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Ph.D Dissertation

“Essays on Industrial Development ”

By:

Rifai Afin

Supervisors: Ilona Cserhádi, PhD and Keresztély Tibor, PhD

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Chapter 1

Introduction

1.1 General Introduction

Manufacturing has a significant role in the economies of both developed and developing nations worldwide (Szirmai and Verspagen, 2015). The data demonstrate that the trade or service sector now dominates in many countries, despite the current debate about the industrial sector's continued importance in driving economic growth. Currently, there is much debate over whether manufacturing in emerging nations should continue to be the primary focus of industrial policy. In truth, our limited comprehension of the significance of the manufacturing sector, especially for middle-income nations, is reflected in the disagreement. Well-documented patterns of structural change across several industries are widely acknowledged as factual reality, in contradiction to theories' predictions.

Therefore, the question of whether a developing nation today needs to be fully industrialized in order to succeed continues to be debatable. Current research highlights how economic development is sector-specific, which is a significant departure from popular conceptions that see growth as sector-neutral. Despite the fact that a number of studies have attempted to emphasize the significance of manufacturing in economic development (Su and Yao, 2016), Haraguchi, Cheng, and Smeets (2017) contend that manufacturing may still be essential to the economic growth of developing nations. In this instance, we may contend that the early deindustrialization is more likely the result of certain nations' incapacity to grow their manufacturing sectors in comparison to others, rather than shifts in the manufacturing sector's development characteristics that may have decreased its contribution to economic development.

This study aims to explore the multifaceted factors influencing firm performance and exports, specifically their intricate interactions within the Indonesian manufacturing sector. Performance, defined here as industrialization, efficiency, company production, and survival, forms a critical focal point and several main factors that are our concern are Information and Communication Technology (ICT), production efficiency, ownership, and the study looked at the impact of industrialization on rural areas. The complex dance, productivity, export, and firm survival has become a crucial element in defining the destiny of businesses in the ever-changing world of international trade. It is becoming more and more clear as we navigate the intricate web of interconnected markets and industries through digital technology that, in order to survive in the current competitive climate, one must have a strategic awareness of how various components combine to determine a company's course. Modern businesses rely heavily on partnerships, whether they be with suppliers, stakeholders, or other businesses. A company can advance by forming and utilizing strategic alliances, which open up new doors, share resources, and encourage creativity. However, in a market that is constantly evolving, a lack of good communication and information access and technology can impede growth and limit adaptability. Productivity affects every aspect of a business and is the cornerstone of long-term success. A productive staff is not just a major factor in long-term viability but also a catalyst for growth, from operational efficiency to employee engagement. Establishing an optimal

equilibrium between innovation and operational excellence is crucial for cultivating a culture of perpetual enhancement. The increasing interdependence have economies throughout the world has made exporting more important than ever for companies looking to grow. International market navigation offers a plethora of opportunities and obstacles. A company's capacity to not only survive but also flourish on a worldwide scale is largely dependent on its ability to navigate regulatory frameworks, market dynamics, and cultural quirks. All of these factors must be carefully considered when developing successful export strategy. Amidst these factors, a company's ability to survive depends on how well it navigates the complex web of relationships, output, and export marketing. By incorporating these components into a comprehensive strategy, a company can be strengthened against market fluctuations and remain flexible and resilient when faced with constantly changing obstacles. This article explores the tactics and best practices that companies need to adopt to steer toward long-term success in the cutthroat global marketplace. It does this by diving into three subtopics: collaboration, productivity, export, and firm survival. Come along as we dissect this complex environment and illuminate the strategies to achieve long-term success in the networked corporate environment of today.

I reduced this main idea into 3 research sub-topics to sharpen the research questions and each sub-topic became a chapter in this part of the study.

1. Chapter 2 has questions, first, is Information and Communication Technology (ICT) access has a significant influence on the welfare of village communities. Two, does ICT have a direct and indirect influence through its role in rural industrialization?. This is important because of two things, namely ICT helps the economic transition from the traditional sector to the modern sector in rural areas, thus opening up new job opportunities and opportunities to earn additional income and higher income from the industrial sector. Both ICT and industrialization open the way to improving the welfare of people in rural areas which have a larger number of poor people and can increase aggregate national welfare. While most studies focus on the direct impact of ICT on rural development or agriculture, this research takes a broader approach by examining both the direct and indirect effects of ICT on rural development. Specifically, it explores how ICT influences indicators such as poverty reduction and overseas migration through changes in the village economic structure or industrialization (mediating and moderating effects). Additionally, this study considers the endogeneity of ICT infrastructure in rural areas, incorporating it into the modeling for a more comprehensive analysis.
2. Chapter 3, the study questions are, Is the technical efficiency of large and medium enterprises important in determining firm survival? Does the impact of technical efficiency on firm survival, exit and entry consistently in aggregate level?. The focus shifts to analysing the progression of survival in large and medium industries within the Indonesian market and its correlation with technical efficiency. This analysis holds importance, as the presence of more thriving large and medium companies in the Indonesian market bodes well for the economy in terms of production, employment, and a favourable investment climate. The hypothesis developed in this chapter posits that technical efficiency directly impacts a company's survival and contributes to an increased influx of companies entering the Indonesian market, while concurrently reducing the number of companies exiting the country. This study contributes by

addressing the endogeneity in measuring industrial technical efficiency, a factor that existing studies often overlook when examining the relationship between efficiency and firm survival. Additionally, it conducts a two-level analysis—at both the firm level and the two-digit ISIC level—to assess whether the estimation results remain consistent across different levels of aggregation. It also examines the consistency of the efficiency effect on firm dynamics, such as exit, entry, and survival, which has not been explored in prior research.

3. Chapter 4 attempts to answer questions including: 1; What is the causality pattern between exports and efficiency or productivity for foreign and domestic companies. 2; Are there differences in causality patterns between the two types of company ownership?. The dissertation delves into the role of ownership in determining the causality between exports and productivity. This examination is critical for understanding government intervention in terms of company ownership, governmental investment, and investment policy objectives as strategic tools for enhancing company productivity. The hypothesis proposed in this chapter suggests that ownership influences both productivity and exports, establishing a two-way causal relationship between the two variables. This study contributes by investigating the causal relationship between exports and technical efficiency, accounting for endogeneity in the production function to prevent bias in the calculation of technical efficiency—an issue often overlooked in related research. Additionally, it analyzes the dynamic effects through a Panel VAR model to explore how a company's technical efficiency influences its exports over time. Furthermore, the study focuses on the differential relationship between technical efficiency and exports in foreign firms (Foreign Direct Investment, or FDI) versus non-FDI firms, as these two types of firms may have distinct marketing orientations according to theory Each chapter is discussed briefly, summarized in the following sub-chapters, namely 1.3, 1.4 and 1.5.

1.2 Indonesia Context

The development of the manufacturing industrial sector in Indonesia faces many challenges, both external and internal. External challenges such as the world economic crisis, prices of imported raw materials, and the dynamics of global market tastes, while internal challenges such as the quality of human resources as a supply of labor in both quantity and quality, industrial sector policies, and the use of domestic resources as the main resource for production materials, and the price of electrical energy means that the industrial sector must be able to find solutions to survive and improve its performance. Many government policies in industrial development have also been implemented in the form of incentives, taxes, credit, development of industrial clusters, as well as development of industrial supporting infrastructure. The Indonesian government's policy in industrial development is designed structurally both based on the time and the strategic industry being developed. Nevertheless, industrial performance is still a challenge for the government in making the industrial sector an engine of growth.

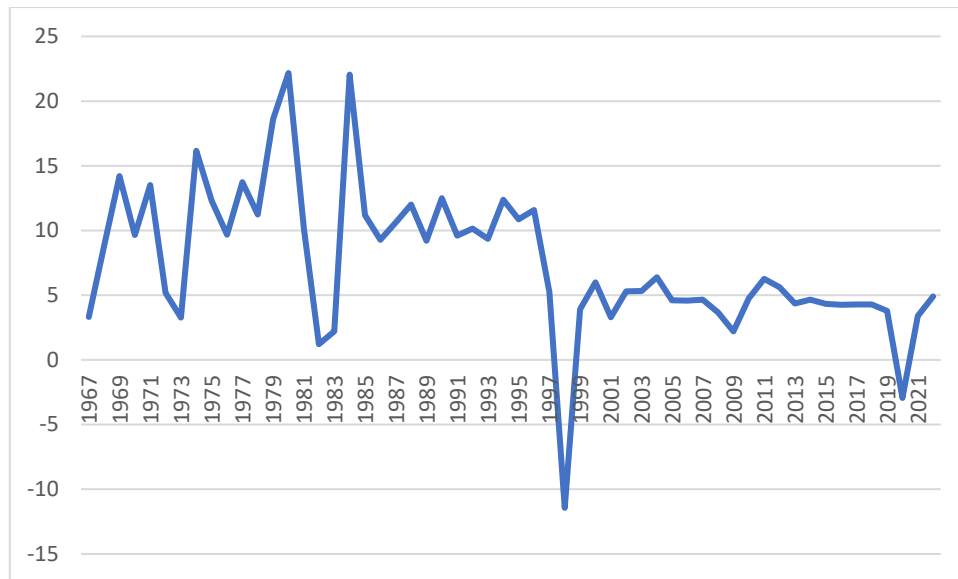


Figure 1. 1 Trend of Manufacturing Value-Added Growth (Percentage of Value-Added Growth)

Source: World Development Indicators, World Bank

If we look at the value-added growth performance, as depicted in Figure 1.1, of the manufacturing sector in Indonesia, the average growth since 1961 has been 6.99 percent per year. However, if divided into two periods before the 1998 economic crisis, the growth in value added in the manufacturing sector in Indonesia from 1999 to 2022 was only 4.24 percent compared to the period before the crisis, 1961-1997, which was 9.27 percent, or more than 2 times higher. It could be said that the industrial sector has not been able to recover to its performance before the 1998 crisis which caused its growth to fall by -11.43 percent. In addition, the economic crisis due to the COVID-19 pandemic caused it to reach negative growth of -2.93 percent, which made it increasingly difficult to restore the manufacturing industrial sector to its glory days before the 1998 crisis. Nevertheless, the growth performance of the Indonesian industrial sector is still better than the world average, which from 1998 to 2021 only reached 2.35 percent. Apart from that, the Indonesian economy still depends on the manufacturing sector. When compared with other countries, the contribution of the manufacturing sector to the national economy has remained higher over the last 20 years. Figure 1.2 shows the contribution of the manufacturing sector to Gross Domestic Product (GDP) compared to the world average. The contribution of the Industrial sector reached its peak in 2002 where its contribution reached 32 percent and after that it slowly decreased until 2022 at 18.33 percent.

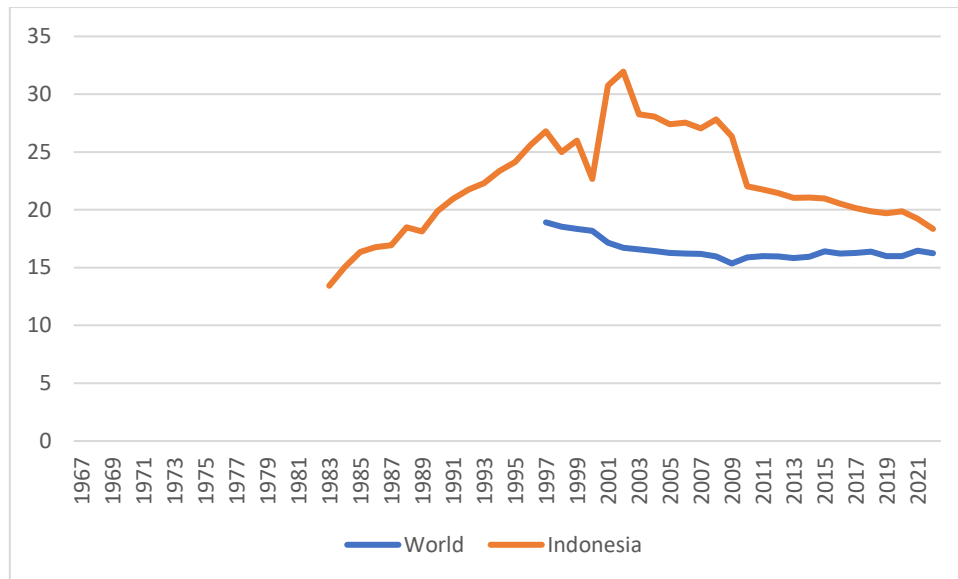


Figure 1. 2 Percentage of Manufacturing Contribution to GDP of Indonesia and Average of The World

Source: World Development Indicators, World Bank

Furthermore, the contribution of the manufacturing sector to Indonesian exports is also very high. This is shown in Figure 1.3, where the contribution of manufacturing sector exports grew rapidly in the early 1980s, reaching more than 50 percent of Indonesia's exports, dominated by industrial sector exports and to date it still contributes 46.92 percent to Indonesia's merchandise exports. Therefore, the performance of the manufacturing industrial sector is still very important for the Indonesian economy.

Manufacturing creates productivity and improves the quality of employment. Industrial optimization requires conducive regulations, business opportunities, availability of resources, a healthy investment and business climate, and the availability of industrial human resources. Industry brings added value to the economy and creates a huge multiplier effect, the result of the uniqueness of the industrial sector which has backward linkage and also forward linkage so that it can provide improvements for all sectors in Indonesia. We have proven this in the 1998 and 2008 economic crises, the resilience of small and medium business actors has proven to be the backbone of national economic resilience. Apart from that, empowering MSMEs (Micro Small, and Medium Enterprises) can expand job opportunities and equalize community income. Apart from that, the Indonesian Government has principles of just and inclusive industry, one of which is realized through the micro, small and medium industry development program. Increasing the role of the SMEs sector as part of the national manufacturing value chain will help the resilience of domestic industry. In the 1998 and 2008 economic crises, the resilience of small and medium businesses has proven to be the backbone of national economic resilience. Apart from that, empowering MSMEs can expand employment opportunities and equalize community income. The support provided by the Government to MSMEs during the pandemic also shows that our MSMEs is resilient. Efforts to develop an industry that is independent, sovereign, advanced and competitive, as well as fair and inclusive must be supported by superior industrial human resources. For this reason, it is necessary for the government to consistently implement education and training patterns aimed at providing basic

skills provision, up-skilling or skills renewal (re-skilling) in vocational schools, industrial training centers and polytechnics based on current industrial needs (Ministry of Coordinating Economic Affairs, 2022).

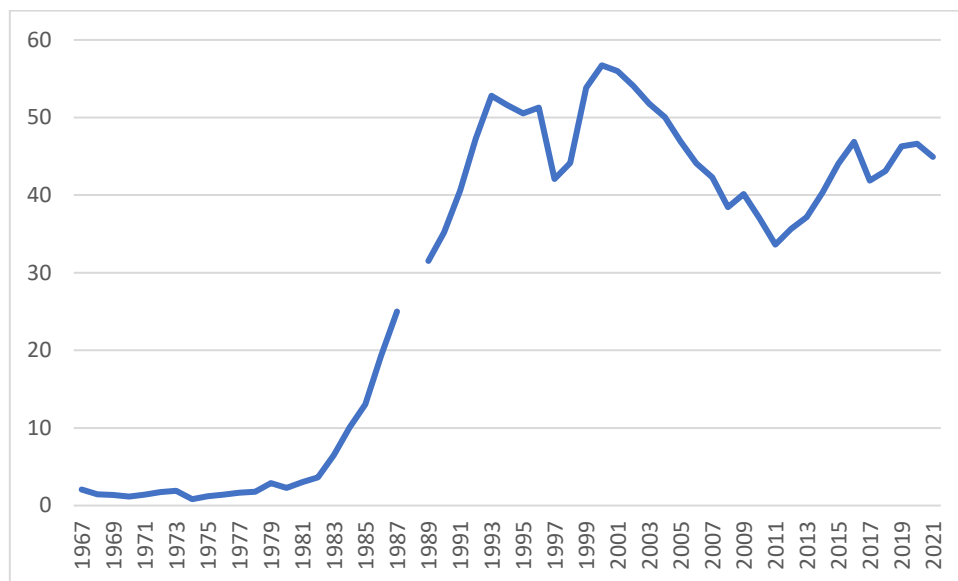


Figure 1. 3 Percentage of Manufacturing Contribution to Indonesia Merchandise Export

Source: World Development Indicators, World Bank

The comparative analysis of Indonesia's manufacturing sector performance against various industrialized nations is visually represented in Figure 1.4, showcasing the Competitive Industrial Performance (CIP) Index. Additionally, Figure 1.5 illustrates the CIP ranking. Over the period from 1990 to 2021, Indonesia demonstrates an average CIP index of 0.078. While this places the country slightly above the global CIP average of 0.073, it falls marginally below the regional average for Southeast Asia (SEA). This discrepancy poses a noteworthy challenge for Indonesia, particularly as the largest economy in the SEA region. Addressing this gap is imperative to enhance the industrial sector's performance, a pivotal pillar supporting the overall economy.

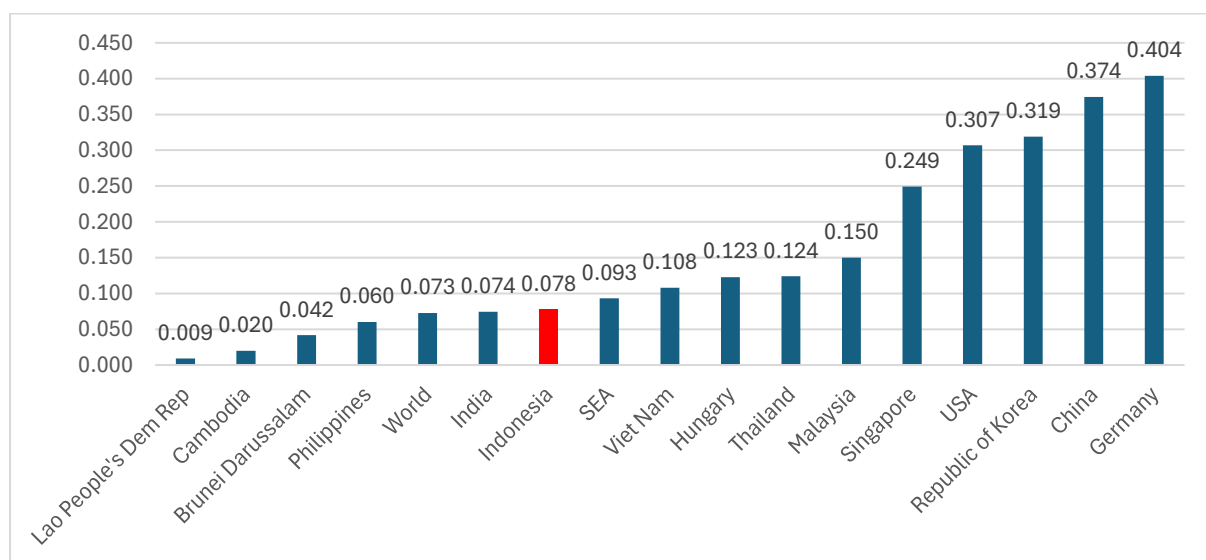


Figure 1. 4 Average Competitive Industrial Performance Index (1990-2021)

Source: United Nations Industrial Development Organizations (UNIDO)

In the global context, Indonesia holds the 39th position out of 153 surveyed countries in the 2021 Competitive Industrial Performance (CIP) ranking. However, within Southeast Asia, a region boasting several substantial economies, Indonesia finds itself in the 5th position among the 9 countries surveyed. This relatively lower standing, despite being the largest economy in the region, underscores a challenge. Encouragingly, there is positive momentum as Indonesia has ascended from its 52nd position in 1990 to the 39th position in 2021. This progress highlights the potential for growth. Focusing on fortifying the industrial sector emerges as a strategic pathway toward realizing Indonesia's ambitious goal of becoming a developed nation by 2045, aligning with its golden vision.

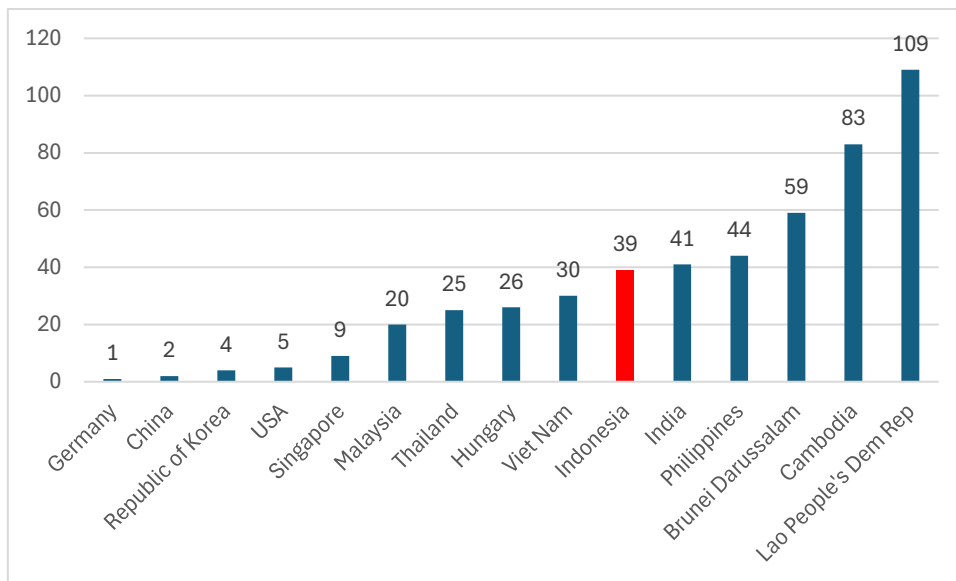


Figure 1. 5 Competitive Industrial Performance Index (2021)

Source: United Nations Industrial Development Organizations (UNIDO)

One crucial factor that influences the manufacturing sector's performance is the risk associated with a company's location. Location-based risks can stem from various sources, including macroeconomic conditions and the potential bias of policymakers in shaping policy. Additionally, the social and cultural dynamics of the local community can play a significant role. Coface (2024), a trade credit risk management company, provides a country risk assessment for conducting business, as shown in Figure 1.6. According to this assessment, Indonesia remains generally favorable for investment and business operations. Among Southeast Asian countries, Malaysia ranks the best, marked by a light green indicator that signifies low risk and satisfactory conditions for business. In contrast, other Southeast Asian nations, such as Vietnam, Laos, Myanmar, Cambodia, and Timor-Leste, are associated with higher risks.

160 COUNTRIES UNDER THE MAGNIFYING GLASS

A UNIQUE METHODOLOGY

- Macroeconomic expertise in assessing country risk
- Comprehension of the business environment
- Microeconomic data collected over 70 years of payment experience

BUSINESS DEFAULTING RISK

A1 VERY LOW A2 LOW A3 SATISFACTORY A4 REASONABLE B FAIRLY HIGH C HIGH D VERY HIGH E EXTREME

UPGRADES DOWNGRADES

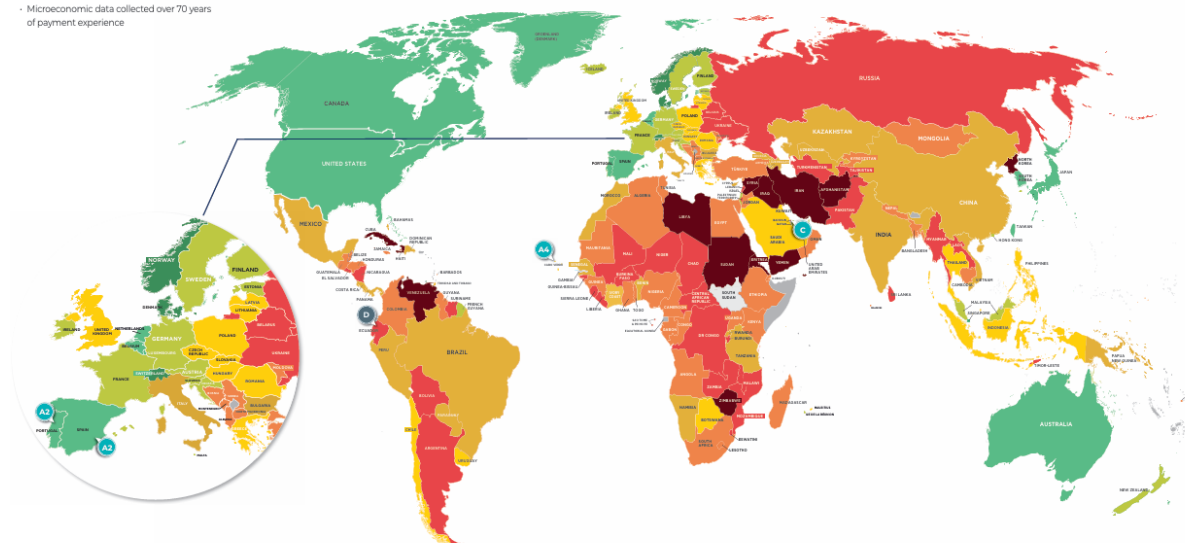


Figure 1. 6 Country Business Assessment

Source: <https://www.coface.com/news-economy-and-insights/business-risk-dashboard/country-risk-map>

More specifically, Cushman and Wakefield releases 2022 global manufacturing risks data also published the risks faced by the manufacturing sector in various countries with several scenarios, including baseline, cost, and risk scenarios. After three years of the COVID-19 pandemic, the world is trying to achieve a new balance including the manufacturing industry. Each country is trying to revive the manufacturing sector with various policies to overcome the various risks and costs faced by the industrial sector. The survey conducted by Cushman and Wakefield involved 45 countries involving several condition factors including the Business environment, the availability of talent/labor and access to markets, Costs including Operating costs including labor, electricity and real estate and risks consisting of Political, economic and environmental.

In each weighting scheme, as shown in the Table 1.1, the distribution of weights differs. In the baseline scheme, the largest weights are assigned to existing conditions and costs, each at 40 percent, with risk weighted at 20 percent. In the cost-focused scheme, both conditions and risks are given equal weights of 20 percent, while costs are assigned a higher weight of 60 percent. Conversely, in the risk-focused scheme, the highest weight, 60 percent, is allocated to risk, while conditions and costs each receive 20 percent. China holds the top position in the baseline scenario due to its relatively low labor costs, despite the rising wage trends. The country benefits from strong support for its manufacturing sector through access to new raw materials and energy sources, including innovations in energy transition. As a result, Chinese manufacturing companies maintain a dominant market position in many countries. Following China, India, Indonesia, Malaysia, and Thailand rank highly in the Manufacturing Risks Index. These countries share several key factors with China, such as abundant, affordable labor

(Brandt et al, 2016) and governments actively seeking to attract both domestic and foreign investment (Ahuja and Nabar, 2012).

Additionally, their large domestic markets for manufactured goods and strategic geographic locations further strengthen their manufacturing sectors. The two North American nations, the United States and Canada, have experienced comparatively stable cost environments in the meanwhile, but they have also witnessed an increase in risk factors, mainly exposure to natural disaster risks, as well as difficulties with business conditions, specifically a decrease in unemployment and consequently access to labor. Mexico has somewhat improved in the cost rankings while likewise modestly declining in risk. Because of this, Mexico is now seen as a desirable alternative for assisting in the return of some manufacturing to the US in order to diversify the supply chain. On the other hand, Poland is now the top-ranked nation in Europe, marginally surpassing the Czech Republic in the Baseline rankings. Poland's ascent can be partially attributed to cheaper labor and electricity prices relative to its neighbors in Eastern Europe, including Romania, Lithuania, Bulgaria, and the Czech Republic, as well as to Western and Northern European countries. However, these costs are still modest when compared to other European nations. However, several European nations have experienced increased economic risk as energy security issues pose a short-term threat to economic growth (Stöllinger et al, 2013). Bailey and Propriis (2016) also raised the issue of local labor related to new manufacturing industries and the availability of capital in European countries as important matters for intervention.

Based on the cost scheme, the best locations for manufacturing are mostly in the Asian region in Asia. They all enjoy relatively stable or even slightly lower costs for the main elements of labor and electricity. Three countries including China, Indonesia, and India continue to benefit from abundant cheap labor supplies and lower costs in electricity and real estate construction. In addition, several Latin American countries such as Colombia and Peru are in the top quartile. In Europe and the Mediterranean, Turkey, Poland, Morocco and Tunisia. One of the factors that helped these countries enter the top quartile is the relatively low energy costs including electricity and fuel prices which of course help industrial performance in production. The risk of energy prices due to the Russian and Ukrainian wars is a challenge for industries in Europe so it is necessary to find alternatives or solutions to meet energy needs for industries in the European region.

When assessing risk as a key factor in location decisions, China continues to rank at the top. This is largely due to its strong performance in business conditions and cost factors, as well as improvements in corporate and economic risk factors. Indonesia remains steady in the 4th position, maintaining its place in the top quartile. Meanwhile, South Korea and the Czech Republic hold the 2nd and 3rd positions, respectively, bolstered by government macroeconomic policies and stimulus measures that have strengthened their standings. Malaysia and Indonesia have also seen significant gains in their rankings, driven by improvements in corporate risk factors and their ability to meet sustainability targets—an increasingly important consideration for businesses in energy-intensive sectors. In contrast, the United States and Canada continue to face relatively high levels of political and natural disaster risks. European countries, while typically enjoying low conflict, are now facing heightened risks due to increasing geopolitical tensions, both regionally and globally.

Table 1.1 Global Manufacturing Risk Index

Baseline				Cost				Risks			
Top Quartile	Second Quartile	Third Quartile	Fourth Quartile	Top Quartile	Second Quartile	Third Quartile	Fourth Quartile	Top Quartile	Second Quartile	Third Quartile	Fourth Quartile
China	Portugal	Singapore	Germany	China	Morocco	Greece	France	China	Austria	Vietnam	Belgium
India	Sri Lanka	Morocco	France	Indonesia	Bulgaria	Canada	Norway	Republic of	Australia	Switzerland	Ireland
Indonesia	Bulgaria	Finland	Austria	India	Mexico	Republic of	Austria	Korea	India	Norway	Turkey
Malaysia	Republic of	Japan	Norway	Malaysia	Slovakia	Korea	Germany	Republic	Indonesia	Lithuania	Italy
Thailand	Philippines	United	Netherlands	Vietnam	Tunisia	Spain	Ireland	Indonesia	Japan	Netherlands	Mexico
Poland	Turkey	Kingdom	Belgium	Thailand	Hungary	United States	Belgium	Canada	Thailand	Spain	Tunisia
Vietnam	Canada	Greece	Denmark	Sri Lanka	Portugal	Singapore	Netherlands	Finland	Slovakia	Hungary	Greece
Czech	Peru	Brazil	Ireland	Colombia	Argentina	Japan	Denmark	Singapore	France	Colombia	Brazil
Republic	Romania	Sweden	Switzerland	Philippines	Czech	United	Switzerland	Poland	Peru	United	Argentina
Colombia	Lithuania	Tunisia		Peru	Republic	Kingdom	Sweden	Sweden	Kingdom	Philippines	
United	Spain	Argentina		Turkey	Romania	Finland	Malaysia	Malaysia	Denmark	Romania	
States	Mexico	Australia		Poland	Lithuania	Australia	United States	United States	Morocco	Portugal	
Hungary		Italy			Brazil	Sweden	Germany	Germany	Bulgaria	Sri Lanka	
Slovakia						Italy					

Source: Cushman and Wakefield, (2022), <https://www.cushmanwakefield.com/en/insights/global-manufacturing-risk-index>

The following are a few intriguing factors that inspired the author to look into Indonesia's industrial development:

1. Indonesia's economy remains heavily reliant on its industrial sector. The manufacturing sector contributes approximately 20% to the country's GDP, which is above the global average, and accounts for around 50% of total exports. However, despite Indonesia being the largest economy and having the largest workforce in ASEAN, it ranks only 5th among ASEAN countries in the Competitive Industrial Performance Index on the global stage.
2. In terms of business risk, Indonesia—particularly in the manufacturing sector—offers a relatively favorable environment for business development. According to surveys by Coface, Indonesia holds a solid position on the global business risk map, indicating that the industrial sector still has significant growth potential. A study by Cushman & Wakefield further supports this, placing Indonesia among the top-ranked countries in their baseline, cost, and risk assessments for the manufacturing sector. Therefore, business risk is not seen as a significant hindrance to the development of manufacturing in Indonesia.
3. Kim and Sumner (2019) argue that many developing countries are experiencing de-industrialization, with Indonesia serving as a notable case. The Indonesian government has responded to the challenge of "premature de-industrialization" by mobilizing state-owned enterprises to drive re-industrialization efforts. However, Indonesia's high-tech industry remains less competitive compared to its peers in other developing nations. To address this, the government has prioritized infrastructure development, boosting high-tech manufacturing, and revitalizing downstream resource industries.
4. Furthermore, Grabowski and Self (2020) highlight Indonesia as a very good example where industrialization and de-industrialization coexist, influenced by the price of staple foods. The rapid expansion of labor-intensive manufacturing sectors between the 1970s and the late 1990s coincided with agricultural growth, particularly in rice production, the country's primary food staple. Low rice prices enabled the manufacturing sector to expand quickly, as the state successfully stabilized domestic rice prices in line with global levels, preventing cost increases that could hinder industrial growth.

1.3 Summary of Dissertation Chapters

Based on these facts, this dissertation is interested in discussing empirically the development of the manufacturing industry in Indonesia. I pay attention to the manufacturing industrial sector in Indonesia, both large and medium industries, as well as micro and small industries.

1.3.1 Assessing the Effect of Information and Communication Technology (ICT) on Rural Development Through Small Industrialization: Evidence from Indonesia Village Level Survey

This study analyses the profound impact of Information and Communication Technology (ICT) on the well-being of rural residents, with a specific focus on both the direct and indirect implications of ICT through the lens of industrialization in rural areas. Utilizing survey data gathered at the village level in Indonesia for the years 2018 and 2021, encompassing all villages in the country as published by the Central Statistics Agency (BPS), the research employed Instrumental Variables (IV) with 2 Stage Least Square (2SLS) estimation. The results of the

estimation reveal a positive correlation between ICT and rural industrialization. Factors such as the number of cellular operators, telephone signal strength, and internet accessibility contribute to the advancement of rural industrialization by fostering an increase in manufacturing companies, the formation of industrial communities, and a shift in people's primary income source toward the industrial sector. Additionally, the study underscores the role of ICT in enhancing the welfare of rural communities, manifesting through reductions in poverty rates and the number of individuals engaged in overseas migrant work. The interaction variable between ICT and industrialization, as indicated by estimation results, exhibits a significant influence on key village welfare indicators. This underscores the symbiotic relationship between ICT and industrialization, illustrating their combined positive impact on elevating the overall welfare of rural communities.

1.3.2 Firm Performance and Markets: Survival Analysis of Medium and Large Manufacturing Enterprises in Indonesia

The second study is entitled "Firm Performance and Markets: Survival Analysis of Medium and Large Manufacturing Enterprises in Indonesia". The impact of firm performance, particularly efficiency, on business survival is determined by this study. In order to address the endogeneity issue in the production function estimation, this work uses efficiency calculations utilizing a translog model based on both time-invariant and time-varying production functions as well as the Akerberg-Caves-Frazer (ACF) model. The medium and large manufacturing business censuses with an observation period spanning from 1995 to 2015 provide the firm-level data that were used. Poisson regression and the Cox proportional hazard model were the two estimate methods employed in this investigation. While the Poisson regression is performed using aggregate data for 2-digit ISIC, I estimate the Cox regression using firm-level data. Evidence at the firm level demonstrates that a company's efficiency either shortens its survival time or lowers its hazard ratio. Additionally, in line with firm-level findings, the aggregate-level estimation demonstrates that efficiency lowers the rate at which businesses leave the Indonesian market and raises their odds of surviving and entering the country. This demonstrates how crucial a company's technological proficiency is to the survival of Indonesian manufacturing enterprises. This chapter has been published in international peer-reviewed journal, *Journal of Industrial and Business Economics* which can be found in the following link <https://link.springer.com/article/10.1007/s40812-024-00302-7> .

1.3.3 Firm Ownership, Productivity, and Export

The third study is entitled "Dynamic Triangular Relationship of Firm Ownership, Export, and Firm Productivity: Evidence from Indonesia Firm-Level Survey. This study is to examine the relationship between productivity and exports under various ownership statuses as well as the impact of foreign ownership on productivity and exports. We draw the conclusion that foreign ownership significantly affects productivity and exports based on the estimation results. In addition, export productivity benefits from the variable control of foreign investment that enters manufacturing firms, demonstrating the significance of foreign investment in bolstering the success of Indonesian manufacturing enterprises. Furthermore, in our dynamic model, domestic ownership has no discernible impact on productivity. We also discover that the company's exports are positively impacted by both domestic and foreign ownership. This attests to the fact that both forms of business ownership are focused on global markets. The

VAR panel analysis's findings demonstrate that, irrespective of the ownership structure of the business, productivity, and exports have a favourable relationship that benefits Indonesia's manufacturing sector. In order to boost global competitiveness, industrial development policies must target raising productivity, promoting exports, and attracting foreign investment.

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Chapter 2:

Assessing The Effect of Information and Communication Technology (ICT) on Rural Development Through Small Industrialization: Evidence from Indonesia Village Level Survey

2.1 Introduction

Information and communication technology (ICT) and socioeconomic development have a symbiotic relationship that is becoming more and more obvious in an era of unparalleled technological advancements. It is impossible to overestimate the significant impact that technology has on businesses and society at large, especially as the digital landscape keeps changing. ICT's ripple effects reach far beyond corporate boardrooms and into the very core of efforts to reduce poverty, from empowering enterprises to promoting inclusive growth. Existing literature reveals the various ways that ICT drives social change and economic empowerment, revealing a story that highlights how crucial it is to determine how businesses will develop in the future and, in turn, how marginalized people will live. Information ICT has a dynamic and transformative impact on rural firm development that goes well beyond the traditional boundaries of urban areas. ICT shows up as a potent catalyst for promoting economic growth, raising productivity, and closing long-standing developmental gaps in rural areas where access to resources and opportunities can be restricted.

This research is also aimed at looking at the effects of ICT infrastructure in increasing the growth of micro and small industries in rural areas and its impact on poverty. The economic transition period from developing countries to developed countries is generally followed by an increase in the composition of the role of modern sectors such as the manufacturing industry, trade, and services, as well as finance. The contributions of this study include, first, looking at the impact of ICT infrastructure at the village level on poverty with direct estimates. As previously explained ICT can increase access to information, education, and skills directly for individuals. Directly estimates the influence or baseline regression consists of the number of Base Transceiver Stations (BTS), the number of service operators, whether the cell phone signal is very strong, strong, weak or very weak, cell phone/handphone internet signals in most areas in the village) to the number of poor people and the number of micro and small industries in the village. several control variables were also included in the model including village characteristics, village staff or officials, as well as the year fixed effect, and location. This direct estimation strategy of the effect of ICT on poverty has been used in several studies, including Yang et al (2021), Dzator et al (2023), and Afzal et al (2022). On the other hand, direct estimates of information and communication technology penetration of small industries in rural areas were carried out by, among others, Aldashev et al (2021), and Morris et al (2020).

The second is trying to accommodate the assumption that the impact of penetration of information and communication technology on the welfare of rural communities or poverty in villages through changes in the economic structure or the development of the micro-small industry sector or changes in some people's livelihoods from the traditional or agricultural sector to the modern or non-agricultural sector or by In other words, model 2 tries to see

whether the influence of information and communication technology infrastructure is through a mediation or moderation process through the development of micro-small industries or variations in the types of work that exist in the village. The logic built from this mediation model approach is based on literature reviews both theoretical and empirical which suggest that one of the channels where information and communication technology impacts the welfare of society is through the entry of new companies/businesses, both formal and informal businesses (Hjort and Poulsen, 2019), besides that the impact on companies/businesses is more profitable and increases welfare through reducing operational costs (Houngbonon et al, 2022), besides that another way how information and communication technology has an impact through business is by providing space for workers who have expertise or education to starting a new business (Bahia et al, 2021). At this point, it can be said that there are several things that this study contributes, including looking at the direct effect of ICT on several indicators of village community welfare, including small-scale industry growth, poverty, and village residents who become migrant workers. Second, estimate the mediating or moderating impact of small industry growth as a means of ICT transmission on the welfare of village residents. Third, the study uses an instrumental variable approach to overcome several problems in causal inference estimation.

Indonesia, as one of the largest developing countries in the world, relies heavily on the manufacturing sector as an economic driver. In 2022, the industrial sector's contribution will be 20.47 percent, based on data from the Central Statistics Agency (BPS). Meanwhile, export contribution reached 76.37 percent of total national exports, based on Ministry of Industry data. Moreover, micro, small, and medium enterprises still dominate the Indonesian economy with a contribution to the Gross Domestic Product of 60.5 percent and labor absorption of 96.9 percent, Ministry of Economic Affairs, 2022. Therefore, the performance of MSMEs is an important factor in the national economy. On the other hand, poverty in Indonesia is dominated in rural areas, where in 2022, the number of poor people in urban areas will be 9.53 percent while in rural areas it will be 12.36 percent, based on BPS data, 2023. The economic transition in rural areas to a modern direction needs to involve the sector. industry, especially micro and small industries, so that poverty in rural areas experiences an accelerated decline.

This paper is organized as follows, the next chapter discusses a literature review that explains how ICT directly impacts poverty and the growth of micro and small industries, and how small growth also impacts poverty. Chapter three discusses the methodology used in the study including an explanation of the data used and econometric modelling with various alternative approaches. The fourth section explains the estimation results and discusses various consequences of the estimation results. The fifth chapter explains the conclusions.

2.2 Literature Review

This part of the literature study is divided into two parts, namely the first part discusses the influence of ICT on rural economic development, and the second part discusses the influence of the manufacturing sector on poverty.

2.2.1 ICT and Rural Economic Development

The impact of ICT on rural development has been widely studied from various points of view, including direct impacts on the welfare of rural communities such as (Ma et al, 2020, Chatterjee et al., 2020, Diaz et al., 2021, Zhu et al, 2022), as well as through increased entrepreneurship and company performance such as from (Peña et al, 2011, and Martinez-Caro et al., 2020, Destefano et al, 2023). There are at least three aspects of how ICT affects the rural economy,

namely access to information, education and skills development, and economic opportunities. ICT gives rural people access to information that was previously inaccessible or challenging to obtain in terms of information access. ICT and its applications have the potential to improve resource management within the company and speed up internal communication. Information may be transferred more easily between computers connected to a network and shared electronic files, which improves the productivity of data processing, documentation, and other back-office tasks like organizing incoming orders and creating invoices. Sophisticated ICT applications enable businesses to save, exchange, and utilize the knowledge and expertise they have gained. For instance, customer databases with a history of correspondence tailored to individual clients assist managers and staff in providing customers with better service. An electronic data source accessible to the entire company seeks to share staff members' professional experiences—such as advice on how to land a contract—so that other members of the organization can benefit from it. The Internet and e-commerce have the potential to significantly lower transaction costs and improve the speed and dependability of transactions between firms. They can also lessen inefficiencies brought on by a lack of cooperation amongst value chain companies. (OECD, 2004).

The ICT infrastructure in rural areas contains data about government services, healthcare, education, and agriculture. With the help of agricultural best practices, market prices, and weather forecasts, farmers can make well-informed decisions about their crops. While in terms of education and skills development, ICT makes online learning and distance learning possible, expanding educational options to rural locations. People living in rural areas may benefit from improved employability and skill development as a result of this. Adults looking to develop or learn new abilities might benefit greatly from online courses and educational materials. Additionally, ICT creates economic prospects by connecting rural producers with a wider consumer base through digital marketplaces and e-commerce platforms, which in turn expands the market for locally produced goods. Rural residents can now get financial services and internet banking without having to go far thanks to information and communication technology. From a spatial standpoint, it is evident that the platform-oriented group's members are more frequently found in urban areas, while digital manufacturers are more frequently found in rural areas. These results are interpreted as suggesting that small businesses, based on which business model works best in the specific (urban or rural) business environment. In contrast, the location of a small business has little bearing on whether it has already begun the process of digital transformation or has not begun it at all. Research and policy implications are discussed in the paper's conclusion (Thoma, 2023). According to Morris et al. (2022), infrastructure improvements have improved digital connectivity in rural areas; nonetheless, many businesses continue to lack dependable digital connections. Furthermore, results indicate that location and the distance to urban areas are important factors that correlate with satisfactory levels of digital connectivity, with a greater effect in rural areas. This means that there are fewer opportunities for businesses to engage in a variety of activities, which restricts their capacity to grow resilient during difficult economic times. However, they also take into account the fact that the coronavirus pandemic has forced many commercial operations online; as a result, companies with less dependable digital connectivity and no online presence are probably going to face greater challenges in maintaining their resilience.

2.2.2 Manufacturing Development and Poverty Reduction

It cannot be denied that industrialization is a powerful means of improving people's living standards. Aggregate productivity rises when resources are transferred from traditional agriculture to contemporary industries like manufacturing. A significant portion of rural communities' industrial and service sectors are derived from activities that are first and primarily related to agriculture, such as the storage, processing, distribution, and transportation of agricultural inputs and outputs (IEG, 2017). This transition of related activities gives rise to economic transformation in rural areas which increases the role of modern sectors such as the manufacturing sector to develop, especially small industries. However, Erumban and de Vries (2021) argue that changes in sectoral output may or may not have an impact on reducing poverty depending on a number of factors, including, The first, the sector's growth performance, second, the sector's size within the overall economy, third, the indirect effects of those changes on growth in other sectors, and fourth, the degree to which the sector is used by the poor.

The debate in the literature on industrial impacts is not only at the macro scale and large industries but also at the small industrial scale. The view of the need for government intervention in SMEs to reduce poverty is divided into two opposing views. Beck et al (2003) argue that there are two opposing views, namely pro-small medium enterprises (SME) and the second view is sceptical of SMEs. First, proponents of SMEs contend that by fostering entrepreneurship and competition, SMEs improve the efficiency, innovation, and overall productivity growth of the economy. This means that nations will be able to take advantage of the societal advantages that come with more entrepreneurship and competitiveness if they receive direct government support for SMEs. Second, proponents of SME support usually assert that although institutional weaknesses such as the financial market hinder the growth of SMEs, SMEs are normally more productive than large enterprises. Therefore, direct government financial support to SMEs can promote economic growth and development, pending institutional and financial changes. Lastly, some contend that because SMEs require more labor than large firms do, their rise increases employment more than theirs. According to this viewpoint, funding SMEs could be a useful instrument for reducing poverty.

Furthermore, Beck et al (2003) summarized some skeptical views based on four main arguments. First, some studies question the presumptions that underlie the pro-SME viewpoint and highlight the benefits of large businesses. To be more precise, big businesses can take advantage of economies of scale and find it easier to pay the fixed costs of innovation such as research and development (R&D), which can boost productivity. Additionally, some contend that large companies offer better quality jobs that are more stable than those of small companies, which has favorable effects on reducing poverty (Pagano and Schivardi, 2001, Brown et al., 1990). The presumptions that underpin pro-SME arguments are directly contested by a second group of skeptic viewpoints. Specifically, several studies reveal that SMEs are not more labor-intensive than large companies, nor are they better at creating jobs (Little, et al., 1987). A third group of skeptics contests the wisdom of viewing business size as an external factor influencing economic expansion. According to the literature on industrial organization, a country's ideal company size and industrial mix are influenced by its natural resource endowments, technology, policies, and institutions (Kumar, Rajan, and Zingales, 2001). A fourth skeptic perspective on the effectiveness of pro-SME policies, referred to as the "business environment view,"

downplays the significance of SMEs and emphasizes the importance of the business environment that all businesses, large and small, must contend with. According to this viewpoint, a business environment that supports competition and private commercial transactions is characterized by low entry and exit barriers, clearly defined property rights, efficient contract enforcement, and firm access to financing. The business environment perspective focuses on the environment that all businesses must contend with, not just SMEs in particular, even though these factors may support SMEs. Therefore, in line with the other skeptic viewpoints, the business environment viewpoint challenges the recommendation for pro-SME policies that involve funding the growth of SMEs.

2.3 Methodology

2.3.1 Data

The study relies on data obtained from the Village Potential Survey (PODES) conducted in 2018 and 2021. Administered by the Badan Pusat Statistik (BPS), this survey has been carried out three times over a decade. Notably, in 2019 and 2020, updates were limited to essential information. Encompassing a comprehensive overview, the survey spans across all of Indonesia's approximately 83,000 villages. This survey covers the entire village population in Indonesia so it can be said to be a census at the village level. and suppose there is an additional village every year. In that case, it indicates a policy of expanding the village autonomy area so that one village is divided into two or more new villages. The survey captures many aspects, including general details such as status, demographics, geography, and population, as well as various social dimensions like government, crime, education, and health. The economic facets explored involve industry, business centres, employment, and migration. Utilizing the most recent survey results with complete information, this study ensures the incorporation of up-to-date and comprehensive data.

2.3.2 Econometric Strategies

Multiple analysis stages were employed in the econometric assessment of this study, tailored to address specific inquiries. These stages encompassed:

2.3.2.1 BTS Effect on Information and Communication Technology (ICT) Access

The first stage of analysis is to estimate the influence of BTS on telephone and internet signals as well as the number of cellular operators whose signals can enter the village area which is written in equation 3.2 as ICT Access. The telephone signal variable is an ordered dummy, namely 0 for no signal, 1 for a weak signal, 2 for a strong signal, and 3 for a very strong signal. Meanwhile, for the internet signal, the outcome variable is also a dummy variable where 0 if there is no internet signal, 1 if there is a 2.5G/E/GPRS signal, 2 if there is a 3G/H/H+/EVDO signal, and 3 if there is a 4G/LTE signal. For the operator variable, the number of cellular operators in Indonesia is used. There are 7 cellular operators in Indonesia, including Tri, XL, Indosat, Ceria, Telkomsel, and Smartfren. The estimation equation can be written as follows:

$$\begin{aligned}
ICT\ Access_{it} = c_0 + \sum_{k=1}^7 \beta_k Geography_{it} + \rho_2 BTS_{it} + \rho_3 Distance_{it} \\
+ \sum_{j=1}^{12} \beta_j Infrastructure_{it} + \sum_{q=1}^2 \omega_q NICT_q + \varepsilon_{1it}
\end{aligned} \tag{2.1}$$

The estimation of equation 2.1 was carried out using logistic regression to obtain the probability of signal strength and OLS was used to estimate the outcome for the number of operators. Fixed effects of time and subdistrict are also included in the estimation process. Following Olken (2009) who used geography as an instrument variable in estimating the number of television and radio channels, this study also uses geography factors as an instrument in determining the strength of ICT access. Other variables included in the model as control variables include infrastructure and BTS. Because a village that does not have ICT infrastructure such as BTS can sometimes still have ICT access because it can still be reached with ICT from other villages, the variables used are distance from the village that has the most BTS and distance from the village that has the strongest telephone and internet signal access in one sub-district. Angrist and Imbens (1995) demonstrate how TSLS may be applied to a variant of Rubin's causal model that takes covariates, numerous instruments, and variable treatment intensity into account when estimating average causal effects. Specifically, we demonstrate that a weighted average of per-unit treatment effects along the length of a causal response function is identified by applying TSLS to a causal model with variable treatment intensity and nonignorable treatment assignment. The linearity of the correlations between response variables, treatment intensities, and instrument does not determine our results.

2.3.2.2 ICT Effect on Micro and Small Industrialization

This phase delves into assessing the influence of ICT access on industrialization in rural settings. The analysis involves estimating the impact by examining factors such as the presence of cell phone operators and the strength of cellular and internet signals. The modeling process encompasses various outcomes to serve as indicators of village industrialization. These outcomes include the number of micro and small-scale manufacturing companies, the quantity of small industrial clusters, the number of industrial environments, the prevalence of industrial villages, and a binary variable indicating whether the majority of the population earns income in the manufacturing sector (with a value of 1) or not (with a value of 0). Additionally, the model incorporates several control variables, encompassing geographical considerations, susceptibility to natural disasters, existing infrastructure, the efficacy of village governance, proximity to areas with robust cell phone and internet signals, and financial infrastructure metrics, such as the number of bank offices.

$$\begin{aligned}
& \text{Industrializations}_{it} \\
& = c_0 + \sum_{j=1}^{12} \beta_j \text{Infrastructure}_{it} + \sum_{l=1}^3 \gamma_l \text{ICT}_{it} + \sum_{m=1}^6 \theta_m \text{Nature}_{it} \\
& + \sum_{n=1}^9 \delta_n \text{Government}_{it} + \sum_{p=1}^3 \tau_p \text{Financial}_{it} + \sum_{q=1}^2 \omega_q \text{NICT}_q \\
& + \rho_1 \text{Family}_{it} + \varepsilon_{2it}
\end{aligned} \tag{2.2}$$

Estimates were conducted utilizing Ordinary Least Squares (OLS) with robust standard errors, incorporating fixed effects for both year and sub-district. In addition to accounting for ICT presence within the village, Equation 2.2 introduces the variable "distance to neighbouring villages with the strongest telephone and internet signals." This inclusion recognizes the interconnected nature of internet and telephone access across villages, where the presence of ICT in one village can influence access in neighbouring ones. Notably, the data reveals that over 50 percent of villages lacking BTS infrastructure still exhibit robust cellular and internet accessibility.

2. 3.2.3 Effect of ICT and Industrialization on Rural Development

The final segment of the analysis focuses on examining the direct impact of ICT on village development. This study employs two development indicators: the count of rural residents living in poverty and the number of individuals working abroad (Migrant Workers). The migrant variable is bifurcated into two components—the overall tally of migrant workers and the presence or absence of migrant workers within the village. Estimations were conducted through two distinct strategies. The first strategy involved incorporating ICT variables independently, while the second strategy simulated the interaction between ICT variables and industrialization indicators. Apart from looking directly at the effect of ICT on the outcome, this study also assesses the indirect impact (mediating) of ICT on poverty and population migration abroad. The logic of this interaction is that ICT provides an indirect influence through the growth of industry in rural areas, especially by opening up marketing and wider access to information and input transactions. The proliferation of industries in rural areas offers village residents abundant employment opportunities, enabling them to secure supplementary or primary positions as industrial workers. This not only provides the chance to earn higher incomes but also serves to mitigate the migration of village residents seeking employment elsewhere. Small company investment provides an opportunity to increase the scale of production so that labor absorption increases and if this employment involves the poor, it will have an impact on poverty reduction (Nursini, 2020, Rotar et al, 2019). The estimation equation used can be written as follows:

*Village Economic Development*_{it}

$$\begin{aligned}
 &= c_0 + \sum_{j=1}^{12} \beta_j \text{Infrastructure}_{it} + \sum_{l=1}^3 \gamma_l \text{ICT}_{it} + \sum_{r=1}^5 \varphi_r \text{Industrialization}_{it} \\
 &+ \sum_{s=1}^{15} \sigma_s \text{ICT} * \text{Industrialization}_{it} + \sum_{m=1}^6 \theta_m \text{Nature}_{it} \\
 &+ \sum_{n=1}^9 \delta_n \text{Government}_{it} + \sum_{p=1}^3 \tau_p \text{Financial}_{it} + \sum_{q=1}^2 \omega_q \text{NICT}_q \\
 &+ \rho_1 \text{Family}_{it} + \varepsilon_{3it}
 \end{aligned} \tag{2.3}$$

The ICT variable estimated in equation 3.1 is used in equation 3.3 to overcome the endogeneity problem of ICT with economic outcomes. The Instrumental variable scheme in this estimation is needed because by using this method, measurement errors that lead to attenuation bias can be fixed. Finding a variable (or instrument) that has a strong correlation with program placement or participation but not with unobserved variables influencing outcomes is the IV approach's main task (Khandker et al, 2010). In the context of this study, ICT is assumed to be endogenous to the outcome variable. Koutroumpis (2009) revealed that there is a potential for simultaneity bias in the relationship between ICT infrastructure and economic growth which means that translates into two distinct effects: (a) higher economic performance as a result of externalities associated with expanding broadband infrastructure, and (b) higher economic growth as a result of increased demand for broadband services. In addition, while Pradhan et al (2018) emphasized that there are four possible patterns of relationship between ICT infrastructure and economic performance, namely the Supply-Leading Hypothesis (SLH), Demand-Following Hypothesis (DFH), Feedback Hypothesis (FH), and Neutrality Hypothesis (NH). According to the supply-leading hypothesis (SLH), the development of ICT infrastructure is a prerequisite for economic expansion. As a result, economic growth and ICT infrastructure are causally related. According to this theory, information and communication technology (ICT) infrastructure directly supports other infrastructures and production factors, which boosts economic growth. The demand-following hypothesis (DFH), which indicates that causality instead flows from economic growth to ICT infrastructure, is the second proposition. ICT infrastructure is viewed by proponents of the demand-following hypothesis as a byproduct or effect of economic expansion, with little to no contribution from it. The theory is that more ICT infrastructure appears in the economy as it expands. The popular solution that can solve this simultaneity bias problem is the application of the IV method (Angrist et al (1993, Mills, 2014)

Table 2 1 Variable Description

Variables	Description
<i>ICT Access</i>	
Operators	Number of BTS infrastructure and number of cellular phone operators in the village area
Strength of Phone Signal	Quality of phone signal, which is ordered dummy of phone signal level, 0 if there is no signal, 1 if the signal is weak, 2 if the signal is strong, and 3 if the signal is very strong

Strength of Internet Signal	Quality of internet signal, which is ordered dummy of internet signal type, 0 if there is no signal, 1 if 2.5G/E/GPRS, 2 if 3G/H/H+/EVDO, and 3 if 4G/LTE
<i>BTS and NICT</i>	
BTS	Number of Base Transceiver Stations
Distance	Distance to the village that has the most BTS in one sub-district (Km)
NICT1 (Phone Signal)	The closest distance to the village that has the strongest telephone signal in the same sub-district (Km)
NICT2 (Internet Signal)	The closest distance to the village that has the strongest internet signal in the same sub-district (Km)
<i>Industrialization</i>	
Industry	Number of micro and small manufacturing firms
Income from industry	Dummy where the value is 1 if most income of the population in the village comes from industrial sector
Industrial Cluster	Number of Industrial Cluster
Small Industrial Environment	Number of Industrial Environment
Industrial Village	Number of Industrial Village
<i>Infrastructure</i>	
Permanent Markets	Number of permanent markets
Semi-Permanent Markets	Number of semi-permanent markets
Traditional Markets	Number of Traditional markets
Shop Centres	Number of shop centres
Hotel and Restaurants	Number of hotel and restaurants
Hospitals	The total number of health clinics, hospitals, centers of public health (PUSKESMAS)
Pre Schools	Number of Pre Schools
Elementary Schools	Number of elementary schools
Junior High Schools	Number of junior high schools
Senior High Schools	Number of Senior high schools
Vocational Schools	Number of Vocational Schools
Roads	The type of material used for the main village road, which has a value of 1 if the material used is asphalt or concrete and 0 if other
<i>Rural Development</i>	
Poverty	The number of poor people comes from the number of recipients of SKTM (Surat Keterangan Tidak Mampu) issued by the village (in Logaritm)

Dummy Migrant Worker	Dummy variable indicating whether or not village residents work as migrant workers abroad. Where the value is 1 if it exists and 0 if it doesn't exist
Total Migrant Workers	Number of village residents who are migrant workers
<i>Natural Disasters</i>	
Floods	Number of flood events
Earthquakes	Number of earthquake events
Landslides	Number of landslide events
Tidal Waves	Number of tidal waves events
Tornados	Number of tornado events
Droughts	Number of drought events
<i>Family</i>	
Family	Number of families
<i>Government</i>	
Information System	Dummy variable which has a value of 0 if you do not have an information system, 1 if you have an information system but it is not updated, and 2 if you have an information system and it is updated
Government Work Plan	Dummy variable that takes the value 1 if there is a government work plan and 0 if there is none
Village Regulations	Number of village regulations
Village Head Regulations	Number of village head regulations
Age of Village Head	Age of Village head
Gender of Village Head	The dummy variable takes the value 1 if the gender of the village head is male and 0 if otherwise
Village Head Education level	The dummy variable for village head education is 0 if you have not attended school, 1 if you have not graduated from elementary school, 2 if you have graduated from elementary school, 3 if you have graduated from junior high schools, 4 if you have graduated from senior high schools, 5 if you have graduated from elementary school, 6 if you have graduated from undergraduate school, and 7 if you have graduated from undergraduate school. if you pass a master's program, and 8 if you pass a doctoral program
<i>Financial</i>	
State Commercial Banks	The total number of State-Owned commercial bank branch offices
Private Commercial Banks	The total number of Private-Owned commercial bank branch offices
People Credit Banks	The total number of people's credit bank offices

Table 2 2 Descriptive Statistics of Variables

Variable	Observations	Mean	Std. dev.	Min	Max
Poverty	154,875	5.5488	1.4201	0	12.2061
Dummy Migrant Workers	167,474	0.4397	0.4963	0	1
Total Migrant Workers	167,474	12.4770	5.6627	0	1998
Industry	167,474	24.489	69.5566	0	2102
Income from Industry	168,026	0.0350	0.1837	0	1
Industrial Cluster	167,474	0.1228	0.6153	0	9
Small Industrial Environment	167,474	0.0824	0.5393	0	9
Industrial Village	167,474	0.0582	0.4524	0	9
Operator	167,474	270.362	1.8311	0	7
Strength of Internet Signal	161,267	1.3376	0.7382	1	4
Strength of Phone Signal	167,474	1.7915	0.7989	0	3
Distance (BTS)	162,451	6.1649	16.2	0	3104.7
NICT1 (Phone Signal)	167,474	6.1273	17.1	0	3102.1
NICT2 (Internet Signal)	167,474	6.4448	21.6	0	1511.9
Distance to Nearest Neighbour	167,474	1.5474	1.9	0	123.9
Cliff	167,474	2.5791	0.6568	1	4
Flat Land	167,474	0.6575	0.4745	0	1
Sea Border	167,474	0.1509	0.3580	0	1
In Forest	167,474	0.0366	0.1877	0	1
Altitude	167,474	257.8216	472.0712	0	5000
South Latitude	167,474	0.7517	0.4319	0	1
Permanent Markets	168,026	0.1244	0.8526	0	99
Shop Centres	168,026	0.4570	2.5748	0	146
Semi-Permanent Markets	168,026	0.1587	0.8194	0	99
Traditional Markets	168,026	0.1052	0.7527	0	99
Hotel and Restaurants	168,026	16.1003	38.6314	0	116
Pre Schools	167,474	1.3849	2.0863	0	101
Elementary Schools	167,474	2.0942	2.0773	0	36
Junior High Schools	167,474	0.6911	1.0673	0	24
Senior High Schools	167,474	0.2793	0.6695	0	14
Vocational Schools	167,474	0.1672	0.5201	0	13
Hospitals	167,474	0.6595	1.0302	0	19
Roads	167,474	0.2630	0.4402	0	1
Floods	167,474	0.0207	0.3254	0	18
Earthquake	167,474	0.2321	1.0474	0	9
Landslide	167,474	0.1339	0.6044	0	9
Tidal Wave	167,474	0.0346	0.3505	0	9
Tornado	167,474	0.0980	0.4442	0	18
Drought	167,474	0.0920	0.4177	0	16
Family	167,474	971.9599	1604.979	4	9171
Information System	149,540	1.4980	0.8267	0	2
Government Work Plan	151,122	0.9416	0.2344	0	1
Village Regulations	151,122	4.7731	4.2389	0	92

Village Head Regulation	151,122	4.1459	5.7001	0	91
Age of Village Head	156,869	468.915	8.2981	17	90
Gender of Village Head	156,869	0.9375	0.2419	0	1
Village Head Education	156,869	3.2630	2.3262	0	8
Number of Village Staff	168,025	34.9790	29.0096	0	39
Number of Village Discussions	163,491	6.5494	5.6039	0	99
State Commercial Banks	168,026	0.1920	0.74269	0	48
Private Commercial Banks	168,026	0.0844	0.7337	0	65
People Credit Banks	168,026	0.0872	0.5645	0	86

2.4 Results

2.4.1 ICT Development in Rural Area

The Indonesian government, through the Ministry of Communication and Informatics, started an internet access program in villages in 2014 to increase village communities' accessibility to ICT. The quick rise in the population the broader signal coverage and cellular telephone network in Indonesia do not exclude cell phone customers. 93.87 percent of the villages and subdistricts in 2021 had a cell phone signal, according to Podes data. This figure, as shown in Figure 2.1, is higher than that of the previous year, 2018, when just 92.15 percent of villages. Growing numbers of villages and sub-districts with access to strong signals are evidence that signal services have also improved. 61,332 villages/sub-districts (72.93 percent) will get strong signals in 2021. Compared to 2018, when there were only 55,575 (66.22 percent) villages/sub-districts, this number has increased. Every year, fewer villages are losing their signal-deficient status.

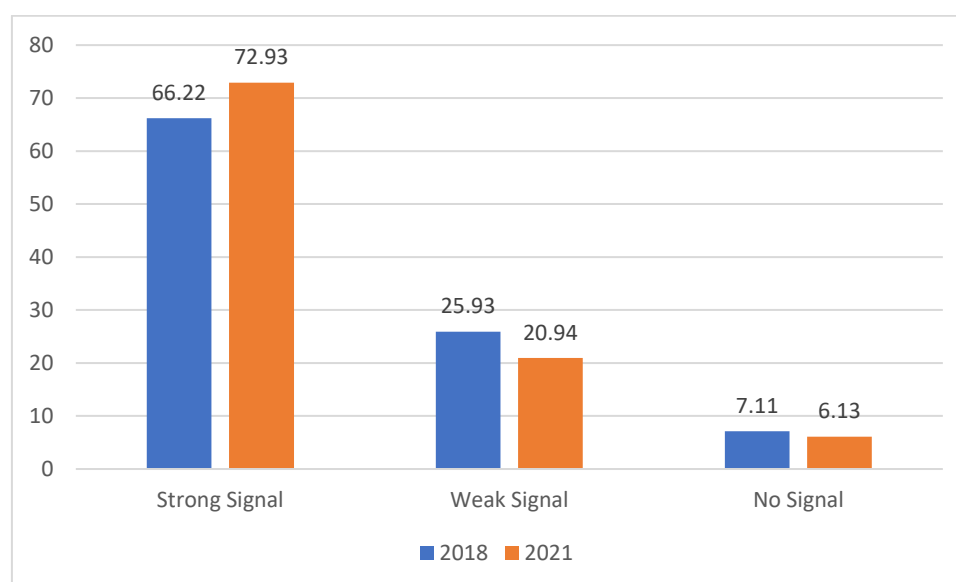


Figure 2. 1 Percentage of Village with Cellular Phone Signals

Sources: Badan Pusat Statistik, Telecommunication Statistics, Calculated by Author

The signal from a cell phone that comes from a tower Base Transceiver Station (BTS) dispersed over the whole country of Indonesia. If the village or subdistrict is inside the service's coverage

radius, it can get a cell phone signal from BTS towers in other locations. The signal's strength and weakness are not always recognized by every region equally because of a variety of factors, such as power, height, distance, location, contour area, and orientation are all transmitted by the BTS tower ahead of the BTS. PODES data collection for 2018 and 2021 is appropriate based on outcomes data. Figure 2.2 shows an increase in the number of BTS in village areas. There were 44.71 percent of villages in 2018 that had BTS and in 2021 this increased to 46.45 percent. Conversely, there was also a decrease in the number of villages that did not have BTS from 55.29 percent to 53.55 percent.

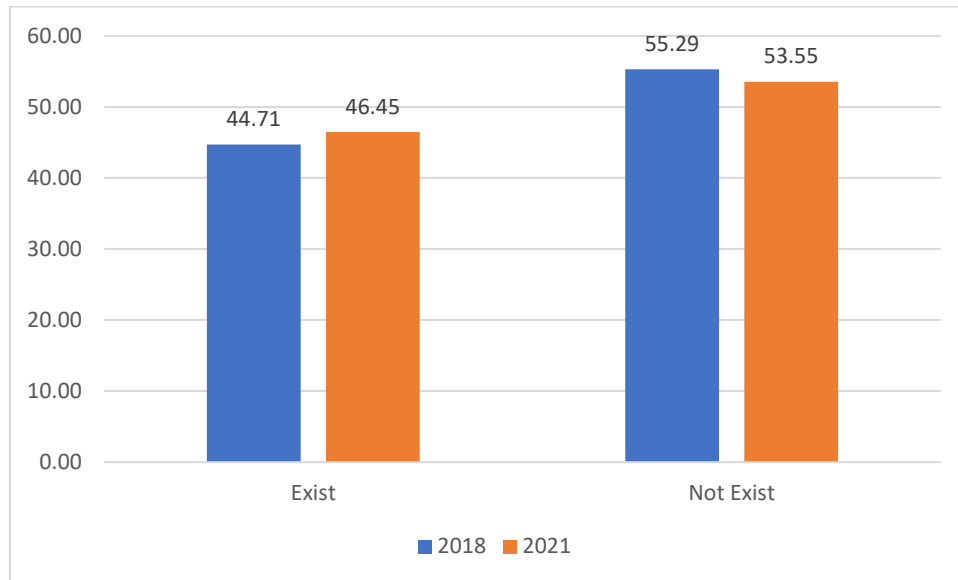


Figure 2. 2 BTS Distribution in Village Area

Sources: Badan Pusat Statistik, Telecommunication Statistics, Calculated by Author

Based on Figure 2.3, it shows that the existence of BTS is important in providing access to communication both via the Internet and telephone for village residents. There are 92.08 percent and 91.96 percent in 2018 and 2021 of villages that have BTS receiving a strong signal. Meanwhile, only 7.79 percent and 7.89 percent received a weak signal and 0.13 percent, and 0.15 percent had no signal access. However, villages that do not have BTS also still receive signals from BTS located in other village locations whose signals can still reach this. This is shown in Figure 2.3 that there are more than 50 percent of villages that do not have BTS still receive strong signals, around 30 percent receive weak signals and around 12 percent do not receive a signal.

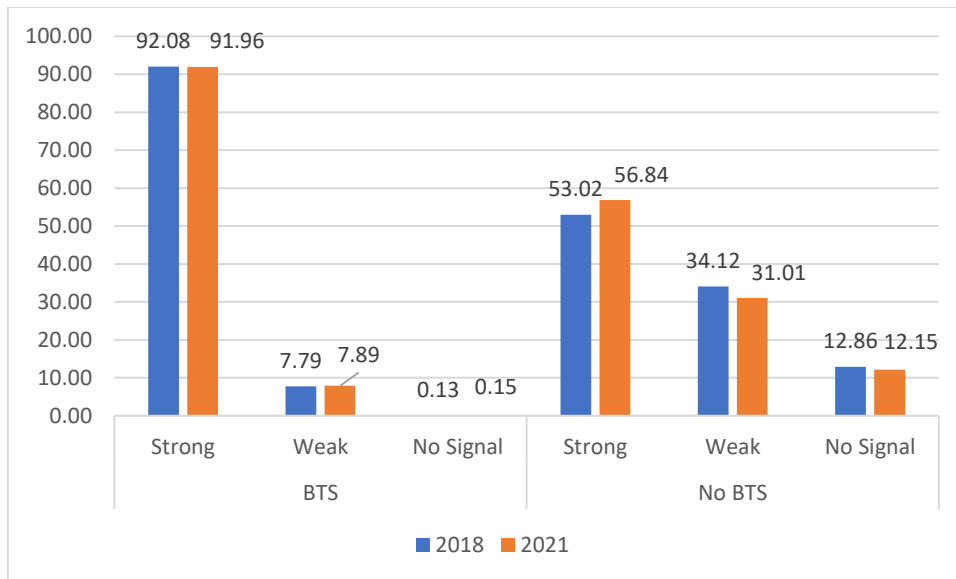


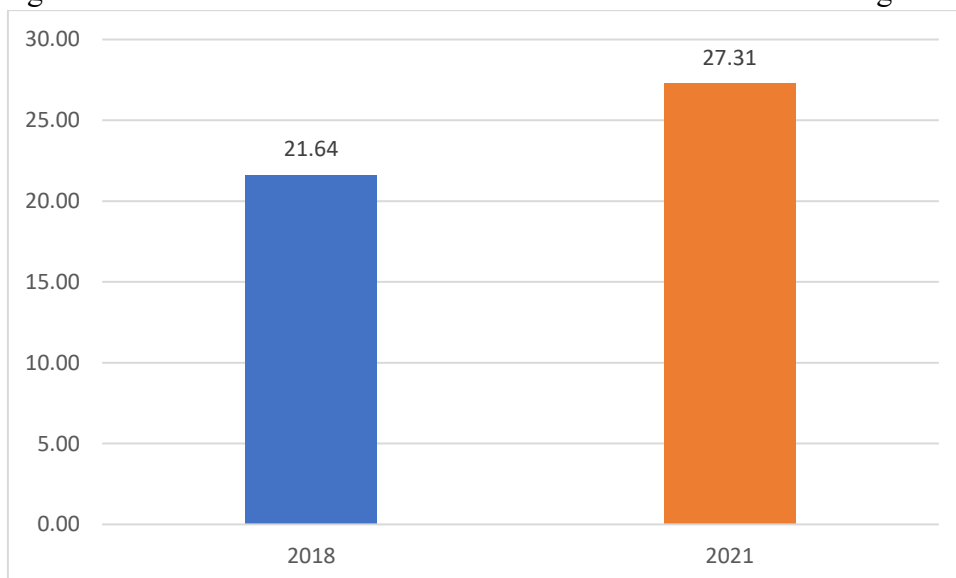
Figure 2. 3 BTS Existence and Signal Strength

Sources: Badan Pusat Statistik, Telecommunication Statistics, Calculated by Author

2.4.2 Rural Economic Development

In the contemporary digital era, the economic development of rural areas presents unprecedented prospects for local communities to amplify their economic transformation, primarily through the augmentation of the industrial sector within these regions. The data depicted in Figure 2.4 vividly illustrates this transformative trend, indicating a substantial upswing in the average number of micro and small industries. Specifically, the graph portrays a noteworthy expansion from 21 industries in 2018 to a commendable 27 micro and small industrial units in 2021, underscoring the palpable strides made in fostering industrial growth within rural landscapes. This compelling trajectory not only exemplifies the tangible progress in economic diversification but also underscores the resilience and adaptability of rural economies in embracing the digital paradigm for sustained and inclusive development.

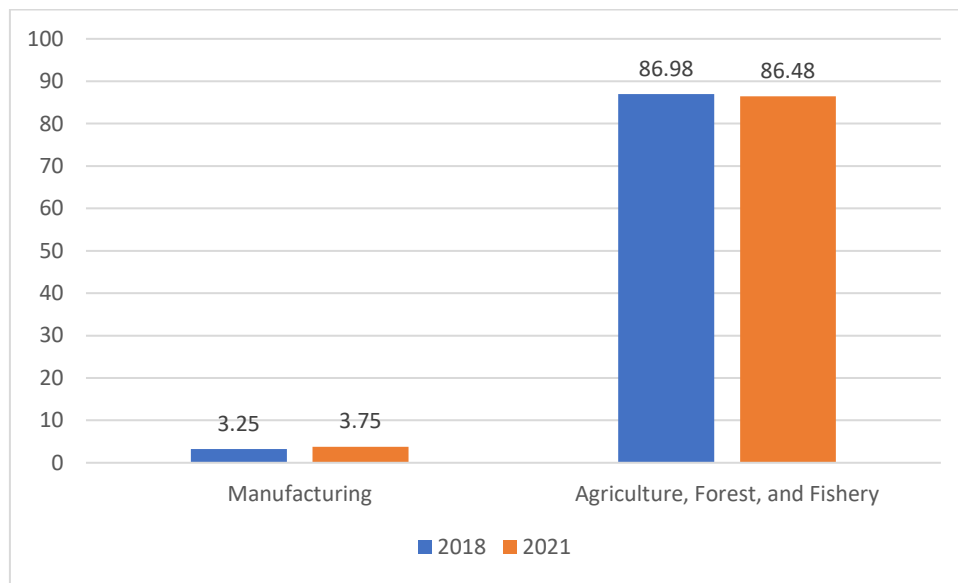
Figure 2.4 The Number of Micro and Small-Scale Industries in Village Area



Sources: Badan Pusat Statistik, Welfare Indicators, Calculated by Author

On the other hand, the growth of the manufacturing sector in rural areas has influenced the income structure of rural communities to shift to the manufacturing sector or to other sectors, although it is still dominated by the agriculture, forestry, and fisheries sectors. Figure 2.5 shows that there is a slight increase in the number of villages whose main income comes from the manufacturing sector from 3.25 percent to 3.75 percent of the total villages.

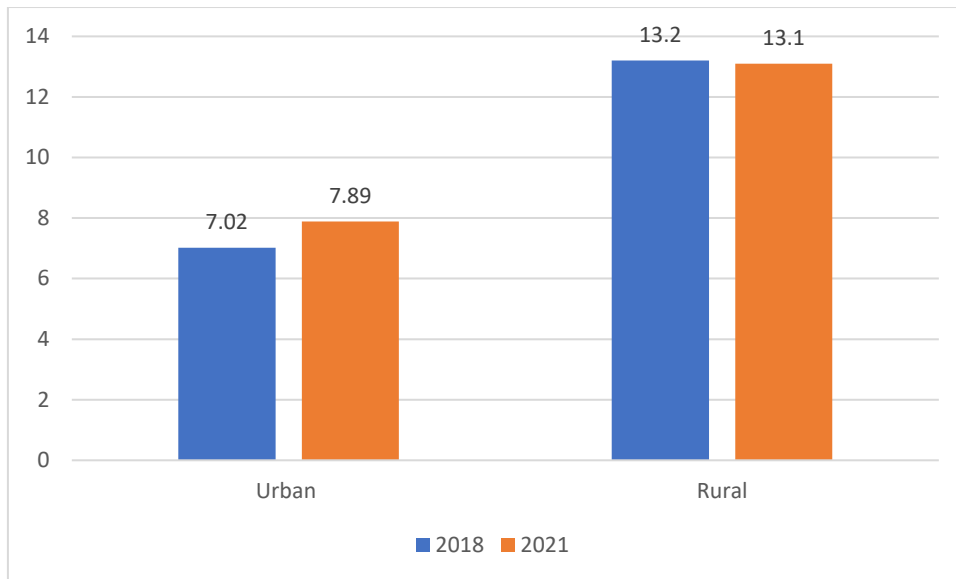
Figure 2.5 The Main Source of Income for Most Village Residents Comes from the Business Sector



Sources: Badan Pusat Statistik, Potensi Desa (PODES), Calculated by Author

On the other hand, the welfare of rural communities is still a challenge in itself, this is shown by the still high level of poverty in rural areas. Poverty in Indonesia is still dominated by rural areas. Figure 2.6 shows that around 13 percent of the poor live in rural areas while around 7 percent live in urban areas. between 2018 and 2021 there was a slight decrease in rural poverty from 13.2 in 2018 to 13.1 percent in 2021, whereas in urban areas there was an increase from 7.02 in 2018 to 7.89 in 2021. Poverty in rural areas has high complexity because various factors are involved, including culture, weather, markets, and public policy.

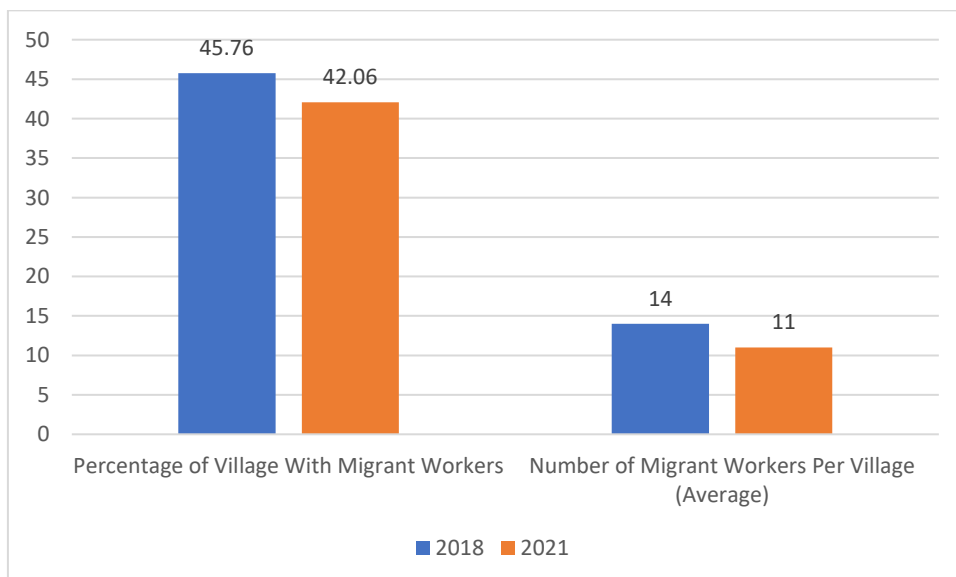
Figure 2.6 Urban and Rural Poverty



Sources: Badan Pusat Statistik, Welfare Indicators, Calculated by Author

The decision of residents to migrate from their villages in pursuit of employment, particularly overseas, is significantly influenced by the availability of job opportunities provided by companies within the village and the prevailing poverty levels. Figure 2.7 delineates changes over two distinct periods in the prevalence of villages with residents employed as migrant workers. Notably, the data reveals a decline in the percentage of villages hosting migrant workers, with a decrease from 45.76 percent in 2018 to 42.06 percent in 2021. This downward trend is further emphasized by the reduction in the average number of migrant workers per village, diminishing from 14 workers in 2018 to a mere 11 workers per village by 2021. These statistical shifts underscore the dynamic interplay between local economic conditions, job availability, and migration patterns, emphasizing the evolving landscape of employment opportunities in rural areas.

Figure 2.7 Percentage of Villages with Migrant Workers and Number of Migrant Workers Per Village (Average)



Sources: Badan Pusat Statistik, Potensi Desa (PODES), Calculated by Author

2.4.3 Econometric Results

2.4.3.1 The Effect of BTS on ICT Access

The analysis of the impact of BTS distribution on key ICT access indicators, namely operators, telephone signal strength, and internet signal strength, is presented in Table 2.3. The results highlight a consistent positive coefficient for BTS across all these indicators. This signifies that an increased presence of BTS correlates with enhanced ICT access. In practical terms, a higher number of BTS installations leads to a greater likelihood of attracting more operators to serve the village, resulting in improved telecommunications services. Moreover, the positive coefficient associated with telephone signal strength indicates that a proliferation of BTS contributes to stronger and more reliable cell phone signals within the village. Similarly, the positive coefficient for internet signal strength underscores the role of BTS as a pivotal infrastructure in bolstering the quality and reach of internet connectivity within the community. In essence, BTS emerges as a crucial element in the provision of ICT access to rural communities, facilitating increased operator presence and improving both telephone and internet signal strengths.

Table 2 3 Regression Results of BTS Effect on ICT Access

VARIABLES	(1) Operators	(2) Phone Signal	(3) Internet Signal
Base Transceiver Station	7.120*** (0.579)	3.723*** (0.586)	2.247*** (0.576)
<i>Distance and NICT</i>			
Distance (BTS)	-0.108*** (0.00294)	-0.0595*** (0.00297)	-0.745*** (0.00525)
NICT1 (Phone Signal)	-0.0151*** (0.00227)	-0.0179*** (0.00253)	-0.0132*** (0.00265)
NICT2 (Internet Signal)	-0.00128*** (0.000319)	-0.00349*** (0.000807)	-0.0377*** (0.00442)
<i>Geographical Determinants</i>			
Distance to the Nearest Neighbour	-0.220*** (0.00497)	-0.256*** (0.00608)	-0.0315*** (0.00524)
Cliff	-0.298*** (0.0279)	-0.0290 (0.0290)	-0.723*** (0.0297)
Flatland	0.199*** (0.0583)	0.0925 (0.0603)	1.295*** (0.0625)
Sea Border	-1.256*** (0.0213)	-0.295*** (0.0226)	-0.274*** (0.0240)
In Forest	-0.633*** (0.0661)	-0.974*** (0.0705)	-0.453*** (0.0720)
Altitude	-0.000444***	-0.000420***	-3.72e-05**

	(1.63e-05)	(1.75e-05)	(1.86e-05)
South Latitude	1.152*** (0.0571)	0.283*** (0.0573)	0.437*** (0.0567)
<i>Infrastructure Determinants</i>			
Permanent Markets	0.166*** (0.0191)	0.0185 (0.0283)	0.0321 (0.0201)
Shop Centres	-0.177*** (0.0157)	-0.0664*** (0.0161)	-0.0292* (0.0157)
Semi-Permanent Markets	-0.174*** (0.0161)	-0.0398*** (0.0138)	-0.0392*** (0.0116)
Traditional Markets	-0.0659*** (0.0153)	-0.0402*** (0.0146)	-0.0250** (0.0122)
Hotel Restaurant	-0.0362*** (0.00338)	-0.0171*** (0.00342)	-0.0528*** (0.00350)
Pre Schools	-0.579*** (0.0574)	-0.253*** (0.0581)	-0.141** (0.0571)
Elementary Schools	-0.799*** (0.0836)	-0.480*** (0.0847)	-0.236*** (0.0833)
Junior High Schools	-0.483*** (0.0314)	-0.237*** (0.0319)	-0.156*** (0.0316)
Senior High Schools	-0.693*** (0.0572)	-0.163*** (0.0579)	-0.147*** (0.0570)
Vocational Schools	-0.977*** (0.0932)	-0.467*** (0.0945)	-0.246*** (0.0929)
Hospitals	-1.480*** (0.121)	-0.731*** (0.122)	-0.412*** (0.120)
Roads	0.768*** (0.0123)	0.562*** (0.0130)	0.130*** (0.0132)
Observations	162,451	162,451	158,556
Districts FE	YES	YES	YES
Year FE	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Conversely, the geographical variable exhibits noteworthy coefficients, encompassing both positive and negative influences. Notably, variables such as Cliff, sea border, and in forest demonstrate negative values, indicating that, on average, these areas exhibit a lower presence of operators, along with telephone and internet signals that are comparatively weaker than in other regions. In contrast, villages situated in Flatland and southern latitudes showcase more favorable access conditions, as evidenced by significantly positive coefficients. Meanwhile, the infrastructure variables predominantly display negative coefficients, suggesting that an abundance of built infrastructure is associated with lower signal reception for both telephone and internet services. The density of buildings and user concentrations may potentially exert an influence on the quality of signal reception in these areas (Septian et al, 2021). Meanwhile, road infrastructure has a positive impact on signal strength as shown by a positive coefficient.

2.4.3.2 The Effect of ICT Access on Industrial Development

During this phase of estimation, calculations were conducted using the ICT access indicator variable derived from equation 3.2. Additionally, several supplementary control variables were incorporated into the analysis. These variables include the nature of the natural disaster that impacted the area (Nature), indicators gauging the quality of the village government (Government), the total number of households in the village (Family), and the presence of bank branch offices (Financial). These additional variables aim to capture and account for factors beyond ICT access that might influence the outcomes under consideration, thereby enhancing the comprehensiveness and accuracy of the estimation process.

The subsequent phase of estimation aims to scrutinize the impact of ICT access variables, namely operators, telephone signal, and internet signal, on indicators of industrial development within the village. These indicators encompass the number of micro and small industrial companies (referred to as Industry), the count of industrial environments, the tally of industrial villages, the number of industrial clusters, and a binary variable indicating a predominant income source from the micro and small industrial sectors. The outcomes of this estimation are succinctly presented in Table 4.3. The results unveil a substantial and positive role played by ICT access in influencing various facets of industrial development. Specifically, heightened ICT access, facilitated by operators, robust telephone signal strength, and resilient internet signal strength, demonstrate a significant positive correlation with industrial development indicators. This association is particularly pronounced in the context of the number of small and micro manufacturing firms. Moreover, the influence extends to other dimensions of industrial development, with telephone signal strength significantly impacting the number of industrial clusters, and internet signal strength exerting an influential role in the growth of industrial villages. These findings underscore the pivotal role played by robust ICT access in fostering and shaping diverse aspects of industrial development within the village. Other studies also strengthen these findings, including those from Viollaz (2018) which show that ICT can increase labor productivity, reallocate jobs and expand permanent employment, while Bettiol et al (2021) show that ICT has the impact of improving Industry 4.0.

On the flip side, various control variables exhibit diverse outcomes, encompassing both positive and negative impacts. Notably, market infrastructure variables such as permanent and semi-permanent markets, shops, and traditional markets yield adverse effects, particularly impinging on the growth of micro and small industries within the community. Given that a significant portion of the village population derives their income from the micro and small industrial sectors, these negative effects raise concerns. The influx of retail goods from external sources, coupled with the diverse array of products available in local shops catering to the village's needs, has proven consequential for the micro and small industries in the village. The proliferation of markets, while offering a platform for trading local industrial goods, concurrently facilitates the entry of numerous external products into the village. This dynamic not only amplifies the competition for local industries but also underscores the challenge of balancing local production with external trade.

Table 2 4 Regression Results of The Effect of ICT Access on Industrialization

VARIABLES	(1) Number of Small and Micro Firms	(2) Number of Manufacturing Clusters	(3) Number of Small Industrial Environment	(4) Number of Industrial Village	(5) Main Source of Income from Manufacturing
<i>ICT Access Determinants</i>					
Operators	2.390*** (0.448)	0.00681 (0.00461)	0.00552 (0.00359)	0.000231 (0.00312)	0.135** (0.0681)
Strength of Phone Signal	2.320*** (0.483)	0.0150*** (0.00528)	0.000766 (0.00374)	0.00107 (0.00339)	0.889*** (0.117)
Strength of Internet Signal	0.727 (0.706)	0.0116* (0.00642)	0.00720 (0.00543)	0.0123*** (0.00472)	0.279*** (0.0940)
<i>Infrastructure Determinants</i>					
Permanent Markets	0.452 (0.279)	0.00328 (0.00349)	-0.000608 (0.00311)	0.00293 (0.00248)	-0.303*** (0.0638)
Shop Centres	-0.0867 (0.280)	0.000994 (0.00136)	0.000907 (0.00122)	-7.29e-05 (0.000868)	-0.0386*** (0.0127)
Semi-Permanent Markets	-0.517** (0.226)	-0.000887 (0.00380)	-0.00120 (0.00368)	0.000899 (0.00298)	-0.435*** (0.0651)
Traditional Markets	-0.385** (0.190)	0.00607 (0.00488)	0.0158 (0.0115)	0.00238 (0.00253)	0.153** (0.0637)
Hotel Restaurants	0.133*** (0.0338)	0.000464 (0.000286)	0.000125 (0.000239)	0.000580*** (0.000213)	0.00526 (0.00367)
Pre Schools	1.071*** (0.297)	0.00770*** (0.00218)	0.00545*** (0.00185)	-0.000287 (0.00150)	0.138*** (0.0195)
Elementary Schools	4.493*** (0.295)	0.00565** (0.00227)	0.00499** (0.00210)	0.00729*** (0.00184)	0.180*** (0.0216)
Junior High Schools	1.207*** (0.450)	-0.000259 (0.00368)	0.00444 (0.00333)	0.00427 (0.00295)	0.0440 (0.0282)

Senior High Schools	-0.208 (0.614)	-0.00226 (0.00516)	0.0129*** (0.00474)	0.00572 (0.00397)	0.269*** (0.0467)
Vocational Schools	2.913*** (0.692)	0.00871 (0.00695)	0.00157 (0.00603)	0.00920* (0.00521)	-0.0542 (0.0449)
Hospitals	2.551*** (0.323)	-0.00460 (0.00324)	-0.00406 (0.00248)	0.00419* (0.00218)	0.0683*** (0.0234)
Roads	3.301*** (0.542)	0.00754 (0.00467)	0.0110*** (0.00402)	0.0122*** (0.00341)	
<i>Natural Disasters Determinants</i>					
Floods	-0.958 (0.717)	0.000988 (0.00427)	0.00387 (0.00455)	-0.00515** (0.00213)	-0.226** (0.0967)
Earthquakes	0.107 (0.140)	-0.00302*** (0.00117)	0.000899 (0.00120)	0.000378 (0.000972)	-0.0387** (0.0169)
Landslides	-2.701*** (0.480)	0.00239 (0.00327)	-0.00873** (0.00353)	-0.00674** (0.00263)	-0.0394 (0.0344)
Tidal Wave	0.225 (0.504)	0.000167 (0.00428)	0.00901 (0.00634)	0.00778 (0.00617)	-0.219*** (0.0348)
Tornado	-4.427*** (0.600)	-0.0244*** (0.00464)	-0.0168*** (0.00430)	-0.0187*** (0.00458)	-0.117*** (0.0353)
Drought	-0.656* (0.393)	-0.0154*** (0.00432)	-0.0165*** (0.00387)	-0.0209*** (0.00456)	-0.474*** (0.0734)
<i>Family Determinant</i>					
Family	0.0042*** (0.0006)	0.00002*** (5.31e-06)	0.000016*** (4.58e-06)	0.000145*** (3.40e-06)	0.0005*** (0.00004)
<i>Neighbour ICT (NICT)</i>					
Distance to the Nearest Village with the strongest Phone signal	-0.0457*** (0.00880)	0.000238 (0.000157)	8.25e-05 (5.90e-05)	2.91e-05 (4.55e-05)	0.000600 (0.00138)
Distance to the nearest village with the Strongest internet signal	-0.0310***	-0.000136***	-4.86e-05*	-4.05e-05*	-0.0334***

	(0.00378)	(3.31e-05)	(2.69e-05)	(2.19e-05)	(0.00547)
<i>Government Determinants</i>					
Information System	1.787*** (0.201)	0.0180*** (0.00208)	0.0108*** (0.00169)	0.00799*** (0.00140)	0.0880*** (0.0277)
Village Government Working Plan	2.935*** (0.621)	0.000601 (0.00722)	-0.00773 (0.00627)	-0.00317 (0.00468)	0.284** (0.122)
Village Government Regulations	0.291*** (0.0537)	0.000309 (0.000482)	0.000837* (0.000452)	0.000765* (0.000433)	0.00658 (0.00461)
Village Head Regulations	0.0863** (0.0412)	-5.66e-05 (0.000385)	-0.000427 (0.000286)	-0.000280 (0.000266)	-0.000773 (0.00299)
Age of Village Head	0.0921*** (0.0224)	0.000656*** (0.000207)	0.000229 (0.000184)	0.000127 (0.000158)	0.00917*** (0.00226)
Gender of Village Head	-1.265 (0.995)	-0.00301 (0.00801)	-0.00478 (0.00753)	0.00107 (0.00601)	-0.109 (0.0787)
Village Head Education	0.0121 (0.253)	-0.00197 (0.00185)	-0.000653 (0.00186)	-0.000701 (0.00152)	0.116*** (0.0250)
Number of Village Staff	0.270*** (0.0151)	0.00114*** (0.000119)	0.000750*** (0.000110)	0.000557*** (9.11e-05)	0.0118*** (0.000872)
Number of Village Discussions	0.0380 (0.0370)	0.000611 (0.000426)	0.000924*** (0.000315)	0.000238 (0.000287)	-0.0128*** (0.00367)
<i>Financial Determinants</i>					
State Commercial Banks	1.983*** (0.742)	0.00442 (0.00598)	0.000532 (0.00510)	-0.00633 (0.00435)	0.137*** (0.0435)
Private Commercial Banks	3.260** (1.385)	0.00137 (0.0100)	0.00106 (0.00632)	0.00122 (0.00572)	0.000507 (0.0368)
People Credit Banks	6.744*** (1.925)	0.0126* (0.00662)	-0.000914 (0.00461)	-0.00192 (0.00287)	0.0448** (0.0216)
Number of Families	0.00422*** (0.000603)	2.55e-05*** (5.31e-06)	1.67e-05*** (4.58e-06)	1.45e-05*** (3.40e-06)	0.000560*** (3.87e-05)
Constant	-11.68***	-0.0657***	-0.0216	-0.0481***	-6.600***

	(2.500)	(0.0212)	(0.0190)	(0.0151)	(0.296)
Observations	132,448	132,448	132,448	132,448	131,205
R-squared/Pseudo R-Squares	0.490	0.322	0.416	0.315	0.267
Districts FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Furthermore, the increased presence of markets contributes to the absorption of labor in the trade sector, providing residents with opportunities for employment and income generation through trade-related activities. Consistent with Raff and Schmitt (2011) who demonstrate that the noted transition in employment from manufacturing to retailing, the elevation in the range of products offered by retailers, and the introduction of slotting allowances in numerous retail markets align with the worldwide integration of product markets. Meanwhile, the increased concentration in retail markets is most accurately attributed to technological advancements within the retail sector.

Conversely, the presence of hotels and restaurants indicates that essential amenities such as schools, hotel restaurants, hospitals, and well-constructed roads wield a positive influence on the process of industrialization. This underscores the pivotal role of infrastructure in fostering the advancement of the industrial sector, particularly in the realm of micro and small industries. A corroborating study by Rogger et al (2023) aligns seamlessly with the findings of this investigation, underscoring the crucial role of government investments in local infrastructure. Their research underscores the significance of robust local infrastructure as a catalyst for nurturing the growth of small businesses within a region. In essence, the collective evidence emphasizes the symbiotic relationship between well-developed infrastructure and the flourishing landscape of local industries, particularly those of a smaller scale.

Another factor that plays a role in influencing industrialization in villages is the occurrence of natural disasters. There are several identified natural disasters, including floods, earthquakes, landslides, Tidal Waves, tornadoes and droughts, which are natural disasters that often occur in rural areas in Indonesia. Patankar (2019) shows empirical evidence of the impact of natural disasters, especially floods, which have a negative impact on small home businesses. The expense of climate change can be reduced with the aid of risk management. Sturdy risk management plans combine borrowing, reserving, and insurance as financial methods to handle various risk factors. By giving businesses the money, they require when a crisis strikes, this promotes recovery. However, making an investment in risk management comes with immediate expenses. Payment of premiums in advance is required for insurance. Maintaining money set away for a rainy day is necessary for cash reserves (Collier and Ragin, 2022)

Furthermore, the variable representing the number of families in an area exerts a positive influence on the level of industrialization. The upward trajectory of rural population figures coupled with a decline in available agricultural land has transformed the industrial and entrepreneurial sectors into pivotal instruments for labor absorption. Additionally, the variable measuring the distance from neighboring villages with optimal telephone signal and internet access demonstrates a negative impact. This implies that the farther a village is from another village boasting superior ICT infrastructure, the more detrimental the effect on the local industry. Graph 4.3 provides a visual representation, revealing instances where certain villages lack BTS (Base Transceiver Station) yet maintain access to ICT services. This phenomenon can be attributed to the strategic positioning of neighboring villages, allowing them to benefit from the available BTS coverage.

Another control variable under consideration is the quality of government and village leadership, assessed through parameters such as the village information system, the village

development work plan, the number of village regulations, regulations set by the village head, age and gender of the village head, educational background of the village head, the number of village office staff, and the frequency of village meetings. The results of the estimations presented in Table 4.3 unveil a positive correlation between the quality of village governance and the level of industrialization. This conclusion finds reinforcement in studies conducted by Nguyen (2023), Dong et al (2022), and Wittberg et al (2024), all of which furnish empirical evidence supporting the notion that the efficacy of local government plays a pivotal role in influencing the trajectory of industrialization. Furthermore, an additional set of control variables encompasses the domain of banking infrastructure. Banking, serving as a crucial intermediary, facilitates the provision of funds for investments and working capital, particularly beneficial for small and micro industries. Three variables are employed to gauge financial infrastructure, representing government, private, and people's credit banks. An examination of Table 4.3 reveals that the banking variables exhibit a positive coefficient, indicating a significant and positive impact on industrial development. This influence is particularly pronounced in variables associated with the growth of small and micro industries, as well as in the majority of income derived from employment within the industrial sector.

2.4.3.3 ICT, Industrialization and Rural Development

This section delves into an examination of the influence exerted by Information and Communication Technology (ICT) on key village development indicators, specifically poverty levels and the emigration of individuals seeking employment abroad—both direct consequences of ICT integration. Additionally, the analysis extends to exploring the impact of industrialization on these village development indicators. It scrutinizes the interplay between ICT accessibility and industrialization, aiming to comprehend their collective influence on overall village development. The statistical estimations were conducted utilizing the Ordinary Least Squares (OLS) method, incorporating robust standard errors and accounting for district and year-fixed effects. The variables related to ICT and Industrialization in this analysis draw from the earlier estimates presented in equations 2.2 and 2.3. A comprehensive summary of the estimation results is presented in Table 2.5. The estimation results indicate that the coefficient for the number of operators is statistically significant at the 1 percent level, ranging between 0.201 and 0.214 for poverty. This suggests that a higher number of operators is associated with a 20 to 21 percent reduction in poverty. Additionally, the direct effect of operators on the likelihood of residents becoming migrant workers is reflected in coefficients of 0.33 and 0.31, as shown in columns 3 and 4. This implies that an increase in operators raises the probability of residents becoming migrant workers by 31 to 33 percent. However, the number of operators does not have a direct impact on the total number of migrant workers in the village, as evidenced in columns 5 and 6, where the effect of operators on total migrant workers is not statistically significant. Conversely, the interaction between operator and industry variables is often found to be insignificant, with only the small industrial environment showing a significant effect on the presence or absence of migrant workers in the village. However, the interaction between phone signal and industrial clusters significantly influences whether villagers work as migrants. Additionally, the strength of the internet signal has a significant independent effect on poverty, with stronger signals associated with a 28 percent reduction in poverty. Furthermore, the internet signal also affects poverty through its interaction with the

industry variable, indicating that stronger internet connectivity enables food industries to reduce poverty by 28 percent.

The results of the estimations reveal that village industrialization when considered independently, yields a negative coefficient value for poverty, as well as for the presence or absence of migrant workers and the overall number of migrant workers. This suggests that an increased presence of industries in rural areas correlates with a reduction in poverty rates and a decline in the number of individuals seeking employment abroad. The emergence of industries in rural settings generates job opportunities, enhancing the well-being of local communities and breaking the cycle of poverty. As highlighted by Karahasan (2023), economic progress leads to an immediate decrease in poverty, but it is the mediating effect of industrialization that amplifies this overall impact, with manufacturing employment accounting for more than half of the influence on poverty. Conversely, findings from Liu and An (2023) indicate that deindustrialization contributes to an uptick in poverty. Simultaneously, access to Information and Communication Technology (ICT) demonstrates its significance as a determinant in enhancing the welfare of rural communities. It plays a crucial role in diminishing poverty and fostering employment opportunities, thereby reducing the inclination of individuals to seek work abroad. Furthermore, the interaction between industrialization and ICT access proves to be pivotal in enhancing welfare. This implies a mutual support system wherein ICT and industrialization complement each other in advancing village well-being.

Table 2 5 Regression Results of The Effect of ICT Access and Industrialization
On Rural Development

VARIABLES	(1) Direct Effect on Poverty	(2) Effect on Poverty with Manufacturing Interaction	(3) Direct Effect on Migrant	(4) Effect on Migrants with Manufacturing Interaction	(5) Direct Effect on Total Migration	(6) Effect on Total Migration with Manufacturing Interaction
<i>Industrialization Determinants</i>						
Industry	-0.267** (0.134)	-1.987*** (0.497)	-0.00242*** (0.000172)	-0.000576 (0.000358)	-0.0316*** (0.00504)	-0.0309** (0.0128)
Income from Industry	-0.4571*** (86.04)	-1,011*** (322.5)	-0.664*** (0.0453)	0.0974 (0.114)	-21.59*** (0.879)	-2.056 (1.853)
Industrial Cluster	-17.56 (20.10)	-58.65 (44.41)	-0.0438*** (0.0117)	0.0381 (0.0250)	-0.302 (0.333)	-1.192* (0.653)
Small Industrial Environment	-0.4429** (22.14)	-58.62 (58.60)	0.0119 (0.0136)	-0.00685 (0.0302)	-0.319 (0.343)	0.258 (0.760)
Industrial Village	-1.096 (22.06)	4.019 (43.82)	0.0196 (0.0170)	-0.0981*** (0.0362)	-1.688** (0.675)	-3.161*** (1.207)
<i>ICT Access Determinants</i>						
Operators	-0.201*** (69.81)	-0.214*** (69.83)	-0.338*** (0.0184)	-0.318*** (0.0183)	-0.587 (0.405)	-0.484 (0.417)
Operator*Industry		-0.556*** (0.112)		-0.00118*** (0.000125)		-0.00154 (0.00370)
Operator * Income from Industry		-138.1** (65.53)		0.0315 (0.0266)		-0.0391 (0.495)
Operator * Industrial Cluster		-5.054 (11.41)		0.00754 (0.00870)		-0.619*** (0.212)
Operator * Small Industrial Environment		-15.24		-0.0191**		-0.227

		(12.13)		(0.00951)		(0.253)
Operator * Industrial Village		-3.136		-0.0251**		-1.369***
		(13.02)		(0.0124)		(0.413)
Strength of Phone Signal	54.19	51.94	-0.0157	0.0390	-2.060***	-2.077***
	(97.25)	(98.07)	(0.0238)	(0.0241)	(0.441)	(0.461)
Strength of Phone Signal * Industry		-0.317**		-0.00199***		0.00541
		(0.144)		(0.000270)		(0.00544)
Strength of Phone Signal * Income from Industry		-44.81		-0.703***		-14.41***
		(73.47)		(0.0781)		(1.895)
Strength of Phone Signal * Industrial Cluster		-49.49***		-0.0119		0.0815
		(18.51)		(0.0191)		(0.434)
Strength of Signal Phone * Small Industrial Environment		-44.03***		-0.0289		0.0711
		(14.97)		(0.0180)		(0.506)
Strength of Signal Phone * Industrial Village		-3.084		0.0110		-1.844**
		(25.94)		(0.0259)		(0.794)
Strength of Internet Signal	-0.288***	-0.284***	-0.121***	-0.118***	0.568	0.794
	(75.89)	(76.03)	(0.0284)	(0.0283)	(0.498)	(0.508)
Strength of Internet Signal * Industry		0.156***		-0.000117*		0.00187
		(0.0362)		(6.25e-05)		(0.00185)
Strength of Internet Signal * Income from Industry		-8.028		-0.0249*		-1.573***
		(22.75)		(0.0144)		(0.306)
Strength of Internet Signal * Industrial Cluster		1.766		0.00838		-0.397***

		(7.502)		(0.00567)		(0.153)
Strength of Internet Signal *		-14.17**		-0.0128**		-0.179
Small Industrial Environment						
		(6.670)		(0.00547)		(0.162)
Strength of Internet Signal *		-2.092		0.00191		-0.652**
Industrial Village						
		(7.778)		(0.00656)		(0.306)
<i>Infrastructure Determinants</i>						
Permanent Markets	6.907	2.103	-0.0265**	-0.0221**	0.120	-0.0151
	(22.94)	(22.82)	(0.0108)	(0.0108)	(0.175)	(0.179)
Shop Centres	-0.2339***	-0.2534***	-0.0191***	-0.0115**	-0.670***	-0.598***
	(6.900)	(6.812)	(0.00529)	(0.00521)	(0.102)	(0.106)
Semi-Permanent Markets	-0.6414***	-0.6640***	-0.0329**	-0.0351**	-0.512***	-0.583***
	(22.19)	(22.14)	(0.0136)	(0.0142)	(0.194)	(0.200)
Traditional Markets	16.66	11.67	-0.0161	-0.0153	0.673***	0.684***
	(45.67)	(46.33)	(0.0102)	(0.0105)	(0.260)	(0.262)
Hotel and Restaurant	0.1069***	0.1078***	-0.00582***	-0.00484***	-0.0190	-0.0189
	(3.115)	(3.116)	(0.00122)	(0.00122)	(0.0256)	(0.0260)
Pre Schools	-0.3594**	-0.392***	-0.0408***	-0.0272***	0.293	0.403
	(15.01)	(14.96)	(0.00644)	(0.00657)	(0.256)	(0.257)
Elementary Schools	-0.5234**	-0.5600**	-0.0898***	-0.0878***	-5.013***	-4.794***
	(23.80)	(23.84)	(0.00875)	(0.00851)	(0.361)	(0.359)
Junior High Schools	23.61	28.28	-0.00885	-0.0125	-3.149***	-3.036***
	(32.64)	(32.67)	(0.0113)	(0.0113)	(0.484)	(0.482)
Senior High Schools	-53.50	-59.79	-0.0127	-0.00274	-2.476***	-2.552***
	(49.06)	(49.04)	(0.0169)	(0.0170)	(0.720)	(0.720)
Vocational Schools	-8.051	-14.49	-0.0361*	-0.0230	-1.730**	-1.617**
	(51.25)	(51.20)	(0.0203)	(0.0203)	(0.696)	(0.695)
Hospitals	59.38*	59.03*	-0.173***	-0.166***	-5.195***	-5.034***
	(32.81)	(32.92)	(0.0104)	(0.0103)	(0.306)	(0.305)

Roads	-0.151*** (50.70)	-0.153*** (51.12)	-0.227*** (0.0171)	-0.190*** (0.0174)	-3.643*** (0.466)	-3.388*** (0.470)
<i>Natural Disaster Determinants</i>						
Floods	8.524 (85.61)	10.26 (85.58)	0.0554*** (0.0183)	0.0603*** (0.0178)	0.107 (0.281)	0.115 (0.282)
Earthquakes	1.672*** (35.99)	1.673*** (36.00)	0.0393*** (0.00618)	0.0384*** (0.00619)	0.711*** (0.103)	0.727*** (0.103)
Landslides	34.62 (39.28)	37.89 (39.29)	0.0483*** (0.0117)	0.0459*** (0.0118)	2.220*** (0.225)	2.207*** (0.226)
Tidal Waves	113.6 (84.69)	115.4 (84.72)	0.00723 (0.0188)	0.00315 (0.0188)	0.278 (0.497)	0.213 (0.500)
Tornado	99.56** (40.17)	98.60** (40.16)	0.155*** (0.0166)	0.153*** (0.0166)	-0.123 (0.384)	-0.180 (0.384)
Drought	-92.49 (56.87)	-88.96 (56.93)	0.0680*** (0.0147)	0.0711*** (0.0147)	0.312 (0.364)	0.325 (0.362)
<i>Number of Family Determinants</i>						
Family	0.245*** (0.0411)	0.232*** (0.0417)	0.000264*** (2.68e-05)	0.000280*** (2.50e-05)	0.00547*** (0.000724)	0.00638*** (0.000718)
<i>Neighbour ICT Determinants</i>						
Distance to the Nearest Village with the strongest Phone signal	3.487*** (0.988)	3.697*** (0.988)	0.00923*** (0.00157)	0.00834*** (0.00154)	0.00668 (0.00850)	0.00362 (0.00901)
Distance to the nearest village with the Strongest internet signal	0.583 (0.459)	0.598 (0.458)	0.00816*** (0.00144)	0.00782*** (0.00142)	0.0215*** (0.00324)	0.0208*** (0.00327)
<i>Government Determinants</i>						
Information System	-3.144*** (36.22)	-3.141*** (36.20)	-0.236*** (0.00883)	-0.230*** (0.00885)	0.0410 (0.172)	0.0431 (0.172)

Village Government Working Plan	-22.77 (149.4)	-15.14 (149.5)	-0.417*** (0.0363)	-0.410*** (0.0363)	-0.596 (0.714)	-0.684 (0.712)
Village Regulations	3.128 (13.49)	3.020 (13.50)	-0.0274*** (0.00207)	-0.0259*** (0.00205)	-0.164*** (0.0489)	-0.163*** (0.0492)
Village Head Regulations	1.508 (5.197)	1.439 (5.204)	0.000533 (0.00125)	0.000103 (0.00125)	-0.0374 (0.0300)	-0.0365 (0.0299)
Age of Village Head	7.571*** (2.870)	7.752*** (2.872)	0.00750*** (0.000775)	0.00702*** (0.000777)	0.0565*** (0.0198)	-0.0578*** (0.0197)
Gender of Village Head	-62.71 (92.34)	-64.46 (92.34)	0.0390 (0.0292)	0.0386 (0.0292)	1.921*** (0.721)	1.878*** (0.721)
Village Head Education	-0.2414*** (49.09)	-0.2404*** (49.09)	-0.0819*** (0.00864)	-0.0788*** (0.00866)	-0.489** (0.234)	-0.473** (0.234)
Number of Village Staff	-0.485 (0.861)	-0.405 (0.869)	0.0147*** (0.000442)	0.0140*** (0.000430)	0.00875 (0.0150)	0.00487 (0.0149)
Number of Village Discussion	-7.370 (5.588)	-7.350 (5.591)	0.0136*** (0.00124)	0.0132*** (0.00124)	0.127*** (0.0313)	0.130*** (0.0316)
<i>Financial Determinants</i>						
State Commercial Banks	-30.60 (37.68)	-33.78 (37.74)	-0.133*** (0.0223)	-0.139*** (0.0244)	-3.266*** (0.542)	-3.356*** (0.543)
Private Commercial Banks	6.953 (43.07)	7.658 (42.93)	-0.172*** (0.0476)	-0.134** (0.0558)	-0.380 (0.666)	-0.191 (0.647)
People Credit Banks	9.231 (19.58)	0.280 (18.19)	-0.224*** (0.0477)	-0.224*** (0.0518)	-1.353*** (0.394)	-1.400*** (0.407)
Constant	3,198*** (385.1)	3,212*** (385.4)	-3.359*** (0.0934)	-3.310*** (0.0932)	-4.748** (2.111)	-4.961** (2.114)
Observations	132,448	132,448	131,302	131,302	132,448	132,448
R-squared	0.329	0.337	0.315	0.324	0.499	0.401
Districts FE	YES	YES	YES	YES	YES	YES

Year FE

YES

YES

YES

YES

YES

YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Kim and Cohen (2010) elucidate that the decision-making process for individuals working abroad is influenced by a myriad of conditions, prominently featuring the characteristics inherent to the country of origin. Expanding on this notion, Gibson and McKenzie (2009) underscore the multifaceted nature of these determinants, shedding light on a spectrum of economic factors within the country of origin. Additionally, they emphasize the role played by cultural dynamics and the intricate interplay of family and social life in shaping the decisions surrounding migration and the subsequent return to one's country of origin.

The infrastructure variable emerges as a significant contributor to the enhancement of welfare within village communities. The presence of essential facilities such as schools, markets, hotels, restaurants, and well-maintained roads not only mitigates poverty but also diminishes the likelihood of village workers resorting to migration. This correlation is substantiated by various studies, including those conducted by Desalegn and Solomon (2020), Timilsina et al. (2020), and Wiratama et al. (2023). Their research collectively reinforces the pivotal role played by robust infrastructure in fostering improved living conditions and curbing the necessity for villagers to seek employment opportunities elsewhere. It is necessary to give the impoverished greater access to markets for products, jobs, credit, water and sanitation, and health and education services. In addition, reducing the impoverisher's susceptibility to economic shocks is necessary to improve their well-being, promote human capital investment, and encourage higher-risk, higher-return ventures. Investing in physical infrastructure and reforming public policies will make a big difference in pursuing socially inclusive development (Ali and Pernia, 2003).

Natural disasters in rural areas exert a discernible impact on the well-being of village residents. The positive coefficient associated with the natural disaster variable implies that an escalation in the frequency of such events correlates with heightened poverty rates and an increased number of individuals seeking employment abroad. This phenomenon is substantiated by the findings of Rentschler (2013), Qianwen and Junbiao (2007), and Arouri et al. (2015), collectively affirming the adverse effects of natural disasters on the welfare of rural communities. The vulnerability of rural areas to natural disasters is exacerbated by their geographical predisposition, residing in regions prone to various calamities such as volcanoes, landslide-prone hillsides, and coastal areas susceptible to tidal waves and tsunamis. Compounding this vulnerability is the reliance of many village communities on the agricultural sector for their sustenance, a sector particularly susceptible to the direct impact of natural disasters. In this context, the presence of a modest industrial sector proves pivotal, enabling the diversification of employment risks and mitigating dependence on livelihoods directly influenced by unpredictable natural conditions prone to disasters.

Another influential variable is the number of families, exhibiting a positive coefficient, signifying that an increase in the village's family count corresponds to higher levels of poverty and a rise in migrant workers. Conversely, the distance variable to neighbouring villages with robust telephone and internet signals demonstrates a negative coefficient, indicating that heightened poverty aligns with increased proximity to villages with superior ICT access. ICT access, crucial for village welfare, can be sourced either from the local ICT infrastructure or neighbouring villages accessible for communication. The Village Government variable emerges as a substantial factor, displaying a noteworthy coefficient in influencing multiple

indicators of village welfare. Corroborating evidence from study by Jindra and Vaz (2019) underscores the pivotal role of government quality as a key instrument in the successful reduction of poverty. Furthermore, the financial infrastructure variable lacks significance in influencing poverty directly but proves impactful in curbing emigration for employment. Banking facilities provide tangible avenues for village communities to save and access credit, aiding individuals across various employment sectors in meeting consumption, working capital, or investment needs. For prospective research endeavors, consideration could be given to incorporating variables such as the number of residents or micro-small industries that receive credit, evaluating their potential impact on overall village welfare.

2.5 Conclusion

This study endeavours to examine the profound impact of Information and Communication Technology (ICT) accessibility in rural areas on the overall well-being of village residents. In addition to directly discerning the influence of ICT access on key village welfare indicators, such as poverty levels and the prevalence of village residents migrating for employment, this research also delves into the intricate transmission mechanisms through which ICT access affects village development, specifically focusing on the avenue of village industrialization.

Various indicators of industrialization are employed in this study, including the count of micro and small-scale manufacturing companies, the presence of industrial clusters, the number of industrial environments, and the existence of industrial villages. Additionally, a dummy variable is incorporated to ascertain whether the majority of the village population is engaged in the industrial sector. The study outcomes unequivocally demonstrate that ICT plays a pivotal role in fostering the development of industrialization in rural areas, with stronger signals for telephone and internet connectivity correlating positively with increased industrial growth. Beyond the ICT access factor, the study encompasses control variables reflecting village characteristics such as infrastructure, financial resources, governance by the village administration, and the impact of natural disasters on the village. These control variables reveal their own significant contributions to the promotion of industry in rural areas, as evidenced by diverse indicators influencing the trajectory of industrialization.

Furthermore, the study's findings underscore the substantial influence of ICT on village development. Quality access to ICT services, including robust internet and telephone signal strength and an increased number of operators, emerges as a crucial factor in propelling rural development. The availability of accessible information facilitates economic transactions and enhances the knowledge base of the population, thereby contributing to heightened community productivity. Notably, the interaction variable between ICT access and industrialization reveals a synergistic relationship that significantly impacts the welfare of village communities. This dynamic interaction underscores the mutually reinforcing nature of ICT access and industrialization in propelling the economic advancement of rural communities toward a modern and sustainable transition. In essence, the study underscores the transformative potential of ICT in catalyzing positive socio-economic change in rural areas and emphasizes the interconnectedness of technological access and industrial development in fostering a modern and sustainable economic landscape for these communities.

The findings of this study have important implications for both policy and business practices. On the policy side, It is therefore necessary to maintain and expand the government's project, which was started approximately 10 years ago, to provide internet connectivity to villages, since many Indonesian villages still do not have access to dependable, reasonably priced internet. Even though this initiative has reached a standstill, to prioritize rural internet infrastructure, the government must once again support it and form alliances with telecom companies and ISPs. Improved ICT infrastructure would be especially beneficial to rural dwellers, who are frequently among the poorest in the nation and are most likely to relocate in search of low-skilled employment. Increased employment prospects are provided by the transition of traditional industries like agriculture to industrialization, which can serve as villagers' primary and secondary sources of income. Thus, local welfare, poverty, and the quantity of low-skilled workers can all be improved.

On the business side, specifically, cellular network developers, operators, and internet service providers must carefully assess several factors when investing in the expansion of services in rural areas to enhance the quality and coverage of telephone and internet signals. Key considerations include the number of base transceiver stations (BTS), geographical conditions (such as the distance to the nearest BTS, proximity to villages with strong signals, and natural land features like hills, seas, cliffs, and elevations), as well as the availability of supporting infrastructure like markets, schools, healthcare facilities, and roads. These factors are critical to ensuring that investments in rural ICT services improve both the accessibility and quality of connectivity.

Moreover, expanding access to technology in rural areas not only supports existing local industries but also attracts new industrial sectors, including those from urban and international locations. The combination of lower labor costs and improved infrastructure, including ICT services, creates significant opportunities for investors to establish businesses in rural areas. This opens the door for both domestic and foreign investments, fostering economic development and job creation in these regions

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Chapter 3

Firm Performance and Markets: Survival Analysis of Medium and Large Manufacturing Enterprises

3.1 Introduction

Manufacturing is an important contributor to the economies of countries around the world, both developed and developing (Szirmai and Verspagen, 2015). Although there has been a recent debate about whether the industrial sector is still an important component of economic growth, the facts show that the dominance of the trade or service sector has shifted in many countries. The debate over whether manufacturing should continue to be the primary focus of industrial policy in developing countries is currently a matter of significant contention. Indeed, the lack of agreement reflects our weak understanding of the importance of the manufacturing sector, particularly for middle-income economies. In contrast to the predictions that arise from a particular theory, the well-documented patterns of structural change in different industries are generally accepted as empirical reality. Thus, it remains controversial whether a developing country today must be fully industrialized to become prosperous. Contemporary literature emphasizing the sectoral uniqueness of economic development also differs markedly from popular ideas that view growth as sector-neutral. Although several papers have attempted to highlight the importance of manufacturing in economic development (Su and Yao, 2016), Haraguchi, Cheng, and Smeets (2017) argue that manufacturing may continue to play a critical role in developing country economies. In this case, we could argue that the premature deindustrialization is not due to changes in the development characteristics of manufacturing that may have reduced its contribution to economic development, but rather to the inability of some countries to develop their manufacturing sector relative to others.

In the trajectory towards advancement, developing nations require a robust industrial sector to catalyse fostering income growth. The efficacy of the industrial sector constitutes a pivotal determinant of a nation's economic advancement. Notably, the average production growth in Indonesia's industrial sector between 2007 and 2019 stood at 4.02 percent, a figure that falls short when compared to the performance of low-income countries, which attained a growth rate of 5.28 percent, and middle-income countries, which achieved a more substantial rate of 6.09 percent (Global Economic Monitor, 2023). Furthermore, at the regional level, Indonesia, despite being the largest economy in Southeast Asia, is placed fifth in industrial performance according to the Competitive Industrial Performance (CIP) Index, after Singapore, Malaysia, Thailand, and Vietnam (UNIDO, 2020). On the other hand, Indonesia, as one of the fourth largest countries in terms of population, is still very dependent on the industrial sector to absorb labor. According to Badan Pusat Statistics (BPS), by 2022, more than 14 percent of the labor force in the manufacturing sector, or about 19,171 million workers. Graph 1 illustrates the shifts in the composition of the manufacturing workforce in

Indonesia as compared to various key economic sectors. The manufacturing sector holds the third position among the sectors with the highest employment rates, following the agricultural and trade sectors. The trends indicate an economic transition from the traditional agriculture sector to the modern sector, as evidenced by the growing proportion of the workforce engaged in non-agricultural activities.

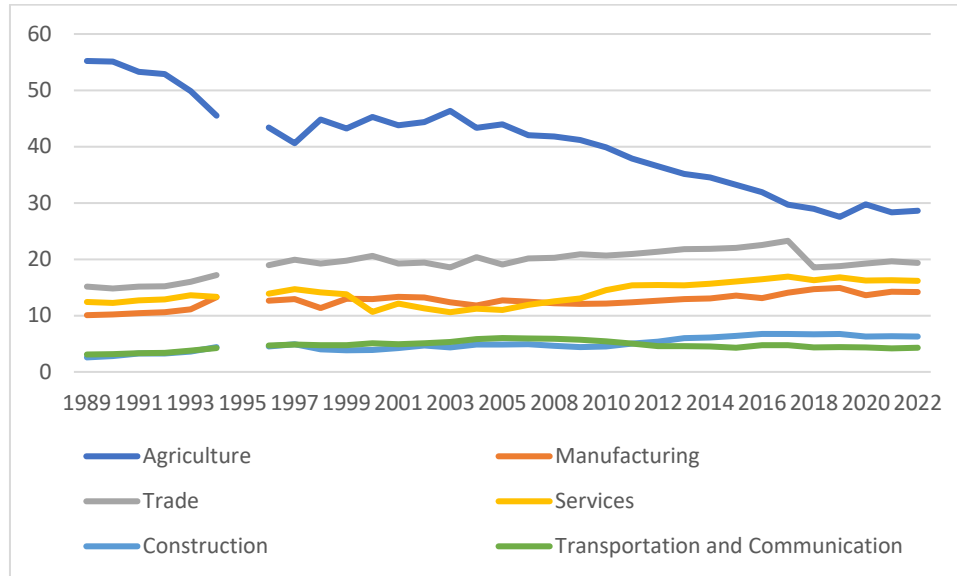


Figure 3. 1 Annual Trend of Employment Distribution among Key Economic Sectors

Source: Badan Pusat Statistik, Author's Calculation

BPS observed that an economic transition period commenced in the early 1990s, with the industrial sector emerging as the leader and the primary driving force of the national economy. Graph 2 illustrates the prevailing dominance of the manufacturing sector, which is projected to continue contributing approximately 18 percent to Indonesia's GDP until the year 2022. This is, of course, an important testament to the Indonesian economy that the industrial sector is still one of the driving forces of the economy.

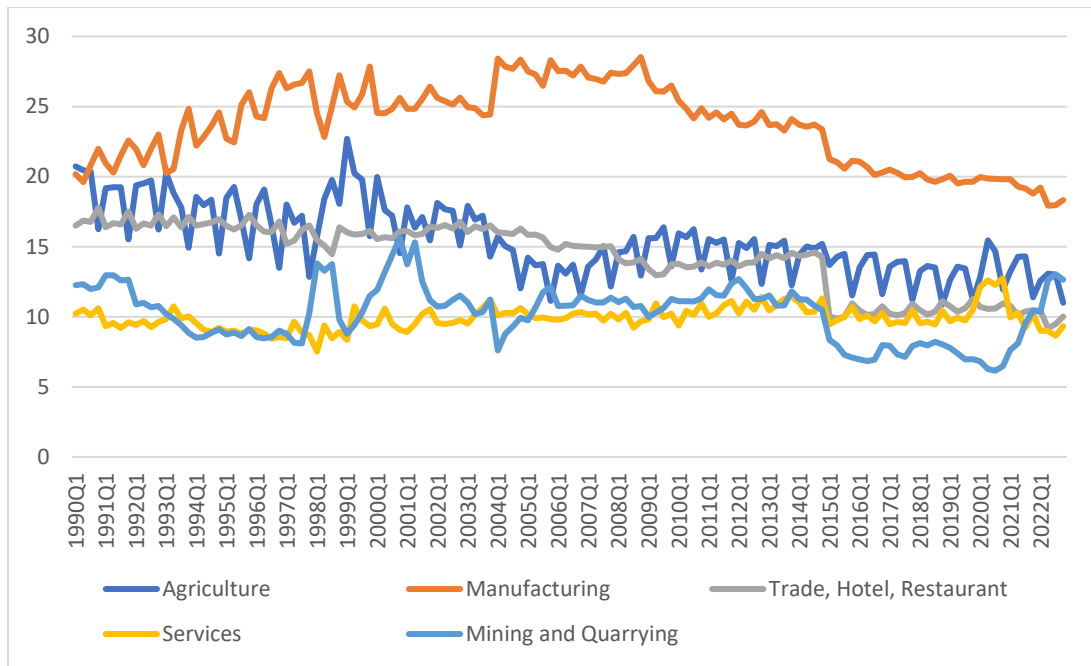


Figure 3. 2 Quarterly Trend of GDP Composition among Key Economic Sectors

Source: Badan Pusat Statistik, Author's Calculation

The growth of the industrial sector is one of the hopes for Indonesian workers to get decent jobs and income, so manufacturing companies need a good environment to develop in Indonesia. Industrial enterprises in Indonesia are engaged in various manufacturing sectors, which consist of micro, small, medium, and large enterprises. Micro industry with 1 to 4 employees, small industry with 5 to 19 employees, medium industry with 20 to 99 employees, and large industry with 100 or more employees. BPS noted that in 2022, the number of micro and small enterprises was 4.2 million enterprises, while medium and large industries were more than 30 thousand enterprises, and the number of these enterprises fluctuated quite a bit each year, as shown in Graph 3 in panel (a) for medium and large enterprises and micro and small enterprises in panel (b). However, this trend in numbers does not reflect the problems in the industry market, i.e., entry and exit or survival of the industry. Of course, high turnover can be a problem because a company is expected to perform well not only in terms of numbers but also in terms of assets, profits, and employment. Therefore, studies on this topic are important.

The issue of industrial sector growth is of great importance to Indonesia, and one aspect that has received little attention from academia is the survival of firms in Indonesia. The availability of longitudinal data for firms in the industrial sector is not widespread, especially for a large number of small and micro firms; however, a survey of large and medium industries conducted by the government covers all large and medium firms, so it is possible to conduct a survival analysis of firms with large and medium sizes.

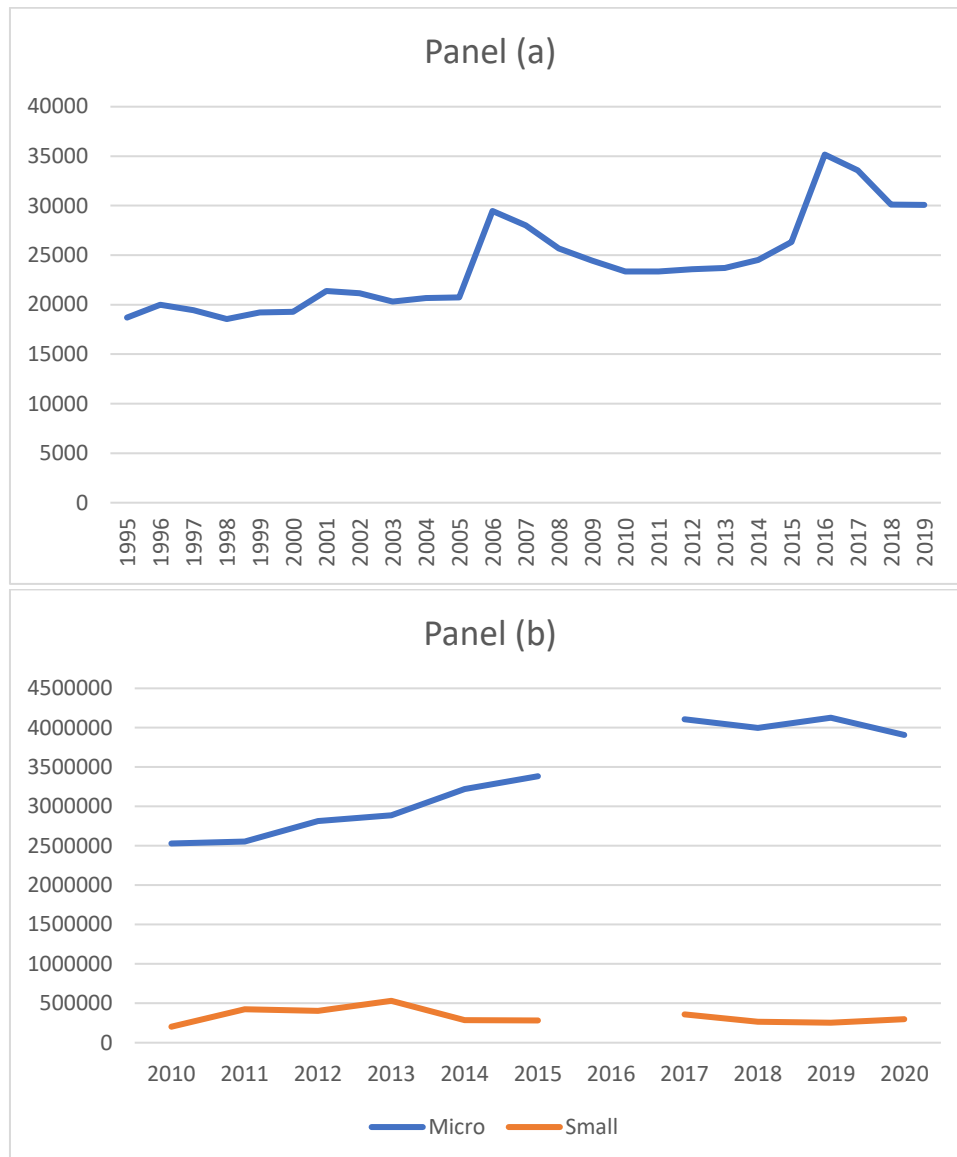


Figure 3. 3 Trend of Manufacturing Enterprises Number

Source: Badan Pusat Statistik, Author's Calculation

Panel (a) is the trend of medium and large manufacturing firms, and Panel (b) shows the micro and small-size manufacturing firms. There is no data record in 2016 for micro and small firms.

The ability of firms to enter and survive in the market depends on several factors, such as market structure, factor productivity, e.g., human capital, and financial access. The entry and survival patterns of firms, the number and size of new firms entering the market, the duration of their survival, and their market power over time are key determinants for understanding the competitive dynamics in the market. New entrants bring new products to the market and expand them into existing markets, putting competitive pressure on incumbent firms (Esteve-Pérez and Castillejo, 2006). The gradual changes of firms in the market, from creation to demise, can have a significant impact on the economy. Enterprise creation could

contribute to the creation of more jobs, the development of new products and technologies, the transformation of market structures, the development of the supply chain, and the reduction of social exclusion. However, the failure of productive enterprises can lead to a waste of social, financial, and material resources.

This study investigates the determinants, especially efficiency, market competition, and other key determinants of manufacturing firm survival in Indonesia. Not only looking at the factors that influence manufacturing companies in surviving operations in Indonesia but also looking at what causes them to enter and leave the market. This study is concerned with performance factors, especially technical efficiency, market structure, macroeconomic conditions, and company characteristics. We employ firm-level panel data from Indonesia's large and medium enterprises survey from 1995–2015. The contributions of this study are twofold. Firstly, the research employs the Akerberg-Caves-Frazer (ACF) method to compute technical efficiency, mitigating endogeneity issues in estimating the production function as the foundation for efficiency score calculation. To our knowledge, this study represents the inaugural use of the ACF technique in investigating the association between efficiency and firm survival. Previous studies relied on diverse methodologies, including the utilization of innovation proxies (Buddelmeyer et al., 2006), Data Envelopment Analysis (DEA) by Dimara et al., (2008), certain financial health indicators (Manello and Calabrese, 2017), and conventional stochastic frontier approximation (Tsionas and Papadogonas, 2006). Secondly, beyond examining the impact of efficiency on firm survival, the study explores its effects on both firm exit and entry. This exploration aims to ascertain the consistency of estimation outcomes at both the firm and aggregate levels (Two-digit ISIC), as well as the consistency of the influence of efficiency on firm survival, exit, and entry.

The estimation was carried out in two stages, namely calculating efficiency using a stochastic frontier analysis model based on the translog production function, both time-invariant and time-varying. In addition, the efficiency score calculation is also based on the ACF model estimation to overcome the endogeneity problem in the estimation of the production function. The second stage is estimating the influence of technical efficiency and other control factors on firm survival using the Cox proportional hazard model, and this process is carried out in an analysis at the individual company level. Cox (1972, 1975) uses the hazard function to investigate the relationship between the likelihood of an event occurring and several regressors. The next estimation strategy is to estimate, in a panel structure with cross-sectional entities, the number of companies entering, exiting, and surviving per 2-digit ISIC sector. The analysis of regressors is developed without specifying a hazard function under the condition of "hazard proportionality," which states that the proportion of two types of hazards remains constant over time. The inter-relationship among survival ability, entering and exiting the markets, efficiency, market power, other characteristics of the firms, and macroeconomic performance is included in the area to be discussed in this study. There are not many publications about the survival of companies in Indonesia. One publication that is focused on survival in Indonesia was written by Bruçal and Mathews (2021), who looked at the survival of medium and large firms after a flood disaster occurred at the district level.

The rest of the chapter is organized as follows. Section 2 summarizes existing literature related to the survival analysis of firms and their determinants with an emphasis especially those related to the determinant factors that will be analyzed in this study. Section

3 discusses the sources, structure, observations, and basic treatment performed. Besides that, analysis techniques and modeling strategies are also the main topics discussed in this section. Section 4 shows empirical results and discusses some of their interpretation and consequences. Section 5 provides concluding remarks, limitations, and recommendations for future research.

3.2 Literature Review

There is a growing body of literature on business survival analysis, and some of it provides general factors, while others address specific issues. This section provides previous literature discussing the effect of efficiency and some key determinants of firm survival.

3.2.1 Efficiency and Firm Survival

This study focuses on the issue of the relationship between efficiency and firm survival; however, we also include control variables that adequately represent the determinants of firm survival. The relationship between efficiency and firm survival has been empirically tested in several previous studies. Jitsutthiphakorn (2021), which measures productivity by calculating total factor productivity, while Muzi et al. (2023) use labor productivity; however, Buddelmeyer et al. (2006) indirectly observed technical efficiency using two sets of innovation variables; Esteve-Pérez and Man ez-Castillejo (2006) take productivity and competition (price cost margins) into account in their firm survival study. While Tsionas and Papadogonas (2006) calculated technical efficiency as a measure of efficiency and looked at the influence of technical efficiency on firm exit, On the other hand, Manello and Calabrese (2017) used a non-parametric data envelopment analysis (DEA) approach to calculate efficiency scores. More productive firms survive in a well-performing market with fair competition, while less productive firms exit. A dynamic like this allows for the continuous reallocation of resources to their highest value. In the highly competitive business environment, existing firms are under pressure to improve their efficiency, often through innovative activity. In the fields of microeconomics and industrial organization, the connection between firm survival and productivity has been theoretically developed as a standard. Firms in standard frameworks act with the goal of profit maximization and are constrained by a budget function. Exits from the market occur when profits fall below the variable cost threshold in its most basic form.

3.2.2 Control Variables

3.2.2.1 *Competition and Firm Survival*

In industrial organization literature, market competition is an essential factor in determining the company's performance in a market. The higher the level of competition, the more companies are required to be productive. A high concentration of industries may permit new entrant firms to operate on a suboptimal scale, providing some space for survival initial period after entering the markets. However, highly concentrated industries may have a higher

potential for incumbent collusion and, as a result, more aggressive behavior toward new entrants. At empirical evidence, competition is measured by some indicators, e.g number of competing firms, market share/concentration, and price cost margin. In the case of firm survival study, some papers e.g Audretsch and Mahmood (1995), Lopez et al (2017) employ price cost margin, whereas Audretsch (1991), and Garcia and Puente (2006) use market concentration, Kato (2009) uses industry density and size with quadratic relationship, and Jeong et al (2016) indicate competition by number of competitors. They find that market structure increases the ability of firms to survive. The research on how competition impacts firm survival is mixed. Some studies find that competition reduces firm survival, while others find the opposite effect or no significant effect. Two studies found that competition decreases firm survival. Suarez (1995) found that firms in industries with dominant designs, indicating intense competition, had lower survival. Similarly, Utterback (1993) argued that firms founded during periods of high competition will have higher failure rates. In contrast, other studies found that competition increases firm survival. Børing (2015) found that product-innovative firms, which likely face high competition, had higher acquisition rates, indicating greater survival. Naidoo (2010) found that Chinese manufacturing SMEs with competitive advantages, developed through marketing innovation in response to competition, had greater perceived survival likelihood. Some studies found no significant effect of competition on firm survival. Januszewski (2002) found no effect of competition on productivity growth for German firms. Guadalupe (2008) found that while competition caused firms to flatten their hierarchies, it did not impact firm survival. The effect of competition also depends on firm characteristics. Naidoo (2010) and Guadalupe (2008) found that the positive impact of competition on survival was enhanced by strong corporate governance and organizational restructuring. In summary, while some studies find that competition reduces firm survival, the overall research is mixed. The effect of competition seems to depend on factors like firm and industry characteristics, governance, and the ability to restructure in response to competition.

3.2.2.1 Foreign, Domestic Investment, and Ownership

The effects of foreign direct investment (FDI) also depend on a firm's experience and timing of entry. Early entrants gain higher market shares but lower survival rates, as Murray et al. (2012) show in a study of foreign firms in China. However, Shaver et al (1997) find that firms with more experience investing in a host country and firms entering industries with a larger existing foreign presence have higher survival rates. This suggests experience and following other foreign investors can help firms overcome the disadvantages of being early movers. The type of FDI also matters. Chen et al (2000) show that "expansionary" FDI seeking to exploit competitive advantages boosts firm growth and survival, while "defensive" FDI seeking cheap labor only boosts survival. Exporting, which often accompanies FDI, has similarly complex effects. Dzhumashev et al. (2016) find that while exporting initially increases the hazard of firm failure in the short term, in the long run, exporters benefit more from productivity gains and have lower failure rates. In summary, while foreign investment can threaten firm survival by increasing competition, it also frequently boosts survival by providing knowledge and market access. The net effect depends on a firm's experience, timing, industry conditions, and FDI motivations. With the right strategies and circumstances, FDI can ultimately strengthen rather than weaken a firm's viability. Qu and Harris (2018) show that financial assistance and

the strength of political links have a greater likelihood of survival. On the other hand, Kubo and Phan (2019) show that government ownership has a nonlinear impact on company performance depending on the type of partnership. This non-linearity is also confirmed by Nguyen et al (2022) who show that there is a threshold where increasing government ownership beyond a certain point will hurt company performance.

3.2.2.3 Openness

Trade openness is a means for companies to obtain better and cheaper resources or a wider market. However, problems arise for the company if it is unable to overcome the problems from the risks of international trade. This related empirical study confirms that ambiguity exists. International market activity raises the risk of volatility, which could have either positive or negative effects on the business, leaving the overall outcome unclear (Buch et al., 2009). According to Esteve-Pérez and Mañez-Castillejo (2006), a company's chances of surviving are decreased when it exports a lot. Wagner (2013) finds that exports will influence firm survival as long as there is two-way trade, or, in other words, the company also imports. This was added by Gibson and Graciano (2011): importing companies get two benefits at once, namely the relative price and the embodied technology of the input.

3.2.2.4 Capacity Utilization

Several studies show the effect of capacity utilization on firm survival. Lecraw (1978) found that capacity underutilization in firms was negatively correlated with firm survival. Firms that operated at lower capacity utilization rates had lower projected profits and perceived higher risks, leading to lower survival rates. Lieberman (1989) supported this and finds that higher capacity utilization was positively associated with firm survival in chemical industries. Firms that expanded capacity in line with demand growth and had lower variability were more likely to survive. Ray (2021) took a cost-based approach, finding that firms operating at less than full capacity had higher average costs and lower survival rates. To minimize costs and ensure survival, firms needed to increase output and capacity utilization. Nikiforos (2012) argued that the desired rate of capacity utilization for cost-minimizing firms is endogenous. As returns to scale decrease with higher production, firms have an incentive to increase capacity utilization, leading to higher survival rates. In addition, Chatzoudes (2021) supported this, finding financial constraints reduced short- and long-term survival, especially during economic crises. Performance drivers like capacity utilization and access to finance were key to the firm's survival.

3.2.2.5 Change Inventory (Inventory)

Basu and Wang (2011) argue that there was a negative relationship between inventory changes and firm performance. Additionally, this relationship is slightly mitigated for businesses that are typically low-carrying organizations as well as those in the wholesale and retail sectors. According to their research, there are significant mediators of the relationship between inventory fluctuations and business performance, including macroeconomic and

industry-specific conditions. Bao (2004) suggests that the informativeness of change in inventory positively affects firm valuation. On the other hand, Lin et al (2022) explore the impact of inventory productivity on venture survival and find a converse U-curve relationship. Additionally, financial constraints moderate the effect of inventory productivity on survival. Elsayed and Wahba (2016) propose that inventory performance depends on the firm's life cycle stage, with firms in the expansion and revival stages exhibiting better inventory performance compared to firms in the inception or maturity stages.

3.2.2.6 Location (Java)

Choosing a production location and market is very important for the company's survival. Locations that provide infrastructure facilities and attractive market trends for companies provide advantages in production operations and the distribution of production results. This is supported by several studies. Manzato et al. (2010) found that variables such as accessibility to infrastructure supply, regional effects, demographic and economic aspects, and rent prices significantly affect firm survival rates. Shu (2018) focused on traded industries and found that regional concentrations of related industrial firms (localization) can moderate the effects of founder team industry and start-up experience on firm survival. Stearns et al (1995) specifically argue that new businesses located in urban, suburban, or rural areas can have a significant impact on performance outcomes. Urban areas may have more competitors, but they also have a wealth of different resources. Although they may be less diverse, rural areas can help companies fill gaps in the market in the absence of competition. Bagley (2019) contends that taking into account a firm's geographic location within an industrial cluster, there may be a nonlinear relationship. He indicates a link that is inversely U-shaped. Furthermore, new enterprises benefit at extremely short distances from the cluster centroid. Any benefits from co-location are lost at intermediate distances, which in this case encompass the densest part of the cluster, possibly as a result of competition effects. As distance increases, this negative externality disappears.

3.2.2.7 Size

Company size and its impact on company performance or survival are theoretically ambiguous. In many industries, larger firms tend to have a survival advantage over smaller ones. This is often attributed to their greater access to resources, economies of scale, and established customer bases. Larger firms may have more diversified product lines, geographic reach, and financial stability, which can help them weather economic downturns and industry fluctuations more effectively. Small firms, while more vulnerable to economic shocks and competition, can exhibit resilience due to their agility and ability to adapt quickly. Niche markets, specialized expertise, and innovative solutions can enable small firms to carve out unique positions in the market, allowing them to survive and thrive. The papers present mixed findings on the relationship between firm size and firm survival. Palestrini (2015) explores the survival bias in the firm size distribution. Agarwal and Michael (1999) argues that the relationship between firm size and survival depends on the stage of the industry's life cycle.

Some studies use some proxies for firm size such as assets by Agarwal and Audretsch, (2001), sales and assets (Dzhumashev et al., 2016), and number of employees (Bosio et al., 2020; Cefis and Marsili, 2005; Fernandez et al., 2021).

3.2.2.8 *Macroeconomic Variables*

In addition to performance and market factors, macroeconomic factors must also be seen as important factors in determining whether a company should operate in a market. Macroeconomic conditions, workforce quality, and good economic policies will make companies choose to continue operating in a market. Holmes et al. (2010) identified firm survival by including macroeconomic variables such as interest rates and sectoral economic growth as drivers. Audretsch et al. (1997) also did the same thing with sectoral growth variables. Macroeconomic conditions can affect the company both from the input and output market sides. From the input side, companies that are oriented to the domestic market as their output market certainly hope for demand-side strength from the economy to absorb their production, while from the input side, such as energy prices that may represent capital utilization (Ghosal, 2003), policies, quality, and quantity of labor (Acs et al, 2007), can provide a boost to production. However, according to Bartoloni et al. (2020), complex events like recessions produce highly erratic and unstable corporate conditions. Production efficiency has a limited impact on a company's ability to survive such situations. Instead, it depends on one's aptitude for handling such complexity. They discovered that companies using talents and competencies to navigate environmental challenges more often are less likely to exit during a downturn compared to those that do not.

3.3 Methodology

3.3.1 Data

The data used in this study were collected from a survey of large and medium-scale manufacturing industries conducted by BPS. The survey is conducted annually and covers all large and medium-listed companies. This study uses a survey period from 1995 to 2015. In one census year, there were around 20,000 companies registered and surveyed. The results of the compilation of all observations amounted to 461,764. Each company has an identity code and a 5-digit ISIC (International Standard Industrial Classification) code, which indicates the global standard for categorizing productive activities. This study uses companies that existed in the last year of observation as existing companies, both those that have just entered the industry and those that have existed before. In addition to micro survey data, this research also uses macro data as an indicator of economic conditions, especially at the national level or at the location where the company operates. Both micro survey data and macro data are all from BPS, and World Development Indicators are from the World Bank. The company's data in the survey will simulate possible observations indicates in the selection of the age period that is the benchmark in the survival period. The cleaning of general survey data is carried out to see whether the responsiveness of the respondents is sufficient for some of the basic information needed for analysis. This study conducts a cleaning of company respondents who

do not answer basic questions such as total cost or total energy required for production because we view that this information must be present in the production process, and we consider that responses not answered are considered unobserved.

3.3.2 Econometric Model Specification

3.3.2.1 Modeling of Efficiency

The variable indicated is efficiency, which is calculated using stochastic frontier analysis (SFA) based on the production function to calculate the efficiency score. Refer to Coelli et al. (1998) and Tesema (2022). The production function is used to measure the technical efficiency (TE) score, where technical efficiency is estimated using the production function, and the technical efficiency score is calculated using the ratio of the predicted value of the production function to the actual production value data. The production function is estimated using the standard frontier model with a linear log form for both inputs and outputs. There are four inputs included in the model: the number of workers, total energy consumption including gasoline, diesel, gas, lubricant, coal, and electricity, fixed capital such as buildings, machinery, land, and vehicles, and raw materials. While allocative efficiency is calculated based on the estimation of the cost model function on output, input prices include energy prices, labor prices, capital prices, and raw material prices, which are calculated with the unit value of each input per unit amount of consumption and total expenditure for these inputs.

Raw material inputs that do not have an input price per unit are proxied using the producer price index. In general, the production function can be estimated with the following equation (1) and (2):

$$\ln(y) = x\beta + v - u \quad (1)$$

$$TE = \frac{y}{\exp(x\beta)} = \frac{\exp(x\beta - u)}{\exp(x\beta)} = \exp(-u) \quad (2)$$

where y_{it} represents the value of output for firm i in the t period, and x_{it} represents a $(1 \times K)$ vector with the values are functions of inputs consisting of labor, materials, energy, and capital (buildings, vehicles, machinery, lands, and other assets), and other explanatory variables for firm i in the t period, while β is a $(K \times 1)$ vector of unobserved coefficients to be measured. In addition, V_{it} is assumed to be error disturbance and distributed independently and identically and possess normal distribution with zero mean and unobserved variance, σ_v^2 , and U_{it} are non-negative, unobservable random variables connected to technical production inefficiencies, meaning that the observed output is not as high as it could be given the technology and input levels used. Based on the specifications of the stochastic production frontier model described in Equation 1, the technical efficiency value can be formulated as in Equation 3

$$TE_{it} = \exp(-U_{it}) \quad (3)$$

Where TE_{it} is the technical efficiency for i firm at t period. Coelli et al. (1998) argue that the stochastic frontier function has various forms, and the most common is the Cobb-Douglas form, which is from the simplest form to the most complex form, namely translog. Although the

translog frees the production function from these constraints, it does so at the expense of having a form that is more challenging to handle analytically and susceptible to degrees of freedom, sufficient observation, and collinearity issues. Since the translog function is a flexible functional form. Although the Cobb-Douglas model is simple, it has limitations in terms of the elasticity of production inputs, which are constant, including the production scale of each observation entity. In addition, the elasticity of the substitution function is also 1. The basic difference between the Cobb-Douglas and translog model specifications is that the simple Cobb-Douglas model only includes production input variables without including interaction variables between variables in the estimation model as shown by Equation 3 and 4 as follows

$$\ln y_{it} = \alpha_0 + \sum_{m=1}^n \beta_m \ln x_{it} + V_{it} - U_{it} \quad (3)$$

$$\ln y_{it} = \alpha_0 + \sum_{m=1}^n \beta_m \ln x_{it} + \frac{1}{2} \sum_{m=1}^n \beta_{mm} \ln x_{it}^2 + \sum_{m=1}^n \sum_{l \neq m}^n \beta_{lm} \ln x_{it} + V_{it} - U_{it}$$

If we compare the two equations, it can be seen that equation 3 only contains the linear coefficient input variables without including derivative variables such as interactions and quadratic forms of production input variables. However, the translog production function is superior to the Cobb-Douglas function in approximating unknown production functions (Kymn and Hisnanick, 2001; Shih et al, 1977). The translog relaxes strong assumptions of the Cobb-Douglas like homotheticity, homogeneity and separability (Tzouvelekas 2000; Kymn and Hisnanick 2001). By not imposing these restrictions, the translog allows for variable returns to scale and non-neutral technical change (Kim 1992; Tzouvelekas 2000). Several studies found the translog specification preferable to the Cobb-Douglas. Tzouvelekas (2000) and Kymn and Hisnanick (2001) could not reject the translog in favor of the Cobb-Douglas. Heyer et al (2004) also found the translog superior when accounting for factor utilization. However, Konishi and Nishiyama (2002) could not reject the translog for Japanese manufacturing. The translog's flexibility allows it to account for complex production structures with multiple factors (Kymn and Hisnanick 2001; Binswanger 1974). The translog can be estimated with panel data to gain efficiency, as shown by Tzouvelekas (2000). It can also incorporate technical and allocative inefficiency, as Kumbhakar (1989) demonstrated. It can provide a superior fit to data and account for complex production structures and inefficiency. Though it faces issues with zero values, solutions have been developed to facilitate its use.

Stage 1 of the analysis method begins with estimating a stochastic frontier model based on the production function. Several approaches of estimation can be employed including standard stochastic frontier analysis models on panel data with time-invariant (TI) or time-varying decay (TVD) models based on maximum likelihood estimation technique. There is an ongoing debate in the literature on whether to use TI or TVD inefficiency models in panel data stochastic frontier analysis. Some papers argue for TI models, citing their simplicity and ability to control for unobserved heterogeneity (Greene 2001; Paul and Shankar 2020). However, others argue that time-varying models are more realistic, as inefficiency is unlikely to remain constant over long time periods (Peyrache and Rambaldi, 2012; Colombi, 2013; Colombi et al., 2011). Time-invariant proponents point out that their models can adequately control for unobserved heterogeneity by using random effects (Paul and Shankar 2020), fixed effects (Greene 2001), or latent class specifications (Greene 2001). For example, Paul and Shankar (2020) propose a random effects model that allows for time-invariant inefficiency and unobserved heterogeneity.

Through Monte Carlo simulations and an empirical example, Paul and Shankar (2020) show this model can perform well even in small samples. On the other hand, advocates of time-varying models argue that inefficiency is unlikely to remain static over time. Peyrache and Rambaldi (2012) propose a state-space model that allows for time-varying inefficiency and temporal variation in unobserved heterogeneity. Colombi (2013) proposes using the closed skew normal distribution to model time-invariant and time-varying inefficiency in panel data. The choice ultimately comes down to a trade-off between parsimony and flexibility in modeling temporal variation.

In addition, we use the Akerberg-Caves-Frazer (ACF) method proposed by Akerberg, Caves, and Frazer (2015) to overcome the endogeneity problem in the estimation of the production function. Manjón and Mañez (2016) argue that because the error term of the model typically contains output determinants that are observed by the firm but not by the analyst (firm's productivity or efficiency), inputs are likely to be endogenous variables if firms choose the level of inputs demanded in the production process optimally (that is, as the solution of a dynamic profit maximization problem). This indicates that estimations produced by conventional estimation techniques like ordinary least squares (OLS) are inconsistent. Additionally, more complex techniques like the fixed-effects estimator or instrumental variables within-groups estimator do not appear to be very effective (Griliches and Mairesse 1995). The technique promoted by Levinsohn and Petrin (2003), according to Akerberg, Caves, and Frazer (2015), may have identification problems. The method demonstrates that the labor input might not fluctuate independently of the nonparametric function that is being estimated using the low-order polynomial unless extra assumptions are made about the processes that generate the data. Moreover, Akerberg, Caves, and Frazer (2015) suggest an estimation procedure that borrows elements from both the two-stage Olley and Pakes (1996) and Levinsohn and Petrin (2003) approaches but predicts all the input parameters in the second stage. This avoids the functional problem of dependence. By considering the advantages of the ACF method, we carried out a final analysis based on the efficiency values calculated using the ACF approach, and efficiency estimation using the standard stochastic frontier approach with the TVD and TI models only as comparisons.

3.3.2.2 Modeling of Firm Survival

The second stage of this study investigates the impact of technical efficiency on firm survival, employing two distinct approaches: one at the firm level and another at the 2-digit ISIC level, both structured as panels as outlined in section 3.1. This exploration aims to assess the consistency of results across both individual firms and the aggregate level. Additionally, the categorization of observations into survives, exit, and entry groups enhance the comprehensiveness and coherence of depicting how technical efficiency influences a company's survival. The firm-level analysis adopts the Proportional Hazard Model approach, while the 2-digit ISIC analysis utilizes Poisson regression. Subsequent sections elaborate further on the methodology employed.

Muzi et al (2023) argue that there is a possibility of bidirectional causality (reverse causality) between efficiency/productivity and firm survival where companies that can gradually survive are also able to learn to become more efficient and one way that can be used to overcome this is to use a lag variable. Therefore, the firm survival estimation in this study uses the first lag of technical efficiency as the concern variable for this study.

Firm Level Evidence

Two approaches are often used to look at factors that influence firm survival, namely the logit approach and the hazard model approach. This binary approach is used by many firm survival studies, including those by Audretsch (1991), Audretsch and Mahmood (1995), Banbury and Mitchell (1995), Lopez et al. (2017), Cefis and Marsili (2012), and Fernandes and Paunov (2015). However, several works of literature discuss binary models for survival analysis, raising several concerns. Binary models are not always applied or interpreted appropriately, and predictive inference from these models can be inaccurate (Henderson, 1995). Rychnovsk (2018) found that survival models outperformed logistic regression in predicting the probability of default. Koletsi and Pandis (2017) note that Cox regression, a popular survival analysis method, provides hazard ratios and confidence intervals, allowing for the adjustment of covariates. Nevertheless, logistic regression can still be useful for survival analysis when the proportional hazards assumption does not hold (Lim et al., 2010; MacKenzie 2002). The use of logistic regression for analyzing firm survival is a popular but problematic approach, as evidenced by these papers. A key issue is that logistic regression cannot properly account for duration dependence—the tendency of hazard rates to initially increase, peak, and then decrease over a firm's lifetime (Kaniovski and Peneder, 2008; Gupta et al., 1999; Mahmood, 2000; Holmes et al., 2010). Alternative approaches like hazard models are better suited for this (Audretsch 1995; Kaniovski and Peneder, 2008; Gupta 1999; Mahmood 2000; Holmes et al., 2010).

This study focuses on the use of Cox proportional hazard models. I estimate factors determining surviving firms during the period 1996 to 2015 by estimating the survival time of the companies using the Proportional Hazard Model, Cox Regression. Building a model of firm exit (survival) using standard estimation techniques such as Ordinary Least Square (OLS) introduces a sampling bias because some firms are more likely than others to remain in business (Lopez et al, 2017). According to Clayton and Hills (1993), due to the common form of the contribution to the partial log-likelihood, it has been demonstrated that the Cox model may be fitted using a Poisson GLM (Generalized Linear Model) by dividing follow-up time into as many periods as there are events. Since the sample period ends before most of the firms exit the market, this creates an additional problem. As a result, a censored data problem emerges, and we require alternative methods to address it. The use of information on survivor firms is a problem when performing survival analysis. To perform event history analysis, a common approach employs the proportional hazard model. This analysis allows us to look at what happens before an event occurs; in this case, the event is the firm exit. The specification of the survival function, describing the likelihood of firms' survival until a certain time has elapsed, is a critical process in event history analysis. Cox proposed the proportional hazards model with explanatory variables first (1972, 1975). The Cox model's logic is straightforward and elegant. The hazard factor for the i_{th} firm can be written in the following equation 5:

$$h_t = h_0(t)exp(\beta'x) \tag{5}$$

where $h_0(t)$ is the general hazard function and $\beta'x$ are the covariates and regression coefficients. In addition, the hazard ratio of the two hazards can be written as follows:

$$\frac{h_i(t)}{h_0(t)} = exp(\beta'(x_i - x_j)) \tag{4}$$

Equation 3 is the standard Cox hazard model, whereas equation 4 is the Weibull model, which is the ratio of two hazards, which demonstrates that the ratio remains constant over time. Even though both the Weibull and Cox models are members of the proportional

hazard family of models, there is one significant difference between the Cox model and the proportional hazard models discussed (Box-Steffensmeier and Jones, 2004). Cox regression models lack an intercept term because the baseline hazard rate is not specified. To demonstrate this, consider the Cox model in scalar form as follows:

$$h_i(t) = \exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki}) h_0(t) \quad (5)$$

In the form of log ratio hazard model, we rewrite equation (4) into:

$$\log \left\{ \frac{h_i(t)}{h_0(t)} \right\} = \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} \quad (6)$$

Cox (1972, 1975) developed a nonparametric method called partial likelihood to estimate the parameters in equation (6). The parameter values are estimated using maximum partial likelihood estimation, which differs from MLE in several ways that will be discussed as follows:

$$\log L = \sum_{j=1}^D \left[\sum_{i \in D_j} x_j \beta - d_j \log \left\{ \sum_{k \in R_j} \exp(x_k \beta) \right\} \right] \quad (7)$$

where j shows the ordered failure times $t_{(j)}$, $j=1,2,\dots,D$; D_j is the collection of d_j observations which fail at $t_{(j)}$; d_j denotes the number of failures at $t_{(j)}$; and R_j is the bundle of observations k which are at risk of failure at time $t_{(j)}$ (that is, all k such that $t_{0k} < t_{(j)} \leq t_k$). The Peto–Breslow approximation is used to handle ties in this $\log L$ formula for unweighted data.

Cox regression is the technique of comparing subjects who fail to subjects who are at risk of failing; the latter set is referred to colloquially as a risk pool. When there are linked failure times, we must decide how to compute the risk pools for these linked observations. Assume that two observations fail in quick succession. The first observation is not included in the risk pool in the calculation involving the second observation because failure has already occurred. If the two observations have the same failure time, we must decide how to calculate the risk pool for the second observation and the order in which the two observations should be calculated. There are, at least, four approaches to handling the tied failure on the Cox regression in this study, which are Breslow, Efron, exact marginal likelihood, and exact partial likelihood.

Aggregate Level Evidence

The third analysis method used is aggregate level estimation for firm survival, firm entry, and firm exit. The data used is 2-digit ISIC aggregate data, which is built from the microdata used in the previous estimation. This is done to find out two things: first, whether the relationship between efficiency and survival is consistent with aggregate data, and second, how company efficiency influences not only company survival but also companies leaving or entering

Indonesia. The estimation technique used is Poisson regression with a population averaged (PA) model. Poisson regression is specifically designed for count data, where the outcome variable represents the number of occurrences of an event within a fixed unit of time or space. Endogenous regressors and panel data are problems that the Poisson model is considerably better able to handle (Cameron, 2013). Gujarati (2004) argues that it is well-suited to situations where the outcome variable follows a Poisson distribution, which is often the case for count data. The probability distribution is Poisson probability distributions are particularly suitable for counting data. The general estimation model for the probability distribution function (PDF) of the Poisson distribution is given by equation 10 below:

$$Y_i = \frac{\mu^Y e^{-\mu}}{Y!} + \mu_i \quad (10)$$

If the likelihood that the variable Y has non-zero integer values is denoted by f(Y), and where Y! (refer to the Y factorial), Y in the estimates in this section is the number of companies in the 1998 cohort that survived until 2015, the number of companies that exited (exit), and the number of companies that entered Indonesia each year (entry). The efficiency variable used is the average of company efficiency in each year and every 2 digits of ISIC. Meanwhile, some of the control variables used are adjusted for the aggregate level. Variables in the form of categories are added up, such as investment status (domestic or foreign), location (Java), size, and inventory. On the other hand, the variables openness, PCM, HHI, percentage of ownership, and capacity are calculated as an average per 2 digits of ISIC.

3.3.3 Variable Description

This section discusses variable descriptions in more detail. Table 3.1 summarizes the technical description of the variables:

Table 3. 1 Variable Description of Firm Survival

No	Variable	Description	Expected Sign	Literature
Production Function				
1	Loutput	Natural Logarithm of Firm Output	Dependent Variable in Production function	Levinsohn, James, Petrin (LP), Amil. (2003), Akerberg, D. A., Caves, K., & Frazer, G (ACF), (2015), de Roux et al (2021)
2	Labor	Natural logarithm of total production workers	Positive	LP, ACF, de roux et al (2021)
3	Capital	Natural Logarithm of total capital (buildings, lands, machinery, vehicles)	Positive	LP, ACF, de Roux et al (2021)
4	Energy	Natural logarithm of total energy consumption including electricity, fuels, and lubricant)	Positive	Honma and Hu (2018), and Shui, Jin, and Ni (2015)
5	Materials	Natural logarithm of total value of materials	Positive	LP, ACF, de Roux et al (2021)
Firm Survival Model (Effect Variables on Hazard Ratio)				
5	Technical efficiency (TE)	Calculated using Stochastic Frontier Analysis (SFA) both production and cost frontier approach. The production function is used to measure the technical efficiency score, and cost function is used for measure allocative efficiency score. The scores range between 0 and 1, the closer the score to 1 the more efficient the firm. At aggregate level, we use the mean of efficiency score for every group of firms	Negative	Buddelmeyer et al (2006), Dimara et al (2008), Jitsutthiphakorn (2021)
6	Competition	Measured by Cost Price Margin (PCM) developed by Domowitz et al (1986) which can be formalized as follows: $PCM = \frac{Value\ of\ Sales + \Delta Inventories - Payroll - Cost\ of\ Materials}{Value\ of\ Sales + \Delta Inventories}$	Ambiguous	

		Herfindahl–Hirschman-Index		(Lopez et al 2017, Audretsch and Mahmood, 1995), (Suarez,1995, Utterback (1993)
7	Size	It is a dummy variable where 1 is a firm that has 100 workers or more (It is the definition of large enterprises according to BPS) and 0 for otherwise	Ambiguous	Lopez et al, 2017, Buddelmeyer et al (2006), Naz et al (2023), Agarwal 2001, Rodeiro-Pazos et al, (2021)
8	Openness	It is the sum of the percentage of exported output and imported input	Ambiguous	Topalova (2004), Wagner (2013), Kao and Liu (2022)
9	Central Government Ownership (CGO)	Percentage of central government ownership	Ambiguous	Qu and Harris (2018), Kubo and Phan (2019), and Nguyen et al (2022)
10	Foreign Ownership (FO)	Percentage of foreign ownership	Negative	Shaver et al. (1997), Alfaro and Chen (2012), Wagner and Gelübcke (2012)
11	Domestic	Investment status of the firm (Domestic Investment), dummy variable where 1 if the firm is domestic investment, 0 otherwise	Ambiguous	Mata and Portugal (2002), Kokko and Thang (2014)
12	Foreign	Foreign Investment, a dummy variable where 1 if the firm is foreign investment, 0 otherwise	Ambiguous	Mata and Portugal (2002), Kokko and Thang (2014)

13	Capacity	Percentage of capacity used in the production process	Negative	Lecraw (1978), Lieberman (1989), Nikiforos (2012), Ray (2021)
14	Inventory	Change of inventory of the firm	Ambiguous	Basu and Wang (2011), Bao (2004), and Lin et al (2022)
15	Java	Dummy variable of firm location, 1 if the firm is in Java Island, and 0 otherwise. Java is the most crowded and most developed region in Indonesia in terms of infrastructure, and human capital development	Ambiguous	Bagley (2019), Stearns et al (1995), and Shu (2018)
16	Growth	Economic growth (percent)	Negative	Buddelmeyer et al (2006), Klapper and Richmond (2011)
17	Growthvar	Economic growth variability (Growth Uncertainty). Measured by $growth = \left(\frac{growth - mean\ growth}{N} \right)^2$	Positive	Ghosal (2003), Arza et al (2019), Kumar 2023
18	HDI	Human Development Index	Negative	Acs et al (2007), Huggins et al (2017)
19	Inflation	Inflation measured by consumer price index changes in percent	Ambiguous	Wu and Zang (2001), Tarcom and Ujah (2023), Kumar (2023)
20	Inflationvar	Inflation variability. Measured by the same equation for calculating growthvar	Positive	Ghosal (2003), Arza et al (2019), Kumar 2023, and Yotzov et al (2023)

21	Lending Rate	Lending rate (Egbunike, 2018)	Ambiguous	Audretsch and Mahmood (1995), Buddelmeyer et al (2006) Guariglia et al (2015), Hambur and Cava (2018), and Lee and Werner (2022)
22	Dummy Crisis	This is a dummy variable for 1998 Economic Crisis the value is 1 from 1995 to 1998 and 0 from 1999 to 2015	Positive	Muzi et al (2023), and Özsuca (2023) ,

3.4 Results and Discussion

3.4.1 Estimation of Stochastic Frontier Model

We begin this section by analyzing the results of estimating the production function with a stochastic frontier approach based on the translogarithm model, as summarized in Table 2. The model is estimated under the assumption that time is invariant.

Table 3. 2 Estimation of Production Function

VARIABLES	Coefficient		
	Time-Invariant Model (TI)	Time-Varying Decay (TVD)	Akerberg-Caves- Frazer (ACF)
Labor	0.8873*** (0.00788)	0.9639*** (0.0077)	0.8345*** (0.02754)
Capital	0.01901*** (0.00069)	0.0113*** (0.00066)	0.0058*** (0.00029)
Material	0.07907*** (0.00324)	0.1099*** (0.00313)	0.5119*** (0.0329)
Energy	0.2963*** (0.00283)	0.2791*** (0.00274)	0.0772*** (0.0081)
Labor ²	0.0442*** (0.00086)	0.0378*** (0.00083)	
Material ²	-0.0486*** (0.00015)	-0.0459*** (0.00015)	
Energy ²	0.0132*** (0.00016)	0.0151*** (0.000156)	
Capital ²	-0.0047*** (0.000047)	-0.0033*** (0.0000456)	
Labor * Capital	0.000195 (0.0001214)	0.00094*** (0.0001151)	
Labor * Material	0.0795*** (0.00054)	0.078*** (0.00052)	
Labor * Energy	0.0092*** (0.00055)	0.0095*** (0.00052)	
Capital * Material	0.00326*** (0.0000629)	0.00284*** (0.000059)	
Capital * Energy	0.00047*** (0.0000614)	0.00017*** (0.0000582)	
Material * Energy	0.03762*** (0.0002592)	0.0381*** (0.00024)	
Constant	8.4413*** (0.5540)	10.2855*** (0.07093)	

mu	4.349*** (1.677)	3.2467*** (0.03216)	
LnSigma ²	-1.1468*** (0.00367)	-1.1011*** (0.00470)	
Lgtgamma	-0.2867*** (0.00885)	0.3200*** (0.00881)	
Observations	423,505	423,505	433,183
Number of psid	52,162	52,162	
2 Digit ISIC Fixed Effect	YES	YES	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The estimation results show that the input coefficient is positive, which means that an increase in input increases output. The test results of the number of coefficients of both the TI and TVD models are close to 1, but after the constant return to scale test, it turns out that both models show rejection of the hypothesis that the estimation results are constant return to scale with a value of more than 1. The TVD and TI models show 1.36, and 1.28, while the ACF is 1.43, so it shows more of an increasing return to scale pattern at the 1 percent level. Those three models are quite consistent in terms of the character of the production estimation results, including the coefficients of the most dominant input variables and those with the least influence on output. Labor is the most dominant variable, followed by energy, materials, and capital. The results of the Sargan-Hansen test show a value of 1.42, which means that there is no rejection of the moment conditions used to specify the model.

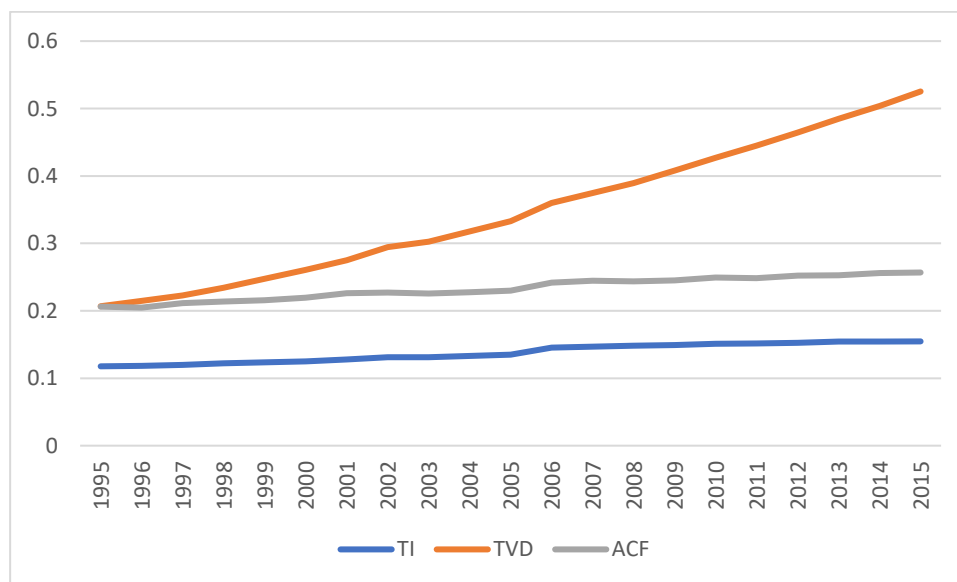


Figure 3. 4 Annual Average Trend of Efficiency Score

Source: Author's Calculation

Figure 3.4 shows that there is a positive trend in the average TE every year. The three measurements from the TVD, TI, and ACF models show efficiency values that tend to

increase. The TE value of the TVD model shows relatively faster growth than other models, while the ACF model has a moderate value between TVD and TI. From the average value of the entire period, the TE values of the TVD, TI, and ACF models are 0.34, 0.15, and 0.23 respectively. Meanwhile, based on the average per sector of 2-digit ISIC, as shown in Graph 5, the manufactured drink firms' sector (No. 11) has the highest efficiency values of 0.85 and 0.36, and 0.3 for the TVD, TI, and ACF models, respectively. Meanwhile, the lowest efficiency value is owned by the Machinery and Equipment Repair and Installation sector (No. 33), with values of 0.22, 0.13, and 0.21 for the TVD, TI, and ACF models, respectively. This performance picture is supported by studies from the World Bank (2012) and the Asian Development Bank (2019) which show that the food and beverages sector still dominates the performance of the industrial sector in general in Indonesia.

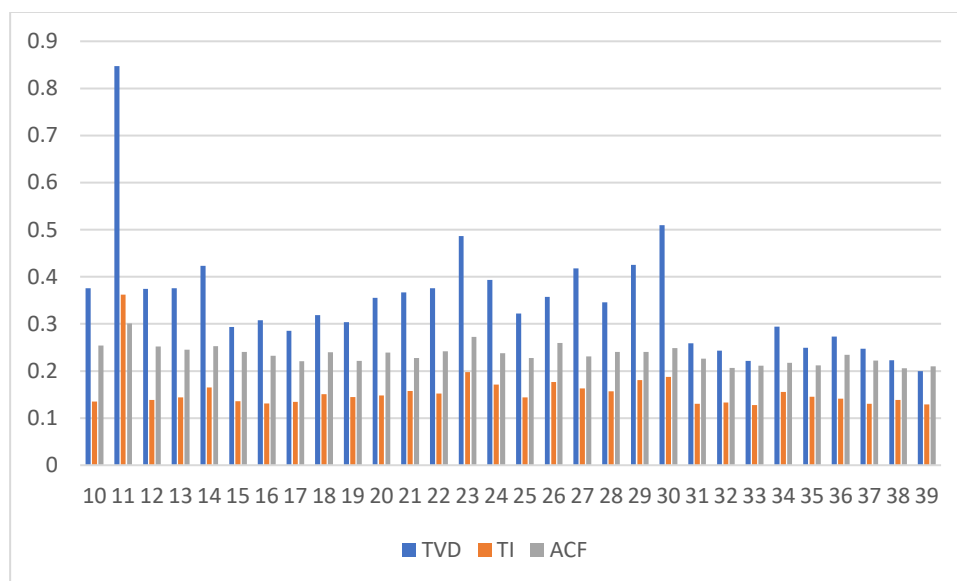


Figure 3. 5 Two Digits ISIC Average of Efficiency Score

3.4.2 Estimation of Firm Survival

The descriptive statistical tabulation results for each variable are summarized in Table 3.3 and Table 3.4 provides a correlation table between independent variables.

Table 3. 3 Descriptive Statistics of Variables (Survival Model)

Variable	Obs	Mean	Std. dev.	Min	Max
Log Output	453,283	15.0611	2.2769	6.7007	25.6290
Log Capital	455,399	8.0375	6.9528	7.1738	34.5071
Log Energy	455,399	10.6634	3.1098	8.4513	23.2081
Log Material	433,184	14.1683	2.4798	12.3108	16.6668
Log Labor	455,399	4.1683	1.2247	3.8789	11.6617
Efficiency (ACF)	433,183	3.5584	0.8236	0.35	0.9413
Efficiency (TI)	424,117	0.139	0.0063	0.2221	0.4861
Efficiency (TVD)	410,961	0.359	0.0185	0.2921	0.9448
Domestic	455,399	0.1504	0.3575	0	1
Foreign	455,399	0.0770	0.2667	0	1

Income (Log)	453,284	14.056	2.2447	1.7917	24.8518
PCM	453,255	0.2318	5.8944	-12378.69	33719.32
HHI	453,061	0.2535	0.0852	0.2001	0.9919
Openness	453,284	16.2935	62.2615	0	33837.25
Capacity	453,284	61.4750	35.3325	0	960
Inventory	453,284	7022897	1.39E+09	-8.96E+10	5.52E+11
Foreign Ownership	453,284	6.8529	23.8136	0	100
Central Government Ownership	453,270	1.3159	11.1840	0	100
Java	455,399	0.8676	0.3388	0	1
Size (Labor)	455,399	164.8514	744.5438	0	116052
HDI	455,399	0.6357	0.0379	0.569	0.695
Inflation	453,284	10.0785	10.6386	3.6886	58.4510
Inflationvar	453,284	0.6488	0.1681	0.1230	0.8367
Growth	453,284	4.6032	3.9021	-13.1267	8.2200
Growthvar	453,284	0.7631	0.0591	0.6991	0.9523
Lending Rate	453,284	16.3822	4.9506	11.6575	32.1541
Dummy Crisis	455,399	0.1639	0.3702	0	1

Source: Author's Calculation

Figure 3.6 shows the survival pattern based on Kaplan-Meier while Figure 3.7 shows the survival time pattern from the results of the Cox Proportional Hazard Model.

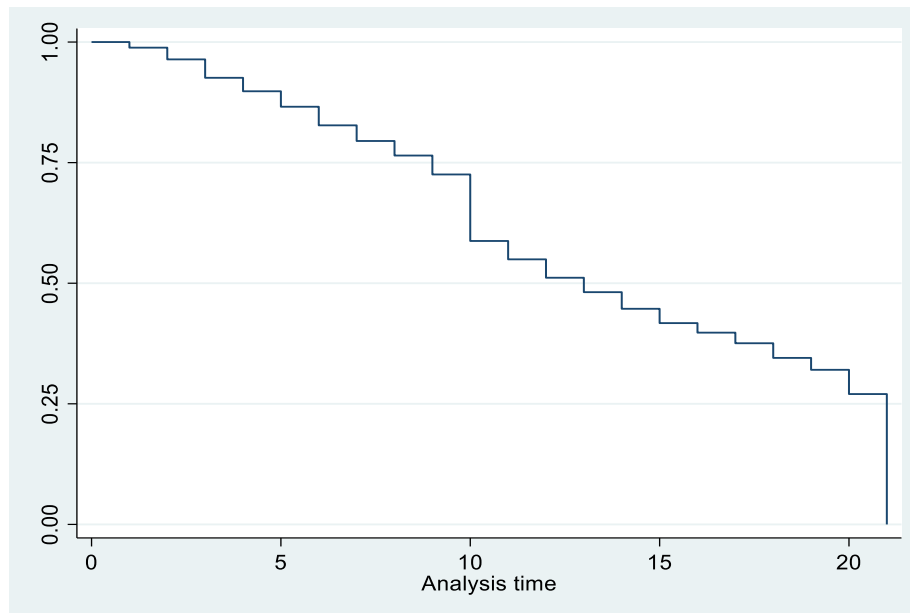


Figure 3. 6 Kaplan-Meier Survival Estimate

Source: Author's Calculation

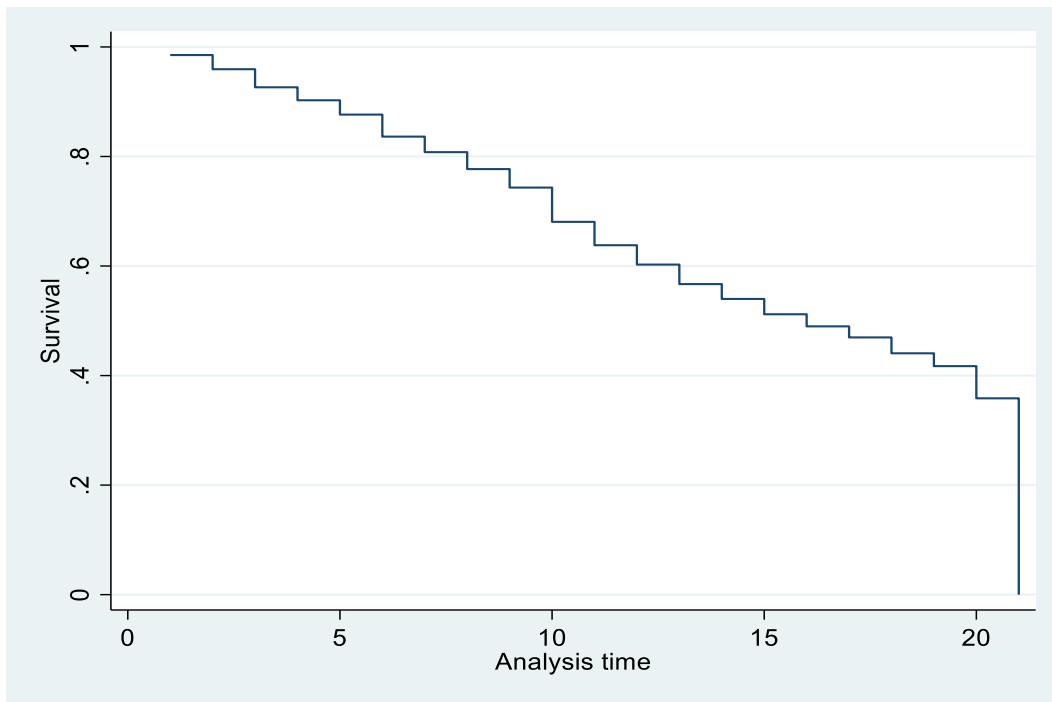


Figure 3. 7 Cox Proportional Hazard Model Estimation (ACF Efficiency with Time Varying Model)

Source: Author's Calculation

The same number, 13, is displayed as the median survival value in both the Kaplan-Meier and Cox proportional hazards curves. However, the underlying function explains why the two have different patterns. The survival probabilities are determined using the Kaplan-Meier method, which divides the total number of people at risk by the number of survivors. The collective survival experience of a community is revealed by this curve. However, the Cox Proportional Hazard Model goes beyond survival analysis by accounting for the impact of factors on survival. It is assumed that the baseline hazard function varies with time and that the hazard rate is a linear combination of variables (Andrade, 2023). The Cox Proportional Hazards model is used to represent the relationship between covariates and the hazard rate, whereas the Kaplan-Meier estimator is used to estimate survival probability and cope with censored data. These two techniques are frequently combined in survival analysis to provide a thorough comprehension of time-to-event data. The first descriptive analysis employs the Kaplan-Meier estimator, whereas more detailed statistical modeling and hypothesis testing employ the Cox model (Nieto and Coresh, 1996).

Table 3.4 summarizes the correlations between variables. Cases of multicollinearity are rarely observed in survival studies. Based on this table, it can be seen that those that have a high correlation are between macro variables, especially growth, growthvar, inflationvar, and inflation whose correlation coefficient is above 0.9. Liverani et al (2020) argue that in survival studies strong correlations between the explanatory variables can lead to unstable or erroneous estimates of the regression coefficients, as well as incorrect, non-significant p-values, inflated standard errors, and deflated partial t-tests. This assertion is further supported by Xue et al (2007). Unfortunately, there is no consensus on how much correlation is

considered to damage the estimation results. On the other hand, Gujarati (2004) argues that multicollinearity is a linear regression assumption, where if an exact linear relationship occurs it will violate the regression assumption. Exact linear means that the correlation coefficient is 1 between the variables. It is demonstrated that the OLS (Ordinary Least Square) estimators maintain their BLUE (Best Linear Unbiased Estimator) characteristics even in situations when multicollinearity is extremely strong, such as in the case of near multicollinearity (Gujarati, 2004).

Table 3. 4 Correlation of Firm Survival Determinants at Firm Level (Cont.)

	TE (ACF)	TE (TI)	TE (TVD)	Domestic Investment	Foreign Investment	Income	PCM	HHI	Openness	Capacity	Inventory
TE (ACF)	1.0000										
TE (TI)	0.3756	1.0000									
TE (TVD)	0.5762	0.8846	1.0000								
Domestic Investment	0.0194	0.0609	0.1158	1.0000							
Foreign Investment	0.0307	0.1136	0.1564	-0.1203	1.0000						
Income	0.2863	0.2591	0.4401	0.3138	0.3227	1.0000					
PCM	-0.03	0.001	0.0004	-0.001	0.0053	0.0016	1.0000				
HHI	0.0095	-0.0118	-0.0113	-0.0252	-0.0109	-0.0481	-0.0014	1.0000			
Openness	-0.0385	0.0239	0.0478	0.0494	0.1817	0.1752	0.0017	0.0097	1.0000		
Capacity	-0.0574	-0.0481	-0.0571	-0.0549	-0.0452	-0.1305	0.001	0.0111	-0.0056	1.0000	
Inventory	0.009	-0.0004	0.0046	0.0029	0.0047	0.0122	0.0001	0.0019	0.0028	0.0014	1.0000
Foreign Ownership Central Government Ownership	0.0325	0.1194	0.1636	-0.0655	0.775	0.3199	0.0056	-0.0071	0.1899	-0.0222	0.0057
Java	-0.0213	0.0464	0.0495	0.2047	-0.0242	0.1241	0	0.0002	0.0116	0.0028	0.0002
Size	-0.1266	-0.0913	-0.1226	-0.0953	-0.0162	-0.0922	0.0019	0.0024	-0.024	-0.0055	-0.0018
HDI	-0.2416	0.0302	0.0653	0.1247	0.1474	0.3572	0.0015	-0.0299	0.1034	-0.0061	0.0077
Inflation	0.5497	0.2073	0.5323	0.0856	0.0439	0.3973	-0.0007	0.0103	0.0232	-0.004	0.0061
Inflationvar	-0.2044	-0.0798	-0.2051	-0.0774	-0.0091	-0.1505	0.0001	-0.0074	-0.0222	0.0016	-0.0015
Growth	0.2489	0.0948	0.2537	0.075	0.0177	0.1812	-0.0004	0.0058	0.0204	0.0173	0.002
Growthvar	0.1382	0.061	0.1437	0.0831	0.0023	0.0946	-0.0006	0.0042	0.0197	0.0289	0.0005
Lending Rate	-0.2484	-0.0946	-0.2529	-0.0759	-0.0173	-0.1807	0.0004	-0.0058	-0.0203	-0.0176	-0.002
Dummy Crisis	-0.4279	-0.166	-0.4121	-0.1046	-0.0256	-0.3059	0.0007	-0.0098	-0.0187	-0.0261	-0.0033
	-0.3875	-0.1423	-0.3344	-0.0331	-0.0234	-0.2899	-0.0016	-0.0177	-0.0074	0.0754	-0.002

	Foreign Ownership	Central Government Ownership	Java	Size	HDI	Inflation	Inflationvar	Growth	Growthvar	Lending Rate	Dummy Crisis
Foreign Ownership	1.0000										
Central Government Ownership	-0.0263	1.0000									
Java	-0.0186	-0.0736	1.0000								
Size	0.1458	0.074	0.0104	1.0000							
HDI	0.0444	-0.0146	-0.1124	-0.0043	1.0000						
Inflation	-0.0143	0.0066	0.043	0.0013	-0.3996	1.0000					
Inflationvar	0.0199	-0.0054	-0.047	-0.0001	0.4887	-0.87	1.0000				
Growth	0.0047	-0.0056	-0.0417	-0.0031	0.2792	-0.9382	0.7238	1.0000			
Growthvar	-0.0196	0.0055	0.0473	0.0001	-0.4875	0.8796	-0.9997	-0.7384	1.0000		
Lending Rate	-0.0306	0.013	0.0903	0.0045	-0.7829	0.7858	-0.7803	-0.747	0.7877	1.0000	
Dummy Crisis	-0.0355	0.0154	0.0665	0.0039	-0.6444	0.4303	-0.2996	-0.307	0.3032	0.5963	1.0000

Source: Author's Calculation

The Cox Proportional Hazard model is estimated for each efficiency score generated by the models' TI, TVD, and ACF, and each model is estimated using robust and time-varying techniques summarized in Table 6. To improve the estimation, the results of the robust estimation are tested with a proportional hazard to see if the value of the hazard ratio is constant over time. Several variables are shown to meet the assumptions of the hazard model, including foreign, PCM, HHI, and stock, with probabilities of 0.25, 0.29, 0.24, and 0.89, respectively, while other variables are significant at the 1 percent level, as shown in Table 5. Under this condition, a survival model can be estimated using the time-varying covariates method as recommended by Zhang et al (2018), and Wang et al (2018). We use the time-varying method as the basis for our analysis and provide a robust method for comparison only. Apart from that, the efficiency calculation model with ACF is the model that we use as the basis of our analysis, and as a comparison, we also provide the results of the survival model estimation with the TE variable produced by the method TI and TVD.

Table 3. 5 Test of Proportional Hazards Assumption

Variables	Rho (Cox Model with Robust Regression)		
Efficiency (ACF)	-0.03554***		
Efficiency (TI)		0.02039***	
Efficiency (TVD)			-0.00562***
Domestic Investment	0.04014***	0.04519***	0.04631***
Foreign Investment	0.00468**	0.00495**	0.00228
Income	0.04628***	0.08045***	0.06737***
PCM	-0.00348	-0.00172	-0.00558
HHI	-0.00446**	-0.00282	-0.00217
Openness	0.00354**	0.00373**	0.00337**
Capacity	0.07535***	0.07754***	0.07869***
Inventory	0.00259	-0.00059	-0.00038
Foreign Ownership	0.01599***	0.01529***	0.02156***
Central Government Ownership	0.01322***	0.0106***	0.01125***
Java	0.05224***	0.05137***	0.04844***
Size	-0.01597***	-0.01527***	-0.01628***
HDI	-0.05084***	-0.06365***	-0.0506***
Inflation	-0.00865***	-0.00949***	-0.01055***
inflationvar	-0.01071***	-0.00728***	-0.00541***
Growth	-0.03869***	-0.03741***	-0.03757***
Growthvar	-0.01066***	-0.00728***	-0.00542***
Lending Rate	-0.01283***	-0.01415***	-0.01426***
Dummy Crisis	-0.06962***	-0.06583***	-0.0637***

*** p<0.01, ** p<0.05, * p<0.1

The coefficient TE appears to be negative in all models and significant at the 1 percent level, implying that the more efficient the firm is, the lower the risk and survival. The effect of efficiency calculated with the TI and TVD models on firm survival is higher than the effect of efficiency calculated with the ACF. The endogeneity treatment of the ACF model on the estimated effect of efficiency on firm survival makes a fairly large difference. The coefficient TE in the ACF model with a TVC estimate of 0.16, reduces risk or increases survival. This is

consistent with the theoretical expectation that efficient firms are able to advance in the market, and this result is also confirmed by previous studies such as Dimara et al. (2008) and Tsionas and Papadogonas (2006). Income can also be considered a measure of productivity or efficiency, as done by Bosio et al. (2020), using income or profit to represent efficiency or productivity and see its impact on firm survival. In this study, income shows negative significance, which means that increasing company income has the impact of reducing hazards or increasing the company's survival time.

The impact of domestic and foreign investment variables on company characteristics is consistent across all models, revealing a shared influence. In all instances, these variables exhibit a negative effect on the hazard ratio or an increase in survival time. Notably, a higher proportion of foreign capital ownership within a company significantly diminishes the hazard, indicating prolonged survival time, as evidenced by the foreign variable. Both domestic and foreign investment statuses demonstrate a heightened probability of survival compared to the average. In the context of manufacturing companies in Indonesia, there exist three investment statuses: domestic, foreign, and non-facility. Presently, the majority of manufacturing companies in Indonesia, accounting for 76.16 percent, fall under the non-facility category. Domestic and foreign investments constitute 15.76 percent and 8.08 percent, respectively. Additionally, non-facility companies exhibit a lower average efficiency value (0.34) compared to domestic (0.40) and foreign (0.46) companies, as well as a lower average total firm value (0.36). Moreover, its median survival time is 12 years, while domestic and foreign investment has a median survival time of 18 and 17 years. This is supported by the findings of Kokko and Thang (2014) who found that both domestic and foreign companies have heterogeneity in survival, especially in the horizontal and upstream sectors.

The percentage of central government ownership also shows a negative influence on the hazard ratio, meaning that the greater the central government's ownership, the greater the chances of survival. The government's role in making strategic decisions may be more necessary in the initial conditions of company operations or companies that are experiencing a decline in performance. Meanwhile, government interference in company decisions, when the company is growing well, can trigger acts of corruption that causes cost and investment inefficiencies and end in company bankruptcy (Ghazali et al, 2022). Foreign Ownership (FO) has a negative effect on the hazard ratio, which means that an increase in the percentage of foreign capital ownership in the company increases the survival of the company. This is in line with previous studies such as those from Bernard and Sjöholm (2003) and Baldwin and Yan (2011). On the one hand, foreign investment can boost firm survival by providing knowledge spillovers and linkages to help new ventures (Burke et al., 2008). However, this effect depends on industry dynamics: FDI has a net negative effect on firm survival in dynamic, rapidly changing industries but a net positive effect in static, stable industries. Foreign ownership has a contribution to make in determining the survival of the company. The FO parameter shows a negative value, which means that multinational companies have a lower hazard ratio than other types of ownership, which means that multinational companies have a higher survival time than other types of ownership. Indonesia is still a good place for investors. Apart from absorbing labor, technology transfer is a clear benefit for the domestic

economy. On the other hand, government ownership of the company has a negative impact on the company's survival. The influence of ownership varies greatly in literature studies, depending on political conditions and bureaucracy, which can lead to inefficient resource allocation, unwise investments, and a lack of long-term strategic planning, all of which can negatively impact the firm's survival.

Meanwhile, market structure factors are represented by price-cost-margin (PCM) and the Herfindahl Hirschman Index. Only HHI has a significant positive effect on the hazard ratio, meaning that the less competition, the less firm survival which means that the more monopolized the market, the more the company is unable to survive in it. Based on these findings, manufacturing companies in Indonesia hope that a good competitive climate, and healthy competition between companies in the market can improve company performance. Competition can drive firms to become more innovative and productive. When firms need to outperform their rivals, they often invest in research and development, leading to the creation of new and improved products and services, but at a certain point if it creates a price war and bad competition will hurt the company. A competitive market can force companies to innovate in production, marketing, or even financial strategies to improve their performance and enable them to survive the competition, but companies that are unable to do this will end up leaving the market. The impact of competition on firm performance is not solely positive or negative and depends on the firm's ability to adapt, differentiate itself, and effectively respond to competitive pressures. Firms that can balance the challenges and opportunities presented by competition are more likely to thrive in competitive markets. Additionally, government regulations and industry-specific factors can also influence how competition affects firms. The findings of this study are consistent with several other studies such as those from Garcia and Puente (2006), Burke and Hanley (2009), and Brito and Brito (2014). Nevertheless, Brito and Brito (2014) show that there is a heterogeneity effect between industries in responding to competition in the market, while Burke and Hanley (2009) reveal that the heterogeneity of firm response to market competition depends on the dynamics of entry and exit firms in markets where firms that can survive in the market if the entry and exit levels are high. Higher market concentration (less competition) is associated with lower firm survival, or the likelihood that businesses will prosper in monopolized markets, according to the Herfindahl Hirschman Index (HHI). The advantages of healthy competition A competitive environment benefits Indonesian manufacturing companies by fostering innovation, productivity, and performance enhancements. Healthy competition encourages businesses to spend money on R&D, which results in improved goods and services. Dangers of Overly Competitive Markets: Excessive competition, including price wars, can hurt businesses even while it can improve company performance. Companies must find a balance to prevent unhealthy competition that could hurt their bottom line. Flexibility Is Essential: Businesses have a better chance of surviving and growing if they can innovate in their production, marketing, and financial strategies in response to competitive constraints. Businesses that can't stand out from the competition and innovate will struggle and possibly fail. Industry-Specific Competition Dynamics: Different industries are affected by competition differently, and they react to market forces in different ways. A company's capacity to handle the stresses of competition is influenced by things like market entry and exit dynamics. The impact of government rules and

regulations, in conjunction with industry-specific considerations, on the behavior of enterprises in the face of competition contributes to the intricacy of market dynamics.

On the other hand, the negative coefficient shown by openness means that openness reduces the hazard ratio. Trade openness can provide firms with access to larger and more diverse markets. This can be particularly beneficial for firms that produce goods or services with a global demand. Increased market access can lead to higher sales and revenue, which can enhance a firm's survival prospects. Apart from the market side, the company's ability to survive through openness can also be achieved by supplying inputs at relatively cheaper prices, so that the company has an input price advantage. The results of this study are supported by a study from Kao and Lin (2022) which shows that companies that trade in both exports of production products and imports of raw materials have a higher chance of survival. The production capacity used by the company has a negative impact on the hazard ratio, which means that the higher the production capacity used, the greater the survivor time. Capacity utilization refers to the extent to which a company is using its production capacity to meet its production targets. When a firm operates at a high level of capacity utilization, it can spread its fixed costs (e.g., machinery and facilities) over a larger volume of production. This can lead to lower average costs per unit, making the firm more competitive and financially stable. On the other hand, inventory does not play a role in determining the company's survival.

The location variable (Java) also shows a negative and significant influence on the hazard ratio, which shows that manufacturing companies located on the island of Java are better able to survive than companies located on other islands. Java, which is the center of economic activities, contributes, according to BPS, 56.47 percent to the total gross domestic product (GDP) of Indonesia, even though it covers only 6.75 percent of the total area of Indonesia and is inhabited by 56 percent of Indonesia's population. Many industries decide to operate on the island of Java, including micro, small, medium, and large industries, which account for 80 percent of companies. Stearns et al. (1995) argue that location has an important role in company performance where more advanced locations, such as cities, have a carrying capacity for companies to live longer, and this is consistent with the findings of our study where the island of Java is the national capital and, with infrastructure facilities and human resources, is the center for the economic life of the population. A densely populated location as a market for industrial output and infrastructure that is spread evenly may still be the goal of most firms in Java to survive.

Macroeconomic variables have a significant role in determining the survival of companies in Indonesia. Inflation and inflation variability have a positive impact on the hazard ratio, while economic growth has a negative impact on the hazard ratio, and growth variability has the opposite or positive impact on growth. This means that price stability and economic growth increase the survival rate of manufacturing companies. Apart from that, HDI as an indicator of human resource quality has a negative contribution to the hazard ratio or increases the company's survival time. Increasing the quality of the workforce provides companies with the opportunity to obtain quality workers, thereby increasing the company's productivity and survival. On the other hand, good human quality is a good contribution to the market for high-

tech products for the company. Furthermore, lending rates have a positive impact on the hazard ratio, which means higher lending rates reduce the possibility of film survival. Lending rates as the main capital costs for companies are a burden for companies to invest or expand production scale.

Table 3. 6 Firm Survival Estimation (Cox Proportional Hazard Model)

VARIABLES	Time-Varying Decay Efficiency		Time-Invariant Efficiency		ACF Efficiency	
	Robust	Time-Varying	Robust	Time-Varying	ACF Robust	ACF Time Varying
TE_{it-1}	-5.469*** (0.220)	-5.976*** (0.233)	-14.651*** (0.3941)	-15.707*** (0.4370)	-0.161*** (0.00217)	-1.205*** (0.00265)
Domestic	-0.127*** (0.00391)	-0.129*** (0.00392)	-0.122*** (0.00383)	-0.125*** (0.00384)	-0.115*** (0.00383)	-0.119*** (0.00386)
Foreign	-0.0205** (0.00804)	-0.0243*** (0.00826)	-0.0240*** (0.00766)	-0.0278*** (0.00780)	-0.0217*** (0.00758)	-0.0252*** (0.00773)
Income	-0.0981*** (0.00105)	-0.100*** (0.00105)	-0.0970*** (0.000922)	-0.0976*** (0.000890)	-0.0934*** (0.000858)	-0.0929*** (0.000866)
PCM	9.15e-08 (1.01e-05)	-2.88e-07 (1.10e-05)	-3.28e-06 (1.23e-05)	-3.51e-06 (1.29e-05)	2.50e-06 (1.01e-05)	2.46e-06 (1.15e-05)
HHI	0.0621*** (0.0161)	0.0672*** (0.0161)	0.0662*** (0.0158)	0.0741*** (0.0158)	0.0739*** (0.01572)	0.0749*** (0.01569)
Openness	-0.000552*** (4.39e-05)	-6.57e-05*** (2.47e-06)	-0.000532*** (4.28e-05)	-6.50e-05*** (2.42e-06)	-0.000635*** (4.27e-05)	-7.90e-05*** (2.46e-06)
Capacity	-0.00130*** (4.57e-05)	-0.00127*** (4.56e-05)	-0.00117*** (4.41e-05)	-0.00113*** (4.39e-05)	-0.00112*** (4.39e-05)	-0.00110*** (4.38e-05)
Inventory	0 (0)	0* (0)	0 (0)	0* (0)	0 (0)	0** (0)
Foreign Ownership	-0.000509*** (8.93e-05)	-0.000305*** (9.20e-05)	-0.000796*** (8.54e-05)	-0.000616*** (8.72e-05)	-0.000799*** (8.45e-05)	-0.000604*** (8.63e-05)
Central Government Ownership	-0.00240***	-0.00260***	-0.00258***	-0.00280***	-0.00229***	-0.00240***

	(8.52e-05)	(8.45e-05)	(8.14e-05)	(8.10e-05)	(8.58e-05)	(8.73e-05)
Java	-0.326***	-0.335***	-0.330***	-0.344***	-0.329***	-0.335***
	(0.00487)	(0.00494)	(0.00478)	(0.00484)	(0.00480)	(0.00485)
Size	-2.75e-05***	-4.14e-07***	-2.28e-05***	-5.10e-07***	-1.62e-05***	-1.98e-06***
	(2.30e-06)	(7.44e-08)	(2.07e-06)	(5.80e-08)	(1.45e-06)	(1.32e-07)
HDI	-4.391***	-0.0906***	-5.582***	-0.0113*	-3.830***	-0.148***
	(0.138)	(0.00760)	(0.127)	(0.00675)	(0.129)	(0.00697)
Inflation	0.0145***	0.00200***	0.0127***	0.00192***	0.0113***	0.00252***
	(0.00152)	(7.19e-05)	(0.00149)	(6.97e-05)	(0.00149)	(6.98e-05)
Inflationvar	4.437***	1.161***	3.639***	1.105***	1.297	1.497***
	(1.060)	(0.0541)	(1.039)	(0.0530)	(1.032)	(0.0533)
Growth	-0.0353***	-0.00330***	-0.0322***	-0.00321***	-0.0334***	-0.00396***
	(0.00280)	(0.000137)	(0.00275)	(0.000133)	(0.00274)	(0.000135)
Growthvar	14.53***	3.594***	12.08***	3.420***	5.181*	4.618***
	(3.183)	(0.162)	(3.120)	(0.158)	(3.100)	(0.159)
Lending Rates	0.0277***	0.00336***	0.0273***	0.00320***	0.0268***	0.00388***
	(0.00204)	(0.000103)	(0.00200)	(0.000100)	(0.00199)	(0.000101)
Dummy Crisis	0.112***	0.0755***	0.0944***	0.0636***	0.0620***	0.176***
	(0.0124)	(0.0110)	(0.0122)	(0.0106)	(0.0122)	(0.0105)
Observations	360,804	360,804	373,658	373,658	381,600	381,600
2-Digit ISIC FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.4.3 Determinant of Firm Survival, Entry, and Exit (Aggregate Two Digits ISIC)

This section provides additional analysis with aggregate data at the 2-digit ISIC level. Table 3.7 provides summary statistics for the determinant variables of companies that survive, enter, and exit. Because there was a change in the ISIC code numbering in 1998, observations at the aggregate level were carried out from 1998-2015.

Table 3. 7 Descriptive Statistics of Aggregate Level

Variable	Obs	Mean	Std. dev.	Min	Max
Survive	517	1301.309	1317.244	6	6089
Entry	517	135.3404	284.5422	0	2699
Exit	499	105.0561	143.8918	0	1016
TE (ACF)	517	3.7318	0.3987	2.9227	4.9211
Domestic Investment	517	133.4159	166.2886	0	1192
Foreign Investment	517	61.0174	49.7479	0	236
PCM	517	0.1190	0.9390	-8.4389	4.7806
HHI	517	0.2463	0.0727	0.2024	0.9713
Log (Income)	517	21.3499	1.6777	12.5623	24.2601
Openness	517	18.2993	13.0820	0	77.4589
Capacity	517	66.2061	6.9006	40	81.5
				-	
Inventory	517	1.42+10	9.52+10	7.03+10	9.20E+11
Foreign Ownership	517	6.7513	23.7186	4.9168	24.6599
Central Government					
Ownership	517	1.559	12.3679	7.4785	27.1451
Java	517	20,442	15825.51	0	44,006
Size	517	244.3346	217.1153	80.1603	308.7155

Source: Author's Calculation

Source: Author's Calculation

Apart from that, this section also provides additional analysis of factors that influence company entry, survival, and exit. Estimation is carried out using the Poisson regression with a population-averaged model. The results of the Poisson regression estimation are summarized in Table 8. Equation 8 was estimated three times by changing the outcome variables for survival, exit, and entry. It can be seen in the table that the efficiency variable significantly influences companies that survive, enter, and exit, where efficiency has a positive influence on companies that survive, has a positive influence on the number of companies entering, and has a negative influence on the number of companies leaving the Indonesian market. It means that the more efficient the company, the greater the possibility of surviving in Indonesia, encouraging companies to enter and preventing companies from leaving the market.

Table 3. 8 Panel 2 Digits ISIC Poisson Regression Model Results (Population Averaged Model)

VARIABLES	(1) Survive	(2) Entry	(3) Exit
TE_{it-1}	4.637*** (0.0535)	1.585*** (0.154)	-2.588*** (0.212)
Domestic	0.00112*** (2.98e-05)	0.000678*** (0.000105)	-0.00503*** (0.000120)
Foreign	0.00459*** (0.000138)	0.0107*** (0.000481)	-0.00439*** (0.000459)
PCM	-0.00353** (0.00205)	-0.0484*** (0.00696)	0.0571*** (0.00771)
HHI	-0.00223*** (4.56e-05)	-0.000734*** (0.000149)	0.00272*** (0.000165)
Income	0.0188*** (0.00262)	0.0589*** (0.00888)	-0.133*** (0.00963)
Openness	0.00939*** (0.000203)	0.0110*** (0.000693)	-0.0177*** (0.000697)
Capacity	0.00585*** (0.000384)	0.0160*** (0.00136)	-0.0190*** (0.00147)
Inventory	0*** (0)	0*** (0)	0*** (0)
Foreign Ownership	2.56e-05*** (1.83e-06)	0.000186*** (6.47e-06)	-5.64e-05*** (6.95e-06)
Central Government Ownership	5.86e-05*** (2.76e-06)	0.000223*** (8.83e-06)	-0.000136*** (9.83e-06)
Java	0.000372*** (1.36e-05)	0.000647*** (4.51e-05)	-8.27e-05* (4.59e-05)
Size	0.000526*** (4.27e-05)	0.00570*** (0.000154)	-0.00505*** (0.000170)
HDI	1.97647*** (0.17306)	0.1715 (0.6445)	-5.1896*** (0.6586)
Inflation	-0.0465*** (0.00164)	-0.0118** (0.00569)	7.081*** (0.194)
Inflationvar	-14.57*** (1.039)	-68.56*** (3.616)	739.4*** (18.61)
Growth	0.0553*** (0.00334)	0.0248** (0.0125)	-0.237*** (0.0141)
Growthvar	-40.94*** (3.094)	-191.6*** (10.76)	2,729*** (69.55)
Lending Rates	-0.0294*** (0.00168)	-0.00198 (0.00619)	0.0580*** (0.00662)

Constant	30.09*** (3.012)	187.6*** (10.44)	2,492*** (63.48)
Observations	489	489	477
Number of PSID	485	485	474
2-Digit ISIC Fixed Effect	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimation at the aggregate level shows some differences and consistency with the firm-level results. The estimation results at the aggregate level show that TE has a positive effect on the number of companies that survive, the higher the average efficiency, the more companies will gradually survive. On the other hand, the average company efficiency positively influences the number of companies entering Indonesia and vice versa, the higher the average efficiency, the lower the number of companies leaving. In addition, company revenues, as expected, also show an influence on increasing the number of surviving companies and entering and reducing exiting companies. A company's high income increases the attraction of other companies to enter to seek their fortunes in the same market and reduces the possibility of companies leaving the market. Another variable that has a positive effect on the increasing number of companies entering is Domestic and Foreign investment which also has a positive effect on the number of companies that are able to survive in Indonesia. The more companies with domestic and foreign investment status, the more companies will be able to survive. Apart from that, in terms of their influence on the number of companies entering and leaving, both variables have a positive impact on the number of companies entering and a negative impact on companies leaving. The large number of companies with domestic status and foreign companies provides a positive signal for other companies to enter Indonesia and reduces the number of companies leaving. Openness also shows a positive effect on increasing the number of companies that survive and enter, and reducing the number of companies that leave. Access to international markets provides its own advantages, both production markets and competitive markets for input prices which may be more reasonable for the company's production cost structure.

In contrast, market structure influences fewer businesses to come and survive while increasing the number of businesses to go. The variables PCM and HHI demonstrate this. Strong competition may lead to the development of entry barriers, which will make it more challenging for new businesses to enter the market. There are frequently high entry barriers where there is fierce rivalry. These obstacles may consist of expensive initial startup costs, scale efficiencies that current rivals have, strong customer brand loyalty, and legal or regulatory constraints. It could be difficult for a fledgling business to get beyond these obstacles. Price wars, which are a common result of fierce competition, can reduce profit margins. This could work against newcomers, particularly if they don't have the economies of scale that more established rivals would have.

Consistent with the results at the firm level, average production capacity increases the number

of surviving firms and new firms entering and conversely reduces the number of exiting firms. A company may benefit from economies of scale when it is running at or close to capacity. This indicates that when output rises, the average cost per unit of production falls. A company's ability to compete in a new market might be strengthened by lower average costs, particularly if the company can reach comparable levels of capacity utilization. Moreover, a high-capacity utilization rate may indicate a high level of interest in the company's goods or services. This encouraging signal might draw in new lenders, partners, or investors, which would make it simpler for the business to get the funding and assistance it needs to enter a new market.

In contrast to the results at the firm level, which show no significance, the estimation results at the aggregate level show strong significance of inventory. Inventory changes increase the number of companies that survive and enter and also increase the number of companies that leave. Effective inventory control is necessary to maximize working capital. An excessive amount of inventory takes up money that could be invested in expansion prospects, paid off debt, or utilized to solve operational issues. Conversely, keeping too little inventory might result in stock-outs, which can harm sales and customer satisfaction. The total cost structure of a company is influenced by the costs associated with holding inventory, such as storage, insurance, and obsolescence risk. Effective inventory management contributes to cost containment. A company that has an expensive structure because of poor inventory management may find it difficult to stay competitive, which could eventually threaten its future.

In the realm of macroeconomic factors, variables associated with uncertainty, namely inflationvar and growthvar, have a discernible impact on the dynamics of corporate survival, entry, and exit within the market. Manufacturing enterprises, particularly in Indonesia, express a distinct preference for a stable economic environment to bolster their ongoing operations. Notably, inflation plays a dual role by not only diminishing the number of surviving and entering firms but also amplifying the count of exiting firms. Conversely, economic growth emerges as a pivotal factor, contributing to an upswing in the survival and entry rates while concurrently mitigating the exit frequency. Recognized as a catalyst for market expansion, economic growth creates an advantageous climate for manufacturing entities. Delving into the financial landscape, lending rates exhibit a negative correlation with the survival and entry of companies, concurrently escalating the departure of firms from the market. Elevated lending rates continue to pose a challenge for companies, particularly those reliant on financial backing from local banks in Indonesia for investment and production expansion. Simultaneously, the quality of human resources, as measured by the Human Development Index (HDI), demonstrates a positive correlation with the number of surviving firms. However, it is noteworthy that while HDI does not function as a decisive factor influencing firms to enter the market, it significantly contributes to reducing the number of firms exiting.

However, several things need to be considered when looking at the results of both. The difference between aggregate and microdata is a real difference in distribution. Because we

are looking at several components of the data, the data's nature itself may generate discrepancies in results. Aggregating data can lead to aggregation bias, where important variations within subgroups or individuals are lost. For example, if data on individual incomes are aggregated to compute average income by region, we may miss important disparities within each region that could be significant at the microdata level. Microdata often reveals individual-level heterogeneity that aggregate-level data might obscure. Individual characteristics and behaviors may vary significantly within a given group, and these variations can be important for understanding relationships between variables. Even though many differences may occur in the data-generating process into aggregate data to become count data in Poisson regression, Carstensen (2019) proves that whatever can be done by the Cox regression model can also be applied with Poisson regression, especially using split data. By converting to Poisson modeling, there is no loss but rather a significant increase in capability. The Cox model is significantly more computationally efficient and makes it simpler to create a survival curve using common software, which is important for most clinical investigations. The too-intricate modeling of survival curves has a downside in that it may cause small humps and notches on an estimated curve to be misinterpreted. The capabilities in the typical Cox analysis programs restrict how the desired interactions can be modelled when stratification or time-dependent variables are included and divert the user from understanding that alternative interactions between covariates may be of relevance. Another study from Selmer (1990) also found results that were close between Poisson and Cox, while Loomis et al (2005), by estimating ungrouped data, provided results that were equivalent to the results of estimating Cox Proportional Hazard and Poisson Regression. Loomis et al (2005) argue that using simulated data, Poisson regression analyses of ungrouped person-time data yield results equivalent to those obtained via proportional hazards regression: the results of both methods gave unbiased estimates of the “true” association specified for the simulation. Analyses of empirical data confirm that grouped and ungrouped analyses provide identical results when the same models are specified. However, bias may arise when exposure-response trends are estimated via Poisson regression analyses in which exposure scores, such as category means or midpoints, are assigned to grouped data.

3.5 Conclusion

This study aims to identify the factors that determine firm survival, exit, and entry using survey data from large and medium manufacturing companies in Indonesia. The focus of this study is the influence of a company's technical efficiency as a performance indicator. Technical efficiency is calculated using several approaches, namely stochastic frontier with a translog model, both time-invariant and time-varying, as well as the ACF (Akerberg-Caves-Frazer) method, which treats endogeneity in the estimation of the production function in order to produce unbiased efficiency values. Several groups of control variables were identified in this study, including firm performance indicators such as income and capacity utilization; the second group of variables is the market structure represented by the Herfindahl-Hirschman Index (HHI) variable; and price cost margin (PCM). The third group of variables are variable characteristics, which include ownership, investment status, openness, location, and size. The fourth group is macroeconomic condition variables, which include inflation, economic

growth, inflation variability, and growth variability as a proxy for risk. Another macro variable is the lending rate.

The Cox proportional hazard model estimation results show that technical efficiency reduces the hazard ratio or increases company survival for all models used. This confirms that the company's ability to achieve efficient production is an important factor in supporting the company's ability to survive. Apart from that, the aggregate data and Poisson regression models show that company efficiency increases the number of companies that survive during the observation period and increases the number of companies that enter. On the other hand, efficiency has a negative effect on the number of companies leaving the market; in other words, the more efficient the company, the smaller the possibility of the number of companies leaving the market. Although there are differences in data structure at the micro and aggregate levels that have methodological consequences, The corresponding results of the two estimation techniques, both the Cox proportional hazard model and Poisson, are supported by several previous applied statistics studies that show that the Poisson and proportional hazard models are equivalent

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Chapter 4

Causality of Export and Productivity: The Role of Ownership

4.1 Introduction

In the current global era, the performance of an industry is determined by three main factors that are consistently addressed in industry and trade economics literature: firm ownership, productivity, and exports. These factors can mutually influence each other. Regarding ownership, it impacts a company's productivity, and this impact depends on whether the ownership is private or government-controlled, as indicated by numerous studies, including Liljeblom et al (2020), Eisenhardt (1989), Hart and Moore (1990), Phi et al (2019), and foreign ownership, which also affects company productivity, as demonstrated in studies by Bentivogli and Miranda (2017), Driffield et al (2018), and Harris and Robinson (2003). Moreover, ownership structure, including shared ownership, has its own distinct influence, as evidenced in studies by Demsetz and Villalonga (2001), Du et al (2021), and Lichtenberg and Siegel (1987). Furthermore, company ownership plays a crucial role in determining a company's international trade expansion through exports, as supported by various studies, including those by Athukorala et al (1995), Gaigne et al (2017), Kostevc (2022), and Vega Salas and Deng (2017). On the other hand, the interaction between exports and firm productivity is a recurring topic in the literature, with two-way arguments frequently presented. Exports can affect productivity, and conversely, productivity can influence a firm's exports. This argument is substantiated by several studies, such as those by Wagner (2007), Aw and Hwang (1995), and Greenaway and Yu (2004). These three factors are of paramount importance in both academic discussions and policy considerations, thus necessitating a comprehensive examination.

The interaction among the three factors affecting company performance is often overlooked in the literature discussion. Typically, the literature tends to examine the interaction of only two, such as ownership effect on productivity or ownership effect on export, of these three factors separately, which can lead to biased conclusions or an incomplete understanding of how all three factors interact. Several factors contribute to common occurrences, especially when examining the causal relationship between productivity and exports in the absence of ownership considerations. Foreign ownership plays a significant role in boosting exports in two distinct ways. Firstly, foreign companies or Foreign Direct Investment (FDI) tend to engage in exports when their primary market isn't within the host country. They do so to access more abundant resources or take advantage of relatively cheaper prices. Conversely, some FDI is primarily focused on accessing the host country's market for production, with the majority of the output intended for domestic consumption. Furthermore, foreign companies, with their larger scale, experience in both their home country and other nations, and access to advanced technology, often exhibit higher levels of productivity compared to domestic companies. Due to these considerations, studies investigating the causal relationship between exports and productivity must take into account the influence of ownership. Therefore, this study aims to contribute by enhancing the literature's discussion on the simultaneous interaction of these

three factors, providing a more comprehensive analysis of studies related to this issue. The study addresses several key questions: What are the characteristics of companies with a tendency to export? Do the relationships between productivity and exports vary among different ownership statuses?

To conduct this analysis, we utilize micro-panel data from large and medium manufacturing industries in Indonesia, covering the period from 1995 to 2015. To measure productivity, we employ the Akerberg, Caves, and Frazer (2015) technique, which calculates the Total Factor Productivity (TFP) for efficient estimations. This approach helps address endogeneity issues in estimating production functions, providing more accurate TFP and efficiency values. For the analysis of the relationship between productivity and exports, we use the Panel Vector Auto Regression (PVAR) test developed by Abrigo and Love (2016) and conduct group analyses based on the investment company status and capital ownership of companies. The productivity and trade of this industrial sector still plays an important role in the economies of developing countries, including Indonesia. Indonesia, as the fourth most populous developing country with 275 million people, witnessed the manufacturing industry sector contributing 18.34 percent to the Gross Domestic Product (GDP) in 2022 (Central Bureau of Statistics, 2023). Moreover, the industrial sector accounted for 76 percent of the country's exports (Ministry of Industry, 2022), highlighting the pivotal role of manufacturing companies in the country's economic progress.

This paper is structured as follows: The next section contains a literature review that addresses the impact of company ownership on exports and company productivity. It also explores the interaction between exports and productivity, both within the framework of theoretical arguments and through examination of existing empirical studies. The third section covers data sources, observations, and methodologies, including estimation models and post-estimation tests. Following that, the fourth section presents the results and provides a discussion of the model estimation results, offering interpretation and analysis. Finally, the fifth section concludes with the study's findings.

4.2 Literature Review

This section explains the relationship between firm ownership, productivity, and exports in 3 separate sections to provide an overview of the interactions between these three variables. A summary of the interactions between the three variables can be depicted in Figure 4.1 as follows:

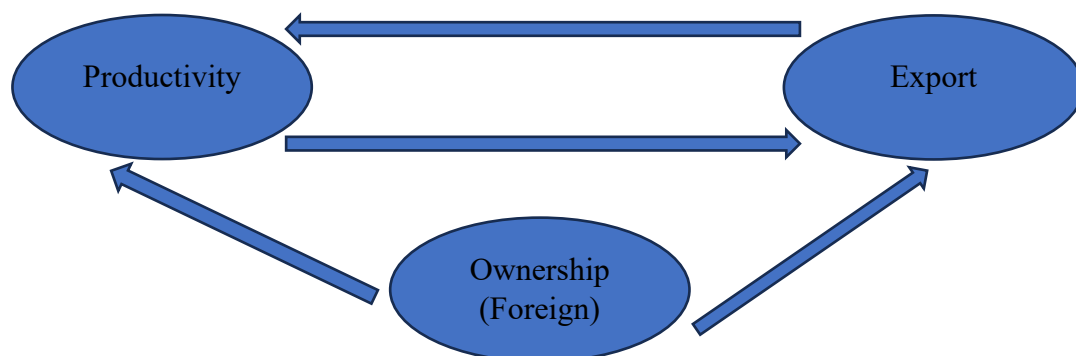


Figure 4. 1 Productivity, Export, and Ownership Triangle Relationship

4.2.1 Firm Ownership and Productivity

The impact of firm ownership on company productivity has been a subject of significant interest among economists, offering diverse perspectives. Several viewpoints discussed in various literature sources include how different forms of ownership, such as domestic private, foreign, or state ownership, can affect a company's productivity.

For instance, Liljeblom et al (2020) begin their exploration of state ownership by assessing its advantages and disadvantages, particularly in companies listed on the stock market. State ownership can provide non-market advantages, such as preferential treatment in government contract competitions, access to financial resources, raw materials, and reduced regulatory scrutiny. However, when political connections are used to extract non-market rents, the benefits must outweigh the costs for it to be advantageous for corporate value. In certain state-dominated industries, reduced competition may lead to higher profits, potentially outweighing the drawbacks associated with state ownership due to agency issues.

On the other hand, Phi et al (2019) argue that state ownership serves as a tool for governments to control natural monopolies, provide public goods, implement regional strategies, and address employment or social challenges. Profit maximization is not the primary objective in this context. Conversely, some opposing viewpoints suggest that state ownership primarily serves the interests of the governing elite (Goldeng et al. 2008) and may be ineffective even when markets fail (Megginson and Netter 2001). Goldeng et al (2008) propose that the differences in economic performance between state and private ownership are primarily driven by management incentives, costs, and exposure to market forces.

Additionally, Hart and Moore (1990) introduce the property rights theory, suggesting that the variety and division of property rights in the context of public businesses contribute to the inefficiency of state-owned companies. Due to diffuse ownership, it's challenging to create comprehensive contracts that align agents' incentives with profit maximization. In contrast, private sector firms with more clearly defined property rights are better equipped to motivate managers to maximize profits.

Bentivogli and Mirenda (2017) present two main views derived from the literature. The first hypothesis pertains to the belief that multinational companies have inherent advantages over purely domestic firms, as proposed by Hymer (1960) and Dunning (1988). In cases where there is heterogeneity in productivity among firms in the same sector, only the more productive firms engage in foreign direct investment (FDI) due to the high fixed costs associated with entering foreign markets, as noted by Helpman et al. (2004). This leads to the transfer of proprietary assets from the multinational parent company to its foreign subsidiary, resulting in a foreign ownership premium (FOP).

The second view comes from the literature on corporate control, emphasizing ex-ante selection bias as the primary explanation for the varying performance of foreign-controlled enterprises. Manne (1965) contends that successful overseas businesses target underperforming domestic firms for acquisition (negative selection) to eliminate ineffective managers and maximize the firm's potential. High information asymmetries regarding the caliber of the acquired local company could result in negative selection. It's also possible that only the top domestic

enterprises engage in overseas acquisitions, in which case a portion of their superior performance can be attributed to the selection process (positive selection).

4.2.2 Firm Ownership and Export

The characteristics of a company, in general, play a significant role in its decision-making, including the decision to engage in international trade. Companies with extensive experience, a deep understanding of international markets, economies of scale in production, and a competitive advantage relative to others in the same industry are more likely to become export-oriented firms. In such cases, foreign ownership is believed to exert a greater influence on export decisions due to several factors, including productivity, technological superiority, and international networks (Athukorala et al, 1995). However, it's worth noting that foreign ownership can also have a potentially negative impact on a company's export orientation. Foreign companies investing in other countries often aim to increase profits by accessing their product market centers or cheaper inputs, thus achieving production economies of scale.

Another argument arises from the theory of international investment, which suggests that multinational companies tend to excel over local firms in product areas where technology is least standardized, economies of scale exist, and marketing entry barriers are high. In contrast, in the initial stages of export expansion, less developed countries often have market niches primarily in light manufactured goods produced with standardized and widely diffused technology. In such product areas, foreign firms may not have the technological capacity to outperform local firms, even though they might have an edge over local firms through their access to developed country markets. Abdel-Malek (1974) presents three primary arguments: first, the host nation market is often the main area of interest for manufacturing subsidiaries; second, these subsidiaries may incur higher production costs compared to their parent firms and other more productive overseas producers, limiting their export potential; third, even if the subsidiary is capable of competing in overseas markets, constraints from the parent company may hinder its ability to do so, often to protect the latter's market or other markets in countries where its subsidiaries operate.

The influence of company ownership extends beyond its status to encompass the structure of ownership and who contributes to ownership. Gaigne et al (2018) provide a theoretical perspective on ownership structure in the context of vertical ownership, which plays a role in a company's export orientation. They argue that producers are more likely to receive favorable terms through an intermediary when they offer more benefits, have lower transaction costs, and engage with larger trading partners. By vertically integrating, producers can address the double marginalization issue, reduce access costs to foreign markets, and, consequently, firms with ownership stakes in their intermediaries are more likely to engage in exports and achieve higher export sales compared to non-owning producers. Kim and Park (2011) explain that a concentrated ownership structure implies that owners have limited involvement in decision-making, as extensive involvement can be costly for individual owners, resulting in a free-rider problem. This suggests that firms with more concentrated ownership tend to perform better.

4.2.3 Export and Productivity

The relationship between exports and productivity has been a subject of significant interest among academics in the fields of industry and international economics, who seek to understand how these two variables are interconnected. At both macro-aggregate levels, be it at the country or manufacturing sector level, several studies, including those conducted by Jung and Marshall

(1985), Chow (1987), Kunst and Marin (1989), and Ahmad (2001), have explored the various forms of the relationship between exports and productivity. In these macro-empirical studies, productivity is often represented by economic growth. This exploration includes the export-led growth hypothesis, which posits that exports contribute to economic growth, as well as the reverse, where growth or productivity influences export performance. The direction of influence may also vary, leading to hypotheses such as the growth-reducing export hypothesis, or the possibility of no significant influence between the two.

Kunst and Marin (1989) offer four key points supporting the idea that exports may promote productivity. Firstly, they suggest that exports concentrate investment in the most productive economic sectors where the nation holds a competitive advantage, leading to increased specialization and higher production. Secondly, the presence of the local market is believed to foster greater economies of scale activities when combined with exports. Third, the expansion of exports exposes domestic industries to foreign competition, encouraging them to maintain low costs and adopt technological advancements that boost productivity. Finally, the growth of exports is thought to have positive externalities on other economic activities, ultimately raising overall productivity.

Conversely, an alternate perspective posits that growth or productivity influences exports. This hypothesis originates from the technological theory of trade and the processes of learning and technical change, as explained by Jung and Marshall (1985) and Kunst and Marin (1989). This viewpoint suggests that in developing economies, rapid changes in learning and technology occur in a few industries. These developments are more closely associated with the accumulation of physical capital, human capital, industrial experience over time, and technological transfers from outside sources through licensing or direct investment. This implies that fundamental causes of uneven growth may not necessarily be linked to specific incentives for promoting exports but can still contribute to growth even in the absence of such incentives.

Empirical studies on the relationship between exports and productivity have yielded mixed results, with some demonstrating a positive correlation while others show less robust results or significant heterogeneity in their conclusions. Researchers like Bernard and Jensen (1999) and Li and Bender (2007) have focused on exploring causality in productivity and export studies within the manufacturing industry.

4.3 Data and Methodology

4.3.1 Data Resources

The data utilized in this study comprise annual survey data from medium and large companies. BPS (Badan Pusat Statistik) classifies business scale based on the number of employees, designating companies with 20 to 99 employees as medium-sized and those with 100 or more employees as large. The study's timeframe spans from 1995 to 2015. Industrial survey data offer the advantage of comprehensive observations, with all manufacturing firms serving as respondents. Some survey information has undergone changes, including details about the general characteristics of companies and their workforce. These alterations will undoubtedly impact the study's variable formation, determining whether it will incorporate compelling information about characteristics or maintain the observation period. Such variations are typical in microdata panel survey results. This dataset is constructed through annual matches of company IDs. Several companies enter and exit the dataset for various reasons, such as

closure or relocation to another country. Given the aim of capturing information on all companies entering Indonesia, the dataset takes the form of unbalanced data.

Table 4.1 provides a technical description of variables, while statistical descriptions of all variables are presented in Table 4.1b

Table 4. 1 Technical Description of Variables

Variables	Description
Output	Total value of production (in Natural Logarithm)
Foreign Ownership	A dummy of investment status, 1 if the investment is foreign, and 0 otherwise. There are three answer options for the question which are foreign, domestic, and non-facility.
Domestic Ownership	A dummy of domestic investment, 1 if the investment is domestic, and 0 otherwise
Capital Stocks	The total value of capital stocks, buildings, machinery, tools, and lands (natural logarithm)
Materials	Total value of materials (in logarithm)
Energy	The total value of energy consumption, fuels, lubricants, Gas, and electricity (in logarithm)
TFP (Total Factor Productivity)	Estimated from production function (ACF Model)
Labor	Number of production workers (in natural logarithm)
Export	The total value of export (in natural logarithm)
Foreign Capital	Percentage of foreign capital contribution
Private Capital	Percentage of private domestic capital contribution
Central Government	Percentage of central government capital contribution
HHI	Herfindahl–Hirschman Index (5, Output)
Capacity	Percentage of actual production to production capacity
Inventory	Inventory at the beginning and at the end of the year
Tax Rate	Tax payment to the total output (in percent)
World Growth	World real GDP growth (in percent), International Monetary Fund (IMF)
Growth	National Economic Growth (in percent), Data sources are taken from World Development Indicators, World Bank
Foreign Exchange	Official Exchange Rate (in natural logarithm), USD per IDR. Data sources are taken from World Development Indicators, World Bank
Inflation Variability	Inflation Variability. Measured by:

$$\text{Inflation Variability}_t = \left(\frac{\text{Inf}_t - \text{Mean Inf}}{N} \right)^2$$

Where Inf_t is the inflation rate at time t (in percent), Mean Inf is the average of inflation rate, and N is the total inflation in the observed period.

Table 4. 2 Descriptive Statistics of Variables

Variable	All Observations					FDI					Non-FDI				
	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max	Obs	Mean	Std. dev.	Min	Max
TFP	453,284	1.701	1.261	12.166	20.395	35,111	1.698	1.519	10.188	18.363	418,173	1.701	1.237	12.166	20.395
EXP	453,289	2.052	5.388	0.510	28.708	35,112	6.696	8.447	0.542	24.713	418,177	1.662	4.849	0.510	28.708
Capital Stock	453,289	2.492	4.641	0.693	22.766	35,112	5.456	6.385	0.781	22.766	418,177	2.243	4.373	0.231	21.793
Energy	453,289	9.363	3.923	0.663	23.556	35,112	10.914	4.516	0.634	23.556	418,177	9.233	3.841	0.548	22.690
Materials	453,289	13.556	3.795	0.562	25.117	35,112	15.685	4.508	0.445	25.013	418,177	13.377	3.673	1.234	25.117
Labor	453,289	12.765	1.868	0.756	21.738	35,112	14.699	1.710	0.471	21.281	418,177	12.603	1.788	0.847	21.738
Output	453,284	15.061	2.276	6.700	25.629	35,111	17.631	1.880	7.590	25.629	418,173	14.845	2.172	6.700	25.274
Domestic Private Investment	453,275	84.064	35.639	0	100	35,099	27.569	36.906	0	100	418,176	88.806	31.178	0	100
Central Government Investment	453,275	1.315	11.183	0	100	35,099	0.380	4.564	0	100	418,176	1.394	11.565	0	100
HHI	450,414	0.306	0.132	0.200	0.997	34,604	0.302	0.127	0.200	0.993	415,810	0.306	0.133	0.200	0.997
Capacity	453,289	61.474	35.332	0	960	35,112	56.169	37.343	0	226	418,177	61.919	35.122	0	960
Inventory	453,289	7,022	1.399	-8.961	5.521	35,112	0.371	3.020	0.528	4.331	418,177	4.501	1.160	-8.961	5.521
Tax Rate	453,289	0.012	0.404	0	13.421	35,112	0.034	1.155	0	134.212	418,177	0.010	0.255	0	99.240
Growth	453,289	4.603	3.902	1.312	8.220	35,112	4.696	3.686	-13.126	8.220	418,177	4.595	3.919	13.126	8.220
Inflation Variability	453,289	0.648	0.168	0.123	0.836	35,112	0.662	0.163	0.123	0.836	418,177	0.647	0.168	0.123	0.836
World Growth	453,289	3.803	1.325	-0.1	5.6	35,112	3.846	1.306	-0.1	5.6	418,177	3.799	1.327	-0.1	5.6
Inflation	453,289	10.078	10.638	3.688	58.451	35,112	9.560	10.193	3.688	58.451	418,177	10.122	10.673	3.688	58.451
Exchange Rates	453,289	9.009	0.4622	7.718	9.502	35,112	9.068	0.401	7.718	9.502	418,177	9.004	0.466	7.718	9.502

4.3.2 Methodology

There are several stages involved in identifying a triangular relationship. Stage 1 is to estimate Total Factor Productivity (TFP) using Akerberg, Caves, and Frazer (2015) to produce TFP by considering endogeneity in the production function. Second, is the estimation of the effect of foreign ownership or FDI on TFP and Exports. This stage also includes TFP and exports in the model to test their relationship. The interaction shows the moderation effect of FDI for exports and TFP. Estimations are carried out using Fixed and Random Effect models and to overcome the problem of endogeneity of TFP exports and other variables in the model, System GMM is used.

4.3.2.1 Estimating Production Function

The initial step we took was to measure Total Factor Productivity (TFP) as an indicator of company productivity by estimating the production function. Estimating the production function is a key topic in applied econometrics. On the flip side, consistently estimating the parameters of a production function might pose challenges because the model's disturbance typically includes factors determining output that are observed by the firm but not by the analyst. Inputs may become endogenous variables if firms optimally choose the number of inputs consumed in the production process, which is often the case for companies aiming to dynamically maximize their profits (Manjón and Mañez, 2016). This suggests that estimations produced by conventional techniques like Ordinary Least Squares (OLS) are inconsistent. Moreover, more intricate methods such as the fixed-effects estimator or instrumental variables within-groups estimator do not seem to be very effective (Griliches and Mairesse, 1998). The use of instrumental variables is ineffective because determining a feasible and strong instrument in the working case modeling is uncertain. In this study, I employ an estimation method developed by Akerberg, Caves, and Frazer (ACF, 2015). The ACF approach emerged as a response to criticism of previous approaches in the endogenous treatment of production function estimation, as previously developed by Olley and Pakes (1996), and Levinsohn and Petrin (2003). ACF observed that previously developed methods might pose identification problems. ACF demonstrates that one of the inputs, such as labor, may not vary independently of the nonparametric function being estimated using a low-order polynomial unless additional assumptions are incorporated about the processes generating the data. The estimation of the production function involves inputs such as labor, capital stock, energy, and electricity. I use value added as y (output), labor as the free variable, and proxy variable namely raw materials, while energy including fuel, electricity, and lubricants as intermediate inputs, and company capital as the state variable. Both output, free, proxy, and state are needed in estimating the ACF model.

4.3.2.2 Export, FDI, and TFP Relationship

At this juncture, our focus pivots towards gauging the intricate interplay among Foreign Direct Investment (FDI), investment origins, and export dynamics. To unravel this complexity, we deploy a dual-pronged estimation approach. Firstly, we employ panel data estimation techniques, incorporating various model specifications such as fixed effects, random effects, and the Generalized Method of Moments (GMM) system to address endogeneity concerns. The GMM technique is used considering its flexibility in treating multiple endogenous variables in unbalanced panel data (Roodman, 2009). Concurrently, we delve deeper into the dynamic interaction between exports and Total Factor Productivity (TFP) through a Panel Vector Auto Regression (PVAR) model. This model encapsulates both FDI and Non-FDI contexts across the entirety of observations, shedding light on the nuanced dynamics at play. Meanwhile, the capital ownership structure considers the percentage of capital, encompassing percentages from the local government, central government, national private, or foreign sources. This study analyses only the central government and domestic private. I estimate the effect of FDI on exports and productivity and the interaction of FDI with the capital structure which is considered endogenous because capital owners seek to maximize their profits by enhancing access to company ownership if the company's performance improves. Additionally, I explore the effects of capital status independently and in interaction with the percentage of capital ownership within the company. The estimation model for both capital status and ownership effects on export performance is formulated in the same manner as Equation 2. The estimation model, equations 1 and 2 can be expressed as follows:

$$TFP_{it} = \alpha_{10} + \beta_1 FDI_{it} + \beta_3 DPI_{it} + \beta_4 CGI_{it} + \beta_6 FDI * DPI_{it} + \beta_7 FDI * CGI_{it} + \gamma_q \sum_{p=0}^q EXP_{it-p} + \delta_l \sum_{k=1}^l X_{it} + \varepsilon_{1it} \quad (4.1)$$

$$EXP_{it} = \alpha_{20} + \beta_8 FDI_{it} + \beta_{10} DPI_{it} + \beta_{11} CGI_{it} + \beta_{13} FDI * DPI_{it} + \beta_{14} FDI * CGI_{it} + \gamma_r \sum_{s=0}^s TFP_{it-s} + \sum_k \delta_k Z_{it} + \varepsilon_{2it} \quad (4.2)$$

In the first stage, TFP represents total factor productivity, while "FDI" denotes foreign ownership (Foreign Direct Investment). Separate estimates are conducted using a dummy variable where 1 indicates foreign investment status and 0 represents other statuses. Further estimates involve interactions between company ownership and capital contribution whether domestic private (DPI), or central government (CGI). This analysis aims to assess the moderating effect of changes in structure or capital participation on the impact of company investment status on performance and exports. On the other hand, the export variable is derived from the nominal value of exports (EXP). Variables X and Z constitute a set of control variables in the model, encompassing market competition (measured by market share and Herfindahl-Hirschman Index), capacity utilization, inventory change, firm size (measured by total assets and workers), firm tax ratio, economic growth, inflation rate, and year and two-digit industrial sector fixed effects.

The third strategy employed to identify the triangular relationship among ownership, productivity, and exports utilizes Panel Vector Auto Regression (PVAR) based on the General Method of Moment (GMM) estimation developed by Abrigo and Love (2016). Previous studies, such as those by Bernard and Jensen (1999), Li and Bender (2007), and Arnold and Hassinger (2004), have utilized Granger causality to examine the interaction of productivity and exports at the industry and company levels using time series and panel databases. The bivariate PVAR in our study is formulated as follows:

$$TFP_{it} = \alpha_0 + \sum_{k=1}^n \delta_k TFP_{it-k} + \sum_{k=1}^n \beta_k EXP_{it-k} + \mu 1_{it} \quad (3)$$

$$EXP_{it} = \alpha_0 + \sum_{k=1}^n \delta_k TFP_{it-k} + \sum_{k=1}^n \beta_k EXP_{it-k} + \mu 2_{it} \quad (4)$$

The PVAR model assumes that both the EXP (export) and TFP variables are endogenous. The estimation of the PVAR model, equations 3 and 4, is conducted separately for foreign company groups and other capital statuses, such as domestic companies. Additionally, the estimation of the PVAR model is also performed with simulations to assess robustness. This involves changing EXP to both nominal value and dummy exports, and introducing one additional variable, specifically the capital structure, with a focus on the contribution of foreign capital.

4.4 Results and Discussion

4.4.1 Results

The estimation results of the production model are summarized in Table 4. 2 employed ACF, and estimated the model for all observations, Foreign Direct Investment (FDI) firms, and Non FDI firms—for comparison, with the TFP value estimated from the ACF method used as an approach to estimating the production function that addresses endogeneity. The estimation outcomes reveal that all inputs are positive and statistically significant across the three models. Furthermore, consistency between estimation techniques is observed in terms of the magnitude of the coefficients, with labor, materials, energy, and capital stocks, in that order, exhibiting the largest values.

The estimation results, detailed in columns 1, 2, and 3 of Table 4.2, provide insightful comparisons between groups based on total observations, Foreign Direct Investment (FDI), and Non-FDI. Notably, in the case of total observations and FDI, the presence of multiple coefficients suggests increasing returns to scale, indicating potential efficiency gains with scale expansion. Conversely, for non-FDI, the coefficient value hovers around 1.0079, insignificantly deviating from unity, thus implying constant returns to scale. This observation gains further credence through the Wald Test, which only renders the non-FDI group's statistical value as insignificant, affirming the notion of constant returns. Additionally, the Sargan-Hansen test reinforces the validity of the model's moment conditions, as evidenced by the insignificance of estimates at both 5 and 1 percent thresholds, thus offering robustness to the constructed model.

Table 4. 3 Production Function Estimation

	(1)	(2)	(3)
VARIABLES	All Observations	FDI	Non FDI

Capital	0.0101*** (0.000832)	0.0851*** (0.00239)	0.0179*** (0.00154)
Energy	0.01204*** (0.00391)	0.0122*** (0.00115)	0.276*** (0.0131)
Materials	0.0862*** (0.00210)	0.0792*** (0.00689)	0.578*** (0.0153)
Labor	1.254*** (0.00761)	1.022*** (0.0204)	0.136*** (0.0114)
Observations	396,382	31,971	364,411
Wald Test of Constant	3827.03***	23.77***	2.38
Return to Scale (Chi ²)			
Sargant-Hansen J- Statistics	1.714	2.463	1.897

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The second stage involves the estimation of the TFP model as written in equations 1 and 2, and it is summarized in Table 4.3, employing four estimation techniques: Fixed Effects, Random Effects, and the Two Step Generalized Method of Moment (GMM) for comparison, this technique is utilized to identify the most suitable approach for addressing internal issues. The fixed effect model incorporates year and ISIC 2 digits, and the joint test indicates the statistical significance of both, emphasizing the importance of the fixed effect year and ISIC. Moreover, based on the Hausman specification test, the Chi value of 3357.11 and 3363.93 suggests that the fixed effect model is more appropriate for estimation. In addition, the fixed effect models are estimated using clustered standard error. As a solution to the endogeneity problem in fixed effects, I use GMM. GMM, developed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), is designed for conditions with a relatively small number of time observations (T) and a large number of cross-sectional entities or panels (N). This study adheres to the GMM design due to the relatively small number of time observations (21) and the large number of individual companies, approximately 20 thousand per year. This estimation technique is popularly designed for cases where the number of T is small, and the panels N are large (Roodman, 2009).

I employ the standard panel regression procedure that is fixed dan the random effect model as the comparison of the two-step system GMM based on optimal results from post-estimation serial correlation or Arellano-Bond tests and specifications of the Sargan-Hansen overidentifying restriction test. The GMM technique is applied to both the TFP and export models, summarized in Tables 4.3 The two-system GMM used here is theoretically developed by Ahn and Schmidt (1995) for nonlinear moment conditions and practically by Kripfganz (2019). The estimation results summarized in Table 4.3 show the best results after various simulations carried out. The test results with the overidentification test also show that there is no serial corellation as indicated by the probability of the Arellano and Bond tests which exceed 5 percent as well as the overidentification test whose probability shows it exceeds 0.05.

The analysis delves into the outcomes of the Generalized Method of Moments (GMM) estimation, utilizing a comprehensive model that incorporates interaction variables detailed in Table 4.3, column (6). The findings unveil a pivotal relationship: exports exhibit a favorable

impact on Total Factor Productivity (TFP), with Foreign Direct Investment (FDI) serving as a moderator, as evidenced by the coefficients. Specifically, the Export variable demonstrates a positive coefficient of 0.0711, while its interaction with FDI displays a more pronounced effect of 0.156. Moreover, the independent FDI coefficient highlights that FDI enterprises boast an average TFP of 7.28. Additionally, the origin of investment funds yields considerable influence, particularly those sourced from domestic private entities and the central government. Intriguingly, domestic private investment independently fosters productivity positively, whereas central government investment exerts a negative impact. Conversely, foreign investment fails to demonstrate significant effects.

Table 4. 4 Total Factor Productivity Model

VARIABLES	(1) Fixed Effect	(2) Random Effect	(3) Fixed Effect Interaction	(4) Random Effect Interaction	(5) System GMM	(6) System GMM Interaction
Value of Export (EXP)	0.00147*** (0.000441)	0.00145*** (0.000397)	0.00242*** (0.000497)	0.000535 (0.000445)	0.0253*** (0.00383)	0.0711*** (0.0158)
EXP * FDI			0.00376*** (0.000953)	0.00400*** (0.000894)		0.156*** (0.0593)
Domestic Private Investment	0.000374*** (0.000111)	0.000410*** (0.000108)	0.000402*** (0.000111)	0.000446*** (0.000108)	0.000269 (0.000437)	0.00954*** (0.00198)
Central Government Investment	-0.00143*** (0.000299)	-0.00151*** (0.000251)	-0.00147*** (0.000300)	-0.00157*** (0.000252)	-0.0847*** (0.0155)	-0.105*** (0.0253)
FDI	7.313*** (2.532)	5.317** (2.353)	5.931** (2.559)	4.250* (2.375)	6.184*** (0.0835)	7.280*** (0.0143)
FDI * Domestic Private Investment			0.000343 (0.000754)	5.58e-05 (0.000733)		0.556*** (0.191)
FDI * Central Government			0.00180 (0.00175)	0.00140 (0.00166)		0.569** (0.258)
FDI * Year	0.00368*** (0.00126)	0.00266** (0.00117)	0.00297** (0.00128)	-0.00209* (0.00119)	0.307*** (0.0416)	0.337*** (0.0751)
HHI	-0.101*** (0.0138)	-0.0675*** (0.0131)	-0.101*** (0.0138)	-0.0671*** (0.0131)	0.262 (0.264)	-2.002*** (0.380)
Capacity	0.000149** (5.93e-05)	0.000178*** (5.39e-05)	0.000151** (5.93e-05)	0.000168*** (5.39e-05)	-0.000661 (0.000955)	-0.00130 (0.00136)
Inventory	0* (0)	0** (0)	0* (0)	0** (0)	0 (0)	-0 (0)
Tax Rate	-0.0474*** (0.00415)	-0.0400*** (0.00404)	-0.0475*** (0.00415)	-0.0401*** (0.00404)	-0.744* (0.380)	-0.692* (0.419)

Macroeconomic Variables

Growth	5.446*** (0.0759)	1.403*** (0.0670)	5.449*** (0.0759)	1.407*** (0.0670)	0.113*** (0.0184)	0.176*** (0.0209)
Inflation Variability	-1,572*** (0.000728)		-1,572*** (0.000728)		0.276 (0.000553)	-1.073*** (0.000931)
World Growth	-1.530*** (0.0167)	1.213*** (0.0132)	-1.531*** (0.0167)	1.212*** (0.0132)	-0.0307*** (0.00703)	-0.0722*** (0.0145)
Inflation	-62.95*** (0.472)	-0.193*** (0.00750)	-62.95*** (0.472)	-0.194*** (0.00750)	-0.0149*** (0.00554)	-0.0321*** (0.00706)
Exchange Rates	6.495*** (0.158)	2.991*** (0.153)	6.499*** (0.158)	2.999*** (0.153)	-2.861*** (0.265)	-4.273*** (0.371)
Constant	1,465*** (11.22)	-41.08*** (1.753)	1,466*** (11.22)	-41.17*** (1.753)	23.87** (11.34)	36.31 (33.14)
Observations	431,931	431,931	431,931	431,931	392,092	392,092
R-squared	0.084		0.084			
Number of PSID	53,612	53,612	53,612	53,612	48,145	48,145
Two Digit ISIC FE	YES		YES			
Year FE	YES		YES			
Hausman (Chi ²)		3357.11***		3363.93***		
Arellano-Bond Test AR (1)/Probability					0.221	0.319
Arellano-Bond Test AR (2)/Probability					0.568	0.430
Sargan Test (Probability)					0.242	0.401
Hansen Test (Probability)					0.160	0.273

Standard errors in parentheses (Fixed Effect is estimated by clustered Standard Error)

*** p<0.01, ** p<0.05, * p<0.1

Notably, the interaction between the FDI variable and central government investment holds significance. Despite the inherent negative impact of government investment on productivity, when directed towards FDI enterprises, it paradoxically yields positive effects. This phenomenon, termed FDI interference, underscores the nuanced dynamics of direct or indirect interventions, contingent upon host country government policies and contractual agreements governing FDI, as elucidated by Adarkwah (2021). Government investment in companies often spawns a web of bureaucratic complexities and corruption, casting a shadow over the corporate landscape. In nations plagued by high levels of corruption, potential collaborators in Foreign Direct Investment (FDI) tread cautiously, wary of entanglement (Smarzynska and Wei, 2000). Conversely, Broll (2003) illuminates a contrasting narrative, suggesting that when host country governments share investment costs with FDI entities, it can serve as a form of insurance for multinational firms. This cost-sharing mechanism not only bolsters the credibility of government policies but also acts as a safeguard, mitigating risks inherent in international ventures. Private domestic investment wields considerable influence, as evidenced by its substantial positive coefficient of 0.556. This underscores the pivotal role it plays in enhancing company productivity. Jiang et al. (2018) provide further insights, demonstrating that collaborative ventures between foreign and domestic enterprises, especially in joint capital forms, can notably augment company productivity. Among the contributing factors, the transfer of technology between collaborating entities emerges as a significant catalyst, fostering innovation and efficiency within the corporate landscape.

The export model's estimation results, detailed in Table 4.4, reveal intriguing insights. The examination of fixed and random effect models indicates the superiority of the fixed effect model, as indicated by the Hausman Test, which demonstrates robust significance. Moreover, employing the GMM model, with lag 1 as the optimal lag, presents favorable outcomes for the autocorrelation test (Arellano-Bond Test) and overidentification tests, specifically the Sargan and Hansen tests, all registering probabilities above 0.05. The GMM estimation outcomes for the EXP model unveil a notable positive coefficient of 0.525, underscoring the pivotal role of productivity in facilitating companies' foray into international markets. Furthermore, the validation of the self-selection hypothesis corroborates the intertwining dynamics of exports and productivity. This substantiates the dual perspectives—self-selection and learning by exporting—about exports and productivity, particularly within the Indonesian context. This finding aligns with prior research, exemplified by the studies of Greenaway and Yu (2004) as well as Wassie (2019), further bolstering the credibility of these hypotheses in a cohesive framework.

Table 4. 5 Export Model Estimation

VARIABLES	(1) Fixed Effect	(2) Random Effect	(3) Fixed Effect Interaction	(4) Random Effect Interaction	(5) System GMM	(6) System GMM Interaction
Total Factor Productivity (TFP)	0.0200** (0.00802)	-0.00883 (0.00576)	0.0181** (0.00759)	0.000726 (0.00605)	0.804*** (0.07361)	0.525*** (0.0132)
TFP*FDI			0.0759*** (0.0176)	0.0880*** (0.0178)		1.976 (2.276)
Domestic Private Investment	0.00404*** (0.000500)	0.00388*** (0.000404)	0.00513*** (0.000457)	0.00359*** (0.000406)	0.0938*** (0.00827)	0.0487*** (0.0142)
Central Government Investment	0.000105 (0.00209)	0.00864*** (0.000983)	-0.00111 (0.00205)	0.00908*** (0.000987)	1.433*** (0.235)	0.757*** (0.251)
FDI	2.441*** (0.271)	2.018*** (0.089)	1.168*** (0.0974)	1.979*** (0.0903)	3.684*** (0.311)	3.738*** (0.453)
FDI*Domestic Private Investment			0.00423 (0.00259)	-0.00888*** (0.00274)		2.149*** (0.660)
FDI*Central Government Investment			0.000433 (0.00708)	-0.0207*** (0.00627)		4.567** (2.323)
FDI*year	0.123*** (0.0135)	0.102*** (0.00444)	0.0599*** (0.00486)	0.0999*** (0.00450)	1.841*** (0.155)	1.917*** (0.233)
Herfindahl-Hirschman Index	-0.153*** (0.0563)	-0.469*** (0.0493)	-0.165*** (0.0490)	-0.467*** (0.0493)	-30.07*** (4.298)	-28.86*** (5.022)
Capacity	0.00982*** (0.000414)	0.0109*** (0.000205)	0.00715*** (0.000350)	0.0109*** (0.000205)	0.0791*** (0.0161)	0.0806*** (0.0196)
Inventory	0 (0)	0 (0)	0 (0)	0 (0)	-0 (5.05e-11)	6.55e-11 (1.17e-10)
Tax Rate	-0.00847 (0.00818)	-0.0129 (0.0151)	0.00202 (0.00760)	-0.0146 (0.0151)	0.275 (1.299)	1.283 (1.793)

Macroeconomic Variables

Growth	-2.056*** (0.177)	-2.279*** (0.248)	-1.637*** (0.158)	-2.308*** (0.248)	-3.157*** (0.499)	-2.580*** (0.588)
Inflation Variability	95.31*** (23.28)		74.69*** (21.62)		-53.03*** (8.035)	-36.49*** (9.682)
World Growth	0.228*** (0.0353)	0.292*** (0.0495)	0.176*** (0.0316)	0.284*** (0.0495)	1.845*** (0.220)	1.695*** (0.275)
Inflation	3.699*** (0.936)	0.205*** (0.0278)	2.892*** (0.869)	0.208*** (0.0278)	0.745*** (0.218)	0.589** (0.255)
Exchange Rate	4.193*** (0.374)	4.565*** (0.568)	3.250*** (0.331)	4.631*** (0.568)	66.60*** (5.828)	50.06*** (6.850)
Constant	-43.48* (22.29)	54.73*** (6.498)	-33.68 (20.68)	55.53*** (6.498)	-2,896*** (278.0)	-1,918*** (413.1)
Observations	431,931	431,931	431,931	431,931	392,092	392,092
R-squared	0.105		0.296			
Number of PSID	53,612	53,612	53,612	53,612	48,145	48,145
Two Digit ISIC FE	YES		YES			
Year FE	YES		YES			
Hausman (Ch ²)	3146.18***		16730.68***			
Arellano-Bond Test AR (1)/Probability					0.113	0.273
Arellano-Bond Test AR (2)/Probability					0.106	0.215
Sargan Test (Probability)					0.214	0.381
Hansen Test (Probability)					0.125	0.102

Robust standard errors in parentheses (Fixed Effect is estimated by clustered Standard Error)

*** p<0.01, ** p<0.05, * p<0.1

As discussed in the literature review, there is theoretically a bi-causal relationship between exports and productivity. Therefore, in estimating the TFP and export models, this includes the export variable in the export model and the TFP variable in the export model. The dynamic relationship between TFP and exports is further analysed in stage 3 of the analysis with Panel VAR scheme practically developed by Abrigo and Love (2016). Some studies related to this study were also carried out in previous works namely Chaos et al (2022) which analyzed at the country level, especially developing countries, and Arnold and Hussinger (2005) at the company level. Unlike Arnold and Hussinger (2005) which used a simple linear model, the study used GMM-based estimation techniques suggested by Abrigo and Love (2016). PVAR was first described as being developed by Holtz-Eakin et al. (1988), who presented instrumental variables (IVs)-based estimation. More recent research includes Hahn and Kuersteiner (2002), Binder et al. (2005), Arellano (2003), Cao and Sun (2011), Hayakawa (2016), and Juodis (2018).

Addressing the stationarity quandary in time series modeling stands as a pivotal concern, particularly evident in the estimation of linear dynamic panel models via GMM. Blundell and Bond's seminal work in 1998 spotlighted the susceptibility of GMM estimators to the weak instruments issue, notably when the variable under scrutiny hovers near a unit root. When such a root exists, moment conditions lose their relevance entirely. Employing techniques akin to those used in time-series VAR, such as pre-transforming variables through growth rates or differencing, emerges as a viable strategy to circumvent this challenge (Abrigo and Love, 2016). Therefore, in estimating models 3 and 4 this study uses first difference transformation to avoid this problem. VAR, Granger causality, and impulse response model estimates were carried out for total observations, FDI, and non-FDI to determine differences between groups and in general. The simulation of the bivariate Panel VAR model includes determining the lag length based on optimal lag or order selection, relying on Hansen's (1982) J statistic and the corresponding p-value, as well as the Moment Model Selection Criteria (MMSC) proposed by Andrews and Lu (2001). Instrument specifications developed by Holtz-Eakin, Newey, and Rosen (1988) for GMM-style in VAR panel estimation are applied to both the TFP and EXP models. The results of the VAR estimation with lag one produces a Hansen's J statistic P value of 0.1458 for the TFP model, while for the export model, it produces a Hansen J statistic P value of 0.4176. This suggests that the lag 1 model accepts the overidentifying restriction hypothesis, while the second and third lags show significant P values, or more precisely, below 5 percent, indicating a rejection of the over-identification restriction.

The next test for the VAR Panel assesses the stability of the VAR model, and the results are summarized in Table 4.5. This table illustrates the outcomes of stability tests for total observations, foreign firm groups, and domestic firm groups. The VAR panel model is considered stable if the modulus value is no greater than 1. Upon examination of Table 4.5, the modulus values are all less than 1 for all observations, foreign, and domestic firms.

Table 4. 6 Stability Test of Panel VAR Model

Group of Observations	Eigen Value		Modulus
	Real	Imaginary	
All Observations	0.5463	0	0.5463
	0.5382	0	0.5382
	-0.4521	0	0.4521

	-0.2411	0.3611	0.4342
	-0.2411	-0.3611	0.4342
	-0.0675	0	0.0675
	0.6101	-0.3081	0.6835
	0.6101	0.3081	0.6835
Non FDI	-0.6451	0	0.6451
	-0.1838	-0.3179	0.3673
	-0.1838	0.3179	0.3673
	0.1086	0	0.1086
	0.9331	0	0.9331
	0.6313	0	0.6313
FDI	-0.6003	0	0.6003
	-0.2011	-0.2802	0.3449
	-0.2011	0.2802	0.3449
	0.1019	0	0.1019

In the subsequent stage, we conducted Granger causality tests on TFP and Export, separating the groups for all observations, the foreign ownership group, and the domestic company group. The results of the Granger tests are presented in Table 4.6. Our interest lies in understanding whether past values of the export variable are useful in forecasting the values of another variable, productivity, conditioned on past values of productivity. The null hypothesis posits that the parameters on all lags of an endogenous variable are jointly equal to zero. In such a case, the coefficients may be excluded from an equation of the panel VAR model, and this is implemented as independent Wald tests. The test to determine whether the coefficients on the one lag of productivity appearing in the export equation are all zero is presented in Table 4.6 below:

Table 4. 7 Granger Causality Test of TFP and Export

Group	Equation/Excluded		Chi2
All Observations	TFP	Export	786.097***
		All	786.097***
	Export	TFP	2090.015***
		All	2090.015
Foreign Ownership	TFP	Export	119.000***
		All	119.000***
	Export	TFP	274.205***
		All	274.205
Domestic Ownership	TFP	Export	82.075***
		All	82.075***
	Export	TFP	259.056***
		All	259.056***

*** p<0.01, ** p<0.05, * p<0.1

At a 99 percent confidence level, the null hypothesis that productivity does not Granger-cause export is rejected; conversely, the null hypothesis that EXP does not Granger-cause TFP is accepted. The second test, known as ALL, examines whether all lag coefficients of endogenous variables, excluding those of the dependent variable, are jointly zero. This test is analogous to the first test since the panel VAR model comprises only two endogenous variables. According to the Granger causality test, TFP and EXP exhibit interaction in two directions, indicating a bi-causal relationship.

The next estimation step involves the use of the Impulse Response Function (IRF), with three variants in the VAR panel model: simple IRF, orthogonalized IRF based on Cholesky decomposition, and cumulative IRF. In this work, the second type, orthogonalized IRF, is utilized. Furthermore, confidence bands for the fitted panel VAR model are calculated using a Gaussian approximation based on Monte Carlo draws. The IRFs suggest that export has a significant effect on productivity, as the confidence interval does not include the zero line in Figure 4.1. Conversely, TFP also has a significant effect on EXP in all observations as shown in Figure 4.2. In the initial period, the effect is positive, while in the second period, it decreases and turns positive again. The impact of total factor productivity on export, and vice versa, illustrated in Figure 4.1, exhibits a similar behavior to that in Figure 4.2.

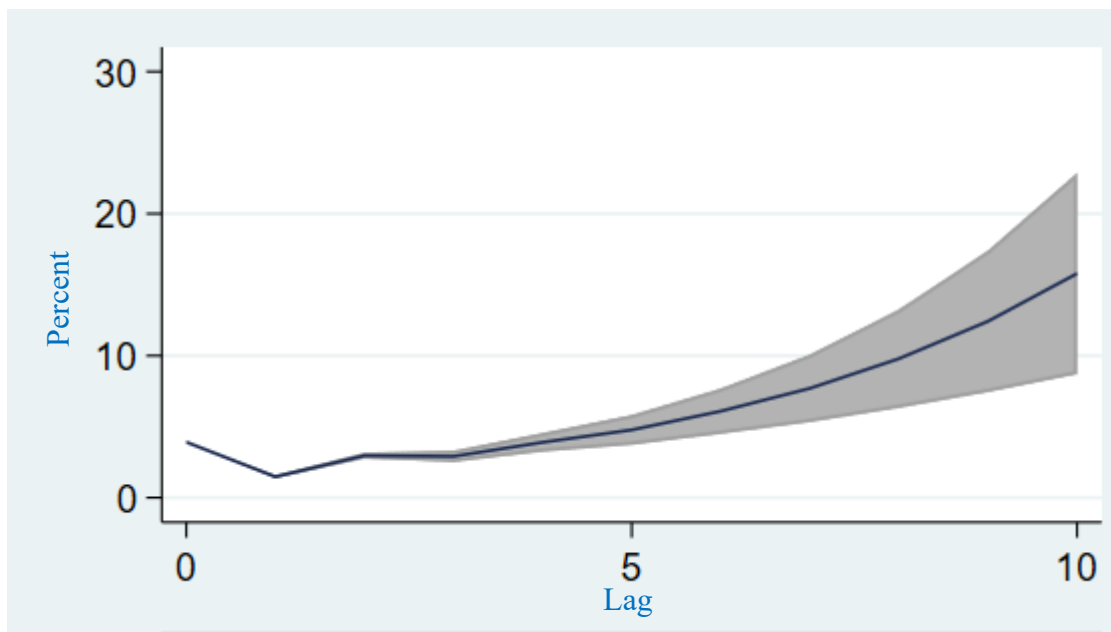


Figure 4. 2 IRF of Export to Total Factor Productivity for All Observations

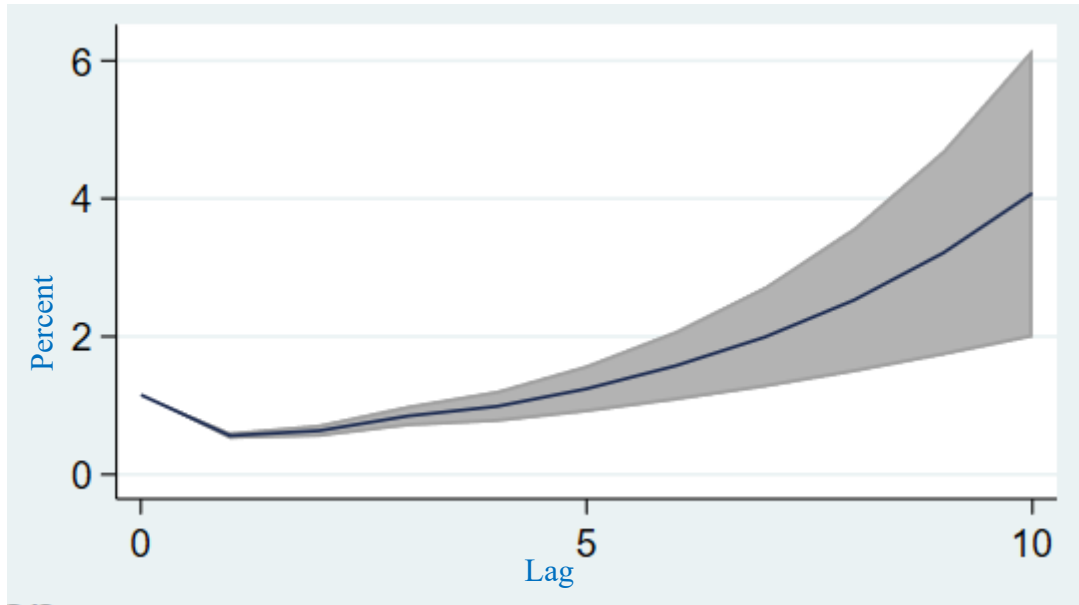


Figure 4. 3 IRF of Total Factor Productivity to Export for All Observations

The analysis of foreign company subgroups indicates that exports have no effect on total factor productivity, as depicted in Figure 4.3. This is evident because the confidence intervals include the zero line. However, in the period following the initiation of the export effect, total factor productivity becomes significant and gradually decreases to nearly zero in the subsequent period. In contrast, total factor productivity exhibits a significant effect on exports in the group of foreign companies, as illustrated in Figure 4.4. The significant effect begins from the initial period, followed by a rising impact. After the third period, the effect diminishes until it approaches zero.

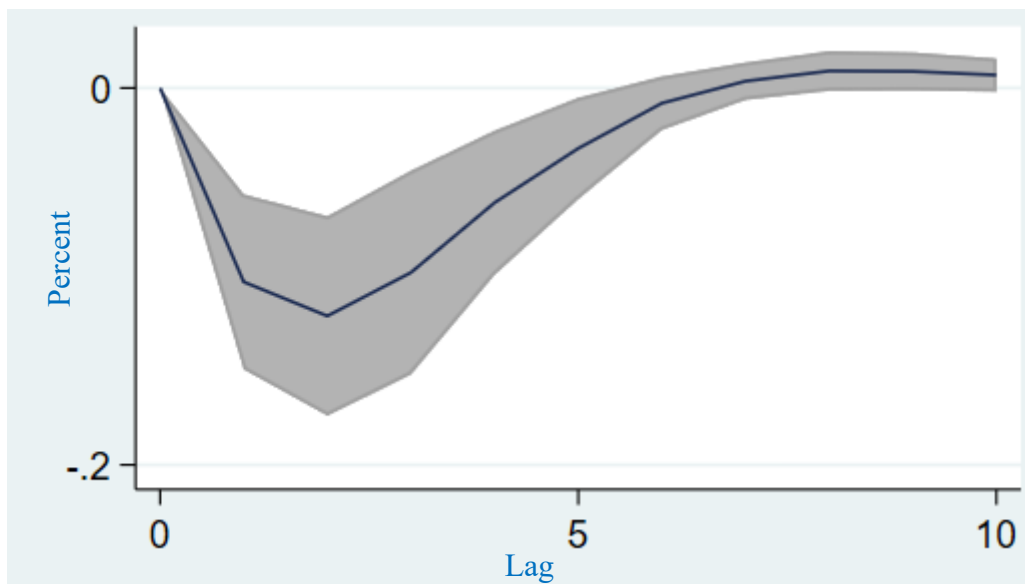


Figure 4. 4 IRF of Export on TFP (FDI)

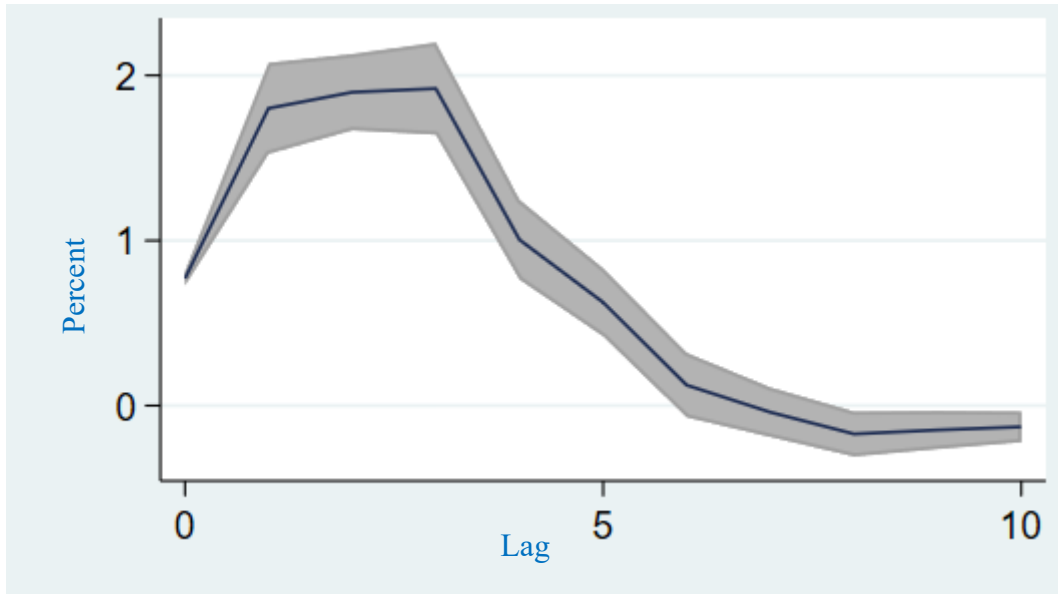


Figure 4. 5 IRF of TFP on Export (FDI)

For the analysis of the Non-FDI subgroup, refer to Figure 4.5 and 4.6. Figure 4.5 illustrates the impact of exports on TFP, displaying a notably positive and non-linear trend. Initially, the impact is positive as it is positioned above the zero line, then it gradually decreases to reach zero. Regarding the effect of TFP on exports, Figure 4.6 demonstrates that at the beginning of the period, the influence is positive. However, after the first period, the impact of total factor productivity diminishes, approaching zero.

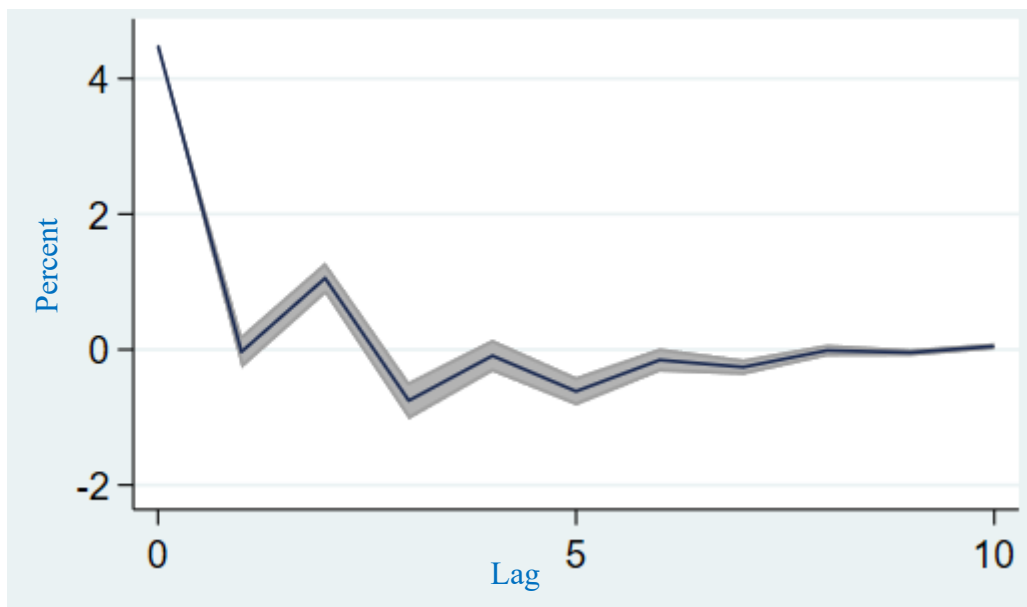


Figure 4. 6 IRF of Export on TFP (Non-FDI)

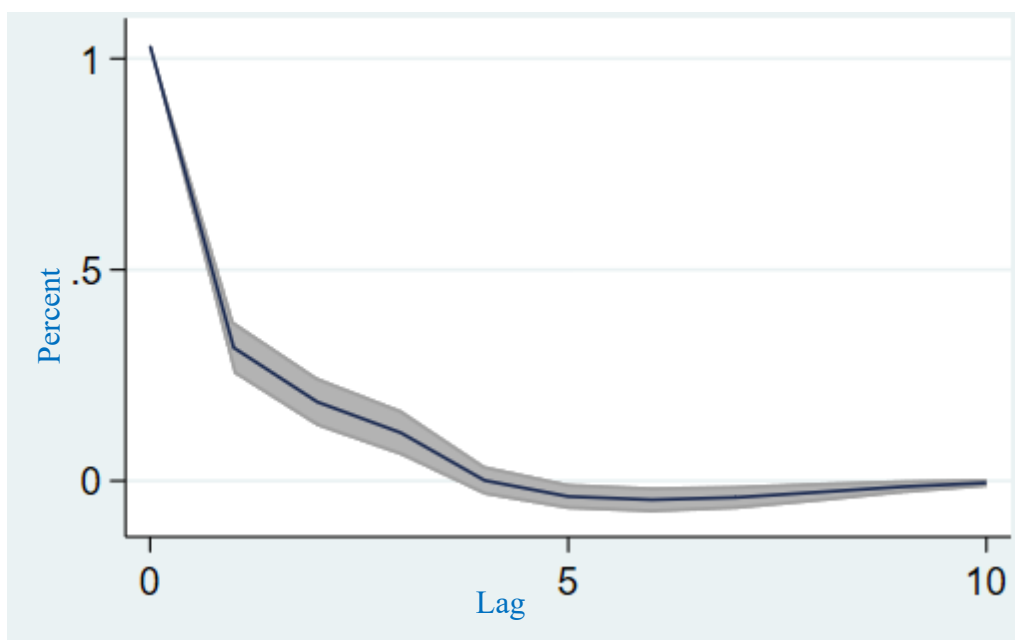


Figure 4. 7 IRF of TFP on Export (Non-FDI)

4.5 Concluding Remarks

This study aims to examine the impact of foreign ownership (FDI) on productivity and exports and explore the relationship between productivity and exports under different ownership statuses. Based on the examined estimation results in the previous section, a relationship between FDI and productivity and exports is identified. The estimation outcomes derived from both the single and unrestricted Panel Vector Autoregression (VAR) models, utilizing the Generalized Method of Moments (GMM) system, reveal a consistent pattern when examining the interplay among Foreign Direct Investment (FDI), exports, and Total Factor Productivity (TFP). The static coefficients derived from equations 1 and 2 find reinforcement in the Granger causality conclusions and the system of equations 3 and 4, affirming a reciprocal relationship among the variables. While the Granger results might not explicitly delineate the positive and negative aspects of the export and TFP coefficients, the Impulse Response Functions (IRF) provide a dynamic perspective on the influence dynamics of these variables. This dynamic perspective is discernible both independently for the FDI and Non-FDI cohorts, as well as across the entirety of observations, shedding light on the nuanced dynamics at play.

The single equation estimation findings from both the export and Total Factor Productivity (TFP) models illuminate a reciprocal relationship: TFP exerts a significant positive impact on exports, while exports, in turn, bolster productivity. This study delves into the intricate nexus among productivity, exports, and ownership, with a specific focus on Foreign Direct Investment (FDI), recognizing their interconnected nature. Notably, FDI emerges as a potent force, distinctly shaping outcomes irrespective of productivity and export levels. The interaction between FDI and exports yields a profound influence, surpassing the impact of exports in isolation on productivity. This is attributed to the inherent inclination of FDI firms towards assimilating the learning curve inherent in exporting activities. Jiao et al. (2018) corroborate this notion, highlighting how industries with foreign capital ownership enhance productivity through international trade endeavors.

Conversely, governmental and private investments in FDI exhibit a positive and substantial influence, signifying the constructive role of joint ventures between foreign and domestic investors in enhancing company productivity. In the export model, TFP significantly influences export performance, yet the interaction between FDI and TFP fails to yield a discernible effect on exports. However, FDI autonomously exerts a substantial impact on company exports, indicative of its propensity to spur export activities on average. In tandem with its influence on productivity, the interaction variable of FDI with private and governmental investments manifests a positive impact, underscoring how collaborative efforts between foreign and local investors drive up export values. These two estimated models reveal a triangular interaction pattern among FDI, productivity, and exports, wherein FDI influences both productivity and exports, while exports and productivity reciprocally influence each other in a bi-causal relationship, as illustrated in Figure 2.1 In conclusion, all these findings support the existence of a triangular relationship between firm ownership (FDI), productivity, and exports. Manufacturing companies in Indonesia, both foreign and domestic, play a role in increasing productivity and exports. Foreign companies, typically from developed countries, often bring higher technology levels, seeking markets and production cost advantages.

Moreover, we find that both foreign and domestic ownership have a positive impact on the company's exports, indicating that both types of ownership are geared towards international markets. The results from the VAR panel analysis demonstrate that productivity and exports positively influence each other, regardless of the form of company ownership. This underscores the continued importance of increasing productivity and promoting exports for manufacturing companies in Indonesia. Industrial development policies should be aimed at enhancing productivity, promoting exports, and attracting foreign investment to enhance global competitiveness.

The findings of this study have implications not only for policymakers but also for other economic actors, including foreign and non-FDI companies. For policymakers, government intervention is crucial to boosting productivity and exports. The Indonesian government is currently developing policies to establish tax-free industrial zones to attract investors. As part of its medium-term strategy, the Ministry of Industry aims to develop 11 industrial areas. Achieving a trade surplus requires concerted efforts to enhance productivity and improve international marketing strategies. Companies should also assess the need for business partnerships with the government. The study's results suggest that capital cooperation between the government and foreign direct investment (FDI) has positively impacted economic prosperity. However, companies must carefully determine the balance of authority and control within these partnerships, as mismanagement could lead to conflicts of interest.

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Chapter 5

Conclusion

The manufacturing sector in Indonesia still plays an important role in the national economy, especially during the transition process to becoming a developed country. Since the economic crisis occurred in 1998, the industrial sector has experienced successive challenges, including the world financial crisis in 2008, and most recently the economic crisis due to the COVID-19 pandemic. This certainly affects the performance of the industrial sector in achieving its optimal contribution to economic development. The problems faced by the manufacturing sector need intervention from the government through programs and policies that have a direct or indirect impact on the performance of the manufacturing sector. External economic shocks also pose another challenge for the manufacturing sector, especially for companies that have entered the global market either through exports of their products or imports of raw materials. The general hypothesis is that the factors that influence company performance in the industrial sector that is the focus of this study, such as partnership, efficiency, and ownership, show inconsistency with theoretical expectations, including how these three components interact in this study. The three derivative topics discussed in this study have been summarized in the following paragraphs.

The purpose of the first study is to investigate the significant effects that rural information and communication technology (ICT) accessibility has on village inhabitants' general well-being. This research explores the complex transmission mechanisms through which ICT access influences village development, with a particular focus on the path of village industrialization. It also directly determines the impact of ICT access on important village welfare indicators, such as poverty levels and the frequency of village residents moving for work. The results of the study clearly indicate that Information and Communication Technology (ICT) plays a crucial role in promoting industrialization in rural areas, with stronger signals in telephone and internet connectivity showing a positive correlation with increased industrial growth. In addition to ICT access, the study incorporates control variables that encompass various village characteristics, including infrastructure, financial resources, governance by the village administration, and the impact of natural disasters. These control variables exhibit their own noteworthy contributions to fostering industrial development in rural areas, as evidenced by diverse indicators shaping the course of industrialization. The inaugural study makes a significant scientific contribution in the following ways:

1. This research delves into the impact of Information and Communication Technology (ICT) on the welfare of village communities at the village level. It not only explores the direct consequences but also delves into the indirect effects on village welfare, specifically through the growth of the micro and small industrial sector. Unlike many existing studies that predominantly concentrate on either direct impacts on industry or the immediate effects on community welfare, this study provides a comprehensive examination of both dimensions.

2. The study employs a multi-stage analysis, commencing with an exploration of the determinants of ICT access. It then investigates the influence of ICT access on industrialization, poverty, and the migration of village residents for employment. This holistic approach allows for a nuanced understanding of the intricate relationships between these variables, providing valuable insights that go beyond the scope of many previous studies.
3. The determination of ICT access in this study incorporates various factors such as ICT infrastructure, including BTS, geography, and general infrastructure. The ICT access considered encompasses cellular operators, telephone and internet signal strength. In parallel, the study introduces novel indicators for industrialization, which were not previously utilized in similar research endeavors. This expansion in scope and inclusion of previously overlooked indicators enhances the depth and richness of the study's findings, contributing to a more comprehensive understanding of the dynamics at play.

Moreover, the study's findings emphasize the substantial impact of ICT on village development. Effective access to ICT services, encompassing robust internet and telephone signals and an expanded number of operators, is a pivotal factor driving rural development. Accessible information facilitates economic transactions and enriches the knowledge base of the population, contributing to heightened community productivity. Particularly noteworthy is the interaction variable between ICT access and industrialization, revealing a synergistic relationship that significantly influences the welfare of village communities. It highlights the critical importance of infrastructure development in Indonesia's rural areas, which comprise a larger portion of the country compared to urban regions. Public infrastructure, such as roads, education, healthcare, finance, and markets, is essential, but in today's digital era, Information and Communication Technology (ICT) has become especially vital. This research demonstrates that ICT not only directly but also indirectly improves the welfare of the rural population. ICT enables small and micro industries to access information more efficiently and affordably, facilitating market expansion and providing easier access to inputs at competitive prices.

As a result, the government's initiative to extend internet access to villages, which began about a decade ago, must be continued and further developed, as many villages in Indonesia still lack reliable and affordable internet. Although this program has stalled, it requires renewed support from the government and partnerships with internet service providers and telecom operators to prioritize rural internet infrastructure. With better ICT infrastructure, rural residents, who are often among the country's poorest and most likely to migrate for low-skilled jobs, stand to benefit significantly. The shift from traditional sectors like agriculture to industrialization offers increased employment opportunities, both as primary and supplementary income sources for villagers. This, in turn, can enhance local welfare, reduce poverty, and decrease the number of low-skilled workers seeking jobs abroad.

The second paper aims to identify the factors that determine firm survival, exit, and entry using survey data from large and medium manufacturing companies in Indonesia. The focus of this study is the influence of a company's technical efficiency as a performance indicator. Technical efficiency is calculated using several approaches, namely stochastic frontier with a translog model, both time-invariant and time-varying, as well as the ACF (Akerberg-Caves-Frazer) method, which treats endogeneity in the estimation of the production function in order to produce unbiased efficiency values. The correlation between efficiency and company

longevity underscores the necessity for firms to give priority to operational efficiency through the optimization of resource use and production processes. Additionally, efficient businesses have a higher chance of entering and remaining in the market, which strengthens their advantage over rivals due to their superior performance. The correlation between efficiency and company longevity underscores the necessity for firms to give priority to operational efficiency through the optimization of resource use and production processes. Additionally, efficient businesses have a higher chance of entering and remaining in the market, which strengthens their advantage over rivals due to their superior performance. Businesses may need to make investments in systems and procedures that increase their technological efficiency since doing so might be crucial to their ability to compete. According to the research, more firm efficiency can result in fewer companies leaving the market and more entering it, suggesting that as efficiency rises, competition in the industrial sector would likely get fiercer. For businesses to remain competitive in this dynamic market environment, efficiency must be continuously improved.

Several groups of control variables were identified in this study, including firm performance indicators, the second group of variables is the market structure represented by the Herfindahl-Hirschman Index (HHI) variable; and price cost margin (PCM). According to the research, more firm efficiency can result in fewer companies leaving the market and more entering it, suggesting that as efficiency rises, competition in the industrial sector would likely get fiercer. For businesses to remain competitive in this dynamic market environment, efficiency must be continuously improved. The third group of variables are characteristics, which include ownership, investment status, openness, location, and size. The fourth group is macroeconomic condition variables, which include inflation, economic growth, inflation variability, and growth variability as a proxy for risk. Another macrovariable is the lending rate. Variable characteristics comprise ownership, investment status, openness, location, and size, making up the third group of variables. Macroeconomic condition variables, which include growth in the economy, inflation, and growth variability as a stand-in for risk, as well as lending rate make up the fourth group.

The results of the Cox proportional hazard model estimation demonstrate that, for all models used, technical efficiency lowers the hazard ratio or increases company survival. This demonstrates that the company's capacity to produce goods efficiently is a critical component that supports the business's ability to thrive. Aside from that, company efficiency increases both the number of companies that enter and survive during the observation period, according to the aggregate data and Poisson regression models. However, efficiency has a negative correlation with the number of businesses that exit the market; that is, the more efficient a company, the lower the likelihood of a business exiting the market. The corresponding results of the two estimation techniques, the Poisson and the Cox proportional hazard model, are supported by several prior applied statistics studies that demonstrate the equivalency of the Poisson and proportional hazard models, despite methodologically significant differences in data structure at the micro and aggregate levels. The contributions of this study include:

1. In this study, the ACF method is employed to calculate technical efficiency, particularly in examining the impact of firm efficiency on firm survival. The ACF method stands out for its effectiveness in addressing the endogeneity problem inherent in estimating the production function within the stochastic frontier analysis technique. Notably, the application of the ACF technique to investigate the relationship between efficiency and firm survival is unprecedented to the best of the author's knowledge. This is a critical aspect, as overlooking the endogeneity issue in technical efficiency calculations could

introduce bias, potentially distorting both efficiency measurements and the conclusions drawn regarding the interplay between efficiency and firm survival.

2. The study adopts a two-stage estimation approach, conducting analyses at both the micro level and the 2 Digit ISIC level. This dual-stage estimation strategy is designed to assess the consistency of results across different scales, examining both micro and macro levels. Additionally, the objective is to scrutinize the stability of the impact of technical efficiency on key factors such as firm survival, exit, and entry. By undertaking analyses at multiple levels, the study aims to provide a comprehensive understanding of the nuanced relationships between technical efficiency and various aspects of firm dynamics.

The study focused on efficiency and firm survival and highlighted the critical role that efficiency plays in the sustainability of large and medium-scale industries in Indonesia. Given the importance of industry to the Indonesian economy, the government must implement policies that enhance industrial efficiency. These may include policies on input costs, such as energy pricing, import duties on raw materials, income tax, and value-added tax, as well as fair labor policies. In addition, sunk costs in company operations and company establishment permits are long-standing issues in the private sector in Indonesia. Such measures would help industries remain competitive and continue operating in Indonesia.

Labor issues also require special attention, particularly concerning wage systems and the relatively low productivity levels in Indonesia. The workforce is predominantly low-skilled, with 53.7% having only completed junior high school, compounded by unequal educational quality across regions. Therefore, improving the skills and quality of the workforce is essential. Labor-intensive industries, which dominate Indonesia's industrial sector, need better-trained workers to improve labor productivity and reduce production costs. The recent departure of major manufacturing companies like Giant, Pepsi, Panasonic, Toshiba, and LG has raised concerns, with labor issues often cited as a contributing factor. Addressing these challenges will not only improve company efficiency and productivity but also make Indonesia more attractive to high-tech companies by providing a skilled workforce capable of handling advanced technologies.

The third paper intends to examine the relationship between productivity and exports under various ownership statuses as well as the impact of foreign ownership on productivity and exports. We draw the conclusion that foreign ownership significantly affects productivity and exports based on the estimation results. In addition, export productivity benefits from the variable control of foreign investment that enters manufacturing firms, demonstrating the significance of foreign investment in bolstering the success of Indonesian manufacturing enterprises. Furthermore, in our dynamic model, domestic ownership has no discernible impact on productivity. I also discover that the company's exports are positively impacted by both domestic and foreign ownership. This attests to the fact that both forms of business ownership are focused on global markets. The VAR panel analysis's findings demonstrate that, irrespective of the ownership structure of the business, productivity and exports have a positive relationship that benefits Indonesia's manufacturing sector. In order to boost global competitiveness, industrial development policies must target raising productivity, promoting exports, and attracting foreign investment. The scientific contributions of this study include:

1. This study looks at the causality between productivity and exports where productivity is calculated using ACF to get the Total Factor Productivity (TFP) value. Previous

studies did not consider the endogeneity of TFP in the causal relationship between these two variables.

2. Another analysis added to this study is the use of Panel VAR for productivity and export causality for micro panel data at the company level. This is to enrich the analysis which in previous studies this had not been done.

This study reveals a bidirectional causality between efficiency and exports, indicating that they mutually reinforce each other. Both the single export model estimation and total productivity factors, supported by the Granger causality test and impulse response function, demonstrate this reciprocal relationship. Companies engaged in exports must maintain high productivity, while productive companies are more likely to export because it offers access to international markets, knowledge transfer, and economies of scale. This pattern is evident in the sub-group analysis of both FDI and non-FDI firms. For foreign direct investment (FDI) in Indonesia, the country is not only attractive for its large domestic market and abundant labor but also serves as a strategic production base for foreign companies aiming to export.

Government policies that promote company efficiency and productivity, as discussed in the second study, also affect the causal relationship between productivity and exports identified in this analysis. Trade policies, especially those concerning exports and imports, require careful consideration, including tariff and non-tariff regulations, restrictions on the importation of industrial raw materials, and the underutilization of export ports. For instance, the rising port container tariffs pose a significant barrier to exports for manufacturing industries. Policy support in these areas is critical, not just for improving industrial efficiency and exports but also for shaping the overall development of Indonesia's manufacturing and trade sectors.

The Indonesian economy's industrial sector is still its mainstay, closely entwined with other economic sectors, governmental policies, and international economic dynamics. It functions as a pivot, and its survival depends on cooperative support networks. Most importantly, the cornerstone of this comprehensive strategy is the government's unwavering commitment to supporting the manufacturing sector through focused policies. Through the resolution of bureaucratic complexities and the reduction of related expenses, these measures not only improve the performance of individual companies but also act as a stimulant to raise the sector's overall economic contribution to the Indonesian economy and abroad.

By balancing these three essential components—development of human resources, strategic government support, and improved infrastructure—the Indonesian manufacturing sector not only strengthens its resilience but also positions itself to be of greater importance in the world economy. With this combined effort, the industry is better positioned to not only weather the current storm but also to become a major force behind continued prosperity and expansion in both the domestic and global arenas.