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THE EFFECT OF NEW TECHNOLOGIES ON THE INDONESIAN ECONOMY:

AN ECONOMY-WIDE ASSESSMENT

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Abstract

This paper attempts to estimate the economy-wide impact of technological change, particularly robotization and digitalization, on various aspects of the Indonesian economy. A simulation using a recursive-dynamic multiregional computable general equilibrium (CGE) model of the Indonesian economy called IndoTERM is introduced through sector-specific labor productivity shocks representing the effect of the new technological changes to the model, from 2020 onward. The results show that Indonesia's gross domestic product (GDP) will be 11% higher in 2040 as a result of productivity growth. This will increase long-term annual growth from 5.2% without technological change to 5.7% per year. The distribution of the growth is, however, not regionally balanced. Java will be the main beneficiary of the growth, while other islands will not benefit as much. The top gainers, in terms of output expansion, would be machinery and motor vehicles, along with finance to a lesser extent. Low gainers include the extractive and agricultural sectors and food processing industries. Employment impact varies by sector, but Industry 4.0—the term given to the fourth phase of the industrial revolution, characterized by digitization, robotization, and artificial intelligence (AI)—will help alter the structural transformation away from agriculture and toward certain manufacturing or service sectors. Factors such as the relative size of productivity shocks, production technology (elasticity of substitution and factor intensity), income elasticity of demand and international tradability each play a role in how new technology will eventually affect the nature of the expansion of production in each sector. The relative impact on income of different production factors does not indicate an unfavorable distributional effect. However, agricultural workers will lose out compared to workers in other sectors, particularly those with intermediate skill levels.

Keywords: Technological change, robotization, digitalization, economy-wide, Indonesia

1 Introduction

The role of technological progress as the primary driver of a sustained increase in per capita income has been widely acknowledged (Romer, 1986; Lucas, 1988). Despite its importance, the role of technological progress or productivity growth has been almost absent in discussions on the sluggishness of Indonesia's recent economic growth (Resosudarmo and Abrurohman, 2018). Being stuck at 5% economic growth, despite the need for a higher rate in order to escape from the middle income trap, has been blamed mostly on a lack of "perspiration"[1] in the form of infrastructure deficiency and foreign direct investment instead of "inspiration" in how slowly Indonesia's research capacity is catching up with that of its neighbors. Recent debate and concerns surrounding Industry 4.0, automation, robotization and the Internet of Things (IoT) may serve as a reminder to bring back inspiration-led growth into our agenda.

Although it is commonly known as "disruptive" technology, the most recent phenomenon of new technology is not really new. Technological progress has been the backbone of human civilization since the start of the industrialized revolution. The "4.0" in Industry 4.0 is itself a reminder of the continuity of progress. The internet has revolutionized service industries since the 1990s. Robots have long helped automotive manufacturing. Of course, there are IT revolutions such as AI that can be seen as unprecedented, yet the way these new technologies have impressed people is similar to the way the past technologies astounded people when they first emerged.

There are alternative explanations as to why recent technological advances may have created more concerns, including those related to the current context of economic development issues: the economic growth of many countries, including developing countries like Indonesia, is slowing; inequality within countries is on the rise in many places; deindustrialization (prematurely, in some cases); and stagnant global trade, accompanied by rising protectionism or even trade wars. Technological progress can be labor-augmenting or labor-saving. The former is a significant concern given the current trend of rising inequality, for example.

Indonesia is facing almost all those challenges: slower growth, rising inequality and premature deindustrialization. Other pressing issues facing Indonesia are persistent high labor informality and youth unemployment. Certain technologies like robotization and automation, when increasingly adopted by developed countries, may worsen the stagnation of the manufacturing sector in Indonesia. The adoption of these new technologies could potentially displace labor in Indonesian industries. This may worsen the already high income inequality and unemployment.

However, there are also more optimistic views. History suggests that technological progress is not necessarily labor-displacing. There are certain tasks that cannot be replaced by robots such as those that rely on human face-to-face interaction. Moreover, new types of jobs may be created following the loss of old ones. The classic story of the invention of automatic teller machines (ATMs) is a good example of how new technology did not necessarily reduce the number of tellers. More ATMs in fact increased demand for new branches, and more tellers were still needed. In short, it is still uncertain whether Industry 4.0 will be a potential threat or an opportunity for employment.

However, despite these rising concerns including the uncertainty surrounding the issue, studies estimating the economic impact of robotization and automation on the Indonesian economy, to the best of our knowledge, do not yet exist. This paper aims to be an early attempt to fill that gap.

[1] Borrowing from Krugman (1994).

The objective of this report is to estimate the potential impact of new technology, or disruptive technology, on various aspects of the Indonesian economy. In particular, we will look at the potential impact of robotization and digitalization on economic growth, sectoral output, employment, and distributional implications.

This report is organized as follows. Section 2 will discuss relevant previous studies we found in the literature. We focus on studies that use the same methodology as this report, i.e. those that use CGE models. Section 3 discusses the methodology used in this report, with a brief description of the CGE model we used. A detailed description is available in the appendix. Section 4 discusses the results of simulations using the model, and Section 5 offers a conclusion.

2 *Previous Studies*

We will limit the literature to those that analyze the impact of various aspects of disruptive technology using an economy-wide model. Most of the studies we found are recent. First is De Becker and Flaid (2017) which, as part of its overall analysis, analyzes the impact of digitization of production for Organization for Economic Cooperation and Development (OECD) countries using a CGE model called Modelling Trade at the OECD (METRO). Second is PricewaterhouseCoopers (PwC) (2018a), which studies the global economic impact of AI using a global spatial CGE model. Third is PwC (2018b), which studies the impact of AI on the United Kingdom's economy using a spatial CGE model for the UK. Fourth is PwC (2018c), using the case of Ireland, and last is Bekkers et al (2018), which examines the impacts of robotization, big data and AI, additive technology (3D printing), and e-commerce on the global economy using a CGE model called the World Trade Organization (WTO) Global Trade Model (GTM). We will describe each of these studies, particularly how they specify the scenarios and the highlights from the results of their simulations.

De Becker and Flaidn (2017) analyze the impact that digitization may have on the OECD economy in the coming 10-15 years (toward 2030). The OECD METRO model is a static CGE model derived from the Social Accounting Matrix (SAM)-based CGE model GLOBE. The Global Trade Analysis Project (GTAP) version 9 database is used to calibrate the model. For the digitization effect, De Becker and Flaidn (2017) use a German study undertaken by Bitkom and Fraunhofer (2014), which analyzed the impact of Industry 4.0 (due to robotics, automation and the IoT). The results indicate that digitalization, as facilitated by an increase of productivity across countries and industries, will increase both global trade and world GDP.

PwC (2018a) studies the global economic impact of AI using a spatial CGE model called S-CGE. The dynamic S-CGE models economic interactions between different players in the economy—firms, households, and the government. The 'general equilibrium' nature of the model means that it represents a closed system which tracks flows of resources from one area or player to another (i.e. there is natural accounting within the model). The model captures a number of complexities of the real world economy, including: household expectations about the economy and its development; passive government policy; general consumer optimization; trade flows between sectors within and across countries (based on historic data); and investment patterns within and between countries. PwC (2018b) and PwC (2018c) use a similar kind of model. The size of the productivity shocks that represent the impact of AI are estimated using econometric analysis. In this analysis, labor productivity is specified as a function of an index of AI uptake and various control variables. The model is estimated as a fixed effects model. The data used for the econometric analysis is the Capital, Labour, Energy, Materials and Services (KLEMS) database. The results suggest that in their main scenario, global GDP could be up to 14% higher in 2030 as a result of AI—the equivalent of up to $15.7 trillion, more than the current output of China and India combined. All geographic regions of the global economy will experience economic benefits from AI, with North America and China set to see the biggest economic gains (by 26.1% and 14.5% in 2030, respectively). It should be noted that the impact of AI uptake on developed regions of Asia is 10.4% of GDP (See Table 1: GDP Impact in PwC (2018a) Study.

Table 1: GDP Impact in PwC (2018a) Study

%	GDP impact associated with productivity	GDP impact associated with product enhancement	Total GDP impact
North America	6.7	7.9	14.6
China	13.3	12.8	26.1
Developed Asia	3.9	6.5	10.4
Northern Europe	2.3	7.6	9.9
Southern Europe	4.1	7.5	11.6
Latin America	1.7	3.7	5.4
Africa, Oceania and other Asian markets	1.1	4.5	5.6

GDP = gross domestic product.

Source: (PwC, 2018a, Table 7.2)

PwC (2018b) uses the UK as its case study, with more or less the same approach. The simulations increase UK GDP by up to 10.3% in 2030 as a result of AI. In the case of Ireland, PwC (2018c) estimates that the impact on GDP could be 11.6% in 2030.

Bekkers et al (2018) examine the impact of robotization, big data and AI, additive technology (3D printing), and e-commerce on the global economy using a CGE model called WTO GTM. The GTM is a recursive dynamic CGE model, featuring multiple sectors, multiple factors of production, intermediate linkages, multiple types of demand (final and intermediate demand by firms), non-homothetic preferences for private households, a host of taxes, and a global transportation sector.

In their model, there are agents representing private consumers, firms, and governments. Private consumers spend their income on goods and services under utility maximization. Meanwhile, firms display profit-maximizing behavior, choosing the optimal mix of factor inputs and intermediate inputs. Governments collect tax revenues and spend on goods and services. Savings are allocated to investments in different regions. The model is calibrated to the current GTAP database, which has 141 regions and 57 sectors.

Bekkers et al (2018) model technological changes as a result of robotization and AI following the approach in Aghion et al. (2017). For the productivity shocks, Bekkers et al (2018) refer to two studies: Bitkom and Fraunhofer (2014) and Boston Consultancy Group (2015). The former projects productivity growth in six sectors until 2025 in Germany as a result of Industry 4.0, predicting an average yearly growth of 1.27% until 2025. The latter examines the impact of robotization on productivity across sectors and countries, predicting an average cost reduction of 16% until 2025 (from 2015). Based on these studies, Bekkers et al (2018) assume that the average yearly productivity growth is 1.25%. The sectoral variation used by Bekkers et al is based on other studies, such as Bitkom and Fraunhofer (2014), Boston Consultancy Group (2015), Booz and Company (2011), and McKinsey Global Institute (2015). For the country variation they used the Network Readiness Index (NRI) of the World Economic Forum, as published in Baller et al (2016).

The results are focused on global trade, particularly the change in the global export share for all goods and for manufacturing in different regions. The results suggest, for example, that the European Union is gaining global export shares, whereas the United States (and also China) is losing exporter market share.

There are some studies on Indonesia, but they do not use general equilibrium methodology. One of them is Oxford Economics (2016), which estimates the effect of the growth of the information and communications technology sector on Southeast Asian economies, including Indonesia. They use an econometric and forecasting approach by estimating the economic impact of the observed changes in mobile internet penetration since 2010, and forecast the future impact of the expected change in mobile internet penetration from 2015 to 2020. For Indonesia, they found that each percentage point increase in mobile penetration over the five years would add $640 million to GDP by 2020. Given their forecast for healthy penetration growth, this means creating an additional $30.1 billion (2.4%) of GDP in 2020. Job creation impacts could also be considerable, with an extra 500,000 formal jobs generated by 2020 by encouraging higher participation in the labor market.

3 *Methodology*

3.1 IndoTERM CGE Model[2]

CGE is an economic model that represents the whole national economy, but an aggregation of detailed microeconomic behavior. The model itself is represented in a system of *n* non-linear equations with *n* endogenous variables and many more exogenous variables. The system of equations determines prices and quantities of commodities and inputs (including primary inputs such as labor, capital, and land, as well as intermediate inputs). The equations specified in the CGE model are a representation of optimizing rational economic agents, in this case producers and consumers that interact in a competitive market economy. These form the demand for and supply of commodities that are cleared in the marketplace, represented in the model as the market-clearing conditions or equilibrium.

IndoTERM[3] is a bottom-up multiregion CGE model. Bottom-up means that the national economy is an aggregation of subnational economies. Unlike a top-down multiregional CGE model, with this model each commodity has different market-clearing equations for each region. Therefore, prices for each

[2] A more comprehensive discussion on the model's description can be read in Yusuf, Roos, and Horridge (2017).
[3] IndoTERM is a collaborative effort of various institutions that include Center for Economics and Development Studies (CEDS), Universitas Padjadjaran, Indonesia; Center of Policy Studies (CoPS), Monash University, Australia; Asian Development Bank; AusAID; and Indonesia's National Development Planning Board (BAPPENAS).

commodity are differentiated across regions. With this kind of model, region-specific shocks can be easily formulated.

IndoTERM is a version of The Enormous Regional Model (TERM), which is an interregional model originally developed for the Australian economy. TERM is a “bottom-up” CGE model for Australia, which treats each region as a separate economy. TERM was created specifically to deal with highly disaggregated regional data while providing a quick solution to simulations. This makes it a useful tool for examining the regional impacts of shocks that may be region-specific (Horridge, Madden, and Wittwer, 2005).

The theoretical structure of IndoTERM is conventional for static general equilibrium models. The strongest feature is how each subnational economy is linked through interregional trade of commodities and factors. In particular, the equations in IndoTERM represent the following economic behavior.

In each region, production sectors minimizing the cost of production are given constant elasticity of substitution (CES) technology. A factor demand equation system is derived and specified in the model. This relates the demand for each primary factor to industry outputs and prices of each of the primary factors (labor, capital, land, and intermediate inputs). This reflects the assumption that factors of production may be substituted for one another in ways that depend on factor prices and on the elasticities of substitution between the factors.

In each region, users of commodities−including industries, households, investors, and government sectors−form a system of demand equations. The demand system for each of these users consists of three layers (nested demand system). First, in each region, for each of the commodities, they choose the optimal combination of the origin of the commodities, responding to the different prices they have to pay for commodities coming from their own or other regions. Here, the users are cost-minimizing given the CES demand specification. Second, consumers/users choose the optimal combination of domestically produced and imported commodities. The last layer is that they choose the optimal combination of different commodities responding to the prices and budget constraints they face. For households, a linear expenditure system (LES) is specified. Meanwhile, households supply skilled and unskilled labor, as well as capital and land.

The model distinguishes four kinds of labor: agricultural labor, manual/production work, clerical work, and managerial work. These are ‘nested’ within the industry production functions. In each industry, all kinds of labor enter a CES production function to produce ‘labor’, which itself enters a further CES production function for industry output.

A set of export demand functions indicate the elasticities of foreign demand for Indonesia’s exports to the rest of the world. Import tariffs and excise taxes across commodities, business tax rates, value-added taxes and corporate income taxes across industries, and rates of personal income taxes across household types, reflect the structure of the Indonesian tax system. A set of macroeconomic identities ensures that standard macroeconomic accounting conventions are observed.

In general, the demand and supply equations for private-sector agents are derived from solutions to these agents’ microeconomic optimization problems (cost minimization for firms and utility maximization for households). The agents are assumed to be price-takers, with producers operating in competitive markets with zero-profit conditions, reflecting the assumption of constant returns to scale.

IndoTERM belongs to a class of recursive dynamic CGE models. In IndoTERM we model three dynamic mechanisms: a stock-flow relation between investment and capital stock, which assumes a one-year gestation lag; a positive relation between investment and the rate of profit; and a relationship between wage growth and employment.

Regarding the database and its construction, the data that forms the parameters of the IndoTERM model come from various sources including: the Indonesian National Input Output Table 2010; regional share of production for each commodity over various years; trade statistics, export-import database by sector and regions; labor force surveys; the Indonesian Interregional Input Output Table 2010; and other data sources.

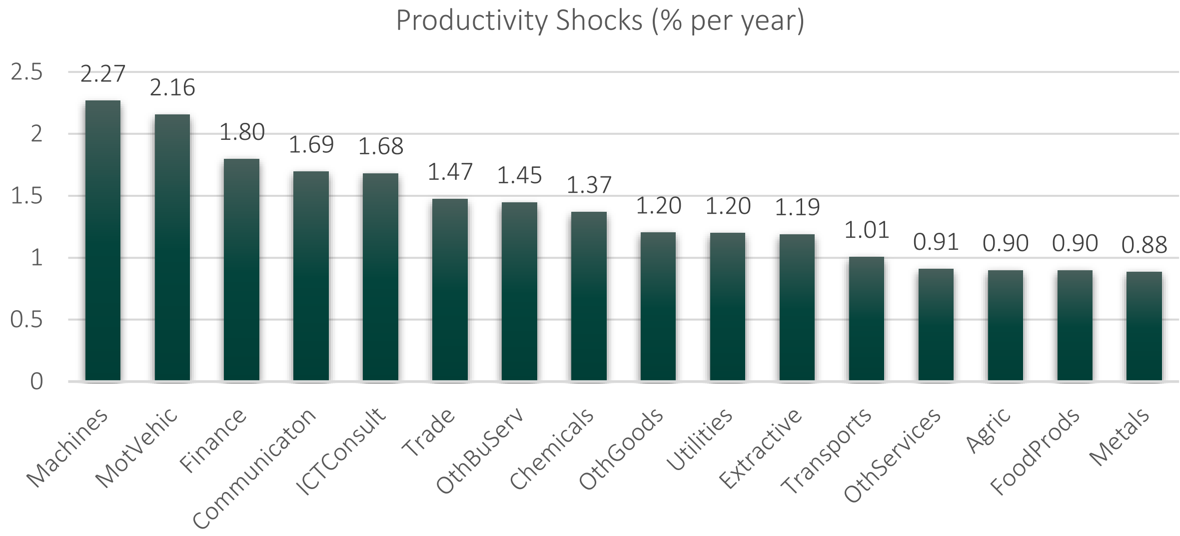
The process of constructing the INDOTERM database is described in Horridge (2012) and Horridge and Wittwer (2008). The regional database consists of a set of matrices, capturing the 2005 structure of the Indonesian economy. We begin by creating a USE matrix valued at the producers' price. This matrix shows the flow of commodity (c) from source (s) to user (u). Values at the producers' price are the sum of the flows of commodity from source to user, at a base price and the associated indirect tax. We also have a matrix capturing the margins that facilitate the flow of commodities.

Value-added matrices include labor payments by industry and occupation, capital, and land rentals by industry, as well as production taxes by industry. The database is balanced in that the costs equal sales for each sector. From the national database we create regional input-output data and interregional flows of commodities. Detailed regional data are not available in the required format. We use regional output shares to inform us on the regional distribution of inputs and outputs. We then construct interregional trade matrices that show the trade of commodities between regions. Our task is made easier by assuming that industry-specific technologies are similar across regions. Given these assumptions, we ensure that regional data are consistent with national data. For a detailed description of the TERM database, see Horridge (2012).

3.2 Scenario and Shock Formulation

We follow closely the scenario and shock formulation of Bekkers et al (2018) that uses the WTO GTM, a recursive multicountry CGE model, to estimate the potential impact of new technology on digitization, robotization, and AI. Based on the studies by Bitkom and Fraunhofer (2014) and Boston Consultancy Group (2015), Bekkers et al (2018) come up with global average productivity shocks of 1.25% per annum. The variation of the degree of productivity shock across sectors was based on four studies from Bitkom and Fraunhofer (2014), Boston Consultancy Group (2015), Booz and Company (2011), and McKinsey Global Institute (2015). In this particular study—as done by Bekkers et al (2018)—we use the Network Readiness Index from the World Economic Forum, described by Baller et al (2016), to scale the productivity shock on Indonesia using the value or Indonesian Network Readiness Index relative to the global average. Figure 1: Productivity Shocks Due to Industry 4.0 below shows the productivity shocks applied to Indonesia's CGE model IndoTERM.

Figure 1: Productivity Shocks Due to Industry 4.0



Source: Author's calculations

The shocks are formulated by making all workers more productive. A 2.27% increase in labor productivity means 2.27% less labor can be used to produce the same amount of output. While this tends to increase output, the amount of additional output depends on many other factors, such as the price elasticity of the product in the market price. How productivity shocks change employment in those particular sectors also depends on how output expands. If demand is sensitive to price, output will expand significantly, offsetting the force to layoff labor by increased demand for it. In a general equilibrium framework, labor can also be laid off in one sector but relocated to other sectors. So, lower aggregate employment is not the only possibility, especially in the long run.

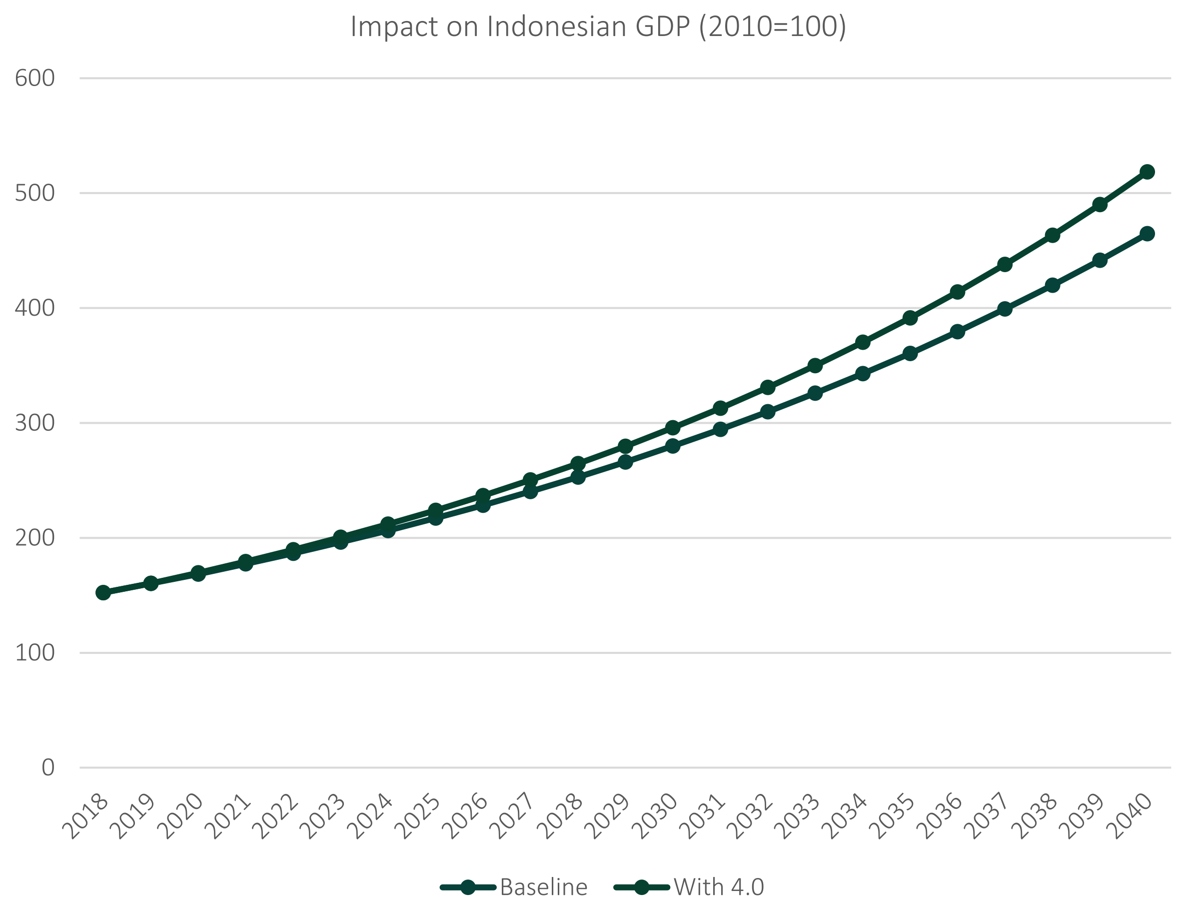
4 Results and Discussion

4.1 Macroeconomic Impact

The impact of technological change brought about by Industry 4.0 (digitization, robotization, and AI) is quite significant for the Indonesian economy. As illustrated in Figure 2, by 2040 Indonesian GDP will be 11% higher, with a productivity change relative to the baseline. This can be translated into additional annual economic growth of 0.55% from 2020-2040 (

Table 2: Simulated Impact on National and Regional Economic ***Growth***). As the baseline economic growth that the model projects is 5.2% per annum, this gain in economic growth increases to 5.75% per year. In the context of the sluggishness of recent economic growth, which is quite low at around 5% compared to the decade before the 2000s, Industry 4.0 is a potential new source of higher economic growth for Indonesia. The country aspires to escape from the middle income trap, and growth above 5% is necessary to achieve that.

Figure 2: Simulated Impact on National GDP in 2040 (2010=100)



Source: Author's calculations

Table 2: Simulated Impact on National and Regional Economic Growth (% per year)

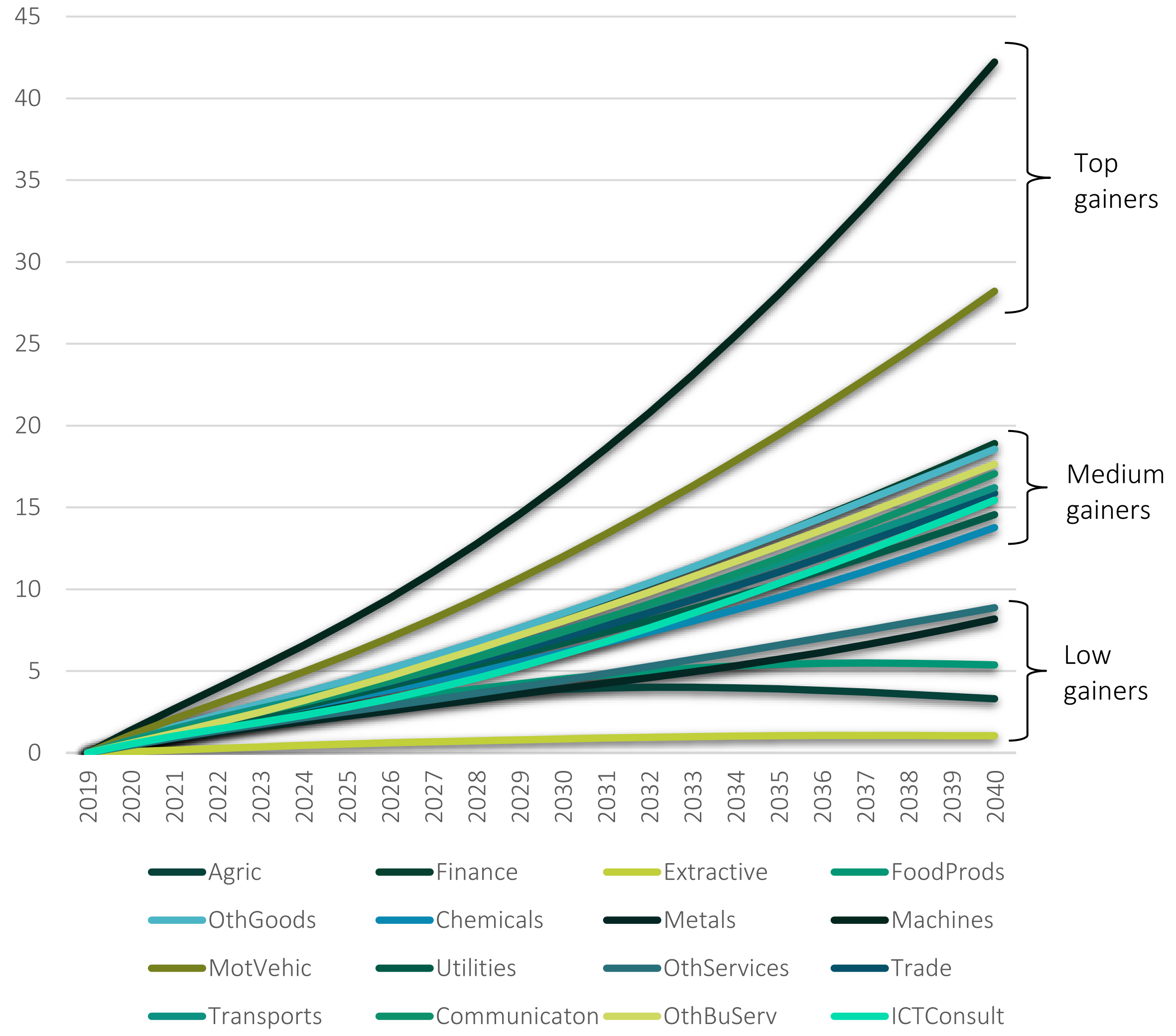
	National	Sumatra	Java	Kalimantan	Sulawesi	Bali NT	Papua Maluku
Baseline							
2020-2030	5.20	4.60	5.85	3.81	4.72	4.79	3.42
2030-2040	5.20	4.38	5.88	3.84	4.53	4.83	3.56
2020-2040	5.20	4.49	5.87	3.83	4.63	4.81	3.49
With Industry 4.0							
2020-2030	5.73	5.00	6.48	4.15	5.14	5.22	3.72
2030-2040	5.77	4.64	6.65	4.12	4.83	5.20	3.80
2020-2040	5.75	4.82	6.57	4.14	4.99	5.21	3.76
Growth gain							
2020-2030	0.53	0.40	0.63	0.35	0.42	0.43	0.30
2030-2040	0.57	0.26	0.77	0.28	0.30	0.37	0.24
2020-2040	0.55	0.33	0.70	0.31	0.36	0.40	0.27

Source: Author's calculations

4.2 Sectoral Output and Employment Impact

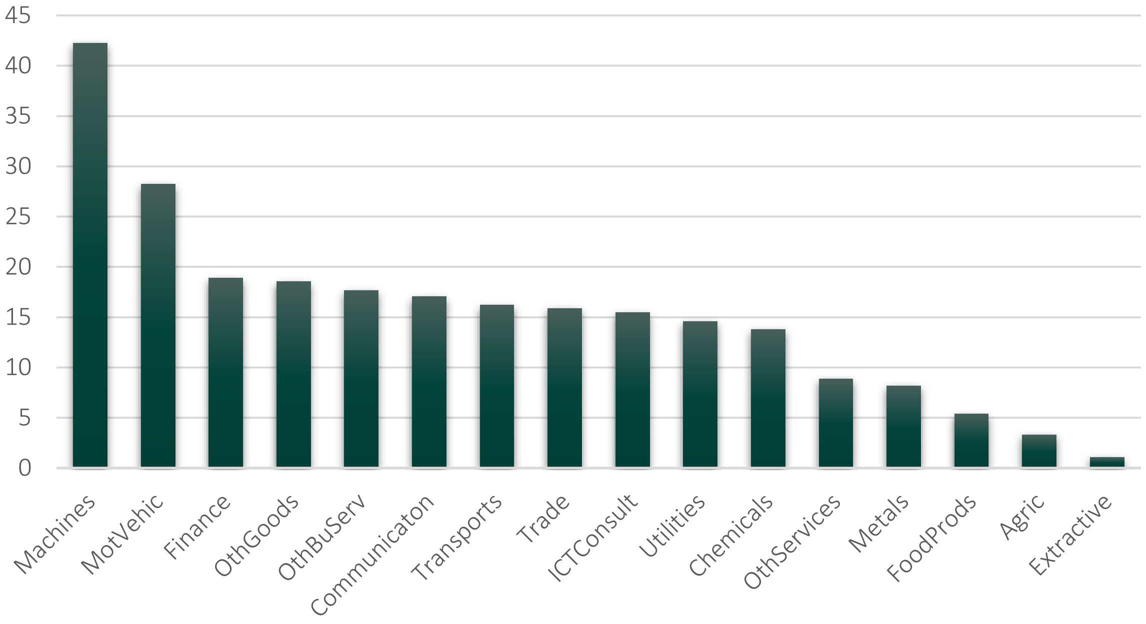
Figure 3: Simulated Impact on Sectoral Output (% deviation from baseline) below shows the impact on the output of 16 sectors in the economy. For illustration, Figure 4: Simulated Impact on Industry Output in 2040 (% deviation from baseline) shows impacts in 2040. We can identify two sectors as top gainers from productivity shocks in terms of output expansion: machinery and motor vehicles. These two sectors, not surprisingly, are those with the biggest productivity shocks. In 2040, the machinery industry's output will be 42% above its baseline, while the motor vehicle sector could expand 28% from its projected baseline without Industry 4.0. The third biggest expansion comes from the financial sector, but despite its comparable productivity shocks with machinery and vehicles, the impact on its output is lower (19% of baseline). Low gainers from Industry 4.0 shocks include the extractive, food processing and agriculture sectors, as well as metal and mineral products.

Figure 3: Simulated Impact on Sectoral Output (% deviation from baseline)



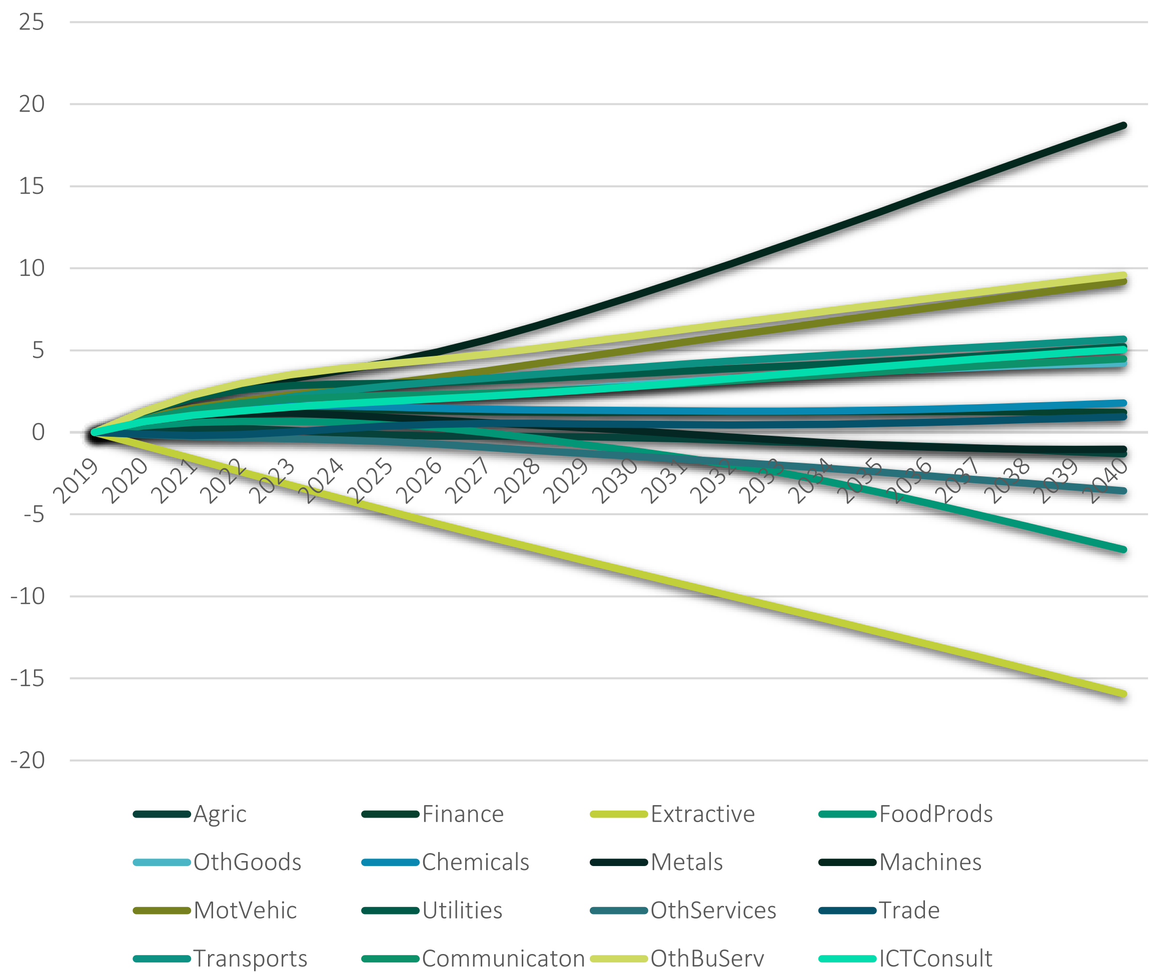
Source: Author's calculations

Figure 4: Simulated Impact on Industry Output in 2040 (% deviation from baseline)



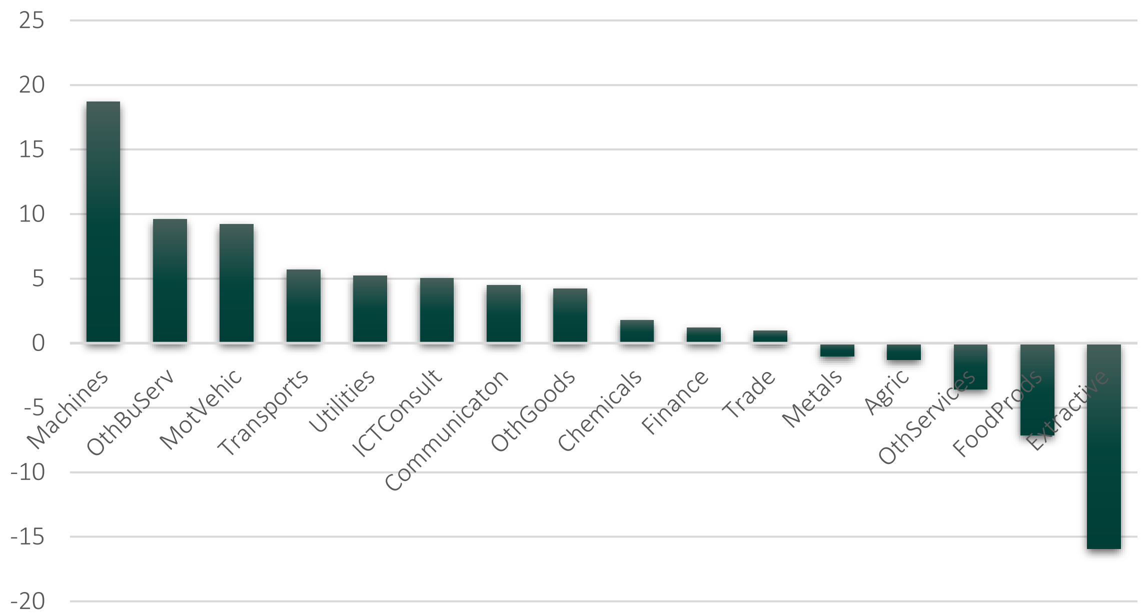
Source: Author's calculations

Figure 5: Simulated Impact on Sectoral Employment (% deviation from baseline)



Author's calculation

Figure 6: Simulated Impact on Sectoral Employment in 2040 (% deviation from baseline)



Source: Author's calculations

Indonesia's Trade Ministry (2018) in recent studies identifies sectors such as food and beverages, textiles and apparel, automotive, electronics, and chemicals. Except for food and beverages, and textiles and apparel, this seems to be in line with the simulation results.

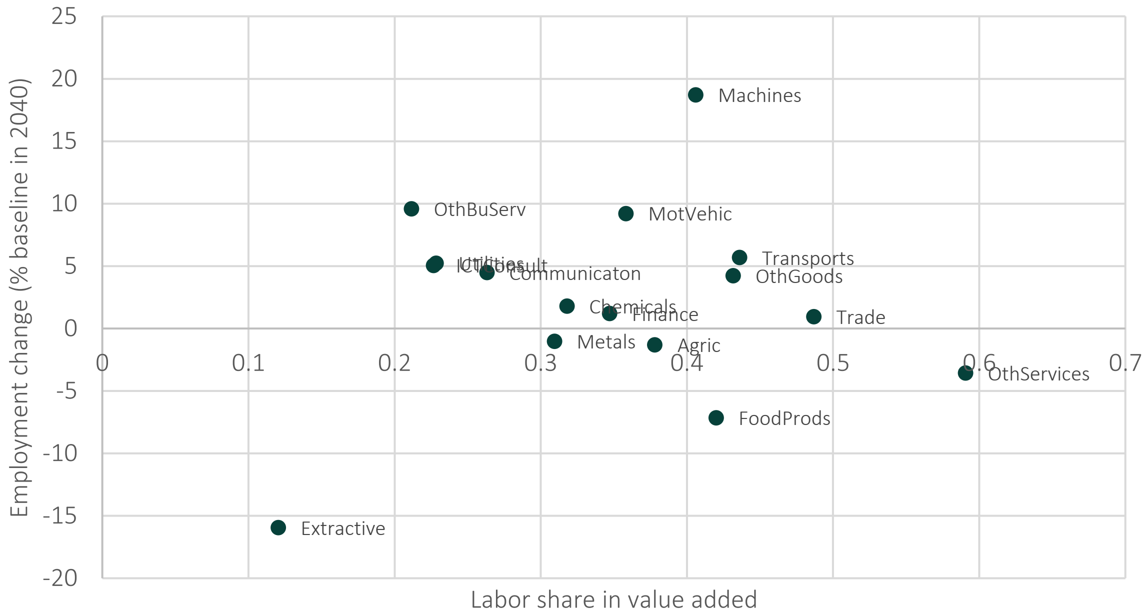
It should be noted that finance as the third gainer and business services as the fifth gainer in the simulation have already been observed in recent Indonesian economies. A wide range of e-commerce platforms, including homegrown platforms that sell everything from goods (Tokopedia and Bukalapak) to travel (Traveloka, Tiket.com) have grown exponentially in terms of usage. Digitally facilitated transportation services such as Grab and GoJek operate food delivery, ride-hailing and logistics. Financial services technology, or fintech, which includes services like lending, payments, insurance, and investment, has also started contributing notably to Indonesian GDP (LPEM, FEB UI, 2019).

In addition, though it is again very early to evaluate, big Indonesian startups, which are significantly increasing their R&D spending in digital economy issues, will not only support their industry's productivity but also the productivity of other sectors in the economy.

The heterogeneous impact on each Indonesian production sector, as discussed previously, implies that technological disruptions have the potential to markedly alter Indonesian structural change. In terms of output, the economy will move away from extractive and agricultural activities (including related sectors) toward manufacturing and services. As discussed before, all sectors in the economy will indiscriminately expand (with varying degrees) as a result of Industry 4.0. However, in terms of employment, the transformation looks even more dynamic. The following sectors will have lower employment than their projected baseline: the extractive industry, food processing, other services, food production, agriculture, and metal/mineral products. Sectors such as machinery, other business services, and motor vehicles have much higher employment than their projected baseline. The financial sector, despite having comparable Industry 4.0 intensity with the top gainer, does not create much employment, with a rate barely higher than its projected baseline (1.2% compared to 19% for the machinery sector).

One may argue that this has to do with the nature of production in each of these sectors, particularly their labor intensity. As Figure 7: Correlation Between Labor Intensity and Impact on Employment shows, a correlation between labor intensity and impact on employment supports that notion, but only partly. Sectors such as machinery, motor vehicles and finance have more or less similar labor intensity (and similar shocks to their productivity), yet their employment impacts are markedly different. Therefore, there must be other factors that explain these employment impact variations.

Figure 7: Correlation Between Labor Intensity and Impact on Employment

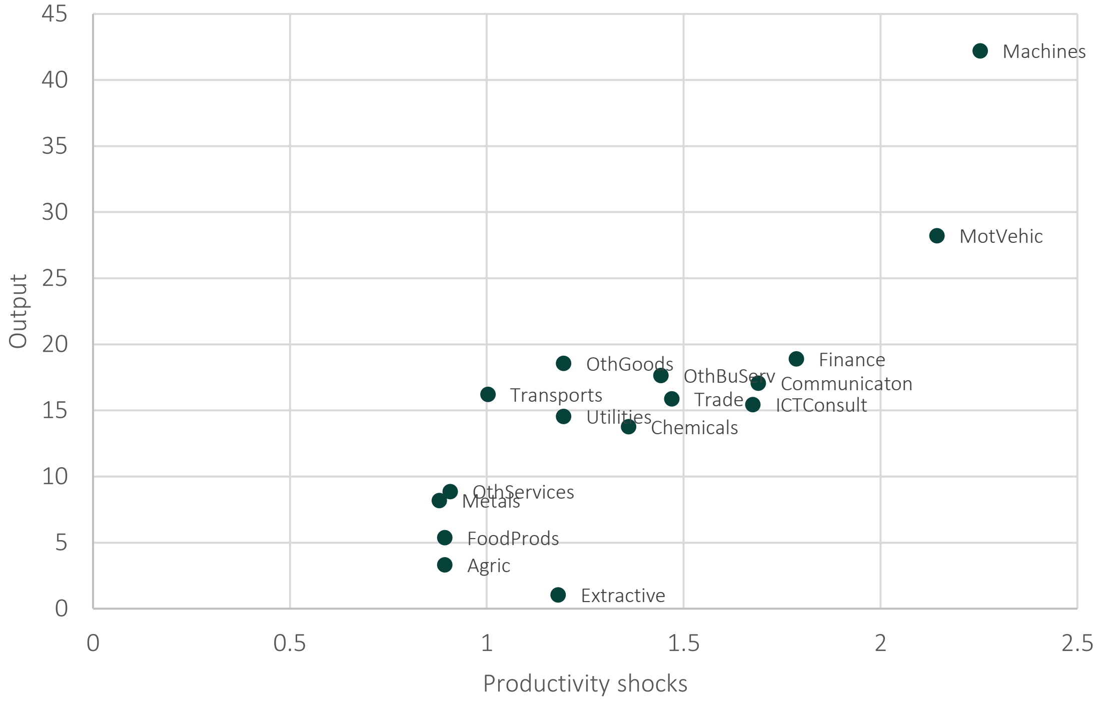


Note: The x-axis is the share of labor payment (outlays) in total value added. Value added contains the labor payment and return to capital.

Source: Author's calculations

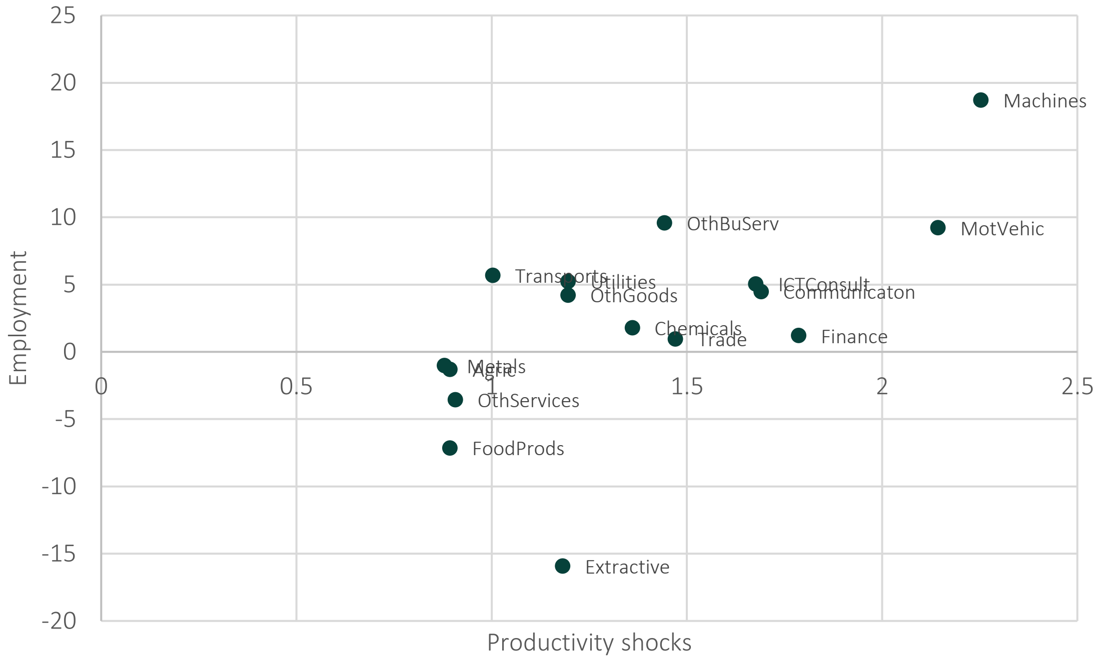
Figure 8: Correlation Between Output Expansion vs Productivity Shock Size to Figure 12: Correlation Between Income Elasticity and Output Expansion below may help to make sense of how certain sectors can gain or lose more from the productivity shocks attributed to Industry 4.0.

Figure 8: Correlation Between Output Expansion vs Productivity Shock Size



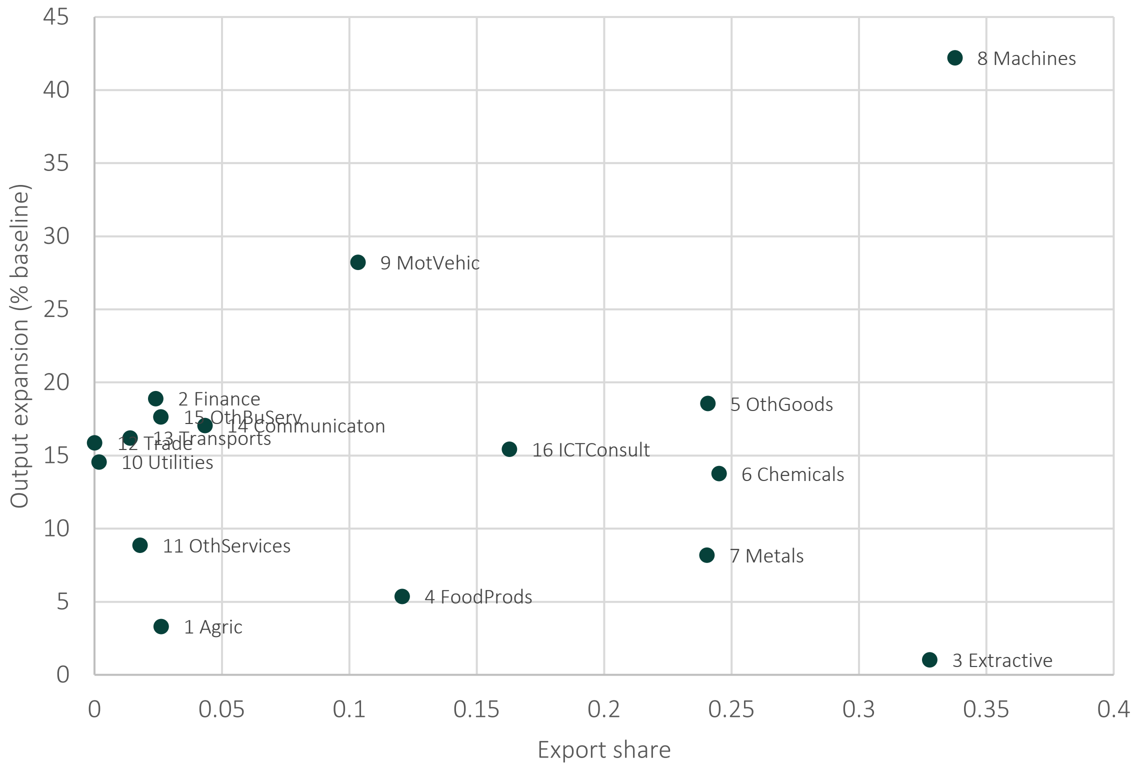
Source: Author's calculations

Figure 9: Correlation Between Employment Impact and Shock Size



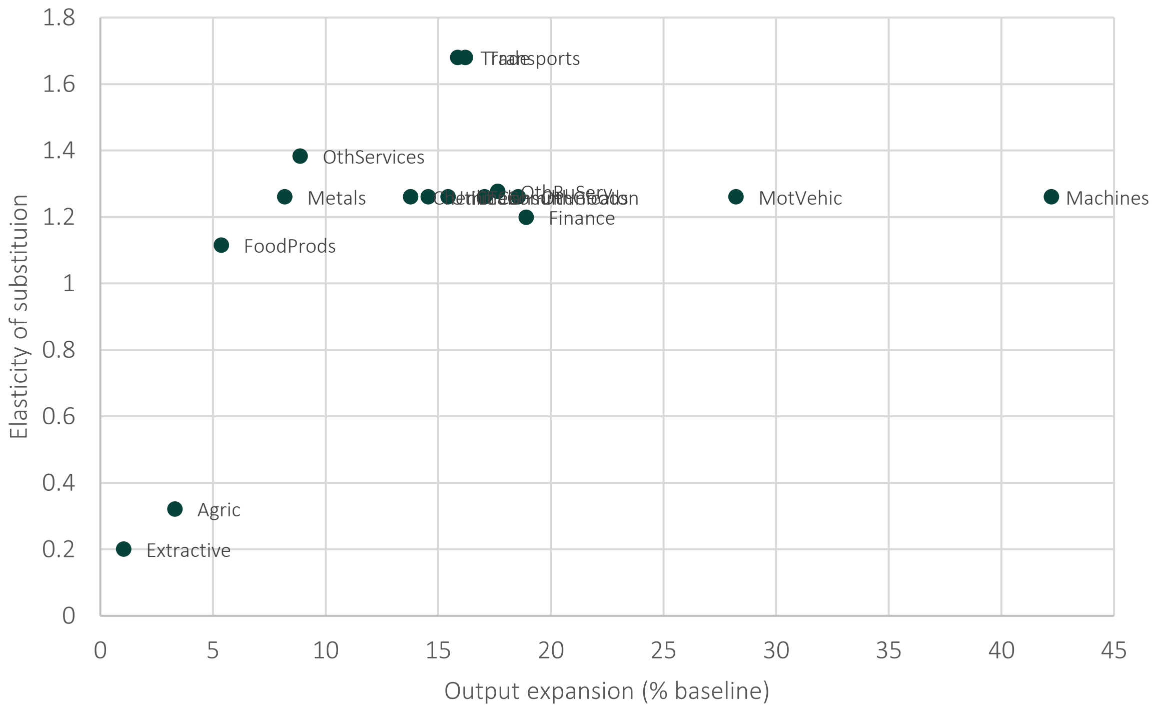
Source: Author's calculations

Figure 10: Correlation Between Export Share and Output Expansion



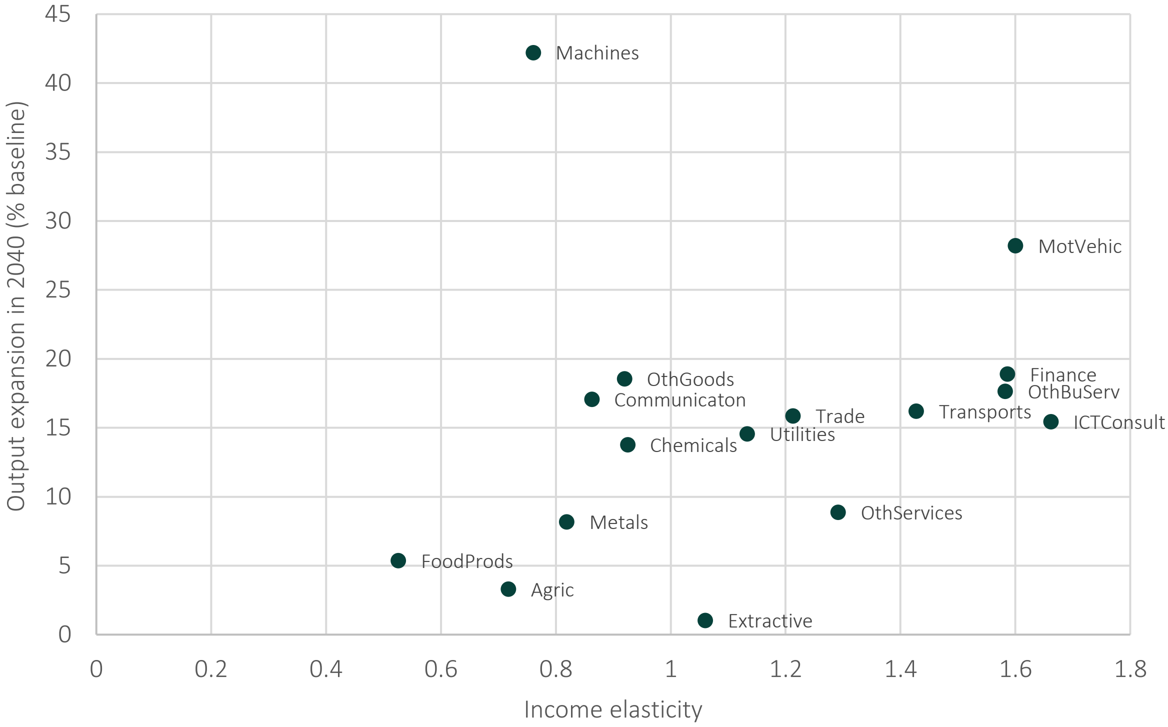
Source: Author's calculations

Figure 11: Correlation Between Elasticity of Substitution and Output Expansion



Source: Author's calculations

Figure 12: Correlation Between Income Elasticity and Output Expansion



Source: Author's calculations

Theoretically speaking, the sectoral relative impact on output (or production expansion) as a result of productivity shocks (in this case labor-saving technical progress) in a general equilibrium framework depends on various factors, including, but not limited to:

- The size of the productivity shocks.
- The elasticity of substitution between primary factors of production (labor, capital and land). The more flexible (the higher the elasticity of substitution), the larger the room for production to expand because it can increase its effective inputs that experience the productivity shocks and substitute its other inputs (such as capital) and vice versa.
- The initial level of factor intensity. An industry with lower labor intensity, for example, will not benefit much (in terms of expanding capacity) when there is an increase in labor productivity due to automation. Point b and c are among the supply-side factors, but there are also demand factors.
- Income elasticity of households. As output expands, primary factor payments increase and household incomes naturally increase. Following the income growth, demand for commodities will increase and products that have higher income elasticity will get higher new demand compared to those with lower income elasticity.
- Export share of the commodity sales. Commodities that are traditionally exported will have more new demand coming from abroad when their prices fall due to productivity increases, through downward sloping export demand function.

Figure 8: Correlation Between Output Expansion vs Productivity Shock Size illustrates that in general, outputs expand more in sectors with bigger shocks, but there are also variations among those with the same size of shocks. Agricultural products, manufactured food products, metal and mineral products, and other services have similar productivity shocks, yet see quite heterogeneous impacts. Meanwhile, there is also a group of sectors that have similar output gains despite varying degrees of productivity shocks.

Several observations of the results deserve further explanation. First, the finance sector sees less output expansion than other sectors with a similar size of shocks. Finance has relatively high income elasticity, so domestic demand may not be a constraint (Figure 12: Correlation Between Income Elasticity and Output Expansion). Yet, it has very low tradability (low export share) so cannot benefit much from world market demand. From the supply side, finance has moderate elasticity of substitution and its labor share seems to be comparable to other sectors. So, a factor that may explain the relatively lower output gain compared to, for example, machinery and motor vehicles, is its lower tradability.

Second, the manufactured food product and agriculture sectors are among the lowest gainers, even compared with sectors that experienced a similar level of productivity shock. The most likely explanation relates to two factors: their low income elasticity, which means the demand increase that follows the productivity shocks does not have an impact as large as on other sector with high income elasticity (Figure 12: Correlation Between Income Elasticity and Output Expansion); and their low elasticity of substitution, meaning they do not have the flexibility of other sectors that can substitute their inputs more easily (Figure 11: Correlation Between Elasticity of Substitution and Output Expansion). Third, the extractive sector, despite having the largest export share and thus the highest tradability, is among the lowest gainers. It is not a sector with the lowest productivity shocks. The most likely explanation relates to its large capital intensity and its low elasticity of substitution. There will not be much benefit from improved labor productivity when the sector employs very little labor in the first place.

4.3 Indicative Distributional Implication

The model does not have explicit multihousehold groups according to different socioeconomic indicators. Therefore, no explicit analysis can be done for a distributional effect of the technological change. At best, what happens to the income of various different production factors may give an indication of the distributional implications (Figure 13: Impact on Labor Market Indicators (% deviation from baseline).

Figure 13: Impact on Labor Market Indicators (% deviation from baseline)

The model recognizes three broad primary factors of production: labor, capital and land. Some assumptions should be restated here for clarity. First, land (used in production activities) is immobile (sector-specific) and, as a result of the productivity shocks we introduce, the size of land, both in aggregate or its distribution across sectors, does not change. Second, capital increases over time with the addition of net investment. Investment by sector is driven by the profitability of that sector, which is in turn affected by the productivity shocks we introduce. Third, there are four kinds of labor—agricultural labor, manual workers, clerical workers, and managerial or administrative workers. The first two can be considered unskilled workers and the last two can be considered skilled workers. There is no mobility of skills but, for each skill, labor can move between industries. Aggregate employment goes back to long-term trends whenever there is an increase due to the introduction of shocks. It should be acknowledged that this is a very weak representation of the labor market setting for analyzing the impact of Industry 4.0 as ideally skills mobility or task mobility occur due to the introduction of shocks. What drives the factor market result and labor market result here is mostly the sectoral response to the introduction of sectoral productivity change.

As seen from Panel A of Figure 13: Impact on Labor Market Indicators (% deviation from baseline), productivity growth (induced by Industry 4.0) will increase the capital intensity of the economy. However, to understand its implications on factorial distribution of income, we also need to know what happens to the price of those factors. Panel B of Figure 13 shows exactly that. All prices of factors of production are higher than the baseline as a result of productivity shocks. The difference between simulated and baseline price of land reaches 20% in 2040 (the highest compared to labor and capital), followed by the price of labor (wages) 7% above the baseline. The price of capital goes back to the baseline level in the long run. The increase in the price of land is quite natural because in the model, land is a fixed factor. As the economy expands, including sectors that use land as inputs for production, the demand for more land increases more than the supply can provide. As Figure 13b shows, the price of capital increase eventually moves back to its baseline. This happens because, as a rising price of capital induces new investment, and new investment increases the supply of capital, and eventually the price of capital will return to normal.

However, a better measure of the distributive effect is what happens to the income of the owners of capital and labor. What happens to the price of labor (wages) and price of capital (rent) only explains half of the story. Laborers will not necessarily be better off after wages rise if they are displaced, for example. Therefore, income is the multiplication of the quantity of factors of production used (labor and capital) and its price (wage and rent). This is shown in Panel C of Figure 13. The income of the three broad factors of production (land, capital and labor) is higher than the baseline value (without the shocks). This means all factors of production gain from the technological changes we introduce. However, land gains the most, followed by labor and then capital. As land constitutes only a small share of national primary factor income, what mostly drives the (factorial) distribution effect is the relative change of factor income between labor and capital. As the impact on labor is higher than on capital income, this tends to reduce tensions on income inequality. Looking at the effect on different kinds of labor, Panel D suggests that not all types of labor benefit from technological change. Agricultural workers lose out, as their real income is lower than the baseline, while it is higher for other kinds of labor, particularly clerical or semiskilled labor.

5 Concluding Remarks

This report attempts to estimate the economy-wide impact of new technological changes (representing part of Industry 4.0) on various aspects of the Indonesian economy. The method we use is a recursive-dynamic multiregional CGE model for the Indonesian economy, called IndoTERM. To analyze the impact of technological changes, we introduce a sector-specific labor productivity shock to the model from 2020 onward. The sector-specific shocks we introduce are based on similar work (a CGE model approach) found in the literature. The technological changes that are represented in the scenarios are robotization, automation, digitization and AI.

Our simulation results shows that the Indonesian economy will benefit greatly from Industry 4.0. GDP will be 11% higher in 2040 as a result of productivity growth. Indonesia's long-term economic growth (2020-2040) is predicted to hit 5.7%, compared to only 5.2% per annum without Industry 4.0. The distribution of growth is, however, not regionally balanced. Java will be the main beneficiary, while other regions will not see as much growth. This is due to the sectoral nature of the impacts.

The top gainers, in terms of output expansion, would be machinery and motor vehicles, as well as finance to a lesser extent. The low gainers include extractive industries, agricultural sectors and food processing industries. Employment impact varies by sector, but Industry 4.0 will help to alter the structural transformation away from agriculture to certain manufacturing or service sectors. Factors such as the relative size of productivity shocks, production technology (elasticity of substitution and factor intensity), income elasticity of demand and international tradability each play a role in how Industry 4.0 will eventually affect the nature of the expansion of production in each sector.

The capital intensity of the economy will be higher, but all factors of production (labor, capital, and land) will gain as a result of technological change because the factor income from each of these three factors of production is higher than the baseline. Labor income will rise higher than capital income, but land income will increase more than the other factors. However, as land rent constitutes only a small share of total primary factor costs in the economy, the larger gain of labor relative to capital indicates that the distributional effect of technological change is favorable. It does not place more serious tension on inequality compared to the situation when the rise in capital income is larger than labor income. Capital owners are normally rich groups, while those who earn an income from labor are typically not rich. Thus, so long as capital income does not rise faster than labor income, income inequality is less likely to rise. Looking at the effect of technological change on incomes for different kinds of labor suggests, however, that intermediate-skilled workers will gain more than other types of labor, and agricultural workers will lose as their real wage deteriorates. This, in contrast, has a tendency toward increasing inequality, particularly among wage earners.

Several policy recommendations can be drawn from this exercise. Though Industry 4.0 can enhance much-needed economic growth for Indonesia, the magnitude may not be enough for the country to escape from the middle-income trap. Other sources of growth should be explored, including the enhancement of human capital and skill formation. A non-Java bias of impacts should be anticipated by better spatial planning. Openness and international tradability seem to be complementary to Industry 4.0, as the size of market segments determines the size of benefits. Relying on the domestic market to sell the final products from enhanced production is not sufficient. The primary sector, particularly agriculture, is among the least likely to benefit from productivity change. As agricultural products typically have lower income elasticity, the sector can benefit more from Industry 4.0 if its share of export markets can be expanded, directly or indirectly, through agricultural-processing manufacturing catering specifically to global markets.

Despite being among the few academic exercises to estimate the impacts of Industry 4.0, the method applied here has many shortcomings. First, due to the lack of relevant national studies, the sectoral variation of productivity shocks is borrowed from developed country studies. Second, not all aspects of Industry 4.0 are incorporated in the simulation. Third, the assumed timeline of technological adaption may not be linear. Most importantly, the model does not incorporate skill mobility, i.e. that workers can change tasks and adapt skills to new technological conditions. We leave this for further research.

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