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The Effect of Artificial Intelligence on The Total Factor Productivity in Iranian Industries

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Abstract

This research examines the impact of investments in artificial intelligence (AI) on total factor productivity (TFP) across Iranian industries from 1997 to 2020, utilizing a comprehensive dataset organized by four-digit International Standard Industrial Classification (ISIC) codes. We employ the generalized method of moments (GMM) approach to address challenges such as endogeneity and collinearity within a dataset comprising over 200 cross-sectional variables.Our results reveal that both physical and intangible investments significantly influence TFP; a 1% increase in physical investment results in a 0.514% rise in TFP, while intangible investment leads to a 0.288% improvement. A key innovation of this research is the introduction of an AI measurement variable in the production function, employing the Corrado, Hulten, and Sichel (CHS) methodology for a clearer assessment of AI's productivity effects.Although AI investment positively correlates with TFP, its current impact is limited, reflecting the gradual adoption of advanced technologies in Iranian industries. This highlights the need for a comprehensive strategy to fully realize the productivity benefits of AI. We recommend policies aimed at facilitating technology integration and workforce specialization, including investing in training, providing incentives for AI adoption, and promoting partnerships between businesses and educational organizations to enhance productivity and competitiveness in the global market.

Highlights

- Physical and intangible investments significantly enhance TFP in Iranian industries.
- This research introduces an AI measurement variable in the production function using the CHS methodology.
- The limited impact of AI investment highlights the need for comprehensive strategies to better leverage advanced technologies

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1. Introduction

AI has become a game changer across multiple sectors. It is revolutionizing how businesses operate, enhance efficiency, and improve customer experiences. Examples include automating routine tasks in manufacturing, providing personalized recommendations in retail, and enabling predictive analytics in healthcare. The integration of AI is reshaping existing processes and creating entirely new opportunities for innovation and growth. The integration of AI technologies into business processes has not only revolutionized traditional operations but has also created new opportunities for economic growth and efficiency. As AI continues to evolve, its applications span multiple sectors, including healthcare, finance, manufacturing, and retail, underscoring its ubiquitous influence on the modern economy. In recent years, advancements in machine learning, natural language processing, and data analytics have significantly enhanced the capabilities of AI systems. According to Brynjolfsson and McAfee (2014), the rapid acceleration of AI technologies is leading to profound changes in how businesses operate, emphasizing the need for organizations to adapt to this new landscape. AI's ability to analyze large datasets and detect patterns allows businesses to make informed decisions, optimize supply chains, and improve customer experiences (Davenport & Ronanki, 2018). In the healthcare sector, for instance, AI-driven applications have been utilized for patient diagnosis, treatment personalization, and administrative efficiencies that ultimately lead to better patient outcomes (Jiang et al., 2017). In finance, AI algorithms enable firms to automate trading, manage risks, and detect fraud at a previously unattainable scale (Dahlberg et al., 2021). Furthermore, in the manufacturing sector, AI facilitates predictive maintenance, which minimizes downtime and reduces operational costs (Tian et al., 2021).

The economic implications of AI are profound. According to a report by the McKinsey Global Institute in 2018, artificial intelligence has the potential to add $13 trillion to the global economy by the year 2030, emphasizing its role as a key driver of productivity across industries. Nonetheless, the implementation of AI brings along difficulties, particularly in terms of ethical issues, workforce displacement, and the need for robust governance frameworks (Binns, 2018). Organizations must navigate these complexities while striving to harness the benefits of AI. In summary, AI's position in industry is not only pivotal but also increasingly indispensable. As technology progresses, the incorporation of AI into various sectors will yield further innovations, enhancing efficiency and enabling businesses to tackle complex challenges.

The manufacturing industry has witnessed a dramatic transformation due to the integration of AI technologies, leading to significant enhancements in operational efficiency, product quality, and overall productivity. As manufacturers increasingly adopt AI-driven solutions, they are able to harness data analytics, automation, and machine learning to streamline their processes, reduce costs, and remain competitive in a rapidly evolving market. One of the key uses of AI in the manufacturing sector is predictive maintenance. Conventional maintenance methods typically depend on predetermined schedules downtime, which can lead to unexpected disruptions and high costs. However, AI enables manufacturers to adopt a predictive maintenance approach by analyzing data from machinery and equipment to forecast failures before they occur. A report from the McKinsey Global Institute (2020) indicates that implementing predictive maintenance can lead to a reduction in maintenance expenses of as much as 30% and enhance equipment availability by 10-20%.The shift not only minimizes unexpected breakdowns but also extends the lifespan of machinery, enhancing overall operational efficiency. AI also has a vital role in quality control. Advanced computer vision systems powered by AI can inspect products at a much faster rate than human workers, identifying defects and deviations in real-time. For example, a study by Jha et al. (2021) demonstrates how manufacturers implementing AI-driven visual inspection systems achieved significant improvements in defect detection rates, leading to reductions in waste and rework costs. By ensuring that only high-quality products reach the market, manufacturers can improve customer satisfaction and strengthen their competitive position.Moreover, AI boosts supply chain management by predicting demand changes and optimizing inventory levels, leading to reduced costs and improved efficiency. A research article by Choi et al. (2020) indicates that AI algorithms can examine historical sales data analysis along with external factors (e.g., economic trends, seasonal variations) to forecast demand accurately. This capability allows manufacturers to adjust their production schedules and inventory management practices proactively, reducing excess stock and minimizing stockouts. The AI integration into supply chain logistics has the possibilities to save manufacturers an estimated 15-30% in inventory costs while improving service levels (Kamble et al., 2020).Additionally, the adoption of AI is facilitating the shift towards smart manufacturing. This concept involves the IoT(Internet of Things) integration devices with AI to create connected ecosystems within manufacturing plants. For instance, AI can analyze real-time data from IoT sensors to optimize manufacturing processes dynamically. A report by the World Economic Forum (2021) highlights that AI-driven smart manufacturing can cause to a 10-30% increase in general equipment effectiveness (OEE) by minimizing waste and enhancing process efficiency.Furthermore, AI is revolutionizing product design and innovation in manufacturing. Generative design algorithms powered by AI can create multiple design alternatives based on specified parameters, enabling engineers to explore innovative solutions that would have been difficult to conceive through traditional methods. A case study by Autodesk (2021) illustrates how companies utilizing generative design achieved reductions in material usage by up to 80%, thereby decreasing costs and environmental impact.In conclusion, the integration of AI into the manufacturing industry is driving substantial changes that enhance efficiency, improve quality, and foster innovation. As manufacturers continue to explore AI technologies, the potential for increased operational performance and competitive advantage becomes increasingly evident. However, the successful implementation of AI also requires a strategic approach, including investment in workforce training and the development of robust data governance frameworks to capitalize on the opportunities that AI presents.

Productivity in industries is a critical measure of efficiency that directly impacts economic performance, competitiveness, and overall growth. High productivity allows firms to maximize output while minimizing input costs, thereby enhancing profitability and contributing to economic development. In the last few years, the adoption of AI has appear as a transformative force for improving productivity across various sectors. AI technologies can automate routine tasks, optimize supply chain operations, and facilitate data-driven decision-making, which collectively contribute to significant gains in operational efficiency. For instance, AI systems can process large datasets to recognize patterns and insights and forecaste maintenance needs, ultimately reducing downtime and operational costs (McKinsey Global Institute, 2021). Furthermore, AI has the potential to significantly enhance product quality through sophisticated analytics and machine learning capabilities, which empower manufacturers to identify defects in real-time and elevate overall product standards (Jäger et al., 2021). However, it is crucial to acknowledge that the effective implementation of Artificial Intelligence (AI) is contingent upon the integration of intangible assets, including skilled human capital and innovative organizational practices. Jäger et al. (2021) emphasize that without a conducive ecosystem fostering collaboration between technology and human expertise, the anticipated advantages of AI may not be fully actualized, leading to scenarios where investments do not yield the expected productivity gains. Similarly, Brynjolfsson and McAfee (2014) argue that the successful adoption of AI technologies necessitates an organizational culture that embraces continuous learning and adaptability. Consequently, while AI can markedly enhance productivity through intelligent automation and optimized operational processes, a lack of strategic alignment with existing workflows and capabilities may result in stagnation or even a decline in productivity outcomes (McKinsey Global Institute, 2021). This duality highlights the significance of a comprehensive approach to integrating AI, where both technological advancements and organizational competencies are aligned to achieve sustainable improvements in productivity (Jäger et al., 2021; Brynjolfsson & McAfee, 2014).

In 2005, Corrado, Halton, and Sechel introduced a seminal framework for understanding intangible investment, categorizing it into three distinct types: computer information, innovative assets, and economic merits. This framework has proven particularly relevant in the context of the evolving investment landscape over the past two decades, from 2000 to 2022. Empirical studies indicate that intangible investments have become increasingly influential on economic performance, reflecting a notable shift in corporate investment strategies, particularly in Europe and the United States, where firms have progressively allocated resources toward a combination of tangible and intangible assets. The effects of this shift were particularly pronounced during the Great Recession, a period during which tangible investments plummeted and struggled to regain prerecession levels. Conversely, intangible investments demonstrated a more robust recovery in the United States, attributed to their inherent flexibility and adaptability in fluctuating economic conditions. However, the rebound in Europe was less vigorous, highlighting a disparity in how different regions capitalize on intangible assets (Corrado, Haskel, Jona-Lasinio, & Iommi, 2018). Building on the foundational insights offered by Corrado et al. (2018), our study emphasizes the measurement of AI investments through the same framework established in their 2022 research. We aim to explore how the characteristics of intangible investments, specifically in relation to artificial intelligence, contribute to enhancing productivity and economic growth. By applying their approach to the context of AI, this study seeks to elucidate the complexities and nuances involved in quantifying these investments, thereby providing a comprehensive understanding of their impact on contemporary economic dynamics.

In this study, we adopt the framework previously outlined to measure investments in Artificial Intelligence (AI) and to scrutinize its effects on productivity across various industrial sectors. Specifically, we focus on data sourced from four-digit ISIC-coded industries, encompassing establishments with ten or more employees. This dataset spans the period from 1997 to 2020, providing a rich temporal dimension that enables us to investigate trends, correlations, and shifts in productivity related to AI investments over time. The methodology employed for data analysis utilizes a Generalized Method of Moments (GMM) model. This statistical approach is particularly advantageous as it allows us to address potential endogeneity issues that may arise in our empirical specifications, ensuring more reliable and valid estimates of the impact of AI investments on productivity. By leveraging panel data, we can control for both cross-sectional and time-series variations, thereby enhancing the robustness of our findings.Through this rigorous analytical framework, our research aims to elucidate the intricate dynamics between AI investments and productivity gains in various industries. We anticipate that our findings will not only contribute to the existing literature on technology and productivity but also provide actionable insights for policymakers and industry leaders seeking to leverage AI for enhancing operational efficiency and economic growth. By examining the relationship between AI investments and industrial performance, we hope to shed light on the strategic importance of intangible assets in the modern economic landscape.

This paper is organized into seven distinct sections. The introduction provides the context our exploration. The subsequent section provides the research background, delving into the existing literature on investments in artificial intelligence (AI), its relationship with productivity, and its importance across various sectors.Next, we present the theoretical framework that underpins our analysis. We then move on to discuss the measurement of intangible investments and the application of AI within the context of our model. Following that, we will outline the econometric results, evaluating the impact of AI on TFP growth, particularly within sectors identified by 4-digit industry codes.The concluding section summarizes our findings, reflects on their policy implications, and proposes potential directions for future research. Through this comprehensive exploration, we aim to provide valuable insights into the role of AI in industrial practices and its broader economic effects.

2. A Review of the Related Literature

Recent research on artificial intelligence (AI) and its impact on productivity in organizations has garnered significant attention from academics and economic experts. A study conducted by Corrado, Haskel, & Jona-Lasinio (2020) adopts an intangible assets approach to investigate how AI influences productivity.This study demonstrates that AI technologies specifically affect organizational productivity, necessitating the existence of other intangible assets, including knowledge, workforce skills, and social capital. One of the key points highlighted in this research is that productivity growth arises not only from investments in new technologies but also from investments in these intangible assets and managerial capabilities that can effectively leverage these technologies.Furthermore, this study explores the mechanisms through which AI can contribute to enhanced productivity. These mechanisms include optimizing processes, improving accuracy and reducing errors in decision-making, and enhancing capabilities in data simulation and analysis. Ultimately, the findings emphasize the importance of investing in education and workforce skill development to fully capitalize on the potential of AI technologies.

In the study of Marianne Saam(2024) investigates the macroeconomic productivity effects of AI. She posits that AI fundamentally transforms production processes and labor dynamics, enhancing productivity through mechanisms like task automation, improved data analysis, and more effective decision-making.Saam emphasizes that realizing AI's productivity benefits depends on complementary investments in human capital and infrastructure, highlighting the importance of an educated workforce and supportive institutional frameworks. Thus, effective policy interventions should account for the broader socioeconomic context to maximize AI's potential.

In “The Productivity J-Curve: How Intangibles Complement General Purpose Technologies,” Erik Brynjolfsson (2021) examines the relationship between intangible assets and the productivity impacts of general-purpose technologies (GPTs). He introduces the "productivity J-curve," which illustrates a temporary decline in productivity following the adoption of new technologies, followed by a rise as firms invest in complementary intangibles, such as employee training and organizational innovation.Brynjolfsson emphasizes that the full benefits of GPTs like AI and automation often require firms to adapt their processes and invest in intangible resources. His findings suggest that organizations that effectively harness these intangibles can accelerate productivity improvements and enhance overall economic performance .Furthermore, emphasizing the significance of making strategic investments in both technological advancements and intangible assets is crucial.

In the article "The Simple Macroeconomics of AI," Daron Acemoglu (2022) examines the macroeconomic implications of artificial intelligence (AI), offering a theoretical framework to understand its impact on productivity, innovation, and the labor market. Acemoglu argues that AI serves as a general-purpose technology that can drive significant economic transformation.A core tenet of Acemoglu's analysis is the recognition of intangible capital and the role it plays alongside AI in enhancing productivity. He posits that the successful integration of AI technologies depends on complementary investments in human capital, organizational structure, and institutional frameworks. This emphasizes the importance of policy measures that not only promote AI development but also invest in education and training programs to prepare the workforce for the evolving job landscape.Additionally, Acemoglu highlights the potential for structural changes in the labor market as a result of AI. While AI has the capability to automate routine tasks, it also creates demand for more skilled labor, suggesting a dual effect on employment dynamics. This necessitates a careful consideration of labor policies to address inequality and ensure that the benefits of AI advancements are widely shared across community. Overall, Acemoglu's work provides valuable insights into the interplay between technology and economic structures, underscoring the need for a comprehensive approach that integrates technological advancements with strategic investments in human capital and supportive policies.

In the paper "Artificial Intelligence and Firm-Level Productivity," Dirk Czarnitzki, Gastón P. Fernández, and Christian Rammer (2022) investigate the effect of AI on productivity at the firm level, highlighting AI as a general-purpose technology that significantly enhances operational efficiency. The authors emphasize the role of intangible assets—such as knowledge and training—in maximizing the productivity gains from AI adoption. They argue that the successful integration of AI depends on a firm's ability to harness these intangibles, underscoring the importance of human capital and organizational capacity.Furthermore, while AI can drive substantial productivity improvements, the benefits vary across firms based on factors like size, industry, and management quality. This variation suggests that policymakers should promote equal access to AI technologies and training to mitigate disparities in productivity enhancements.Overall, the paper illustrates that leveraging AI for productivity requires not only technological advancements but also strategic investments in human resources.

In the research paper titled "The Economics of Artificial Intelligence: A Survey," Laura Abrardi, Carlo Cambini, & Laura Rondi (2019) provide a comprehensive examination of the economic implications of AI. The authors explore various dimensions of AI, focusing specifically on its influence on productivity and economic structures.A central theme of the paper is the examination of AI as a transformative technology that can potentially reshape industries by enhancing efficiency and fostering innovation. The authors assert that AI impacts productivity by automating routine tasks, optimizing processes, and enabling more informed decision-making. This aligns with the understanding that AI can serve as a catalyst for comparative advantage in many sectors, altering competitive dynamics in both established and emerging industries.The survey emphasizes the critical role of complementary investments in human capital and infrastructure alongside AI implementation. It highlights that while AI can drive productivity gains, these benefits are contingent upon the development and integration of capabilities of organizational and training programs. The authors argue that productivity improvements from AI are not solely derived from technology; rather, they often depend on a firm's ability to assimilate and utilize AI effectively.Moreover, Abrardi, Cambini, and Rondi discuss the potential economic disparities that may arise as a result of uneven AI adoption. They emphasize the importance of policy interventions that promote inclusive access to AI technologies, ensuring that the productivity benefits are broadly shared across different sectors of the economy. Overall, the paper provides a foundational understanding of the economic dimensions of AI, significantly contributing to the discourse on how AI can enhance productivity while addressing societal challenges.

According to a report by the OECD (2024), Artificial Intelligence (AI) significantly impacts productivity, distribution, and economic growth by enhancing efficiency through automation, fostering innovation, and reshaping labor markets. Initial evidence indicates that sectors that adopt AI experience notable productivity gains; however, concerns about income inequality arise as benefits may disproportionately favor technology owners and skilled workers. Policymakers face challenges in creating regulatory frameworks, addressing workforce skill gaps, and strengthening social safety nets to reduce the disruptive impacts of AI.

In their commentary, Baily & Kane (2024) discuss the transformative effect of Artificial Intelligence (AI) on productivity, highlighting that AI technologies are poised to enhance efficiency across various sectors. The authors argue that AI can automate routine tasks, allowing human workers to focus on higher-value activities, which can lead to significant productivity gains. Furthermore, they emphasize that the integration of AI into business processes will spur innovation by enabling more data-driven decision-making and optimizing resource allocation. However, the authors caution that to fully realize these potential gains, organizations need to invest in workforce training and adopt strategies to effectively manage the transition to more AI-centric operations.

Jan et al. (2022) conduct a systematic review of the role of AI in the context of Industry 4.0, highlighting its diverse applications, inherent challenges, and potential opportunities. The authors outline how AI technologies, such as machine learning and data analytics, are increasingly integrated into manufacturing processes to enhance operational efficiency, improve decision-making, and enable predictive maintenance. However, they also identify significant challenges, including data privacy concerns, the need for standardized protocols, and the workforce's adaptability to new technologies. The study emphasizes the importance of strategically addressing these challenges to leverage AI's full potential in the industrial sector, ultimately driving innovation and competitive advantage.

3. The Study Model

3.1 Theoretical Foundations of Productivity, Production Function, and the Influence of Technology

The production function is a mathematical expression of the relationship between various inputs (such as labor, capital, and technology) and the output (goods or services produced). The production function can be expressed in a general form as:

$$Q = f(L, K, T) \quad (1)$$

where: Q: Quantity of output ,L: Labor input ,K: Capital input ,T: Technology input

This function illustrates how different combinations of resources can lead to varying levels of production (Varian, 1992). Productivity refers to the ratio of output (product) to input (resources such as labor and capital) and is used as a measure of the efficiency of economic systems. Productivity can be calculated as follows:

Productivity=Output/Input.

Total Factor Productivity reflects the effects of technology and managerial efficiency on productivity. Changes in TFP indicate improvements or declines in output relative to the combined inputs, making it a critical factor in explaining economic growth (Solow, 1957).

Technology, especially new technologies like artificial intelligence (AI), significantly influences productivity in production processes. New technologies lead to the automation of production processes, reducing production time and increasing efficiency. The implementation of robotics and AI systems in manufacturing can diminish costs while enhancing speed and accuracy (Brynjolfsson & McAfee, 2014).Advanced technologies such as machine learning and big data analytics assist in optimizing supply chains, forecasting demand, and managing inventories, all leading to lower operational costs (Chui, Manyika, & Miremadi, 2016). New technologies allow firms to create a broader range of products and services with higher quality and lower costs, thereby enhancing diversity and attracting new customers (Porter & Heppelmann, 2014).

Neoclassical production models explore the impact of inputs and technology on production, emphasizing the interactions between labor, capital, and technology. These models highlight the importance of returns to scale and human capital in production (Mankiw, Romer, & Weil, 1990,1992).

The Solow growth model investigates how capital accumulation and technological progress influence production capabilities and economic expansion. Within this framework, technological advancements are regarded as the central factor contributing to economic growth and enhancements in productivity (Solow, 1956).

The introduction of technology into the production function also comes with challenges, including:

Investment and Costs: The significant expenses involved in adopting and sustaining cutting-edge technologies can pose challenges for numerous companies (Susskind & Susskind, 2015).

Training and Workforce Skills: To fully leverage new technologies, the workforce needs training and skill enhancement (Bessen, 2019).

Social and Economic Concerns: Technological changes may impact labor markets and create social unrest, necessitating appropriate management and policy measures (Frey & Osborne, 2017).

Technology, particularly artificial intelligence, is recognized as a critical factor in enhancing productivity and optimizing the production function. Understanding these theoretical foundations helps researchers and decision-makers improve economic performance and effectively utilize new technologies. However, the integration of technology also requires careful consideration of challenges and barriers to ensure that productivity gains translate into sustainable economic growth.

3.2 Calculating Productivity Using the Divisia Index

The Divisia Index is a widely utilized method for calculating productivity measures, especially Total Factor Productivity (TFP). This index assists in capturing the changes in both input quantities and output, yielding a comprehensive understanding of productivity dynamics over time.

The general formula to calculate TFP using the Divisia Index is:

$$TFP_t = \frac{Y_t}{\prod_{i=1}^{n} X_{it}^{w_{it}}} \tag{2}$$

Where:TFPt = Total Factor Productivity at time t,Yt = Total output (e.g., GDP or production) at time t,Xit = Quantity of the ith input at time t,wit = Time-varying weights representing the share of the ith input in total output, and n = Total number of inputs being considered (Diewert, 1976).

To calculate Total Factor Productivity (TFP) using the Divisia Index, the first step is to determine the total output, denoted as Yt, which involves measuring the total production or GDP for the period under analysis. Next, it is essential to identify the inputs involved in the production process, such as labor, capital, and other relevant resources, represented as Xit. Following this, the weights (wit) for each input must be calculated to determine their shares, expressed as

$$\mathrm{w_{it}} = \frac{\mathrm{P_{it}X_{it}}}{\mathrm{P_0Y_t}} \tag{3}$$

where Pit is the price of the input i at time t and P0 is the price level at a base period (Caves, Christensen, & Diewert, 1982). After calculating these values, the Divisia Index can be computed by inputting the results into the formula to derive TFP. Finally, by analyzing how TFP changes over time, researchers can evaluate the impacts of technological advancements, efficiency improvements, and other factors that influence productivity (O'Mahony & Vecchi, 2005).

The Divisia Index offers several significant advantages that enhance its utility in measuring productivity. One of its primary strengths is its ability to account for substitution effects among inputs, thereby providing a more accurate reflection of productivity changes. Additionally, the Divisia Index captures variations in technological advancements and efficiency improvements more precisely than alternative indices, making it particularly valuable in dynamic economic environments. Furthermore, this index is adaptable to various types of data, allowing for adjustments related to prices and different categories of inputs, which increases its applicability across diverse sectors and research scenarios (Jorgenson, 1986).

3.3 Methodology for Estimating Capital Stock Including Physical, Intangible, and Artificial Intelligence Investments

To determine the capital stock, we employ a comprehensive approach that encompasses physical capital, intangible assets, and new investments in artificial intelligence. Specifically, we apply the Perpetual Inventory Method (PIM), which estimates the current capital stock based on past investments and depreciation rates (Jorgenson, 1963). This method starts with an initial capital stock value, typically derived from historical data, and adds new investments made during the period while subtracting depreciation.

The formula for calculating capital stock (Kt) at time t using the PIM is as follows:

$$K_t = K_{t-1} + I_t - \delta K_{t-1} \tag{4}$$

where Kt−1 is the capital stock from the previous period, It represents new investments made in period t, and δ indicates the depreciation rate. Through this approach, we can incorporate both physical assets, such as machinery and infrastructure, and intangible assets, including intellectual property and brand equity (Kendrick, 1976). Importantly, our analysis also considers the rapidly evolving field of artificial intelligence as a new form of investment, recognizing its potential to significantly impact productivity and economic growth (Brynjolfsson & McAfee, 2014).

By systematically adopting this method, our study aims to provide a robust evaluation of capital stock that reflects both traditional and modern forms of investment. This dual focus enables a more nuanced understanding of how various types of capital contribute to overall economic performance (Corrado, Hulten, & Sichel, 2006).

3.4 Methodology for Estimating Capital Stock Including Physical, Intangible, and Artificial Intelligence Investments

The CHS framework has been utilized to assess intangible investments, categorizing them into three main groups:

Table 1. Classification of Intangible Investments Using the CHS Framework

Group Name	Type of Knowledge Capital
Computerized Information	Software, Database
Innovative Property	R&D, Mineral Exploration, Design, Creative Works (e.g., literature and art)
Economic Competencies	Training, Market Research and Branding, Business Process Re-engineering

***Source**: Corrado, Haskel, Lasino (2005)*

Table 1 presents a classification of intangible investments categorized under three distinct groups: Computerized Information, Innovative Property, and Economic Competencies.

1. Computerized Information: This category includes assets such as software and databases. These components are crucial in today's digital economy, providing organizations with the necessary tools to store, manage, and analyze data efficiently.

2. Innovative Property: This group encompasses research and development (R&D), mineral exploration, design, and creative works, such as literature and art. Investments in this category reflect a firm's commitment to innovation and creativity, which are essential drivers of long-term economic growth and competitive advantage.

3. Economic Competencies: This classification includes various forms of training, market research, branding, and business process re-engineering. These competencies enhance a firm's capabilities, ensuring that it can adapt to changing market conditions and improve operational efficiency.

The classification provided in this framework highlights the diverse nature of intangible investments and their integral role in fostering innovation and economic development. Understanding these categories allows organizations to strategically allocate resources toward enhancing their knowledge capital, ultimately leading to improved performance and competitiveness.

Corrado et al. (2005) further refined this classification, expanding it to nine distinct categories of intangible investments:

Table 2: Detailed Classification of Intangible Investments According to the CHS Framework

a) Computerised information **1.** 1 Computer Software: Encompasses costs associated with software developed for in-house use, including three components: personal use software, purchased software, and bespoke applications. **2.** Computer Databases
b) Innovative investment: 3. Scientific and Engineering R&D: Refers to expenses related to the development of new products and production processes, typically resulting in patents or licenses; particularly relevant in the manufacturing, software publishing, and telecommunications sectors. 4. Mineral Exploration: Involves costs associated with discovering new mineral deposits, mainly within the mining industry. 5. Copyrights and Licenses: Pertains to investments for developing creative arts and entertainment, notably in the information sector (excluding software publishing). 6. Other Product Development Costs: Covers expenditures on design and research that do not necessarily result in patents or copyrights, commonly found in financial services and other sectors. c) economic qualifications 7. Brand Equity: Relates to advertising and market research costs for brand and trademark development, including the purchase of advertising services and conducting market studies. 8. Special Human Capital: Represents expenses for enhancing employee skills through job training and tuition for job-related education. 9. Organizational Structure: Encompasses costs associated with organizational changes and development, including company formation, although comprehensive statistical data in this area may be lacking.

source: *Corrado, Haskel, Lasino (2005)*

Table 2 provides a comprehensive classification of intangible investments aligned with the CHS framework, subdividing these investments into three main categories: Computerised Information, Innovative Investment, and Economic Qualifications.

a) Computerised Information

1. Computer Software: This includes all costs associated with software developed for in-house use. The category is further divided into three components: personal use software, purchased software, and bespoke applications tailored to specific organizational needs.

2. Computer Databases: Investments in databases that facilitate data management and analysis are included in this category, enhancing an organization's ability to leverage information effectively.

b) Innovative Investment

3. Scientific and Engineering R&D: This category covers expenses related to the development of new products and production processes, often leading to patents or licenses. It is particularly relevant in sectors such as manufacturing, software publishing, and telecommunications.

4. Mineral Exploration: Costs incurred in discovering new mineral deposits fall under this investment, primarily relevant to the mining industry.

5. Copyrights and Licenses: Investments aimed at developing creative works in the arts and entertainment sectors, especially in information-related fields, are captured here, excluding those related to software publishing.

6. Other Product Development Costs: This encompasses expenditures on design and research activities that may not result in patents or copyrights but are crucial for innovation in various sectors, including financial services.

c) Economic Qualifications

7. Brand Equity: This involves costs related to advertising and market research aimed at developing and sustaining brand identity, including expenses for advertising services and market studies.

8. Special Human Capital: Investments in training and tuition for employees to enhance their skills through job-related education fall under this category, emphasizing the importance of workforce development.

9. Organizational Structure: This encompasses costs associated with changes in organizational dynamics, including company formation. However, comprehensive statistical data in this area may be limited.

This detailed classification underscores the multifaceted nature of intangible investments and their significance in fostering innovation, enhancing operational capabilities, and achieving competitive advantage in today's economy.

In the context of Iran's economy, estimating intangible investments in industrial enterprises poses challenges due to limited statistical data. However, it is possible to leverage ISIC (International Standard Industrial Classification) codes to obtain more accurate assessments. Using data from the Iranian Statistics Center, the nine components of the CHS (Corrado, Haskel, Lasino, 2005) framework can be effectively grouped into four main categories represented by four-digit ISIC codes. These categories include Computer Software Data, which encompasses investments in software development crucial for enhancing operational efficiencies; Research and Laboratory expenditures, reflecting spending on scientific research and development activities vital for innovation; Advertising, Marketing, Exhibitions, and Media costs, which capture investments aimed at brand building and market penetration; and Educational Services, highlighting expenditures for employee training and skill enhancement. By employing this approach, researchers and policymakers can obtain a clearer picture of intangible investments within Iran's industrial sector, enabling more informed decision-making and fostering economic growth.

AI is increasingly recognized as a transformative force in the economy, but a significant challenge lies in effectively quantifying its impact and properly integrating these measurements into national accounts. Experts categorize AI as a blend of hardware, software, and databases, suggesting that investments in AI should be classified as productive investments (Brynjolfsson & McAfee, 2014). A pressing question is how to accurately represent these costs in national economic indicators while understanding the implications of not accounting for them on the estimated growth of total factor productivity (TFP). In this framework, AI expenditures can be viewed as expenses primarily associated with software and databases and analyzed in accordance with existing methodologies for intangible investments. For instance, pursuant to Corrado et al. (2006), intangible investments can be classified into three categories.: Computerized Information (which encompasses software and databases), Research and Development (focusing on the design and advancement of new products), and Brand Equity and Organizational Development (covering training and organizational restructuring). AI investments undoubtedly fall into the first category, yet the development of novel algorithms fits into the realm of R&D, highlighting AI's dual role in enhancing both software capabilities and product innovation. Furthermore, the implementation of AI tools is likely to intersect with marketing research and IT consultancy, fostering improvements in organizational efficiency and overall process optimization. Companies that effectively integrate AI into their operations may find themselves benefiting from enhanced innovation and diversification, positioning themselves advantageously within the marketplace (Chui et al., 2016). This multifaceted interrelationship highlights the importance of a comprehensive approach to understanding and quantifying AI's economic contributions, ultimately influencing growth trajectories and strategic resource allocation in various sectors.

3.5 Model

To assess the significance of incorporating these assets, we can analyze growth trajectories both with and without their inclusion. A detailed formal model is presented in the Appendix; however, in this discussion, we aim to convey our findings with minimal reliance on mathematical expressions.

Examining growth without accounting for these investments highlights the critical importance of including them in our evaluations. To facilitate this understanding, we have formally outlined a model to assess the impact of such technological investments.

In an economy characterized by labor L, added value can be represented as Q, with tangible investment labeled as Kand intangible investment noted as R.

Productivity can be deduced A^Q through a specific formulation. Consequently, production growth is expressed as follows:

$$dq = \sigma_L^Q \, dl + \sigma_K^Q \, dK + \sigma_R^Q \, dR + da^Q \quad (5)$$

In this equation, du denotes the change in the natural logarithm of the variable u, σ_x^Q, while the proportion of the input X with respect to Q signifies the production elasticity concerning inputs L, K, and R. The term da^Q represents variations in the productivity of the utilized inputs, in addition to any growth effects stemming from inputs, such as "spillover" benefits resulting from the partial applicability of intangible assets.

Now, we can rewrite the previous equation as follows:

$$dv = \sigma_L^v \, dl + \sigma_K^v dk + dt_m^{Nonintan} \quad (6)$$

Here, $dt_m^{NoIn\tan}$ is calculated as the residual. The relationship between $dt_m^{NoIn\tan}$ and d_a and other variables is expressed by:

$$dt_m^{Nonintan} = \underbrace{da^Q}_{tech\ spillovers} - \underbrace{\omega_N^Q (dn - dv)}_{missing\ new\ intan\ output} + \underbrace{\sigma_R^Q dr}_{intan\ input} + \underbrace{\left(\sigma_X^Q - \sigma_X^V\right) dx}_{K,L\ sharemismeas} \quad (7)$$

In this equation, dn represents the change in intangible investments, while its w_N^Q proportionate impact on Q and x alongside inputs K and L (excluding R) is considered. The left side of Equation ۷ represents TFP as measured, using V as the output , K, and L as inputs.

The right side of the equation elucidates what this measured residual signifies. Firstly, it indicates any changes in AQ, which may reflect shifts in technology or efficiency. Secondly, it highlights the unaccounted effects of intangible investments.

4. Empirical Results

As previously mentioned, this study employs the International Standard Industrial Classification (ISIC) codes for Iranian industries, organized into four-digit classifications, to implement our analytical model. We utilized the Generalized Method of Moments (GMM), which is particularly beneficial when the number of cross-sectional units (N) exceeds the number of time periods (T). In our analysis, the dataset comprises over 200 cross-sectional units, which surpasses the number of years under consideration. The application of the GMM methodology, specifically within the context of Dynamic Panel Data, provides several advantages, including the incorporation of individual heterogeneity, improved informational efficiency, and the reduction of biases commonly associated with cross-sectional regressions. These benefits culminate in more accurate estimates with diminished collinearity.

GMM offers several advantages that make it a preferred estimation technique in econometric analysis. One of the primary benefits is its capability to address the endogeneity of institutional variables by treating lagged and differenced variables as potential instrumental variables, thereby reducing bias associated with unobserved errors (Green, 2008). Additionally, the inclusion of lagged dependent variables mitigates collinearity issues within the model, as it minimizes the likelihood of correlation between differenced and level variables related to institutions and other factors such as human capital. Dynamic GMM also effectively eliminates time-invariant variables, including cultural and environmental factors that could introduce bias in the estimation of per capita income and development (Baltagi, 2008). Furthermore, this method enhances the temporal dimension of the analysis, allowing for the identification of long-term relationships among variables, which is often lacking in cross-sectional studies. In our GMM model, the variable Lp represents total factor productivity (TFP), while Ll and Lk denote labor and capital inputs, respectively, encompassing both physical and intangible investments, excluding artificial intelligence components. According to the CHS study, intangible investments comprise computer information, research and development, and economic qualifications, with a particular focus on the ICT sector. To effectively capture the contributions of various technologies, we employed the LAI parameter classifies sectors into four different tiers: low-tech, moderately low-tech, moderately high-tech, and high-tech.. By stratifying these industries and assigning greater weight to high-tech sectors through a dummy variable, we enhanced the robustness of our model.

Overall, this research investigates the impact of a novel investment, specifically artificial intelligence, on the productivity of Iranian industries from 1997 to 2020. We employed a CHS framework to quantify AI investments, assigning higher weights to industries with advanced technologies. This variable is denoted as AI. The TFP variable corresponds to total factor productivity within the industries, while the K variable is derived from intangible and physical investments, excluding those related to artificial intelligence. The L variable represents the workforce engaged in the industries under study. Prior to estimating the model, we assessed the stability of the variables using the Levin, Lin, and Chu (LLC), Im, Pesaran, and Shin (IPS), and Fisher (ADF) tests. The results presented in Table ٣ indicate that most variables, regardless of time trends and differencing, and some with first-order differencing at the 99% level of significance, dismiss the null hypothesis of the unit root examination.. This confirms that all variables utilized in the model are stationary.

Table 3. The results of the unit root test of model variables

	Tests		
ADF	IPS	LLC	Variable

First order difference	Level	First order difference	Level	First order difference	Level	
823.78 (0.0000)	189.42 (1.0000)	-19.06 (0.0000)	5.15 (1.0000)	-15.03 (0.0000)	-5.09 (0.0029)	TFP
1145.02 (0.0000)	168.02 (0.7029)	-24.00 (0.0000)	4.01 (0.8925)	-19.56 (0.0000)	-2.09 (0.0356)	K
695.03 (0.0000)	350.05 (0.0000)	-18.03 (0.0000)	-2.68 (0.0023)	-15.02 (0.0000)	-10.02 (0.0000)	L
856.02 (0.0000)	107.05 (0.3546)	-19.85 (0.0000)	-0.36 (0.5237)	-12.65 (0.0000)	-3.26 (0.0000)	AI

Source: *Authors' own calculations*

In this section, we present the estimation of Equation 5 utilizing the GMM model, based on company size data obtained from the Statistical Center of Iran. The results are summarized as follows:

Table 4. AI and TFP*

(Prob.)	(Std. Error)	(Coefficient)	(Variable)
0.0000	0.0025	0.213	LTFP(-1)
0.0000	0.0194	0.514	LK
0.0000	0.0275	0.2881	LL
0.0218	0.023	0.0538	LAI
2906	Number of observations (N)	195.235 (0.503)	Sargan, J-statistic
137	Instrument Rank	0.781	S.E. of regression
	: Arellano-Bond Serial Correlation Test		
0.942 (0.2573)	AR(2)	-3.481 (0.0001)	AR(1)

* L refers to the logarithm

Source: *Authors' own calculations*

The findings presented in Table 4 reveal critical insights into the determinants of Total Factor Productivity (TFP) within Iranian industries. Specifically, both physical and intangible investments (LK) and labor inputs (LL) exhibit a significant positive impact on TFP. The analysis shows that a 1% increase in physical capital is associated with a substantial 0.514% rise in TFP, reflecting the essential role of tangible and intangible investments in enhancing productivity. Similarly, labor inputs contribute positively, with a 1% increase resulting in a

0.288% increase in TFP. These coefficients underscore the effectiveness of traditional investment strategies in driving productivity improvements in the industrial sector[1].

In contrast, the effect of artificial intelligence (AI) investment (LAI) is markedly different. Although the statistical analysis indicates that AI investment does exert a positive influence on TFP, with a coefficient of only 0.0538, this represents a relatively modest contribution. A 1% increase in AI investment leads to just a 0.0538% increase in TFP. This modest impact suggests that while there is significant potential for AI to enhance productivity, its current role in Iranian industries is limited. These industries continue to rely heavily on conventional technologies rather than fully integrating advanced AI solutions, which may hinder their overall productivity growth.

Therefore, these findings highlight the necessity for Iranian industries to not only focus on enhancing physical and labor investments but also to prioritize the adoption and effective integration of AI technologies. By doing so, they can unlock the potential benefits of AI and foster a more robust increase in TFP, ultimately contributing to enhanced economic performance.

5. Concluding Remarks

Productivity is a crucial metric that quantifies the efficiency of resource utilization—specifically labor and capital—in the production of goods and services. In industrial contexts, productivity refers to the effectiveness of transforming various inputs, such as labor, materials, and capital, into outputs. This metric serves as a vital indicator for assessing the performance and competitiveness of businesses, reflecting their ability to generate value from available resources. Several factors influence Total Factor Productivity (TFP) within industries, including innovation through research and development, advancements in technology, and the skills and education of the workforce. Effective management practices and organizational structures further enhance productivity, while economies of scale can lead to reduced average costs and improved TFP.

Additionally, competitive market conditions drive industries to optimize resource utilization and enhance efficiency. The quality of infrastructure, encompassing transportation and communication systems, plays a significant role in shaping TFP, as does the legal and regulatory environment, which can facilitate or hinder innovation. Furthermore, investment decisions concerning machinery and equipment directly affect TFP, as well as the availability of high-quality raw materials and energy resources. Collectively, these factors contribute to a comprehensive understanding of productivity dynamics within industries,

[1] Previous studies have confirmed the same results, indicating that both types of investments—tangible and intangible—as well as labor, have a meaningful and positive impact on productivity(Esmaeilysadrabadi et al.(2021 and 2023)

highlighting the interplay between innovation, resource management, and external conditions that drive overall performance.

Focusing on these factors and striving for continual improvement are essential for achieving higher TFP and fostering sustainable economic growth. Previous studies indicate that investments aligning with the aforementioned categories—and including both professional and non-professional labor—can significantly impact TFP. Notably, Iranian industries are no exception, as supported by the findings of our research.

The AI integration into industrial processes can lead to noteworthy improvements in TFP by enhancing operational efficiency, reducing costs, and promoting innovation. Numerous studies conducted in European and American industrial contexts corroborate this assertion. However, our research focusing on Iranian industries, specifically employing four-digit International Standard Industrial Classification (ISIC) codes from 1997 to 2020, reveals discrepancies with findings from other countries. Despite identifying a positive impact of AI investment on TFP, the magnitude of this effect remains minimal, indicating that Iranian industries have yet to embrace emerging technologies comprehensively.

Given the rapid advancement of technology, it is crucial for Iranian industries to modernize their production processes. We recommend facilitating the introduction of AI technologies and investments within the production sector, followed by a focus on enhancing the factors affecting production through technological updates. This may necessitate the acquisition of more advanced machinery and the cultivation of a more specialized workforce.

In summary, AI has the potential to significantly transform Iranian manufacturing by enabling the automation of repetitive tasks, thereby increasing production rates, lowering labor costs, and minimizing human error. Furthermore, AI can optimize energy consumption in manufacturing processes, contributing to cost reductions and sustainability initiatives. Overall, AI is poised to revolutionize manufacturing through enhanced efficiency, reduced costs, and greater innovation and flexibility in production processes.

Author Contributions

Conceptualization, all authors; methodology, C.C. and C.N.C.; validation, C.C. and C.N.C.; formal analysis, all authors; resources, C.N.C. and C.M.; writing—original draft preparation, C.N.C. and C.M.; writing—review and editing, all authors; supervision, C.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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Appendix A: Intangible Capital and TFP: A Theoretical Analysis

The traditional Cobb–Douglas production function, which includes the conventional inputs of physical capital and labor, is formulated as follows:

$$Y_{it} = A_i \; K_{it}^{\beta_1} \; L_{it}^{\beta_2} e^{it} \qquad (1)$$

where:

- Y is the value added,
- K is the stock of capital,
- L is the labor units,
- A stands for the efficiency level,
- e is the error term,
- i=1,2,…,N=135 (for the four-digit ISIC codes), and
- t=1,2,…,T=26 (for the period of 1996–2020).

The production function is estimated in a log-linear form within a lag framework. The specification of the empirical panel model is as follows:

$$LTFP_{it} = \propto_i + \beta_1 \Delta lnL_{it} + \beta_2 \Delta lnK_{it} + \beta_3 \Delta lnR_{it} \; + \beta_4 \Delta lnLTFP_{it} + u_{it} \qquad (2)$$

R represents real intangible capital. The primary method employed for calculating inventory capital (both tangible and intangible) is the Perpetual Inventory Method (PIM) as outlined by Meinen et al. (1998). Additionally, the Divisia index has been utilized to estimate Total Factor Productivity (TFP), referencing the works of Diewert (1993) and Divisia (1925; 1926).

For measuring TFP in Iran, the Divisia method combined with the Trenquist approximation is deemed appropriate, particularly for discrete statistical data. This approach is advantageous as it recognizes that the contributions of production factors vary across different activities and can change annually, while also accounting for variations in the quality of these production factors.

In this study, a production function has been employed to calculate TFP, where output Y is expressed as a function of three inputs: labor LL, physical capital inventory K, and intangible capital inventory II. The formula used for calculating TFP is as follows:

$$TFP = \frac{Y_t}{K_t^{\propto} \, L_t^{\beta} \; I_t^{1-\propto-\beta}} \qquad (10)$$

In this context, Y denotes the output value, K represents the value of investment services, L indicates the number of employees, and I corresponds to the value of intangible investments. The parameter β is defined as the ratio of employee compensation to total production, while the production elasticity of intangible investment is determined by dividing the payments made for intangible investments by the overall output. The parameter α is calculated by taking the difference between the two aforementioned ratios.

In Equation 9, the variables for physical investment inventory and intangible investment inventory are treated as independent factors contributing to the productivity of total production factors. To compute these inventories, the accumulation data for both physical and intangible investments is derived using the following formula:

$$INT_{it} = (1 - \delta_i)INT_{it-1} + \frac{intangible_{it}}{P_t} \tag{3}$$

In this framework, INTit represents the accumulated intangible investment for the four-digit economic activity classification code ii at time t. The variable t signifies the intangible investment for the respective classification code of the four-digit economic activity rank ii at time t. Numerous studies have explored methodologies for calculating the depreciation rate of intangible assets. For this research, we have utilized the approach proposed by Amini (2008), which varies for each classification code.

Appendix B

A more elaborate model is divided into two components: the upstream segment, which focuses on the segmentation of knowledge generation into innovation, and the downstream segment, which involves transforming knowledge into tangible production. The upstream segment is characterized by the incorporation of fresh ideas and innovations, represented by Nt. Conversely, the downstream production segment leverages the accumulated experience of business knowledge for its output. In this context, the downstream segment effectively "leases" knowledge, denoted as R. Each component features a production possibilities frontier based on Jorgenson (1966) and includes a flow equation that ensures revenues are sufficient to cover expenses, which we will examine later under conditions of imperfect competition.

Let: L = Labor , I = Investment (into new tangible capital),K = Tangible capital stock,PL and PK = market prices for the services provided by labor and capital in a competitive environment, respectively.

Stock Evolution

According to the net stock equations, the accumulation of intangible assets progresses as follows:

$$\Delta R = N - \delta^R R_{t-1} \tag{4}$$

And the stock of tangible capital is expressed as:

$$\Delta K = I - \delta^R K_{t-1} \tag{5}$$

We define X as a combination of L and K, while σX and σR represent payments for the use of inputs X and R expressed as a proportion of the overall value generated. A signifies a change in the production function, representing an amalgamation of external technological advancements and genuine knowledge spillovers (i.e., increases in freely available knowledge). du indicates a change in the natural logarithm of variable u.

Flow Payments and Production Relations

1. N-Sector Generating Intangible Assets

The relationship between flow payments and production is described as follows:

$P^N N = P^X\ X^N; dn = \sigma_X^N\ dx^N\ + da^N$ (6)

2. Tangibles- Generating I-Sector:

The connection between production and flow payments is articulated as follows:

$P^I\, I = P^X X^I\ ;\ di = da^I\ + dX^I \sigma_X^N$ (7)

GDP and Growth Accounting with Intangibles as Intermediate Goods

Imagine a scenario where intangibles are treated as intermediate goods utilized by the downstream sector that produces both tangible and intangible goods for consumption. In this case, the relevant flow payments account for the total flow of new intangibles (PNN), meaning that the value added in this sector is calculated by deducting PNN from total sales.

$P^C\ + V^C\ \equiv P^C\, C -\ P^N\ N\quad ;\quad dc = \sigma_X^C dx^c + \sigma_N^C dn^c + da^c$ (8)

The overall value added across the economy is derived from the aggregate value added of various industries.

$P^V\, V \equiv P^C\, V^C +\ P^I I + P^N N$ (97)

Hence, GDP can be expressed as:

$P^V\, V \equiv GDP = P^C\, C +\ P^I I\ ;\ \ dv =\ \sigma_X^V\ dx + da^V$ (18)

When Intangibles Are Considered as Capital

If we consider the upstream intangibles-producing N-sector as producing capital, we need to adjust the downstream sector to ensure that it rents the stock of intangibles R:

$P^C\ = P^C\, C\quad ;\quad dc = \sigma_X^C dx^c + \sigma_R^C dr^c + da^c$ (10)

Thus, the total economy-wide value added becomes:

$P^Q Q \equiv P^C\, V^C\ +\ P^I I + P^N\ N$ (20)

Consequently, GDP is now expressed as:

$P^Q Q \equiv GDP = P^C\, C +\ P^I I + P^N\ N$ (21)

This leads us to the overall output represented by:

The factors contributing to growth develop in the following manner. When intangibles are excluded, the calculated total factor productivity (TFP) can be represented as:

Changes in Growth in an AI Economy

The sources of growth evolve as follows. In the absence of intangibles, the measured total factor productivity (TFP) is given by:

$dt_m^{Nontan}\ \ \equiv dv - \sigma_X^V\ \ dv$ (11)

This establishes a relationship between dtmNoIntan, da, and the unaccounted intangibles, as discussed in earlier sections.

Appendix C: GMM

Given that the dependent variable is positioned as an interval on the right side of the equation in the research model, we encounter a dynamic pattern in the panel data. The general structure of such a dynamic model in panel data analysis can be represented as follows:

$$Y_{it} = \alpha Y_{i\,t-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \tag{12}$$

In this context, Yit represents the dependent variable, while Xit is the set of independent variables that are also utilized as instrumental variables. The term μi denotes the error component associated with the individual sections, and ϵit is the error term specific to the i-th section at time t.

When the dependent variable is expressed as an interval on the right side of the equation in a panel data model, ordinary least squares (OLS) estimators become unsuitable (Arellano & Bond, 1991). Consequently, it becomes necessary to employ the two-stage least squares (2SLS) method introduced by Anderson and Hsiao (1981) or the GMM proposed by Arellano and Bond (1991). Matyas & Sevestre (2008) note that 2SLS estimation can lead to large variances in the coefficients due to challenges in selecting appropriate instruments, resulting in estimates that may lack statistical significance. To address this issue, Arellano and Bond recommend using the two-stage GMM method, which is formulated through the following differential equation:

$$Y_{it} - Y_{it-1} = \alpha(Y_{it-1} - Y_{it-2}) + \beta(X_{it} - X_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{13}$$

Initially, differentiation is performed to eliminate the effects associated with the sections or μi of the model . In the subsequent stage, the remaining residuals from the first stage are utilized to adjust the variance-covariance matrix. This process generates what are referred to as instrumental variables, which are essential for achieving reliable and impartial estimates (Baltagi, 2008).

The reliability of the GMM estimator relies on the premise that there is no serial correlation in the error terms and instruments. This premise can be analyzed through two tests outlined by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell & Bond (1998). The first of these is the Sargan test, which evaluates the appropriateness of the instruments by looking at predetermined constraints. The statistic from the Sargan test, referred to as the J-Statistic, has a distribution that corresponds to the degrees of freedom based on the number of overidentifying restrictions.

The second test investigates the potential for second-order serial correlation in the error terms that have been first-order differenced, utilizing the M2 statistic for this purpose. It is essential for the consistency of the GMM estimator that these first-order differenced errors do not exhibit any second-order serial correlation. If the null hypothesis for both tests is upheld, it reinforces the assumptions regarding the absence of serial correlation and the appropriateness of the instruments employed.

In this study, the Sargan test was conducted to verify the consistency of the GMM estimator. Furthermore, EViews 13 and MATLAB software were employed for the statistical and econometric analyses.