The impact of the 2020 crisis on the Mexican economy: an input-output approach with inoperability

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Abstract

The article presents two input-out models with inoperability that analyze the effects of the Covid-19 pandemic in Mexico. Both use methodological developments in which contributions were made in their specification. The first, a static model, generates a vulnerability index of the economic branches, establishing their priority for attention with economic policy instruments. The second, a dynamic model, estimates possible trajectories of economic recovery of the sectors, their possible duration, and their resilience capacities in the face of persistent phenomena of the pandemic. The models are adjusted to the short-term indicators produced by the INEGI, reflecting a heterogeneous behavior between the sectors; some have a medium-term tendency not to return to their normal productive capacity.

Keywords: input-output models; general balance and imbalance; input demand analysis.

1. INTRODUCTION

The pandemic caused by the SARS-Cov-2 virus has had social, political and economic effects due to the global confinement measures which countries employed in an effort to contain it (Brodeur *et al*., 2021; Jackson *et al*., 2021). From an economic point of view, this situation is unprecedented given that it is a crisis by design, arising from measures adopted at the global level, both on the supply and demand side of goods and services. The crisis is characterized by how fast it spread and by having a greater risk of affecting economies with a strong dependence on supplies, through global value chains (Giammetti *et al*., 2020; Borio, 2020).

Even though the short-term consequences of the present crisis are without a doubt dramatic (considering indicators such as economic growth and unemployment), there was very little destruction in terms of the infrastructure supporting economies, unlike other crisis processes (Jackson *et al*., 2021; Borio, 2020). Understanding such a complex phenomenon requires the use of an approach which takes into account not only short-term changes in supply and demand, but also the configuration of the productive apparatus (structure) of the economy at the time of the crisis and the interactions between its sectors.

In order to understand the economic effects of the pandemic, most models focus on the impact on macroeconomic indicators such as GDP, employment, health, gender, environment, or losses in large sectors (primary, secondary and tertiary), and on some specific sectors (automotive, airport, tourism or pharmaceutical) (Herrera, 2021; Aguirre, 2020; Farhan *et al*., 2020). Other works mainly focus on understanding the effects on companies at the human, financial and tax levels (Brodeaur *et al*., 2021; Guardado *et al*., 2020), on the effects of financial policies and economic stimuli which different countries have used to mitigate the effects of the crisis (Elgin *et al*., 2020; Brodeaur *et al*., 2021) or on changes in income distribution and poverty (Lustig and Martínez, 2020). Most of these studies use statistics-based methodologies, such as linear regressions (simple, probit, and instrumental variables), differences in differences, time series, quantile regressions, primary components and multivariate analysis, even game theory, percolation, or cluster analysis (Brodeaur *et al*., 2021; Farhan *et al*., 2020).

Nevertheless, these studies do not allow one to differentiate the effects in different sectors and economic clusters, nor to identify those that need bolstering to minimize the crisis' negative effects (Oosterhaven, 2017). On the other hand, structural models for the diagnosis of economic effects and their likelihood for recovery can be used to evaluate and analyze the impacts of disasters and evaluate the resilience of the productive apparatus. They are thus able to solve the other models' aforementioned deficiencies as the majority of countries' productive structure will experience changes within a range that can be captured with multisectoral analytical tools. (Dávila and Valdés, 2021; Oosterhaven, 2017).

This article therefore takes on the task of analyzing the effects of the Covid-19 crisis, from a structural and multisectoral perspective, evaluating the economic reach of the changes the pandemic caused and identifying the specific economic sectors which need buttressing to minimize the crisis' negative effects on the Mexican economy, given their importance and interrelations with other sectors. We also adapted the models of Santos and Haimes (2004) and Lian and Haimes (2006), based on current data from INEGI (2020), so that the findings could reflect the reality of the Mexican economy. The former helps to measure and prioritize the impact caused by the partial closure of economic activities at the sectoral level, while the latter makes an evaluation of the short and medium-term recovery dynamics possible.

These models are rooted in production and general equilibrium theory and are able to place the focus of research on the distinction between a disaster's direct effects and its repercussions, through its economic spread. Using these inoperability models made it possible to identify production branches and sectors with the greatest vulnerability, sectors unaffected by the crisis, the most and least resilient, as well as the recovery rate, medium-term trends and the economic cost of the pandemic.

After the introduction, this document is organized as follows. The second section addresses the Covid-19 pandemic's impact in Mexico, emphasizing the recovery recently observed. The third section presents the methodology used for the study, based on input-output analysis applied to disaster assessment, enriched by resiliency measures and the sectors' resilience. The fourth presents the quantitative results of the models' operation, along with relevant observations. The last section presents some general comments and contributions for further works.

2. IMPACTS ON THE MEXICAN ECONOMY

The Covid-19 pandemic continues around the world. While some countries have managed to control the outbreak, others are still experiencing a continued increase in the number of new cases, in spite of social distancing and personal care measures meant to prevent its spread[1] and efforts to vaccinate the population (Mendoza *et al*., 2020). Within the context of this global crisis, the world economy decreased by 3.3%[2] and there was an 8.8% drop in work hours in 2020 when compared to those registered in 2019. This is equivalent to the loss of 225 million full-time jobs according to ILO data.

The closure of most productive activities caused at the beginning of the pandemic a drop in almost all sectors of the economy, even interrupting parts of the supply chain at the international level. This caused the closure of some companies and businesses and most of the world's countries' unemployment rate to increase (ILO laboratory, 2020). This downturn is historic, the largest since the Great Depression back in the 1930s (Jackson *et al*., 2021). The World Bank warned that the global economic outlook is uncertain and remains subject to various risks arising from inequality in different countries' recovery rate.[3]

In the case of Mexico, the drop in GDP was 8.2% with around 13 million people losing their jobs or being underemployed in 2020. The drop brought with it an increase in poverty and extreme poverty levels. The economic impact hit the middle and lower middle classes the hardest as this is where owners of small and medium-sized businesses are to be found. Given their vulnerability, they were the ones that suffered the most from the closure of activities (Lustig and Martínez, 2020). The services sector lagged the most, especially tourism and informal activities (Ruiz, 2020; Salas *et al*., 2020; Aguirre, 2020). These effects were strongly felt in various industries such as maquila and air transport (according to Herrera (2021) there was a 53% drop in passenger flow and 12% in cargo flights in 2020). However, Mendoza (2020) deduces by means of a prospective analysis of the Mexican economy that the greatest impact in the medium term will come from a slowdown of the economic cycle in the United States, followed by the repercussions of confinement and restrictions in the country. By 2021, the economy's growth was at a real 4.8% and the number of jobs recovered in December 2021, according to data from INEGI (2021).

Impacts on the Mexican economy by sector

Dávila and Valdés (2021) studied the impacts of closing non-essential sectors of the economy in the months of April and May 2020, using Social Accounting Matrices, estimating their cost to the value of production, disposable income and private consumption. The industrial sector was hit the hardest by the crisis with a nosedive of 10.2%, which is explained to a large extent by the closure of companies in that period, except for those considered essential, and by external demand which recovered very slowly. Then came the services sector with a drop of 7.9%. Here commerce and hospitality had to face a slew of capacity and scheduling restrictions. Furthermore, tourism, which is very important in the northwest and southeast of the country, experienced a reduction of 58% of travelers arriving by air in 2020. Finally, the primary sector, with a 2% growth, was the only activity that held steady during the pandemic. Thus, the fall in economic growth by sector in 2020 was heterogeneous.[4]

In Q4 of 2020, the economy signaled an improvement compared to previous months, thanks to the ongoing reopening of productive activities. Between October and December of that year, industry grew 3.3% and services 3%. Even so, comparing this period with the Q4 of 2019, there was a 4.6% YoY drop in economic activity, much smaller than Q2 and Q3, where the YoY drop was 18.7% and 8.6%, respectively. Likewise, a review of the numbers for the Mexican economy's performance in mid-2021 demonstrates better performance than expected due to the rebound effect from the internal reactivation, thanks to advances in vaccination, the gradual elimination of restrictions on mobility and the strength of external demand. However, there was significant slowdown in the second half of the year, with growth at the end of the year at just 5.0%, well below what was expected (INEGI, 2022). This resulted in the recovery process slowing down, starting in 2021.

3. METHODOLOGY

The study of disasters and their consequences has become an important area of analysis to try to mitigate economic effects and their spread in strongly interconnected systems in today's societies (Borio, 2020). Economic theory has a renewed interest in these topics, meaning that various different analysis frameworks are used for evaluating consequences at the micro, mezzo and macroeconomic scales (Santos and Haimes, 2004). However, there are three dominant classes of economic models for analyzing losses due to disasters: simultaneous equation econometric models, input-output models and computable general equilibrium (CGE) models. The first is based on the construction of vulnerability or resilience indices (Elgin *et al*., 2020). The last two are commonly used and better documented in disaster impact analysis (Okuyama and Yu, 2019).

Input-output models offer an orderly way to define the links between industries and supply-demand structure, but they have structural rigidities. On the other hand, the CGE framework introduces greater flexibility and the ability to represent a broad spectrum of demand functions and supply-side elasticities, as well as behavioral responses, at the expense of more elaborate assumptions which are necessary to describe the mutual adjustment of prices and quantities (Solís, 2015). Furthermore, input-output models are preferred for short-term estimation, while CGE models are used for long-term estimation (Solís, 2015).

This article used techniques derived from input-output analysis, which has garnered attention as a tool for the rapid assessment of disasters' cascading economic effects. The recent evolution of the discipline has been aimed at supporting a better understanding, measurement and development of instruments that help counteract complex disaster scenarios that affect societies and economies. Furthermore, classical models of supply and demand have been expanded considerably in order to take into account the dynamics of critical events and responses to crises (Santos and Haimes, 2004).

The estimation of forward and backward linkages in this type of models allow one to identify key sectors, assess different sources of change in exogenous variables and the sensitivity of the system, and compare different economies subject to similar phenomena. Furthermore, this approach has inherent affinities with the methodologies for analyzing cascading events from other fields, as well as those for assessing the economic imbalance that occurs due to a major disaster, thereby facilitating its integration (Benassy, 1982).

Vulnerability index for sectors facing the Covid-19 pandemic

This section presents a static model whose main result is the creation of a sectoral vulnerability index, which measures sectors' propensity to be affected by a disaster. The input-output techniques applied to the analysis of disasters or contingencies describe the structural connectivity of economic systems and have four aspects in common: *1*) the magnitude of the economic impact, *2*) propagation capacity, *3*) size of the sectors involved and *4)* the risk of inoperability for sectors studied (Santos and Haimes, 2004; Lian and Haimes, 2006; Yu *et al*., 2020).

The index consists of four indicators related to the points detailed above. In the first, final demand of non-essential sectors is reduced and inserted into the input-output model, generating a decrease in global activity. The second proposes an approach using Hilbert spectral analysis, within which the simultaneous propagation of purchase and sales levels carried out by each of the sectors is measured, both directly and indirectly (Solís, 2015). The size of each sector is represented by the percentage of their contribution to the country's GDP. Finally, the risk of inoperability is measured by the ratio between the Leontief output multiplier and the Ghosh output multiplier (Yu *et al*., 2020).

The measurement of the first component was carried out on a quarterly basis, thereby capturing the sectors' movements in terms of their vulnerability, depending on the economic results brought about by the economy's partial closure.

Associated with the output levels, induced by the purchases and sales relations that satisfy the requirement of final demand, are the employment requirements, i.e., the demand for goods implies the demand for employment. Therefore, the vulnerability index was estimated using a similar job by job matrix calculated based on Leontief's, which emerges from the intersectoral relationships themselves, using a change of base (King *et al*., 2012). These intrinsic properties of the matrices allow for the broadest study of the employment and production structure. As such, we calculate two vulnerability indices, one for each of these concepts.

Persistent dynamic inoperability model

The inoperability of an economic sector is defined as the relative loss of productive capacity with respect to a base level (planned, ideal, pre-disaster, etc.), such that an inoperability of 0.1 indicates that the sector produces 10% less than it should or could produce in the absence of a disaster or economic shock. As such, the inoperability of a sector is an indicator that remains between zero and one (Santos and Haimes, 2004; Lian and Haimes, 2006). In the case of the economic contingency which the SARS-Cov-2 virus brought about, the inoperability of the sectors was initially caused by the premeditated closure of non-essential economic activities, while in the second (and longer) stage, the closure was eased, but a modification in the population's consumption and behavioral patterns was added to the mix. Given the risk of contagion, the demand for services that require a high degree of contact with other people was discouraged (i.e., inoperability was due to both a reduction in supply and demand).

In order to measure the effects of a disaster on an economy, which behaves like a complex system, Haimes and Jiang (2001) developed a methodology based on the input-output model in physical terms, which allows one to measure the efficiency of risk management and economic impact evaluation resulting from the damages to the physical infrastructure and a country closing down companies in an emergency situation. This model is known as the Inoperability Input-Output Model (IIM). This model was later taken up again by Santos and Haimes (2004) to be used in monetary terms, assuming a reduction in the final demand of goods and services, which facilitated its application to data on real economies. Lian and Haimes (2006) present a new methodological advance with the dynamic version of the inoperability input-output model (DIIM), based on Leontief's dynamic model. Rather than taking into account the economy's growth dynamics, it models the dynamics by which the system returns to a state of equilibrium between supply and demand, given the initial imbalance caused by an economic disaster.

This allows us to define the inoperability vector *q* (broken down by economic activity) based on the gross value of the economy's base output, given by x^*, and the realized output value *x* (under the effects of the disaster), so that $q = \hat{x}^{*-1}(x^* - x)$, where $\hat{x}^*$ is the diagonal matrix of base output. Likewise, if *G* is the Ghosh matrix or delivery matrix, and $c = \hat{x}^{*-1}(f^* - f)$ is the difference between the base final demand f^* and the realized final demand *f* as a proportion of the gross output value. The equation that describes the dynamics of an economy with inoperability is:

$$q(t+1) = q(t) + K[Gq(t) + c(t) - q(t)] \quad (1)$$

where the term in brackets can be interpreted as the gap between the supply ($q(t)$) and the demand ($Gq(t) + c(t)$) of goods and services. The *K* matrix is diagonal, and its values k_{ii} represent the proportion of the gap (supply-demand) that will close in the next period.

The *k* matrix values are known as resilience coefficients, given that sectors with greater resilience in disasters tend to recover in less time. Factors affecting a sector's resilience level include: *i*) restoration of the countries' damaged productive capacities, *ii*) use of backup capacity (idle capacity), *iii*) substituting supplies produced by affected sectors, *iv*) changing the location of production to unaffected areas, or *v)* in case of disasters caused by a disease, a reduction in the risk of contagion among the population, which encourages consumption and businesses reopening.

The value of these parameters is acquired with the equation:

$$k_{ii} = \frac{ln\left[\frac{q_i(0)}{q_i(T_i)}\right]}{T_i}\left[\frac{1}{1 - g_{ii}}\right] \quad (2)$$

where $q_i(0)$ represents the initial inoperability, T_i the time it takes for sector *i* to reach inoperability level $q_i(T_i)$, while g_{ii} is the value over the main diagonal of the Ghosh matrix for sector *i*, which means that $\left[\frac{1}{(1-g_{ii})}\right]$ is a measure of the sector's dependence on the rest of the economy's demand.

The dynamic inoperability model then allows one to measure the economic loss derived from a disaster, while all sectors try to return to the previous equilibrium level between supply and demand ($q_i = 0$), or a new equilibrium in the case that final demand patterns are modified ($c_i \neq 0$) (Lian and Haimes, 2006).

Nevertheless, during the Covid-19 crisis, the sectors' return to their original levels was not without interruption. The fact that there was more than one wave of infections, along with new health contingency measures, resulted in new imbalances in the system before the previous ones had been corrected. In this context, Yu *et al*. (2020) propose a modification to the DIIM that allows one to estimate the impact of Covid-19's waves of infection through a Persistent Inoperability Input-Output Model (PIIM) which models sectors' reduced capacity that persists during the closures (partial or total) imposed by the government. This model provides useful information on prolonged inoperability in various sectors of the economy and how they affect other sectors, assuming that during the closure the operability level matches the impact on final demand c_i. However, this approach is inadequate in the context of the input-output model, given that, as Oosterhaven (2017, pp. 456-457) points out, shocks in final demand are very limited when one seeks to model a disaster that affects the supply of goods and services. Furthermore, if the value of c_i is not weighted by the weight of final demand in the sector's total output, sectors' inoperability will be overestimated. This article proposes an alternative formulation for calculating inoperability, assuming two types of behavior. The first assumes that inoperability occurs during periods of economic closure due to contingency measures, and the second that the effect is persistent over time.

τ will be the periods during which the sanitary measures are applied and *S* the sectors affected by these measures. Then, if $q_i^D(t)$ is the inoperability value of sector *i*, estimated by the dynamic model defined in equation (1), and $q_i^P(t)$ the value of persistent inoperability for sector *i*, its inoperability is defined as:

$$q_i(t+1) = \{q_i^P(t+1) \ , \quad t \in \tau \ \text{ and } \ i \in S, q_i^D(t+1) \ \text{ otherwise} \qquad (3)$$

The value of q_i^P can be estimated based on observed data, if any, or as hypothetical shocks based on announced health measures and previous experiences. Essentially, the estimate of q_i^P is not different from the estimate of $q_i(0)$.

4. RESULTS

To estimate this vulnerability indicator and the dynamic persistent vulnerability model, we used the input-output matrices (IOM) published by the INEGI as part of the Mexican Social Accounting Matrix (INEGI, 2020). We worked with the 2018 IOM, disaggregated to the level of branch of economic activity.

Economic vulnerability index

The production value of the Mexican economy is concentrated in a few branches and is quite asymmetrical. The ten most important branches account for more than 45% of the national economy's total output. Tables 1 and 2 only present the Mexican economy's ten main branches' ranking with regards to the vulnerability index, analyzing the gross output value (see table 1) and the largest number of jobs (see table 2). The number in each column indicates each branch's relative position. First place indicates the greatest vulnerability and, inversely, the lower the branch's position, the less vulnerable it is. The index's results are listed quarterly, starting in 2020 when the effects of the pandemic were still marginal, until the second quarter of 2021, taking into account only the first two waves of infections, which brought great restrictions to the economy.

Thus, we see that with respect to the gross output value (see Table 1) in the second quarter of 2020, the industries of vehicle parts, manufacturing of automotives and auto parts had the third and first highest vulnerability levels, respectively. They later had a high level of recovery, even though since the beginning of 2021 they have returned once again to the highest spots in terms of vulnerability. This reflects these branches' fragility, branches which benefited from the "rebound effect," but which find themselves unable to maintain sustained growth due to their association with exports, which began to fall in 2021.

Table 1. Ranking of production's quarterly relative vulnerability for the ten branches with the highest gross output value

Branch	2020				2021	
	Q1	Q2	Q3	Q4	Q1	Q2
4600 - Retail trade	3	4	1	1	1	4
4300 - Wholesale	2	2	2	4	3	6
5311 – Lessors of real estate	4	14	4	3	5	7
3361 – Motor vehicle manufacturing	6	1	8	11	2	1
2361 - Residential building construction	13	6	5	6	7	3
3363 – Motor vehicle parts manufacturing	5	3	9	12	2	5
4841 – General freight trucking	10	7	6	7	10	13
3241 – Petroleum and coal products manufacturing	1	5	3	2	4	2
2111 - Oil and gas extraction	7	9	10	8	15	14
2362 - Non-residential building construction	28	11	14	9	12	11

Source: created by the authors with the results of the vulnerability model.

Residential and non-residential construction experienced a significant increase in their vulnerability level, going from 13th and 28th place in Q1of 2020, to 3rd and 11th, respectively in Q2 of 2021. The opposite is true when we look at the performance of oil and gas extraction, retail and wholesale trade as they all reduced their vulnerability; the first of these did so in a sustained manner throughout the period and the other two did so suddenly in Q2 of 2021. Freight trucking presents a unique behavior; it increased its vulnerability considerably during the last three quarters of 2020 but by 2021 it returned to its original vulnerability levels. These results line up with the low dynamism of domestic demand and exports resulting from global health contingency measures.

On the other hand, in Table 2, the branches are ranked according to their share of the number of jobs. Here, retail trade and employment services remained the most vulnerable branches throughout the period.

The Private households branch, along with restaurants and other eating places, increased their vulnerability from Q2 of 2020 to Q1 of 2021, yet they seem to have bounced back in Q2 of 2021. Other crops farming behaved inversely, presenting a decrease in its relative vulnerability from Q2 of 2020 to Q1 of 2021, only to go back to a high vulnerability ranking in Q2 2021. Furthermore, jobs in residential and non-residential construction continued to experience difficulties throughout the period, as their vulnerability consistently increased. These results are logical as the branches that together generate a large number of informal jobs always consistently placed first in terms of vulnerability.

Table 2. Job vulnerability ranking for the ten branches with the highest number of jobs (quarterly data)

Branch	2020				2021	
	Q1	Q2	Q3	Q4	Q1	Q2
4600 - Retail trade	1	1	1	1	1	1
5613 - Employment services	2	2	2	2	2	2
8141 – Private households	6	5	3	3	3	6
2361 - Residential building construction	13	4	8	9	8	3
6111 – Elementary, Secondary and special need schools	19	34	9	10	13	17
2362 - Non-residential building construction	15	12	12	8	11	11
4300 - Wholesale	4	3	4	4	4	7
484 - Freight trucking	11	10	11	13	14	15
7225 – Restaurants and other eating places	9	6	5	5	5	9
1119 - Other crop farming	3	13	14	12	9	4

Source: created by the authors with the results of the vulnerability model.

Persistent inoperability model

For the persistent inoperability model, we used 2018's input output matrix's economic activity broken down into 20 sectors, which allowed us to use some of the INEGI's short-term indicators. The inoperability values were estimated based on the Global Indicator of Economic Activity (IGAE) and the Monthly Survey of Services (EMS),[5] especially the total income index for the supply of goods and services, using the activity level seen in December 2019 as the pre-disaster base level for comparison ($\hat{x}^*$).

May 2020 was chosen as the starting point (t = 0) for the model since the data indicates that it was the month with the largest overall drop in economic activity. Disruptions in final demand are assumed to be null, with the goal being that all sectors converge at that value. Some sectors, such as primary activities, financial and insurance services, corporate and government activities, were not affected by this crisis so they are considered to have an initial inoperability level of 0. Sectoral resilience values (k_i) were calibrated based on the recovery observed in the sectoral activity index, using equation (2). The values of the estimated parameters T_i and $q(T_i)$ are in Table 3.

The values in Table 3 capture the recovery process between the first and second waves of Covid-19 in Mexico. The most resilient sectors were manufacturing, health services, and wholesale and retail trade. These sectors produce goods and services which cater to people's basic needs, so, despite suffering the effect of restrictions and partial closures, they showed a rapid recovery thanks to the effect of final demand. On the other hand, the sectors with the least resilience were business support services, temporary accommodation, restaurants and other eating establishments, and transportation services, due to the restrictions on their operation and their inherent need for a high level of interaction between people and, in the case of business support services, to the implementation of work from home measures adopted by many companies and public institutions.

Table 3. Estimated resilience parameters

Sector	T_i	Month corresponding to T_i	$q(T_i)$	k_i
11 - Agriculture, forestry, fishing and hunting	-	-	-	0.287*
21 – Mining	5	October 2020	0.021	0.269
22 – Utilities	5	October 2020	0.040	0.242
23 - Construction	11	April 2021	0.078	0.147
31-33 - Manufacturing	5	October 2020	0.009	0.819
43 - Wholesale	4	September 2020	0.021	0.647
46 - Retail trade	5	October 2020	0.035	0.453
48-49 – Transportation and warehousing	7	December 2020	0.210	0.120
51 - Information	6	November 2020	0.095	0.136
52 – Finance and insurance	-	-	-	0.287*
53 - Real estate Rental and Leasing	7	December 2020	0.058	0.194
54 - Professional, Scientific and Technical Services	7	December 2020	0.151	0.133
55 – Management of Companies and Enterprises	-	-	-	0.287*
56 – Administrative and Support and Waste Management and Remediation services	6	November 2020	0.114	0.064
61 - Educational Services	4	September 2020	0.088	0.245
62 - Health Care and Social Assistance	4	September 2020	0.019	0.721
71 – Arts, Entertainment, and Recreation	4	September 2020	0.545	0.120
72 – Accommodation and Food Services	5	October 2020	0.427	0.108
81 - Other Services (except Public Administration)	4	September 2020	0.101	0.169
Article 93 – Public Administration, Law Enforcement and International and Extraterritorial Entities	-	-	-	0.287*

Note: *initial average of affected sectors.

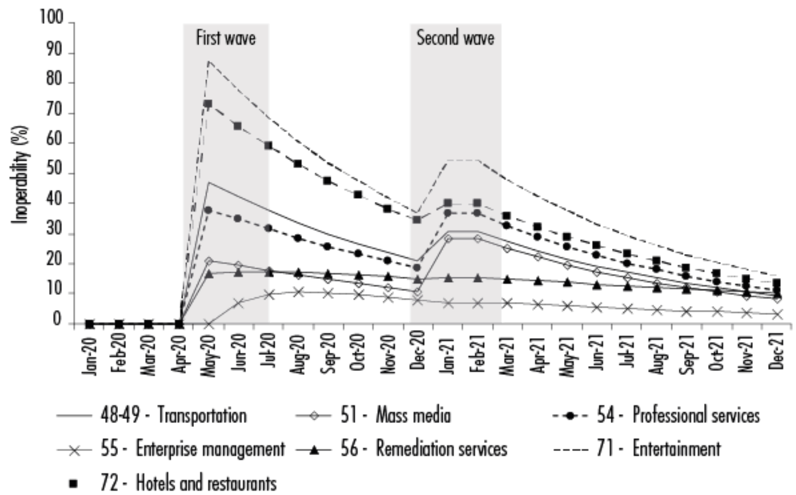
Source: created by the authors.

The gap between the most and least resilient sector shows there is great heterogeneity in the economy's resilience. Manufacturing activities can recover, according to the model, at a rate almost 13 times faster than business support services, and seven times faster than hotels and restaurants. This difference can be amplified if one considers the effect of long-term changes in the population's consumption patterns, who could, for example, decide to keep consumption low in restaurants as a precautionary measure, even after the pandemic's rate of contagion has dropped considerably.

The dynamic model illustrates how the pandemic impacted the 20 different sectors of the economy used in the IOM during the first two waves of Covid-19 infections. With the model's results, we identified the sectors that suffered increased inoperability during the second wave. Those considered most affected were manufacturing industries; retail trade; transportation, mail and storage; information in mass media; real estate services; professional, scientific and technical services; business support services; leisure, cultural and sporting services; temporary accommodation and restaurants and food services. For these sectors, a persistence level equal to the average inoperability in January and February 2021 is imposed. These two months are the ones which displayed the greatest impact due to the restrictions imposed in response to the second wave of infections.[6]

In Figure 1 we find the trajectories of the inoperability indices for the seven most affected sectors (transportation, professional services, remediation services, hotels and restaurants, mass media, corporate and entertainment services). The reduction in demand these sectors suffered generated high levels of inoperability as most of them were closed in an attempt to curb the number of infections in the country. Confinement policies had a high impact on them due to their high dependence on final demand, meaning they experienced the greatest increase in inoperability during the second wave of infections. Furthermore, we can see that the first wave of infections had a greater impact than the second in terms of inoperability, even though the second wave was more severe in terms of health, with a significantly higher number of infections and deaths recorded in late 2020 and early 2021 than during the first wave (Jackson *et al*., 2021). This was due to the fact that confinement measures were less restrictive during the second wave and that the population and economic sectors had managed to adapt and thereby avoided a higher inoperability than they experienced at the beginning of the pandemic.

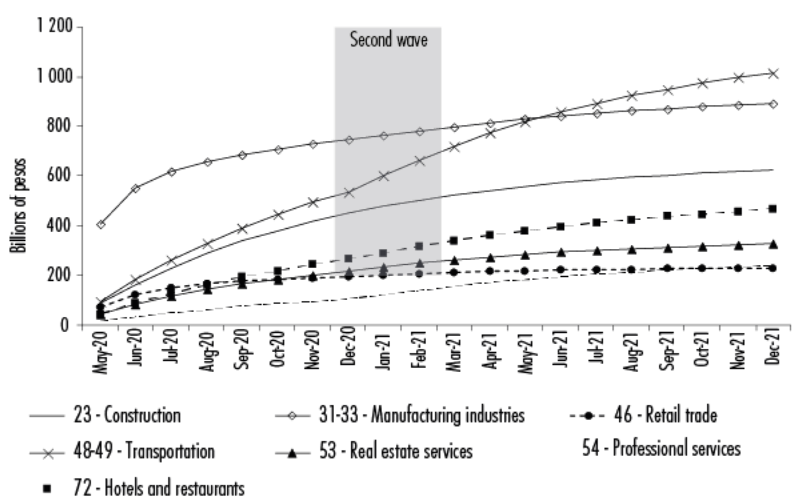
Figure 1. Inoperability index of the seven sectors most impacted by the pandemic



Source: created by the authors based on the PIIM model.

The dynamic model also manages to capture the economic cost to different economic activities due to the pandemic. Figure 2 shows the seven sectors with the greatest economic loss due to the crisis (construction; manufacturing; retail trade; transportation; real estate services; professional services and the hotel and restaurant sector). This was estimated with the model and the accumulated losses totaled $3,796,072 million MXN at the end of 2021. Taking all the countries' economic activities into account, the economy's 20 sectors' monetary loss was $4,934,498 million MXN. This means that the economic losses of the seven sectors listed in figure 2 account for 77% of total losses, showing that these sectors' recovery is key to reducing the monetary cost of the pandemic for the Mexican economy. One can also see that these activities do not coincide with the sectors with the greatest inoperability as their contribution to the economy's total GDP is so high that even a low inoperability implies a great economic loss.

Figure 2. Estimated economic loss for the seven most affected sectors

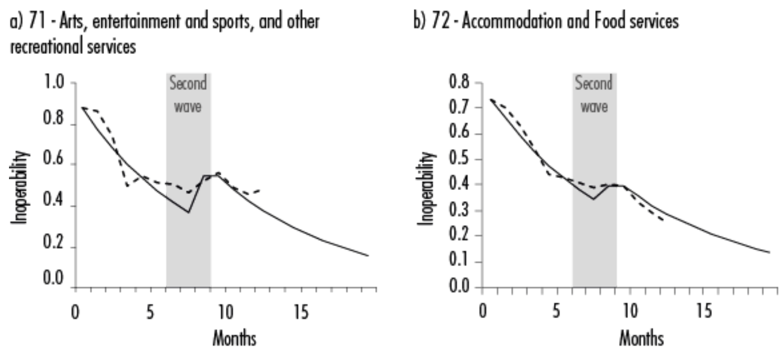


Source: created by the authors based on the PIIM model.

The different economic sectors' path to recovery can be divided into three categories: sectors affected by the second wave, sectors with little to no impact in the second wave, and sectors not initially affected by the contingency measures but which had an increase in inoperability as a result of the economy's general low operability.

Among the sectors affected by the second wave are transportation; mass media; financial services; real estate services; professional services; corporate management; business support services; entertainment, culture and sports services and hotels and restaurants. Social distancing measures affected these considerably as most of them require contact or proximity to customers. These sectors are the most sensitive to new waves of infections, so it is important to have support plans in place for this type of contingency. Figure 3 shows two characteristic examples of these sectors' recovery trajectory.

Figure 3. Two examples of sectors affected by the second wave



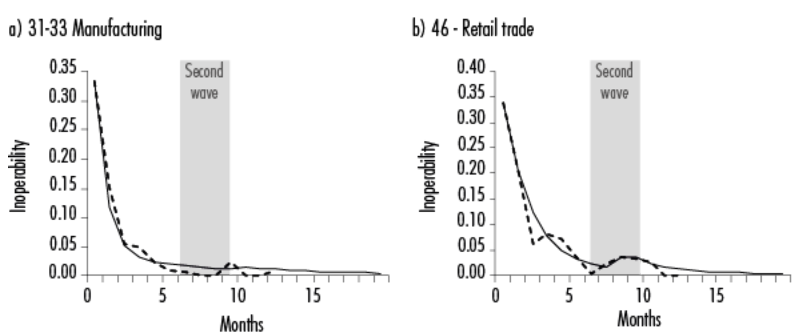
Note: The solid line represents the results of the model; the dotted line represents the behavior of the IGAE.
Source: created by the authors using data from the IGAE and the PIIM model.

The sectors unaffected by the second wave are: mining; electrical energy; construction, manufacturing; wholesale trade; retail trade; educational services; health services and other services. These sectors are characterized by being important producers of intermediate goods, having a strong presence in exports (which recovered faster than the domestic market), or accounting for a significant share of the public sector. These sectors' recovery was not significantly affected either by the restrictions of the second wave or by the indirect repercussions of other sectors' inoperability.

The two sectors that set the trend for inoperability in this second group are manufacturing and retail trade due to their importance in the economy and their rapid recovery. An example of a productive branch in this type of sector is the automotive one (as part of the manufacturing sector), which had a significant recovery when the contingency measures were lifted, even though its vulnerability index showed a relapse in the first half of 2021 due to a drop in exports and domestic demand (see table 2).

Figure 4 shows that the model's calculated inoperability presents a continuous decrease. Their trajectories are similar to those of inoperability calculated from IGAE data (represented by the dotted lines). The shape of their trajectories indicates that these sectors are the most resilient as they did not suffer significant losses in the infrastructure supporting them. This means that the re-opening of activities and an increase in demand driven by exports were enough to reduce their levels of inoperability. Thanks to this, we believe these sectors will not need much support to fully recover.

Figure 4. Two examples of sectors with a rapid recovery



Note: The solid line represents the results of the model; the dotted line represents the behavior of the IGAE.
Source: created by the authors using data from the IGAE and the PIIM model.

Finally, among the sectors not significantly affected by the contingency measures we find agriculture, finance and insurance services, and corporate and government activities. These are all characterized by having zero inoperability at the beginning of the pandemic. However, due to sectoral interconnectedness, their inoperability increased belatedly due to indirect repercussions from other sectors in the economy. That is why these sectors will benefit indirectly from the support for recovery that other sectors receive.

5. FINAL COMMENTS

The Covid-19 pandemic affects production capacity and generates a monetary loss for the economy's different sectors. The vulnerability model makes it possible to identify which sectors need support from economic development and support institutions. In this work, the use of two inoperability models (one static and one dynamic) made it possible to identify the branches and sectors of production with the greatest vulnerability to the Covid-19 crisis. It described the interactions and relative changes in vulnerability while taking into account the interactions between them (static case), as well as projecting the performance trend of the sectors' recovery (dynamic case).

The first model identified the sectors with a significant increase in their vulnerability with respect to gross output value (residential and non-residential construction) and those that presented persistent inoperability (such as those related to the automotive industry). Likewise, it was possible to observe the branches whose relative vulnerability decreased (such as oil and gas extraction, retail and wholesale trade), showing that their performance was not that affected by the crisis. Moreover, with regards to vulnerability due to the number of jobs generated by economic branches, we saw that branches where informal employment prevails are those that either remained the most vulnerable or increased their vulnerability significantly (retail trade, employment services, private household employees, food and beverage services, and residential and non-residential construction).

On the other hand, the dynamic model made it possible to identify the sectors unaffected by this crisis, such as primary activities, finance and insurance services, and corporate and government activities; the most resilient sectors, such as manufacturing, health services, and wholesale and retail trade; and those with less resilience (composed mainly of small businesses, where their level of inoperability put several of them out of business), such as business support services, temporary accommodation, food and beverage services and transportation services.

It was also possible to estimate the rate of recovery, the effects of the second wave of restrictions, medium-term trends and the economic cost of the pandemic to the different economic sectors. The results of the PIIM model showed that the sectors with the greatest vulnerability do not necessarily coincide with those with the greatest economic loss in monetary terms due to their high contribution to total GDP. Among the sectors affected by the second wave are transportation; mass media; financial services; real estate services; professional services; corporate services; business support services; entertainment, culture and sports services and hotels and restaurants; while the sectors unaffected by the second wave are mining; electrical energy; construction, manufacturing; wholesale trade; retail trade; educational services; health services and other services.

Furthermore, the model identified those sectors that are not working at "normal" production levels. These can be spurred to make better use of their installed capacity. In the short term this constitutes a more efficient alternative to investing in sectors that require new companies to be established, meaning it would yield greater benefits in terms of economic recovery than a strategy of austerity and strategic investment, such as the one the current government proposes. These sectors include transportation, professional services, business support services, hotels and restaurants, and recreational services.

This article proposes different lines of research to be carried out in order to delve deeper into its conclusions and improve its real-world applicability in the economy. On the one hand, it identifies the need to propose methodologies which allow further study of recovery strategies, using expanded optimization and general equilibrium models. We also believe the use of models at the regional level to be necessary, due to the heterogeneous impact of the pandemic throughout the nation.

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[1] Using a panel data analysis for various countries, Alfano and Ercolano (2020) showed that measures which closed companies and businesses have been effective in reducing infections in said countries. They suggest that these measures be eased gradually and strategically in order to avoid experiencing relapses.

[2] This decline was not uniform throughout the world's different regions. According to data from the World Bank, Latin America experienced a decrease of 6.8% while emerging countries in Asia only experienced a decrease of 1%. We will likewise find, upon analyzing individual countries, that France experienced a decline of 8.1% whilst the US' was only 3.5% and China, to the contrary, grew 2.3%.

[3] The 5.5% uptick in the world economy's growth was mainly led by the largest economies as many emerging markets and developing countries continue to struggle with the Covid-19 pandemic and its aftermath. This struggle is such that the per capita income losses are not expected to be reversed by 2022 in two thirds of these economies. Furthermore, the situation in low-income economies or in those with persistent growth inequalities make the situation even more complex as the effects of the pandemic have undone the advances achieved in reducing poverty, aggravated insecurity and they could even exacerbate social unrest. As such, the World Bank (2021) suggests that governments prepare short and mid-term recovery and support strategies for companies and businesses so as to avoid major consequences. They also suggest that they prepare public policies which make it possible to face the pandemic's lasting effects and that they take steps to foster ecological, resilient and inclusive growth. They also recommend protecting macroeconomic stability as the losses could negatively affect access to health and educational services, as well as decrease the quality of life (Jackson *et al*., 2021).

[4] According to the classification made by the Federal Government for restrictions on activities at the beginning of the pandemic, published in the *Official Journal of the Federation*.

[5] TL note: INEGI, IGAE and EMS come from the original Spanish *Instituto Nacional de Estadística y Geografía*, *Indicador Global de la Actividad Económica*, and *Encuesta Mensual de Servicios*, respectively.

[6] This method for including the second wave of contagion can be implemented to describe the economic effects of more waves which bring with them more restrictions for production or consumption.