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Modeling social, economic, and health perspectives for optimal pandemic policy decision-making

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ABSTRACT
While different control strategies in the early stages of the COVID-19 pandemic have helped decrease the number of infections, these strategies have had an adverse economic impact on businesses. Therefore, optimal timing and scale of closure and reopening strategies are required to prevent both different waves of the pandemic and the negative economic impact of control strategies. This paper proposes a novel multi-objective mixed-integer linear programming (MOMILP) formulation, which results in the optimal timing of closure and reopening of states and industries in each state to mitigate the economic and epidemiological impact of a pandemic. The three objectives being pursued include: (i) the epidemiological impact, (ii) the economic impact on the local businesses, and (iii) the economic impact on the trades between industries. The proposed model is implemented on a dataset that includes 11 states, the District of Columbia, and 19 industries in the US. The solved by augmented $\varepsilon$-constraint approach is used to solve the multi-objective model, and a final strategy is selected from the set of Pareto-optimal solutions based on the least cubic distance of the solution from the optimal value of each objective. The Pareto-optimal solutions suggest that for any control decision (state and industry closure or reopening), the economic impact and the epidemiological impact change in the opposite direction, and it is more effective to close most states while keeping the majority of industries open during the planning horizon.

1. Introduction

Sudden Acute Respiratory Syndrome – Coronavirus-2 (SARS-Cov-2), which produces the resulting disease of COVID-19, was declared a pandemic by the World Health Organization (WHO) on January 9, 2020 [1]. In the US, COVID-19 had its first confirmed case in Washington State on January 19, 2020 [2] and as of June 20, 2021, the US has seen over 33.5 million infected cases and around 603,000 deaths. Different states started the statewide stay-at-home in late March 2020 [3], and critical states have considered various control strategies such as quarantine, stay-at-home, and lockdown. States, counties, and municipalities around the US have had to balance different adverse impacts of the pandemic: implement a few strategies to control the spread of the virus and potentially experience increased hospitalizations and deaths or implement more stringent lockdown strategies and risk economic losses across several key industries. Lockdowns and business shutdowns in various states have led to business closures, increased unemployment [4], and workforce losses in critical businesses [5], and a lack of supply produced by specific industries [3].

As shown in Fig. 1, with the growth in the active COVID cases, the number of unemployment claims increased suddenly in late March and early April, when many states and businesses started to shut down. Also, consumer behavior has changed, and the inflation rate has grown with two months delay in late July 2020. Fig. 1 also shows that the shutdown of the states in late March, decreased the number of active COVID cases while reopening the states in late April triggered the second wave of the COVID-19 cases.

Since the evolution of the COVID-19 pandemic, various research studies have analyzed the pandemic’s social, economic, and epidemiological impacts at international and national levels, as well as providing a wide range of policies to mitigate the crisis effect of this pandemic [7–13]. Table 1 summarizes selected non-clinical literature that offers a qualitative, quantitative, descriptive, and prescriptive analysis of the impact of COVID-19 on economic and societal health. According to the literature, the epidemiological impact and the economic impact of the pandemic are tied to each other. Some research has focused on only epidemiological impact analyses through mathematical and simulation models such as different versions of the SIR (Susceptible-Infected-Recovered) model [16, 15].

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industry levels. The focus of decision-making is considered at the state level because, according to the literature, the population density of states, the work environment, and the type of job can increase the chance of getting infected. The infection rate differs from one industry to another, and it depends on how people need to interact in that industry [48,49]. Limiting close interactions in the workplace can contribute to slowing the infection and epidemiological impacts. Also, attending social activities, parties, and entertainment, for example, contributes to the infection rate growth [48]. State-level policies can decrease the number of such activities and the resulting chance of the spread of the virus. Second, this paper proposes a novel multi-objective mixed-integer linear programming (MOMILP) model that integrates a modified version of the susceptible-infected-recovered-deceased (SIRD) epidemiological model, a modified maximum network flow problem, and a model to measure the economic impact on local businesses. The three models are connected through state-level and industry-level decisions to represent the dynamic competition between the economic and epidemiological aspects of the controlling policy, where decisions at each period are affected by the previous period’s decision. The optimization-based model provides prescriptive solutions that can balance the adverse economic and epidemiologic impacts. Third, the integrated model results in a temporal decision and allows decision-makers to identify the optimum pandemic policy for a desired planning time horizon.

The remainder of this paper is organized as follows. Section 2 presents the details of the model for optimizing the control strategies over time and during the pandemic crisis. Section 3 describes the illustrative example, of the data sources and the input parameters used in the model. Results, sensitivity analyses, and the discussion on the required policies are explained in section 3. Finally, Section 4 concludes the work and offers future research directions.

2. Proposed optimization model

The proposed MOMILP evaluates and minimizes the effects of the dynamic closure and reopening strategies during the pandemic crisis, providing the optimal control strategies to decision-makers for (i) each industry, (ii) each state, and (iii) each period. With such an optimization framework, we look to address different decision-making perspectives:
state-level decisions, national-level decisions, industry-level decisions, and how any of these trade-off with each other.

The proposed model considers three objectives including (i) the epidemiological impact of the pandemic in terms of the percentage of the infected population, (ii) the economic impact of the pandemic on the local businesses in terms of the percentage of decrease in the business’s employees, and (iii) the economic impact of the pandemic on the amount of commodity traded between industries in terms of the unmet demand percentage in industries and states. The epidemiological and economic impacts on businesses and industries are the very first tangible impact of the pandemic [50,51]. A non-comprehensive state and industry-level policy for controlling pandemics would propagate the epidemiological and economic impact of a pandemic to the other aspects of socio-economic systems, causing other negative impacts such as social in-equity, unequal poverty changes, unbalanced vaccination distribution, adverse change in education systems, among others [52,53]. Each of these impacts can be considered an individual objective when one tries to optimize the pandemic policy. However, controlling the early impacts can help with minimizing the later impacts. Therefore, in this study, we are only considering the two impacts caused by state and industry closure and reopening, as the building blocks for early analysis and a decision tool that provide short-term emergency actions.

Fig. 2 shows the dynamics of the impacts created by the state- and industry-level decisions on the economic and epidemiological aspects.

The closure of states and industries would lead to adverse economic consequences while decreasing the adverse epidemiological impacts. The economic impact is measured here as a two-fold effect, including (i) the economic impact on trade and (ii) the economic impact on local businesses. The economic impact of industry closure is measured by the met/unmet demand of each state from the commodity of each industry at each time. This measure represents the inability of industries to satisfy the inter-industry and consumer demand at the state level, caused by policy-driven closure or by workforce productivity losses due to the pandemic. In this paper, we refer to this effect as the economic impact on trade. Also, the state closure would decrease the demand for certain service businesses such as entertainment, accommodation and food services, hotels, transportation, and education, among others. According to Ref. [51], the pandemic and related social distancing, quarantine, and state closure policies have hurt different industries by shrinking the number of active businesses due to the shift in the demand for those industries. The drop in the number of active businesses causes a negative economic impact mainly through a higher unemployment rate. We measure the economic impact of the state closure policies by the percentage of shrinkage in these local businesses in terms of the percentage of employees whose jobs were lost. In this paper, we refer to this effect as the economic impact on local businesses. On the other hand, the increase in the negative epidemiological impact would result in workforce losses, leading to the inability of industries to have optimal productivity and

Table 1
The literature on the analysis of COVID-19 impact on the economy and societal health.

| Reference | Economic impact analysis | Epidemiological impact analysis | Target country | Prescriptive, predictive, and quantitative model | Descriptive and qualitative model | Main considered indices |
|-----------|--------------------------|---------------------------------|----------------|-----------------------------------------------|-------------------------------|-------------------------|
| [14]      | *                        | *                               | Multiple       | –                                             | *                             | COVID cases, GDP        |
| [15]      | *                        | –                               | Multiple       | –                                             | *                             | Trade                   |
| [16]      | –                        | *                               | US             | SEIR                                          | –                             | COVID cases             |
| [17]      | –                        | *                               | China          | SEIR                                          | –                             | COVID cases             |
| [18]      | *                        | *                               | Multiple       | –                                             | *                             | GDP                     |
| [19]      | *                        | *                               | Multiple       | –                                             | *                             | COVID cases, GDP, tourism, consumption, trade |
| [20]      | *                        | –                               | Malaysia       | Data-driven clustering                        | –                             | COVID cases             |
| [21]      | *                        | –                               | India          | –                                             | *                             | Agricultural commodity prices, food and waste management |
| [22]      | –                        | *                               | US             | –                                             | *                             | Employment, revenue, consumption, stimulus payments, loans |
| [23]      | –                        | –                               | Indonesia      | –                                             | *                             | Poverty                 |
| [24]      | –                        | *                               | Japan          | Agent-based modeling                          | –                             | COVID cases             |
| [25]      | –                        | –                               | UK             | –                                             | *                             | Social well-being       |
| [26]      | –                        | *                               | Colombia       | Input-output model                            | –                             | Trade                   |
| [27]      | –                        | –                               | Multiple       | –                                             | *                             | Various manufacturing and service indices |
| [28]      | –                        | –                               | Global         | –                                             | *                             | Poverty                 |
| [29]      | –                        | –                               | Global         | Global general equilibrium                    | –                             | GDP, trade              |
| [30]      | –                        | –                               | Italy          | HAR and ARIMA model                           | –                             | COVID cases             |
| [31]      | –                        | –                               | –              | Standard macroeconomic AD-AS model            | –                             | GDP, trade, exchange rates, economic growth |
| [32]      | –                        | –                               | India          | –                                             | *                             | COVID cases, GDP, trade, electricity demand |
| [33]      | –                        | –                               | Multiple       | –                                             | *                             | GDP, trade              |
| [34]      | –                        | –                               | Multiple       | SIRD                                          | –                             | COVID cases             |
| [35]      | –                        | –                               | Multiple       | Game-theoretic epidemiological model          | –                             | COVID cases             |
| [36]      | –                        | –                               | Global         | Machine learning methods                      | *                             | COVID cases, deaths     |
| [37]      | –                        | –                               | Global         | SEAIRD                                        | –                             | COVID death cases, GDP  |
| [38]      | –                        | –                               | Global         | SIRD-input-output model                       | *                             | COVID death cases, Economic loss |
| [39]      | –                        | –                               | US             | SIRD-input-output model                       | *                             | COVID death cases, Economic loss |

List of the abbreviations used in Table 1.
GDP: Gross Domestic Product.
SEIR model: Susceptible-Exposed-Infectious-Recovered model.
SIRD model: Susceptible-Infected-Recovered-Decaseased model.
SEAIRD model: Susceptible-Exposed-Asymptomatic-Infectious-Recovered-Decaseased model.
AD-AS model: Aggregate Demand-Aggregate Supply model.
HAR model: Heterogeneous Auto-Regressive model.
ARIMA model: Auto-Regressive Integrated Moving Average.
may result in business closures. Since there is no reliable data available for such an impact, the model does not consider the later effect of the pandemic in the analysis.

The epidemiological impact in terms of the percentage of the infected population is measured based on the four main population categories: infectious, susceptible, recovered/immune, and deceased individuals. It is assumed that the pandemic growth rate differs by state and industry, as the population density and the employment density vary by state and industry. More adverse epidemiological impacts result in more industry and state closures, while more substantial economic impacts would result in more significant industry and state reopening. Therefore, the economic and epidemiological impacts compete for any control strategy, and the model tries to find a balanced strategy that simultaneously minimizes economic and epidemiological impacts.

To measure the economic impact on trade due to an industry closure, we are using the multi-commodity maximum network problem. Also, the economic impact on local businesses is caused by a state closure and is measured by the number of employees that lose their job in local businesses. The epidemiological impact of industry and state reopening strategies is measured with the modified SIRD model. To depict the economic and epidemiological impact of state and industry closure and reopening, the three models are combined with two decision variables: state status and industry status. In the following, we explain the concepts of the MNFP and the SIRD models that are used later in the proposed mixed-integer programming model.

2.1. Maximum network flow problem

Let $G = (N, L)$ be an undirected connected network, where $N$ is the set of states represented by nodes, and $L$ is the set of trade links between each pair of states. $K$ is a set of industries producing specific commodities divided into two subsets. The first subset is the set of industries producing commodities traded between two states ($K_1 \subseteq K$ and $K_1$ is the set of industries producing tradable commodities). The second subset is the set of industries producing commodities consumed only inside the state ($K_2 \subseteq K$ and $K_2$ is the set of industries producing non-tradable commodities, including local businesses such as restaurants and theaters, among others). Each state can be considered either a supply, demand, or transshipment node in the MNFP model, for each commodity of industry $k \in K$ and at each time. Therefore, one dummy supply node is capacitated with the state production level for each commodity, and one dummy demand node is defined for every state. In the MNFP, $N$ denotes the set of nodes that consist of $N_s$ as the actual states and the transshipment nodes, $N_c$ as the set of dummy supply nodes, and $N_d$ as the set of dummy demand nodes. Each link $(i, j) \in L$ has a specified capacity $u_{ij}$ for transferring the flow of materials of any kind, shown in constraint (2), in which $x_{ij}^k$ denotes the flow of commodity of industry $k$ between state $i$ and $j$ at time $t$. The multi-commodity maximum network flow problem tries to maximize the flow between two nodes [54] such that it satisfies the demand of each node from each commodity, considering the constraints of the link capacity, $u_{ij}$, supply capacities, $c_s$, and demand $d_t$.

![Diagram](image)

Fig. 2. The dynamics of the relationship between pandemic policy and the economic and epidemiological impacts.

shown in constraints (2)–(4). This formulation can also be equivalent to an optimization problem that minimizes the total unmet demand in the network stemming from the non-optimum flow between every two nodes, as shown in the objective function in Eq. (1). Eq. (1) measures the total unmet demand over all commodities and states by quantifying the difference between the inflow of each commodity into each state at each time ($\sum_{k \in K} x_{ij}^k$) and the state’s demand for that commodity ($d_t^k$), then summing over all calculated unmet demands over states, commodities, and the time horizon. In addition, in our proposed MNFP problem, the supply capacity, $c_s$, will be forced to be zero for closed industries. Constraint (5) shows the flow balance in transshipment nodes. Constraint (6) ensures that in a balanced economic system, the total supply of each commodity of industry $k \in K$ should be equal to the total demand for that commodity. We add one more constraint to the MNFP model to ensure that the trade of non-tradable commodities, $k \in K_2$, between states is not allowable, as shown by constraint (7).

$$\min \sum_{t=1}^{T} \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} (d_t^k - \sum_{l \in K} x_{ij}^l)$$  

(1)

$$\sum_{k \in K} x_{ij}^k \leq u_{ij}(i, j) \in L, t = 1, \ldots, T$$  

(2)

$$\sum_{i \in N} x_{ij}^k \leq c_s(i) \in N_s, t = 1, \ldots, T, \forall k \in K$$  

(3)

$$\sum_{j \in N} x_{ij}^k \leq d_t^k(i, j) \in N_t, t = 1, \ldots, T, \forall k \in K$$  

(4)

$$\sum_{j \in N} x_{ij}^k - \sum_{j \in N} x_{ij}^k = 0 \forall i \in N_s, t = 1, \ldots, T, \forall k \in K$$  

(5)

$$\sum_{i \in N} \sum_{j \in N} x_{ij}^k - \sum_{i \in N} \sum_{j \in N} x_{ij}^k = 0 \forall t = 1, \ldots, T, \forall k \in K$$  

(6)

$$\sum_{i \in N} x_{ij}^k = 0 \forall i, j \in N_s, t = 1, \ldots, T, \forall k \in K_2$$  

(7)

2.2. Modified SIRD model

The susceptible-infected-recovered-deceased (SIRD) model is a well-known mathematical representation of the dynamics of an epidemic or a pandemic [55]. SIRD model extends the SIR model with an addition of the population density and the employment density varies by state and industry. The susceptible-infected-recovered-deceased (SIRD) model is a well-known mathematical representation of the dynamics of an epidemic or a pandemic [55]. SIRD model extends the SIR model with an addition of

$$\text{Let } a = N \cdot L$$  

The dynamics of the relationship between pandemic policy and the economic and epidemiological impacts.
relation between the numbers of susceptible cases \( S(t) \), infected cases \( I(t) \), recovered cases \( R(t) \), and deceased cases \( D(t) \) at each time and in a certain population. The differential equations of the SIRD model, shown in Eqs. 8-11, describe the changes in each of the four categories of cases based on the infection rate, \( \alpha \), recovery rate, \( \rho \), and mortality rate, \( \gamma \), while \( n \) is the sum of the susceptible cases \( S(t) \), infected cases \( I(t) \) and recovered cases \( R(t) \).

\[
\frac{dS(t)}{dt} = -\frac{\alpha}{n} I(t)S(t) \quad (8)
\]

\[
\frac{dI(t)}{dt} = -\frac{\alpha}{n} I(t)S(t) - \rho I(t) - \gamma I(t) \quad (9)
\]

\[
\frac{dR(t)}{dt} = \rho I(t) \quad (10)
\]

\[
\frac{dD(t)}{dt} = \gamma I(t) \quad (11)
\]

The SIRD model is a highly nonlinear and complex model that simulates the pandemic dynamics considering the initial infectious and the infection, recovery, and mortality rates. To adapt the SIRD model to the COVID pandemic specifications in our proposed MOMILP, we add the following assumptions to the SIRD model.

1. The susceptible population gets infected with a specific infection rate of \( \alpha \) in state \( i \).
2. The infected population is recovered with a recovery rate \( \rho \) and after a specific time of \( t_0 \) since infection, or they die at a specific time \( t_0 \) periods after their infection, with a death rate of \( \gamma \).
3. The recovered population maintains immunity status for a specific immunity time of \( t_0 \) before they go back to the susceptible population.

Fig. 3 shows the schematic of the relationship between susceptible \( S(t) \), infectious \( I(t) \), recovered \( R(t) \), and deceased \( D(t) \) cases considering the required modifications in the time concepts. By incorporating the recovery time and the immunity time, the infected population who will recover from the disease would enter the susceptible population after \( (t_0 + t_1) \).

### 2.3. Proposed MOMILP model

The proposed model combines the modified MNFP and the modified SIRD model to optimize the timing of the implementation of control strategies. Eqs. 13-43 show the proposed MOMILP model in the form of a mixed-integer program. The definition of sets and the notation of the parameters and decision variables are shown in Table 2, Table 3, and Table 4, respectively.

The proposed MOMILP model contains three distinct objective functions shown in Eqs. 13-15, including (i) the epidemiological impact in terms of the percentage of the infected population across the states (F1), (ii) the economic impact on local businesses (LB) in terms of the percentage of total unemployment due to the state closure across industries and states (F2), and (iii) the economic impact on trade in terms of the percentage of total unmet demand across industries and states (F3). As shown in Fig. 2, the epidemiological impact (F1) and the economic impacts (F2 and F3) compete such that any strategy that decreases the epidemiological impact by state and industries closure would increase economic impact due to a higher percentage of unmet demand and shrinkage of local businesses, and vice versa. Therefore, the MOMILP model balances all three objectives simultaneously: Eqs. (13)-(15).

The modified MNFP is represented in constraints (16)-(22). Constraints (16)-(19) generate the bounds on supply, demand, and trade between states. When the objective function F3 minimizes the unmet demand in each state at each time, the flow of commodities between states is maximized to its upper bound level. Constraint (16) limits the amount of trade of commodity of industry \( k \) between states \( i \) and \( j \) up to the capacity of the transportation channel between two states. The upper bound for the trade capacity, \( u_k \), is calculated from the amount of actual trade between two states. Constraint (17) balances the supply of industry \( k \) in each state \( i \), if and only if the industry \( k \) is open in that state. The binary variable \( y_k^i \) forces the constraint (17) to consider the supply capacity of industry \( k \) in state \( i \), if that industry is open at time \( t \). If industry \( k \) in state \( i \) does not exist or is not open, then the state \( i \) demands or transships the commodity of industry \( k \) in that case, the net input of the commodity of industry \( k \) onto state \( i \) cannot surpass the actual demand of state \( i \) for the commodity of industry \( k \). These conditions are shown in constraints (18) and (19). Constraint (20) ensures the flow balance for all nodes, and constraint (21) ensures that for non-tradable industries, the flow of commodity of industry \( k \) between states is zero. Constraint (22) guarantees that the total produced commodity of industry \( k \) in the entire network of states is equal to the total consumed commodity of industry \( k \).

Constraints (24)-(35) generate the bounds for the modified SIRD model and the linearization process of this model. Constraint (23) updates the number of patients at each time based on the number of patients in the previous period, the newly infected people (\( W_k \)), the number of recovered cases at the time \( t - t_0 \) and the number of deceased cases at the time \( t - t_0 \). Constraint (24) updates the number of new infectious (patients) based on the status of industries and states. It is assumed that every susceptible person may become infected during their work life or social life (except during work hours). Constraint (24) is formulated to avoid double counting an employee’s chance of infection during their work life and social life.

The epidemiological impact measures the number of infected people who are infected either in their social life or during their work time. Depending on the status of the states and industries, the number of new patients can be calculated using Eq. (12), which is used as a constraint in the MOMILP model to update the number of infected people. If the states are open (\( s_{0_1} = 1 \)) and the industries are open (\( \phi^i_k = 1 \)), then there will be some new infections in each state equal to \( a_0 \delta_{i,0_1} s_{0_1} \phi^i_k \), and there will be some new infections in each industry equal to \( \sum_{k \in N} \beta^k_{i,j} y^k_{i_1} \phi_{i,j} \).

\[
W_k = a_0 \left( a_{i,0_1} s_{0_1} - \sum_{k \in K} \beta^k_{i,j} y^k_{i_1} \phi_{i,j} \right) + (1 - (1 - \alpha))(1 - \beta^k_{i,j}) \sum_{k \in K} \beta^k_{i,j} y^k_{i_1} \phi_{i,j} \forall i, t = 1, \ldots, T
\]

However, the above formulation is nonlinear and needs to be linearized to be added to the MOMILP formulation. New decision variables \( r_{i_0} \) and \( \phi^i_k \) are defined to linearize Eq. (12) and transform it into constraints (25)-(32). We replace decision variables \( s_0 \) and \( \phi^i_k \) in Eq. (12) with new decision variables \( r_{i_0} \) and \( \phi^i_k \) and turn this constraint into constraint (24). Constraints (25)-(28) update the number of susceptible populations in each state at each time, considering the status of that state. If the state \( i \) is open at time \( t \), then \( r_{i,0_1} = s_{0_1} \phi^i_k \) will be used in constraint (25)-(28), otherwise \( r_{i,0_1} = 0 \) and there are no new infections in state \( i \). Constraints (29)-(32) update the level of available workforce in industry \( k \) in each state at each time, considering the status of that industry. If industry \( k \) in state \( i \) is open at time \( t \), then \( n_{i,0_1} = \phi^i_k \) is used in constraints (29)-(32), otherwise \( n_{i,0_1} = 0 \) and there will be no new infections in industry \( k \) in state \( i \).
Table 2
Model indices and sets.

| Set | Definition |
|-----|------------|
| $N$ | Set of all states indexed by $i \in I$ and $j \in J$ (e.g., state 2) |
| $N_i$ | Set of all dummy supply nodes indexed by $i \in N$ |
| $N_a$ | Set of all dummy demand nodes indexed by $i \in N$ |
| $K$ | Set of all industries indexed by $k \in K$, such that $K_i, K_a \subseteq K$ and $k \in K$, indexes the industry producing tradable commodities and $k \in K_a$ indexes the industry producing non-tradable commodities. |
| $L$ | Set of all links connecting two states indexed by $k \in L$ |

Table 3
Model parameters.

| Parameters | Definition |
|------------|------------|
| $\alpha_k$ | The supply capacity of the state $i$ for the commodity of industry $k$ |
| $\rho_k$ | The demand of state $i$ from the commodity of industry $k$ |
| $\omega_i$ | The capacity of the link $i$ in $L$ |
| $\gamma_i$ | The infection rate in state $i$ |
| $\beta_i$ | The recovery rate in country $i$ |
| $\alpha_i$ | The capacity of the link $i$ in $L$ |
| $b_i$ | The initial number of patients in state $i$ |
| $r_i$ | The initial status of the state $i$ |
| $\rho_k^a$ | The initial status of the state $i$ for industry $k$ |
| $\beta_k$ | The initial number of employees in state $i$ for industry $k$ |
| $\gamma_k$ | The shrinkage of industry $k$ in $K_a$ (local businesses) in terms of the percentage of employees whose jobs were lost due to the state closure. |
| $\beta_k^a$ | The initial number of employees in state $i$ for industry $k$ |
| $\beta_k^a$ | The shrinkage of industry $k$ in $K_a$ (local businesses) in terms of the percentage of employees whose jobs were lost due to the state closure. |
| $\beta_k^a$ | The initial number of employees in state $i$ for industry $k$ |
| $\rho_k^a$ | The demand of state $i$ from the commodity of industry $k$ |
| $\omega_i$ | The capacity of the link $i$ in $L$ |
| $\gamma_i$ | The infection rate in state $i$ |
| $\beta_i$ | The recovery rate in country $i$ |
| $\alpha_i$ | The capacity of the link $i$ in $L$ |
| $b_i$ | The initial number of patients in state $i$ |
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| $\beta_k^a$ | The initial number of employees in state $i$ for industry $k$ |
| $\rho_k^a$ | The demand of state $i$ from the commodity of industry $k$ |
| $\omega_i$ | The capacity of the link $i$ in $L$ |
| $\gamma_i$ | The infection rate in state $i$ |
| $\beta_i$ | The recovery rate in country $i$ |
| $\alpha_i$ | The capacity of the link $i$ in $L$ |
| $b_i$ | The initial number of patients in state $i$ |
| $r_i$ | The initial status of the state $i$ |
| $\rho_k^a$ | The initial status of the state $i$ for industry $k$ |
| $\beta_k$ | The initial number of employees in state $i$ for industry $k$ |
| $\gamma_k$ | The shrinkage of industry $k$ in $K_a$ (local businesses) in terms of the percentage of employees whose jobs were lost due to the state closure. |

Table 4
Model decision variable.

| Variable | Definition |
|----------|------------|
| $x_{ik}^{y_{ij}}$ | The flow of commodity of industry $k$ on link $(i,j) \in L$ at time $t = 1 \ldots T$, continuous |
| $y_{ij}^{t}$ | The met demand of commodity of industry $k$ in the state $i$ at time $t = 1 \ldots T$, continuous |
| $p_i$ | Number of patients in state $i$ at time $t = 1 \ldots T$, integer |
| $W_i$ | Number of new patients in state $i$ at time $t = 1 \ldots T$, integer |
| $S_i$ | Number of total susceptible people in state $i$ at time $t = 1 \ldots T$, integer |
| $r_i$ | Number of susceptible people in infection state $i$ at time $t = 1 \ldots T$, integer |
| $\beta_k$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |
| $\beta_k^a$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |
| $\beta_k^a$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |
| $\beta_k^a$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |
| $\beta_k^a$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |
| $\beta_k^a$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |
| $\beta_k^a$ | Number of total susceptible employees in state $i$ and industry $k$ at time $t = 1 \ldots T$, integer |

The conceptual schema for the relationship between susceptible $S(t)$, infectious $I(t)$, recovered $R(t)$, and deceased $D(t)$ cases in the modified dynamic SIRD model.

F3: \[
\min_{t=1}^{T} \sum_{i \in I} \sum_{j \in J} x_{ik}^{y_{ij}} \left( 1 - \frac{y_{ij}^{t}}{z_{ij}} \right)
\] (14)
$a^0_i = \nu^0_i = \delta^0_i \forall i \in N_i, \forall k \in K, t = 0$ (37)

$p^0_i = h^0_i \in N_i, t = 0$ (38)

$z^0_i = g^0_i \in N_i, t = 0$ (39)

$\gamma^k_i = \alpha^k_i \in N_i, \forall k \in K, t = 0$ (40)

$\gamma^k_i \in \{0, 1\} \in N_i, \forall k \in K, t = 1, \ldots, T$ (41)

$\delta^k_i \in \{0, 1\} \in N_i, t = 1, \ldots, T$ (42)

$p_{ij}, s_{ij}, r_{ij} \geq 0 \forall i \in N_i, t = 1, \ldots, T$ (43)

$a^0_{it}, n^0_{it}, \gamma^k_{it} \geq 0 \forall i \in N_i, \forall k \in K, t = 1, \ldots, T$ (44)

$\gamma^k_{ij} \geq 0 \forall (i, j) \in L, \forall k \in K, t = 1, \ldots, T$ (45)

Constraints (33)–(35) limit the infected and susceptible populations in each state to its total population and the infected workforce of industry k in state i to its total number of employees. Constraints (36)–(42) define the initial value for each decision variable at time $t = 0$, and constraints (43)–(45) denote the nature of decision variables.

While the original formulation of MNFP presented in Eqs. (1)–(7) is discrete over the time interval $t$, the value of the variables in the integrated model (combination of MNFP and SIRD) is derived from the interactions between consecutive time intervals $t$. That is, the decision in each period is based on the results of the previous period’s decision.

3. Illustrative example

The proposed model is illustrated with several sources of data describing industry productivity, as well as state and COVID pandemic characteristics.

3.1. Data

The data used in this research are divided into two categories as follows.

1. COVID-19 data: These data include COVID-19-related rates, including the infection, recovery, and death rates at the state level in the United States. These data are gathered from the COVID-19 Impact Analysis Platform compiled by the University of Maryland [6]. The average proportion of the total recovery to the total active cases all around the US is equal to 0.6. Data related to the recovery time, death time, and immunity time frame are gathered from the literature and reports from the Centers for Disease Control and Prevention (CDC)¹. The infection rate in each industry is derived from the Washington state department of health report [57]. These data show the COVID infection rate in different industries in Washington state, and we have used the same rate for similar industries in all other states.

2. Economic data: The required data for the MNFP model is derived from the Commodity Flow Survey published by the Bureau of Transportation Statistics [58]. These data show the yearly trade from each commodity/industry and between each pair of states in 2017. It is assumed that the links between the two states can handle the flow of commodities up to their yearly trade. Each state’s supply and demand capacity for each industry is also calculated from the same survey such that Eqs. (46) and (47) hold, where $f^k_{ij}$ is the actual flow of commodity produced by industry k ($1/1000, \text{traded between from state } i \text{ to state } j$).

$\gamma^k_i = \sum_{j \in N_j} f^k_{ij} \forall i \in N, \forall k \in K$ (46)

$\delta^k_i = \sum_{j \in N_j} f^k_{ji} \in N, \forall k \in K$ (47)

Note that to consider the supply of each state from the commodity of the industries which exist in that state, we need to consider all nodes as supply nodes (using dummy supply nodes). Therefore, we do not calculate pure supply and demand nodes by subtracting the output flow from the input flow of each commodity in each state; alternatively, we use the results of Eqs. (46) and (47) to calculate the actual supply and demand capacity. Employment statistics at the state and industry levels are derived from US Bureau of Labor statistics.²

In this study, we are using a reasonably large-scale data set including different states and industry categories to sufficiently illustrate the generalizability of the model. Therefore, the model can be used for the same or smaller scales of data from other geographical locations (including other countries). The data from 11 states, the District of Columbia (including the states in New England and the mid-Atlantic), and 19 industries are considered. Table 5 shows the definition of the industries and their North American Industry Classification System (NAICS) code, along with their industry-specific rate of COVID-19 infection and the rate of local business shrinkage due to state closure. Fig. 4 shows the infection and death rate at the state level and the size of each industry in each state based on the number of employees in that industry. It is assumed that industries only use the freight network within the US to trade commodities. Therefore, each state is connected to its closest neighboring states, and 352 arcs are considered in the modified MNFP model.

Table 5

The definition of the industries considered in this study.

| NAICS code | Industry definition | Infection rate (%) | Business shrinkage (%) |
|------------|---------------------|--------------------|------------------------|
| Tradable industries (K₁) | | | |
| 21 | Mining, Quarrying, and Oil and Gas Extraction | 1 | – |
| 31–33 | Manufacturing | 9 | – |
| 42 | Wholesaler’s trade | 3 | – |
| 45 | Retail trade | 10 | – |
| 49 | Transportation and Warehousing | 5 | – |
| 51 | Information | 1 | – |
| 55 | Management of Companies and Enterprises | 2 | – |
| Non-tradable industries (K₂ or local businesses) | | | |
| 11 | Local Agriculture, Forestry, Fishing, and Hunting | 9 | –0.875 |
| 23 | Local Construction | 8 | 3.375 |
| 48 | Local Transportation and Warehousing | 5 | 2.75 |
| 52 | Finance and Insurance | 2 | 1.5 |
| 53 | Real Estate and Rental and Leasing | 2 | 2.125 |
| 56 | Administrative and Support, and Waste Management and Remediation Services | 4 | 2.125 |
| 54 | The Professional, Scientific, and Technical Services | 4 | 2.25 |
| 61 | Educational Services | 4 | 4.875 |
| 62 | Health Care and Social Assistance | 24 | 2 |
| 71 | Arts, Entertainment, and Recreation | 1 | 4.375 |
| 72 | Accommodation and Food Services | 5 | 2.75 |
| 81 | Other Services (except Public Administration) | 3 | 6.5 |

¹ https://www.cdc.gov.
² https://www.bls.gov/.
each state to the other states. According to these data, Pennsylvania and New York are the states with the highest export and import of commodities. Also, the Manufacturing industry has the highest value of products being traded between states, followed by the Wholesale trade and Warehouse and storage. Therefore, the closure of these industries is expected to cause a high rate of unmet demand system.

According to Kyrychko et al. (2020), the mean value of time to recovery, \( t_R \), is 15.3 days, and the mean value of the time to death, \( t_D \), is nine days. Therefore, the time interval in our analysis is assumed to be equivalent to 10 days and \( t_R = 2 \) (equivalent to 20 days) and \( t_D = 1 \) (equivalent to 10 days). According to the CDC\(^3\) (Center for Disease Control and Prevention), evidence suggests that reinfection is uncommon 90 days after the initial infection. Hence, we consider the immunity time \( t_V = 9 \) in the model. At the initial time \( t = 0 \), all industries and states are considered open.

### 3.2. Solution approach

Recall that the proposed objective functions in Eqs. 13–15 have different ranges and scales. Therefore, we utilize the augmented \( \varepsilon \)-constraint (AUGMECON) method proposed by Ref. [59] to solve the proposed MOMILP model. AUGMECON is an efficient version of the \( \varepsilon \)-constraint method, accelerating the process of generating Pareto-optimal solutions by avoiding redundant iterations. We consider the epidemiological impact (F1) as the primary objective function with the secondary objectives being the economic impact on local businesses (F2) and the economic impact on trade (F3). The AUGMECON formulation will be represented as follows, in which \( s_l \) is the non-negative slack variable showing the amount of deviation of the secondary objective function \( l \) from its optimum value. The RHS value of constraint (49) is \( e_l = u_l - (L_l \times r_l) / g_l \) where \( u_l \) is the upper bound of the secondary objective function \( l \) and \( L_l \) is the iteration counter of the grid points in the solution grid of \( g_l \). Term \( r_l \) is the range of the secondary objective function \( l \) in the payoff matrix (upper bound, \( u_l \), to lower bound, \( l_b \)), respectively. \( X \) is the feasibility area for the original MOMILP. A similar structure is built for the cases in which the economic impact on local businesses (F2) or the economic impact on trade (F3) is considered the primary objective.

\[
\min \sum_{t=1}^{T} \sum_{i \in N} \sum_{k \in K} \left( 1 - \frac{I_{kl}}{I_{kl}^{\text{max}}} \right) - \varepsilon \left( s_1 \frac{1}{r_1} + s_2 \frac{1}{r_2} \right)
\]

s.t.
\[
\sum_{t=1}^{T} \sum_{i \in N} \left( \frac{p_i}{a_t} \right) + s_1 = \varepsilon_1
\]
\[
\sum_{t=1}^{T} \sum_{i \in N} \left( \sum_{k \in K} \frac{q_{ik}^t}{\sum_{k \in K} e_k^t} \right) + s_2 = \varepsilon_2
\]
\[
y_k^t, z_k^t, p_k, s_k, \alpha_k, \beta_k, \gamma_k, x_{ij}^t \in X
\]

Details on the AUGMECON method and solution algorithm can be found in Ref. [59]. All the implementations in this study are performed on a 64-bit desktop system with 12.0 GB RAM and the Core-i7-6500U CPU@2.5GHz. The proposed framework is modeled and solved with Gurobi in Python, and for the selected time horizon \(T\), the average run time is reported in the next section.

4. Results

In this study, we consider four different scenarios, as shown in Table 6, in which we analyze the quality of calculated solutions by solving the model for different objective functions. The model considers only one objective in the first three scenarios and a multi-objective MILP by considering one of the objectives as the primary objective function.

The MOMILP model will result in a set of Pareto-optimal solutions instead of a single optimal solution. To generate the Pareto optimum solutions, we consider \(6 \times 6\) grid points and solve scenario 4. Table 7 shows the payoff matrix and the parameters required for implementing the AUGMECON algorithm. Fig. 6-a shows the result of the AUGMECON algorithm used to solve the proposed MOMILP. Fig. 6-b magnifies the Pareto optimal solutions for the last four values of \(F_1\) (0.4, 0.6, 0.8, and 1.0) from Fig. 6-a.

As shown in Fig. 6-a (and Fig. 6-b), the epidemiological impact \(F_1\) and the economic impact on local businesses \(F_2\) are negatively correlated. As more states open local activities, the impact on local businesses decreases while the number of patients increases. While the model tries to minimize the adverse economic impact on trade \(F_2\), it opens more industries in each city, which will increase the number of infected employees, thereby increasing the number of infections.

In scenario 4, the epidemiological and economic impacts on trade are negatively correlated. Therefore, the model tries to decrease the economic impact on trade by keeping more industries open (tradable industries, \(K_1\), and non-tradable industries, \(K_2\)). However, since opening states and all industries would significantly increase the number of patients, the model chooses to close more states and less demanded local

### Table 6

The definition of the scenarios.

| Scenario | Objective function | Objective |
|----------|--------------------|-----------|
| 1        | Min F1             | Minimizing the epidemiological impact \(F_1\) |
| 2        | Min F2             | Minimizing the economic impact on local businesses \(F_2\) |
| 3        | Min F3             | Minimizing the economic impact on trade \(F_3\) |
| 4        | Min MOMILP         | Minimizing the MOMILP using the AUGMECON method |

### Table 7

The normalized payoff matrix and range of three objective functions.

|       | \(F_1\) value | \(F_2\) value | \(F_3\) value |
|-------|---------------|---------------|---------------|
| Min F1 | 0.000         | 1.000         | 1.000         |
| Min F2 | 1.000         | 0.000         | 0.813         |
| Min F3 | 0.668         | 0.973         | 0.000         |
industries, so the economic impact on trade would be minimized. Therefore, the feasible solution region and the Pareto-optimal solutions for the MOMILP show a convex and nonlinear behavior. Deriving the Pareto-optimal solutions for the convex and nonlinear multi-objective functions using other approaches is adequately addressed in the literature \cite{[60][61]}. In this example, the optimality gap equals 5%, and all the Pareto solutions are non-dominated.

For each scenario presented in Table 6, we measure the value of the three objective functions, including the average percentage of patients (F1), the average trade impact (F2, measured by the percentage of unmet demand), and the average local businesses impact (F3, measured by the percentage of business shrinkage). For the sake of compression of the four scenarios, we choose a solution from the Pareto-optimal solutions set that results in the minimum cubic distance from the lower bound of each objective in that specific scenario. The selected Pareto solution results in the normalized values of the three objective functions such that F1 = 0.692, F2 = 0.918, and F3 = 0.000.

The results obtained from scenario 4 show significantly different outcomes compared to the first three scenarios. In this scenario, the optimal values of each objective are roughly close to each other, while in the first three scenarios, the range of each objective is significantly higher. The Pareto-optimal solutions suggest that for any control decision (state and industry closure or reopening), the economic and epidemiological impacts change in the opposite direction. At the same time, it is more effective to close most states and keep the majority of industries open. The results show that the economic impact of industries and state closure overcome the epidemiological impact.

Fig. 7 shows the optimal value of each objective changing over the time horizon of $T$ = 10 for each of the four scenarios presented in Table 6. Results for scenario 4 belong to the selected solution among the Pareto-optimal set, with the minimum cubic distance from the lower bound of F1, F2, and F3. As shown in Fig. 7, objective function Min F1 in scenario 1, decreases the percentage of patients quickly as the model forces more states and industries to be closed. This decrease results in a higher economic impact on local businesses and trade, as shown in Fig. 7b and c. With objective function Min F2 in scenario 2, the percentage of patients decreases more slowly than in scenario 1 as scenario 2 minimizes the economic impact on local businesses by closing fewer states. While fewer states and local businesses are closed, to keep the number of patients lower than its upper bound, the model closes more industries, leading to an increased impact on trade. Objective function Min F3 in scenario 3 minimizes the economic impact on trade, so it tries to keep more industries open. Since open industries result in higher employee infection, the model forces more states to close to keep the number of infections lower than its upper bound. In this case, the economic impact on local businesses is higher than in scenario 2, while the number of patients is less.

As shown in Fig. 7b, the percentage of patients decreases over time, as all MOMILP models force more states to close. The MOMILP model keeps more industries open since they value the economic impact on trade. In the selected Pareto-optimal sets in scenario 4, the epidemiological and economic impacts oscillate during the time horizon as the MOMILP models give a different sequence of openings and closures. As shown in Fig. 7, the epidemiological impact in the three MOMILP models in scenario 4 is decreasing with closer values than in scenarios 1, 2, and 3.

Finally, each optimal solution controls policies over the time horizon. Fig. 8 shows the optimal opening and closure policy for each state and industry over the time horizon and scenarios 1–4. All the policies regarding the opening and closure of states and industries comply with the results explained in Fig. 7. The MOMILP model mostly keeps more industries open to decrease the unmet demand, while they keep more states closed to decrease the percentage of patients. More specifically, in Scenario 4, large states such as New York, New Jersey, Massachusetts, Maryland, New Hampshire, and Maine contribute to 69% percent of the population in this study, and they are closed more often in the Pareto-optimal solution. Another reason for the closure of these states is the high infection rate and death rate (refer to Fig. 4). Respectively the infection and death rate are highest in Maine (0.012,0.05), New Hampshire (0.0117, 0.07), Massachusetts (0.0113,0.09), New York (0.0112, 0.05).

Connecticut, Delaware, and Pennsylvania are staying open more often. These three states contain 26% of the total population in this study. The infection rate in these three states (0.011) is almost equal to the average infection rate (0.01099) of the 11 states. However, the death rate in Connecticut (0.11) is higher than the average (0.078), in Delaware (0.05) is much less than average, and in Pennsylvania (0.079) is almost equal to the average. While the model avoids epidemiological impact by closing larger states, it minimizes the economic impact on local businesses by opening a few other large states (Connecticut, Delaware, and Pennsylvania).

Considering the industry-specific infection rate and the scale of each industry in Vermont, Rhode Island, Delaware, Maine, New Hampshire, the District of Columbia, Connecticut, Pennsylvania, Maryland, New Jersey, and New York (refer to Fig. 4), the closure of these states results in a lower economic impact on local businesses. Therefore, with the combination of the closure of the other states, the model opens the latter three states to minimize the cumulative economic impact on the local businesses.

Moreover, the industry status is decided based on the amount of trade between states for a specific commodity. In MOMILP majority of industries are open due to the high economic impact their closure may cause. The industries that are closed more often are located in the District of Columbia. According to Fig. 5, the District of Columbia mainly supplies a small number of commodities, mainly from the Wholesale trade and Manufacturing industries. The Wholesale trade industry is
respectively. Results show that the economic impact on trade is significantly important, and therefore the important industries with high trade, horizon. In Vermont, where the export of commodities is lower, industries are closed during the whole planning horizon. In New York, which has the second-highest export value, the Accommodation industry is closed at times \( t = \{1, 3, 4, 5, 6, 9\} \), \( t = \{1:9\} \), and \( t = \{5, 6, 8, 9\} \) respectively. The other industries are closed accordingly. In New York, which has the second-highest export value, the Transportation and Accommodation industries are closed at time \( t = \{5\} \) and \( t = \{3\} \) respectively. In Maryland, Manufacturing is closed at time \( t = \{6\} \), and in Delaware and Maine, the Management industry is closed at times \( t = \{1:10\} \) and \( t = \{5\} \), respectively. Results show that the economic impact on trade is significantly important, and therefore the important industries with high traded values in specific states (e.g., Manufacturing, Wholesale trade, Warehouse, and storage) are staying open more often during the planning horizon.

The tradeoff between epidemiological and economic impacts is the critical aspect of the model. Particularly, the timing of closures and reopenings influences the extent of the three adverse impacts. At the start of planning \( (t = 0) \), all states and industries are open, which will cause some level of epidemiological impact in the next period \( (t = 1) \). In scenario 2, for example, the majority of states are open more often compared to scenario 1. At \( t = 2 \), Maine, Rhode Island, Vermont, and Washington DC are closed to lower the epidemiological impact with the combination of the closure of the other states to minimize the economic impact on local businesses. The lower percentage of the economic impact on local businesses in these four states results in their closure for much of the planning horizon.

Similarly, the closure and reopening decisions of industries are affected by the economic impact they cause and the simultaneous state reopening and closure decisions at each time to control the epidemiological impact. For example, in scenario four, the closure of the industries is caused by the tendency to reduce the epidemiological impact. For example, in Rhode Island, the majority of closures occur in Mining at \( t = \{1 \rightarrow 10\} \), Information at \( t = \{4 \rightarrow 10\} \), Management at time \( t = \{8 \rightarrow 10\} \), Transportation at \( t = \{7, 9, 10\} \), and Manufacturing at \( t = \{7, 9, 10\} \). These closures, along with the other closures at the end of the planning horizon, will cause a moderate economic impact on trade. In fact, keeping more industries open and more states closed causes a minimum level of average economic impact on trade during the planning horizon when the epidemiological impact caused by open states at time \( t = \{0, 1\} \) would cease until time \( t = \{10\} \).

5. Concluding remarks

This research explores a practical decision-making tool that can improve state-level and industry-level operational decisions during a pandemic. We propose a novel decision framework that integrates SIRD and MNFP models with unemployment measures into a mixed-integer linear programming formulation to estimate the best control strategy over a specified time horizon. The contribution of this paper lies in (i) accounting for the two-fold economic (supply and demand perturbation and raised unemployment level) and epidemiological mechanisms of the pandemic, simultaneously, (ii) incorporating the interdependency between industry- and state-level pandemic-driven decisions, and (iii) providing a decision support tool for optimizing the temporal closure and reopening strategies during the desired planning period.

The proposed framework minimizes three main components: (i) the economic impact on the supply and trade equilibrium measured by the MNFP formulation, (ii) the economic impact on local businesses based on their unemployment rate, and (iii) the epidemiological impact based on the number of the infections as measured by the SIRD formulation. While the reopening of the industries decreases the negative economic impact, it also contributes to increasing the infected population. Also, the state reopening contributes to the number of infected individuals, which ultimately impacts industry workforce effectiveness, and finally, it impacts the economy of the states. Therefore, the timing and the choice of closure and reopening of states and industries are important for minimizing both the economic and the epidemiological impact of the pandemic.

The model is implemented on COVID-19 data for 11 states plus the District of Columbia and 19 industries in the US. It is found that with a different combination of economic and epidemiological components, some states have shown a high percentage of patients in some scenarios while others have shown a high level of negative economic impact. Furthermore, the closure of each industry in one state may affect the unmet demand in another state and therefore affect the closure or opening of industries in the same or other states. The proposed MOMILP result in more state closure rather than industry closure. Three large states such as New York, New Jersey, Massachusetts, and Maryland, are
Fig. 8. Closure and reopening policies at the state and industry level over the time horizon of $T = 10$ in scenarios 1–4.
closed more often, while the high economic impact on local businesses keeps Pennsylvania, Connecticut, and Delaware open more often. District of Columbia has small sizes of industries that have a small contribution to supply for the demand and have less export to the other states; therefore, those industries are closed more often. The industries that are closed more often include 

Management, Information, Retail trade, Mining, and Manufacturing, mostly in the District of Columbia, Vermont, and New York. The reason for the closure of these industries in a specific state is the low output level that they have.

While temporal industry- and state-level policies are vital for controlling the early-stage impacts of the pandemic, several other impacts need to be considered in the later-stage decisions. It has been proven that a pandemic’s epidemiological and economic impact propagates to other aspects of life, including socio-demographic vulnerabilities, perception of social equity in access to resources, fair vaccination distribution, and community-level job loss vulnerability, among others. On the other hand, the scale of closure and reopening, specific to each state and each industry in each state, significantly affects the efficiency of control strategies. As such, future work will explore (i) quantifying the direct effect of business and industry closure in one state on the business and industry in other states (i.e., multi-regional interdependent ecosystems), (iii) incorporating the fairness of the controlling policy based on direct effect of business and industry closure in one state on the business there, therefore, those industries are closed more often. The industries that are closed more often include Manufacturing.

Data availability

Data will be made available on request.

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