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The Impacts on Greenhouse Gases Emission during the COVID-19 lockdown in the US: An Economic Input-Output Life Cycle Assessment

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Abstract

The SARS-CoV-2 virus pandemic (COVID-19) is causing disruptions to energy, finance, tourism, and trade industries all around the world. These disruptions are the result of quarantining and lockdowns that cause reductions in production and consumptions. This change in production and consumption rates has environmental consequences. This study investigates the environmental effects of COVID-19 lockdown in the United States by Input-Output Life Cycle Assessment (IO-LCA) approach. The analysis is based on extraction of economic data in the US. The simulated results are based on different durations and strategies of lockdown measures. Among all industrial categories, utilities, which include power generation and supply, water supply, and natural gas supply sectors, saw the most significant reductions by approximately 110 kt CO₂-eq in the first quarter and 265 kt CO₂-eq in the second quarter of 2020. The assessed reductions were the results of both direct emission reductions caused by the shutdown of certain industries and also indirect emission reductions from upstream industries. The proposed methodology provides an effective guideline to predict the greenhouse gases emissions, which can be used as a prediction method for different regions in the world.

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1. Introduction

Severe acute respiratory syndrome coronavirus 2 [1], which was first reported in Wuhan, China in late 2019 [2], caused the global infectious disease, COVID-19 [3]. The United States (US) reported the first case on January 20, 2020 in Washington State [4]. The World Health Organization named COVID-19 as a pandemic on March 11, 2020 with more than 118,000 confirmed cases in 114 countries, and 4,291 deaths [5]. Countries reacted to the outbreak by limiting the movement of people with different measures all around the world. Approximately 3 billion people asked to stay at home [6]. The COVID-19 pandemic caused estimated global consumption loss of \$3.8 trillion, job losses equivalent to 147 million full-time positions, and loss of \$2.1 trillion in wages and salaries [7]. However, decreases in production and change in consumption habits cause notable change on greenhouse gases emission.

Several studies investigated mitigation of atmospheric pollution during the COVID-19 outbreak all around the world [8-12]. However,

the majority of the studies are local and based on measurements of specific air quality compounds. Satellite images from the Centre for Research on Energy and Clean Air (CREA), NASA, and the European Space Agency (ESA), show a major decline in Nitrogen dioxide (NO₂) emissions over recent months [13]. This can be the direct results of reduction of operating factories and the use of vehicles. A recent study assessed decline in PM_{2.5} (11.3%) and NO₂ (25.5%) during the pandemic in the US [14]. Satellite data showed a similar 30% reduction in NO₂ during the month of March in the urban northeastern US [15]. Similar studies have been conducted all around the world. Bao et al. [8] showed that on average, the air quality index decreased by 7.80% in China due to lockdown term. Also, SO₂, PM_{2.5}, PM₁₀, NO₂, and CO decreased by 6.76%, 5.93%, 13.66%, 24.67%, and 4.58%, respectively as an average of 44 cities in China. Rugani et al. [10] estimated a decrease in the carbon footprint burden by 20% compared with 2015-2019 in Italy. The satellite imagery is helpful to analyze the atmospheric pollutants [16]; however, this methodology is not helpful to investigate Greenhouse Gas (GHG) reductions due to their long-term storage in atmosphere [17]. In addition, recent studies

focused on understanding the overall impacts due to the lockdown but did not address impacts due to the life cycle of industrial productions [8, 10, 15].

Life Cycle Assessment (LCA) method was developed to evaluate the environmental impacts of a product's or a process' full life cycle, including raw material extraction, manufacturing, use phase, and end-of-life [18]. LCA is a useful and popular method to estimate the impacts through the life cycle of different products or industries. For one product or process, performing an LCA study is relatively straightforward; however, when many industries are involved, especially when they are interconnected, the scope becomes complex and the evaluation of impacts becomes time-consuming. To deal with complex scopes, researchers from Carnegie Mellon University introduced Input-Output LCA (IO-LCA) [19-21]. The IO-LCA model adapted the input-Output theory developed by the Nobel Prize Winner Laureate Wassily Leontief. The theory helped to analyze the relationships between consumption and production in the economy [22]. Based on the theory, the IO-LCA method uses economic exchange values to estimate the environmental emissions and the required materials and energy resources associated with the goods and services produced and traded by countries. The objective of this study is to investigate the environmental impacts of the change in US economics due to COVID-19 lockdown with an IO-LCA method.

2. Methods

In an IO-LCA model, an A matrix is used to include exchange information between all industries in a predefined system. The system is often a country's or a region's whole economy. Equation 1 represents the basic formula to estimate environmental impacts in IO-LCA models [19]. Matrix A shows the exchanges between industries within the system; matrix R shows the information regarding environmental effects from each industry in the system. Each entry in the R matrix represents the quantified environmental effect (e.g. total CO₂) caused by the production of one functional unit of goods or services from the industry shown in the corresponding entry of the A matrix. Formula $(I - A)^{-1}$ is called Leontief inverse, it is used to calculate total required output considering all the exchanges. When developing an IO-LCA model, the model developers define the system, gather information and data to build these matrices and incorporate this information into the model. When using an IO-LCA model, users can only define the y vector, which represents the production of one or more industries. The model calculates vector B, which represents the total environmental impacts of the production from the industry. These impacts include both the direct impacts from the industry under study as well as the upstream industries on the whole supply chain.

$$B = R(I - A)^{-1}y \quad (1)$$

Because of its clear system boundary and ability to capture both direct and indirect environmental impacts, IO-LCA models are widely used in estimating overall environmental impacts due to changes in industrial outputs. Lenzen et al. [7] conducted a multi-regional input-output analysis and estimated a 2.5 metric gigaton reduction in greenhouse gasses, as well as significant reductions for other air pollutants, including PM_{2.5}, SO₂, and NO_x gases. Popularly used US based IO-LCA models include EIO-LCA developed by the Green Design Institute of Carnegie Mellon University [23] and US Environmentally-Extended Input-Output (US-EEIO) model developed by US EPA [24]. A few studies have focused on input-output analyses by using national input-output tables for estimating the potential economic impacts of the COVID-19 in China and Japan [25]. However, to our knowledge, there is no study on quantifying the environmental impacts of the pandemic by IO-LCA. The aim of this study is to provide a comprehensive estimate of how the pandemic in the US affect the GHGs. The proposed methodology can be

implemented on other regions. It is crucial to understand the causes and effects of potential impacts to provide useful information on carbon footprint of lockdown measures.

In this study, we used a modified USEEIO model [24] as our IO-LCA model. The data for the A matrix was estimated based on the US Bureau of Economic Analysis (BEA)'s input-output tables and we adapted the methodologies provided by US-EEIO model to estimate the values in the A matrix. The raw data for the estimation is from the 2012 commodity by industry (C x I) model provided by US BEA.

The values in the GHGs R matrix were estimated based on the allocation method provided by the USEEIO. Overall, there were 405 industrial sectors in the model and four environmental effects including total GHGs emissions.

The total economic output values for the sectors in the USEEIO model were estimated based on data for 21 US industrial categories provided by US BEA's quarterly Gross Domestic Product [27]. 405 industrial sectors were aggregated to 21 industrial categories for the model. The available information is up to the second quarter of 2020 chained to the 2012 dollar value. Table 1 shows the results of real GDP changes for the 21 industrial categories in quarter 1 and quarter 2 of 2020.

To calculate the total emission changes during the first or second quarter, we first found the economic changes due to activity switches for all US industries. These changes were based on the differences in total economic output values between 2020 Quarter 1 (or Quarter 2) and 2019 Quarter 1 (or Quarter 2) for each industry (Table 1). Then, the economic data for 91 sub-categories were allocated to 405 IO sectors by each sector's total economic output share within its industrial category. The economic output shares were calculated from data provided by US BEA's 2012 Use Table (2020). There were quarterly economic data for 405 IO sectors after the two rounds of allocations.

To calculate the total emissions from all industries, the economic changes for each quarter for all 405 sectors were defined as values in the y vector in Equation 1. The results in the B vector represent the changes of GHGs emissions due to the change of economic activities. We also separately calculated the effects to all other industrial categories due to the changes of one industrial category. This was performed by defining a y vector that shows the changes of sectors in only one of the 21 industrial categories and separate B values into individual industrial categories.

In the US, to restrict the spread of the disease, each state enforced lockdown during different time intervals. During the lockdown, the US saw a decrease in transportation, along with reducing power generation and industry operations. We see the main economic impact in the second quarter for the majority of industrial categories (Table 1). The economic data for the third quarter is not available yet, so the scope of this study is limited for the first half of 2020.

Table 1 shows that beginning of pandemic term impacted *accommodation and food services*; *Arts, entertainment, and recreation*; and *wholesale trade* industries negatively in the first quarter. On the other hand, there was a positive change for a few industries in the same quarter; *agriculture, forestry, fishing and hunting*; *utilities*, and *information*. The real impact becomes more significant in the second quarter especially for *arts, entertainment, and recreation* (60%); *accommodation and food services* (45%); *other services* (21%); *transportation and warehousing (domestic)* (22%); *mining, quarrying, and oil and gas extraction* (19%); *health care and social assistance* (16%); *durable goods manufacturing* (14%); and *wholesale trade* (14%). We explored the results of the economic changes in both quarters and compared with the previous year.

Table 1. Economic impacts of COVID-19, economic difference between 2020 and 2019 in billions of chained 2012 dollars

Industrial Categories	Abbreviation	Q1	Q2	Q1	Q2
		(2020 and 2019 Q1)	(2020 and 2019 Q2)	(2020 and 2019 diff.)	(2020 and 2019 diff.)
Agriculture, forestry, fishing and hunting	Agr	31	-3	13.2%	-1%
Mining, quarrying, and oil and gas extraction	Mining	-11	-100	-2.2%	-19%
Utilities (include electricity generation, water supply and natural gas distribution)	Utilities	20	1	7.0%	0%
Construction	Const	10	-39	1.5%	-6%
Durable goods manufacturing (Manufacturing)	Durable	-14	-178	-1.1%	-14%
Nondurable goods manufacturing (Manufacturing)	N-durable	48	-25	5.2%	-3%
Wholesale trade	Wholesale	-65	-156	-5.6%	-14%
Retail trade	Retail	-5	-105	-0.5%	-9%
Transportation and warehousing (domestic)	Transpt	5	-122	0.9%	-22%
Information	Info	79	44	6.7%	4%
Finance and insurance	Finance	-25	2	-2.1%	0%
Real estate and rental and leasing	Real estate	44	-36	1.8%	-1%
Professional, scientific, and technical services	Prof-serv	50	-93	3.3%	-6%
Management of companies and enterprises	Mangt	8	-9	1.9%	-2%
Administrative and support and waste management and remediation services	Admin	0	-89	0.1%	-15%
Educational services	Edu	7	-17	3.2%	-8%
Health care and social assistance	Health	-16	-237	-1.1%	-16%
Arts, entertainment, and recreation	Arts	-12	-120	-5.8%	-60%
Accommodation and food services	Accom	-30	-232	-5.8%	-45%
Other services (except government and government enterprises)	Other	-9	-79	-2.4%	-21%
Government and government enterprises	Gov	38	-78	1.7%	-4%

3. Results and Discussion

The economic slowdown resulted in reduction of GHGs emissions for the first half of 2020. Figure 1 shows the change in total GHGs emissions in the first and second quarter of 2020 compared to 2019 for 20 industrial categories (*Management of companies and enterprises* category was combined with *Professional, scientific, and technical services* category due to their similarity). The total GHGs values were calculated by converting the substances CO₂, N₂O and CH₄ to the impact unit kt CO₂-eq using the Global Warming impact characterization factors provide by IPCC 2016 (100-year) [29]. The overall emissions fell by 9% during the COVID-19 lockdown, which was close to the forecast of the International Energy Agency [28]. We listed the results under 20 industrial categories in Table 2. In the first quarter, we observed the major reduction from *Utilities* by 109.8 kt CO₂-eq. We saw a change in the order of heavily affected sectors in the second quarter when main lockdown measures were applied. There was a drastic GHGs emission reduction from *Utilities* by 265 kt CO₂-eq, while 65.6 kt CO₂-eq. from the *mining, quarrying, and oil and gas extraction*. Another major change in total GHGs occurred as a result of decrease in *agriculture, forestry, fishing, and hunting*. In the first quarter, emissions increased by 70.5 kt CO₂-eq, on the other hand, it fell by while 41.5 kt CO₂-eq in the second quarter. This change was a result of strict lockdown measures and slowdown in manufacturing in between April and June of 2020. Another important decline was from *transportation and warehousing*; we did not see the main impact in the first quarter, while the total GHG decreased by 101.6 kt CO₂-eq in the second quarter. The industrial allocation for each GHGs compound for both quarters of 2020 is outlined in Fig. 1.

Utilities (42% of the total greenhouse gas emission reduction in the second quarter) – This industrial category includes Electric Power Generation, Transmission, and Distribution; Natural Gas Distribution; Water, Sewage, and Other Systems. There was a dramatic shift from 2019 to 2020 in the total GHGs emissions. We saw significant increase in the first quarter (109.8 kt CO₂-eq), that was possibly due to normal increase and first reaction to the pandemic. We saw the main effect of the lockdown measures in Q2 by reduction of 265.3 kt CO₂-eq. Fig. 1 shows the allocation of greenhouse gasses for each industrial category. The main compound was CO₂ with 106.5 kt out of 109.8 kt CO₂-eq total GHGs in the first quarter, while this reverse emission increased to 259.7 kt out of 265.3 kt CO₂-eq.

Mining, quarrying, and oil and gas extraction (10% of the total greenhouse gas emission reduction in the second quarter) – There was a minor increase in the first quarter by 1.9 kt CO₂-eq in the total GHGs emissions, this change decreased 65.6 kt CO₂-eq in the second quarter. The main gas was CO₂ by 39.7 kt in the second quarter.

Transportation and warehousing (16% of the total greenhouse gas emission reduction in the second quarter) – There is no significant decrease in the first quarter. In the second quarter, transportation activities significantly decreased due to lockdown, which resulted in 101.6 kt CO₂-eq decrease in total GHGs. The historical data showed that this industrial category generated the largest share of greenhouse gas emissions. The GHGs emissions from *transportation and warehousing* primarily came from burning fossil fuel for vehicles. Unlike other industrial categories, we saw an important amount of CH₄ in the second quarter since the largest share of the fuel used for *transportation and warehousing* was petroleum based. Note that transportation GHGs from international transportations were not included in the data. In Q2, with certain international travel bans, the emissions from international travels can be expected to have a decrease.

Agriculture, forestry, fishing and hunting (7% of the total greenhouse gas emission reduction in the second quarter) – The main emissions in this industrial category came from livestock (e.g. cows), agricultural

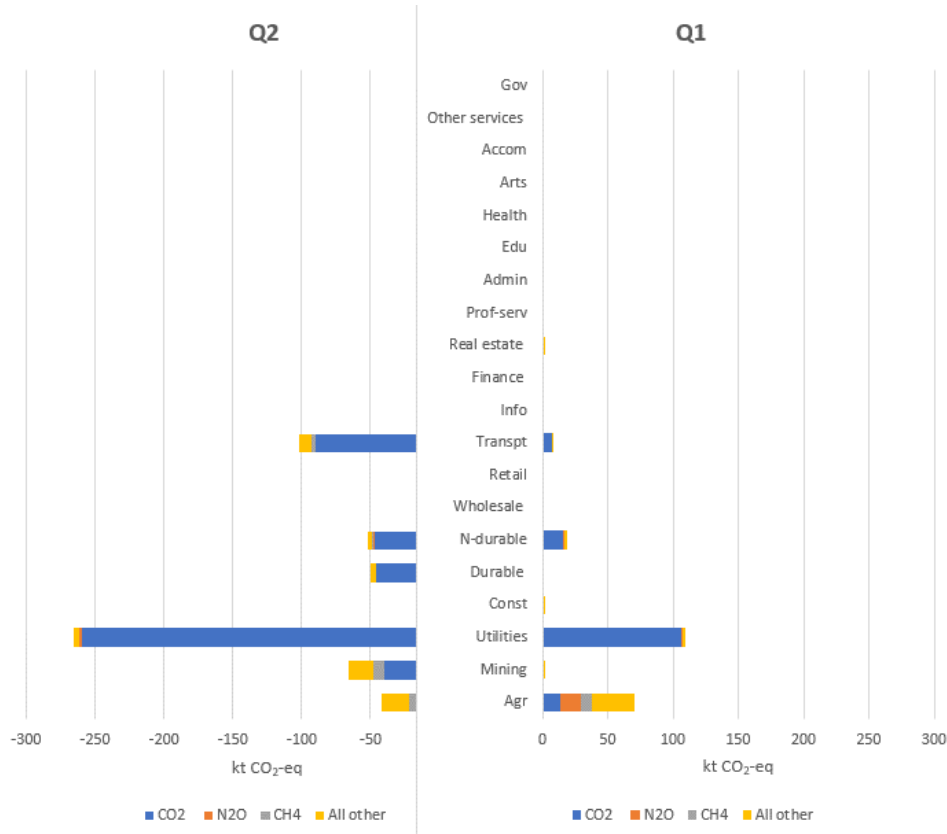


Fig. 1. Estimated total and allocated Greenhouse Gas Emissions from twenty (20) different industrial categories during the first quarter (Q1) and second quarter (Q2) of 2020 compared to 2019 (ktCO₂-eq). The values “0” show there is no emission from that category.

soils, and rice production. We saw an increase of 13.8 kt CO₂ and 7.9 kt CO₂-eq of CH₄ out of total 70.5 kt CO₂-eq in the first quarter. The impact of economic slowdown observed in the second quarter with the new restrictions; 8.5 kt CO₂-eq from CO₂ emissions out of 41.5 kt CO₂-eq in total. Due to the nature of the sector, unlike other sectors CO₂ was not the major GHGs for agricultural industries.

Nondurable goods manufacturing (8% of the total greenhouse gas emission reduction in the second quarter) – In the first quarter, we saw an increase of the total GHGs (18.7 kt CO₂-eq), on the other hand, we saw the impact of the lockdown by a sharp decrease of the total GHGs, 52.3 kt CO₂-eq.

Durable goods manufacturing (8% of the total greenhouse gas emission reduction in the second quarter) – In the first quarter there was a small increase by 0.1 kt CO₂-eq in the total emissions. However, in the second quarter, we saw a similar trend as *Nondurable goods manufacturing*, the impacts became more visible with 50.4 kt CO₂-eq decline.

Construction (1% of the total greenhouse gas emission reduction in the second quarter) – In the first quarter, we saw a moderate loss of business, in the second quarter, the risk of production downtown rose due to lack of personnel. As a result, we saw a 8.2 kt CO₂-eq decline in the total emissions.

Administrative and support and waste management and remediation services (3% of the total greenhouse gas emission reduction in the second quarter) – The impact of the COVID-19 lockdown measures were relatively small in the first quarter, however, the main impact was significant in the following quarter with a 17.4 kt CO₂-eq sharp decrease of the total GHGs. We did not observe any reverse emission from *information* category in the first quarter. This result was expected

due to the lockdown measures in the selected time interval. Similarly, we saw a slight decrease from *wholesale trade; finance and insurance; arts, entertainment and recreation; accommodation and food services; and other services; educational services; and health care and social assistance* categories in the second quarter.

Fig. 2 shows the relative sensitivity of each industrial category in each quarter based on the change from the previous year’s same quarter. These values are the results of the total GHGs emissions in kg CO₂-eq from individual industrial categories. Each column represents the effects from the change of the column industrial category to other industrial categories (rows). For example, Fig. 1 shows the change of *mining* category (Column 2) caused 1.8 kt CO₂-eq GHGs reduction from the *utilities* category. We highlighted the values to show the greatest decreases (green) and the greatest increases (red). To evaluate the values in each row, we defined a y vector that only changes the sectors in the column industry. This means that each column only shows the impacts from its column category, not the changes of the whole economy. For the first quarter, there were still increases in GHGs emissions because most of the industries were still open. Whereas in the second quarter, all industrial categories saw GHGs emission reductions because all of the industries were facing economic losses. The results also showed that change in one category can result in significant changes in other categories. For example, the increase in economic activities in *agriculture, forestry, fishing, and hunting* resulted in significant GHGs emission increases in *utilities*.

Another example is the emission decrease in *utilities* due to the economic change in *accommodation and food services* in both Q1 and Q2. These results showed that because industries were highly connected and depended on each other, there could be significant indirect emissions due to the change of one industry. Therefore, although the direct economic values see an increase for utility sectors in both Q1 and Q2, the GHGs emissions had certain reductions due to

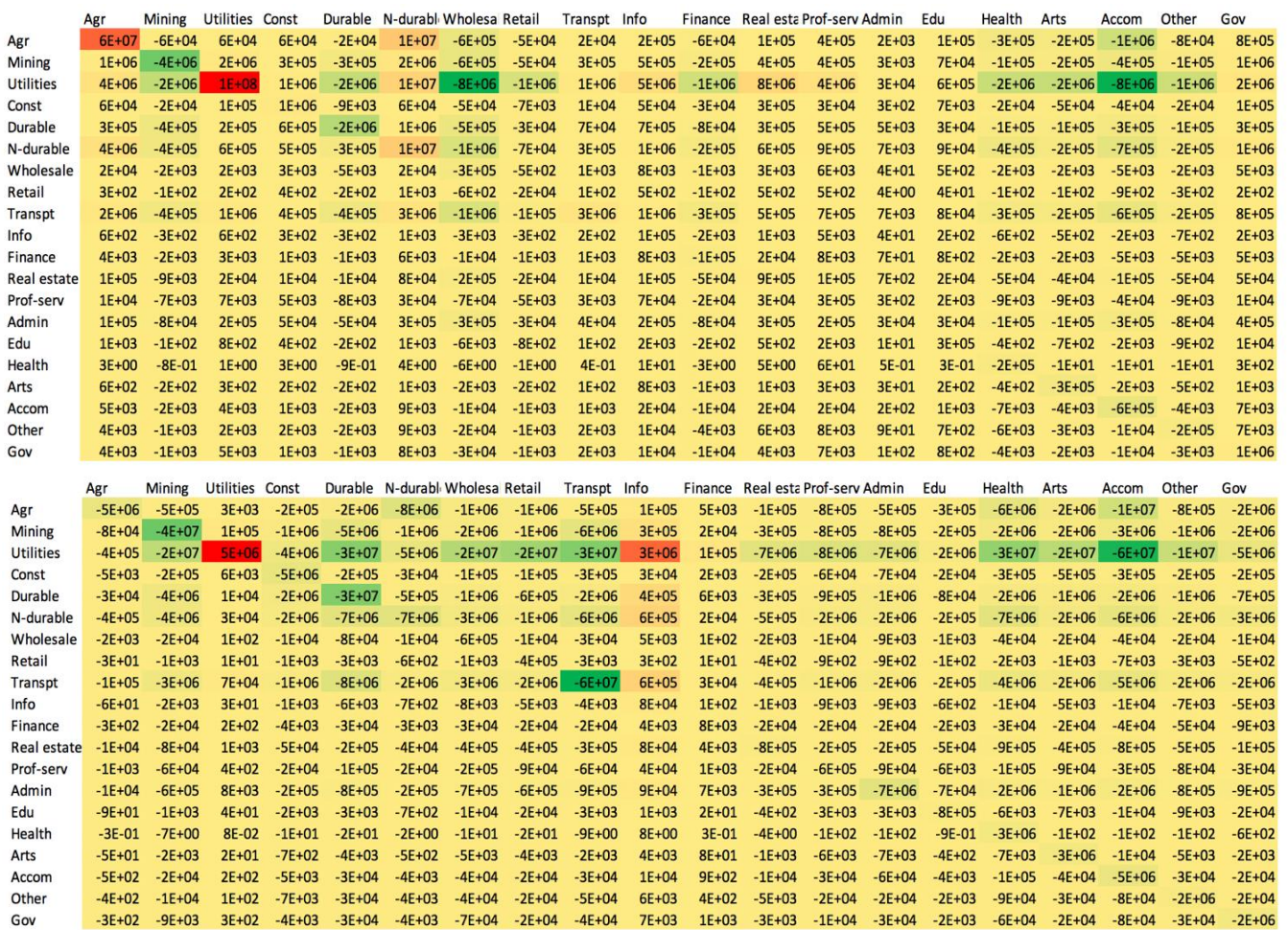


Fig. 2. Relative sensitivity of industrial categories for the first (Q1) and second (Q2) quarter (kg CO₂-eq). (These are the results of the effects from industrial categories. Each column represents the effects from the change of the column to other categories (rows). The greatest decreases are highlighted in green and the greatest increases are highlighted in red.)

indirect utility usage. The results also indicated that *Utilities*, *durable goods* and *non-durable goods manufacturing* and *transportation* categories were most sensitive to the changes from other categories, due to their unique important role in the whole economy.

The main objective of this study is to investigate the reductions in overall GHGs emissions due to slow down in economy. This result will be updated when there are publicly available data for the second half of 2020. We did not predict the overall GHGs for 2020.

There are two main limitations of the predicted results. The first important limitation comes with the IO-LCA model, which has inherent uncertainty due to the nature of the model [30]. In general, there are three main sources of uncertainty in IO-LCA models: parameter uncertainty, scenario uncertainty, and model uncertainty [31]. In this study, the main uncertainty is related to the model, which is caused by spatial differences and model assumptions. We used highly aggregated US economic data for the analysis; detailed economic changes due to regional differences were not considered. Second, the economic outputs for the second half of 2020 are not available yet. This can be improved when economic data are publicly available. We believe the methodology used in this research can be applied when better data are available. In addition, the lockdown measures varied state to state, therefore, another limitation is predicting the overall results for the whole country instead of using economic data for each state.

This study also has several strengths. Comparison to empirical studies, this study shows a novel approach to predict the overall impacts of the

pandemic lockdown measure and also industrial change, which provides useful long-term information for decision makers. This is the first study, to our knowledge, to quantify the impacts on GHGs emissions during the pandemic by EIO-LCA.

4. Conclusion

This study provides a comprehensive estimation of GHGs effects due to the COVID-19 outbreak lockdown in the US. The results showed that overall, the total GHGs emissions from all US industries reduced by almost 10% since March 2020 compared to associated quarters of 2019. These reductions were the results of both direct emission reductions that caused by the shutdown of certain industries and also indirect emission reductions from upstream industries. Among all industrial categories, *utilities*, which include *power generation and supply*, *water supply*, and *natural gas supply* sectors saw the most significant reductions. This was because they served as the most important upstream sectors for almost all sectors in the whole economy. Despite the limitations due to unavailable data, the method we discussed in this paper can be used to estimate both direct and indirect emissions or energy consumptions due to further economic changes. The proposed methodology can be implemented on other regions.

5. References

- [1] WHO, World Health Organization, Director-General's opening remarks at the media briefing on COVID-19—11 March 2020. Available from <https://www.who.int/dg/speeches/detail/who-director-general-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020>.
- [2] Lu, Roujian, Xiang Zhao, Juan Li, Peihua Niu, Bo Yang, Honglong Wu, Wenling Wang, Hao Song, Baoying Huang, Na Zhu, Yuhai Bi, Xuejun Ma, Faxian Zhan, Liang Wang, Tao Hu, Hong Zhou, Zhenhong Hu, Weimin Zhou, Li Zhao, Jing Chen, Yao Meng, Ji Wang, Yang Lin, Jianying Yuan, Zhihao Xie, Jinmin Ma, William J. Liu, Dayan Wang, Wenbo Xu, Edward C. Holmes, George F. Gao, Guizhen Wu, Weijun Chen, Weifeng Shi, and Wenjie Tan. 2020. "Genomic characterisation and epidemiology of 2019 novel coronavirus: implications for virus origins and receptor binding." *The Lancet* no. 395 (10224):565-574. doi: 10.1016/s0140-6736(20)30251-8.
- [3] Zhu, N., D. Zhang, W. Wang, X. Li, B. Yang, J. Song, X. Zhao, B. Huang, W. Shi, R. Lu, P. Niu, F. Zhan, X. Ma, D. Wang, W. Xu, G. Wu, G. F. Gao, W. Tan, Investigating China Novel Coronavirus, and Team Research. 2020. "A Novel Coronavirus from Patients with Pneumonia in China, 2019." *N Engl J Med* no. 382 (8):727-733. doi: 10.1056/NEJMoa2001017.
- [4] Holshue, M. L., C. DeBolt, S. Lindquist, K. H. Lofy, J. Wiesman, H. Bruce, C. Spitters, K. Ericson, S. Wilkerson, A. Tural, G. Diaz, A. Cohn, L. Fox, A. Patel, S. I. Gerber, L. Kim, S. Tong, X. Lu, S. Lindstrom, M. A. Pallansch, W. C. Weldon, H. M. Biggs, T. M. Uyeki, S. K. Pillai, and V. Case Investigation Team Washington State -nCo. 2020. "First Case of 2019 Novel Coronavirus in the United States." *N Engl J Med* no. 382 (10):929-936. doi: 10.1056/NEJMoa2001191.
- [5] WHO, World Health Organization, Naming the coronavirus disease (COVID-19) and the virus that causes it 2020, 2020b. Available from [https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technicalguidance/naming-the-coronavirus-disease-\(covid-2019\)-and-the-virus-that-causes-it](https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technicalguidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it).
- [6] BusinessInsider. A third of the global population is on coronavirus lockdown. 2020. Available from <https://www.businessinsider.com/countries-on-lockdown-coronavirus-italy-2020-3?r=DE&IR=T>.
- [7] Lenzen, M., M. Li, A. Malik, F. Pomponi, Y. Y. Sun, T. Wiedmann, F. Faturay, J. Fry, B. Gallego, A. Geschke, J. Gomez-Paredes, K. Kanemoto, S. Kenway, K. Nansai, M. Prokopenko, T. Wakiyama, Y. Wang, and M. Yousefzadeh. 2020. "Global socio-economic losses and environmental gains from the Coronavirus pandemic." *PLoS One* no. 15 (7):e0235654. doi: 10.1371/journal.pone.0235654.
- [8] Bao, R., and A. Zhang. 2020. "Does lockdown reduce air pollution? Evidence from 44 cities in northern China." *Sci Total Environ* no. 731:139052. doi: 10.1016/j.scitotenv.2020.139052.
- [9] Bashir, M. F., B. Ma, Bilal, B. Komal, M. A. Bashir, D. Tan, and M. Bashir. 2020. "Correlation between climate indicators and COVID-19 pandemic in New York, USA." *Sci Total Environ* no. 728:138835. doi: 10.1016/j.scitotenv.2020.138835.
- [10] Rugani, B., and D. Caro. 2020. "Impact of COVID-19 outbreak measures of lockdown on the Italian Carbon Footprint." *Sci Total Environ* no. 737:139806. doi: 10.1016/j.scitotenv.2020.139806.
- [11] Sicard, P., A. De Marco, E. Agathokleous, Z. Feng, X. Xu, E. Paoletti, J. J. D. Rodriguez, and V. Calatayud. 2020. "Amplified ozone pollution in cities during the COVID-19 lockdown." *Sci Total Environ* no. 735:139542. doi: 10.1016/j.scitotenv.2020.139542.
- [12] Zheng, H., S. Kong, N. Chen, Y. Yan, D. Liu, B. Zhu, K. Xu, W. Cao, Q. Ding, B. Lan, Z. Zhang, M. Zheng, Z. Fan, Y. Cheng, S. Zheng, L. Yao, Y. Bai, T. Zhao, and S. Qi. 2020. "Significant changes in the chemical compositions and sources of PM_{2.5} in Wuhan since the city lockdown as COVID-19." *Sci Total Environ* no. 739:140000. doi: 10.1016/j.scitotenv.2020.140000.
- [13] NASA. Airborne Nitrogen Dioxide Plummets Over China. Earth observatory. Washington D.C., USA: North American Space Agency 2020. Available from <https://earthobservatory.nasa.gov/images/146362/airbornenitrogen-dioxide-plummets-over-china>.
- [14] Berman, J.D., Ebisu, K.. 2020. Changes in U.S. air pollution during the COVID-19 pandemic, *Science of the Total Environment*, 739, doi: 10.1016/j.scitotenv.2020.139864
- [15] Blumberg, S.. 2020. Data shows 30 percent drop in air pollution over northeast U.S. NASA, URL
- [16] Collivignarelli, M. C., A. Abba, G. Bertanza, R. Pedrazzani, P. Ricciardi, and M. Carnevale Miino. 2020. "Lockdown for CoViD-2019 in Milan: What are the effects on air quality?" *Sci Total Environ* no. 732:139280. doi: 10.1016/j.scitotenv.2020.139280.
- [17] IPCC, Intergovernmental Panel on Climate Change. 2005. Carbon Dioxide Capture and Storage. 40 West 20th Street, New York, NY 10011–4211, USA: Cambridge University Press.
- [18] Matthews, H. S., C. T. Hendrickson, and D. H. Matthews. 2015. Life cycle assessment: Quantitative approaches for decisions that matter. Pittsburgh: Carnegie Mellon University.
- [19] Lave, L. B., Cobas-Flores, E., Hendrickson, C. T., & McMichael, F. C.1995. Using input-output analysis to estimate economy-wide discharges. *Environmental Science & Technology*, 29(9), 420A-426A.
- [20] Cobas, E., Hendrickson, C., Lave, L., & McMichael, F. (1995, May). Economic Input/Output analysis to aid Life Cycle Assessment of electronics products. In Proceedings of the 1995 IEEE International Symposium on Electronics and the Environment ISEE (Cat. No. 95CH35718) (pp. 273-278). IEEE.
- [21] Hendrickson, C., Horvath, A., Joshi, S., & Lave, L. (1998). Peer reviewed: economic input–output models for environmental life-cycle assessment. *Environmental science & technology*, 32(7), 184A-191A.
- [22] Leontief, W. 1986. Input-output Economics: Oxford University Press.
- [23] EIO-LCA. Economic Input-Output Life Cycle Assessment (EIO-LCA). Carnegie Mellon University Green Design Institute 2008. Available from <http://www.eiolca.net>.
- [24] Yang, Y., Ingwersen, W. W., Hawkins, T. R., Srocka, M., & Meyer, D. E. 2017. USEEIO: A new and transparent United States environmentally-extended input-output model. *Journal of cleaner production*, 158, 308-318.
- [25] Inoue, H., and Y. Todo. 2020. The Propagation of the Economic Impact through Supply Chains: The Case of a Mega-City Lockdown against the Spread of COVID-19. SSRN 2020. Available
- [26] U.S. BEA. (2020, August 15). Supplemental Estimate Tables: Use Tables/After Redefinition/Producer Value - 2007, 2012: 405 Industries. Retrieved from Input - Output Accounts Data: <https://www.bea.gov/industry/input-output-accounts-data>
- [27] 2020b. Gross Domestic Product by Industry, 1st Quarter 2020. edited by US Department of Commerce BEA, Bureau of Economic Analysis. URL: <https://apps.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdrn=1#reqid=70&step=1&isuri=1&acrdrn=1> Accessed Nov. 17.2020.
- [28] IEA, International Energy Agency. 2020. Global Energy Review: 2020. from:<http://dx.doi.org/10.2139/ssrn.3564898>.
- [29] IPCC, 2019: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. In press.
- [30] Chen, Xiaoju, W. Michael Griffin, and H. Scott Matthews. 2018. "Representing and visualizing data uncertainty in input-output life cycle assessment models." *Resources, Conservation and Recycling* no. 137:316-325. doi: 10.1016/j.resconrec.2018.06.011.
- [31] Chen, X. 2017. Uncertainty Estimation in Matrix-based Life Cycle Assessment Models, Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA, USA.