The Economic Impact of Lockdowns: A Persistent Inoperability Input-Output Approach

Krista Danielle S. Yu [1,*] **, Kathleen B. Aviso** [2] **, Joost R. Santos** [3] **and Raymond R. Tan** [2]

1   School of Economics, De La Salle University, Manila 0922, Philippines
2   Chemical Engineering Department, De La Salle University, Manila 0922, Philippines;
     kathleen.aviso@dlsu.edu.ph (K.B.A.); raymond.tan@dlsu.edu.ph (R.R.T.)
3   Department of Engineering Management & Systems Engineering, The George Washington University,
     Washington, DC 20052, USA; joost@gwu.edu
*   Correspondence: krista.yu@dlsu.edu.ph; Tel.: +63-28-524-4611

check for
updates

Abstract: The COVID-19 pandemic has forced governments around the world to implement unprecedented lockdowns, mandating businesses to shut down for extended periods of time. Previous studies have modeled the impact of disruptions to the economy at static and dynamic settings. This study develops a model to fulfil the need to account for the sustained disruption resulting from the extended shutdown of business operations. Using a persistent inoperability input-output model (PIIM), we are able to show that (1) sectors that suffer higher levels of inoperability during quarantine period may recover faster depending on their resilience; (2) initially unaffected sectors can suffer inoperability levels higher than directly affected sectors over time; (3) the economic impact on other regions not under lockdown is also significant.

Keywords: COVID-19; disease outbreak; pandemic; economic impact assessment; input-output analysis; inoperability input-output model

1. Introduction

The COVID-19 pandemic continues to disrupt the world as the number of cases continues to escalate. While some countries have managed to bring the outbreak under control in the past months, others are still experiencing a continuous increase in the number of new cases. Several countries in Europe are now experiencing a second wave. In the absence of a vaccine, there is a need to "flatten the curve" to avoid overwhelming each country's healthcare system (Flaxman et al. 2020). Governments have adapted non-pharmaceutical interventions (NPIs) to control the transmission of the disease. Extreme measures such as lockdowns and mandatory business and school closures have been implemented in most countries (Ullah and Khan 2020). In addition to causing direct economic losses during the closure, the extended lockdowns pose the socioeconomic risk of irreversible closure of businesses, with the attendant ripple effects. Travel restrictions remain (International Air Transport Association 2020), causing airlines to incur losses. Tourism-intensive economies have experienced increasing unemployment resulting from the decline in tourism demand (United Nations Conference on Trade and Development 2020). Commercial establishments have observed mandatory closures during the lockdown period. Limited availability of public transportation services has caused mobility and accessibility problems for consumers and workers alike (Suman et al. 2020). Amid school closures, businesses largely dependent on students and school employees as their clientele, especially in college towns, may have to close (Wong 2020). In the United States alone, a total of 72,842 establishments listed on Yelp have permanently shut down (Pesce 2020). Close to two-thirds of small businesses, which account for nearly half of American employment, are at risk of permanent closure resulting from the

COVID-19 pandemic (Powe and Wagner 2020). Similar difficulties are being experienced in virtually all countries affected by COVID-19. Significant declines in GDP have been reported worldwide as a direct consequence of the pandemic (International Monetary Fund 2020).

International organizations have further decreased their economic forecasts for 2020 due to the pandemic (Asian Development Bank 2020; International Monetary Fund 2020; World Bank 2020). Economies around the world are expected to experience negative levels of growth despite the stimulus packages that each government has implemented. Numerous studies have been conducted to assess the impact of COVID-19 to the economy. Using a cross-country panel data analysis, Alfano and Ercolano (2020) were able to show that lockdowns have been effective in reducing the basic reproduction number (R_0) across countries and they asserted that relaxing lockdown measures should be done with caution to avoid reversal of such effects. Nicola et al. (2020) discussed the impact of COVID-19 on several economic sectors and recommend that governments prepare for medium- and long-term recovery strategies. Laing (2020) observed that the mining industry is not immune to the short term negative impacts of COVID-19. Yu and Aviso (2020) identified models for assessing the impact of disease outbreaks to the economy through its dependence on supply chains, and highlighted the potential for cross-border effects through global value chains. In addition to the reduced demand for workers, forced workforce absenteeism may further amplify the decline in economic output (Santos 2020a).

Input-output models have been used to identify the sectoral impacts of operational disruptions due to the pandemic. Xiao et al. (2020) illustrated the global value chain and identified the large economies such as China, Germany, and the United States as regional centers for trade. This study provides insights on how trade will be affected as factories shut down in some parts of the world. Giammetti et al. (2020) used a partial hypothetical extraction technique to demonstrate how the "locked value added" approach can be used to model the reduced capacity of various sectors in Italy resulting from the lockdown. However, this methodology does not factor in the resilient nature of sectors to recover over time. Santos (2020b) implemented a dynamic inoperability input-output model (DIIM) to estimate the impact of forced workforce absenteeism due to the COVID-19 pandemic and simulated the impact of potential strategies for "flattening the curve" such as containment, suppression, and mitigation with workforce continuity.

Previous studies have explored the occurrence of pandemics, and provide an overview of potential policies that governments may opt to implement. Hak et al. (2006) proposed an arithmetic decision tree model approach to measure the health and economic impacts of a possible influenza pandemic on the Dutch economy through considering demographic categories, varying attack rates, and healthcare information. They found that to minimize total mortality and achieve the maximum net economic returns, interventions targeted towards people ages 20 to 64 will yield the best results as they have the highest transmission and contact rates. Most analyses have considered pandemics to cause disruptions that last up to four months. Furthermore, these studies looked into pandemics that are contained within a country. For example, Smith et al. (2009) assessed the economy-wide impact of a pandemic influenza in the UK. They presented several pandemic mitigation measures such as vaccination, school closures, and prophylactic absenteeism. Prager et al. (2016) categorized the impact of an influenza outbreak on the economy through its effect on workforce participation, medical expenditures, avoidance behavior, and economic resilience. These are measured through reduction in the workforce, increase in spending on medical services, working from home, keeping children from school, reduction in inbound and outbound international travel, reduction in domestic travel and leisure activities, reduction in public transportation use, and recapturing production through overtime or increased shifts. While these measures can control the spread of the pandemic, they have substantial repercussions. Persistent avoidance behavior will lead to changes in behavior that can extend beyond the pandemic.

Inoperability input-output models have been used to assess the impact of previous pandemics on the economy. Orsi and Santos (2010) extended the dynamic inoperability input-output model to account for workforce absenteeism through the FluWorkLoss database with varying attack rates.

Santos et al. (2013) considered the impact of the 2009 H1N1 that had two waves over a 42-week interval. These studies were able to identify the critical economic sectors during a pandemic. El Haimar and Santos (2015) proposed a stochastic recovery model that factors inoperability and economic losses as risk metrics with a possible surge in the pandemic. The current pandemic has gone on longer than imagined, with a global scope and no commercially available pharmaceutical intervention to date. The world has resolved to adapt non-pharmaceutical measures that have severely affected the global economy.

This work develops a persistent inoperability input-output model (PIIM), which models the reduced capacity of sectors that persist during a lockdown period mandated by the government. Unlike previous models, the PIIM will provide insights on the impact of prolonged inoperability in various sectors of the economy. This model builds on the input-output model as discussed in Section 2. Section 3 introduces the PIIM model. The PIIM models the sectoral impacts of persistent disruptions to the economy as a whole and does not account for differences of impact on individual firms. Section 4 provides a demonstration of how the model can be implemented using the Philippines as a case study. Section 5 presents the conclusions and areas for future research.

2. Input-Output Foundations

Input-output (I-O) modeling has been used to capture the interdependencies that ripple through the economic sectors across an economy. Leontief (1936) developed a system of linear equations to represent the transaction flows between each sector in the economy as given in Equation (1):

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{c} \tag{1}$$

where $\mathbf{x}$ is the output vector, $\mathbf{A}$ is the technical coefficients matrix and $\mathbf{c}$ is the final demand vector. The total output vector, $\mathbf{x}$, is the sum of the intermediate consumption, $\mathbf{A}\mathbf{x}$, and final demand, $\mathbf{c}$.

Haimes and Jiang (2001) developed a physical representation of the I-O model for critical infrastructure systems with the introduction of inoperability, or the inability of a system to operate at its full capacity. The initial inoperability input-output model (IIM) was reformulated into a demand-reduction IIM that can be used with standard I-O tables expressed in monetary terms (Santos and Haimes 2004); this step allowed the IIM concept to be operationalized and calibrated using readily available statistics. The demand-reduction IIM provides two useful metrics for estimating the impact of an external disruption on an economic system—inoperability and economic loss. Inoperability is specified as:

$$\mathbf{q} = \mathbf{A}^*\mathbf{q} + \mathbf{c}^* \tag{2}$$

where $\mathbf{q}$ is the inoperability vector, $\mathbf{A}^*$ is the interdependency matrix, and $\mathbf{c}^*$ is the initial demand perturbation vector. The inoperability vector is defined as the vector of normalized economic losses and can be derived as $\mathbf{q} = [\mathbf{diag}(\mathbf{x})]^{-1}[\mathbf{x} - \tilde{\mathbf{x}}]$, where $\mathbf{x}$ is the as-planned level of output and $\tilde{\mathbf{x}}$ is the degraded level of output and its elements have values between 0 and 1. The interdependency matrix, $\mathbf{A}^*$, contains elements, a_{ij}^*, which show the additional inoperability that sector i contributes to sector j. It can be derived as $\mathbf{A}^* = [\mathbf{diag}(\mathbf{x})]^{-1}\mathbf{A}[\mathbf{diag}(\mathbf{x})]$. The product of the interdependency matrix and the inoperability vector, $\mathbf{A}^*\mathbf{q}$, yields the intermediate inoperability. The initial demand perturbation vector, $\mathbf{c}^*$, is the normalized degraded demand vector derived as $\mathbf{c}^* = [\mathbf{diag}(\mathbf{x})]^{-1}[\mathbf{c} - \tilde{\mathbf{c}}]$, where $\mathbf{c}$ is the as-planned level of final demand and $\tilde{\mathbf{c}}$ is the degraded level of final demand resulting from the exogenous system disruption. Economic loss is computed using Equation (3):

$$EL_i = q_i * x_i \tag{3}$$

where EL_i is the economic loss of sector i resulting from the total inoperability level, q_i, multiplied by the as-planned output level, x_i. These two metrics differ such that the inoperability metric is a

dimensionless metric that measures the functional impact on the economic system while the economic loss yields the monetary value lost resulting from the external disruption.

Lian and Haimes (2006) extended the IIM to account for time dynamics and recovery. They introduced the dynamic inoperability input-output model (DIIM) which is specified as:

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}[\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t) - \mathbf{q}(t)] \tag{4}$$

where $\mathbf{q}(t+1)$ is the inoperability vector at time $t + 1$, and $\mathbf{K}$ is the industry resilience coefficient matrix. $\mathbf{K}$ is a diagonal matrix which has elements, k_{ii}, that represent the inherent ability of sector i to recover from the disruption.

Despite the significant number of publications that extended the theory and methodology in support of the inoperability-based IO model, it has not become immune to criticisms pertaining to issues ranging from novelty (Dietzenbacher and Miller 2015) to plausibility (Oosterhaven 2017). Nonetheless, the concept of inoperability—which has been integrated to the basic I-O model—has served as the unprecedented bridge between traditional economic analysis and other fields like engineering reliability and disaster risk management. Okuyama and Yu (2018) have defended the IIM and emphasized its merits, particularly in the context of disaster resilience modeling. The practicality and intuitiveness of the IIM have paved the way to a myriad of articles that continue to explore and extend inoperability-based theories and applications.

Miller and Blair (2009) discuss the simple location quotient (SLQ) approach to derive regional I-O tables. Most countries collect I-O data at the national level, and SLQ is a way to estimate regional I-O tables using location-specific economic data, such as industry production outputs. SLQ for region r is defined as:

$$SLQ_i^r = \frac{\frac{x_i^r}{x^r}}{\frac{x_i^n}{x^n}} \tag{5}$$

where SLQ_i^r is the simple location quotient for sector i in region r, x_i^r is the total output of sector i in region r, x^r is the total output of all sectors in region r, x_i^n is the national total output of sector i, and x^n is the national total output of all sectors. The elements of the regional technical coefficient matrix, a_{ij}^{rr}, can be obtained by:

$$a_{ij}^{rr} = \begin{cases} SLQ_i^r a_{ij}^n & \text{if } SLQ_i^r < 1 \\ a_{ij}^n & \text{if } SLQ_i^r \geq 1 \end{cases} \tag{6}$$

where a_{ij}^n is the technical coefficient from the national input-output table. When sector i in region r is self-sufficient or an exporter of goods for other regions, the regional technical coefficient for sector i is assumed to be the same as the technical coefficient at the national level. However, if it is not self-sufficient and relies on other regions to satisfy its demand for sector i, the national technical coefficient is multiplied by the SLQ for sector i.

The interregional trade component is accounted for through the introduction of the interregional trade coefficients matrix, $\mathbf{T}$, which is written as:

$$\mathbf{T} = \begin{bmatrix} \mathbf{T}^{11} & \mathbf{T}^{12} & \cdots & \mathbf{T}^{1m} \\ \mathbf{T}^{21} & \mathbf{T}^{22} & \cdots & \mathbf{T}^{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{T}^{m1} & \cdots & \cdots & \mathbf{T}^{mm} \end{bmatrix} \tag{7}$$

where each submatrix $\mathbf{T}^{rs}$ shows the proportional consumption of region s of commodities produced in region r with p number of regions. Each submatrix is an $n \times n$ diagonal matrix with the ith element specified as:

$$t_i^{rs} = \frac{z_i^{rs}}{y_i^s} \tag{8}$$

where t_i^{rs} is the proportion of commodity i consumed by region s produced by region r, z_i^{rs}, in relation to the total consumption of commodity i by region s produced by all regions, y_i^s.

The multiregional input-output model is defined as:

$$\mathbf{x} = \mathbf{TAx} + \mathbf{Tc} \tag{9}$$

and this can be extended to account for inoperability (Crowther and Haimes 2010) as:

$$\mathbf{q} = \mathbf{T}^*\mathbf{A}^*\mathbf{q} + \mathbf{T}^*\mathbf{c}^* \tag{10}$$

where $\mathbf{q}$ is an $nm \times 1$ vector of inoperability, $\mathbf{T}^*$ is an $nm \times nm$ matrix computed as $\mathrm{diag}\left[\left(x^1, x^2, \ldots x^m\right)\right]^{-1} \mathbf{T}\mathrm{diag}\left[\left(x^1, x^2, \ldots x^m\right)\right]$, $\mathbf{A}^*$ is an $np \times np$ matrix with diagonal submatrices of $n \times n$ dimension interdependency matrices for m regions and $\mathbf{c}^*$ is an $nm \times 1$ vector of demand perturbation vector.

The dynamic representation of the multiregional inoperability input-output model (MRIIM) is given as:

$$\mathbf{q}_{\mathrm{DMRIIM}}(t+1) = \mathbf{q}(t) + \mathbf{K}\left[\mathbf{T}^*\mathbf{A}^*\mathbf{q}(t) + \mathbf{T}^*\mathbf{c}^*(t) - \mathbf{q}(t)\right] \tag{11}$$

3. Persistent Inoperability Input-Output Modeling

Community quarantines and countries under lockdown have forced several sectors in the economy to remain inoperable at certain levels for a period of time. This means that inoperability remains constant for sectors initially affected by the lockdown. This paper measures the persistency of the inoperability through Equation (12):

$$\mathbf{q}_p(t+1) = \begin{cases} 0 & \text{if } t > d \\ \mathbf{c}^*(0) - \mathbf{q}(t) - \mathbf{K}\left[\mathbf{T}^*\mathbf{A}^*\mathbf{q}(t) + \mathbf{T}^*\mathbf{c}^*(t) - \mathbf{q}(t)\right] & \text{if } t \le d \end{cases} \tag{12}$$

where $\mathbf{q}_p$ is the persistent inoperability vector, $\mathbf{c}^*(0)$ is the demand perturbation at the onset of the community quarantine or lockdown, and d is the number of days that the lockdown or community quarantine is enforced. The persistent inoperability vector quantifies the inability of a sector to recover despite its inherent ability to cope with disruptions. Sectors that should have recovered, but are unable to do so, are said to be in a state of persistent inoperability.

Equation (13) illustrates how persistence of inoperability is introduced into the dynamic MRIIM model

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}\left[\mathbf{T}^*\mathbf{A}^*\mathbf{q}(t) + \mathbf{T}^*\mathbf{c}^*(t) - \mathbf{q}(t)\right] + \mathbf{q}_p(t+1) \tag{13}$$

where $t \le d$. The persistent inoperability vector is added to the dynamic MRIIM in Equation (11) to ensure that inoperability for the initially affected sectors remain at a constant level. It can be noted that the first part of Equation (13) is the same as the dynamic MRIIM model specified in Equation (11). Hence, Equation (13) can be rewritten as:

$$\mathbf{q}(t+1) = \mathbf{q}_{\mathrm{DMRIIM}}(t+1) + \mathbf{q}_p(t+1) \tag{14}$$

When the lockdown or community quarantine is lifted, $t > d$, the persistent inoperability becomes a zero vector, thereby reverting to the dynamic MRIIM formulation. Economic sectors are allowed to recover as businesses strive to revert back to business-as-usual levels. However, if a more relaxed lockdown is implemented, another lockdown period is introduced, d_2, and

$$
\mathbf{q}_p(t+1) = \begin{cases} \mathbf{0} & \text{if } t > d_1 + d_2 \\ \mathbf{c}^*(\mathbf{0}) - \mathbf{q}_{\text{DMRIIM}}(t+1) & \text{if } t \le d_1 \\ \mathbf{q}_{\text{DMRIIM}}(t+1) - \mathbf{c}^*(d_1+1) & \text{if } d_1 < t \le d_1 + d_2 \text{ and } \mathbf{q}_{\text{DMRIIM}}(t+1) > \mathbf{c}^*(d_1+1) \\ \mathbf{c}^*(d_1+1) - \mathbf{q}_{\text{DMRIIM}}(t+1) & \text{if } d_1 < t \le d_1 + d_2 \text{ and } \mathbf{c}^*(d_1+1) \ge \mathbf{q}_{\text{DMRIIM}}(t+1) \end{cases} \tag{15}
$$

As more lockdown variations are introduced at different time periods, more levels of persistent inoperability can be observed.

4. Case Study

The Philippines is one of the countries that implemented a lockdown to control the spread of the COVID-19 disease. Most of the cases during the start of the pandemic were from the National Capital Region (NCR). The NCR is the political and economic hub of the country. Although it occupies only 0.2% of the country's total land area, it accounts for 37% of the USD 390 billion national gross domestic product (GDP) (Philippine Statistics Authority 2020a) of a country with a population of 13.8 million (Philippine Statistics Authority 2019a). Thus, an enhanced community quarantine (ECQ) was imposed for the NCR from 15 March to 15 May 2020; this ECQ was then relaxed to a modified enhanced community quarantine (MECQ) from 16–31 May 2020. Economic losses mounted as the lockdown extended for much longer than originally planned. With the worsening economic situation, the government decided to allow more businesses to operate under a general community quarantine (GCQ), which was implemented from 1 June until 3 August 2020. The increasing number of COVID-19 cases in the region forced the government to revisit its lockdown policy, and it reverted back to a MECQ for the period of 4–31 August 2020. Although the number of COVID-19 cases continued to increase, the government decided to relax the quarantine restrictions back to GCQ for the period of 1 September until 31 October 2020. Table 1 presents the definition of the different quarantine scenarios as given in the guidelines published by the Philippine Inter-Agency Task Force for the Management of Emerging Infectious Diseases.

Table 1. Definition of Philippine quarantine scenarios.

Quarantine Scenario	Definition
ECQ	"Implementation of temporary measures imposing stringent limitations on movement and transportation of people, strict regulation of operating industries, provision of food and essential services and heightened presence of uniformed personnel to enforce community quarantine protocols" (Philippine Inter-Agency Task Force for the Management of Emerging Infectious Diseases 2020).
MECQ	"Transition phase between ECQ and GCQ, when the following temporary measures are relaxed and become less necessary: stringent limitations on movement and transportation of people, strict regulation of operating industries, provision of food and essential services and heightened presence of uniformed personnel to enforce community quarantine protocols" (Philippine Inter-Agency Task Force for the Management of Emerging Infectious Diseases 2020).
GCQ	"Implementation of temporary measures limiting movement and transportation of people, regulation of operating industries, and presence of uniformed personnel to enforce community quarantine protocols" (Philippine Inter-Agency Task Force for the Management of Emerging Infectious Diseases 2020).

The prolonged lockdown led to a 16.5% drop in national GDP in the second quarter of 2020, with a large share of the losses being incurred in the NCR (Philippine Statistics Authority 2020b). The NCR services sector, which includes transportation, trade, finance, real estate, private services and government services sectors, is a major contributor to the national economy, accounting for 52.82% of the Philippine services GDP (Philippine Statistics Authority 2019b). Furthermore, NCR's share of the

trade sector is 62.19% of national trade ([Philippine Statistics Authority 2019b](#)). Therefore, the lockdown measures imposed on the NCR have had a significant impact on the nation's economy.

This study uses a 14-sector Philippine I-O table that is disaggregated into two regions, the NCR and the rest of the Philippines (ROP)[1]. The regional acronyms are used as prefixes to the sector codes provided in Table 2 as identifiers.

Table 2. Sector classifications.

Sector Code	Sector Name
S01	Agriculture, Fishery, and Forestry
S02	Mining and Quarrying
S03	Manufacturing
S04	Construction
S05	Electricity, Gas, and Water
S06	Land Transportation
S07	Water Transportation
S08	Air Transportation
S09	Communications and Storage
S10	Trade
S11	Finance
S12	Real Estate and Ownership of Dwelling Palaces
S13	Private Services
S14	Government Services

Initial inoperability estimates were based on [National Economic and Development Authority (2020)](#) estimates of the impact on GDP. The affected sectors are NCR's manufacturing, construction, land transportation, water transportation, air transportation, trade, finance, and private services sectors.

Figure 1 illustrates the levels of persistent inoperability sustained by the initially affected economic sectors. It can be observed that during the initial ECQ, the persistent inoperability level was very low. This was mainly because the lockdown was preventing the affected sectors from recovering. The level of inoperability that persisted on a daily basis was only the supposed recovery for that day. However, upon allowing some sectors to reopen, recovery was not instantaneous and sectors suffered higher levels of inoperability compared to what would be expected from the more relaxed lockdown. Hence, the level of persistent inoperability was the difference between the higher level of inoperability that it was recovering from and the more relaxed lockdown inoperability level. This difference represents an "economic inertia". For example, since the initial inoperability that the NCR trade sector experienced was quite high, the persistent inoperability that it suffered during the first MECQ was initially higher relative to other sectors. During the first GCQ period, the NCR trade sector had the fastest reduction in persistent inoperability, as it continued to recover. This means that sectors are still experiencing inoperability as a residual impact of the previously tighter lockdown. During the second MECQ in August 2020, persistent inoperability spiked for several sectors due to the tighter lockdown; however, this was immediately flattened as the level of inoperability that persisted was only the supposed recovery for that day as in the case of the initial ECQ scenario. Hence we can see that as coming from tighter forms of lockdowns, the persistent inoperability is evident and will take time to decline. If there was no lockdown or the previous type of lockdown was more relaxed or, as in the case of the ECQ from 16 March–15 May 2020 and the MECQ from 4–31 August 2020, persistent inoperability would remain flat during that period. Each sector has a different rate of recovery which is attributable to its inherent resilience and at the same time its interdependence with other sectors. For example, the NCR manufacturing sector has the highest industry resilience coefficient; however, Figure 1 shows that the NCR manufacturing sector exhibited the slowest rate of recovery compared to the rest of the affected

---

1 The data are available upon request from the authors.

sectors. NCR manufacturing has a strong dependence on other sectors; thus, the inoperability from the other sectors caused inoperability to persist for longer periods as evidenced in the graph. On the other hand, the NCR water transportation sector has the lowest industry resilience coefficient; however, it does not depend too much on other sectors for inputs to provide services, thus it exhibited the fastest rate of decline in terms of persistent inoperability.
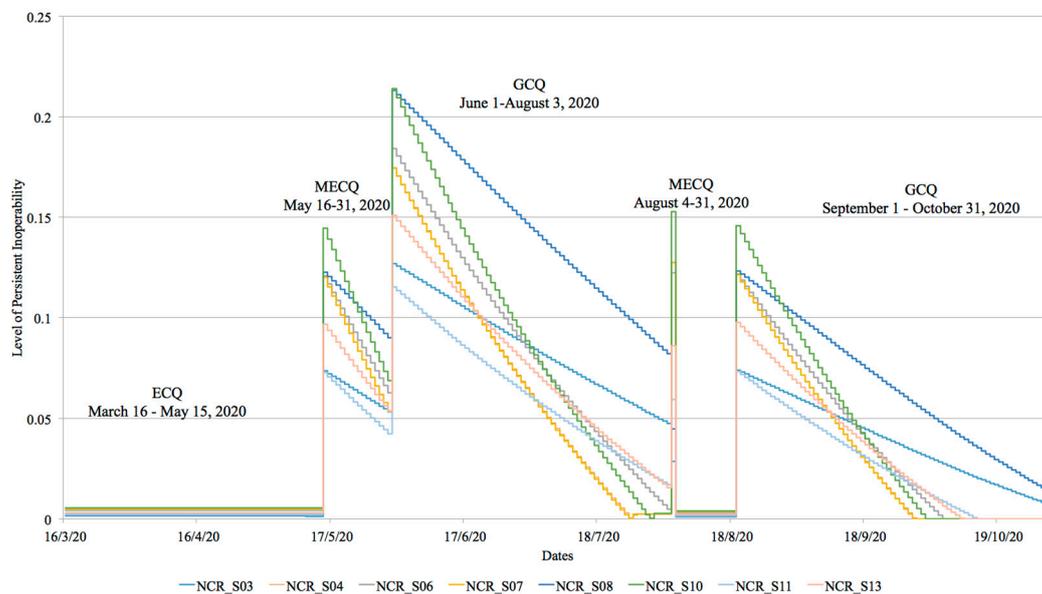

Figure 1. Persistent inoperability across sectors during the lockdown.

Figure 2 presents the ten most affected sectors in terms of inoperability. It can be seen that sectors most affected by the lockdown already had high inoperability levels at the onset and they are unable to recover until lockdowns are relaxed. It can be noted that all sectors in this graph belong to the NCR. Although there is continuous demand for goods produced by the NCR manufacturing sector, raw materials may not necessarily be readily available as some firms may be sourcing raw materials from abroad and the closures of banks delays release of these items from ports (Jiao 2020). The NCR air transportation sector, which connects the Philippines to the rest of the world as it houses the country's main international airport, has canceled and reduced the number of flights. In addition, the public transportation sector is operating at reduced capacity with less passenger demand and with mandatory reduced vehicle occupancy as a social distancing measure. Local public utility vehicles such as "jeepneys" which provide a transportation service on local routes, are not allowed to operate during ECQ and MECQ. Lack of access to public transport has hindered workforce mobility, causing further disruption even in partially operational sectors (Rey 2020).

Sectors that were not initially affected by the quarantine scenarios such as NCR electricity, gas, and water, and NCR communications sectors, have experienced increasing levels of inoperability as the lockdown has progressed. As the labor force shifted to working from home and students shifted to online learning, these sectors suffered an unprecedented surge in demand for their services. NCR has experienced rotating power outages during the lockdown period (Lectura 2020). Internet connectivity was also disrupted due to a network logjam resulting from the shift to telecommuting and online learning. Business process outsourcing (BPO) firms have made similar arrangements for their employees, going as far as purchasing desktops and providing loans to their employees. However, international clients have slowly been pulling out due to a business slowdown in their own countries, which may affect employment (Macaraeg 2020).
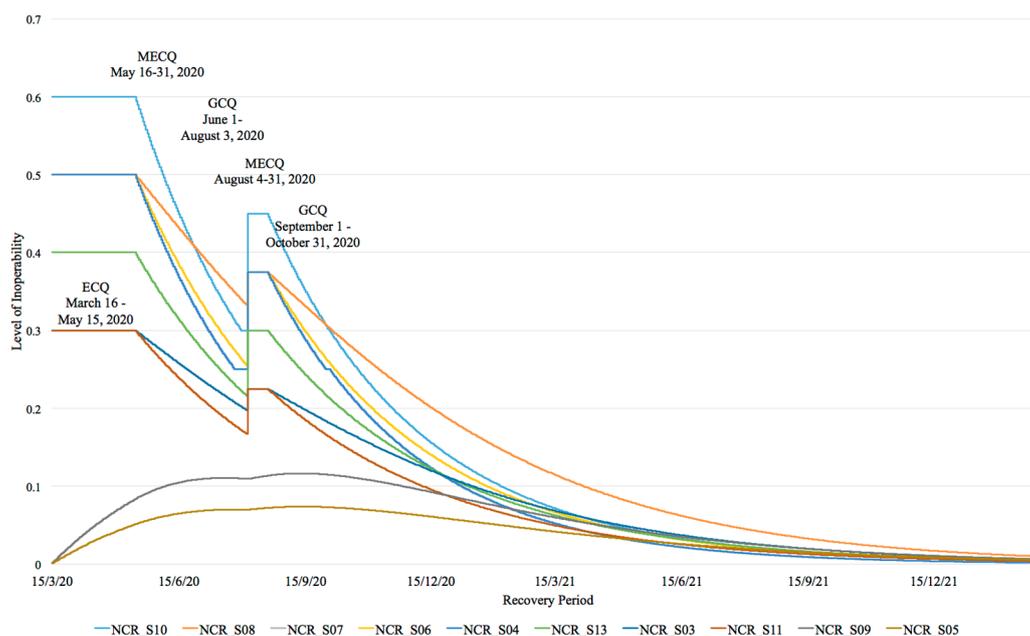
Figure 2. Ten most affected sectors in terms of inoperability.

The healthcare sector has also experienced inoperability due to different reasons as front-line personnel are continuously exposed to high viral loads, and are thus at a disproportionately higher risk of contracting COVID-19. Even if they do not contract the disease, they may need to undergo self-isolation as persons under monitoring (PUM) or patients under investigation (PUI), thus removing them from the active workforce. In addition, if a member of their household is classified as a PUM or PUI, or worse, contracts the disease, they may have to tend to personal matters, which contributes to absenteeism (Santos et al. 2014). Other essential sectors that have remained open, such as supermarkets, banks, and restaurants, among others, are faced with similar predicaments. This situation is alarming as the NCR provides more than one-third of total employment in the Philippines. Table 3 provides a summary of the NCR employment share of national employment for each sector in 2018.

Table 3. National capital region (NCR) and Philippines sectoral employment statistics for 2018.

Sector	NCR	Philippines	NCR Share in National Employment
Agriculture, Fishery, and Forestry	13,249	188,004	7.05%
Mining and Quarrying	3312	39,092	8.47%
Manufacturing	314,785	1,609,781	19.55%
Construction	177,409	289,151	61.36%
Electricity, Gas, and Water	15,977	108,888	14.67%
Transportation, Communication, and Storage	262,664	492,364	53.35%
Wholesale and Retail Trade	611,988	2,264,918	27.02%
Finance	199,004	480,352	41.43%
Real Estate	61,628	112,645	54.71%
Other Services	1,457,654	3,457,868	42.15%
Total	3,117,670	9,043,063	34.48%

Data from: Department of Trade and Industry (2019).

Figure 3 presents the ten most affected sectors in terms of economic losses. The overall economy of the Philippines is estimated to lose PHP 2.1 trillion (approximately USD 42 billion) resulting from the pandemic, accounting for ripple effects. The NCR trade, NCR manufacturing and NCR private services sectors are the hardest hit sectors, accounting for 29.19%, 18.03%, and 13.11% of total economic

losses respectively. In terms of economic loss, the ROP land transportation sector and ROP agriculture sector are also significantly affected. With the closure of NCR from incoming and outgoing travel, the ROP land transportation sector has been affected as provincial bus trips are cancelled. In addition, ROP agriculture is significantly affected as traders are unable to go to the trading posts to purchase produce which is largely sold to the NCR, which resulted in farmers throwing out their truckloads of products (Soriano 2020).
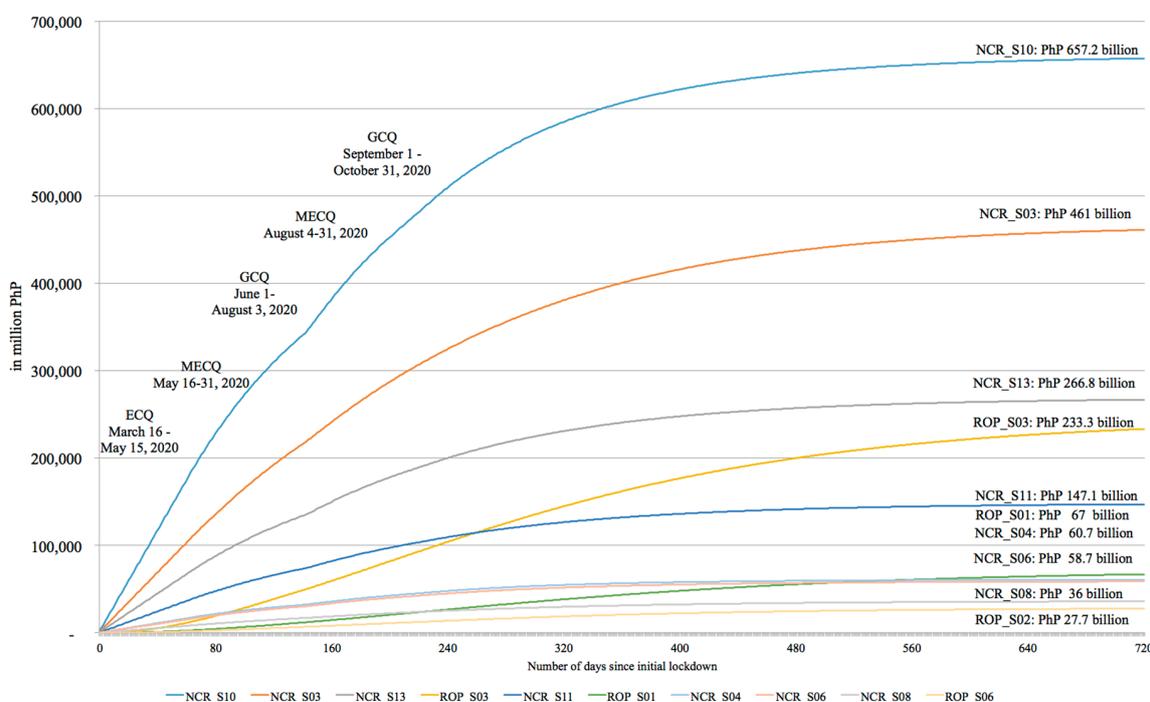
Figure 3. Ten most affected sectors in terms of economic loss.

The inoperability in the NCR economy results from a mix of supply reduction and demand reduction perturbations. Supply reduction perturbations result from supply chain disruptions, as well as workforce reduction due to either travel restrictions or absenteeism. Demand reduction perturbations result from a drop in total purchases of goods resulting from the ECQ. The combination of multiple perturbations increases the complexity of modeling and analyzing the economic impacts associated with scenarios with persistent inoperability, like the prolonged lockdown in the Philippines. Furthermore, these estimates do not include impacts on the informal sector of the NCR economy, but it is plausible to assume that similar losses are incurred there as well. The Philippines has implemented Republic Act 11,469 through formulating the Philippine Program for Recovery with Equity and Solidarity (PH-PROGRESO) which includes programs for various economic sectors (Philippine Department of Finance 2020). However, there is a need to expand the coverage of such programs as required.

5. Conclusions

This work has developed a model to estimate the impact of varying degrees of lockdowns on the sectors in an economy. Results show the degree by which each sector is affected and how much economic loss they incur. Furthermore, we have illustrated that inoperability can persist over time despite the implementation of less stringent lockdowns. Such information will be essential in developing strategies for recovery. This includes developing measures such as extending employment support through businesses to ensure employment retention post-pandemic and optimizing the stimulus packages across various sectors. Future research can explore the integration of our lockdown scenario modeling with optimization models (Baghersad and Zobel 2015; Aviso et al. 2015) to ensure efficient allocation of stimulus packages across sectors. Governments are faced with the problem of

choosing between suppressing the number of cases and pursuing economic survival. Despite efforts in implementing social distancing in public places, most developing countries have high population density in places with limited access to clean water. This poses further challenges in controlling the spread of the virus. Workplace reassignment within a firm can be done using optimization modeling to minimize the impact of prophylactic absenteeism during crisis conditions (Aviso et al. 2018). Extensions on analyzing the impact on supply chain networks across countries (Arto et al. 2015; MacKenzie et al. 2012; Lei et al. 2019; Yu et al. 2020a) may also be explored. This can be coupled with the reassessment of public health expenditure programs (Eissa 2020) in managing the impact of the pandemic on the economy. Further research should be done to estimate the impact of social security programs and stimulus packages of governments to ensure minimal impact on the welfare of their citizens.

Vaccination has been identified as a cost-effective measure to control the spread of pandemics and to minimize economic losses (Prosser et al. 2011). With the recent news of vaccines with significantly high efficacy (Cohen 2020), future research should integrate efficient production and distribution of the vaccine globally (Yu et al. 2020b). This can contribute to mitigating further economic damages and pushing the economy back on track to recovery.

References

Alfano, Vincenzo, and Salvatore Ercolano. 2020. The Efficacy of Lockdown against COVID-19: A Cross-Country Panel Analysis. *Applied Health Economics and Health Policy* 18: 509–17. [CrossRef]

Arto, Iñaki, Valeria Andreoni, and Jose Manuel Rueda Cantuche. 2015. Global impacts of the automotive supply chain disruption following the Japanese Earthquake of 2011. *Economic Systems Research* 27: 306–23. [CrossRef]

Asian Development Bank. 2020. Economic Forecasts: September 2020. Available online: https://www.adb.org/what-we-do/economic-forecasts/september-2020 (accessed on 10 October 2020).

Aviso, Kathleen B., Christina D. Cayamanda, Francesca Dianne B. Solis, Anne Maybelle R. Danga, Michael Angelo B. Promentilla, Krista Danielle S. Yu, Joost R. Santos, and Raymond R. Tan. 2015. P-graph approach for GDP-optimal allocation of resources, commodities and capital in economic systems under climate change-induced crisis conditions. *Journal of Cleaner Production* 92: 308–17. [CrossRef]

Aviso, Kathleen B., Andres P. Mayol, Michael Angelo B. Promentilla, Joost R. Santos, Raymond R. Tan, Aristotle T. Ubando, and Krista Danielle S. Yu. 2018. Allocating human resources in organizations operating under crisis conditions: A fuzzy input-output optimization modeling framework. *Resources, Conservation and Recycling* 128: 250–58. [CrossRef]

Baghersad, Milad, and Christopher W. Zobel. 2015. Economic impact of production bottlenecks caused by disasters impacting interdependent industry sectors. *International Journal of Production Economics* 168: 71–80. [CrossRef]

Cohen, Elizabeth. 2020. Moderna's Vaccine Has a Significant Advantage over Pfizer's. Available online: https://edition.cnn.com/world/live-news/coronavirus-pandemic-11-16-20-intl/h_3c91c6f3b13c0b6d96bd126d9cda9018 (accessed on 18 November 2020).

Crowther, Kenneth G., and Yacov Y. Haimes. 2010. Development of the Multiregional Inoperability Input-Output Model (MRIIM) for spatial explicitness in preparedness of interdependent regions. *Systems Engineering* 13: 28–46. [CrossRef]

Department of Trade and Industry. 2019. 2018 MSME Statistics. Available online: https://www.dti.gov.ph/resources/msme-statistics/ (accessed on 10 October 2020).

Dietzenbacher, Erik, and Ronald E. Miller. 2015. Reflections on the inoperability input–output model. *Economic Systems Research* 27: 478–86. [CrossRef]

Eissa, Noura. 2020. Pandemic preparedness and public health expenditure. *Economies* 8: 60. [CrossRef]

El Haimar, A., and J. R. Santos. 2015. A stochastic recovery model of influenza pandemic effects on interdependent workforce systems. *Natural Hazards* 77: 987–1011. [CrossRef] [PubMed]

Flaxman, Seth, Swapnil Mishra, Axel Gandy, H. Juliette T. Unwin, Thomas A. Mellan, Helen Coupland, Charles Whittaker, Harrison Zhu, Tresnia Berah, Jeffrey W. Eaton, and et al. 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature* 584: 257–61. [CrossRef] [PubMed]

Giammetti, Raffaele, Luca Papi, Desiree Teobaldelli, and Davide Ticchi. 2020. The Italian value chain in the pandemic: The input–output impact of Covid-19 lockdown. *Journal of Industrial and Business Economics* 47: 483–97. [CrossRef]

Haimes, Yacov Y., and Pu Jiang. 2001. Leontief-based model of risk in complex interconnected infrastructures. *Journal of Infrastructure Systems* 7: 1–12. [CrossRef]

Hak, Eelko, Marjan J. Meijboom, and Erik Buskens. 2006. Modelling the health-economic impact of the next influenza pandemic in The Netherlands. *Vaccine* 24: 6756–60. [CrossRef] [PubMed]

International Air Transport Association. 2020. Downgrade for Global Air Outlook. Available online: https://www.iata.org/en/iata-repository/publications/economic-reports/downgrade-for-global-air-travel-outlook/ (accessed on 10 October 2020).

International Monetary Fund. 2020. World Economic Outlook Update, June 2020: A Crisis Like No Other, An Uncertain Recovery. Available online: https://www.imf.org/~{}/media/Files/Publications/WEO/2020/Update/June/English/WEOENG202006.ashx?la=en (accessed on 19 August 2020).

Jiao, Claire. 2020. Philippines' Biggest Port May Shut on Shipping Container Logjam. Available online: https://www.bloomberg.com/news/articles/2020-04-01/shipping-container-pileup-could-shut-philippines-biggest-port (accessed on 15 August 2020).

Laing, Timothy. 2020. The economic impact of the Coronavirus 2019 (Covid-2019): Implications for the mining industry. *The Extractive Industries and Society* 7: 580–82. [CrossRef]

Lectura, Lenie. 2020. Enough Power, But Brace for Brownouts. *Business Mirror.* Available online: https://businessmirror.com.ph/2020/03/08/enough-power-but-brace-for-brownouts/ (accessed on 15 August 2020).

Lei, Zhimei, Ming K. Lim, Li Cui, and Yanzhang Wang. 2019. Modelling of risk transmission and control strategy in the transnational supply chain. *International Journal of Production Research*, 1–20. [CrossRef]

Leontief, Wassily W. 1936. Quantitative input and output relations in the economic systems of the United States. *The Review of Economic Statistics* 18: 105–25. [CrossRef]

Lian, Chenyang, and Yacov Y. Haimes. 2006. Managing the risk of terrorism to interdependent infrastructure systems through the Dynamic Inoperability Input-Output Model. *Systems Engineering* 9: 241–58. [CrossRef]

MacKenzie, Cameron A., Joost R. Santos, and Kash Barker. 2012. Measuring changes in international production from a disruption: Case study of the Japanese earthquake and tsunami. *International Journal of Production Economics* 138: 293–302. [CrossRef]

Macaraeg, Pauline. 2020. Double Whammy: BPO Employees Get Exposed to COVID-19, Lose Income. Available online: https://rappler.com/newsbreak/in-depth/double-whammy-bpo-employees-get-exposed-coronavirus-lose-income (accessed on 16 August 2020).

Miller, Ronald E., and Peter D. Blair. 2009. *Input-Output Analysis: Foundations and Extensions*, 2nd ed. Cambridge: Cambridge University Press.

National Economic and Development Authority. 2020. *Addressing the Social and Economic Impact of the COVID-19 Pandemic*; Pasig City: National Economic and Development Authority. Available online: http://www.neda.gov.ph/wp-content/uploads/2020/03/NEDA_Addressing-the-Social-and-Economic-Impact-of-the-COVID-19-Pandemic.pdf (accessed on 21 March 2020).

Nicola, Maria, Zaid Alsafi, Catrin Sohrabi, Ahmed Kerwan, Ahmed Al-Jabir, Christos Iosifidis, Maliha Agha, and Riaz Agha. 2020. The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International Journal of Surgery* 78: 185–93. [CrossRef]

Okuyama, Yasuhide, and Krista Yu. 2018. Return of the inoperability. *Economic Systems Research* 31: 467–80. [CrossRef]

Oosterhaven, Jan. 2017. On the limited usability of the inoperability IO model. *Economic Systems Research* 29: 452–61. [CrossRef]

Orsi, Mark J., and Joost R. Santos. 2010. Probabilistic modeling of workforce-based disruptions and input-output analysis of interdependent ripple effects. *Economic Systems Research* 22: 3–18. [CrossRef]

Pesce, Nicole Lyn. 2020. 55% of Businesses Closed on Yelp Have Shut Down for Good during the Coronavirus Pandemic. Available online: https://www.marketwatch.com/story/41-of-businesses-listed-on-yelp-have-closed-for-good-during-the-pandemic-2020-06-25 (accessed on 31 July 2020).

Philippine Department of Finance. 2020. The Duterte Administration's Philippine Program for Recovery with Equity and Solidarity (PH-PROGRESO). Available online: https://www.dof.gov.ph/the-duterte-administrations-philippine-program-for-recovery-with-equity-and-solidarity-ph-progreso/ (accessed on 16 August 2020).

Philippine Inter-Agency Task Force for the Management of Emerging Infectious Diseases. 2020. Omnibus Guidelines on the Implementation of Community Quarantine in the Philippines with Amendments. Available online: https://www.doh.gov.ph/sites/default/files/health-update/20200716-omnibus-guidelines-on-the-implementation-of-community-quarantine-in-the-philippines.pdf (accessed on 16 July 2020).

Philippine Statistics Authority. 2019a. Updated Population Projections Based on the Results of the 2015 POPCEN. Available online: http://www.psa.gov.ph/statistics/census/projected-population (accessed on 2 October 2020).

Philippine Statistics Authority. 2019b. 2009–18 Gross Regional Domestic Product. Available online: http://www.psa.gov.ph/grdp/data-series (accessed on 2 October 2020).

Philippine Statistics Authority. 2020a. Quarterly National Accounts Linked Series (Q1 2000 to Q2 2020). Available online: http://www.psa.gov.ph/national-accounts/base-2018/data-series (accessed on 2 October 2020).

Philippine Statistics Authority. 2020b. GDP Drops by 16.5 Percent in the Second Quarter of 2020; the Lowest Starting 1981 Series. Available online: http://www.psa.gov.ph/national-accounts/sector3/Gross%20Domestic%20Product (accessed on 2 October 2020).

Powe, Michael, and Matthew Wagner. 2020. *The Impact of COVID-19 on Small Businesses*. Chicago: National Main Street Center.

Prager, Fynnwin, Dan Wei, and Adam Rose. 2016. Total Economic Consequences of an Influenza Outbreak in the United States. *Risk Analysis* 37: 4–19. [CrossRef]

Prosser, Lisa A., Tara A. Lavelle, Anthony E. Fiore, Carolyn B. Bridges, Carrie Reed, Seema Jain, Kelly M. Dunham, and Martin I. Meltzer. 2011. Cost-effectiveness of 2009 Pandemic influenza A(H1N1) vaccination in the United States. *PLoS ONE* 6: e22308. [CrossRef] [PubMed]

Rey, Aika. 2020. Labor Group Urges Lifting of Public Transport Ban during Modified ECQ. Available online: https://rappler.com/nation/labor-group-statement-public-transport-operate-modified-ecq (accessed on 15 August 2020).

Santos, Joost. 2020a. Reflections on the impact of "flatten the curve" on interdependent workforce sectors. *Environment Systems and Decisions* 40: 185–88. [CrossRef] [PubMed]

Santos, Joost. 2020b. Using input-output analysis to model the impact of pandemic mitigation and suppression measures on the workforce. *Sustainable Production and Consumption* 23: 249–55. [CrossRef]

Santos, Joost R., and Yacov Y. Haimes. 2004. Modeling the demand reduction input-output (I-O) inoperability due to terrorism of interconnected infrastructures. *Risk Analysis* 24: 1437–51. [CrossRef]

Santos, Joost R., Lucia Castro Herrera, Krista Danielle S. Yu, Sheree Ann T. Pagsuyoin, and Raymond R. Tan. 2014. State of the art in risk analysis of workforce criticality influencing disaster preparedness for interdependent systems. *Risk Analysis* 34: 1056–68. [CrossRef]

Santos, Joost R., Larissa May, and Amine E. Haimar. 2013. Risk-based input-output analysis of influenza epidemic consequences on interdependent workforce sectors. *Risk Analysis* 33: 1620–35. [CrossRef]

Smith, Richard D., Marcus R. Keogh-Brown, Tony Barnett, and Joyce Tait. 2009. The economy-wide impact of pandemic influenza on the UK: A computable general equilibrium modelling experiment. *BMJ* 339: b4571. [CrossRef] [PubMed]

Soriano, Michelle. 2020. Cordillera Farmers Throw Away Veggies Due to Lack of Buyers Amid COVID-19 Quarantine. Available online: https://news.abs-cbn.com/business/03/25/20/cordillera-farmers-throw-away-veggies-due-to-lack-of-buyers-amid-covid-19-quarantine (accessed on 3 April 2020).

Suman, Hemant K., Amit Agarwal, and Nomesh B. Bolia. 2020. Public Transport Operations after Lockdown: How to Make It Happen? *Transactions of the Indian National Academy of Engineering*, 1–8. [CrossRef]

Ullah, Saif, and Muhammad Altaf Khan. 2020. Modeling the impact of non-pharmaceutical interventions on the dynamics of novel coronavirus with optimal control analysis with a case study. *Chaos, Solitons & Fractals* 139: 110075. [CrossRef]

United Nations Conference on Trade and Development. 2020. Covid-19 and Tourism. Available online: https://unctad.org/system/files/official-document/ditcinf2020d3_en.pdf (accessed on 25 August 2020).

Wong, Wilson. 2020. COVID-19 Turned College Towns into Ghost Towns and Businesses Are Struggling to Survive. Available online: https://www.nbcnews.com/news/us-news/covid-19-turned-college-towns-ghost-towns-businesses-are-struggling-n1233521 (accessed on 16 August 2020).

World Bank. 2020. Pandemic, Recession: The Global Economy in Crisis. In *Global Economic Prospects*. Washington: World Bank, pp. 1–66. Available online: https://openknowledge.worldbank.org/bitstream/handle/10986/33748/211553-Ch01.pdf (accessed on 10 October 2020).

Xiao, Hao, Bo Meng, Jiabai Ye, and Shantong Li. 2020. Are global value chains truly global? *Economic Systems Research*, 1–25. [CrossRef]

Yu, Derrick Ethelbhert C., Krista Danielle S. Yu, and Raymond R. Tan. 2020a. Implications of the pandemic-induced electronic equipment demand surge on essential technology metals. *Cleaner and Responsible Consumption*, 100005. [CrossRef]

Yu, Derrick Ethelbhert C., Luis F. Razon, and Raymond R. Tan. 2020b. Can global pharmaceutical supply chains scale up sustainably for the COVID-19 crisis? *Resources, Conservation and Recycling* 159: 104868. [CrossRef] [PubMed]

Yu, Krista Danielle S., and Kathleen B. Aviso. 2020. Modelling the Economic Impact and Ripple Effects of Disease Outbreaks. *Process Integration and Optimization for Sustainability* 4: 183–86. [CrossRef]