Measuring the Impact of COVID-19 on Singapore's Economy Using the Dynamic Inoperability Input-output Model

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SCHOOL OF PHYSICAL AND MATHEMATICAL SCIENCES

A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF BACHELOR OF SCIENCE IN MATHEMATICAL SCIENCES

2026

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Abstract

This project studies the impact of COVID-19 on Singapore's economy using the Dynamic Inoperability Input-Output Model (DIIM) [1,2]. The DIIM is useful because it models how disruptions in one sector spread to other sectors through input-output linkages and how the economy recovers over time. Using Singapore's 2019 input-output (IO) table [3], the economy is aggregated into 15 sectors to match the workforce data used to estimate initial inoperability.

In this study, initial inoperability is calculated based on the share of unavailable workers in each sector due to Covid-19, adjusted by how dependent the sector is on labour as an input. The shock period is set to Singapore's "circuit breaker" from 7 April to 1 June 2020 (55 days) [4,5], and recovery is simulated over a longer horizon, with a near-normal level assumed after 751 days. The model produces sector-level paths of inoperability and cumulative economic losses, which are used to identify vulnerable sectors and support recovery prioritisation.

A sensitivity analysis tests how changes in lockdown duration affect total losses. The project also evaluates example risk management policies using a surrogate worth trade-off (SWT) approach [6] to compare policy costs against the economic losses avoided. Finally, the study explores a PCA-based approach for identifying key sectors using only the IO table and compares its performance with DIIM-based selection through simulation.

Acknowledgement

I would like to express my sincere gratitude to my supervisor(s) for their guidance, encouragement, and constructive feedback throughout this project. Their expertise and patience were invaluable in shaping the direction of the work and in helping me develop my research and writing skills.

I am also grateful to the members of my committee and the faculty in the department for their insightful comments and support. I would like to acknowledge the technical and administrative staff whose assistance made it possible to carry out the practical aspects of this work.

I would like to thank my colleagues and friends for the discussions, collaboration, and encouragement that made the process both productive and enjoyable. Their willingness to share ideas and offer help at key moments is deeply appreciated.

Finally, I am profoundly thankful to my family for their unwavering support, understanding, and motivation. Their confidence in me has been a constant source of strength throughout my studies.

Chapter 1

Introduction

When COVID-19 shut down the Singapore economy in April 2020, policymakers faced an urgent question: which sectors were suffering the most, and where should recovery resources be prioritised? While Gross domestic product (GDP) data showed that the economy contracted, they provided no insight into how disruptions rippled through interconnected sectors, what the recovery process was like, or how different policy interventions would trade off cost against benefit.

Given that modern economies are highly interdependent, when one sector stops producing, it does not only affect workers in that sector but also deprives other sectors of the critical inputs they need. A disruption to the construction sector not only harms construction workers but also manufacturers of building materials, transport companies, and equipment suppliers. Understanding these cascading effects requires a framework that captures how economic sectors depend on each other and how disruptions propagate over time.

The Inoperability Input-Output Model (IIM) and its dynamic extension (DIIM) can provide this capability [1,2]. The Shanghai COVID-19 study demonstrated how the DIIM could quantify which sectors experienced the highest production losses relative to its inital production level (inoperability) and which suffered the largest absolute economic damage [2]. That research also showed how policymakers could use the model to compare alternative risk management strategies (eg, whether to invest in early prevention measures or in accelerating recovery) by calculating the return on investment for each option [2]. This study applies the DIIM framework to Singapore's COVID-19 crisis to provide data for recovery policy decisions.

The Leontief input-output model, developed by 1973 Nobel laureate Wassily Leontief, is the foundation for understanding sectoral interdependencies [7]. It represents how different sectors of an economy rely on each other's outputs as inputs, capturing the relationships that define an economy in equilibrium. The basic equation is simple: total output equals intermediate consumption plus final demand.

However, the Leontief model is static. It describes an economy at rest, not an economy in crisis and recovery. To analyse disruptions, researchers developed the Inoperability Input-Output Model (IIM), which measures ”inoperability”. This term is defined as the normalised production loss of each sector expressed on a scale from 0 (normal operation) to 1 (complete shutdown). The IIM measures how an initial shock in one sector propagates through input-output linkages to reduce production in other sectors.

The DIIM extended this framework further by adding time. Real recoveries are not instantaneous. Sectors gradually restore production as supply-demand imbalances resolve. The DIIM models this recovery process using a resilience coefficient for each sector, showing how inoperability and economic losses evolve from the initial shock through full recovery.

Singapore is a city-state heavily dependent on international trade. It experienced both the direct effects of lockdown restrictions and the indirect effects of global supply chain disruptions. With major economic sectors that interact intensively, from manufacturing and financial services to construction and hospitality, we believe that Singapore has been strongly affected by the pandemic.

The objective of this study is to (1) quantify the impact of COVID-19 on Singapore's economy across sectors using the DIIM framework, (2) identify which sectors experienced the highest inoperability and economic losses, (3) understand how disruptions cascaded through supply chains, and (4) evaluate whether alternative risk management policies would have been cost-effective.

Chapter 2

Methodology

This paper uses the DIIM model to assess the impacts of COVID-19 on the inoperability and economic losses of Singapore's sectors. The DIIM model is derived from the Leontief input-output model and is used to investigate the higher-order transmission effect of input-output linkages between sectors on inoperability. Using the DIIM model requires first introducing the concept of "inoperability", which is defined as follows:

$$\text{Inoperability} = \frac{\text{As Planned Production} - \text{Degraded Production}}{\text{As Planned Production}} \tag{2.1}$$

Where "As Planned Production" represents the output level of a sector under normal production, and "Degraded Production" represents the output level of a sector after being shocked in its production process. In this paper, the shock comes from the reduction in demand due to the lockdown caused by COVID-19. The difference between "As Planned Production" and "Degraded Production" describes the degree of output decline of a sector. "Inoperability" takes values between 0 and 1, with higher values indicating greater damage to production caused by the shock. A value of 1 means the shocked sector has completely lost its production capacity, while a value of 0 means the sector is producing at a normal level.

Using the concept of inoperability defined above, the IIM model can be derived from the Leontief input-output model, as shown in Equation (2.2).

$$x = Ax + c \tag{2.2}$$

Where x is the total output vector; A is the technical coefficient matrix; c is the final demand vector. If we define the output levels and the final demand vector of some shocked sectors as $\tilde{x}$ and $\tilde{c}$ respectively, then based on equation (edit), we can construct the input-output relationship between sectors after the shock:

Subtracting Equation (2.2) from the shocked-economy formulation:

$$x - \tilde{x} = A(x - \tilde{x}) + (c - \tilde{c}) \tag{2.3}$$

Defining $\hat{x}$ as a diagonalized matrix of the output vector and left multiplying $\hat{x}^{-1}$ on both sides of Equation (2.3):

$$\hat{x}^{-1}(x - \tilde{x}) = \hat{x}^{-1}A(x - \tilde{x}) + \hat{x}^{-1}(c - \tilde{c}) \tag{2.4}$$

Let $q = \hat{x}^{-1}(x - \tilde{x})$, $A^* = \hat{x}^{-1}A\hat{x}$, $c^* = \hat{x}^{-1}(c - \tilde{c})$; then Equation (2.5) can be derived, which is the IIM model.

$$q = A^*q + c^* \tag{2.5}$$

The details of each matrix in the IIM model are shown in Equations (2.6), (2.7), and (2.8):

$$q = \hat{x}^{-1}(x - \tilde{x}) = \begin{bmatrix} \frac{1}{x_1} & 0 & \cdots & \cdots & 0 \\ 0 & \ddots & & & \vdots \\ \vdots & & \frac{1}{x_i} & & \vdots \\ \vdots & & & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & \frac{1}{x_n} \end{bmatrix} \begin{bmatrix} x_1 - \tilde{x}_1 \\ \vdots \\ x_i - \tilde{x}_i \\ \vdots \\ x_n - \tilde{x}_n \end{bmatrix} \tag{2.6}$$

$$A^* = \hat{x}^{-1} A \hat{x} = \begin{bmatrix} a_{11}\frac{x_1}{x_1} & \cdots & a_{1j}\frac{x_j}{x_1} & \cdots & a_{1n}\frac{x_n}{x_1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1}\frac{x_1}{x_i} & \cdots & a_{ij}\frac{x_j}{x_i} & \cdots & a_{in}\frac{x_n}{x_i} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{n1}\frac{x_1}{x_n} & \cdots & a_{nj}\frac{x_j}{x_n} & \cdots & a_{nn}\frac{x_n}{x_n} \end{bmatrix} \tag{2.7}$$

$$\mathbf{c}^* = \hat{\mathbf{x}}^{-1}(\mathbf{c} - \tilde{\mathbf{c}}) = \begin{bmatrix} \frac{1}{x_1} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \frac{1}{x_i} & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & \cdots & \frac{1}{x_n} \end{bmatrix} \begin{bmatrix} c_1 - \tilde{c}_1 \\ \vdots \\ c_i - \tilde{c}_i \\ \vdots \\ c_n - \tilde{c}_n \end{bmatrix} \tag{2.8}$$

The IIM model can be extended to the DIIM model by introducing a time variable and an elasticity coefficient matrix describing the recovery capacity of sectors. The discrete form of the DIIM model is:

$$q(t+1) = q(t) + K\left[A^* q(t) + c^*(t) - q(t)\right] \tag{2.9}$$

Where K is the elasticity coefficient matrix describing the recovery capacity of sectors after being shocked in production. Assuming that the recovery capacity of a sector depends only on its own production, and is unrelated to the production linkages with other sectors, thus K is a diagonal matrix with diagonal elements greater than 0. The larger the diagonal elements, the stronger the recovery capacity of the corresponding sector in response to shocks. t is the discrete time variable, and q(t) represents the sectoral inoperability vector at time t. Equation (2.9) states that the inoperability of a sector in a period depends on the inoperability in the previous period and the sector's recovery adjustment capacity. Approximating Equation (2.9) to differential form:

$$\dot{q}(t) = K\left[A^* q(t) + c^*(t) - q(t)\right] \tag{2.10}$$

Solving Equation (2.10) we can get the equation describing the evolution of sectoral inoperability over time:

$$q(t) = e^{-K(I-A^*)t} q(0) + \int_0^t K e^{-K(I-A^*)(t-z)} c^*(z)\, dz \tag{2.11}$$

Assuming that the demand shock c^* remains unchanged, and $c^* = 0$, then Equation (2.11) can be simplified to:

$$q(t) = e^{-K(I-A^*)t} q(0) \tag{2.12}$$

Where $q(0)$ represents the initial inoperability vector of sectors after being shocked. As time goes by, the inoperability changes at a rate of $e^{-K(I-A^*)t}$. The initial inoperability $q(0)$ is calculated as:

$$\text{Sector Initial Inoperability} = \frac{\text{Unavailable Workforce}}{\text{Size of Workforce}} * \frac{\text{LAPI}}{\text{Sector Output}} \tag{2.13}$$

where the left side of the formula is the ratio between the number of unavailable workers due to COVID-19 in each sector and the total number of workers in each sector, and the right hand side is how much each sector depends on its workforce as inputs.

Finally, we calculate the elasticity coefficient matrix K describing the recovery capacity of sectors. According to Equation (2.12), the inoperability of sector i at time t is:

$$q_i(t) = q_i(0)e^{-k_i(1-a_{ii}^*)t} \tag{2.14}$$

From Equation (2.14), we can derive the calculation formula for k_i:

$$k_i = \frac{\ln[q_i(0)/q_i(T)]}{T_i(1-a_{ii}^*)} \tag{2.15}$$

Where $q_i(0)$ is the initial inoperability of sector i; $q_i(T)$ is the inoperability of sector i at time T; a_{ii}^* is the element on the diagonal of matrix A^*, representing the self-dependence of sector i.

Under the analytical framework of the DIIM model, the economic losses caused by the shock to sector can be represented by Equation (2.16):

$$EL_i = x_i \int_{t=0}^{t=T} q_i(t)\,dt \tag{2.16}$$

Where x_i is the output value of sector i at time t under normal production, and n is the number of sectors used in the input-output table of this study.

Chapter 3

Data and Model Parameters

3.1 Data selection

3.1.1 Singapore input-output table

The IO transaction data for Singapore is obtained from the Department of Statistics, Singapore [3]. This project uses the 2019 IO table because it is the closest year before COVID-19 and represents the pre-pandemic baseline. The available IO table is aggregated into 20 broad sectors, and this study further aggregates them into 15 sectors to match the Ministry of Manpower dataset used to compute initial inoperability. The mapping is provided in Appendix A (Table 7.1).

From the aggregated IO table, the technical coefficient matrix A is computed. A cross-section of A is provided in Appendix A (Table 7.2).

3.1.2 Initial inoperability data

Initial inoperability is calculated using:

$$\text{Sector Initial Inoperability} = \frac{\text{Unavailable Workforce}}{\text{Size of Workforce}} * \frac{\text{LAPI}}{\text{Sector Output}} \tag{3.1}$$

The workforce unavailability component is obtained from Ministry of Manpower data, and the labour dependence component is derived from the IO table. The initial inoperability values for the 15 aggregated sectors are listed in Appendix A (Table 7.3).

3.2 Model parameters

3.2.1 Lockdown duration

Singapore's lockdown measures ("circuit breaker") were implemented from 7 April to 1 June 2020, which is 55 days [4, 5]. This project sets the shock duration to 55 days.

3.2.2 Final inoperability

In late April 2022 (751 days after the start of lockdown), Singapore's DORSCON level was lowered from Orange to Yellow, and employees were allowed to return to workplaces. This dissertation assumes a final inoperability $q_i(T_i) = 1\%$, meaning economic activity returns to 99% of pre-lockdown levels after 751 days.

Chapter 4

Results

4.1 Inoperability and Economic Loss

Figure 4.1 shows the simulated inoperability trajectories for the 15 aggregated sectors over the shock-and-recovery horizon. Inoperability rises during the shock window as disruptions propagate through input–output linkages, and it declines during recovery as sectors gradually restore production. Because sectors are interconnected, each sector experiences both direct effects from its own disruption and indirect effects transmitted from other sectors.

Figure 4.2 presents the corresponding economic-loss evolution. Sectors with larger baseline outputs can accumulate large absolute losses even if their relative inoperability is not the highest, while smaller sectors may show high inoperability but smaller absolute losses.

The top 15 sectors with the highest inoperability are: [to be inserted].

The top 15 sectors with the highest cumulative economic losses are: [to be inserted].

4.2 Identifying vulnerable Sectors

This section identifies vulnerable sectors using two measures: inoperability (relative production loss) and cumulative economic loss (absolute output loss). Figure 4.3 plots each sector using its rank in inoperability (y-axis) and its rank in economic loss (x-axis), so sectors that rank high in both measures are easy to identify.

To support prioritisation, we define ordinal ”zones” (Top 5, Top 7, Top 10) as the intersection of sectors that appear in the top-k rankings of both measures. For example, the Top 5 zone contains sectors that are simultaneously ranked in the top five for both inoperability and economic loss, highlighting sectors that are both heavily disrupted and economically important.

Differences between the two rankings are expected. For example, a sector such as Arts, Entertainment & Recreation may rank high in inoperability but lower in economic loss if its baseline output is smaller than that of other sectors. Overall, Figure 4.3 provides a practical view for decision-making when policymakers want to balance restoring functionality (low inoperability) and reducing macroeconomic damage (low loss).

4.3 Sensitivity Analysis

To study the effect of lockdown duration, we simulate three lockdown lengths: 40, 55, and 70 days while keeping other parameters unchanged. Across sectors, longer lockdown durations lead to higher cumulative economic losses. The results also suggest the sector rankings of economic loss remain broadly consistent under moderate changes in lockdown duration. Figure 4.4 shows the total economic loss for each of the sector under different lockdown durations.

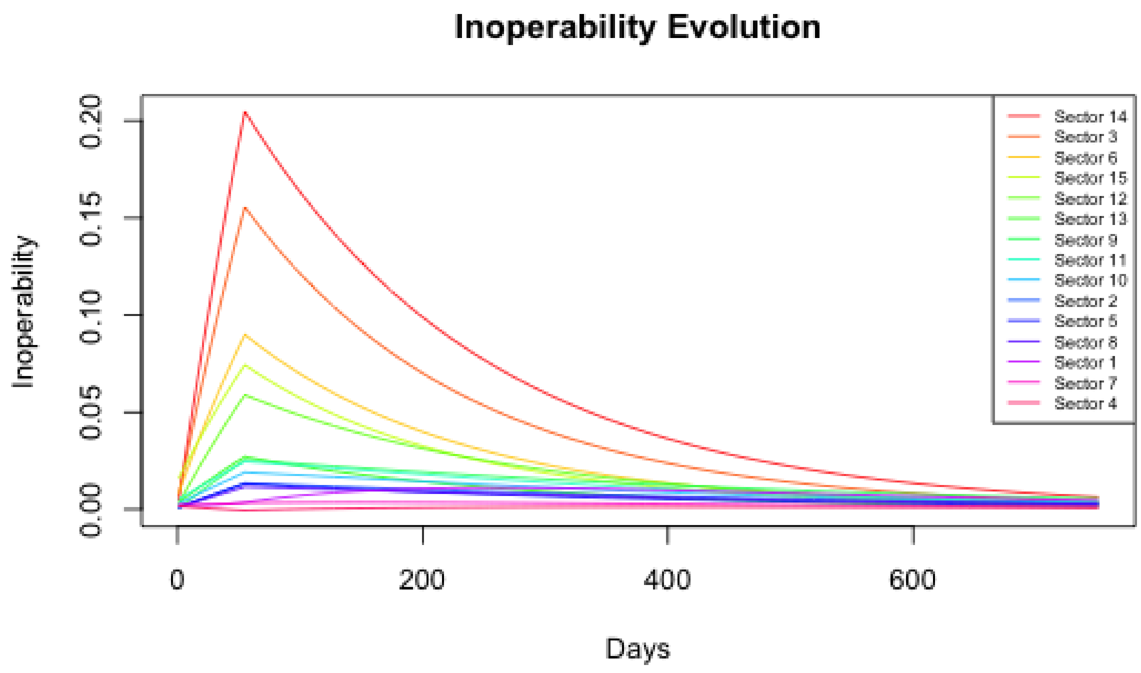

Figure 4.1: Inoperability evolution over the shock-and-recovery horizon.

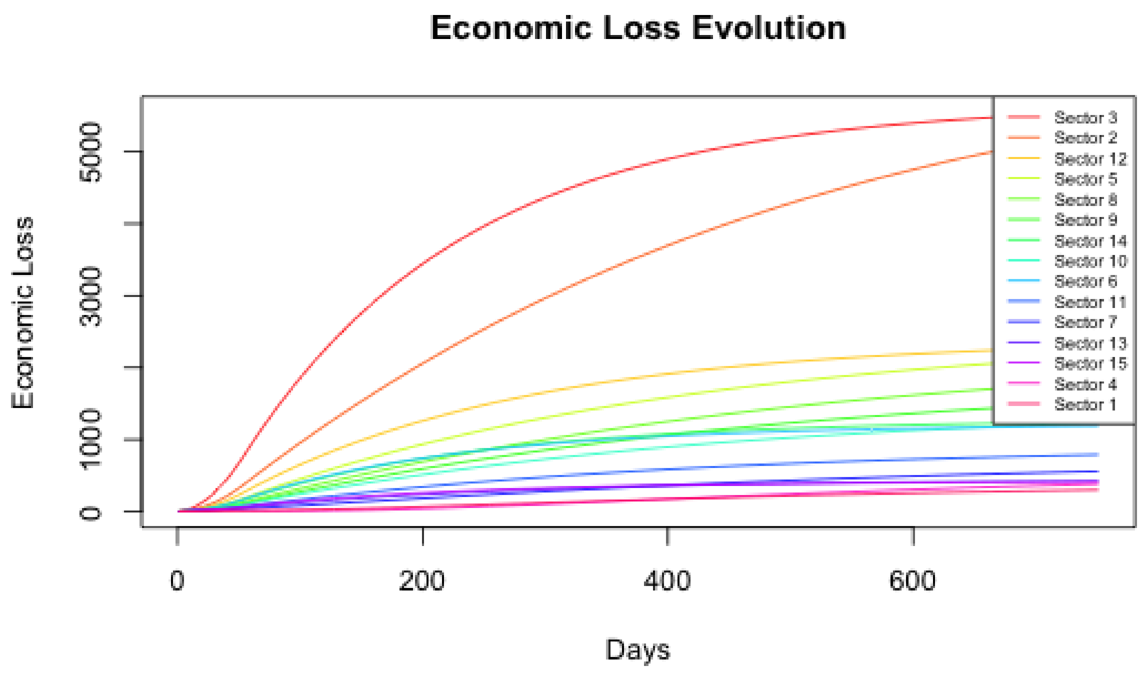

Figure 4.2: Economic loss evolution over the shock-and-recovery horizon.

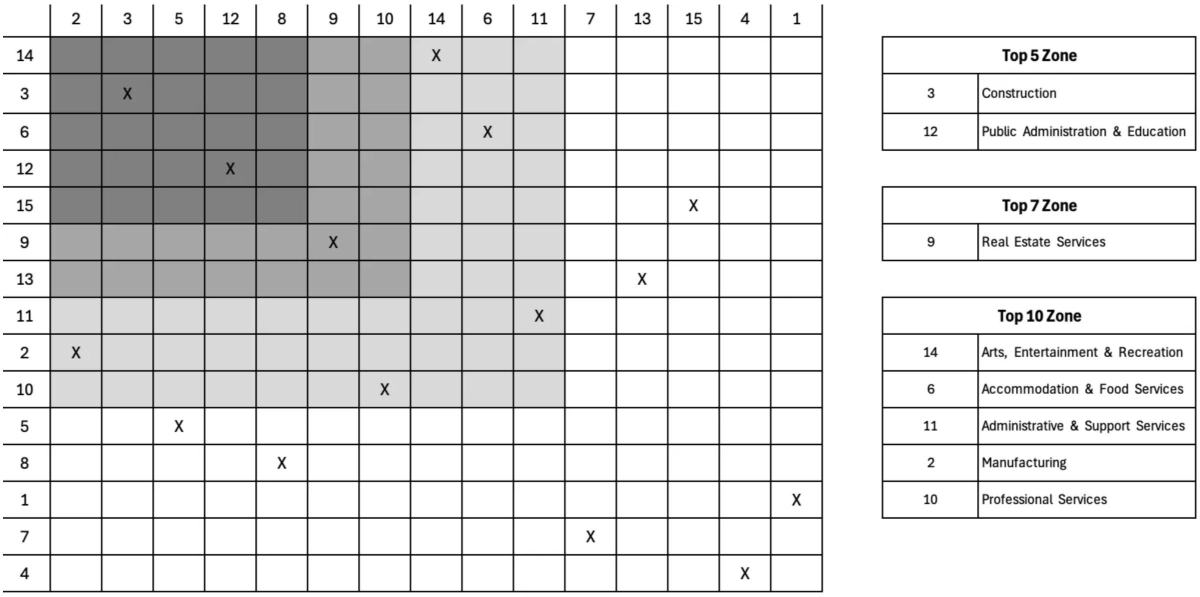

Figure 4.3: Joint impact matrix: inoperability rank (y-axis) vs. economic loss rank (x-axis).

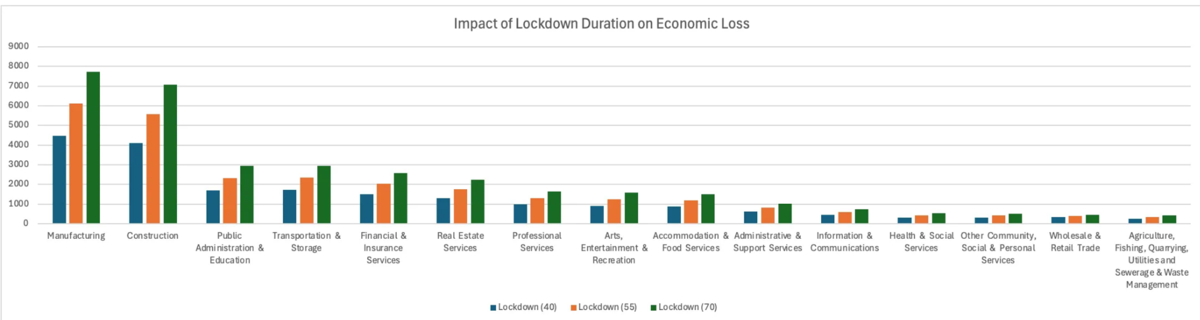

Figure 4.4: Total economic loss under different lockdown durations.

Chapter 5

Risk Management Scenario Analysis

This chapter evaluates risk management alternatives using the surrogate worth trade-off (SWT) method [6], focusing on the trade-off between investment costs and benefits measured as economic losses avoided.

5.1 Net benefit

Net benefit for policy option j is defined as:

$$\delta_j = \Gamma_{w[0]} - \Gamma_{w[j]} - \gamma_j \tag{5.1}$$

Here $\Gamma_{w[0]}$ is the baseline economic loss without policy, $\Gamma_{w[j]}$ is the economic loss under policy j, and γ_j is the cost of implementing policy j.

5.2 Scenario analysis

δ_j basically shows the potential reduction in economic losses after the implementation of a particular risk management policy

5.2.1 Scenario 1 (baseline): no policy, j=0

In Scenario 1, no risk management measures are taken and the model results represent the baseline outcome. The execution cost is 0, and net benefit is set to 0 to serve as the comparison baseline.

$$\delta_j = \Gamma_{w[0]} - \Gamma_{w[j]} - \gamma_j = 0 \tag{5.2}$$

5.2.2 Scenario 2: policy 1, j=1

In this scenario, the government is assumed to spend 1 billion SGD in advance on risk control to reduce the pandemic impact. The policy is assumed to reduce the inoperability impact by 5% per day, meaning each day's inoperability is scaled to 95% of the original level before being used in the DIIM. Under this assumption, our calculation reports that overall economic loss is reduced substantially compared to the baseline, and net benefit is computed accordingly:

$$\begin{aligned}\delta_1 &= \Gamma_{w[0]} - \Gamma_{w[1]} - \gamma_1 = 26967.3 - 2323.01 - 1000 = 23644.29 \text{ million SGD},\\ \lambda_{12} &= \frac{\gamma_1}{\Gamma_{w[0]} - \Gamma_{w[1]}} = \frac{1000}{26967.3 - 2323.01} = 0.04057735\end{aligned} \tag{5.3}$$

5.2.3 Scenario 3: policy 2, j=2

In this scenario, the government is assumed to spend 2 billion SGD in total. The additional spending is assumed to reduce the lockdown period from 55 days to 30 days. Under this assumption, the dissertation reports a reduction in economic loss and computes net benefit and cost-benefit ratio as follows:

$$\begin{aligned} \delta_2 &= \Gamma_{w[0]} - \Gamma_{w[2]} - \gamma_2 = 26967.3 - 17564.99 - 2000 = 7402.31 \text{ million SGD}, \\ \lambda_{12} &= \frac{\gamma_2}{\Gamma_{w[0]} - \Gamma_{w[2]}} = \frac{2000}{26967.3 - 17564.99} = 0.2127137 \end{aligned} \tag{5.4}$$

5.3 Comparing Policies

Policy 1 is reported to obtain 1 SGD of benefit for each 0.041 SGD of investment cost, while Policy 2 obtains 1 SGD of benefit for each 0.21 SGD of investment cost. Under these assumptions and calculations, Policy 1 is preferred because it has a smaller cost per unit benefit.

Chapter 6

Machine Learning for Key Sectors Identification

Recent work suggests that machine learning approaches can be comparable to traditional IO-based methods for identifying key sectors. This dissertation explores whether principal component analysis (PCA) applied to an integrated IO matrix produces sector rankings similar to those derived from DIIM.

6.1 Principal Component Analysis Applied to the IO Matrix

Instead of using A directly, this approach uses an integrated input–output coefficient matrix:

$$H = A(I - A)^{-1}. \tag{6.1}$$

This transformation places more weight on stronger linkages and reflects both direct and indirect effects through the production network. PCA is then applied to H, and the first principal component (PC1) corresponds to the eigenvector with the largest eigenvalue.

Table 6.1 below lists the principal component values. Note that the top three sectors identified by PCA are the same as the top three sectors identified by DIIM.

Sector ID	PC1	PC2
3	0.772976374	-0.158540904
2	0.488575487	0.547564001
5	0.230631604	0.602425551
8	0.173952844	0.31984955
4	0.16376151	0.197548491
10	0.141148665	0.185477914
7	0.107051197	0.232037887
11	0.100445788	0.154054165
1	0.082357584	0.203204452
9	0.065932369	0.120308858
12	0.02097817	0.033819003
6	0.01904942	0.04009044
15	0.010160651	0.015616709
14	0.004471868	0.006256627
13	0.002201633	0.00402146

Table 6.1: Sectors sorted by PC1

6.2 Simulation

This section compares whether the top sectors identified by PCA can reduce losses as effectively as the top sectors identified by DIIM. For each combination of lockdown duration (10, 20, 30, 40 days) and total simulation duration (300, 400, 500, 600 days), the DIIM is run to identify the top five sectors by impact, and then two hypothetical interventions are compared: reducing inoperability in the top five sectors selected by DIIM versus reducing inoperability in the top five sectors selected by PCA.

Our calculation shows that economic loss increases as lockdown duration increases and also increases as total duration increases, which matches intuition. Our calculation also shows that lockdown duration has a stronger effect on economic loss than total duration in Figure 6.1. In Figures 6.3 and 6.4, our calculation also shows that PCA-based prioritisation performs similarly to DIIM-based prioritisation, and upon closer inspection it can perform better for economic loss reduction under the stated assumptions.

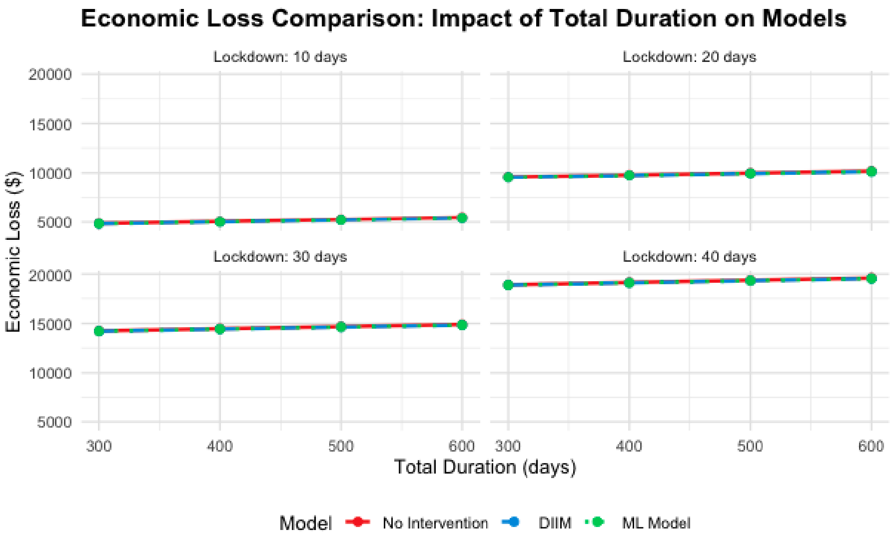

Figure 6.1: Economic loss for different lockdown and total durations

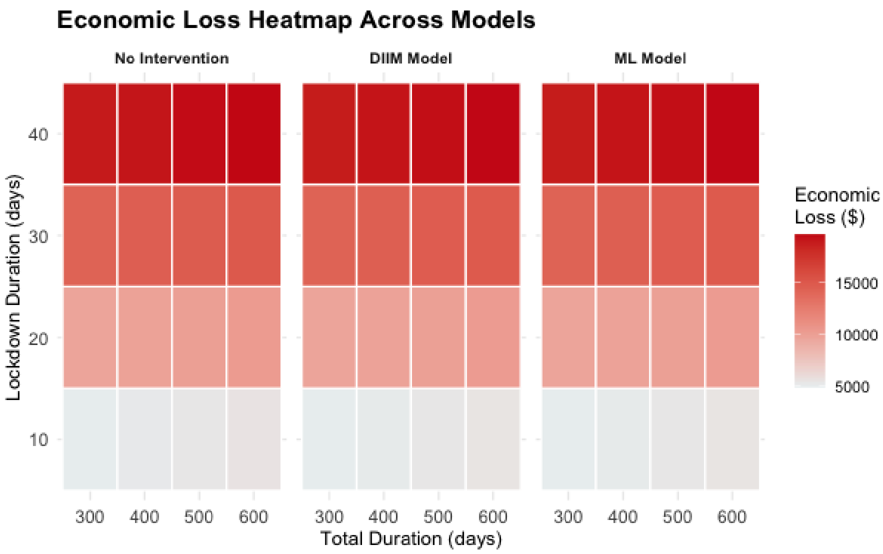

Figure 6.2: Economic loss heatmap across models

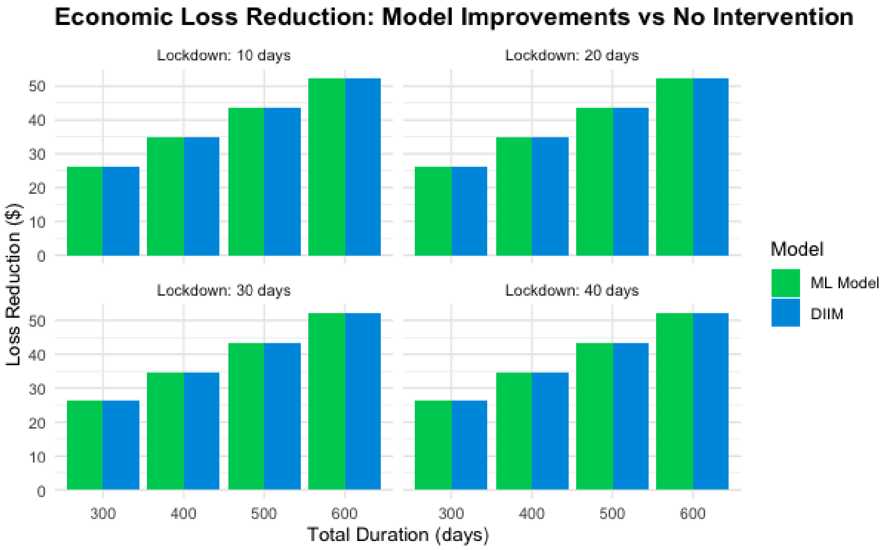

Figure 6.3: Economic loss reduction for ML vs DIIM

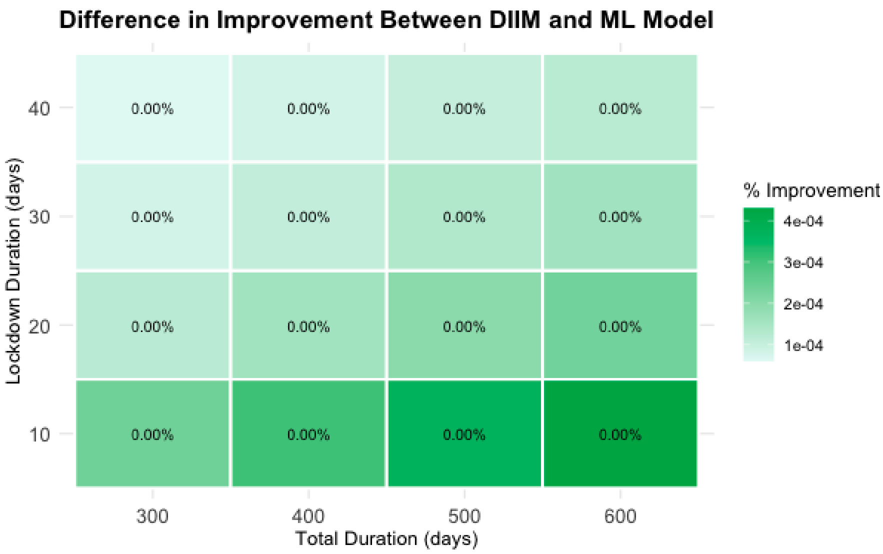

Figure 6.4: Difference in Improvement: ML vs DIIM

Chapter 7

Conclusion

This project applied the Dynamic Inoperability Input–Output Model (DIIM) to study how COVID-19 affected Singapore's economy at the sector level, including how disruptions spread across industries and how recovery evolves over time. Using Singapore's 2019 IO table aggregated to 15 sectors and an initial inoperability measure based on workforce unavailability and labour dependence, the model produced sectoral inoperability paths and cumulative economic loss estimates.

The results show that sector vulnerability should be assessed using both inoperability and economic loss because these measures capture different aspects of impact and can rank sectors differently. The impact matrix (ranking inoperability against ranking economic loss) provides a practical way to identify sectors that are consistently high-impact and should be prioritised when resources are limited. Sensitivity analysis suggests that longer lockdown durations increase losses across the economy, but the main set of highly affected sectors remains broadly consistent.

The dissertation also demonstrated how DIIM outputs can be used to compare example risk management policies using a surrogate worth trade-off (SWT) approach that accounts for both cost and benefit. Finally, a PCA-based method using the integrated IO matrix was tested as a faster alternative for identifying key sectors, and simulations suggest that it can match DIIM-based prioritisation in reducing losses while requiring fewer uncertain crisis-time inputs.

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Appendix A

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6	0.01904942	0.04009044
15	0.010160651	0.015616709
14	0.004471868	0.006256627
13	0.002201633	0.00402146

Table 7.1: Mapping of Sectors

	Agriculture, Fishing, Quarrying, Utilities and Sewerage & Waste Management	Manufacturing	Construction
Agriculture, Fishing, Quarrying, Utilities and Sewerage & Waste Management	4,308.828700	2,985.482100	198.954100
Manufacturing	498.915600	59,777.284000	4,939.792300
Construction	166.973900	498.152500	23,583.027800

Table 7.2: Cross-section of technical coefficient matrix

Sector ID	Sector	Initial inoperability
1	Agriculture, Fishing, Quarrying, Utilities and Sewerage & Waste Management	0.002563
2	Manufacturing	0.000752
3	Construction	0.006890
4	Wholesale & Retail Trade	0.001639
5	Transportation & Storage	0.001107
6	Accommodation & Food Services	0.008462
7	Information & Communications	0.001936
8	Financial & Insurance Services	0.001091
9	Real Estate Services	0.000765
10	Professional Services	0.003087
11	Administrative & Support Services	0.005325
12	Public Administration & Education	0.002954
13	Health & Social Services	0.003429
14	Arts, Entertainment & Recreation	0.004552
15	Other Community, Social & Personal Services	0.015819

Table 7.3: Sector Initial Inoperability

Appendix B

(Code to be added here)