FINAL PROJECT – TI 184833

INITIAL RESPONSE OF INDONESIAN MANUFACTURING COMPANIES ON SUPPLY CHAIN ISSUES DUE TO COVID-19 PANDEMIC

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APPROVAL SHEET

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FINAL PROJECT

Submitted to Qualify the Requirement of Bachelor Degree
Industrial and Systems Engineering Department
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SURABAYA, AUGUST 2020

INITIAL RESPONSE OF INDONESIAN MANUFACTURING COMPANIES ON SUPPLY CHAIN ISSUES DUE TO COVID-19 PANDEMIC

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ABSTRACT

COVID-19 has impacted the global supply availability drastically as the affected nations regulate massive closure and isolation to contain rapid virus transmission. Indonesia has also inevitably impacted by the COVID-19 pandemic, especially on manufacturing companies, which heavily rely on the supply chain to ensure the company continuation. However, the reliable information and literature on COVID-19 initial impact on manufacturing companies regarding supply chain issues in Indonesia are still inadequate. This research aims to examine the initial response of Indonesian manufacturing companies to COVID-19 supply chain issues: (1) factors that influence COVID-19 initial impact severity; and (2) short term action and long term strategy of Indonesian manufacturing companies to manage COVID-19 disruption. The data in this study are obtained from a survey, which comprises of 85 manufacturing company's stakeholders. The analytical method in this study utilizes ordinal logistic regression (OLR) and descriptive statistics. The results indicate that the initial impact of COVID-19 is different among the type of industries and is influenced by material sourcing from affected foreign countries (MS) and decrease in customer demand (DD). The majority of Indonesian manufacturing companies prefer to lower production activity as their short term action and to restructure the supply chain to become more resilient as their long term strategy to overcome COVID-19 disruption.

Keywords: COVID-19 Initial Impact, Supply Chain, Survey, Factors Analysis, Ordinal Logistic Regression (OLR), Descriptive Statistic.

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Praise to Heavenly Father. Because of His grace and blessing, the author can finish this research with the title of "Initial Response of Indonesian Manufacturing Companies on Supply Chain Issues due to COVID-19 Pandemic". This research is conducted to obtain a bachelor degree from Industrial and Systems Engineering Department of Institut Teknologi Sepuluh Nopember (ITS) Surabaya.

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The author realizes that there are still many drawbacks in this research. Therefore, the author is open to any critics and suggestions for this research. Finally, the author hopes that this research can give insights for any interested parties.

Surabaya, August 2020

Author

TABLE OF CONTENT

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LIST OF TABLES

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LIST OF FIGURES

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CHAPTER 1
INTRODUCTION

This chapter will explain about background of research, problem formulation, objective, benefit, limitation and assumption, and research outline.

1.1 Background

Epidemic outbreaks likewise COVID-19 represent one specific case of SC disruption risks−attached to low-frequency high impact events−which is distinctively characterized by long term disruption existence and unpredictable scaling disruption propagation (i.e., the ripple effect), epidemic outbreak propagation (i.e., pandemic effect), and simultaneously disruptions in demand, supply, and logistics infrastructure (Ivanov, 2020). The epidemic outbreaks have different characteristic from other disruption risks, in which it starts small but scale tremendously fast and disperse over many geographic regions creating a lot of unknowns and uncertainties that make it complex to conduct the impact assessment of the outbreak on the SC and the right measure to react (Ivanov, 2020).

In late 2019, the initial outbreak of novel coronavirus (COVID-19) case came from Wuhan, Hubei Province, China, and immediately escalated to a global pandemic with human-to-human infection worldwide. In the period from mid of February and early April 2020, the number COVID-19 confirmed cases has exponentially skyrocketed in Asia-Pacific, Middle East, Europe, and the USA with the total number of 1,662,039 cases on April 11, 2020, according to World Health Organization database, and impacted the nations to regulate closure and isolation.

Furthermore, one of the examples was the massive lockdown and isolation in China−which is the hub of international supply chains−result in the disruption on Chinese exports−the largest exporter of intermediate products (Brown, 2020)−which directly reduced the supply availability drastically in Global Supply Chains, as the 94% of the Fortune 1000 are seeing Coronavirus supply chain disruption considering Dun & Bradstreet analytic firm' estimation that 938 of 1000 companies have tier 2 providers located in a similar phase of China

−in which the patient zero takes place−according to the report by Sherman of Fortune (2020). Moreover, in the case of factories in China stay off-duty for a couple of weeks, global manufacturers will be forced to revise the output targets (Brown, 2020).

Data released by Resilinc, a supply-chain-mapping and risk-monitoring company provided a bigger picture of the supply chain crisis caused by the pandemic of COVID-19 which indicate that the world's largest 1000 companies or their suppliers own more than 12000 facilities operations−factories, warehouses, and other− located in the quarantined regions of China, South Korea, and Italy (Figure 1.1).

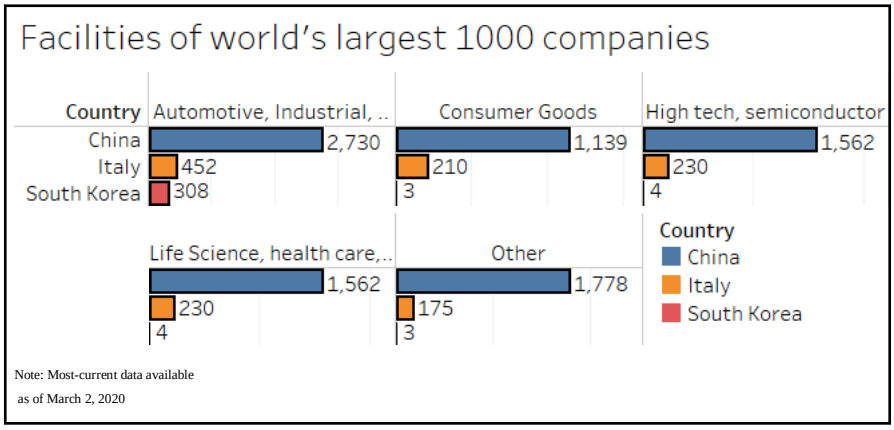

Figure 1.1 Dependence on Quarantined Areas
(Source: HBR & Resillinc, 2020)

Figure 1.1 implicate the roots of the current supply-chain crisis arise from the decisions made far upstream from a single supplier or region for many cases. Such decisions descend through the supply chains, impacting the companies which the materials or product sourcing not directly from China but whose suppliers do (Linton & Vakil, 2020).

Furthermore, Indonesia has also inevitably impacted by the COVID-19 pandemic in terms of health and economics. The number COVID-19 confirmed cases in Indonesia are exponentially escalated to a total of 3,842 confirmed cases along with 327 casualties on April 11, 2020, according to Indonesian *Gugus Tugas Percepatan Penanganan* (GTPP) COVID-19 (2020). Indonesian Minister of Finance, Sri Mulyani Indrawati, assessed that the rapid transmission of coronavirus poses a considerable risk to the national economy since the way to restrain the transmission is by conducting isolation.

Moreover, the economic disruption transpired as the citizen reduce their daily activities that impact the consumption demand−which the household consumption contribute 57.32% of Indonesia GPD on 2019/Q4 (TheGlobalEconomy, 2020)−or disruption in production (CNN, 2020). Besides, The Organization for Economic Cooperation and Development (OECD) has downgraded its projection on Indonesia's economic growth to 4.8 percent in 2020, a 0.2 percentage point cut from its initial projection November (Jakarta Post, 2020).

One of the ways to reveal the national economic circumstances with its companies in COVID-19 pandemics is by examining the nation's stock market situation by considering the changes in the primary composite and its sectoral indices. Table 1.1 shows the changes in Indonesia stock market composite, while Table 1.2 shows the changes in Indonesia sectoral market indices.

Table 1.1 Indonesian Stock Market Composite Changes during Early COVID-19 Pandemic in Indonesia
First Confirmed Case Announced on 3/2/2020 until 3/23/2020
(Source: Mirae Asset Sekuritas Neo HOTS Mobile)

		IDX	IDX30	LQ45
1/2/2020		6283.58	552.40	1011.62
2/28/2020		5452.70	526.94	879.53
3/2/2020		5361.25	522.20	859.33
3/23/2020		3989.52	321.35	583.41
Changes				
Change 1/2/20 - 3/2/20	*(%)*	-14.68%	-5.47%	-15.05%
Change 3/2/20 - 3/23/20	*(%)*	-25.59%	-38.46%	-32.11%
Change 1/2/20 - 3/23/20	*(%)*	-36.51%	-41.83%	-42.33%

Table 1.2 Indonesian Stock Market Sectoral Indices Changes during Early COVID-19 Pandemic in Indonesia
(Source: Mirae Asset Sekuritas Neo HOTS Mobile, 2020)

	Agri-culture	Mining	Basic Indutry and Che-mical	Misce-llaneus Indus-try	Con-sumer Goods	Con-struc-tion, Pro-perty, & Real Estate	Insfra-struc-ture, Utility, & Trans-porta-tion	Finan-ce	Trade, Servi-ce, & Inve-stment	Manu-facture
1/2/20	1490.8	1538	970.5	1106	2058.9	502.4	1125.8	1356.4	767.7	1457.3
2/28/20	1156.7	1339.1	758.8	989.4	1742.9	427.1	956.8	1249.3	671.3	1195.1
3/2/20	1148.6	1317.9	747.6	1011.4	1729.3	421.9	942	1211.3	667.3	1188.8
3/23/20	819.6	1062.3	517.1	667.7	1397.7	316.9	703.8	860.6	550.3	888.9
Changes										
Change (%) 1/2/20 - 3/2/20	-22.95%	-14.31%	**-22.97%**	-8.55%	-16.01%	-16.02%	-16.33%	-10.70%	-13.08%	-18.42%
Change (%) 3/2/20 - 3/23/20	-28.64%	-19.39%	-30.84%	**-33.99%**	-19.17%	-24.89%	-25.29%	-28.95%	-17.53%	-25.23%
Change (%) 1/2/20 - 3/23/20	-45.02%	-30.93%	**-46.72%**	-39.63%	-32.12%	-36.92%	-37.49%	-36.55%	-28.32%	-39.00%

Note. Indonesian stock market's first session in 2020 was started on 1/2/2020. Moreover, the first confirmed COVID-19 cases in Indonesia were announced on 3/2/2020, and the present data which is collected to make the comparison is on 3/23/2020

The first occurrence of novel coronavirus (2019-nCoV) case was on 12/31/2019 in Wuhan, Hubei Province, China; thus 1/2/2020 stock market data is utilized to indicate the effect of the outbreak towards Indonesia stock market, which reflects some projection on Indonesian companies in the present and future condition according to the analysis and perspective of stock investors. Table 1.1 shows the condition of Indonesian stock market composite (IDX)−which accommodates the aggregated market value of listed Indonesian national companies−is significantly affected by the COVID-19 worldwide and especially in Indonesia. Moreover, IDX value is exponentially reduced from the first outbreak in China and Indonesia (-14.68%, -25.59% respectively; total reduction until 3/23/2020 = -36.51%). Furthermore, IDX value on 3/23/2020 reaches a lower level compared to the lowest level in 2015 in which most Indonesian companies faced some difficult financial struggles (3989.52 < 4223.908; 3/23/2020 < 9/2015).

Thus, Table 1.1 shows an unfortunate fact that the most of the stock investors−especially foreign investor−put aside their trust on the future potential of Indonesian national listed companies as the companies might encounter with the complexities and difficulties on sustaining and improving their business processes in this COVID-19 pandemic, which might also lead to the reduction of potential profitability or ultimately bankruptcy.

To retrieve a deeper understanding of the condition of Indonesian listed companies, Table 1.2 shows the reduction of the market value of industry sectors during the COVID-19 pandemic. According to Table 1.2, all industry sectors in the Indonesian stock market encounter the decreasing market value due to the pandemic−which strengthen the previous fact−with the top loser is on Basic Industry and Chemical sectors. Furthermore, Table 1.2 shows that the top four losers−Basic Industry and Chemical, Agriculture, Misc. Industry, Manufacture (-46.72%, -45.02%, -39.63%, -39.00% respectively)−during the period possess one identical characteristic which is most of the listed companies on the sectors are manufacture industry in which the supply chain takes a considerable role to ensure the company advancement and continuation.

Indonesian manufacturing companies−especially the ones who owned global supply chain network−might get heavily distressed and impacted during the COVID-19 outbreak. However, the reliable information and literature on the impact of COVID-19 pandemics on Indonesian manufacturing companies regarding supply chain issues are still inadequate.

Thus, this research is developed with twofold contributions. First, examine the initial response of Indonesian manufacturing companies toward factors of COVID-19 initial impact regarding supply chain issues. Second, study the action and strategy of Indonesian manufacturing companies toward COVID-19 pandemic disruption. In this research, the survey is conducted on national companies' supply chain stakeholders by developing a questionnaire regarding the impact of COVID-19, response, and strategy on its supply chain. Finally, the questionnaire’s results are processed through statistical tools and further analyzed to provide insights.

1.2 Problem Formulation

Based on the background, this research is designed to examine the factors that influence the COVID-19 pandemic's initial impacts of Indonesian manufacturing companies regarding the supply chain issue. This research also designed to study the short term action and long term strategy preferences of Indonesian manufacturing companies on this disruption.

1.3 Research Objective

The objectives of this research are defined as follows:

1. Examine the factors that influence COVID-19 impact severity on Indonesian manufacturing companies in Indonesia's early outbreak period using the survey method.
2. Study the Indonesian manufacturing companies' short term action and long term strategy toward COVID-19 pandemic using the survey method.

1.4 Benefit

The benefits of this research are listed as follows:

1. Provide information and examination of factors that influence COVID-19 initial impact severity on Indonesian manufacturing companies regarding supply chain issues.
2. Provide a reference for companies to qualitatively predict the severity of COVID-19 impacts in the early outbreak.
3. Provide a reference for companies to plan and develop short term action and long term strategy to contain COVID-19 disruption impacts.

1.5 Scope of Research

The research scope consists of assumptions and limitations used in conducting the research, which is as follows:

1.5.1 Assumption

The assumptions used in this research are defined as follows:

1. The respondent is in a rational state when providing their response in the survey
2. The respondent is qualified to represent the company

1.5.2 Limitation

The limitations of this research determine the research focus and are defined as follows:

1. The unit of analysis in this the research is Indonesian manufacturing firms
2. The focus of the research is only on the supply chain issues
3. The data used is the primary qualitative data of pandemic impacts, short term action, and long term strategy of the firm from an online survey
4. The data used is the data collected from April 2nd to April 10th which is the early outbreak of COVID-19 in Indonesia
5. The research limited up to providing factor analysis of COVID-19 initial impact severity which further up is utilized to provide prediction model for Indonesian manufacturing firms using qualitative data to figure out the degree of COVID-19 initial impact severity by considering SC issues

1.6 Research Outline

The research report outline and a brief explanation for each chapter are defined as follows:

CHAPTER 1 INTRODUCTION

This chapter will explain about background of research, problem formulation, objective, benefit, limitation and assumption, and research outline.

CHAPTER 2 LITERATURE REVIEW

This chapter will explain about definitions, description, theories, and concepts of existing works of literature which have been developed on previous researches and will be harnessed as the basis of this research.

CHAPTER 3 RESEARCH METHODOLOGY

This chapter will discuss the phases of conducting this research systematically. It consists of the processes and flows from the beginning to the end of this research.

CHAPTER 4 DATA COLLECTION AND PROCESSING

This chapter will contain survey data collection, data processing, regression model development, and assumption testing will be presented.

CHAPTER 5 ANALYSIS AND INTERPRETATION

In this chapter, the analysis of COVID-19 initial impact severity level factors on Indonesian manufacturing companies and analysis of Indonesian manufacturing companies' first response and long term strategy will be explained.

CHAPTER 6 CONCLUSION AND SUGGESTION

This chapter will include conclusions and suggestions. The conclusions of the research will be elaborated to answer all of the research objectives while pointing out the research suggestions to future researchers who will conduct similar or more advanced research regarding this topic.

CHAPTER 2
LITERATURE REVIEW

This chapter will explain about definitions, description, theories, and concepts of existing works of literature which have been developed on previous researches and will be used as the basis of this research. The literature presented in this chapter consists of the supply chain disruptive risk, supply chain risk management, and conceptual model.

2.1 Supply Chain Disruptive Risk

2.1.1 Supply Chain Risk

Risk is defined as the probability of realizing an unintended or unwanted consequence that leads to an undesirable outcome such as loss, injury, harm, or missed opportunity (Schlegel, 2012). Moreover, Heckmann et al. (2015) through an extensive literature review on risk concepts, defined supply chain risk as to the potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering-events.

In the present, supply chains span the globe and form intricated network−involve many suppliers, logistic providers, distributors, original equipment manufacturers (OEM), wholesalers, and retailers−which creates complexities in assessing a priori vulnerabilities. It also creates interdependencies that exacerbate these difficulties (Sheffi, 2005). Moreover, Hallikas et al. (2004) stated that when the dependency between companies increases, they become more exposed to the risks of other companies. In the end, supply chain vulnerability is exponentially rising in the decades due to the following drivers/causes (Sheffi, 2015):

a. Trade growth, longer distance and lead times, and an increase in the number of players.

   According to WTO (2013) on World Trade Report, for some decades, world trade has grown on average nearly twice as fast as the world population, which reflects the increasing prominence of international supply chains.

The rapidly declining costs of communications and growing efficiency of logistics (e.g. containerization and larger conveyance size) are the enablers of all world trade, with the result of lengthening of supply chains, and by harnessing the digital communications mean companies enable to readily work with more facilities, supplies, and distribution centers on broader geographical locations. These also result in the lead time from order to delivery lengthened, which indicates that there was more opportunity for things to go wrongs. Moreover, with more players involved in global supply chain−initial suppliers to service providers to multiple governments and regulatory regimes−thereby further increase the complexity and the probability of failure.

b. Increase on variety

   The resultant of global trade, competition and need for differentiation in the marketplace is often to selling more varieties of each product (SKUs) (i.e. increase the ratio of the standard deviation to the mean or called as the coefficient of variation) which caused the complexity of predicting the demand and leading to overstock/understock and higher cost.

c. The rapid development of product technology, more complexity

   Many products have become more sophisticated through the addition of embedded information and communications technology (e.g. automobiles contain between 30 and 100 microprocessors, with each subsystem of the car having its controller and software) which result on the need to utilize more suppliers and turn into more complex supply chains that required deep bills of materials and thus many tiers in the supply chain.

According to Zhalechian et al. (2018) and Sabouhi et al. (2018), the threatening risks in the context of the supply chain can be classified into two main categories: (1) operational risks, refer to those inherent uncertainties such as customer demand, supply, and cost, which frequently occur in nature and are caused by medium to the high likelihood which has low and short term adverse effects; and (2) disruption risks, refer to considerable disruptions which influence the entire chain significantly caused by natural disasters (e.g., tornado, earthquake, and virus outbreak), human-made threats (e.g., terrorist attack, employees strikes), and technological threats (e.g., equipment malfunction) which cause significant social and economic damages and have a low likelihood. Furthermore, Schlegel (2012) categorized supply chain risk into exhaustive four categories: (1) strategic risk, defined as the risks which are most consequential to the ability of an organization to carry out its business strategy, protect asset & brand value, and achieve its corporate objectives; (2) hazard risk, which pertains to random disruption, liability torts, property damages, and natural disasters which are out of control (e.g., tsunami that devastated Japan, SARS epidemic, enormous floods in Thailand); (3) financial risk, which relates to the internal and external financial difficulties−primary and immediate effect related to financial−of the participants within an integrated supply chain; and (4) operational risk, which arise from events related to operational performance failures (e.g., problems related to poor forecasting, internal & external quality problems).

2.1.2 Disruption/Hazard Risk

The disruption risk event is often defined as low-probability/high-impact events, generate magnified outcomes, and their rarity means a lack of experience in estimating both their likelihood and their consequences (Sheffi, 2005). Moreover, Sheffi (2005) stated that high-impact disruptions often have many additional indirect effects, upsetting enterprises deeper than the company may realize. Table 2.1 presents the past and current disruption events and their impact on particular supply chains. Moreover, pandemic outbreak represents one specific disruption risk which has the distinct significant features such as long term disruption existence and unpredictable scaling disruption propagation (i.e., the ripple effect), epidemic outbreak propagation (i.e., pandemic effect), and simultaneously disruptions in demand, supply, and logistics infrastructure (Ivanov, 2020).

Table 2.1 Disruption Events and Its Impact on Supply Chain

Disruption Event	Supply Chain (SC) Impact	Journal of References
China Coronavirus Epidemic Outbreak in March 2020	• Predicted general impact on SC performance (i.e., service level, profit, revenue, and lead time) produced by simulation study: o If the epidemic outbreak is localized upstream the SC, the SC performance reaction is proportional to the duration of the disruption o In case of an epidemic outbreak propagation, the SC performance reaction depends on the timing and scale of disruption propagation (i.e., the ripple effect) as well as the sequence of facility closing and opening at different SC echelons rather than on the disruption duration upstream o The most negative impact on the SC performance is observed in the causes with the very long facility and demand disruption duration downstream the SC regardless of the disruption period in the upstream part o If the upstream facilities (e.g., China producers) are working, but the downstream facilities (e.g., DCs in the USA and Europe) are closed, the inventory, manufacturing, and transportation costs increase, but the revenue is not generated • Operational challenges across the industries: material shortages, drop in demand, worker shortages, cash-flow issues, planning issues, employee engagement and culture, lack of collaboration and cohesion within the organization, the significant increase in demand, and new information security, fraud, and data-theft-related risks	(Ivanov, 2020) (Chenneveau et al., 2020)

Disruption Event	Supply Chain (SC) Impact	Journal of References
Great East Japan Earthquake and Tsunami in March of 2011	• Japanese production facilities inoperable for several weeks and months • Production in many Japanese industries dropped significantly • Final sales to Japanese consumers fell for some industries • Japanese imports and exports fluctuated in the months after the earthquake • A drop in the delivery demand of Japanese industries' suppliers • Aggregated direct and indirect impacts for 17 industries: production losses in Japan $78.1 billion and Japan's gross domestic product lost $41.7 billion from March to May (3.6% of Japan's typical economic output) • Most considerable production losses occurred in minerals and metals manufacturing, transportation equipment, and several service industries • Japanese imports increased by 10.7% during three months following the earthquake and tsunami	(Wassener, 2011) (MacKenzie, 2012)
Hurricane Katrina Gulf of Mexico in August of 2005	• Destroyed 44 platforms and severely damaged 21 others • Destroyed four drilling rigs and severely damaged nine others • Numerous hazardous-materials (hazmat) releases from industrial facilities and storage terminal onshore, in the Gulf of Mexico • Gulf of Mexico is one of the US largest sources of oil and gas production, accounts for 30% of US oil supply and 20% of its natural gas	(Cruz & Karusmann, 2008) (Tubb, 2005)

Disruption Event	Supply Chain (SC) Impact	Journal of References
Hurricane Maria Puerto Rico in September of 2017	• The estimated cost of damages in Puerto Rico and the US Virgin Islands is $90 billion • Damage roads, bridges, ports, and airports, which caused the shipping and distribution impaired • Ports in Puerto Rico which responsible for handling commercial shipping (i.e., total annual trade cargo volume is approximately 10, 686, 817 tons) were shut down for four to nineteen days • Damage power system left 675,000 customers (43% of the island) without electricity and threatened the ability to communicate with supply chain key actors • Loss of power, water, and other critical infrastructure hampered restoration of business activity	(Kim & Bui, 2019)

Moreover, according to Sheffi (2005), the disruptions proceed through several stages, though the severity and duration might differ from case to case. Figure 2.1 illustrates a hypothetical disruption profile that depicts the performance of a company (i.e., production level, customer service, revenue, profit, or other relevant metrics) over time.

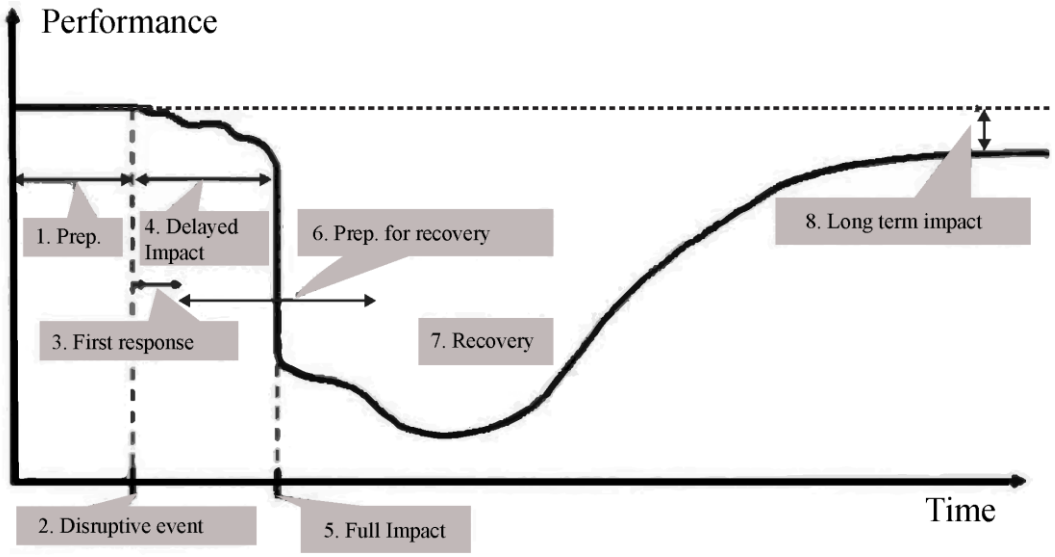

Figure 2.1 Disruption Profile
(Source: Sheffi, 2005)

The eight phases of the disruption profile characterize the nature of disruption and the dynamics of the company's response as follows:

1. Preparation. In some cases, a company might foresee and prepare for disruption to mitigate the effects. The precaution warning might range from the 30-min tornado alert GM had in Oklahoma to several months of observing the deteriorating labor negotiations in the West Coast ports).
2. The disruptive event. At this point is the occurrence of the accident such as the explosion, supplier out of business, or other high-impact/low-probability disruption (i.e., Ebola epidemic, Coronavirus outbreak, etc.)
3. First response. After the disruptive event takes place, the immediate first action is conducted at this point in which the duration might differ from the time required to put out the fire to months to dismantle and clean "Ground Zero" at World Trade Center. The first response might

involve the shutting down processes of the production facility to ensure the safety of the employees, physical assets, and intangible asset, such as information systems.

4. Delayed impact. The immediate full impact might occur in some disruption, whereas others can be delayed to impact a company, depending on the factors such as disruption's magnitude, preparation is undertaken, and inherent resilience of the company and its supply chain.
5. Full impact. Once the full impact arrives at the front door of the company, the performance often drops precipitously (i.e. retailers are often unprepared for a significant increase in demand during panic buying when the pandemic hits, GM's Oklahoma automobile assembly plant was shut down immediately after hit by a tornado, etc.)
6. Preparation for recovery. The recovery preparation is typically initiated in parallel along with the first response or as soon as they commence. These preparations might involve qualifying other suppliers and redirecting resources, as Nokia's aftermath of the 2000 Philips fire; considering other transportation modes alternatives, as airfreight was utilized by NUMMI obtain parts during 2002 West Coast port lockout; etc.
7. Recovery. Revert to the previous company performance by restarting production, repairing damaged infrastructure, reconnecting damaged IT systems, higher-than-normal production plant utilization (overtime) for making up the lost production. These company actions might consume a significant amount of time before its golden era.
8. Long term impact. Although recovery from the disruption might take tremendous, if the customer relationship is damaged, the impact might be lifelong and complicated to recover from. For example, Dell and P&G fired unresponsive suppliers which are impacted during the West Coast port lockout, do nothing significant to resupply the orders; In some cases, the long term impact might be indirect.

For example, after three months of the 9/11 airplane crash, many people who would typically use air flight took the roads instead, which results in a significant increase in the death from automobile crashes (from an average of 22 a year to 353 in 3 months).

2.2 Supply Chain Risk Management

Supply chain risk management (SCRM) is described as the implementation of strategies to manage both every day and exceptional risks along the supply chain based on continuous risk assessment to reduce vulnerability and ensure continuity (Wieland, 2012).

2.2.1 Supply Chain Resiliency

Resilience deals with the ability of a system to sustain or restore its functionality and performance following a change in the condition of the system (disruption, threat, opportunity) (Aven, 2017). Moreover, in contrast to the robustness concept, where potential threats are known in advance and the absorbing system needs to be prepared to face these known threats, resilience is a protective strategy against unknown or highly uncertain hazards (Renn, 2010).

Resilient Supply Chain extends the traditional Supply Chain design approaches concerning the incorporation of redundancies−such as back-up facilities, inventory, and capacity flexibility− which create−at the stage of proactive planning−some flexibility that can be used at the reactive control stage in case of disruptions in SC structures aim to recover system performance and operational processes (Ivanov, 2019).

Resilience analysis and management are specially fitted for confronting unknown and uncertain categories of events (Aven, 2017). The instruments for resilience include the strengthening of the immune system; diversification of the means for approaching identical or similar ends; reduction of overall catastrophic potential or vulnerability, even in the absence of a real threat; design of systems with flexible response options; and the improvement of conditions for emergency management and system adaptation (Renn, 2010).

2.2.2 Supply Chain Risk Assessment Framework

In the practice, outlining and developing supply chain risk management need to adopted a risk assessment framework. One of the well-established risk assessment frameworks for the professional and company is the risk management process framework which is developed by International Organization for Standardization (ISO) in risk management standard ISO 31000:2009 and had been revised in ISO 31000:2018.

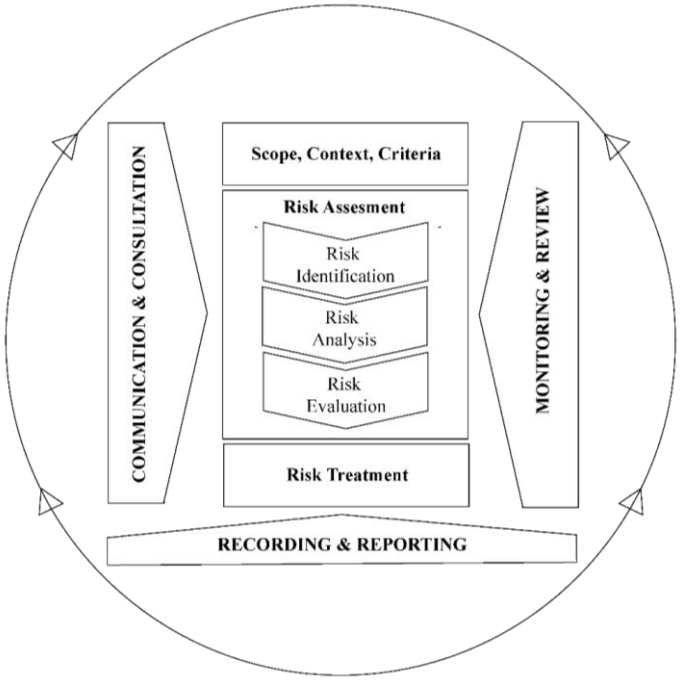

Figure 2.2 Risk Management Process
(Source: BS ISO, 2018)

Risk management process should be an integral part of management and integrated into the structure, operations and processes of the organization, and involves the systemic application of policies, procedure and practices to the activities of communication and consulting, establishing the context and assessing, treating, monitoring, reviewing, recording, and reporting risk. Risk management can be applied at strategic, operational, program, or project levels (BS ISO, 2018).

Moreover, Heckmaan (2015) had outlined several works of literature on supply chain risk management which mathematically model the supply chain risk to minimize supply chain risk as the objective function, and restricted by specific constraints or be balanced by its consideration in risk statement.

Generally, risk measures are introduced in the objective function, whereas the other risk-related parameters are utilized in the constraints. The following is the extensive literature review on supply chain risk modelling with its modelling approach categorization (Heckmaan, 2015).

Table 2.2 Mathematical Modeling Terms
(Source: Heckmaan, 2015)

Category	Methodology & Approach	Abbreviation
Linearity	Linear programming	LP
	Non-linear programming	NLP
	Mixed-integer/integer linear programming	MLP
	Mixed-interger/integer non-linear programming	MNLP
Objective function dimensionality	Single-objective function	SOF
	Multi-objective function	MOF
Risk statement placement	Within objective function	OF
	Within constraints	CON
	Within constraints and objective function	OF/CON
Solution Technique	General solver, exact solution	GSES
	General solver, heuristic solution	GSHS
	Specific algorithm, exact solution	SES
	Specific algorithm, heuristic solution	SHS

Table 2.3 Optimization Modeling for Supply Chain Risk
(Source: Heckmaan, 2015)

Reference	Linear		Non-linear		Objective		Risk statement			Solution Technique			
	LP	*MLP*	*NLP*	*MNLP*	*SOF*	*MOF*	*OF*	*CON*	*OF/CON*	*GSES*	*GSHS*	*SES*	*SHS*
(Azaron et al., 2008)				●		●	●					●	
(Babazadeh & Razmi, 2012)		●			●				●	●			
(Baghalian et al., 2013)				●	●				●	●			
(Ben-Tal et al., 2011)	●				●			●		●	●		
(Cui et.al., 2010)		●			●			●				●	●
(Fang et al., 2013)	●				●		●						●
(Goh et al., 2007)		●			●				●			●	
(Hahn & Kuhn, 2012)		●			●		●			●			
(Huang & Goetschalckx, 2014)		●				●	●					●	
(Kumar et.al, 2010)		●			●		●						●
(Mak & Shen, 2012)	●				●				●			●	
(Oliveira et al., 2013)		●			●				●		●		
(Poojari et al., 2008)		●			●				●	●			
(Sawik, 2013)		●			●	●			●	●			
(Sawik, 2014)		●			●	●			●	●			
(Sawik, 2011)		●			●	●			●	●			
(Shodi, 2005)	●				●				●	●			
(Soleimani & Govindan, 2014)		●			●				●	●			
(Wu & Olson, 2008)	●				●	●			●				●
(Wu, 2006)	●				●				●	●			
(You et al., 2009)	●				●	●			●		●		
(Yu & Goh, 2014)	●					●			●				●

2.3 Conceptual Framework and Hypothesis

This research aims to examine the factors influencing the severity level of COVID-19 impact on national manufacturing companies in the early outbreak period considering supply chain issues. According to the literature and observation, the causal loop diagram of COVID-19 impact in the initial outbreak is developed to figure out the root cause factors and presented by Figure 2.3. The independent variables in this research are company industry type, social distancing policy that prevents people from going to the workplace, material sourcing from affected foreign countries, customer demand contraction, and significant change of exchange rate. The dependent variable of this research is COVID-19 initial impact severity. Based on the literature review, Figure 2.4 shows the proposed conceptual framework that is used in this research. The conceptual framework establishes a direct causal-effect relationship of root cause factors with COVID-19 initial impact severity. The following hypotheses develop this connection.

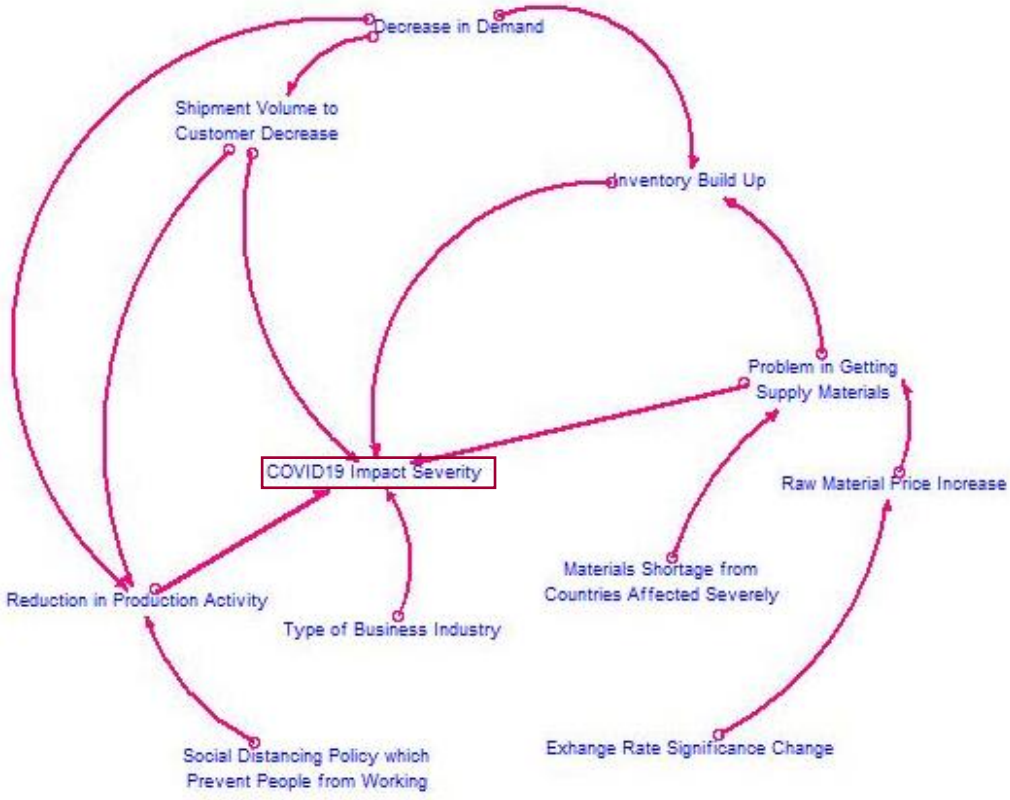

Figure 2.3 Causal Loop Diagram of COVID-19 Impact
Source: Processed Data

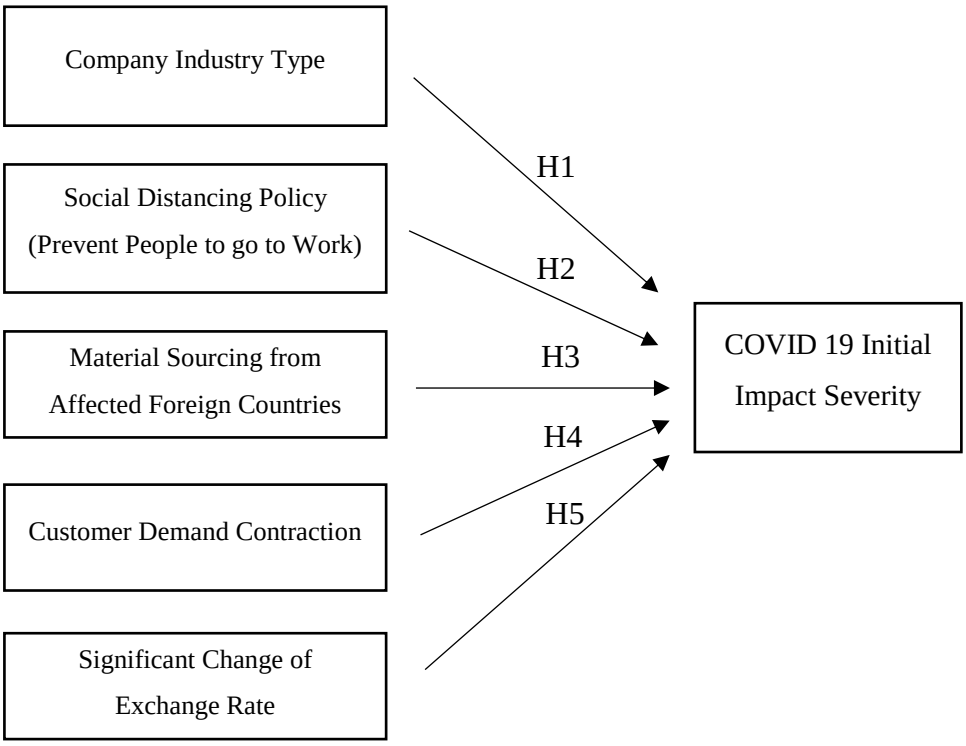

Figure 2.4 Conceptual Framework
Source: Processed Data

Chamola et al. (2020) and Chenneveau et al. (2020) studies show that different industry groups have different exposure to COVID-19 operation issues, hence result in particular severity degree of COVID-19 impact, for instance, the automotive industry has severe pandemic impacts, due to production facility shutdown that disrupt supply flow and social distancing that decline public & private transport, while the food industry has not been severe, given the industry experience increase in demand.

Hypothesis 1*: The initial impact of COVID-19 is significantly different among the type of industries.*

In terms of COVID-19 influence, Shen et al. (2020) state that workforce shortages became a significant issue due to social and travel restrictions. Furthermore, Shen et al. (2020) elaborate that some factories have to slow down or stop production due to workforce shortages, the lack of raw materials or parts from foreign countries, and the finished products cannot be shipped abroad.

In the early outbreak, the Indonesian government has also adopted a control measure to isolate & treat infected people and force people to stay home to reduce the contacts between people. Therefore, given that many businesses in the manufacturing industry require more people to gather, contact, and collaborate, manufacturing companies are greatly affected by the pandemic.

Hypothesis 2*: Social distancing/restriction control measure by the Indonesian government that prevents people from going to work is the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.*

Hypothesis 3*: Material sourcing from affected foreign countries is the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.*

Zulkhibri (2020) on ASEAN Policy Brief of Economic Impact of COVID-19 Outbreak on ASEAN states that beyond the interruption in normal business operations and travel & mobility restrictions, contraction in demand contributes to breaking ASEAN company supply chain. Moreover, according to Chenneveau et al. (2020) on the global manufacturing & supply chain pulse survey, 41 percent of the global respondents face a drop in demand disruption, which establish itself as the second most common disruption faced by global companies after material shortages, 45 percent. Moreover, customer demand contraction will also cause a reduction in shipment & production volume and increase the finished goods inventories.

Hypothesis 4*: Demand contraction/reduction disruption influences COVID-19 initial impact severity for Indonesian manufacturing companies.*

In the early outbreak of COVID-19 in Indonesia−the the first three weeks of March 2020−, Indonesia Rupiah (IDR) loses its power significantly with a 16 percent change (3/2/2020: 14,200 to 3/24/2020: 16,500 USD/IDR). Moreover, in supply chain scope, Mahidhar (2006) elaborates that significant loss on local currency rate affects the price of raw materials, sub-assemblies, and other finished goods imported to increase. Besides, suppliers with large export portfolios and local currency-denominated supply contracts might be exposed to a higher risk of operating margins erosion.

Therefore, a significant change in the exchange rate in USD/IDR in the COVID-19 early outbreak might greatly affect the performance of a company that relies heavily on international sourcing and trade.

Hypothesis 5*: Significant change of currency/exchange rate is the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.*

2.4 Research Position

This research utilizes primary data collected through a questionnaire with the Indonesian manufacturing companies' stakeholder as the respondent and then are processed through statistical tools and further analyzed to provide insights of the initial impacts of COVID-19 pandemic on Indonesian manufacturing companies regarding supply chain issues and their preferred action and strategy of Indonesian manufacturing companies toward COVID-19 pandemic.

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CHAPTER 3

RESEARCH METHODOLOGY

This chapter will discuss the research methodology utilized from the beginning to the end of the research. Generally, methods in this research consist of data collection, descriptive statistics, and ordinal logistic model development. The research framework is represented by the flowchart shown in Figure 3.1.

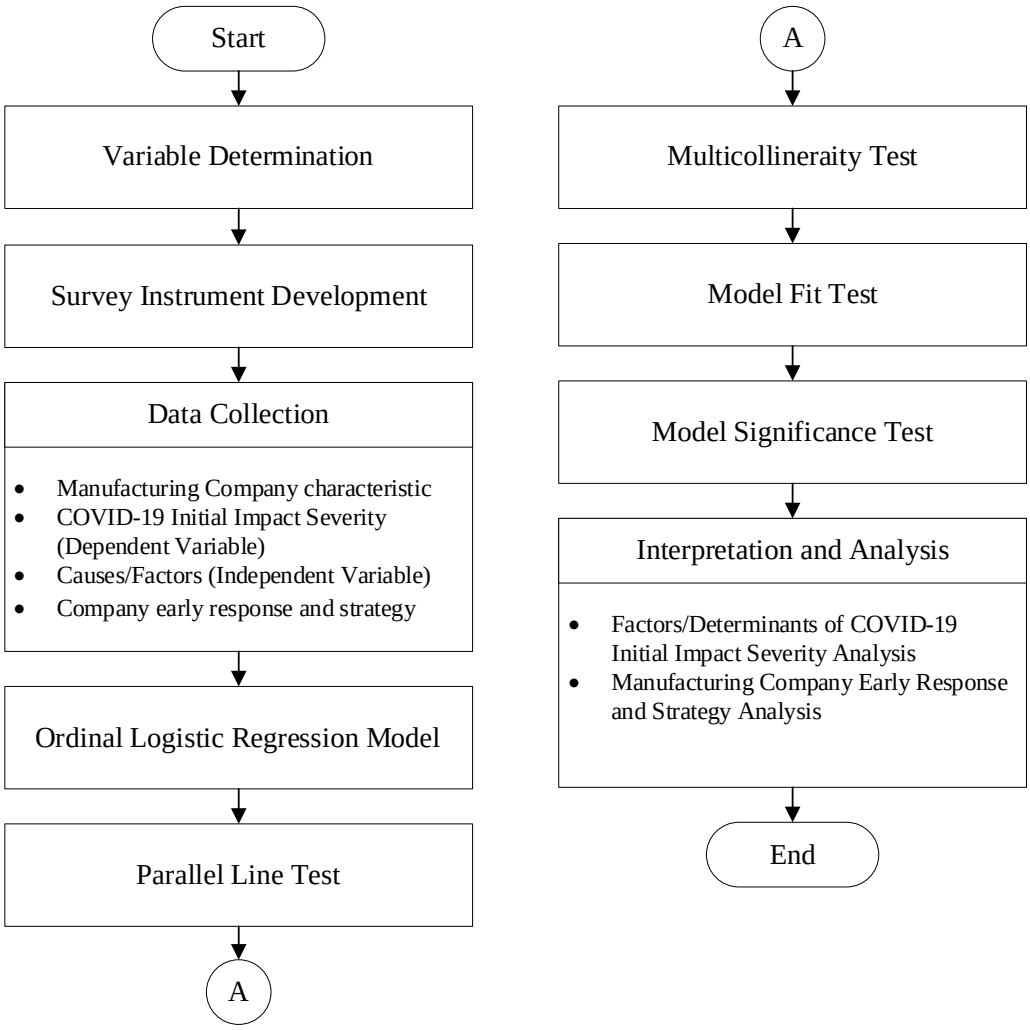


Figure 3.1 Research Methodology Flowchart

3.1 Data Collection

In this stage of research: firstly, the dependent variable and independent variables are determined according to literature findings and existing disruption events, and then the survey instrument is developed and distributed to Indonesian manufacturing companies.

In this research, according to the existing condition of COVID-19 outbreak in Indonesia & related countries and supported by findings, the data that are collected to support this study are COVID-19 initial impact severity; company characteristics, factors of COVID-19, the short term action of companies, and long term strategy. Moreover, according to the literature review and hypothesis, the variables collected to perform analysis of factors that influence the COVID-19 initial impact severity of manufacturing companies, are represented by Table 3.1, which includes dependent and independent variables of the research.

Furthermore, the survey is conducted using an online questionnaire during the early outbreak of COVID-19 in Indonesia from April 2nd to April 10th with the survey participants consist of companies in Indonesia. Furthermore, the inclusion criterion for the valid respondents is an active stakeholder of a particular Indonesian manufacturing company. After that, the collected number of respondents is verified based on the formula as explained below, that can be used for determining the appropriate sample size for ordinal data (Walters, 2004).

$$n = \frac{6\left[\left(z_{1-\frac{\alpha}{2}} + z_{1-\beta}\right)^2 / (\log OR_{Ordinal})^2\right]}{\left[1 - \sum_{i=1}^{k} \bar{\pi}_i{}^3\right]} \quad (3.1)$$

where:

n = sample size

$z_{1-\frac{\alpha}{2}}$ = appropriate values from standard normal distribution $1 - \alpha/2$

$z_{1-\beta}$ = appropriate values from standard normal distribution $1 - \beta$

$OR_{Ordinal}$ = odds ratio

α = two-sided significance level

$1 - \beta$ = power

k = number of categories

$\bar{\pi}_i$ = $(\pi_{ir} + \pi_{ic})/2$

$\bar{\pi}_i$ = average of treatment and control probabilities for category i

$\log OR_{Ordinal}$ = $\log_e OR_{Ordinal}$ (Hardy et al., 1975)

Table 3.1 Research Variables

No	Variable	Category	Data Scale
A	Dependent Variable		
1	COVID-19 Impact Severity (CI)	Extremely large impact Large impact Moderate impact Slight impact No impact	Ordinal
B	Independent Variable		
2	Industry Type (SI)	1: Basic Material (BAS) 2: Pharmaceuticals (PHAR) 3: Agriculture & Animal Feed (AGRI) 4: Advanced Industries (ADV) 5: Durable Consumer Goods (DUR) 6: Food, Beverage, and Tobacco (FOOD)*	Nominal
3	Materials are obtained from Countries Affected Seriously by COVID-19 (MS)	1: absolutely 2: significantly 3: moderately 4: slightly 5: not really*	Ordinal
4	Social Distancing Policy that Prevents People from Working (SD)		
5	Decrease in Demand (DD)		
6	Significant Change in Exchange Rate (ER)		

*Further utilized as the reference category in ordinal logistic regression

3.2 Data Processing and Analysis

In this stage, collected data are processed and analyzed through five steps: descriptive statistic, ordinal logistic regression (OLR) model, model fit test, model significance test, best subset regression, and model interpretation.

3.2.1 Descriptive Statistic

The descriptive statistic is carried out to assess the characteristic of data. In this research, the descriptive statistic is utilized correspond to the frequency or marginal percentage and central tendency for the observed variable and are visualized using the table and chart. The data visualization on this research is conducted with supporting software such as SPSS and Excel.

3.2.2 Ordinal Logistic Regression Model

Ordinal logistic regression (OLR) Model comprehend in conducting analysis involve one dependent variable (outcome) and one or more independent variable(s) (predictor) by treating the dependent variable as an ordered categorical variable, based on cumulative odds principles (Stewart et al., 2019).

OLR possesses an advantage over multiple regressions as the early does not have to assume equal intervals between scoring categories. Thus, the ordinal logistic regression (OLR) model is utilized in this research to incorporate the inferential and predictive purposes of the ordinal categorical dependent variable using SPSS as the supporting software.

The OLR model utilized a logit model with cumulative probability (Agresti, 2019). The cumulative probability of outcome category j or smaller is represented as follows

$$P(Y \leq j) = \pi_1 + \cdots + \pi_j \tag{3.2.1}$$

where:

$$P(Y \leq 1) \leq P(Y \leq 2) \leq \cdots \leq P(Y \leq c) = 1 \tag{3.2.2}$$

$P(Y \leq j)$ = cumulative probabilities

π = dependent probability

Agresti (2019) states that the logits of the cumulative probabilities for outcome category j for the dependent variable Y are

$$\text{logit}[P(Y \leq j)] = \log\left[\frac{P(Y \leq j)}{1-P(Y \leq j)}\right] = \log\left(\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_c}\right) \quad (3.2.3)$$

where:

$\text{logit}[P(Y \leq j)]$ = logits of the cumulative probabilities (cumulative logits)

c = number of dependent categories

The cumulative logit model utilized in this research is the proportional odds model, which compares the likelihood of an equal or smaller response, $Y \leq j$, to the probability of a larger response, $Y > j$ (Hosmer, 2013). Agresti (2019) states that in the proportional odds model, each cumulative logit has particular intercept yet similar slope parameter effects from independent variables (β).

Moreover, the proportional odds model for dependent variable Y is

$$\text{logit}[P(Y \leq j)] = \alpha_j + \sum_{k=1}^{d} \beta_k x_{ik} \quad (3.2.4)$$

where:

$j = 1, \ldots, c-1;\ d = 1, \ldots, q-1$

x_i = independent variable i

q = number of independent variable's categories

α_j = intercept parameter coefficient

β_k = slope parameter coefficient, describing the effect of x_i on the log odds of the dependent variable in category j or below

In this research, the model interpretation is conducted by considering the changes in the dependent variable, which is caused by the independent variables-represented by the slope parameter coefficient of proportional odds model-using odds ratio. The odds ratio shows the odds that categorical outcome will occur given a particular referenced category compared to the odds of the categorical outcome occurring in the absence of that referenced category in each variable. Moreover, Hosmer (2013) elaborates that the odds ratio used for coefficient interpretation of ordinal logistic regression (OLR) is the value that represents the comparison of odds from two or more categories in one particular independent variable as one category held as the reference.

$$\text{OR} = \frac{P(Y \geq j|x=1)/P(Y<j|x=1)}{P(Y \geq j|x=0)/P(Y<j|x=0)}$$

$$\text{OR} = \frac{\left[\frac{\exp(\alpha_j+\beta_k)}{1+\exp(\alpha_j+\beta_k)}\right]/\left[\frac{1}{1+\exp(\alpha_j+\beta_k)}\right]}{\left[\frac{\exp(\alpha_j)}{1+\exp(\alpha_j)}\right]/\left[\frac{1}{1+\exp(\alpha_j)}\right]}$$

$$\text{OR} = \exp(\beta_k) \tag{3.2.5}$$

3.2.3 Parallel Lines Assumption Test

There is an important assumption that belongs to ordinal odds in the ordinal logistic regression model. This assumption states that the parameters should not change for different categories. In other words, the correlation between the independent variable and dependent variable does not change for the dependent variable's categories; also parameter estimations do not change for cut-off points (Ari & Yildiz, 2014). In the parallel lines assumption test, the hypothesis is whether β_k coefficients of the independent variable are equal or not for every single category.

$$H_0\colon\ \beta_{k1} = \beta_{k2} = \cdots = \beta_{k(J-1)} = \beta_k$$

$$H_A\colon\ \beta_{k1} \neq \beta_{k2} \neq \cdots \neq \beta_{k(J-1)} \neq \beta_k$$

Figure 3.2 shows the conditions whether the assumption holds or not (Fullerton & Xu, 2012).

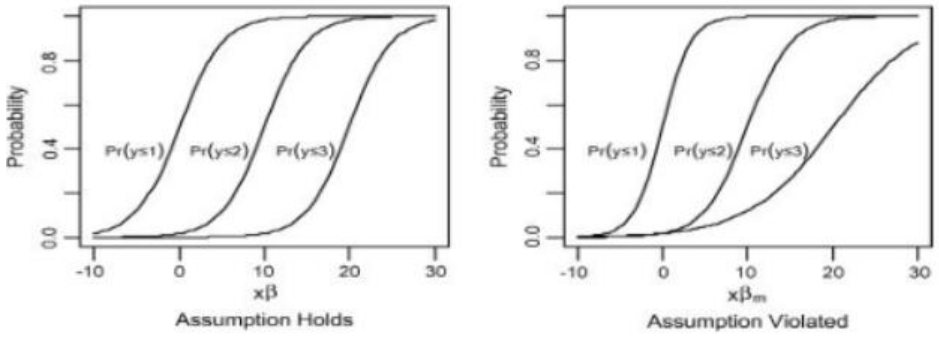


Figure 3.2 Parallel Line Assumption Visualization
(Source: Fullerton & Xu, 2012)

The test statistic utilized in testing parallel line assumption is as follows.

$$PL = -2\ln\left[\frac{l_0}{l_1}\right] \sim \chi^2_{k(j-2)} \tag{3.2.6}$$

where:

l_0 = likelihood function with parallel lines assumption independent variables
l_1 = likelihood function without parallel lines assumption independent variables

Do not reject the null hypothesis when the p-value > α with significance level α and the number of parameter β from 1 to k and J is the number of categories of the dependent variable. If the decision is do not reject the null hypothesis, hence the parallel lines assumption holds.

3.2.4 Multicollinearity Test

Multicollinearity test is conducted to test whether the independent variables used in the regression model have a significant correlation to each other. Multicollinearity test in ordinal logistic regression (OLR) can be performed through Spearman's rank correlation coefficient, which is appropriate to be used when one or both the variables are skewed or ordinal and robust when extreme values are present (Mukaka, 2012). A good OLR model should not have a significant Spearman's correlation among independent variables or multicollinearity. Multicollinearity is absent from the ordinal logistic regression (OLR) model when -0.70 < Spearman's correlation coefficient (r_s) < 0.70 [(Mukaka, 2012), (Vaccaro, 2014)].

3.2.5 Model Fit Test

The Model Fit test the model's goodness of fit or the overall fit of the model. The deviance test is used to test the model goodness of fit which measure the difference between the observed and fitted values$(y - \hat{y})$.

H_0: Model is fit (no significant difference between observed and model fitted values)

H_A: Model is not fit (there is a significant difference between observed and model fitted values)

The deviance test statistic is mathematically represented as the following equation (Hosmer, 2013).

$$D^2 = 2\sum_{i=1}^{I}\sum_{j=1}^{J} O_{ij} \log \frac{O_{ij}}{E_{ij}} \quad (3.2.7)$$

$$\chi^2 = \sum_{i=1}^{I}\sum_{j=1}^{J} \frac{(O_{ij}-E_{ij})^2}{E_{ij}} \quad (3.2.8)$$

where:

O_i = observed count in a cell

E_i = expected count under the null hypothesis

I = number of observed covariate pattern in categorical/independent variable

J = number of category in independent variables (q)

The basis of the decision making is the larger the value of deviance or the smaller the p-value, indicate that the model might not fit the data. Moreover, the H_0 is rejected if $D^2 > \chi^2_{(df)}$ or p-value < α with significance level α and degree of freedom $df = (2I-1)(J-1)-(d-1)$ where d is a number of independent variables, meaning that the model is not fit.

3.2.6 Model Significance Test

In this research, the model significant test proceeds through several tests such as overall significance test, individual significant test, and coefficient determination test with the particular test statistic.

3.2.6.1 Overall Significance Test (Likelihood ratio test)

The likelihood ratio test is utilized to test the significance of the all influence or relationship (β_k) of independent variables (x_i) simultaneously to the dependent variable (Y).

H_0: $\beta_1 = \beta_2 = \cdots = \beta_p = 0$

H_A: $at\ least\ one\ \beta_k \neq 0; k = 1, 2, \ldots, p$

The likelihood ratio test is mathematically represented as the following equation [(Sokal, 1995), (Hosmer, 2013)]

$$G^2 = 2\ln\left[\frac{(likelihood\ without\ the\ variable)}{(likelihood\ with\ the\ variable)}\right] \quad (3.2.9)$$

$$G^2 = 2\sum_{i=1}^{p} O_i \ln\left(\frac{E_i}{O_i}\right) \quad (3.2.10)$$

where:

O_i = observed count in a cell

E_i = expected count under the null hypothesis

The decision making is performed based on the H_0 rejection region which is $G^2 > \chi^2_{(\alpha,df)}$ or p-value $< \alpha$ with significance level α and degree of freedom df. The p-value is the chi-squared right-tail distribution. (Agresti, 2019).

3.2.6.2 Individual Significance Test (Wald Test)

Wald test is utilized to test the level of significance of each influence or relationship (β_k) of the independent variables (x_i) individually to the dependent variable (Y).

H_0: $\beta_k = 0$

H_A: $\beta_k \neq 0; k = 1, 2, \dots, p$

Wald test statistic is mathematically represented as the following equation.

$$W = \frac{\widehat{\beta}_k}{SE(\widehat{\beta}_k)} \tag{3.2.11}$$

where:

$\hat{\beta}_k$ = maximum likelihood estimate (MLE) of the slope parameter of k-th independent variable

$SE(\widehat{\beta}_k)$ = standard error of maximum likelihood estimate of k-th independent variable

$\hat{\pi}$ = estimated proportion (probabilities)

The decision making is performed based on the H_0 rejection region which are $|W| > Z_{\alpha/2}$ or $W^2 > \chi^2_{(\alpha,df)}$ or p-value $< \alpha$ with significance level α and degree of freedomdf [(Hosmer, 2013), (Agresti, 2019)].

3.2.6.3 Coefficient Determination Test (Pseudo R-Square)

In this research, the measurement of the coefficient of determination (Pseudo R-square) is conducted to determine the percentage of independent variables' effect on the changes in the dependent variable. This measurement provides insight regarding how much changes in the dependent variable is explained by the independent variables, while the rest is explained by other cause(s) outside the developed ordinal logistic regression (OLR) model.

3.3 Interpretation and Analysis

3.3.1 Analysis of Factors of COVID-19 Initial Impact Severity on Indonesian Manufacturing Companies

The analysis is carried out to examine significant factors that influence COVID-19 initial impact severity of Indonesian manufacturing companies. Moreover, the results of the ordinal logistic regression (OLR) model are analyzed in this part to provide interpretations regarding the factors.

3.3.2 Analysis of Indonesian Manufacturing Companies' Action and Strategy

The analysis is carried out to examine the preferred short term action and strategy of Indonesian manufacturing companies on managing COVID-19 disruption. Moreover, descriptive analysis is conducted in three perspectives, namely overall, industry type, and business size (number of employees), which aims to provide specific interpretations of short term action and strategy.

CHAPTER 4

DATA COLLECTION AND PROCESSING

In this chapter, survey data collection, regression model development, and assumption testing will be presented.

4.1 Survey Data Collection

This study examines manufacturing companies in Indonesia as the research object. An online survey is conducted during the early outbreak of coronavirus in Indonesia from April 2nd to April 10th with the active stakeholders of Indonesian manufacturing companies as the respondent (sample) to examine the initial disruption impact and response of the companies.

Table 4.1 Research Sample
(Source: primary data processed, 2020)

Criteria of Sample	Total
1. Total Respondents of Survey (April 2nd to April 10th)	109
2. Company located in Indonesia	108
3. Manufacturing Companies in Indonesia	89
4. Valid Active Stakeholders of The Company	85
Total Sample	**85**

The survey is only conducted in April 2nd – April 10th, only using professional online platform due to the safety and health issues to do the offline survey, and not re-conducted given that the study is only targeting the responses on the early outbreak of COVID-19 in Indonesia. Table 4.1 shows the data sorting and clearing, which results in a total of 85 valid respondents.

The sample size is then verified using the formula from sub-chapter 3.1 or formula (3.1), which is adapted from Walters (2004) research on sample size and power estimation. The control probabilities from the gathered data are 0.14, 0.27, 0.47, and 0.12 (extremely large, large, moderate, slight impact respectively), which result 0.28, 0.34, 0.33, and 0.05 in treatment probabilities. Thus, the calculation of the sample size is as follows.

$\alpha = 0.05$
$1 - \beta = 0.8$

$$n = \frac{6\left[\left(z_{1-\frac{\alpha}{2}} + z_{1-\beta}\right)^2 / (\log OR_{Ordinal})^2\right]}{\left[1 - \sum_{i=1}^{k} \bar{\pi}_i{}^3\right]}$$

$$n = \frac{6\left[(1.96 + 0.842)^2 / \log\left(\frac{0.14x(1-0.28)}{(1-0.14)x0.28}\right)^2\right]}{[1 - 0.21^3 + 0.31^3 + 0.4^3 + 0.09^3]}$$

$$n = 73.3 \approx 74$$

The calculated sample size is 74 and is lower than the gathered valid number of respondents in this research, 85. Therefore, the number of samples/respondents used in this study is verified to concluding (inferential) concerning the population of Indonesian manufacturing companies.

4.2 Descriptive Company Characteristic Survey Result

In the first section of the online questionnaire contains company characteristic information consists of the industry type, number of employees, and operating area. The classification of industry type includes six industries in which the detailed breakdowns are shown in the following Table 4.2.

Table 4.2 Characteristics of the Sample

Industry Classification	Sub-Industry
Basic Material (BAS)	Building Material Pulp, Paper, and Packaging Chemical
Pharmaceuticals (PHAR)	Beauty and Healthcare Cosmetics
Agriculture & Animal Feed (AGRI)	Fertilizer, Crop, and Seed Animal Nutrition and Food
Advanced Industries (ADV)	Automotive and Component Rolling Stock Computers and Electronics
Durable Consumer Goods (DUR)	Textiles and Apparel Household goods
Food, Beverage, and Tobacco (FOOD)*	Food and Beverage Tobacco

From 85 respondents, there are 16 (18.8%) basic material, 8 pharmaceuticals (9.40%), 6 (7.10%) agriculture & animal feed, 17 (20%) advanced industries, 19 (22.40%) durable consumer goods, and 19 (22.40%) food, beverage, and tobacco. The data shows that around 64% of the respondents come from advanced industries, durable consumer goods, and food, beverage, and tobacco industries.

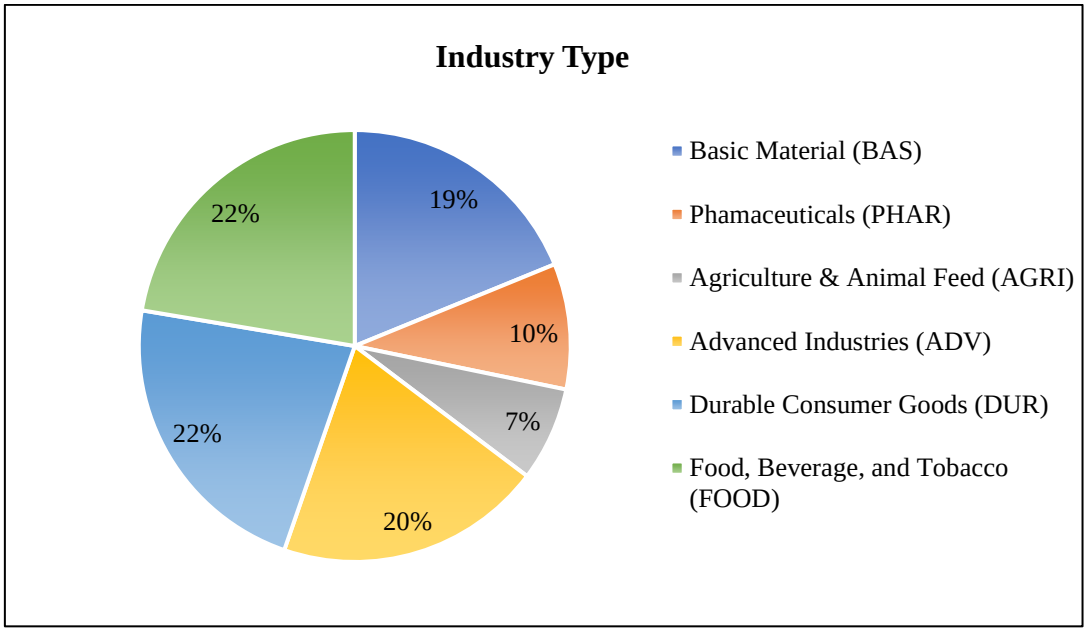


Figure 4.1 Industry Type of Surveyed Respondents

Moreover, from number of employees perspective, from 85 respondents, there are 24 (28.2%) more than 3000, 15 (17.6%) between 1000 and 3000, 18 (21.2%) between 500 and 1000, 19 (22.4%) between 100 and 500, and 9 (10.6%) less than 100 employees.

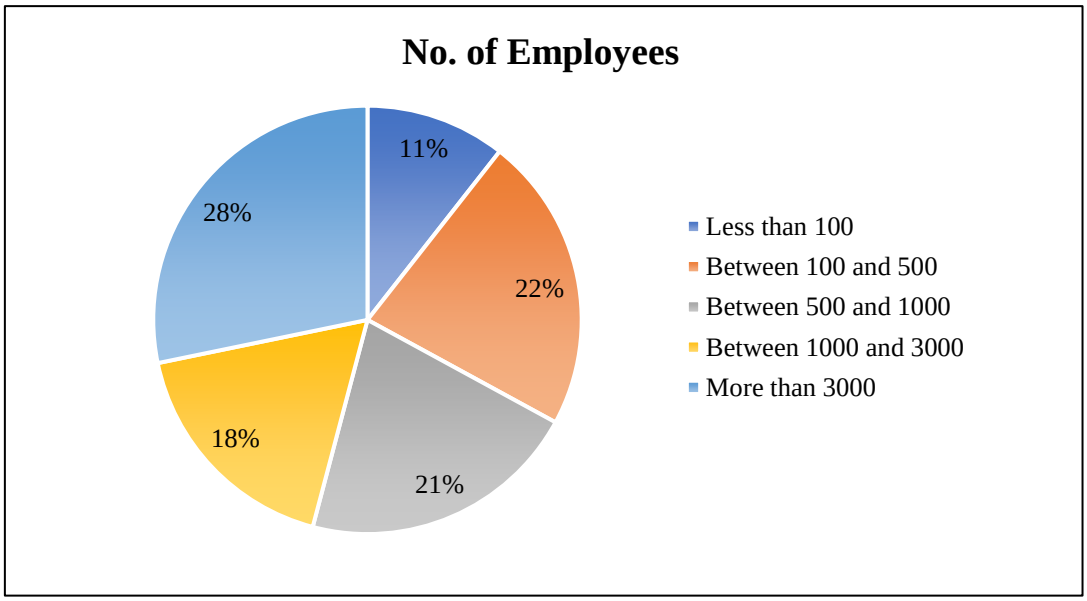


Figure 4.2 No of Employees of Surveyed Respondents

At last, from operating area perspective, from 85 respondents, there are 31 (36.5%) East Java, 21 (24.7%) West Java, 16 (18.8%) Central Java, 15 (17.6%) Jakarta, and 2 (2.4%) Outside Java, which indicate that the respondents are dominated with companies that operate within Java Island.

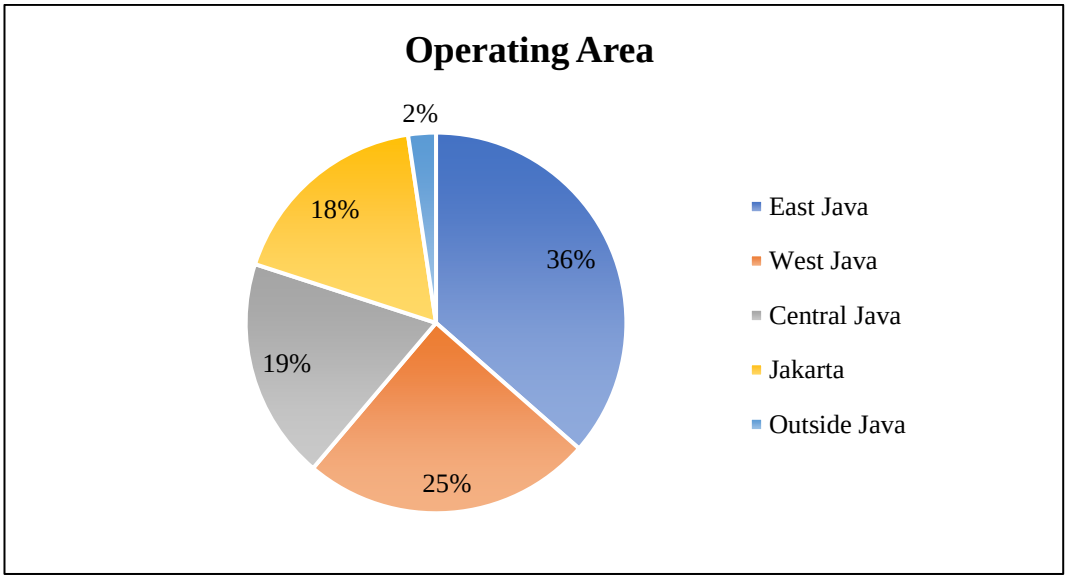


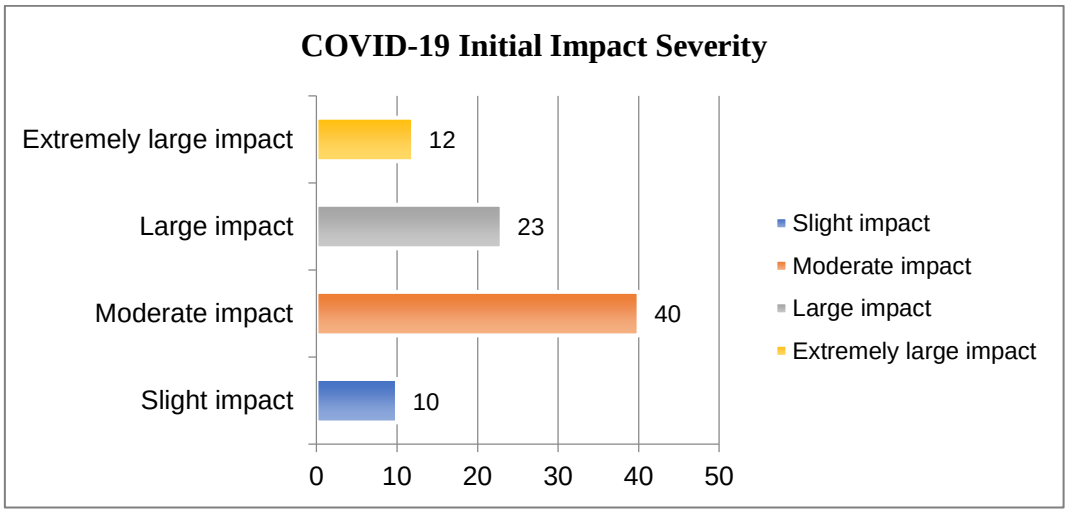
Figure 4.3 Operating Area of Surveyed Respondents

Table 4.3 Characteristics of the Sample
(Source: primary data processed, 2020)

Company Characteristic	Distribution of Response
Industry Type (IT)	Basic Material (18.8%) Pharmaceuticals (9.4%) Agriculture & Animal Feed (7.1%) Advanced Industries (20%) Durable Consumer Goods (22.4%) Food, Beverage, and Tobacco (22.4%)
Number of Employees (NOE)	More than 3000 (28.2%) Between 1000 and 3000 (17.6%) Between 500 and 1000 (21.2%) Between 100 and 500 (22.4%) Less than 100 (10.6%)
Area (AREA)	East Java (36.5%) West Java (24.7%) Central Java (18.8%) Jakarta (17.6%) Outside Java (2.4%)

4.3 Descriptive of COVID-19 Initial Impacts on Indonesian Manufacturing Companies

In this part, descriptive of Indonesian manufacturing companies' initial impacts is conducted. There are three interpretations on this part, which are the description of the COVID-19 initial impacts severity–in the early outbreak–based on industry type and employee size classification.



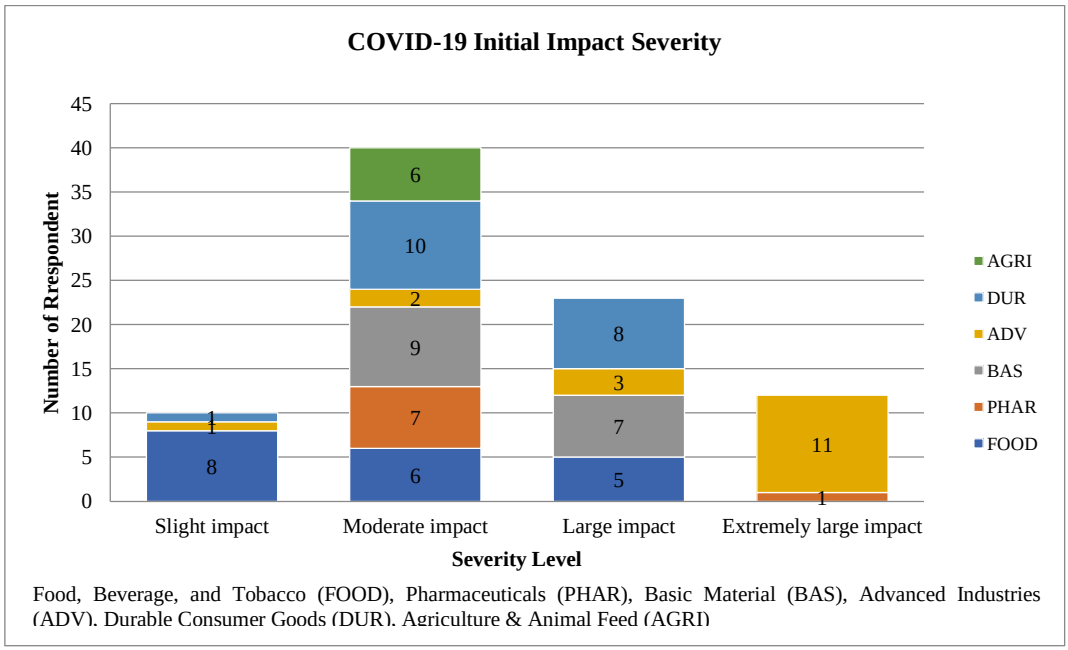


Figure 4.4 COVID-19 Initial Impact Severity to Manufacturing Companies (Industry View)

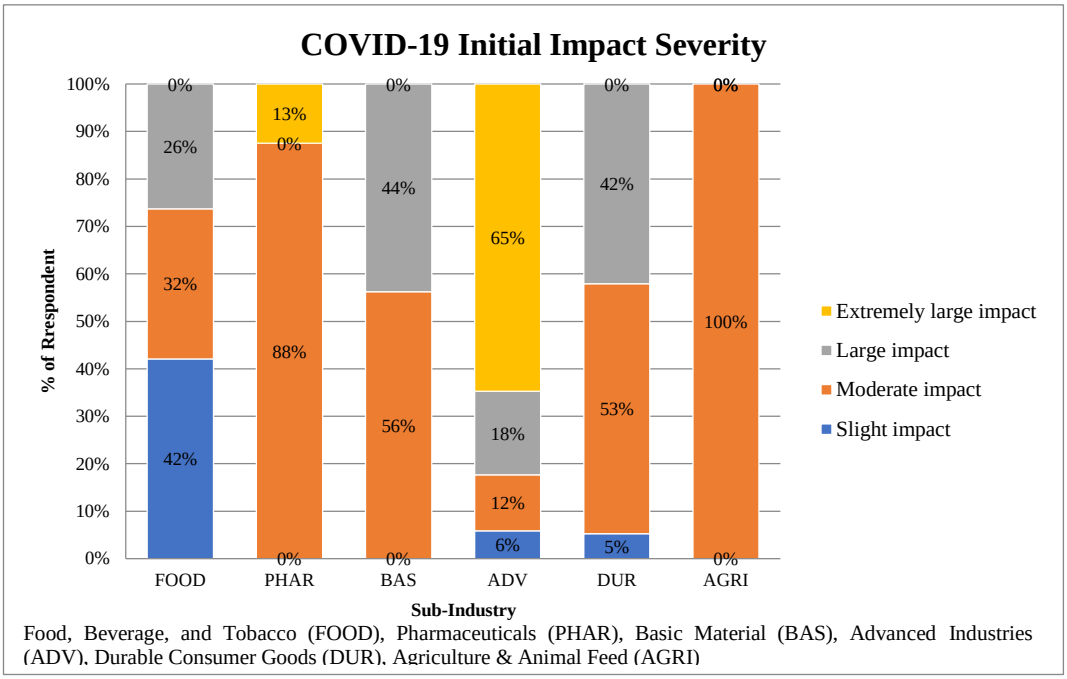


Figure 4.5 COVID-19 Initial Impact Severity to Manufacturing Companies (cont')
(Industry View)

On average, about 88 percent of the respondents say their company was moderately to extremely impacted by COVID-19 in the early outbreak, while the additional 12 percent are slightly impacted. Stakeholders in advanced industries (ADV) are the most likely to be exposed by severe impacts on their business; over 80 percent of ADV respondents (14 respondents) report large to extreme impacts (highest contributor on each category). On the other end are respondents in food, beverage, and tobacco (FOOD), who are the most likely to report slight impacts of COVID-19 on the early outbreak in Indonesia with 40 percent of FOOD respondents (8 respondents).

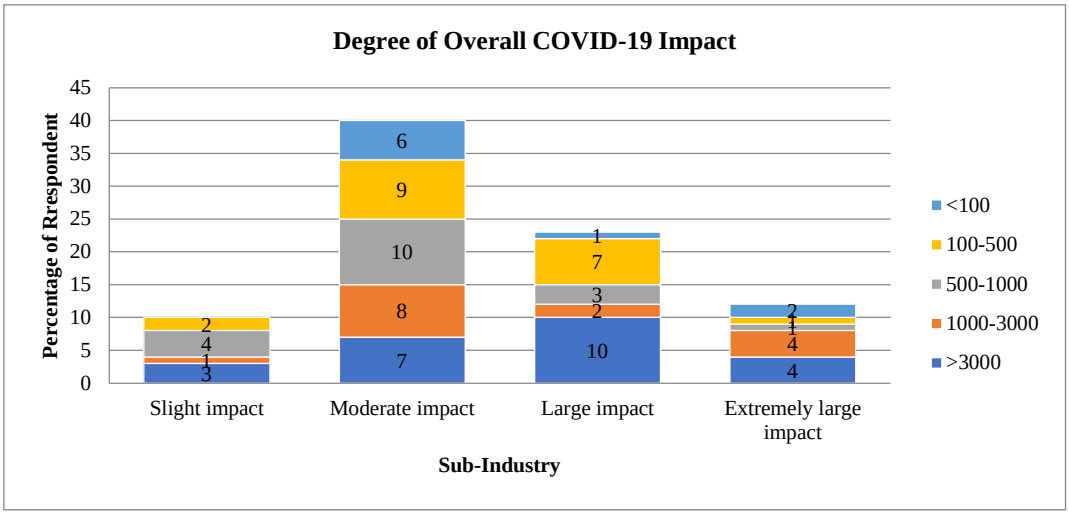


Figure 4.6 COVID-19 Initial Impact Severity to Manufacturing Companies (cont')
(Employees Size View)

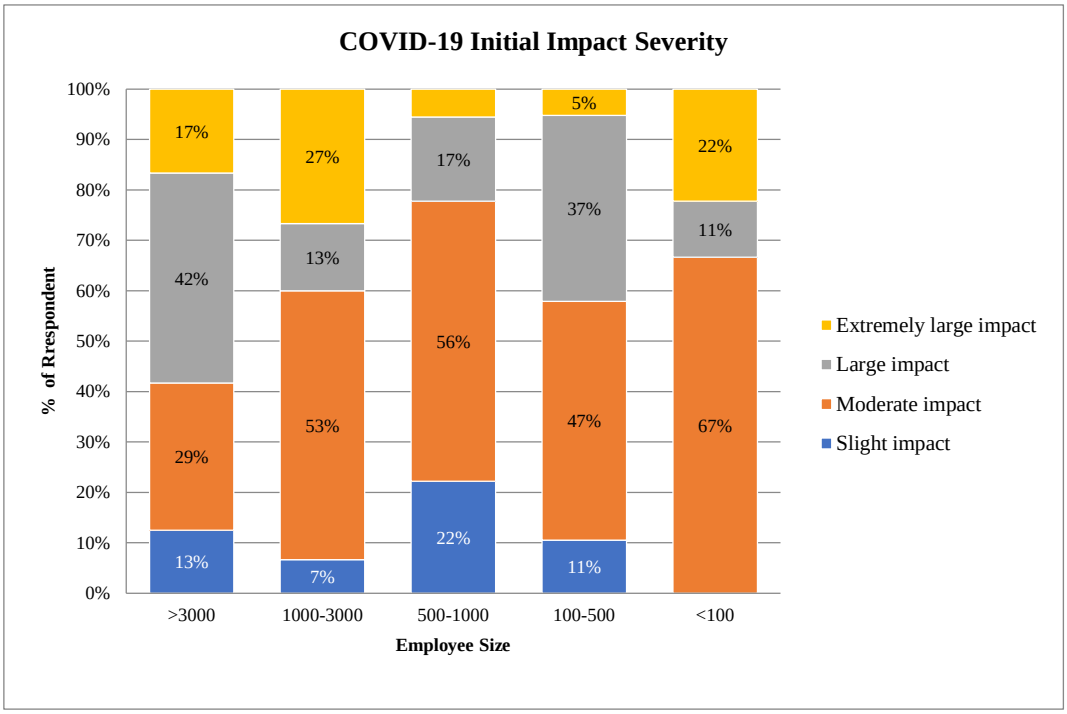


Figure 4.7 COVID-19 Initial Impact Severity to Manufacturing Companies (cont')
(Employees Size View)

Move into the employee size view; companies with >3000 employees are the most likely to be exposed by more severe impacts on their business; around 59% percent of respondents in this class, report large to extreme impacts. However, on the other end are companies with 500-1000, who are the most likely to report slighter impacts of COVID-19 on the early outbreak in Indonesia.

4.4 Ordinal Logistic Regression (OLR) Model

In this section, ordinal logistic regression (OLR) model development and statistical testing results are presented. The statistical testing consists of parallel lines test, multicollinearity test, model fit test, and model significance test. Moreover, according to the performed statistical processes, the following ordinal logistic regression (OLR) equation is obtained:

$$\text{logit}[P(Y \leq j)] = \alpha_j + \sum_{k=1}^{d} \beta_k x_{ik}$$

logit [P(Y≤ Large)] =

$8.542 + 2.392(IT)_{(1)}^{*} - 0.591(IT)_{(2)} + 1.192(IT)_{(3)} + 5.009(IT)_{(4)}^{*} + 0.895(IT)_{(5)} + 1.245(SD)_{(1)} + 0.832(SD)_{(2)} + 0.228(SD)_{(3)} - 0.862(SD)_{(4)} + 3.627(MS)_{(1)}^{*} + 2.272(MS)_{(2)}^{*} + 1.971(MS)_{(3)} + 0.995(MS)_{(4)} + 3.065(DD)_{(1)}^{*} + 2.110(DD)_{(2)}^{*} - 0.699(DD)_{(3)} - 0.559(DD)_{(4)} - 0.053(ER)_{(1)} + 0.808(ER)_{(2)} + 1.125(ER)_{(3)} + 0.148(ER)_{(4)}$

logit [P(Y≤ Moderate)] =

$5.242 + 2.392(IT)_{(1)}^{*} - 0.591(IT)_{(2)} + 1.192(IT)_{(3)} + 5.009(IT)_{(4)}^{*} + 0.895(IT)_{(5)} + 1.245(SD)_{(1)} + 0.832(SD)_{(2)} + 0.228(SD)_{(3)} - 0.862(SD)_{(4)} + 3.627(MS)_{(1)}^{*} + 2.272(MS)_{(2)}^{*} + 1.971(MS)_{(3)} + 0.995(MS)_{(4)} + 3.065(DD)_{(1)}^{*} + 2.110(DD)_{(2)}^{*} - 0.699(DD)_{(3)} - 0.559(DD)_{(4)} - 0.053(ER)_{(1)} + 0.808(ER)_{(2)} + 1.125(ER)_{(3)} + 0.148(ER)_{(4)}$

logit [P(Y≤ Slight)] =

$0.684 + 2.392(IT)_{(1)}^{*} - 0.591(IT)_{(2)} + 1.192(IT)_{(3)} + 5.009(IT)_{(4)}^{*} + 0.895(IT)_{(5)} + 1.245(SD)_{(1)} + 0.832(SD)_{(2)} + 0.228(SD)_{(3)} - 0.862(SD)_{(4)} + 3.627(MS)_{(1)}^{*} + 2.272(MS)_{(2)}^{*} + 1.971(MS)_{(3)} + 0.995(MS)_{(4)} + 3.065(DD)_{(1)}^{*} + 2.110(DD)_{(2)}^{*} - 0.699(DD)_{(3)} - 0.559(DD)_{(4)} - 0.053(ER)_{(1)} + 0.808(ER)_{(2)} + 1.125(ER)_{(3)} + 0.148(ER)_{(4)}$

*) significant at 95 percent confidence level

Table 4.4 Proportion Distribution of Survey Response
(Source: primary data processed, 2020)

Variable	Category	N	Marginal Percentage
COVID-19 Initial Impact Severity Level	Extremely large impact	12	14.10%
	Large impact	23	27.10%
	Moderate impact	40	47.10%
	Slight impact	10	11.80%
Industry Type (IT)	Basic Material	14	18.82%
	Pharmaceuticals	8	9.41%
	Agriculture & Animal Feed	6	7.06%
	Advanced Industries	19	20.00%
	Durable Consumer Goods	19	22.35%
	Food, Beverage, and Tobacco	19	22.35%
Social Distancing Policy that Prevents People from Working (SD)	absolutely	8	9.41%
	significantly	20	23.53%
	moderately	23	27.06%
	slightly	18	21.18%
	not really	16	18.82%
Materials are obtained from Affected Countries (MS)	absolutely	11	12.94%
	significantly	23	27.06%
	moderately	22	25.88%
	slightly	16	18.82%
	not really	13	15.29%
Decrease in Demand (DD)	absolutely	10	11.76%
	significantly	15	17.65%
	moderately	27	31.76%
	slightly	17	20.00%
	not really	16	18.82%
Significant Change in Exchange Rate (ER)	absolutely	12	14.12%
	significantly	30	35.29%
	moderately	26	30.59%
	slightly	10	11.76%
	not really	7	8.24%
	Valid	85	100.00%
	Missing	0	
	Total	85	

Table 4.4 above presents the proportion (marginal percentage) of survey responses for each particular dependent variables and independent variables to show the characteristic of the data.

4.4.1 Parallel Lines Assumption Test

Parallel lines assumption is essential to ordinal odds in the ordinal logistic regression model. If this assumption does not hold, the interpretations about the results of the ordinal logistic regression model will be wrong; thus, this parallel line assumption is crucial to be tested. In this test, the hypotheses are as follows.

H_0: $\beta_{k1} = \beta_{k2} = \cdots = \beta_{k(J-1)} = \beta_k$ β_k (correlation between the independent variable and dependent variable are equal for all dependent variable's categories)

H_A: $\beta_{k1} \neq \beta_{k2} \neq \cdots \neq \beta_{k(J-1)} \neq \beta_k$ (correlation between the independent variable and dependent variable are not equal for all dependent variable's categories)

Table 4.5 Parallel Lines Assumption Test Result
(Source: primary data processed, 2020)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	118.709			
General	88.389	30.320	42	0.910

Table 4.5 shows the significant value or p-value of 0.910. Given that the p-value is higher than 5 percent significant level α (95 percent confidence level), hence the decision is do not rejectH_0, meaning that the parallel lines assumption holds in the developed OLR model, or in other words, the correlation between the independent variable and dependent variable does not change for the dependent variable's categories.

4.4.2 Multicollinearity Test

Multicollinearity test is conducted to test whether the independent variables used in the regression model have a significant correlation to each other. Multicollinearity test in ordinal logistic regression (OLR) can be performed through Spearman's rank correlation coefficient.

Table 4.6 Multicollinearity Test Result
(Source: primary data processed, 2020)

			Industry Type (IT)	Social Distancing Policy that Prevents People from Working (SD)	Materials are obtained from Affected Countries (MS)	Decrease in Demand (DD)	Significant Change in Exchange Rate (ER)
Spearman's rho (r_s)	Industry Type (IT)	Correlation Coefficient	1.000	0.043	-0.071	0.148	-0.029
		Sig. (2-tailed)		0.696	0.517	0.177	0.792
	Social Distancing Policy that Prevents People from Working (SD)	Correlation Coefficient		1.000	0.301	0.293	0.215
		Sig. (2-tailed)			0.005	0.007	0.048
	Materials are obtained from Affected Countries (MS)	Correlation Coefficient			1.000	0.134	0.520
		Sig. (2-tailed)				0.220	0.000
	Decrease in Demand (DD)	Correlation Coefficient				1.000	0.195
		Sig. (2-tailed)					0.073
	Significant Change in Exchange Rate (ER)	Correlation Coefficient					1
		Sig. (2-tailed)					.

Based on the multicollinearity test result on Table 4.6, there are no meaningful or significant correlations within the independent variables indicated by > -0.7 and < 0.70 Spearman's correlation coefficient of each independent variable relationship, though there are some <0.05 p-values. Therefore, the conclusion is that multicollinearity is absent from the developed ordinal logistic regression (OLR) model.

4.4.3 Model Fit Test

The goodness of fit test is conducted using the deviance statistic to test the model fit by comparing the observed value to the predicted value generated from the model with the following hypothesis.

H_0: Model is fit (no significant difference between observed and model fitted values)

H_A: Model is not fit (there is a significant difference between observed and model fitted values)

Table 4.7 Goodness of Fit Test Result
(Source: primary data processed, 2020)

	Chi-Square	df	Sig.
Deviance	117.322	228	1.000

Table 4.7 above shows the value of Deviance of 117.322, and by considering the degree of freedom will result in a significant value or p-value of 1.000. Given that the p-value is larger than 5 percent significant level α (95 percent confidence level), hence the decision is do not reject H_0, meaning that the developed regression model is fit to the data.

4.4.4 Overall Significance Test

The likelihood ratio test or G test statistic is utilized to test the significance of the all influence or relationship (β_k) of independent variables (x_i) simultaneously to the dependent variable (Y). G test statistic is following the Chi-square distribution with the following hypothesis.

H_0: $\beta_1 = \beta_2 = \cdots = \beta_p = 0$ (All independent variables has no influence on the dependent variable)

H_A: $at\ least\ one\ \beta_k \neq 0; k = 1, 2, \ldots, p$ (At least one independent variable has influence on the dependent variable)

Table 4.8 Overall Significance Test Result
(Source: primary data processed, 2020)

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	208.832			
Final	118.709	90.123	21	0.000

Table 4.8 above shows the significant value or p-value of 0.000. Given that the p-value is lower than 5 percent significant level α (95 percent confidence level), hence the decision is to reject H_0. Thus, it can be concluded that there is at least one independent variable that influences the dependent variable. In other words, COVID-19 initial impact severity is influenced simultaneously by the hypothesized independent variables.

4.4.5 Individual Significance Test

The individual significance test is conducted to test the level of significance of each influence or relationship (β_k) of the independent variables (x_i) individually to the dependent variable (Y). The statistic used in this test is the Wald test statistic.

H_0: $\beta_k = 0$ (Independent variable-k has no significant influence on the dependent variable)

H_A: $\beta_k \neq 0; k = 1, 2, \dots, p$ (Independent variable-k has a significant influence on the dependent variable)

Table 4.8 presents the result of individual significance test which consists of the influence (β_k) of five hypothesized independent variables to the dependent variable, standard error, wald statistic, and p-value that will be tested with a 95 percent confidence level or 5 percent significant level α.

Table 4.9 Individual Significance Test Result
(Source: primary data processed, 2020)

Variable		Estimate (βk)	Std. Error (SE(βk))	Wald (W)	Sig. (p-value)	95% Confidence Interval	
						Lower Bound	Upper Bound
Industry Type (IT)							
BAS	$(IT)_{(1)}$	2.392	0.958	6.240	**0.012***	0.515	4.269
PHAR	$(IT)_{(2)}$	-0.591	1.071	0.305	0.581	-2.690	1.508
AGRI	$(IT)_{(3)}$	1.192	1.177	1.025	0.311	-1.115	3.500
ADV	$(IT)_{(4)}$	5.009	1.049	22.815	**0.000***	2.954	7.065

Variable		Estimate (βk)	Std. Error (SE(βk))	Wald (W)	Sig. (p-value)	95% Confidence Interval	
						Lower Bound	Upper Bound
DUR	$(IT)_{(5)}$	0.859	0.878	0.958	0.328	-0.861	2.580
FOOD	$(IT)_{(6)}$	Reference					
Social Distancing Policy that Prevents People from Working (SD)							
absolutely	$(SD)_{(1)}$	1.254	1.120	1.253	0.263	-0.9411	3.4481
significantly	$(SD)_{(2)}$	0.832	0.894	0.867	0.352	-0.9195	2.5832
moderately	$(SD)_{(3)}$	0.228	0.827	0.076	0.782	-1.3932	1.8500
slightly	$(SD)_{(4)}$	-0.862	0.867	0.989	0.320	-2.5620	0.8375
not really	$(SD)_{(5)}$	Reference					
Materials Sourcing from Affected Countries (MS)							
absolutely	$(MS)_{(1)}$	3.627	1.226	8.760	**0.003***	1.225	6.030
significantly	$(MS)_{(2)}$	2.272	1.104	4.235	**0.040***	0.108	4.436
moderately	$(MS)_{(3)}$	1.971	1.016	3.762	0.052	-0.021	3.963
slightly	$(MS)_{(4)}$	0.995	1.006	0.978	0.323	-0.977	2.968
not really	$(MS)_{(5)}$	Reference					
Decrease in Demand (DD)							
absolutely	$(DD)_{(1)}$	3.065	1.191	6.622	**0.010***	0.730	5.400
significantly	$(DD)_{(2)}$	2.110	0.901	5.484	**0.019***	0.344	3.876
moderately	$(DD)_{(3)}$	-0.699	0.799	0.765	0.382	-2.266	0.868
slightly	$(DD)_{(4)}$	-0.559	0.904	0.382	0.537	-2.331	1.214
not really	$(DD)_{(5)}$	Reference					
Significant Change in Exchange Rate (ER)							
absolutely	$(ER)_{(1)}$	-0.053	1.389	0.001	0.970	-2.775	2.670
significantly	$(ER)_{(2)}$	0.808	1.121	0.520	0.471	-1.388	3.004
moderately	$(ER)_{(3)}$	1.125	1.107	1.034	0.309	-1.044	3.294
slightly	$(ER)_{(4)}$	0.148	1.206	0.015	0.902	-2.215	2.512
not really	$(ER)_{(5)}$	Reference					

*) significant at 95 percent confidence level

Based on the individual test results that have been shown by Table 4.9, three out of five hypothesized variables have partial significance influence on COVID-19 initial impact severity on Indonesian manufacturing companies, which are indicated by p-value lower than 0.05 (95% confidence level).

The three significant variables are industry type (IT), materials sourcing from affected countries (MS), and decrease in demand (DD).

4.4.6 Coefficient Determination Test

The measurement of the coefficient of determination (Pseudo R-square) in this study is conducted to determine the percentage of changes in the dependent variable that can be explained by independent variables.

Table 4.10 Individual Significance Test Result
(Source: primary data processed, 2020)

Pseudo R-Square	
Nagelkerke	0.714

Pseudo R-square value indicates how much the relationship that occurs between independent and dependent variables. Pseudo R-square values have ranged between 0 and 1; the closer the value of Pseudo R-square with one means that the dependent variable is getting better explained by independent variables. Based on the processed results in Table 4.9, the Pseudo R-Square value obtained is 0.714, meaning that 71.4% of changes in COVID-19 initial impact severity level is explained by the independent variables in this study, while the other 28.6% is explained by other causes outside the developed ordinal logistic regression (OLR) model.

CHAPTER 5
ANALYSIS AND INTERPRETATION

In this chapter, the analysis of COVID-19 initial impact severity level determinants on Indonesian manufacturing companies and analysis of Indonesian manufacturing companies' first response and long term strategy will be explained.

5.1 Analysis of Factors of COVID-19 Initial Impact Severity on Indonesian Manufacturing Companies

The results show that from five hypothesized independent variables, three variables have a significant influence on COVID-19 initial impact severity of Indonesian manufacturing companies; industry type (IT) (H1), materials sourcing from affected countries (MS) (H3), and decrease in demand (DD) (H4).

Table 5.1 Odds Ratio of Significant Variables
(Source: primary data processed, 2020)

Significant Variable	**Odds Ratio [exp(βk)]**
Industry Type (SI)	
Basic Material	10.935589
Advanced Industries	149.79708
Materials Sourcing from Affected Countries (RM)	
absolutely	37.616896
significantly	9.6997184
Decrease in Demand (DD)	
absolutely	21.435813
significantly	8.2499586

5.1.1 COVID-19 Initial Impact Severity of Indonesian Manufacturing Companies among Type of Industries

The result shows that different type of manufacturing industry has different COVID-19 initial impact severity. This is indicated by significance p-value of less than $\alpha = 0.05$ for two categories in Industry type (IT); basic material (BAS) and advanced industries (ADV) (p-value = 0.012, 0.000, respectively). Therefore, do not reject Hypothesis 1 (H1): The initial impact of COVID-19 is significantly different among the type of industries.

According to the obtained odds ratio of significance categories, the interpretation can be conducted. Basic material (BAS) industry has an odds ratio of exp(2.392) = 10.94, meaning being exposed to more severe initial impacts of COVID-19 are 10.94 times higher for Indonesian manufacturing companies in basic material (BAS) industry as compared to those in food, beverage, and tobacco (FOOD). Meanwhile for advanced industries (ADV), with an odds ratio of exp(5.009) = 149.79, being exposed to more severe initial impacts of COVID-19 are 149.79 times higher for Indonesian manufacturing companies in advanced industries (ADV) as compared to those in food, beverage, and tobacco (FOOD).

The result from the ordinal logistic regression (OLR) model that states the basic material industry is supported by a comment of a respondent from a cement company, “As the large-scale social restriction or PSBB issues spread all over the areas; we selectively deliver our product to our customer because COVID-19 make the market demand decrease, given that our customer faces financial difficulty in the cash-flow,”.

The result from the ordinal logistic regression (OLR) model that states advanced industry–in which the majority of respondents are automotive companies–is exposed to more severe COVID-19 initial impact is in line with the report from The Association of Indonesian Automotive Industry (GAIKINDO). According to GAIKINDO (2020), automotive manufacturing companies in Indonesia face severe supply issues such as the significant reduction in passenger car sales around 91.25% in April or cumulative 27.20% (Jan-April) as compared to the year 2019, a significant decrease in passenger car production around 80.93% in April or cumulative 18.24% (Jan-April) as compared to the year 2019, and a considerable reduction in the imported car around 45.14% in April or cumulative 35.42% (Jan-April) as compared to the year 2019.

Therefore, it is clear that the disruption of COVID-19 occurs in most aspect of advance industry companies' supply chain: reduction in domestic demand (demand) that lead to decrease in shipment volume as the consumer refrain to use transportation and drawback of offline sales channels; reduction in supply quantity (supply) as the plant shutdown in origin country that's affected by COVID-19 whose advance manufacturing industries rely on procuring spare-part and component; and reduction in production quantity (manufacture) to match the reduced demand, supply shortage, mitigate the risk of spreading disease in the workplace.

On testing industry type (IT) factor, the food, beverage, and tobacco (FOOD) industry is used as the baseline or reference category due to its products familiarity, hence easier to imagine the disruption happen in this industry for most people. However, when the baseline category is switched to other industry, there is always at least one industry or category−advanced industries (ADV) is always significant−that has p-value lower than five percent or significant. Thus, the conclusion remains consistent that different type of manufacturing industry has different COVID-19 initial impact severity.

5.1.2 Influence of National Social Distancing/Restriction Policy on COVID-19 Impact Severity of Indonesian Manufacturing Companies in The Early Outbreak

In this research, the social distancing policy is only referred to the Indonesia policy which restricts direct social interaction by preventing people from working in the office, factory, or any other workplaces. Moreover, this research is not concerning other restriction policy such as vacation travel restriction, community event restriction, etc.

The results obtained are social distancing policy that prevents people from working (SD) does not affect the severity of COVID-19 initial impact on Indonesian manufacturing companies, given that no significant p-value for all categories in the ordinal logistic regression (OLR) model. Therefore, reject Hypothesis 2 (H2): Social distancing/restriction control measure by the Indonesian government that prevents people from going to work is the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.

Table 5.2 Large-Scale Social Restriction (PSBB)
(Source: media and news, 2020)

Large-scale Social Restriction (PSBB) Region	Effective Start Date
Jakarta	10 April 2020
Depok, Bogor, Bekasi (West Java)	15 April 2020
Riau (Sumatera)	17 April 2020
Tangerang, Banten (West Java)	18 April 2020
Bandung metropolitan area (West Java)	22 April 2020
Surabaya, Gresik, Sidoarjo (East Java)	28 April 2020

According to PMK No. 9 Th. 2020 article 13, large-scale social restriction (PSBB) includes (1) school and workplace closure, except services related to military & defence, energy, oil and gas, healthcare, financial, strategical industrial, communication, export & import, distribution, logistic, and other necessities and services, (2) religious activities restriction, (3) public activities restriction, (4) cultural activities restriction, (5) transportation restriction, and (6) all other activities concerning safety. Moreover, large-scale social restriction (PSBB) in Indonesia is applied to a particular region partially−not simultaneously−according to several prerequisites with an effective start date shown in Table 5.2.

As shown in Table 5.2, the first PSBB is started on 10th April 2020, in which this research survey ended (2nd April – 10th April 2020). Thus, most of the respondents are more-likely not exposed to PSBB effects as it started beyond the survey time range. Moreover, only 33.3% of the respondents that are operating in Jakarta state that social distancing policy that prevents people from working as the significant cause, whereas the rest 66.7% state it is only moderate or not really the cause of COVID-19 impact on their companies (moderate: 40%, not really: 26%). In a broader view, only 21.2% of the respondents state that SD as a significant-absolute cause to their large to extremely large COVID-19 initial impacts. The social distancing policy that is applied before PSSB contains some allowances, which allow the manufacturer to run the shop-floor operation and transport goods without worker shortages.

Based on the OLR result and explanation above, it can be summarized that the social distancing policy that prevents people from working (SD) is not the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.

5.1.3 Influence of Material Sourcing from Affected Foreign Countries on COVID-19 Impact Severity of Indonesian Manufacturing Companies In The Early Outbreak

The results obtained are material sourcing from affected foreign countries on COVID-19 (MS) variable has a significance p-value less than $\alpha = 0.05$ on two categories in the ordinal logistic regression (OLR) model. The categories are absolutely and significantly (p-value = 0.003, 0.04 respectively). Thus, this variable (MS) does affect the severity of COVID-19 initial impact on Indonesian manufacturing companies. Therefore, do not reject Hypothesis 3 (H3): Material sourcing from affected foreign countries is the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.

Moreover, according to the obtained odds ratio of significance categories, the interpretation can be conducted as follows; (1) with an odds ratio of exp(3.62) = 37.61 meaning that being exposed to more severe initial impacts of COVID-19 are 37.61 times higher for Indonesian manufacturing companies whose initial impacts are absolutely caused by material sourcing from affected foreign countries (MS) as compared to those whose initial impacts are not really caused by material sourcing from affected foreign countries (MS), and (2) with an odds ratio of exp(2.27) = 9.69 meaning that being exposed to more severe initial impacts of COVID-19 are 9.69 times higher for Indonesian manufacturing companies whose initial impacts are significantly caused by material sourcing from affected foreign countries (MS) as compared to those whose initial impacts are not really caused by material sourcing (MS).

The research result is in line with the research of Shen et al. (2020) that some factories have to slow down or stop production due to a lack of raw materials or parts from affected foreign countries. Moreover, most of these affected countries−which are shown in Table 5.3−applied national lockdown or closure from the end of March to April that lead to a massive shutdown of manufacturing operations, and global deliveries are being called off.

Table 5.3 Indonesia Import Value in 2019 from Affected Countries
(Source: UN COMTRADE, 2020)

Indonesia Import Value (mil USD)	World	China	Saudi Arabia	Korea	Australia
Beverages and Tobacco	826.04	225.8	0.30	21.43	6.46
Mineral Fuels	23,480	511.24	2,834	1,173	1,596
Chemicals	7,715.5	2,072	299.28	359.51	213.61
Metal	825.32	465.56	0.04	33.56	1.71
Plastic, Pulp	10,277	1,813.88	331.03	756.82	87.59
Rubber	2,048.35	341.47	4.45	290.29	14.40
Earth Mineral	887.52	118.40	2.65	14.83	84.82
Parfumery and Cosmetics	1,304.6	228.25	0.13	47.85	16.46
Pharmaceutical	912.23	69.67	0.00	13.97	10.28
Toiletry Agents	548.83	98.94	1.63	38.08	5.03
Machinery, Equipment, and Part	19,767	9,212.83	0.14	1,004	61.22
Vehicles & Railway	7,366	1,161.7	0.03	184.63	38.62
Miscellaneous Manufactures	635.51	343.03	0.00	27.42	0.39
Total	76,594	16,662	3,473	3,965	2,137
%		21.75%	4.54%	5.18%	2.79%

Table 5.4 Indonesia Import Value in 2019 from Affected Countries (cont)
(Source: UN COMTRADE, 2020)

Indonesia Import Value (mil USD)	Italy	France	UK	Spain
Beverages and Tobacco	15.14	6.19	2.67	1.43
Mineral Fuels	0.25	6.09	1.10	1.41
Chemicals	104.62	61.20	22.74	29.76
Metal	6.60	1.97	2.95	0.87
Plastic, Pulp	109.19	167.14	83.53	42.58
Rubber	20.85	18.99	10.09	8.00
Earth Mineral	6.37	3.14	6.63	0.58
Parfumery and Cosmetics	16.48	100.15	28.13	33.68
Pharmaceutical	24.50	80.27	54.38	37.97
Toiletry Agents	5.31	9.53	6.84	3.32
Machinery, Equipment, and Part	167.82	151.75	133.63	46.17
Vehicles & Railway	36.45	47.58	50.01	42.77
Miscellaneous Manufactures	3.04	2.20	0.47	0.31
Total	516.63	656.19	403.18	248.84
%	0.67%	0.86%	0.53%	0.32%

According to the data published by UN COMTRADE shown on Table 5.4, one third−36.64 percent, equivalent to 28,064 million USD−of total manufacturing-related import values in Indonesia, are coming from countries which heavily affected by COVID-19 in early April. This indicates that companies in Indonesia heavily relied on those countries to procure their materials, especially from China (21.73 percent). Therefore, any massive disruptions in those countries (upstream supplier) such as the shutdown of production facilities and global delivery restriction−which resulted from the national lockdowns−, will have absolute impacts on the supply shortages on raw material, semi-finished goods, energy, spare-part, equipment, and tooling for manufacturing companies in Indonesia. For instance, a respondent (supply chain manager) from a company in Central Java commented, “Most of our materials are procured from China and India, and we have already placed the purchase order (PO) to the vendor, but the deliveries are uncertain due to disruption caused by COVID-19.”

5.1.4 Influence of Demand Reduction/Decrease on COVID-19 Impact Severity of Indonesian Manufacturing Companies in The Early Outbreak

The results obtained are demand reduction/decrease (DD) variable has a significance p-value less than $\alpha = 0.05$ on two categories in the ordinal logistic regression (OLR) model. The categories are absolutely and significantly (p-value = 0.010, 0.019, respectively). Thus, this variable (DD) does affect the severity of COVID-19 initial impact on Indonesian manufacturing companies. Therefore, do not reject Hypothesis 3 (H3): Demand contraction/reduction disruption influences COVID-19 initial impact severity for Indonesian manufacturing companies.

Moreover, according to an obtained odds ratio of significance categories, the interpretation can be conducted as follows; (1) with odds ratio of exp(3.06) = 21.435 meaning that being exposed to more severe initial impacts of COVID-19 are 21.435 times higher for Indonesian manufacturing companies whose initial impacts are absolutely caused by the decrease in demand (DD) as compared to those whose initial impacts are not really caused by the decrease in demand (DD), and (2) with an odds ratio of exp(2.11) = 8.25 meaning that being exposed to more severe initial impacts of COVID-19 are 8.25 times higher for Indonesian manufacturing companies whose initial impacts are significantly caused by the decrease in demand (DD) as compared to those whose initial impacts are not really caused by the decrease in demand (DD).

This result is supported by Smith et al. (2020) study, which states that sales in most industries will decline, and the customer behaviour will potentially change (i.e., shifting to online channels) since stay at home is enforced now due to COVID-19 outbreak in Indonesia. Theses affect the companies to struggle in generating revenue and cash flow & debt covenant issues to keep their business running. Moreover, the decrease in customer demand will also cause a reduction in shipment & production volume and increase the semi-finished & finished goods inventories for most manufacturing companies in Indonesia. For instance, a respondent who is a senior manager from an automotive company commented, “COVID-19 impacted a lot to both severe supply condition and demand drop as well, with uncertain timing to recover. Company financial will be a critical issue to ensure how long the company can survive and get through it”.

5.1.5 Influence of Significant Change of Currency/Exchange Rate on COVID-19 Impact Severity of Indonesian Manufacturing Companies In The Early Outbreak

The results obtained are the significant change of currency/exchange rate (ER) has no significant p-value for all categories in the ordinal logistic regression (OLR) model. Thus, it does not affect the severity of COVID-19 initial impact on Indonesian manufacturing companies. Therefore, reject Hypothesis 5 (H5): significant change of currency/exchange rate is the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.

The significant change of Indonesian currency rate phenomenon with 1 USD equivalent to >IDR 16,000 occurs only for two weeks from March 24th until April 9th. This considerable change stays for only a relatively short duration as compared to the previous economic slowdown in 2015 (one month), 2009 (six months). Moreover, there might be only a that are conducted by Indonesian manufacturing companies in this short time as the global supply is also halt or suspended. Thus, the effect on Indonesian manufacturing companies' operation might be minimized as the company able to avoid paying a higher sum of money (cost) when the logistic cost and raw materials price are increased temporally by the exchange rate.

This is supported by the cross-tabulation result that shows only 11.8% of respondents state that significant change on the exchange rate significantly-absolutely result in an extremely large impact of COVID-19. In comparison, the other 22.4% of respondents say those only result in a moderate impact of COVID-19 on their companies.

Based on the OLR result and explanation above, it can be summarized that significant change in the exchange rate (ER) is not the root cause that determines COVID-19 initial impact severity for Indonesian manufacturing companies.

5.2 Analysis of Indonesian Manufacturing Companies Early Action and Strategy

5.2.1 Descriptive Analysis of Company Early or Short Term Actions

In this part, descriptive analysis or interpretation of company short term actions–i.e., the action that is conducted within the period of COVID-19 times–survey results is presented. There are three interpretations on this part, which are general/overall, industry classification, and company size classification based analyses aim to provide broad insight to be adapted by a specific manufacturing company in terms of industry and size.

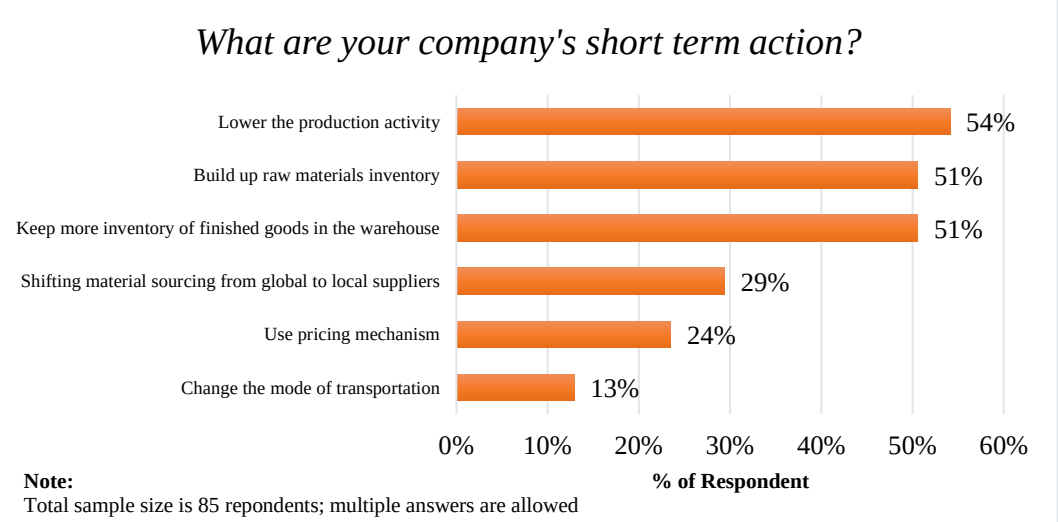
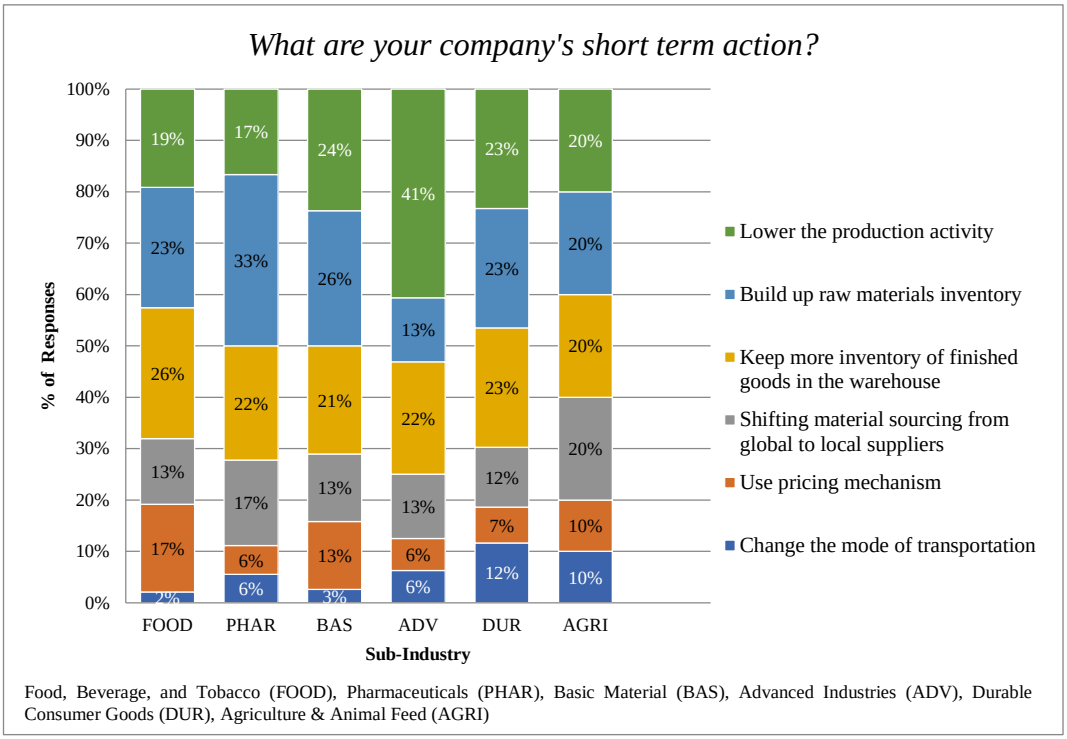


Figure 5.1 Manufacturing Companies Preferences on Short Term Action

Figure 5.1 represents the overall view on manufacturing companies' preferences of the short term actions. The result shows that many of the respondents (54 percent) say they prefer to lower production activity as their main short term action to COVID-19 disruption. On the other hand, a relatively equal proportion of respondents–51 percent–prefer to build up raw materials inventory and keep more stocks of finished goods in the warehouse. These facts show that the manufacturing companies in Indonesia tend to control production output and manage raw material and finished goods inventory as the short term action resulted from COVID-19 initial disruption on the decrease in demand and material shortages.



Food, Beverage, and Tobacco (FOOD), Pharmaceuticals (PHAR), Basic Material (BAS), Advanced Industries (ADV), Durable Consumer Goods (DUR), Agriculture & Animal Feed (AGRI)

Figure 5.2 Manufacturing Companies Preferences on Short Term Actions (Sub-Industry View)

On average, about 70 percent of responses say their companies respond to COVID-19 by either lowering their production activity, building up the inventory of raw materials, or containing more finished goods inventory (24, 23, 22 percent respectively), while an additional 30 percent of responses are fairly divided across other short-term actions. Moreover, stakeholders in pharmaceuticals (PHAR) and basic material (BAS) industries mostly prefer to build up raw materials inventory (33 and 26 percent, respectively) as their short term action in responding to supply disruption. Meanwhile, those in advanced industries (ADV) mostly prefer to lower their production activity (41 percent), as their short term actions.

Responses in durable consumer goods (DUR) industry show an equal preference for lower production activity, build up raw materials, and finished good inventory, while in agriculture & animal feed (AGRI) industry the preference distributed equally to four actions: three before-mentioned strategies plus material sourcing shifting from global to local suppliers. Moreover, stakeholders in food, beverage, and tobacco (FOOD) industry mostly prefer to keep more finished goods inventory or build up raw materials inventory.

There are two other short term actions, namely shifting material sourcing from global to local suppliers and pricing mechanisms. The former is more-likely preferred by agriculture & animal feed (AGRI). Meanwhile, the latter is more-likely preferred by stakeholders in food, beverage, and tobacco (FOOD) and basic material (BAS) industries, which have more feasibility to apply price changes as compare to other industries, given that both produce functional product. However, the preference on pricing mechanism is less attractive in both FOOD and BAS compared to the other short term actions.

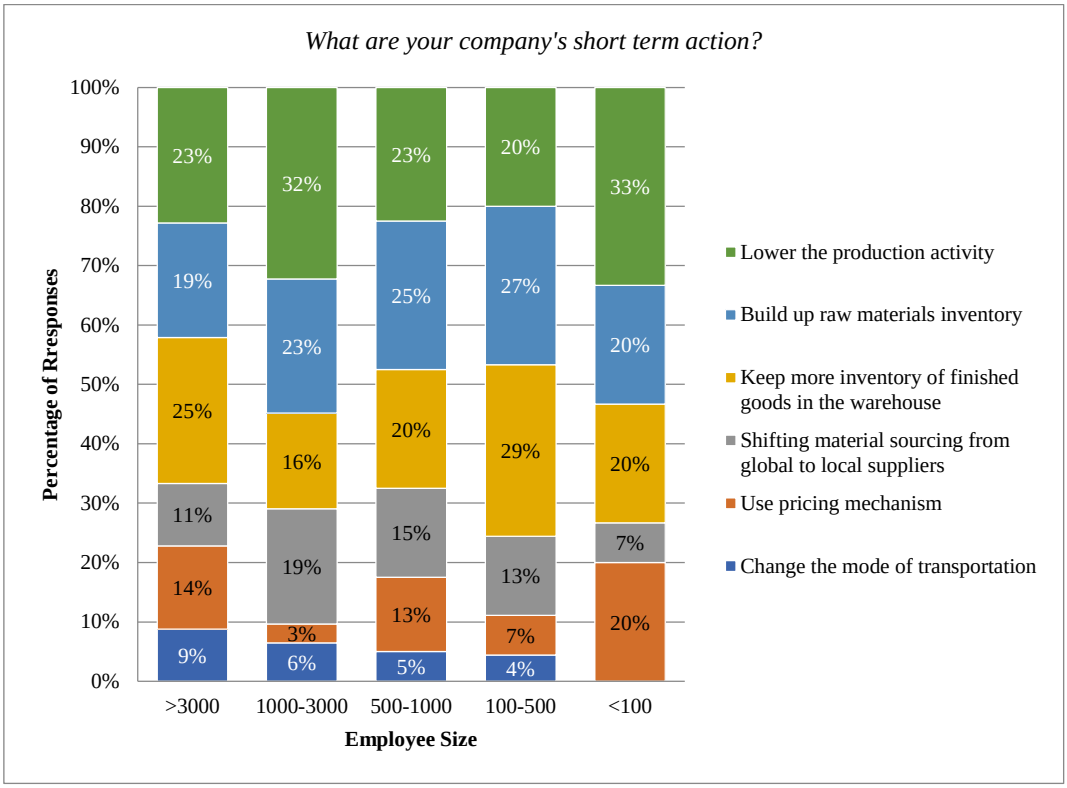


Figure 5.3 Manufacturing Companies Preferences on Short Term Actions
(Employee Size View)

Figure 5.3 shows that the stakeholders in 1000-3000 & <100 employees companies mostly prefer to lower their production activity as their short term action (32-33 percent of responses). In comparison, those in >3000 and 100-500 employees companies mostly prefer to keep more finished goods inventory as their short term SC action.

On the other end, the majority of responses in the 500-1000 employees section indicate that they are more likely to apply raw materials inventory buildup as their immediate action.

There are two other short term actions, namely shifting material sourcing from global to local suppliers and pricing mechanisms. The former is more-likely preferred by stakeholders in 1000-3000 employees companies (19 percent of the responses), while the latter is more-likely preferred by those in less than 100 employees companies (20 percent of the responses).

5.2.2 Descriptive Statistic Analysis on Preferred Long Term Strategies

In this part, descriptive analysis or interpretation on which strategies the companies will pursue in the long term–i.e., beyond COVID-19 period–is conducted. There are three interpretations on this part, which are general/overall, industry classification, and company size classification based analyses, aim to provide broad insight to be adapted by specific manufacturing companies in terms of industry and size.

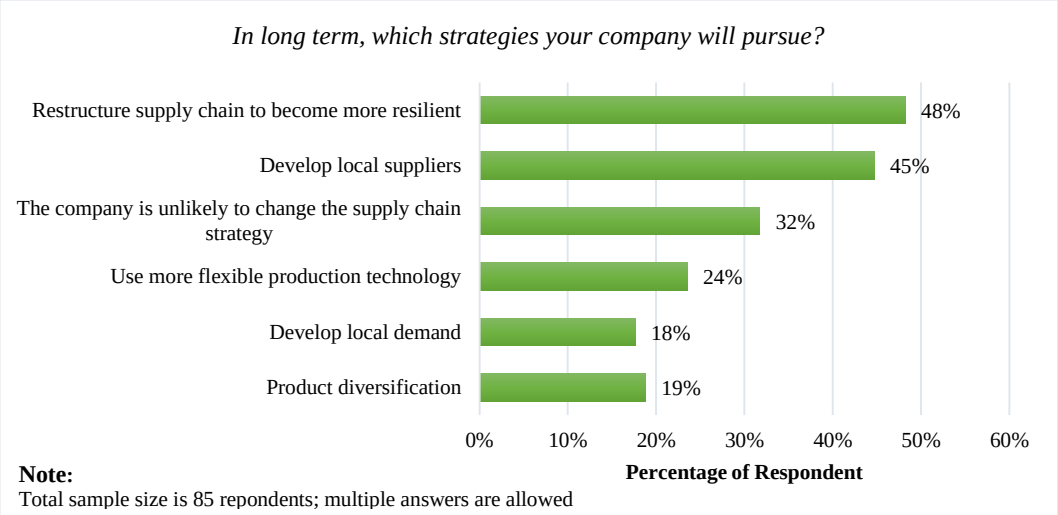


Figure 5.4 Manufacturing Companies Preferences on Pursuing Long Term Strategies

Figure 5.4 represents the broad view on manufacturing companies' preferences of which strategies will pursue in the long term. The result shows that many of the respondents (48 percent) say they prefer to restructure the supply chain to become more resilient as their strategy to overcome COVID-19 disruption. A relatively equal proportion of respondents (45 percent) prefer to develop local suppliers as their strategy. On the other hand, a medium portion of the respondents (32 percent) say that the company is unlikely to change the current supply chain strategy due to several reasoning.

The reason might due to the current SC strategy is already appropriate and consider any other improvement area, e.g., personnel management, health & safety, working capital management, etc.

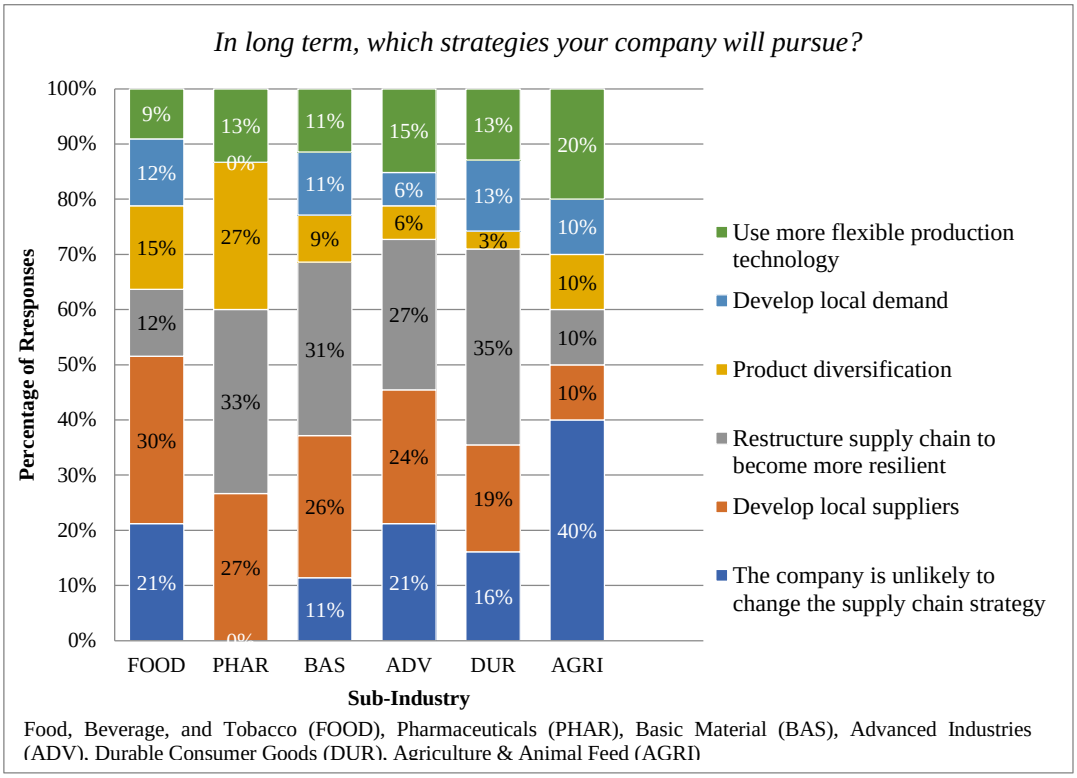


Figure 5.5 Manufacturing Companies Preferences on Pursuing Long Term Strategies (Sub-Industry View)

Figure 5.5 shows that on average, about 66 percent of responses say their companies will restructure the supply chain to become more resilient, develop local suppliers, or apply no change to SC strategy (25, 23, 18 percent, respectively). In comparison, an additional 31 percent of responses are fairly divided across other long term strategies. Moreover, stakeholders in PHAR, BAS, ADV, DUR, industries mostly prefer to restructure their supply chain as the primary long term strategy to overcome COVID-19 disruption and growth their businesses (27 till 35 percent of responses), while those in FOOD industry mostly prefer to develop local supplier. On the other end, the majority of stakeholders' responses in AGRI industries states they are unlikely to change the current SC strategy.

Moreover, there are two other long term strategies, namely, develop local demand in Indonesia and use more flexible production technology. The former is more-likely preferred by stakeholders in FOOD and DUR industries (12-13 percent of responses), while the latter is more-likely preferred by those in AGRI (20 percent of responses).

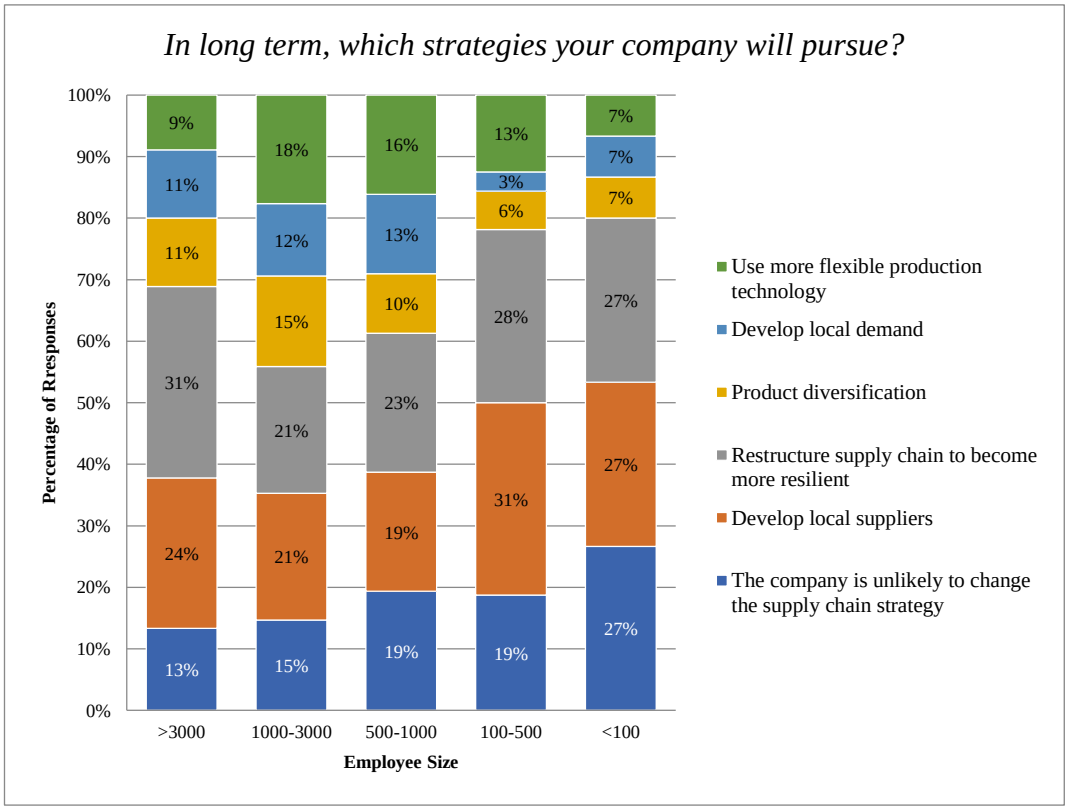


Figure 5.6 Manufacturing Companies Preferences on Pursuing Long Term Strategies (Employee Size View)

Figure 5.6 shows that the stakeholders in various employee size companies have a relatively balanced preference between two leading strategies; restructure supply chain and develop local suppliers; additionally, companies with 100-500 employees are the most likely to applied those two strategies. Moreover, companies with >3000 employees and 500-1000 employees are mostlikely to adapt restructures supply chain strategy.

Moreover, companies with 1000-3000 employees are the most likely to adopt a diversification strategy on their product or utilize more flexible technology on producing them.

On the other end, companies with less than 100 employee size are the most unlikely to change their company supply chain strategy regarding the COVID-19 disruption in the early period. In comparison, those with more than 100 employee size have an average of 10 percent responses say unlikely to change the current supply chain strategy.

CHAPTER 6
CONCLUSION AND SUGGESTION

6.1 Conclusion

Several conclusions that can be derived from this research are as follows.

1. The initial impact of COVID-19 is different among the type of industries which has distinct odds of being exposed to severe COVID-19 initial impact.
2. Based on the inferential analysis using ordinal logistic regression (OLR), the root causes/factors that determine the severity of COVID-19 initial impact of Indonesian manufacturing companies are material sourcing from affected foreign countries (MS) and decrease in customer demand (DD).
3. Based on the conducted survey, the majority of the Indonesian manufacturing companies prefer to lower production activity as their main short term action and to restructure the supply chain to become more resilient as their long term strategy to overcome COVID-19 disruption. However, the adaptation and implementation of both short term action and long term strategy should consider the industry type and business size of the company.

6.2 Suggestion

Several suggestions for future research are as follows.

1. Further impact assessment study should consider the next phase of COVID-19 development in Indonesia.
2. Future works should also consider other sectors to expand the scope.

REFERENCES

Ari E, Yildiz Z. (2014). *Parallel Lines Assumption In Ordinal Logistic Regression And Analysis Approaches. International Interdisciplinary Journal of Scientific Research* ISSN: 2200-9833, pp. 8-23.

Agresti, A. (2019). *An introduction to categorical data analysis* 3rd ed., Hoboken: Wiley.

Aven T. (2017). *How some types of risk assessments can support resilience analysis and management*. *Reliability Engineering and System Safety* 167, 536–543.

Brown, R. (2020). *The Coronavirus Threat To Supply Chains Is A Big Risk*. *Forbes*. Available at: https://www.forbes.com/sites/randybrown/2020/02/10/the-coronavirus-threat-to-supply-chains-is-a-big-risk/#4fc795c23d96 [Accessed March 24 (2020)].

BS ISO (2018). *Risk Management: Principles and Guidelines (BS ISO 31000:2009)*. British Standards, London.

Chamola, V., et al. (2020). *A Comprehensive Review of the COVID-19 Pandemic and the Role of IoT, Drones, AI, Blockchain and 5G in Managing its Impact*. IEEE Access, 1–1.

Chenneveau, D, et. Al. (2020). A resilient return for Asia's manufacturing and supply chains?. *McKinsey & Company Operations Practice*.

CNN, I.M. (2020). *Sri Mulyani Khawatir Corona Ganggu Rantai Pasok*. *ekonomi*. Available at: https://www.cnnindonesia.com/ekonomi/20200318155945-532-484598/sri-mulyani-khawatir-corona-ganggu-rantai-pasok [Accessed March 26 (2020)].

Cruz, A. & Krausmann, E. (2008). *Damage to offshore oil and gas facilities following hurricanes Katrina and Rita: An overview. Journal of Loss Prevention in the Process Industries,* 21(6), pp.620–626.

Fullerton, A. S. and Xu, J. (2012). *The Proportional Odds with Partial Proportionality Constraints Model for Ordinal Response Variables, Social Science Research,* 41, 182-198 p.

GAIKINDO (2020). *Indonesian Automobile Industry Data*. Available at: https://www.gaikindo.or.id/indonesian-automobile-industry-data/ [Accessed July 25, 2020].

GTPP (2020). *Situasi Virus Corona. Covid19.go.id*. Available at: https://www.covid19.go.id/situasi-virus-corona/ [Accessed April 12 (2020)].

Hardy, G.H. & Wright, E.M., 1975. *An Introduction to the theory of numbers*, Oxford, Great Britain: Clarendon Pr. , footnote to paragraph 1.7: *"log x is, of course, the 'Naperian' logarithm of x, to base e. 'Common' logarithms have no mathematical interest"*.

Hallikas, J. et al. (2004). *Risk management processes in supplier networks, International Journal Production Economics 90* pp. 47-58.

Heckmann, I., Comes, T. & Nickel, S. (2015). *A critical review on supply chain risk – Definition, measure and modeling*. Omega, 52, pp.119–132.

Hosmer, D.W., Lemeshow, S. & Sturdivant, R.X. (2013). *Applied logistic regression*, Hoboken, NJ: Wiley.

Ivanov, D. (2020). *Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review*, 136, p.101922.

Ivanov, D. & Dolgui, A. (2019). *New disruption risk management perspectives in supply chains: digital twins, the ripple effect, and resileanness*. *IFAC-PapersOnLine*, 52(13), pp.337–342.

Jakarta Post (2020). Indonesia's economic growth may dive to 4.5% in Q1: Finance minister. *The Jakarta Post*. Available at: https://www.thejakartapost.com/news/2020/03/18/indonesias-economic-growth-may-dive-to-4-5-in-q1-finance-minister.html [Accessed March 26 (2020)].

Kim, K. & Bui, L. (2019). *Learning from Hurricane Maria: Island ports and supply chain resilience. International Journal of Disaster Risk Reduction*, 39, p.101244.

Linton, T. & Vakil, B. (2020). *Coronavirus Is Proving We Need More Resilient Supply Chains*. *Harvard Business Review*. Available at: https://hbr.org/2020/03/coronavirus-is-proving-that-we-need-more-resilient-supply-chains [Accessed March 25 (2020)].

Mackenzie, C.A., Santos, J.R. & Barker, K. (2012). *Measuring changes in international production from a disruption: Case study of the Japanese earthquake and tsunami*. *International Journal of Production Economics*, 138(2), pp.293–302.

Mahidhar, V. (2006). *Managing in the Face of Exchange-Rate Uncertainty*, New York, USA: Deloitte Services LP.

Mirae Asset Sekuritas (2020). Indonesia Stock Market Composite Changes.

Mirae Asset Sekuritas (2020). Indonesia Stock Market Sectoral Indices Changes

Mukaka M. M. (2012). *Statistics corner: A guide to appropriate use of correlation coefficient in medical research*. *Malawi medical journal : the journal of Medical Association of Malawi, 24(3),* 69–71.

Renn, O. (2010). *Risk governance: coping with uncertainty in a complex world*, London: Earthscan.

Sabouhi, F., Pishvaee, M.S. & Jabalameli, M.S. (2018). *Resilient supply chain design under operational and disruption risks considering quantity discount: A case study of pharmaceutical supply chain*. *Computers & Industrial Engineering*, 126, pp.657–672.

Schlegel, G.L. & Trent, R.J. (2014). *Supply chain risk management: an emerging discipline*, Boca Raton: CRC Press.

Sheffi, Y. (2005). *The resilient enterprise: overcoming vulnerability for competitive advantage*, Cambridge, MA: MIT Press.

Sheffi, Y. (2015). *The power of resilience how the best companies manage the unexpected*, Cambridge, MA: MIT Press.

Shen, W., Yang, C., & GAO, L. (2020). *Address Business Crisis Caused by COVID-19 with Collaborative Intelligent Manufacturing Technologies. IET Collaborative Intelligent Manufacturing.*

Sherman, E. (2020). *94% of the Fortune 1000 are seeing coronavirus supply chain disruptions*. *Fortune*. Available at:

https://fortune.com/2020/02/21/fortune-1000-coronavirus-china-supply-chain-impact/ [Accessed March 25 (2020)].

Smith, J. et al. (2020). *COVID-19: Considering the potential business impacts for Indonesia*. Jakarta, Indonesia: PricewaterhouseCoopers.

Sokal, R.R. & Rohlf, F.J (1995). *Biometry: the principles and practice of statistics in biological research. 3rd ed*, New York, NY: W.H. Freeman

Stewart, G. et al. (2019). *Predicting mental health help seeking orientations among diverse Undergraduates: An ordinal logistic regression analysis.* Journal of Affective Disorders, 257, pp.271–280.

TheGlobalEconomy (2020). *Indonesia Consumption as percent of GDP*, December (2019) - data, chart. *TheGlobalEconomy.com*. Available at: https://www.theglobaleconomy.com/Indonesia/consumption_GDP/ [Accessed March 26 (2020)].

Tubb, R. (2005). *MMS director overview impact of hurricanes Katrina and Rita. Pipeline & Gas Journal.*

UN COMTRADE, (2020). *UN Comtrade: International Trade Statistics.* Available at: https://comtrade.un.org/data/ [Accessed July 28, 2020].

Vaccaro, Joan. (2014). Re: *Does multicollinearity exist for ordinal logistic regression? How can we run it in SPSS?*. Retrieved from: https://www.researchgate.net/post/Does_multicollinearity_exist_for_ordinal_logistic_regression_How_can_we_run_it_in_SPSS/5329870bcf57d76e268b4603/citation/download.

WHO (2020). *Novel Coronavirus (COVID-19) Situation*. *Experience*. Available at:https://experience.arcgis.com/experience/685d0ace521648f8a5beeeee1b9125cd [Accessed April 12 (2020)].

Walters, S.J. (2004). *Sample size and power estimation for studies with health related quality of life outcomes: a comparison of four methods using the SF-36. Health Qual Life Outcomes* 2, 26.

Wieland, A. and Marcus Wallenburg, C. (2012). *Dealing with supply chain risks: Linking risk management practices and strategies to performance*, *International Journal of Physical Distribution & Logistics Management*, Vol. 42 No. 10, pp. 887-905.

Wassener, B. (2011). *Exports Drop more than Expected in Japan*. The International Herald Tribune, April 21.

WTO (2013). *World Trade Report: Trends in international trade*. Switzerland: World Trade Organization.

Zulkhibri, M. (2020). *Economic Impact of COVID-19 Outbreak on ASEAN*, Jakarta, Indonesia: Association of Southeast Asian Nations (ASEAN).

Zhalechian, M., Torabi, S.A. & Mohammadi, M. (2018). *Hub-and-spoke network design under operational and disruption risks. Transportation Research Part E: Logistics and Transportation Review*, 109, pp.20–43.

APPENDIX

APPENDIX A. SURVEY INSTRUMENT

Company Characteristic

Your name *

Short-answer text

Your position *

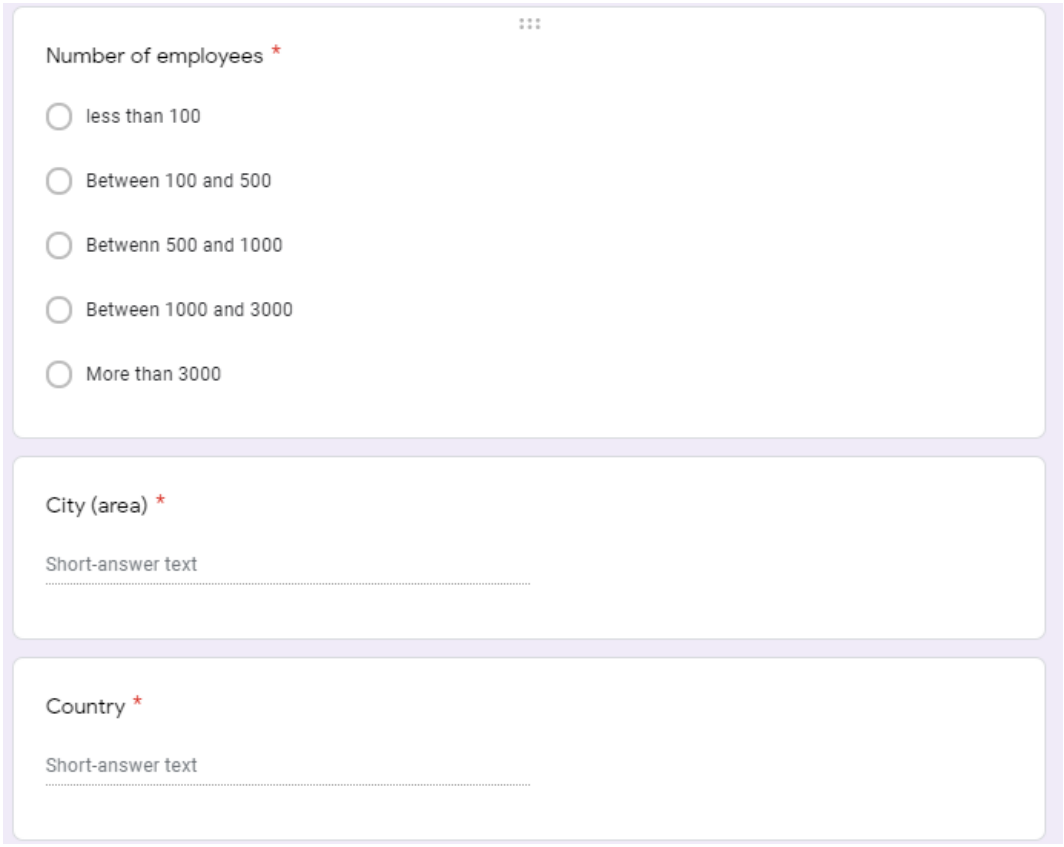
Short-answer text

The name of company you work for *

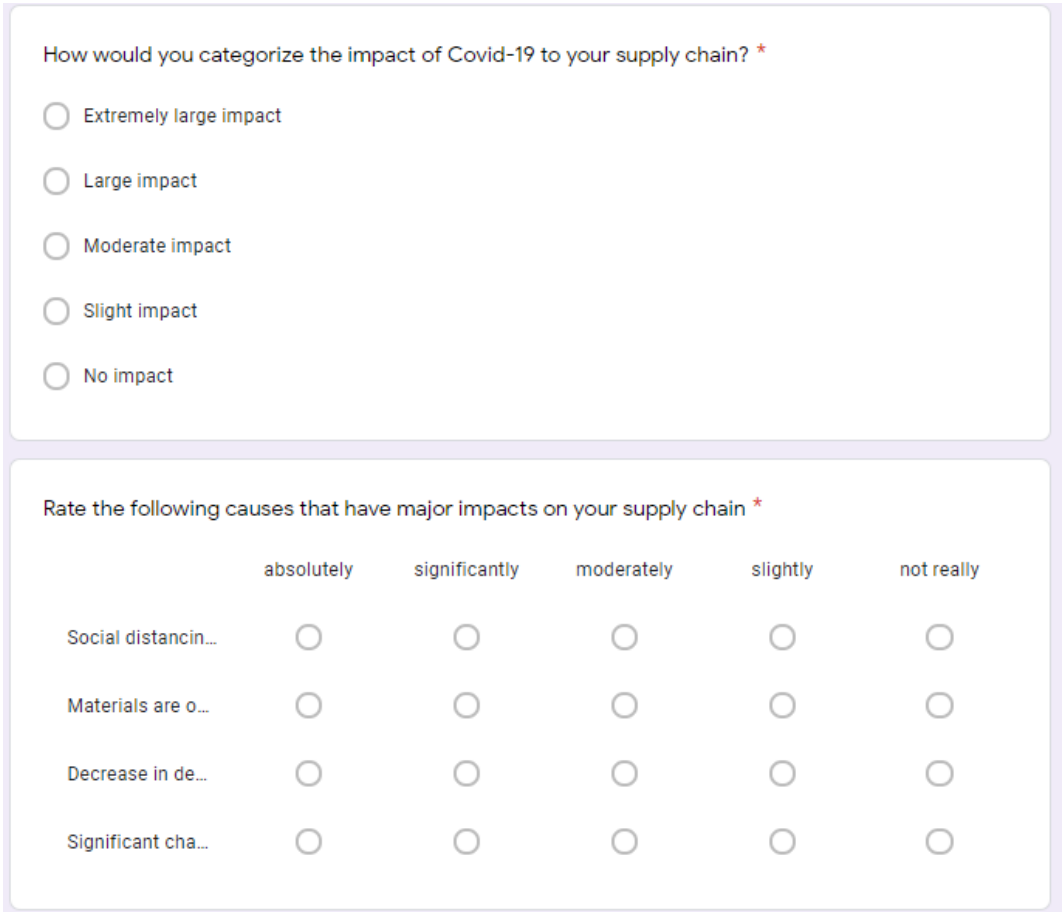
Short-answer text

In which category of manufacturing sector does your company belong *

- Food, Beverage, and Tobacco
- Textiles, Leather, and Apparel
- Wood, Paper, and Printing
- Pharmaceutical
- Automotive
- Computer and Electronics
- Primary Metal, Fabricated Metal, and Machinery
- Building materials
- Other...



COVID-19 Initial Impact and Root Cause



Company short term action and long term strategy

What are your company's short term responses? (In COVID-19 time) Choose all that apply. *

- [ ] Build up raw materials inventory
- [ ] Lower the production activity
- [ ] Shifting material sourcing from global to local suppliers
- [ ] Keep more inventory of finished goods in the warehouse
- [ ] Use pricing mechanism
- [ ] Change the mode of transportation

In the long term (beyond COVID-19 time), which of the following strategies is likely your company will pursue? Click all that apply. *

- [ ] Restructure supply chain to become more resilient
- [ ] Develop local suppliers
- [ ] Develop local demand
- [ ] Product diversification
- [ ] Use more flexible production technology
- [ ] The company is unlikely to change the supply chain strategy

You can add briefly any issue here that you think is important in managing supply chain during the Covid-19 crisis (this is optional)

Long-answer text

BIOGRAPHY

Steven Theja is a bachelor student majoring in Industrial and Systems Engineering at Institut Teknologi Sepuluh Nopember (ITS). During his studies, he has maintained a top 1% GPA of his cohort, involved in various organizational activities, and participated in several international summer programs. He also had been granted a full scholarship from the Ministry of Education and Culture (Beasiswa Unggulan Kemendikbud) due to his performance.

His previous working experience as a project intern at one leading logistics company in Indonesia has refined his practical knowledge of operations. He has been assigned to the transportation asset evaluation and improvement project, which improved the utilization rate and conserved projected ~490 million rupiahs of annual operational expense.

Besides his professional experience, he also contributed to several organizations, including, but not limited to, ITS International Office (as divisional coordinator), Petrolida (as career talk coordinator), and Logistics and Supply Chain Management Laboratory (as teaching assistant). He can be reached out through steven_theja@yahoo.com (email) or linkedin.com/in/steven-theja-ba66a5160/ (linked.in)