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Modeling economic losses and greenhouse gas emissions reduction during the COVID-19 pandemic: Past, present, and future scenarios for Italy

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ABSTRACT

Unprecedented nationwide lockdowns were adopted because of the COVID-19 pandemic. Understanding the socioeconomic impact of the past and future restrictions while assessing the resilience of a local economy emerged as a worldwide necessity. To predict the economic and environmental effects of the lockdowns, we propose a methodology based on the well-established input–output inoperability model, using Italy as a case study. By reconstructing the 2020 restrictions, we analyzed the economic losses and greenhouse gas emissions reductions, identifying the most economically impacted sectors because of the restrictions and the sectoral interdependencies and those avoiding most air emissions. We constructed four partial-lockdown scenarios by minimizing the economic losses for increasing restrictions to highlight the model’s utility as a tool for policymaking. By revealing the most interconnected and, thus, crucial sectors, the simulated scenarios showcase how the restrictions can be selected to avoid sudden and unpredicted economic damage.

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic shocked the world; 2020 has been characterized by unprecedented national and local restrictions on economic activities and the freedoms and mobility of citizens (Bonaccorsi et al., 2020). Stay-at-home restrictions, curfews, and total or partial lockdowns have deeply affected the lifestyle of citizens, provoking mental health and sleep disturbances (Gualano et al., 2020), increasing poverty, and exacerbating income inequalities (Buheji et al., 2020). No one has been left untouched. Firms, industries (Atkeson, 2020), and financial markets (Ashraf, 2020; Daehler et al., 2021) have been strongly impacted by the urgently adopted regulations and laws implemented to slowdown the virus spread. Contrastingly, the sudden interruption of industrial production and a large part of human activities has allowed an evaluation of their environmental impact (Rutz et al., 2020; He et al., 2020). In the first half of 2020, global CO2 emissions decreased abruptly by 8.8% as compared to the same period in 2019; such a reduction in greenhouse gas (GHG) emissions is more significant than that calculated for the World War II period (Liu et al., 2020).

In the past months, academics, practitioners, decision-makers, and policymakers have endeavored to analyze, evaluate, and predict the short and long-term impacts of COVID-19 and its related policies. A predominant approach in predicting the pandemic’s effect has relied on utilizing past epidemics or pandemics, neglecting the importance of specific characteristics of local economies (Donadelli et al., 2021). Overall, the effects of the COVID-19 pandemic, such as the economic losses (Nicola et al., 2020), workforce reduction (Santos, 2020), social and psychological impact (Cerami et al., 2020), mortality, death rate, the spread of the virus (Atkeson, 2020), and air emission reduction (He et al., 2020), have been evaluated at the national and global scale by dozens of different methods, such as anonymous online surveys (Cerami et al., 2020), composite indicators (Lourenço and Rua, 2021), the input–output (IO) model (Haddad et al., 2020), the susceptible–infected–recovered model (Toda, 2020), and carbon footprint analysis (Rugani and Caro, 2020).

However, an in-depth appreciation of the factors shaping the current pandemic’s economic effects seems to be missing. This paper aims to fill this gap by elaborating on the concept of economic resilience.
and developing a framework to appreciate the importance of the configuration of local industrial structures in the unfolding of the effects of external shocks. We follow the idea that the sectoral composition of local economies drives the differential sensitivity of local economies to shocks and capacity to recover (Martini, 2020; George et al., 2021; Reissl et al., 2021). Further, we contend that a pandemic is a peculiar shock, implying exogenous interventions that can exacerbate the adverse economic consequences for specific sectors. Therefore, the differential exposure of sectors to restrictions is an important dimension that deserves careful assessment (Bloise and Tancioni, 2021).

We propose a compelling approach to assess the economic impact of the coronavirus that may take advantage of input–output tables (IOTs) analysis and use the input–output inoperability model (IIM) as a policy evaluation tool for the COVID-19 pandemic. Such an approach has been limited to a few studies (Selerio and Maglasang, 2021). Indeed, IIM was conceived to precisely model the way the inoperability from unexpected accidental events propagates throughout interconnected industry sectors (Galbusera and Giannopoulos, 2018); hence, we consider IIM as the most suitable tool for analyzing the impacts of the COVID-19 pandemic on an economic system.

This study uses the IIM model to quantify the economic implications of the coronavirus spread in Italy and complements the analysis by depicting the associated environmental effects. The adopted methodology consists of three steps as follows: 1) the reconstruction of all the Italian national decrees between March and June 2020 that gradually limited economic activities; 2) the simulation of daily and total economic losses and GHG emission reductions per economic sector and the overall economy; and 3) the simulation of four future scenarios to forecast the effect of the current partial restrictions.

The findings reveal the misalignment among the time a sector was closed, its economic losses, and the related environmental burden reduction. Construction, wholesale trade, and accommodation have suffered the most dramatic economic downturns, partly because of the direct suspension of activity and partly because of their value chain connecting with other heavily affected sectors. The lessened GHG emissions mainly came from electricity suppliers; although the sector never stopped operating, it reflected the shutdown of manufacturing and transport. Our model proves that the extent to which the results hold strongly depends on the time estimated for each sector to recover, i.e., its resilience.

This study has important implications both for academic researchers and policymakers. This paper’s contribution to the existing literature is threefold. First, it contributes to the ongoing debate on the economic and environmental impact of the COVID-19 pandemic, framing the analysis in an innovative empirical setup by exploiting IOTs. Second, it provides an empirical application of the IIM model, thus enriching the literature on Disaster Impact Analysis. Third, it contributes to the literature on economic resilience by examining sector-level dynamics that can be leveraged to customize industrial policies and promote recovery. Furthermore, we provide decision-makers and policymakers with a reproducible and straightforward framework designed to assess the effects of policies being implemented and anticipate possible interventions. The same tool could be employed to support decision-making during other emergencies.

The rest of the paper is structured as follows. We discuss the theoretical underpinnings of the analysis in section 2. The adopted methodology, based on the IOTs, inoperability, and national air emission accounting, is described in detail in section 3. In section 4, the main findings are presented, and the impact of the restrictions is inferred by simulating four scenarios related to partial lockdown. Section 5 concludes the paper, highlighting the main implications for policy and decision-makers.

2. Literature review

2.1. Economic resilience

The literature on economic resilience has increasingly attracted attention since the 2008 economic crisis. Many empirical and theoretical works have been proposed, investigating the pre-conditions allowing firms or regions to recover from declining employment and wealth.

The concept of resilience originated outside economics; the extant literature includes three interpretations of resilience, each originating from a different discipline (Martin, 2012). In engineering studies, resilience is understood as the capacity of a system to return to its stable equilibrium state after a destabilizing shock (Fingleton et al., 2012; Rose, 2004). In ecological sciences, resilience is defined as a system’s ability to respond to disturbances by moving to a new steady-state equilibrium, while preserving its existing structure (Reggiani et al., 2002; Swanstrom, 2008). Finally, in complex systems literature, resilience is defined as “the ability of a system to undergo anticipatory or reactionary reorganization of form and/or function so as to minimize impact of a destabilizing shock” (Martin, 2012, p. 5).

The “adaptive resilience” framework has become popular in the evolutionary economic geography approach. One particular merit of this approach lies in emphasizing the structure of local economies and its evolution as a crucial factor affecting the capacity to respond to destabilizing shocks (Rocchetta and Mina, 2019; Boschma, 2015).

Most former studies investigating the drivers of resilience have looked at aggregate GDP or employment measures, adopting an “equilibrium” approach. Accordingly, the impact of the external shock could be appreciated by examining how much the growth path diverged from the equilibrium or the time needed to recover pre-shock equilibrium levels of GDP or employment. This view is at odds with the evolutionary theory of constantly changing local economies (Hassink, 2010).

The existing literature on regional resilience has focused on several drivers related to the specific characteristics of local economies. Martin (2012) stresses the importance of the concept of economic structure in general, which can involve different dimensions such as industrial or technological structure, the skill composition of local labor markets, or the size distribution of firms (Mina and Santoleri, 2021; Fusillo et al., 2019). This study acknowledges the importance of looking at the sectoral composition of local economies to understand the varying impact of external shocks across different areas as well as how reconfiguring the economic structures can help successfully respond to a crisis (Martini, 2020; Bloise and Tancioni, 2021).

Overall, we contend that not all economic crises are alike, and crises tend to spread unevenly in local economies (George et al., 2021). Therefore, it is important to assess how specific activities are hit to design tailored interventions so as to limit losses and foster recovery. As we explain in the next section, input–output-based analysis can be fruitful in this respect.

2.2. Input–output analysis and COVID-19

Nobel laureate Leontief (1951a) originally introduced IOTs as a statistical tool to analyze his country’s economy. They are widely used by national statistical offices (Eurostat, 2008) to compute the impact of an economic sector on a national economy (George, 2019), its employment rate (Fuster et al., 2019; Gala et al., 2018; Garrett-Peltier, 2017), or, for instance, to assess the effect of the introduction of a new policy (Liu et al., 2009; Zanchetta Borghi, 2017). Recently, the IOTs have been applied on a multi-regional scale (Zhou et al., 2018; Faturay et al., 2020; Boles et al., 2021; Fan and Liu, 2021) using the multi-regional IOT (MRIO) on the evaluation of environmental impact through the
environmental extended (EIO) (De Haan and Keuning, 1996) or physical (PIOTs) (Hubacek and Sun, 2001; Dietzenbacher et al., 2009; Wachs and Singh, 2018) IOTs and on the expansion of the boundary conditions of life cycle assessment (LCA) studies through the IO-based hybrid-LCA (Wang et al., 2020). Finally, the IIM (Haines et al., 2005b,a), originally developed by Haines et al. is an IO model-based methodology to manage the risk of terrorist attacks in interdependent economic systems (Lian and Haimes, 2006). The IIM has been applied to a wide range of scenarios, such as critical infrastructure interdependencies (Setola et al., 2009), natural disasters (Crowther et al., 2007), and manufacturing supply-chain risks (Brosas et al., 2017). It is regarded as one of the most effective models of Disaster Impact Analysis (Galbusera and Giannopoulos, 2018).

Because of the rapid and sudden variations in the \( R_0 \) index (Germann et al., 2006; Vicente and Petrosillo, 2020), it is necessary, more than ever, to quickly and accurately predict the impact of restrictive measures on a country’s economic sectors. Indeed, because of the nearly daily introduction of new regulations to fight the spread of the COVID-19, modeling and predicting the behavior of highly uncertain national economies is still an open challenge. This paper connects, on the one hand, with Gong et al. (2020), Bloise and Tancioni (2021), and Furceri et al. (2021), who provide evidence on the role of industrial structure in the resilience to the pandemic. On the other hand, this study associates with Li and Li (2021) who provide an estimation of the impact on environmental issues like decarbonization. Reissl et al. (2021) attempted to assess the economic impact of lockdowns over the Italian territory through a dynamic IO model, translating the restriction measures as a labor supply shock. Additionally, Giammetti et al. (2020) allocated to several key sectors a direct and indirect “value-added locked,” highlighting their systemic importance within the Italian supply chain. Another stream of literature built on the input–output methodology assesses the economic and environmental repercussions of public measures implemented to contain the spread of COVID-19. For example, Lenzen et al. (2020) used an MRIO analysis to capture the detrimental economic effects of the pandemic together with the reduction of pollutant emissions at the global level. Kanitkar (2020) estimated the scale of losses that the Indian economy is likely to face because of the nationwide lockdown and changes in the power demand, which resulted in sector-related CO2 emission reductions. Furthermore, Wang and Han (2021) evaluated how the US economic slowdown affects the economic output, carbon emissions, and energy consumption of other developing countries.

The IIM refines and extends the traditional IO model. The latter estimates the higher-order effects in terms of monetary or physical units. In contrast, the IIM incorporates the use of the inoperability index, a dimensionless number ranging between 0 (ideal system state) and 1 (total failure state) (Okuyama and Santos, 2014), to account for the inactivity induced by external shocks and spread to the economic system because of the linkages between production entities. Furthermore, the framework is grounded on the concept of resilience, a key aspect in the recovery phase following a sudden disruption caused by a natural or human-made hazard. Finally, after a disaster, the IIM can be computed relatively quickly where the IO tables exist, providing a timely and powerful tool to support decision-making before more sophisticated assessments are available. For all these reasons, the inoperability IO model is an appropriate tool to explore the extent and intensity of damages caused by the COVID-19 crisis and inform recovery strategies.

3. Materials and methods

This section presents the source of data and methodology employed to simulate the effect of the lockdown restrictions on the Italian national economy and predict the consequences of similar future constraints. A three-step analysis process is adopted. First, we perform a detailed reconstruction of all national decrees and laws, introduced in section 3.1 along with a brief description of the Italian case study. Second, the impact of the past lockdown measures is detected through the inoperability IO model. Third, different scenarios are simulated to forecast the consequences of ongoing and possible future restrictions. Sections 3.2 and 3.3 cover the methodological background.

3.1. Case study

The relevance of the Italian case study is absolute, as Italy was the first European country and second in the world (after China) to be deeply impacted by COVID-19. Moreover, it was the first country to adopt a national lockdown. Given that other countries immediately adopted total national lockdowns, the analysis of Italy’s first months of restrictions has a unique relevance. Indeed, during the “first wave,” the restrictions were adopted gradually in Italy. This aspect allows us to analyze the repercussions of punctual restrictions on the economy, i.e., only targeted sectors. Thus, Italy, as an information-rich case study, allows an analytical generalization of the findings to similar economies (Johansson, 2007).

The Italian government declared a state of emergency on January 31st, 2020 (Italian Government, 2020), precisely one month after China’s warning of a cluster of pneumonia of unknown etiology (then identified as new coronavirus Sars-CoV-2) and the day after the World Health Organization declared the coronavirus as a public health emergency of international concern (World Health Organization, 2020).

In Italy, the emergency was mainly regulated through the adoption of Decree-Laws (Decreto Legge, D.L.), Prime Ministerial Decrees (Decreto del Presidente del Consiglio dei Ministri, DPCM), and Orders of the Ministry of Health (Ordinanza del Ministro della salute). In particular, Decree-Law no. 6 of February 23rd, 2020, is the relevant legal basis of the DPCMs adopted in the following period. On the Minister of Health’s advice, the Prime Minister ordered restrictive measures regarding municipalities where at least one person was infected, and the transmission source was unknown. The potential measures included prohibiting access to and departure from the concerned area, suspending public and private events, public offices, school activities, public museums and other places of culture, working activities for specific categories of companies, and closing certain commercial activities.

3.2. Methodology

To predict the impact of the sequential suspensions affecting different economic sectors at different times, we used the IIM (Haines et al., 2005b,a) based on the IO model (Leontief, 1951b, a, 1986). In the classic IO model, the equilibrium or as-planned production \( x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \) of a country or a region is obtained from the interdependent productions of different economic sectors and the final demand \( e = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{bmatrix} \) as

\[
\begin{align*}
A &= \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1N} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & a_{N3} & \cdots & a_{NN} \end{bmatrix} \\
\end{align*}
\]

\[
x = Ax + e.
\]
is the interdependency matrix, composed by elements $a_{ij}$ that represent the production (output) of sector $i$ required by sector $j$ as input source. Thus, the production of sector $i$ is given by the production of all sectors, each weighted by its respective interdependence $q_{ij}$, and the associated final demand, $x_i = \sum_j q_{ij} x_j + c_j$.

The IIM model extends the previous model to cases of recoverable productivity loss. If the production of one or more sectors is reduced because of an external incidence, such as a natural calamity or a governmental intervention, a degraded production can be defined similarly to the equilibrium production as

$$\tilde{x} = A\tilde{x} + \tilde{c}.$$  

(3)

If one defines $r_i = \tilde{x}_i/x_i$ as the production relative to the as-planned production ($0 \leq r_i \leq 1$), then $q_i = 1 - r_i = (x_i - \tilde{x}_i)/x_i$ is the inoperability relative to the normal production ($0 \leq q_i \leq 1$), where $q_i = 0$ represents as-planned productivity and $q_i = 1$ its complete suppression. By using Eqs. (1)-(3), the inoperability $q$ can be written as

$$q = P(x - \tilde{x}) = P\tilde{x} = A^*q + c^*,$$  

(4)

where $P = \text{diag}^{-1}$ is a transformation matrix, and $A^* = \text{PAP}^{-1}$ and $c^* = P(1 - c) = P(1 - 0c)$ are the Leontief matrix and final demand reduction, respectively, after matrix transformation (Haines et al., 2005b).

**Sector inoperability.** Assuming that the incident occurs at time $t_0 = 0$ causing the total suspension of sector $i$, $q_i(t_0) = 1$. As a consequence of sector $i$'s reduced production, the inoperability of the interconnected sectors, which was 0 until $t_0$, will rise at times $t > t_0$. In the dynamic version of the IO model, the production is obtained as a function of time as $x(t) = A^t x(t_0) + e(t) + K^{-1} t x(t_0)$, where $K^{-1}$ is the economy's willingness to invest in capital resources (Miller and Blair, 1985). The differential equation can be written as

$$\dot{x}(t) = K [A^t x(t) + e(t) - x(t)],$$  

(5)

where $K$ is the **industry resilience matrix**. Similarly, then, the dynamic inoperability is written as

$$\dot{q}(t) = K [A^t q(t) + c^*(t) - q(t)].$$  

(6)

or, in discrete form,

$$q(k + 1) - q(k) = K [A^k q(k) + c^*(k) - q(k)].$$  

(7)

For a final stationary demand, the general solution to Eq. (6) is

$$\dot{q}(t) = q_{\infty} + e^{t(1-A^*)}[q(0) - q_{\infty}],$$  

(8)

where $I$ is the identity matrix. For $t \to \infty$, $q(t)$ tends to $q_{\infty} = (1 - A^*)^{-1} c^*$. Thus, the final or equilibrium inoperability is determined solely by the final demand.

The inoperability of the different economic sectors has been modeled according to Eq. (7). The values of $x$, $A$, and $c$ were obtained from the Eurostat database (EUROSTAT, 2020c) and are, thus, expressed in millions of Euros. The DPCM restrictions have been translated into $q_i$ values, representing the impossibility for economic sectors to perform their activity. The Ministerial Decrees enforced the suspension of activities for single subsectors, identified through their ATECO (“ATtività ECONomiche”, i.e., Economic Activities in Italian) codes, the classification of economic activities employed by the Italian National Institute of Statistics (National Institute of Statistics, 2009), representing the national version of NACE (“Nomenclature statistique des Activités économiques dans la Communauté Européenne”, i.e., Statistical nomenclature of economic activities in the European Community in French) codes. First, a value of 0 was assigned to subsectors allowed to operate (i.e., fully open sector) and 1 to those forced to suspend their activity (i.e., fully closed). However, as this study’s IO was sourced by Eurostat (EUROSTAT, 2020c), which provides the aggregate level of the NACE categorization, the $q_i$ values of single subsectors were be aggregated to obtain sectoral values. Thus, the dichotomous 0–1 value assigned to each subsector was multiplied with its production (for NACE codes from B to Q) or gross value added (for NACE codes from R to U) to determine its weight within the sector. Then, the sum of the resulting values was divided by the global sector’s production (or gross value added). The result was a value between 0 and 1 for every relevant NACE code, i.e., the weighted average of the inoperability of its corresponding ATECO subsector, revealing the whole sector’s degree of inactivity. The related codes are listed and defined in Appendix A, Table 1. The obtained $q_i$ values were fixed as the minimum for the period of validity of the DPCM to account for the possible production loss of the open subsectors due to interdependence from suspended subsectors. The time $t_0 = 0$ refers to the DPCM of March 8th, 2020; the previous DPCM referred to geographically limited zones in Italy. The simulation was run for 200 days ($t_{fin} = 200$), i.e., approximately six months.

**Economic Loss.** Once the inoperability at different times was obtained, the total economic loss for sector $i$ can be calculated as the as-planned production multiplied by the integral of the daily $q_i(t)$ over a defined period, i.e.,

$$Q_{\text{loss}}(T) = x_i \int_0^T q_i(t) \, dt,$$  

(9)

where $T$ is the defined final time.

**Reduced air emissions.** Through the environmental extended IOs (Haan and Keuning, 1996), it is possible to evaluate the total air emissions per sector. Eurostat, through the env.ac.aihah.r2 database, provides extended tables for several air emissions (EUROSTAT, 2020b). According to the Eurostat Manual (Tukker et al., 2006), the total direct and indirect emissions of pollutants can be computed as

$$m = B(I - A)^{-1} y = Bx$$  

(10)

where $m$ is the $(1 \times q)$ vector of the total, direct and indirect, pollutant emissions, and $B$ is the **intervention matrix**, a $q \times m$ matrix with the emission factor per million Euro (in the case of Eurostat). $q$ is the number of pollutant emissions considered (e.g., CO$_2$, NOx, ...). To obtain the total direct and indirect emissions per sector, i.e., a matrix $m \times q$, it is enough to diagonalize the vector $x$ into the matrix $X$ with dimension $m \times m$. Thus, by multiplying $x(t)$ at each time-step, the dynamic of the total air emissions can be obtained. Similarly, the reduced air emissions $m'$ due to the inoperability can be quantified by multiplying the matrix $B'$ of the total emissions for the inoperability as follows (Eq. (8)):

$$m'(t) = B'q(t)$$  

(11)

In this work, the avoided greenhouse gases (GHG) emissions have been calculated in thousands of tons of CO$_2$eq. Within the Eurostat env.ac.aihah.r2 database (EUROSTAT, 2021), the GHG total emissions’ environmental pressure is computed through the global warming potential as

$$GHG = CO_2 + N_2O + CH_4 + HFC + PFC + NF_3 + SF_6$$  

(12)

where the emissions of N$_2$O, CH$_4$, HFC, PFC, and NF$_3$, SF$_6$ are expressed in CO$_2$eq. through conversion factors (298 for N$_2$O, 25 for CH$_4$, etc.).

**3.2.1. Industry resilience factors.**

As noted from Eq. (8), the values $k_i$ of the industry resilience matrix $K$ define the rapidity of reaction of a sector to suspensions/reopenings. Thus, they define the response rate to the closing of different interconnected sectors and recovery rate after the restrictions are removed, i.e., the resistance and recovery features of resilience (Martin, 2012; Martini, 2020). In the IIM, as developed by Haines et al. (2005b) and Lian and Haines (2006), $K$ is a diagonal matrix with elements $k_i \equiv k_i$, which define the (exponential) recovery rate of each sector $i$ according to a known recovery period $\tau$,

$$k_i = \ln[q_i(0)/q_i(\tau)]/\tau = \frac{1}{1 - a_{ii}} = \frac{\lambda}{\tau} = \frac{1}{1 - q_{\infty i}},$$  

(13)

where $\lambda/\tau$ is the recovery rate of sector $i$, and $a_{ii}^*$ are the diagonal elements of the interdependency matrix $A^*$, which account for the...
Table 1
DPCM measures.

| DPCM               | Date      | NACE        | Restrictive Measures (Suspension of activities)                                                                 |
|--------------------|-----------|-------------|---------------------------------------------------------------------------------------------------------------|
| DPCM               | March 8th | R90 - J59.14| Theatres' and cinemas' opening                                                                                |
| 2020               | March 9th | R91         | Museums' and cultural places' opening                                                                        |
| DPCM               | March 10th| R92         | Gambling and betting activities                                                                               |
| 2020               | March 10th| R93.1       | Amusement and recreation activities (e.g., dance studios and discotheques)                                    |
| DPCM               | March 9th | R93.2       | Sport facilities' opening (e.g., gyms, sport centers, and swimming pools)                                      |
|                   | March 11th| S94.99      | Cultural and recreational centers                                                                             |
|                   | March 11th| S96.04      | Well-being centers activities                                                                                 |
| DPCM               | March 12th| G47         | Retail trading activities with the exception of those supplying food products and other essential goods (e.g., computer equipment, automotive fuel, household equipment, medical goods, and newspapers) and those not sold in stores |
| 2020               | March 12th| I56         | Food and beverage service activities (e.g., cafes, pubs, restaurants, ice-cream parlors, and confectioneries) excluding home deliveries, canteens, catering services and activities located along the highway, in stations, airports, and in hospitals |
|                   | March 25th| S96.02      | Personal service activities (e.g., hairdressers, barbershops, and other beauty treatments)                      |
| DPCM               | March 25th| B7 - 8      | Mining activity different from the extraction of coal, crude petroleum, and natural gas                         |
|                   | March 26th| C12         | Manufacture of tobacco product                                                                               |
|                   | March 26th| C13 - 14 - 15| Manufacture of textiles, leather and related products (with some exceptions for technical and industrial textiles) |
|                   | March 26th| C16         | Manufacture of wood products                                                                                 |
|                   | March 26th| C23         | Manufacture of glass and glass products (with the exception of those for medical use), manufacture of cement, lime, and plaster |
|                   | March 26th| C24 - 25    | Manufacture of basic metals and fabricated metal products                                                    |
|                   | March 26th| C26 - 27    | Manufacture of computer, electronic and optical products, and electrical equipment (with the exception of electromedical equipment) |
|                   | March 26th| C28 - 29 - 30| Manufacture of machinery, motor vehicles, and other transport equipment                                        |
|                   | March 26th| C31 - 32    | Manufacture of furniture and other goods different from medical instruments                                  |
|                   | March 26th| F41 - 43    | Construction of buildings, demolition and site preparation, building completion and finishing                   |
|                   | March 26th| G45 - 46    | Wholesale trade, except for basic commodities (e.g., agricultural raw materials and animals, food, beverages and tobacco, pharmaceutical goods, newspapers, agricultural machinery, and fuels) |
|                   | March 26th| L68 - N77   | Real estate, rental and leasing activities                                                                    |
|                   | March 26th| M73         | Advertising and market research                                                                               |
|                   | March 26th| N78         | Employment and human resources provision activities                                                          |
|                   | March 26th| N79         | Travel agencies and tour operators                                                                           |
|                   | March 26th| N80 - 81 - 82| A limited number of activities in the service sectors (e.g., landscape services, office administrative and support activities and repair of household goods, except for computers and communication equipment |
|                   | March 26th| G47.76      | Retail sale of flowers, plants, seeds, and fertilizers                                                      |
|                   | May 18th  | G47         | Retail trading activities                                                                                   |
| DPCM               | May 17th  | I56         | Food and beverage service activities                                                                          |
| 2020               | May 18th  | R91         | Museums and cultural places                                                                                    |

(continued on next page)
dependence of sector $i$ from other sectors. In strictly economic terms, resilience is determined by public and private capital investment contributions. More comprehensively, the resilience of an economy stems from its intrinsic capacity to reallocate resources (inherent resilience) and adapt to external shocks (adaptive resilience) (Rose, 2004). These are properties that are characteristic of each sector of an economy, which need a detailed and comprehensive analysis. It was impossible to conduct such analysis in this paper; thus, we have considered one constant $k_i$ value for all sectors and conducted a sensitivity analysis on the final results by using three different values for $k_i$. The industry resilience matrix $K = \text{diag}(k_i)$ was first constructed with $k_i = 0.2$ and then with $k_{i,\text{min}} = 0.1$ and $k_{i,\text{max}} = 0.3$. These values give rise to three different cases as follows: 1) $k_{i,\text{min}}$ represents a full recovery of all sectors in 1–3 months, i.e., a slow recovery process, 2) $k_{i,\text{max}}$ represents a fast recovery (less than two weeks), and 3) $k_i$ the average value, represents an intermediate case where all economic sectors recover in one month.

In all cases, after a certain time, all sectors fully recover to the pre-Covid equilibrium as no reduction in final demand has been modeled (Fingleton et al., 2012; Rose, 2004).

3.3. Scenario analysis

We complement our analysis based on historical data on the first wave of lockdown with a forward-looking approach to understanding and predicting the effects of possible future interventions on the national economy. More precisely, through scenario analysis, we investigate the impact of the individual and simultaneous closure of four economic sectors. The analysis includes sectors whose activity was suspended at the beginning of the pandemic by the decrees in the first half of March, namely, entertainment and culture, sport and well-being, food and accommodation, and retail. National governments worldwide are trying to avoid total lockdowns, given their profoundly adverse impact on the economy, welfare, and labor market. As such, it is reasonable to assume that manufacturing and construction are unlikely to suffer further restrictions. Simultaneously, the services sector has experienced good results because of remote working; thus, it is improbable that it will suffer further limitations. We believe that the focus on the four sectors mentioned above is logical and realistic according to this rationale. Moreover, Giammetti et al. (2020) classified these sectors at medium-high risk according to their epidemiological risk exposure. Thus, our selection is supported by evidence of a higher risk of infection for these sectors, and we perform different scenario analyses. First, we hypothesize the suspension of a single activity, then combine the closure of two, three, and finally all activities. In the simulated scenarios, we assume the same inoperability level provided by the decrees for each sector under scrutiny. Therefore, we assign the inoperability values computed for the first wave and reported in section B of the Supplementary Materials. Scenarios 1 and 2 represent the first reaction of governments to the spread of COVID-19. These first restrictions affect mainly collective activities (e.g., sports, entertainment, and cultural industries). Conversely, Scenario 3 refers to the largely adopted measures against COVID-19 when the virus diffusion increases exponentially, involving the closing of bars, restaurants, and night-life activities as well as catering and public events. Finally, Scenario 4 simulates those restrictions that occur when a country’s national healthcare system approaches the limit of available hospital beds. These restrictions are the last trench before a total lockdown, affecting retail shops and shopping centers.

4. Results and discussion

The Italian economy’s past and future scenarios, used as a relevant case study (Stake, 1995), have been analyzed by evaluating.

1. the trend of the open/closed sectors.
2. the economic losses, per industry and as a whole.
3. the air pollutant emissions avoided due to the inoperability of closed sectors, per industry and as a whole.

An economy’s resilience properties and response to an exogenous shock, in this case, the COVID-19 pandemic, depend entirely on the interdependency matrix, which reflects a national economy and is necessarily context-specific (Martini, 2020; Gong et al., 2020). Thus, to illustrate the Italian economy’s resilience properties, matrix $A$ (Eq. (2)) is shown as a heatmap representation in Fig. 1. The color scale represents the intensity of the exchanges between two sectors. The row-to-column intersections depict the exchanges from the sector corresponding to the row to the one corresponding to the column and vice-versa for columns-to-rows intersections; each sector strongly depends on self-exchanges (diagonal of the matrix). The most interconnected sectors belong to NACE code-groups M, N, Q, R, and S, i.e., the activities related to general services (such as repair of computers, rental, leasing, and employment activities). Group C (manufacturing sectors) mainly connects with itself, with the same occurring for group H (essential transport services), the main contributor to groups A, B, and C.

4.1. Restriction measures to face COVID-19

The first step of our analysis consists of replicating the series of decrees adopted between March and June 2020 that have primarily affected the freedom of economic initiative and halted the spread of the pandemic. On February 23rd, 2020, the Italian Prime Minister adopted the first DPCM (Italian Government, 2020a) in the municipalities of northern Italy most affected by the pandemic (namely, within the regions Lombardia and Veneto). This was implemented to prevent people from moving and interrupting school attendance, cultural activities, and working and commercial activities except those offering essential goods and services. Further DPCMs issued on February 25th (Italian Government, 2020b) and March 1st, 2020 (Italian Government, 2020c) introduced new restrictive measures, extended to other municipalities. The transition from localized to national restrictions occurred with the DPCM on March 8th, 2020 (Italian Government, 2020d). After that, strict measures were implemented, locking the country down until a gradual reopening at the end of April.

The regulations adopted by the Italian government from March to June 2020 are all listed and described in detail below. The restrictions were implemented through DPCMs, generally the day after the DPCM notification. Table 1 summarizes all the concerned DPCMs, including, first, the restrictions and, second, the opening measures. The table describes the main economic sectors affected by the lockdown measures

| DPCM | Date       | NACE      | Restrictive Measures (Suspension of activities) |
|------|------------|-----------|-----------------------------------------------|
|      | May 25th   | R91.1     | Personal service activities                    |
|      | June 15th  | R90 - J59.14 | Sport facilities opening (e.g., gyms, sport centers, and swimming pools) |
| DPCM | June 15th  | R92       | Theaters and cinemas                           |
|      | June 11th  |           | Gambling and betting activities                |
|      | 2020       |           | Cultural and recreational centers             |
|      |            |           | Well-being centers activities                 |

Table 1 (continued)
Table 2
Different scenarios for increasing restrictions measures.

| Scenarios | Restriction description | Affected sectors |
|-----------|-------------------------|------------------|
| Scenario 1 | 1) entertainment industry | J59, 60, R90–92 |
| Scenario 2 | 1) entertainment industry, 2) sports activities | J59, 60, R90–92, R93, S96 |
| Scenario 3 | 1) entertainment industry, 2) sports activities 3) food and accommodation | J59, 60, R90–92, R93, S96, I |
| Scenario 4 | 1) entertainment industry, 2) sports activities 3) food and accommodation 4) retail | J59, 60, R90–92, R93, S96, I, G45, G46, G47 |

and their code in the Statistical Classification of Economic Activities in the European Community (NACE). The complete list of NACE codes and the relative description for each sector are provided in Appendix A, Table 1 within the Supplementary Materials. The inoperability of the Italian activities according to the DPCM is reported in Appendix B, Table 2.

The list focuses on sectors whose activity was suspended, totally or partially:

- DPCM March 8th, 2020: the first measures affected entertainment venues and recreational activities (Italian Government, 2020d).
- DPCM March 9th, 2020: the rules were tightened up, including in the fields of sport and physical well-being (Italian Government, 2020e).
- DPCM March 11th, 2020: new limitations were added to the suspensions announced in the DPCMs on March 8th and 9th, mainly involving retailers (except those supplying essential goods) and restaurant owners. Limitations had to remain in place until March 25th (Italian Government, 2020f).
- DPCM March 22nd, 2020: the previous measures were extended until April 3rd, including the manufacturing sector. It was the first decree directly encompassing the manufacturing (Italian Government, 2020g).
- DM March 25th, 2020 (amending DPCM March 22nd, 2020): non-strategic productive sectors were required to comply with the new rules (Italian Government, 2020h).
- DPCM April 1st, 2020: the effectiveness of the provisions of the DPCMs adopted from March 8th to March 25th was extended until April 13th (Italian Government, 2020i).
- DPCM April 10th, 2020: the effectiveness of the provisions of the DPCMs adopted from March 8th to March 25th was extended until May 3rd, with minor changes involving the productive and service sector. The DPCM also approved the reopening of stationery shops, bookshops, and retail sale of kids clothing from April 14th (Italian Government, 2020j).
- DPCM April 26th, 2020: the beginning of the so-called “phase two,” characterized by a progressive easing of the restrictions. Notably, the DPCM announced that from May 4th, the manufacturing sector, together with constructions and wholesale, were allowed to operate (Italian Government, 2020k).
- DPCM May 17th, 2020: other activities under restriction were sequentially allowed to open, starting with cultural places, retail trade, restaurants, and activities related to personal care, from May 18th, sports facilities from May 25th, and finally, theaters, concert halls, and cinemas from June 15th (Italian Government, 2020l).
- DPCM June 11th, 2020: from June 15th, new rules for the reopening also applied to gambling and betting activities, cultural and recreational centers, and well-being centers. Recreational activities taking place in dance studios and discotheques remained closed (Italian Government, 2020m).
4.2. Economic and environmental impact of the restrictions

Sector inoperability. This paragraph introduces the dynamic of all economic sectors during Italy’s first lockdown. The effect of the restrictive measures, summarized in section 4.1, is described and analyzed in terms of each sector’s inoperability, as previously described in section 3.2. Fig. 2 shows each sector’s day-by-day evolution and the effect of the restrictions for the first 150 days, highlighting the closed and open (i.e., the ones not directly affected by the DPCM) sectors. In particular, the graph indicates the cascade effect of the closed sectors on the open ones, which after a few days decreased their operation. The decay rate is given by the median value of \( k \), \( k = 0.2 \). The dynamic for the minimum \( k = 0.1 \) and maximum \( k = 0.2 \) values is reported in section C of the Supplementary Materials. The abrupt steps correspond to the days when a restriction enters into action. Thus, it has been supposed that the affected sector immediately halted activity the day after a new measure. In contrast, after the governmental restrictions were raised for the opening, it has been supposed that the economic sectors were unable to recover immediately at 100%. The rationale of this hypothesis is to model the post-lockdown hygiene, security, and safety measures and large adoption of smart working practices by many industries and businesses. The day-by-day dynamics indicate the impact of the restrictions on all economic sectors, not only the targeted ones. Indeed, all sectors that smoothly increase their inoperability are only affected by the closure of the others.

On top of the model’s dynamic representations, Fig. 3 shows the percentage of the time a sector was closed during the 200 days, i.e., the average of \( q \) for each sector. The histogram is calculated for a value of \( k = 0.2 \), and the error bars refer to a industry resilience \( k \) of \( k_{\text{min}} = 0.1 \) and \( k_{\text{max}} = 0.3 \). The five most affected sectors, in terms of closing time due to the Italian DPCMs, were R93 (sports activities, amusement, and recreation activities), R90-92 (creative, arts, and entertainment activities), B (mining and quarrying), N77 (rental and leasing activities), and N79 (travel agency and tour operators). In particular, the DPCMs closed R93 and R90-92 for the longest time, starting from March 8th, i.e., since the beginning of the restrictions. N79 and N77 (travel agency and rental activities) closed only between March 23rd and May 4th, but they were strongly affected by their interdependence with other sectors. Finally, the decrees did not close sector B (mining and quarrying) completely. Only the raw materials extraction was closed from March 23rd to April 4th, while petrol and gas-related activities were not touched. Thus, although the DPCMs partially limited mining and quarrying as a direct consequence of the interdependence of economic sectors, the lockdown strongly affected this sector as seen from Fig. 1. Indeed, group B is one of the few economic sectors that depend only on essential services (group H), such as land, water, air transport, warehousing, and postal activities, which were not closed because all other activities depend on them. The first sector directly affected by B is C19 (manufacture of coke and refined petroleum products), to which many manufacturing sectors are strictly tied.
Finally, it is noteworthy to point out the asymmetry of the error bars because of the different values of $k$, i.e., the industry resilience. The lowest value is $k = 0.3$, corresponding to a sector’s rapid response to shocks. Indeed, when $k = 0.3$, nearly all sectors recover full operability in less than one month. Instead, the maximum inoperability is found for $k = 0.1$, when most sectors recover in times of one to two months, though sector B does not fully recover even after 3 months. This result is reflected by the largest error bar on top of the B column in Fig. 3. Thus, a sector’s interdependence may be inferred from the size of the error bar. For instance, although R90-92 and R93 were closed nearly all the time, they are not very dependent on other sectors and thus recover quickly. On the contrary, sectors such as C (manufacturing activities), A02 (forestry), or N (rental, employment, and travel activities) experience a slower recovery.

In addition to these results, we calculated the economic losses and reduction in air emissions to quantify the effect of the lockdown measures.

Economic Losses Fig. 4 shows the total economic losses per sector in Italy (in millions of Euros). Each bar represents a single economic sector. The analyzed period starts on March 8th, the first day of lockdown, and ends at the mid of September, when all activities in Italy had been open for one or two months. The most affected sectors, in absolute values, were as follows: F (construction), G46 (wholesale trade excluding motor vehicles and motorcycles), C28 (manufacture of machinery and equipment), L68B (real estate activities excluding imputed rents), I (accommodation and food service activities), C25 (manufacture of fabricated metal products excluding machinery and equipment), and C13-15 (manufacture of textiles, wearing apparel, leather, and related
Thus, the most impacted activities related to the accommodation, housing rents, and manufacturing sectors. These results are consistent with prior evidence (Reiss et al., 2021; Giammetti et al., 2020) and perfectly fit the Italian economy, primarily based on tourism and small-medium enterprises related to the manufacturing sector (Malanima and Zamagni, 2010). Then, other sectors such as C24 and C29 (manufacture of basic metals and motor vehicles, trailers, and semi-trailers), G47 (retail trade excluding motor vehicles and motorcycles), K64 (financial service activities), and R90-92 (creative, arts, and entertainment activities) have been strongly impacted as well. Thus, the retail, financial services, and entertainment industry sectors also number among the most affected sectors.

It is interesting to compare the economic losses in Fig. 4 with the most closed sectors (Fig. 3). The largest economic losses are those of construction (sector F), which was not completely closed (the construction of private dwelling was blocked; however, that of highways, the public energy, water, transport utilities, and electrical and water-related works continued). Other large economic losses occurred in sectors G46 (wholesale trade, except motor vehicles and motorcycles), K64 (financial service activities), and R90-92 (creative, arts, and entertainment activities) have been strongly impacted as well. Thus, the retail, financial services, and entertainment industry sectors also number among the most affected sectors.

Reduced air emissions. Finally, Fig. 5 shows the reduced GHG emissions because of the reduced operation of the sectors. The error bars refer to the industry resilience $k_{\min} = 0.1$ and $k_{\max} = 0.3$. Most of the avoided emissions correspond to sectors D (electricity, steam, and air conditioning supply), C24 (manufacture of basic metals), E37–39 (sewerage, waste management, and remediation activities), and A01 (crop and animal production, hunting, and related service activities). Other large contributions come from sectors G46 (wholesale trade, except motor vehicles and motorcycles), C20 (manufacture of chemicals and chemical product), B (mining and quarrying), H49 (land transport and transport via pipeline), and C19 (manufacture of coke and refined petroleum product). Thus, the greatest contributors to air emission reduction belong to groups C (manufacturing activities), G (wholesale and retail), and H (essential services’ transport). The avoided emissions of all other sectors are negligible.

The ranking that emerges from this analysis is again completely different from the most economically affected sectors; however, it is in line with the global trend (Lenzen et al., 2020; Kanitkar, 2020). When looking at the avoided GHG emissions, the main contributor was the D sector, i.e., electricity. This can be understood by looking at the interdependence of the D sector from group C (Fig. 1), which was one of the most affected sectors by the lockdown measures. In general, the avoided emissions reflect the intensities of the absolute emissions before the lockdown. Sectors D, A01, C23, E37–39, C19, H49, and C24 are primarily responsible for GHG emissions in regular operation.

Scenario analysis

The scenario analysis consists of the individual and simultaneous closure of four sectors: entertainment and culture, sport and well-being, food and accommodation, and retail. Section D of the Supplementary Materials summarizes the results of all the permutations by closing one, two, three, or all four sectors. In the eventuality of the suspension of a single activity, closing the entertainment sector would cause the minimum economic loss, while a retail closure would trigger a loss five times larger (approaching 30 billion Euros). If we assume the concurrent closure of two industries, the closing of sport and entertainment represents the lowest negative economic impact. The inactivity of the food and accommodation sector, sport, or culture leads to similar losses below 20 billion Euros. The measures that would cause the highest adverse impact on the economy are those affecting retail, food, and accommodation. The magnitude of the impact depends on the high interdependence of these activities with other sectors. If the restrictions were imposed on three sectors, the most serious economic downturn would be suffered...
The error bars refer to the sectors have been calculated for the four scenarios, shown in Fig. 7a. The cumulative economic losses and GHG emissions reduction of all sectors in scenario 2 and 4, respectively, i.e., for two or four sectors closed, through a period of 100 days. The restrictions are assumed to be imposed for 30 days, after which the economic sectors’ recovery is calculated for 70 days. The full evolution of the four scenarios is available in section E of the Supplementary Materials.

The inoperability dynamics of economic sectors for selected future scenarios during 100 days. The restrictions are simulated to be imposed for the first 30 days.

4.4. Limitations and further improvements

Despite the relevance of the results in terms of policy prediction and assessment of the economic losses and air emissions reductions, the presented model has a few limitations, especially in terms of accuracy and resolution.

First, the minimum $q_{\text{min}}$ value assigned to some sectors represents a limitation. Indeed, $q_{\text{min}}$ was set equal to 1 when a DPCM closed all activities in a sector. Different “workaround” strategies adopted by restricted sectors, such as take-away and food delivery for sector S96, or online services were not considered. Furthermore, other approximations have been adopted. For instance, the DPCM on March 9th, 2020, closed large commercial shopping centers and stores during and before holidays. This condition was not modeled, and full activity has been assumed. Regarding the business interruptions of the DPCM on March 22nd, 2020, continuous production cycle lines whose interruption would have undermined the entire plant were allowed to operate (prior notice to local authorities). Due to the lack of data, this was not accounted for, and the corresponding sectors were modeled as closed.

Finally, it is worth highlighting two aspects related to food service activities. First, the March 9th, 2020, DPCM introduced opening hours restrictions (no activity was allowed later than 6:00 p.m.). Second, all restaurants were entitled to work with home delivery during the closure period (after the March 11th DPCM), regardless of their previous license. We adopted different simplifications because of the difficulty of quantifying the measures’ impacts objectively and reasonably. In the former case, the restaurants were considered fully operational; in the latter, only those activities licensed to operate exclusively as take-away (subject of a specific ATECO code) were assumed to be running their businesses, while restaurants and others were considered closed. In any case, the default procedure was to follow the national DPCM.

Third, in some cases, setting $q_{\text{min}} = 1$ resulted in overestimating the impact of the DPCM. Similarly, for partially closed economic sectors, the value of $q_{\text{min}}$ obtained by weighting the closed and open subsectors was set as the minimum value for subsequent steps. This means that possible improvements of the open subsectors’ pre-lockdown production were not taken into account. In other words, the open subsectors cannot compensate for the closed subsectors. Indeed, the production increase can only be modeled through the industry resilience $k$. Government funding, for instance, can boost the decay of the inoperability to its final value (the final demand) once a sector is declared operative. Thus, the sensitivity analysis for different values of $k$ has been conducted because of the difficulty of precisely modeling the last Italian DPCM, i.e., introducing public funding of a few billion Euros to enterprises and citizens. The value of $k = 0.3$ simulates a rapid decay rate (sectors recover in a few weeks), whereas $k = 0.1$ represents a slow one (economic sectors recover in a few months).

Fourth, a limitation in estimating air emissions reduction is because of the EUROSTAT dataset. Indeed, sector L68B (real estate activities excluding imputed rents) was not considered in the computation because there is no direct correspondence within the “env_ac_aiah_r2” EUROSTAT database (EUROSTAT, 2020a).

Finally, in this analysis, no final demand reduction has been considered, i.e., an engineering resilience (Fingleton et al., 2012; Rose, 2004). This is perhaps the most critical limitation. Indeed, this analysis assumes constant final demand, in this case, the initial demand before the lockdown as a simplified hypothesis, similar to Haines et al. (2005b). A more precise analysis should update the final demand at each step, considering the (notable) economic losses and translating them into reducing i) salary and ii) final demand.
Beyond the current limitations, further improvements should be developed regarding accuracy and connection with other real-time datasets. First, to verify their accuracy, the simulated results need to be compared with the updated official statistics, e.g., from the Italian National Institute of Statistics (ISTAT). We note, for now, that the emissions reduction of CO, CH₄, and CO₂ from fossil fuels and biofuels (35.2, 23.8, 26.0, and 15.7%, respectively) computed through our model for the industry sectors (group C and sectors B and F) are in good qualitative agreement with those of the dataset computed by the Copernicus Atmosphere Monitoring Service for the same period using real data (26.8, 19.6, 24.4, and 17.9%, respectively) (Guevara et al., 2020).

Second, the simulated scenarios are built upon the current restrictions adopted in European countries rather than on epidemiological data. Future studies should strictly tie incremental restrictions with data on the daily number of infected people, available beds in public hospitals, and relevant epidemiological data to have a complete monitoring tool for policymakers. Third, as suggested by Lian and Haines (2006), a multijobjective formulation should be implemented to simultaneously optimize future policies in terms of economy, COVID-19 diffusion, and air emissions reduction. Fourth, other air pollutants, such as acidifying gases, tropospheric ozone precursors, or particulate matter, may be considered. Finally, future studies and policy scenarios should consider the psychological implications of specific strategies to avoid political decisions based only on economic reasons. Indeed, the positive effects of physical (Maugeri et al., 2020) and cultural (Restubog et al., 2020) activities on psychological health have been widely reported. Future models and strategies should balance economic losses, long-term psychological effects, and the diffusion of COVID-19 to avoid shortsighted policies. Based on the Italian case, this research may be conceived as a basis for possible applications to other countries. Notably, the employment of the IOTs provided by EUROSTAT allows easy reproducibility of the study for other European member states, while assuring the harmonization of methodologies and comparability of results within the EU. As we reconstructed all Italian restrictions during the study period, the same should be done for the other countries, at which point the applicable methodology is the same.

As this study’s scenarios only represent the policy that minimize economic losses, future studies should perform an optimization on multiple dimensions simultaneously, e.g., economic losses, GHG air emission reduction, or epidemiological data. Such an analysis can be conducted by introducing weighting factors for each dimension, according to the following formula:

\[ P = \min_p \left( \sum_{i=1}^{p} \lambda_i F_{ip} \right), \]

where \( P \) represents all possible permutations (see section D), \( F \) the number of considered factors (e.g., economic losses, air emission reduction), \( F_{ip} \) the corresponding value for permutations \( p \) and factor \( i \), and \( \lambda_i \) is the weight for the dimension \( i \), such that \( \sum_{i=1}^{p} \lambda_i = 1 \), consequently minimizing the corresponding impact.

5. Conclusion

This study analyzed the impact of COVID-19 on the Italian economy in detail using the inoperability methodology and IOTs. First, all the Italian government’s laws and restrictions between March and June 2020 were retrieved, and the economic sectors affected by each measure were identified. Second, the economic losses and greenhouse gas emission reduction were quantified by analyzing the period from March 8th (the first day of restrictions) to mid-September 2020. Third, four scenarios were discussed to predict the impact of sector-specific restrictions in current or future emergencies.

The simulation shows that, in Italy, the most affected sectors during the first wave, in terms of inoperability, were R93 (sports activities, amusement, and recreation activities), R90-92 (creative, arts, and entertainment activities), and B (mining and quarrying). While sectors R93 and R90-92 were closed by national decrees, sector B was open; however, it suffered from dependence on other industries. Concerning the economic losses, the most impacted sectors were F (construction), G46 (wholesale trade, except for motor vehicles and motorcycles), and C28 (manufacture of machinery and equipment). In contrast, most saved GHG emissions were attributed to D (electricity, steam, and air conditioning supply), C23 (manufacture of other nonmetallic mineral products, i.e., glass, clay, ceramic, cement, concrete), and C24 (manufacture of basic metals) sectors.

The scenario analysis shows that the impacts on the national economy are limited to restricting the food and accommodation sector (from scenario 3), although representing approximately 20 billion Euros. This is because economic sectors not directly affected by restrictions are not strongly impacted because of the limited interconnections to the closed sectors. Conversely, in scenario 4 (retail shops), the restrictions influence many other economic sectors, even when not directly targeted by the restrictions. This is mainly because of the dense interconnections among tourism, manufacturing, and other industrial sectors. For instance, the closure of retail shops strongly affects many manufacturing sectors. The total economic losses for the four scenarios range from 3.6 billion Euros for scenario 1 to about 50 billion Euros for scenario 4.

The data availability and ease of computation, which characterize our analytical tool, answer the need for timely and comprehensible estimation of the potential effects of a policy. This makes our framework particularly suitable for assessing the effects of policies being implemented or anticipating possible interventions.

This study provides a comprehensive vision of the complex and sometimes conflicting relationship between economic value creation and environmental preservation. There is consensus that the current COVID-19 crisis has occurred in the middle of other unrelenting global crises (Lenzen et al., 2020). Health emergencies due to infectious diseases, increasing damage caused by extreme weather events, and hostile
conditions of life due to growing temperatures are increasingly likely to exacerbate the difficulties of working in almost every economic sector (Intergovernmental Panel on Climate Change, 2021). A scenario of going back to a business-as-usual is not viable. This study’s analysis sheds light on the vulnerability of our economic system and provides valuable insights for the recovery phase marked by the imperative of the ecological transition. For example, a massive shift toward renewable energy would ease the environmental footprint of all connected sectors, and the electrification of transport and teleworking would help mitigate GHG emissions from the mobility sector. Finally, during the recovery phase, public and private investments should boost the adoption of circular economy strategies and techniques in the most high-impacting sectors, such as agriculture or energy and resource-intensive sectors, such as the metalworking industry.

It is worth noting that the impact assessment tool proposed is not limited to pandemic shocks. Our results indicate that considering the interconnections between productive sectors is mandatory to assess the propagation of economic and environmental repercussions of external shocks, which could be human-made or natural hazards. The analysis conducted in this work reveals the necessity to evaluate national economies in terms of their industrial resilience, raise awareness about eventual restrictions in response to external shocks, avoid economic losses as much as possible, and limit the closure of those sectors which can cause the most significant cascade effect. Furthermore, an analysis of the impacts caused by the restrictions should be carried out simultaneously on the economy and environment to limit economic losses while minimizing GHG emissions and other pollutants.

Further studies are needed to relate the economic losses with the air emission reduction, social impact, and diffusion of COVID-19. Indeed, long-term policies cannot only consider economic losses, as it occurred and is ongoing in Italy, where the cultural sector has been greatly impacted. Instead, the sociological and psychological impact of banning access to museums, galleries, concerts, and sports activities must be considered. Using epidemiological and economic models and simultaneously considering the social effects of the restrictions, other strategies may be adopted in the future, following the example of other countries such as Spain, where the access to museums and cultural places was limited to a maximum occupancy rather than being forbidden outright.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2022.105807.

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