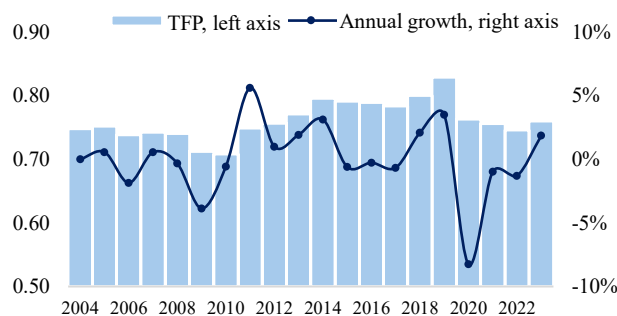
estate brokerage activities has contributed to higher output per unit of capital. In agriculture, investment and capital accumulation are generally low. Nevertheless, in recent years the government has placed particular emphasis on providing policy and financial support for food production, intensive livestock farming, and crop cultivation, which contributed to higher agricultural output in 2023. For example, under the “Food Supply and Security” program initiated by the President of Mongolia in 2022, budgetary financial support of MNT 223 billion was allocated in the 2023 budget. In addition, under this program, concessional financing to support agricultural production and tax policy support facilitated the adoption of new machinery, equipment, and technologies, thereby increasing output in the sector. In manufacturing, the removal of the meat export quota in 2023 boosted meat processing output, while increases in cement and metal product production also made important positive contributions to sectoral output growth.

By contrast, the construction, electricity, and water supply sectors use very high-cost equipment in their operations and require large-scale investment, but the returns on such investment do not materialize in the short term and do not immediately translate into higher output. In addition, the electricity and water supply sectors are characterized by a high degree of government regulation and are supplied to the market at below-cost prices, which may weaken private sector participation and competition and thereby reduce productivity.

Most foreign direct investment (FDI) inflows into Mongolia are concentrated in the mining sector, particularly in the form of capital investment. To achieve a more stable long-term increase in capital productivity at the aggregate economy level, policy support is needed to direct foreign direct investment toward sectors with weak capital productivity, such as water supply and electricity, in order to promote the adoption of innovation and advanced technologies.

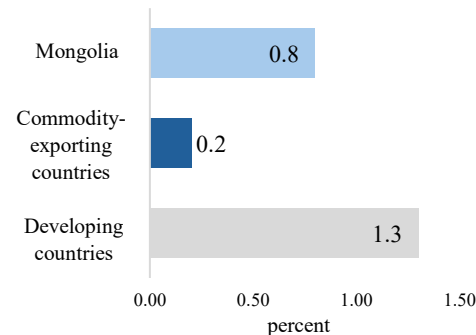
Total factor productivity

Chart 7. Dynamics of total factor productivity, 2004–2023



Source: Authors’ calculations.

Chart 8. Average annual growth of total factor productivity across countries, percent

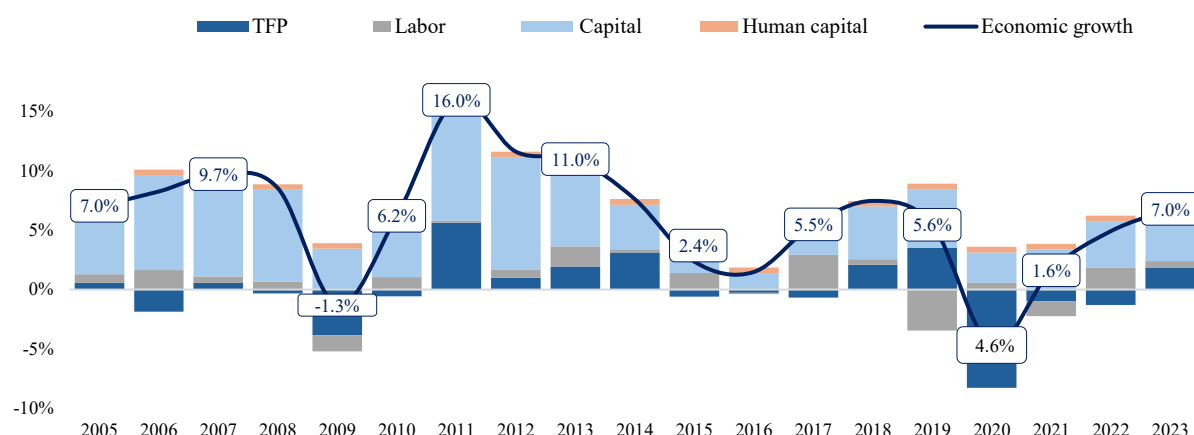


Source: World Bank (2020a).

Average total factor productivity growth over the past 10 years was 0.8 percent, which is higher than the 0.2 percent recorded for commodity-exporting countries, although it remains lower than

that of other developing countries (World Bank 2020a). Although total factor productivity growth declined sharply during the pandemic, it has increased in recent years and turned positive. By sector, total factor productivity is highest in real estate, professional scientific activities, and finance, while it is lowest in construction and water supply. The real estate, professional scientific, and financial sectors make extensive use of technological progress and innovation, resulting in stronger output growth driven by factors other than labor and capital. The factors affecting total factor productivity are examined in greater detail in Section 5.2.

Chart 9. Economic growth by factor contributions

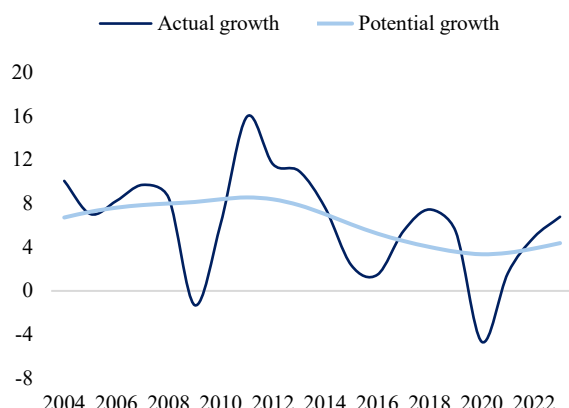


Source: Authors' calculations.

Decomposing economic growth into the contributions of capital, labor, and total factor productivity shows that capital has made the largest contribution over time. The contribution of labor has generally remained positive but weak. Excluding the periods of the global financial crisis and the pandemic, the contribution of total factor productivity to economic growth has increased compared with the early 2000s. These findings are consistent with the results reported in the recent study by Bilguunzul and Khulan (2024), which is based on the latest available quantitative data.

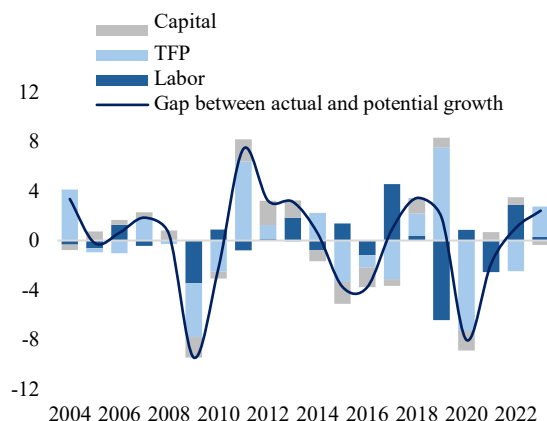
The contribution of capital to economic growth averaged around 6 percent during 2005–2015, but declined by half to around 3 percent during 2016–2023, mainly due to lower investment during the pandemic years. The contribution of total factor productivity averaged -0.9 percent during 2005–2010, but increased to 2.2 percent during 2011–2015, reflecting the sharp rise in foreign direct investment in the mining sector during these years, which facilitated technological progress and the adoption of innovation, thereby increasing productivity. However, during 2016–2023, the average contribution of total factor productivity growth declined to -0.5 percent. This was associated with weaker economic production and activity caused by pandemic lockdowns, border restrictions, domestic and external uncertainty, and natural disasters such as dzud.

Chart 10. Mongolia's actual and potential real economic growth



Source: Authors' calculations.

Chart 11. Factor contributions to the gap between actual and potential growth



Source: Authors' calculations.

The contributions of labor, capital, and total factor productivity (TFP) to the gap between actual and potential economic growth were estimated. As shown in Chart 9, the majority of this gap is explained by total factor productivity, which provides a basis for further detailed analysis of TFP.

5.2 Mining sector

Over the past 10 years, the mining sector alone has accounted for an average of 24 percent of GDP, while the related transportation and trade sectors have contributed an average of 15 percent of GDP. Growth in this sector affects the performance of other sectors both directly and indirectly and constitutes the largest share of overall economic growth. Over the past three years, coal production and the output of copper and molybdenum concentrate (43 percent) have emerged as the dominant components of the mining sector, accounting for 26 percent and 43 percent of the total sectoral production, respectively.

To provide a more granular assessment of productivity dynamics, this study focuses on the coal mining subsector as a representative case. The selection is justified by its dominant contribution to total mining output and the availability of robust firm-level microdata, which facilitates a more rigorous efficiency analysis.

Chart 12. Dynamics of labor productivity in the mining sector

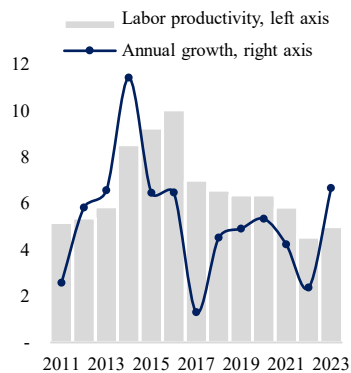


Chart 13. Dynamics of capital productivity in the mining sector

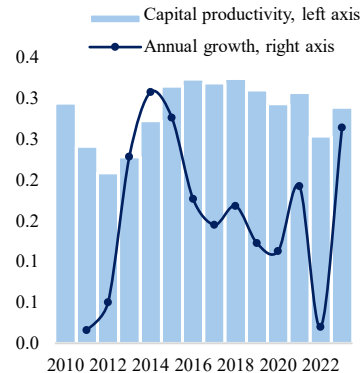
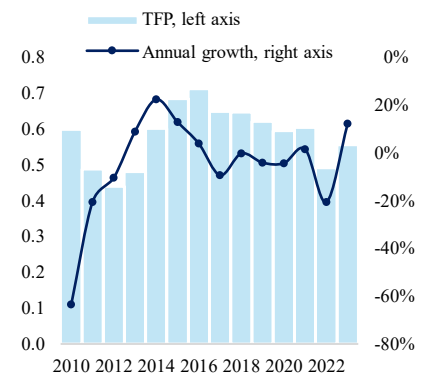


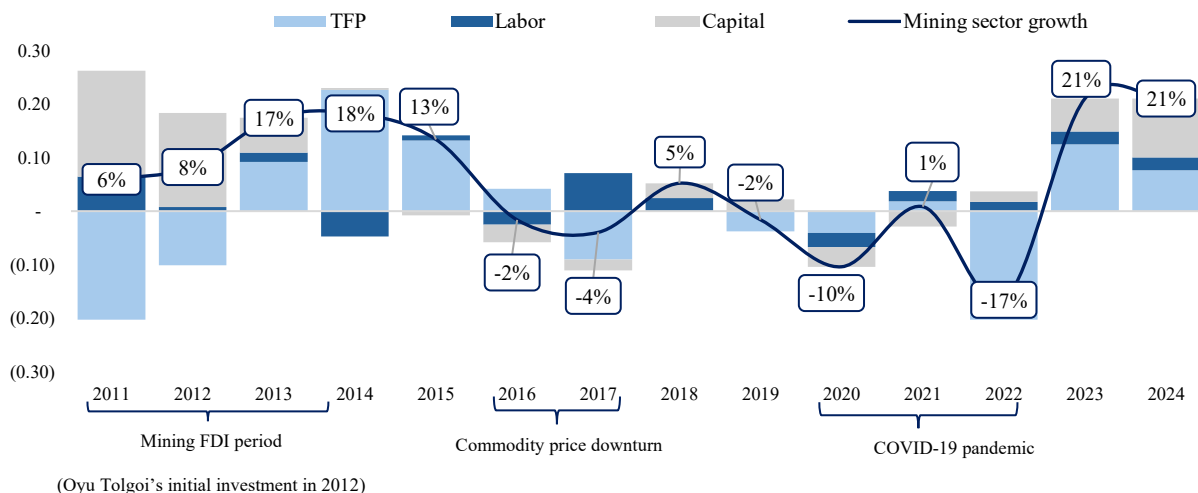
Chart 14. Dynamics of total factor productivity in the mining sector



Source: Authors' calculations.

The dynamics of labor productivity, capital productivity, and total factor productivity in the mining sector show that all three measures reached their highest levels during 2014–2016, following the surge of foreign direct investment inflows observed from 2011 to 2013 within the sector. As foreign direct investment in Oyu Tolgoi began to decline from 2014 onward, labor productivity in the sector also began to fall substantially, while capital productivity remained at a relatively high level. In 2022, the sector contracted by 15 percent due to external factors, including border restrictions resulting from China's "Zero-COVID" policy, leading to declines in labor productivity, capital productivity, and total factor productivity. As the sector began to recover from 2023 onward, all three productivity measures also improved.

Chart 15. Growth dynamics in the mining sector by factor contributions



Source: Authors' calculations.

Decomposing growth in the mining sector into the contributions of labor, capital, and total factor productivity shows that the majority of sectoral growth is explained by total factor productivity.

Between 2011 and 2013, a period characterized by significant foreign direct investment inflows, economic growth was primarily driven by capital accumulation, while total factor productivity emerged as the leading contributor during the subsequent 2014–2015 period. From 2015 onward, foreign direct investment in Oyu Tolgoi declined, and the emergence of turmoil in global commodity markets during 2016–2017 further slowed growth in the sector. During 2020–2022, the sector experienced a substantial contraction due to border restrictions caused by the COVID-19 pandemic, but it has shown signs of recovery since 2023.

5.2.1 Principal component analysis results

In this section, we identify the factors affecting total factor productivity in the mining sector using principal component analysis. International studies often attempt to explain productivity through indicators such as technological progress, infrastructure, and market conditions. For example, Azadeh et al. (2005) used indicators of technological progress and market conditions, while Munkhbayar (2018) employed indicators of technological progress, infrastructure, and market conditions to analyze their effects on productivity using principal component analysis.

In this study, in addition to these indicators, labor force and policy-regulatory factors are included, and the analysis is conducted using a total of 10 variables representing five groups of factors. The results are presented in Table 1. The table reports the simple correlation coefficients between total factor productivity and the variables, together with the first five eigenvectors from the principal component analysis. Based on the principal component test criteria and the gaps between eigenvalues, the optimal number of components is selected as five, which together explain approximately 86 percent of the total variance (Appendix 5).

Table 1. Results of the principal component analysis

Category	Variable	Correlation coefficient	PC 1	PC 2	PC 3	PC 4	PC 5
Technological progress	Productivity growth	1.0	0.47	0.01	0.01	-0.27	-0.06
	FDI stock	0.25	0.24	0.41	0.18	0.42	-0.05
Regulatory environment	Policy regulation	0.75	0.50	-0.17	0.03	-0.11	-0.01
Labor force	Real wages	0.17	0.23	-0.27	-0.03	0.33	0.77
	Share of employees with higher education	0.22	0.26	-0.1	0.47	0.32	-0.36
Infrastructure	Infrastructure expenditure (mining + roads and bridges)	0.34	0.24	-0.35	0.07	0.35	-0.05
	Average air temperature	0.44	0.25	0.43	-0.02	-0.27	0.41
	COVID-period dummy	-0.32	-0.16	0.42	-0.05	0.48	0.07
	Global oil prices	-0.53	-0.37	0.07	0.50	0.01	0.24
Market demand	Mining sector exports	0.46	0.29	0.47	0.03	-0.08	-0.09
	Global GDP growth	0.08	-0.03	-0.03	0.7	-0.31	0.15

Source: Authors' calculations.

The correlation analysis shows that the policy and regulatory environment², infrastructure-related expenditure, and mining sector exports have strong positive effects on productivity growth in the mining sector, whereas increases in global oil prices negatively affect productivity by raising input costs.

Component 1 exhibits the strongest positive correlation with total factor productivity. Notably, fluctuations in the policy and regulatory environment account for 25 percent³ of the variance within this component. To optimize export performance and strengthen corporate governance, the Government of Mongolia introduced a special operating regime for Erdenes Tavan Tolgoi LLC in 2022, appointing a plenipotentiary representative to oversee the company's operations and governance. Furthermore, policy changes were implemented, including the initiation of exchange-based sales of mining products. As a result, while the mining sector contributed an average of 14 percent to economic growth during 2018–2022, its contribution increased to as much as 36.7 percent in 2023. This indicates that the policy changes implemented in Mongolia have had a positive effect on both Component 1 and productivity. Going forward, it would be appropriate to implement policy and regulatory measures aimed at increasing productivity in the mining sector, such as creating a favorable legal environment for foreign direct investment, selling coal through the mining exchange under flexible pricing arrangements, and introducing secondary market trading.

While empirical literature utilizing principal component analysis to estimate mining productivity remains limited, a broad consensus exists among studies employing alternative methodologies that technological advancement acts as a primary catalyst for productivity growth (Ahmad 2023; Hosseinzadeh et al. 2016). The results of our study are consistent with this finding, as fluctuations in foreign direct investment explain the majority of the variance in Components 1–4. With the launch of the Oyu Tolgoi mining project in 2011, foreign direct investment inflows increased substantially, reaching USD 5.7 billion and USD 5.2 billion in 2011 and 2012, respectively. Since then, financing related to the Oyu Tolgoi project alone has averaged USD 2.8 billion per year. In the coming years, foreign direct investment inflows are expected to increase further in connection with the 14 mega-projects planned by the Government of Mongolia, including the recently signed agreement for the Orano Mining uranium extraction project, which is expected to have a positive effect on productivity in the mining sector.

For Component 2, in addition to the technological progress variable, the infrastructure-related variables and the export volume of the mining sector explain approximately 90 percent of the total variance. For Component 3, global oil prices and the share of employees with higher education in the mining sector are of particular importance, together explaining around 50 percent of the total variance.

² The dummy variable representing the policy and regulatory environment is constructed using the years in which amendments were made to the investment law governing the mining sector and other sector-related legislation.

³ The values reported in the table can be squared and expressed as the proportion of the total variance explained.

The component 4 is primarily characterized by infrastructure related variables, with a notably high factor loading on the dummy variable representing COVID-19 pandemic. Regarding Component 5, fluctuations account for approximately 60 percent of its total variance.

5.2.2 Stochastic frontier analysis results

Based on panel data for the 20 largest coal-producing and exporting companies over the past 10 years, Equation (4) is estimated using the maximum likelihood method, and the productivity analysis is conducted using two alternative production function specifications: Cobb–Douglas and translog.

Results of the Cobb–Douglas production function

Using the generalized likelihood ratio (LR) statistic, the null hypotheses of half-normal distribution and time-invariant efficiency—both commonly applied to the distribution of the efficiency term—are tested and rejected for our dataset (Appendix 6). Therefore, the estimation incorporates more flexible assumptions in which firm-level efficiency is allowed to vary over time and the distribution of technical efficiency follows a truncated normal distribution bounded below at zero. The results are presented in Table 2.

The estimation results show that the sensitivities of inputs such as labor and intermediate goods are positive and statistically significant. In particular, changes in intermediate inputs appear to have a strong effect on output, which is consistent with theoretical expectations as well as with the findings of productivity studies in the mining sectors of Australia and Indonesia (Topp et al. 2008; Bloch & Metcalfe 2015). By contrast, the sensitivity of capital input is positive but small in magnitude and is estimated to be statistically insignificant.

Approximately 74 percent of the total variance of the model error is explained by efficiency-related variation, indicating that separating efficiency effects is important in analyzing production productivity in the mining sector. In other words, productivity in the sector is not entirely driven by random fluctuations. In addition, the estimated coefficient of the variable capturing time variation is positive and statistically significant. This suggests that firms' efficiency levels tend to improve over time as a result of technological change, which has a positive effect on total output, consistent with the Hicks-neutral technological change hypothesis.

Table 2. Results of the Cobb–Douglas production function

	Estimate	Standard deviation	Pr(> z)
Intercept	0.91	0.73	0.21
log(Capital)	0.06	0.08	0.47
log(Labour)	0.21	0.1	0.04
log(Intermediate good)	0.78	0.1	0.00
sigmaSq	3.81	1.49	0.01
gamma	0.74	0.11	0.00

mu	-3.37	2.27	0.14
time	0.09	0.02	0.00
Log likelihood		-226.8	

Source: Authors' calculations.

The dynamics of firm-level efficiency, compared with the sectoral average, are illustrated in Chart 16. The average level of efficiency in the sector increased from 40 percent in 2013 to 74 percent in 2023, representing a 34 percentage point increase over the past 10 years. While there were considerable differences in efficiency levels across firms in 2013, companies that were initially below the sectoral average experienced faster growth, showing a tendency to converge toward the sectoral average over time. In addition, Chart 15 compares the 2023 input and output levels of coal companies in the sector with their potential production frontier, that is, the maximum output that could be produced given the existing level of inputs⁴.

Chart 16. Dynamics of firm-level efficiency

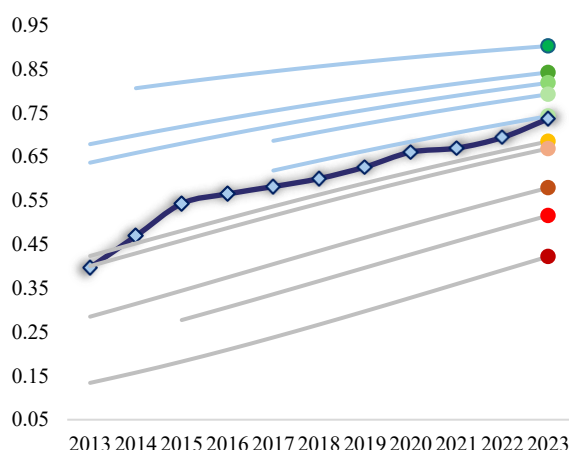
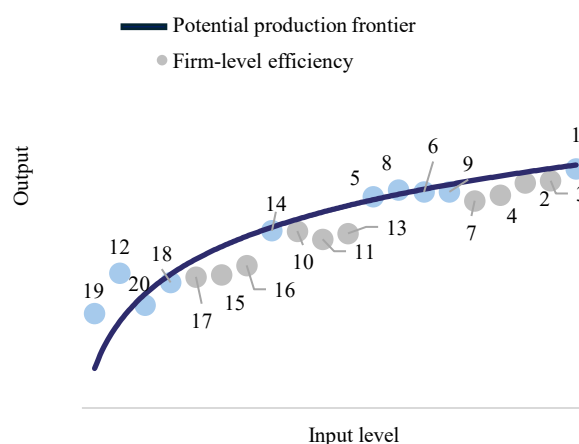


Chart 17. Firms' production levels



Эх сурвалж: Судлаачдын тооцоолол

As of 2023, 50 percent of all enterprises operated at or near the sector's potential production frontier, while the remaining 50 percent operated below potential. Firms operating below potential were, on average, approximately 30 percent less efficient than the potential production level.

Results of the translog production function estimation

The estimation results of the translog model specified in Equation (8) are presented in Appendix 7. The estimation shows that the input sensitivities are positive and larger in magnitude compared with those obtained from the Cobb–Douglas production function. However, the sensitivity of capital input remains statistically insignificant. Under this specification, 84 percent of the total variation in productivity can be explained by efficiency-related variation, which is further decomposed into four types of efficiency as shown in Equations (9)–(12).

⁴ In accordance with the Law on Corporate Secrets of Mongolia, company names are replaced with numerical identifiers in order to preserve business confidentiality.

Box 1 defines these efficiency measures and explains them with examples, while Chart 18 presents their shares in total productivity together with the dynamics of their changes over time. As shown in the chart, **technological change (TC)** has had a positive effect on productivity over time and has made the dominant contribution to growth. This result is consistent with the findings of Coelli et al. (2005), which identify technological change as the main driver of long-term production growth. In addition, international studies on mining sector productivity suggest that, because capital plays a large role in mining production, technical and technological change has the strongest influence on productivity (Humphreys 2001; Tilton & Landsberg 1997).

Box.1

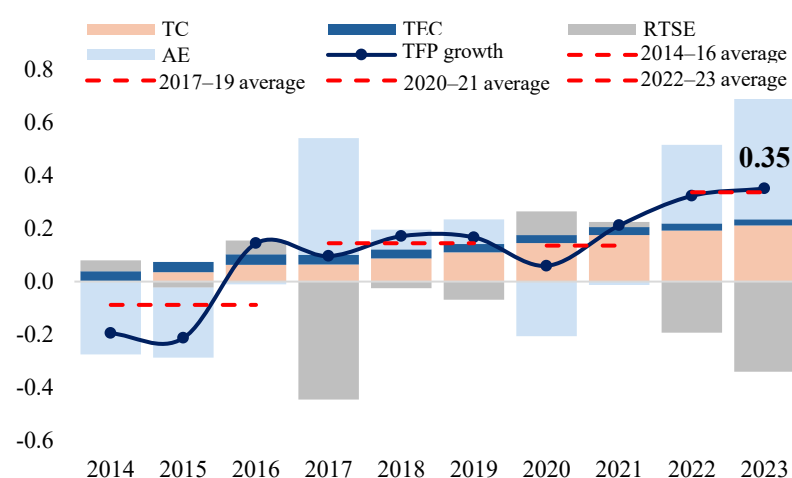
Technological efficiency refers to the efficiency gains generated through the adoption of new technologies, tools, methods, and techniques that make it possible to produce more output with the same or fewer inputs. Examples include automation, new machinery, improved production methods, and innovative products, all of which enhance productivity over the long term.

Technical efficiency measures the extent to which actual production deviates from the maximum possible output that can be produced with a given level of inputs. For example, productivity can be improved in the short to medium term by reducing waste and cutting unnecessary costs.

Scale efficiency is expressed as the relationship between the growth of production inputs and the growth of output. For example, if the growth of inputs exceeds the growth of output, the returns to scale will negatively affect productivity.

Allocative efficiency refers to the optimal allocation of inputs such as labor, capital, and intermediate goods in order to maximize total production. This efficiency can be improved by eliminating excesses or shortages of resources and allocating them in the most optimal way based on productivity indicators.

Chart 18. Decomposition of productivity growth



Source: Authors' calculations

By contrast, changes in **technical efficiency (TEC)** are positive and stable, although relatively small in magnitude. Therefore, further improvements in TEC can be achieved through measures such as optimizing the combination of production inputs, enhancing workers' skills, improving resource management, and increasing automation.

Scale efficiency (RTSE) had a negative effect on productivity growth in 2017, 2022, and 2023. In these years, output growth in the coal sector was unable to keep pace with the sharp increase in

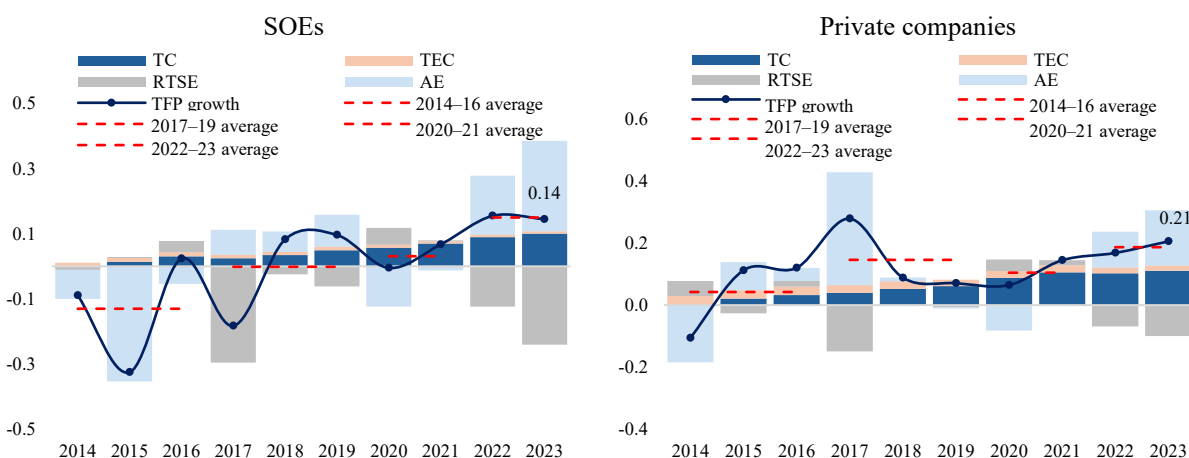
inputs, resulting in lower scale efficiency. Specifically, in 2017, the average capital stock of the 20 coal companies in our sample increased fourfold, while intermediate input costs increased fivefold. In 2022, the average wage cost of companies doubled, intermediate input costs also doubled, the average sectoral wage in mining increased by 20 percent, electricity tariffs rose by 16 percent, and diesel prices increased by more than 40 percent, all of which sharply increased total input costs. In 2023, the average wage cost of companies increased fourfold, intermediate input costs tripled, while the average wage in the mining sector rose by 27 percent, electricity tariffs by more than 30 percent, and diesel prices by 10 percent, further driving up total input costs.

Allocative efficiency (AE) made the dominant contribution to productivity growth over the past two years. During these years, reforms in the management of state-owned enterprises, the introduction of exchange-based trading of mining products, and increases in the capacity of border crossings may have positively affected productivity growth through improvements in allocative efficiency

To illustrate the time dynamics, the average growth of total productivity was measured over two- to three-year intervals and shown in the chart with a dashed line. This indicates that the pace of productivity growth in the mining sector has increased consistently. For example, the average productivity growth of coal mining enterprises was 0.03 during 2014–2019, but increased eightfold to 0.24 during 2020–2023.

The dynamics of productivity growth in private and state-owned companies operating in the coal mining sector are compared in Chart 19.

Chart 19. Decomposition of productivity growth by ownership type



Source: Authors' calculations.

Although productivity growth is observed in both ownership groups, the productivity growth of state-owned enterprises improved sharply in the post-COVID years compared with earlier periods. Allocative efficiency made the dominant contribution to this increase. From 2023 onward, management reforms in state-owned companies, including improvements in corporate management and the introduction of exchange-based trading of mining products, may have contributed to higher allocative efficiency.

Although technological change has had a positive effect on productivity growth over time, its contribution remains lower in state-owned enterprises compared with private companies. This suggests that state-owned companies still have room to upgrade their technology and establish more stable long-term productivity growth.

The contribution of technical efficiency to productivity in state-owned coal companies is about half that of private companies and has shown a declining trend over time. Therefore, measures such as reducing waste, creating a more optimal combination of inputs, and identifying ways to generate greater output with the existing level of production inputs are necessary to improve technical efficiency.

For both state-owned and private companies, scale efficiency negatively affected productivity growth in 2017, 2022, and 2023, although the negative effect was stronger in state-owned enterprises. Going forward, scale efficiency can be improved through measures such as cutting unnecessary expenses, substituting inputs with lower-cost alternatives, and, where reducing input costs is not feasible, improving technical efficiency at the current level of inputs.

6. Conclusion

This study makes a distinctive and comprehensive contribution to the existing literature on the Mongolian economy by providing multi-dimensional analysis of sectoral productivity. Specifically, it identifies key growth determinants and offers a granular efficiency assessment of the coal-exporting sector, filling a significant research gap in the local context.

The findings show that productivity growth in Mongolia has declined in recent years. These declines differ considerably across sectors of economic activity, with labor productivity being lowest in agriculture, education, and health, while capital productivity and total factor productivity are lowest in construction, electricity, and water supply. Most of the low-productivity sectors are characterized by strong government regulation and state involvement. In these sectors, it is necessary to increase private sector participation through price liberalization, reduce government intervention by lowering subsidies and support measures, and implement reforms aimed at improving the efficiency and productivity of state-owned enterprises. The sectors with the highest productivity growth are mining, real estate, finance and insurance, and professional scientific activities. These sectors make greater use of machinery, equipment, digital services, new technologies, and software.

In terms of contributions to economic growth, capital productivity has made the largest contribution over the past 20 years, although it has shown a declining trend. Labor productivity growth has remained positive but weak, while the contribution of total factor productivity has been relatively low but has shown an upward trend, excluding the periods of crisis and the pandemic.

An in-depth analysis of the dynamics and drivers of total factor productivity is carried out with a particular emphasis on the mining sector. The results of the principal component analysis show

that the policy and regulatory environment, together with infrastructure and development investment directed toward the sector, exerts the most important influence on productivity in the mining sector. Further decomposing total factor productivity into four types of efficiency measures shows that technological change has had a positive effect on productivity over time and has made the dominant contribution to total factor productivity growth in the mining sector. By contrast, increases in the prices of raw materials and inputs, including intermediate goods, wages, energy, and diesel, have negatively affected total factor productivity through lower scale efficiency.

In addition, productivity growth in the mining sector is analyzed separately for private and state-owned companies. Over the past two years, the sharp increase in productivity growth among state-owned enterprises compared with earlier periods is associated with improvements in allocative efficiency resulting from management reforms, the introduction of exchange-based trading for mining products, and expanded capacity at border crossings. Going forward, it would be appropriate to further strengthen management reforms in state-owned enterprises, continue the sale of coal through the mining exchange under flexible pricing arrangements, and improve policy and regulatory measures by introducing secondary market trading.

However, compared with private companies, state-owned enterprises still exhibit considerably lower levels of technical and technological efficiency. Therefore, to sustain and improve productivity growth over the long term, it is necessary for state-owned enterprises to upgrade their technology, reduce waste in order to increase output from the currently utilized inputs, and correctly determine the optimal combination of inputs.

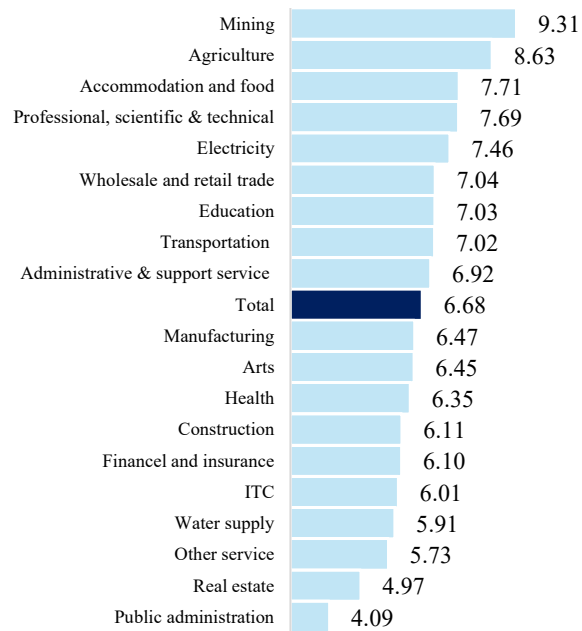
Future research should prioritize the application of this efficiency analysis to underperforming sectors, including electricity and water supply. Identifying the specific bottlenecks within these critical utilities is essential for developing robust strategies to bridge productivity gaps.

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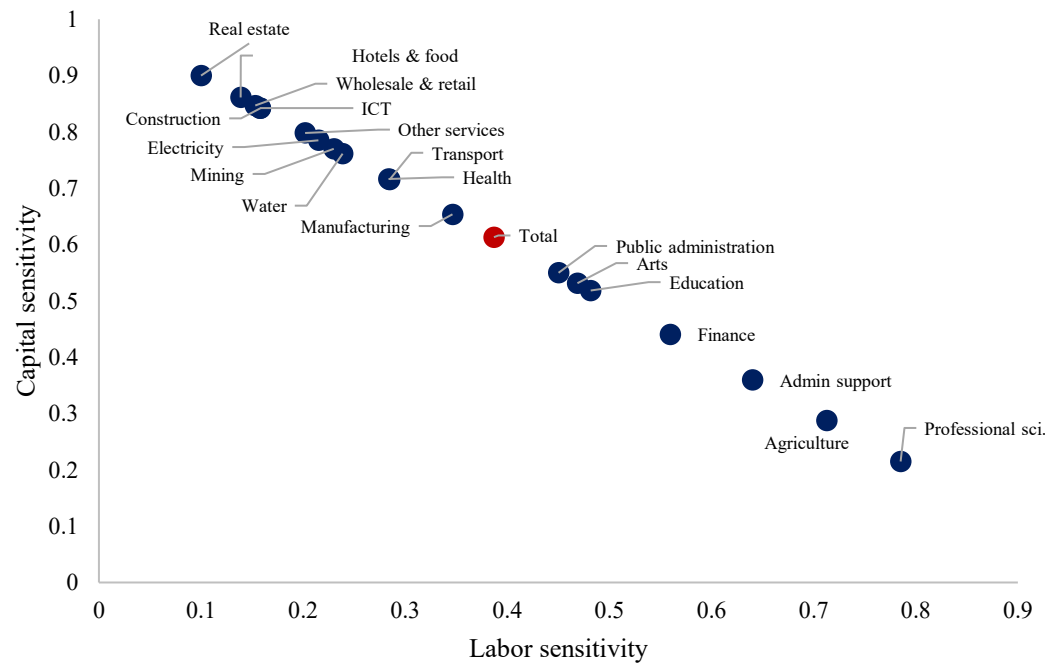
APPENDIX

Appendix 1. Depreciation rates by sector



Source: Authors' calculations.

Appendix 2. Labor and capital sensitivities by sector



Source: Authors' calculations.

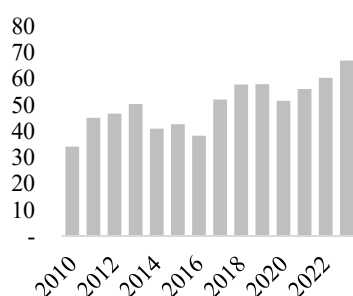
Appendix 3. Growth and decomposition across 19 economic sectors

No.	Sector	Average real growth, 2011–2023	Contribution to average economic growth			
			Labor	Capital	TFP	Human capital
1	Agriculture	6.0%	-1.5%	4.3%	2.3%	0.9%
2	Mining	4.3%	1.2%	3.4%	-0.6%	0.3%
3	Manufacturing	5.8%	1.6%	8.5%	-4.8%	0.4%
4	Electricity, gas, steam, and air conditioning	5.6%	0.6%	1.9%	2.9%	0.3%
5	Water supply	0.6%	0.3%	3.0%	-3.0%	0.3%
6	Construction	6.4%	0.6%	9.0%	-3.3%	0.2%
7	Wholesale and retail trade	6.0%	0.2%	7.1%	-1.5%	0.2%
8	Transportation and storage	6.0%	0.1%	4.7%	0.9%	0.3%
9	Accommodation and food services	7.6%	0.2%	-0.2%	7.5%	0.2%
10	Information and communication	7.8%	0.0%	6.6%	1.0%	0.2%
11	Finance and insurance	16.2%	1.7%	4.0%	9.8%	0.7%
12	Real estate	2.3%	0.2%	6.8%	-4.9%	0.1%
13	Professional scientific and technical activities	3.6%	3.6%	3.7%	-4.8%	0.9%
14	Administrative and support services	5.2%	1.3%	6.2%	-2.9%	0.8%
15	Public administration	2.5%	0.3%	4.2%	-2.5%	0.5%
16	Education	2.0%	1.3%	1.5%	-1.3%	0.6%
17	Human health and social care	3.6%	0.8%	0.8%	1.6%	0.3%
18	Arts, entertainment, and recreation	3.2%	0.2%	9.9%	-7.5%	0.6%
19	Other services	2.0%	0.5%	14.6%	-13.3%	0.2%
20	Total GDP	5.9%	0.4%	4.5%	0.5%	0.5%

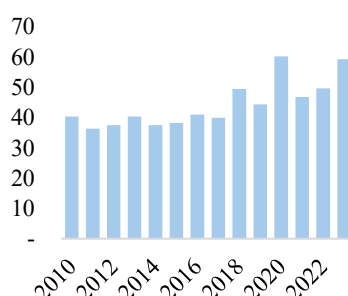
Source: Authors' calculations.

Appendix 4. Number of employees by sector

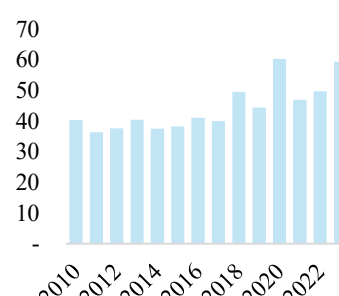
Mining sector employment
(thousand persons)



Health sector employment
(thousand persons)



Education sector employment
(thousand persons)



Source: National Statistics Office.

Appendix 5. Principal component analysis: eigenvalues

Eigenvalues: (Sum = 12, Average = 1)				Cumulative	Cumulative
Number	Value	Difference	Proportion	Value	Proportion
1	3.431	0.510	0.286	3.431	0.286
2	2.921	1.303	0.243	6.352	0.529
3	1.618	0.339	0.135	7.970	0.664
4	1.279	0.220	0.107	9.249	0.771
5	1.059	0.322	0.088	10.308	0.859

Source: Authors' calculations.

Appendix 6. Results of the likelihood ratio test

Null Hypothesis	LogL	$\chi^2_{0.95}$	P-value
No time effect	-232.77	11.86	0.00
No time effect and half normal distribution in the error term	-234.33	14.97	0.00

Source: Authors' calculations.

Appendix 7. Results of the translog model estimation

Variables	Estimate	Std. Error	z value	Pr(> z)
Intercept	-6.800	2.865	-2.374	0.018
log(Capital)	0.312	0.567	0.550	0.582
log(Labour)	1.409	0.693	2.034	0.042
log(Inter good)	0.854	0.570	1.499	0.134
A	0.062	0.274	0.228	0.820
I(0.5 * (log(Labour))^2)	0.037	0.105	0.356	0.722
I(0.5 * (log(Capital))^2)	0.105	0.103	1.026	0.305
I(0.5 * (log(Inter good))^2)	0.168	0.106	1.591	0.112
I(0.5 * (A)^2)	0.026	0.022	1.174	0.240
I(log(Labour) * log(Capital))	-0.038	0.084	-0.459	0.647
I(log(Labour) * log(Inter good))	-0.096	0.093	-1.036	0.300
I(log(Labour) * A)	0.008	0.049	0.162	0.871
I(log(Inter good) * log(Capital))	-0.098	0.082	-1.189	0.234
I(A * log(Capital))	-0.001	0.030	-0.034	0.973
I(log(Inter good) * A)	-0.015	0.037	-0.400	0.689
sigmaSq	5.812	2.470	2.353	0.019
gamma	0.839	0.074	11.347	0.000
mu	-4.418	2.006	-2.202	0.028

Source: Authors' calculations.