

Using input-output analysis to model the impact of pandemic mitigation and suppression measures on the workforce

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ABSTRACT

The “flatten the curve” graphic has recently become a common tool to visualize the extent to which pandemic suppression and mitigation measures could potentially reduce and delay the number of daily infections due to a pandemic. The COVID-19 pandemic has challenged the capacity of the many health-care systems and created cascading economic impacts on interdependent sectors of the global society. This paper specifically explores the impact of pandemics on the workforce. The model proposed in this paper comprises of three major steps. First, sources for epidemic curves are identified to generate the *attack rate*, which is the daily number of infections normalized with respect to the population of the affected region. Second, the model assumes that the general attack rate can be specialized to reflect sector-specific workforce classifications, noting that each economic sector has varying dependence on the workforce. Third, using economic input-output (IO) data from the US Bureau of Economic Analysis, this paper analyzes the performance of several mitigation and suppression measures relative to a baseline pandemic scenario. Results from the IO simulations demonstrate the extent to which mitigation and suppression measures can flatten the curve. This paper concludes with reflections on other consequences of pandemics such as the mental health impacts associated with social isolation and the disproportionate effects on different socioeconomic groups.

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1. Introduction

Disease outbreaks, ranging from mild to severe can lead to cascading losses to interdependent socioeconomic and infrastructure systems (Santos, 2020). A pandemic refers to a widespread outbreak of a disease, often infecting large populations across the globe. Pandemics have disrupted modern civilization in several occasions: H1N1 (Spanish Flu) in 1918, H2N2 in 1957, H3N2 in 1968, H1N1pdm2009 in 2009 (CDC, 2018). The 1918 “Spanish Flu” is considered one of the most catastrophic pandemics in modern times, which led to 50+ million mortalities worldwide and 500,000+ people in the US (Taubenberger and Morens, 2006). Disease outbreaks that are caused by viruses are particularly threatening since they could mutate and migrate at uncertain rates; as well as challenge the efficacy of available vaccines or those that are still under development (Orsi and Santos, 2010). The World Health Organization (WHO), in a document published in 2007, underscored the urgent need for coordinated global scientific initiatives to combat the rise of new infections and the likely threat of a pandemic (WHO, 2007). Fast forward into 2020, the world has indeed borne witness

to the devastating and unprecedented impacts of the SARS-CoV-2, which is the virus associated with the COVID-19 pandemic.

The “flat,ten the curve” concept has already been in use for years; nonetheless, it has particularly spiked in popularity amidst the COVID-19 pandemic. Its purpose is to reduce the number of daily infections (i.e., decrease the peak of the curve) albeit prolonging the pandemic duration so as not to exceed the constraints of the healthcare system (e.g., hospitals, healthcare providers, personal protective equipment, and life-saving equipment like ventilators, among others). The “flatten the curve” concept as depicted in Fig. 1 originated from pandemic guidelines issued by the Centers for Disease Control and Prevention (CDC, 2007, CDC, 2017). Most of the recent extensions to the graphic happened recently such as the use of different colors, animation, and inclusion of additional information. For example, an article in *The Economist* (2020) proposed the use of color contrast to distinguish the two epidemic waves (i.e., baseline versus flattened). Subsequently, a horizontal line was added by Harris (2020) in a twitter post to visualize the capacity of the healthcare system. Such inclusion of the horizontal line further emphasized the urgent need for flattening the curve (Roberts, 2020). Furthermore, the use of animation and other graphics has also been implemented to effectively convey how pandemic mea-

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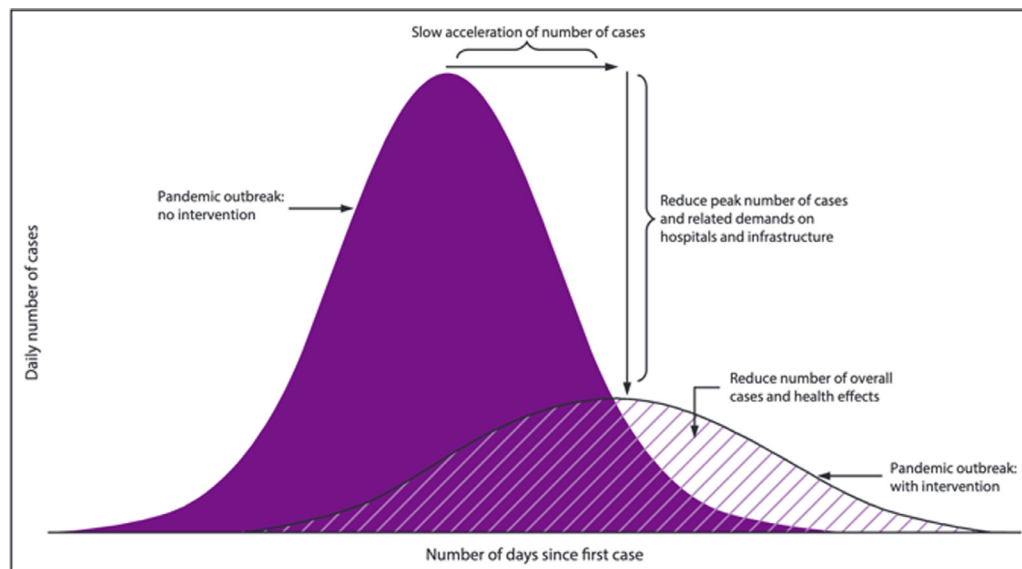


Fig. 1. Visualization of the “Flatten the Curve” Concept (Adapted from CDC 2007, 2017)

asures could potentially flatten the curve (Stevens, 2020; Wiles, 2020).

Laboratory-based surveillance data pertaining to respiratory and enteric viral diseases are published on a regular basis by the CDC (2020). In contrast, syndromic surveillance is a disease surveillance method that utilizes statistical analysis and forecasting based on health records to enable early outbreak detection (Lombardo et al., 2003). In epidemiology literature, the notation R_0 is used as a parameter for modeling the dynamics of spread, typically used in the “Susceptible Infected Removed” (SIR) model, as well as its extensions (Anderson and May, 1992). Disease outbreaks have been studied using population models (Bacaër and Ouifki, 2007; Larson, 2006), mixing models (Edmunds et al., 2006), and spatial analysis (Real and Biek, 2007). Spatial analysis and simulation tools have also been applied to analyze the transmission of diseases across various regions (Perez and Dragicevic, 2009). Economic models have also been developed to estimate losses from pandemics and benefits from implementing intervention measures (Chen et al., 2011; Santos et al., 2013).

As with any other novel coronaviruses, like the one responsible for the COVID-19 pandemic, vaccines are not initially available. For contagious diseases, it is particularly a concerning that the number of infections may threaten to exceed the capacity of health-care systems. Hence, in the absence of vaccines, government and health agencies rely on the so-called nonpharmaceutical interventions (NPIs) to flatten the curve. There are two major categories of NPIs: suppression and mitigation¹. Suppression measures intend to reduce R_0 to values lower than 1, which could be achieved through broad testing, contact tracing, quarantine, border closure, and travel bans (Huzar, 2020; Pueyo, 2020). On the other hand, mitigation measures aim to defer the transmission of the outbreak such that the number of cases will not surpass the capacity of the healthcare system and hopefully achieve herd immunity along the way. Social distancing, cloth face coverings, and hand hygiene have been informally referred to as the “trinity” of mitigation measures. Several other notable studies have performed comparative analyses of various nonpharmaceutical intervention measures in terms of their efficacy to flatten the curve as well as the controversies

surrounding their implementation (Ferguson et al., 2020; Huzar, 2020; James et al., 2020; Pueyo, 2020).

Implementation of mitigation and suppression measures in the midst of a pandemic will consequently disrupt the workforce in various sectors of the economy (Santos, 2020). Recently, government agencies have formulated policy recommendations on how to minimize the impact of pandemics on the workforce (see for example, US Department of Labor, 2020). Most of the previous studies on workforce disruptions in the context of pandemics focus on workforce unavailability (or absenteeism) either because they contracted the disease, or they need to attend to ill family or household members. For events like pandemics that primarily render disruptions to the workforce, the concept of “forced” workforce absenteeism becomes a common phenomenon. Forced workforce absenteeism is an outcome of measures that prohibit physical access to place of work such as lockdown, business/school closures, or travel bans. Some economic sectors have transitioned to virtual delivery of their goods and services to curtail the impact on forced workforce absenteeism.

The primary contribution of this article is to explore the time-varying impacts of suppression and mitigation on the workforce and how their associated economic losses. The subsequent sections of this article are organized as follows. In Section 2, the methodology for modeling of workforce disruptions using input-output modeling is discussed. In Section 3, the results of economic simulations for different suppression and mitigation measures are discussed and analyzed. Finally, the conclusions of the paper and other reflections for future consideration are presented in Section 4.

2. Methods

This paper recognizes the multifaceted nature of pandemic risk management (and disasters, in general). For example, Santos et al. (2020) proposed the acronym WEIGHT (Workforce/Population, Economic, Infrastructure, Geography, Hierarchy, Time) to emphasize the critical factors associated with risk assessment and management of disasters. The novelty of the current article is to focus on the workforce factor in the context of interdependent economic and infrastructure systems, taking into account geographic, hierarchical, and temporal contexts. Specifically, the new contribution of this paper is the application of economic impact

¹ In addition, containment measures can be implemented prior to community spread or after suppression has been effectively implemented to detect and isolate individual cases.

analysis to link the effect of suppression and mitigation scenarios on interdependent workforce sectors.

Previous studies have revealed the staggering losses caused by the disruptions in workforce availability pursuant to disasters. A study by [Ferguson et al. \(2006\)](#) showed an aberrant spike in employee absenteeism rate (as high as 40%) in the aftermath of pandemics; and persons with symptoms have taken prolonged sick leaves (as long as a week). Another study was performed by [Santos et al. \(2009\)](#) to assess the economic losses due to the 2009 H1N1 pandemic for the Commonwealth of Virginia, where it has been found that even a moderate 15% attack rate scenario could lead to a \$5.5 billion loss.

Hence, it is of utmost importance to understand the nature and behavior of workforce recovery in the context of coupled economic-infrastructure systems subjected to disasters. The dependence of different systems to the workforce varies according on the region and the type of sector. The higher the incidence of workforce unavailability, the greater the impact will be on the operation of infrastructure systems even if they are not directly rendered inoperable by a disaster. Particularly for pandemics, the direct impact is concentrated on the workforce and there is virtually no direct damage to the physical infrastructure (i.e., in contrast to other disasters that could cause direct disruption to both people and infrastructure). Ironically, a vast majority of disaster-related articles have placed more emphasis on infrastructure functionality relative to workforce recovery ([Santos et al., 2013](#)). Despite the recognition of how disasters could severely impact workforce availability, much of the recent literature on disaster risk management disproportionately focuses on restoration of critical infrastructure systems rendered inoperable by disasters.²

This paper applies the classical input-output (IO) model ([Leontief, 1936](#)) to explore the impact of various pandemic measures to interdependent workforce sectors of the US economy. The IO model developed by Wassily Leontief has received the prestigious Nobel Prize in Economics in 1973, and since then the model has been used in a myriad of applications ([Miller and Blair, 2009](#)). It is capable of assessing the production and consumption of interdependent economic sectors. Coupled with simulation and optimization, the IO model can be used as a policy tool to further enhance the sustainability of transactions across producers and consumers in the economy. Statistical agencies across the globe are collecting and publishing IO data to support various economic policies and decisions. More sophisticated models like the computable general equilibrium (CGE) also utilizes IO data and social accounting matrices to model nonlinear scenarios such as substitution and price elasticity. IO and CGE models are becoming more and more prominent in the area of disaster risk management. The concept of economic resilience has become more and more embedded in contemporary applications of IO-based models in the context of disaster recovery ([Rose and Liao, 2005](#)).

The concept of inoperability has also been used in conjunction with the IO model. Inoperability is similar to the complement of reliability (or unreliability), which measures the percentage loss of a system's function relative to its ideal output. It is a dimensionless number between 0 and 1, where a value of 0 corresponds to flawless operation while 1 is complete failure ([Santos and Haimes, 2004](#); [Santos, 2006](#)). Integrating time-varying inoperability will be especially relevant for analyzing workforce inoperability scenarios

and their resulting impacts on interdependent sectors of the economy. The formulation of the dynamic inoperability IO model is shown below:

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

The terms in the Eq. (1) are described as follows:

- $\mathbf{q}(t+1)$ and $\mathbf{q}(t)$: sector inoperability at time $t+1$ and t .
- $\mathbf{K}$: matrix of resilience parameters associated with sector-specific recovery rates
- $\mathbf{A}^*$: Leontief interdependency matrix
- $\mathbf{c}^*(t)$: demand disruption

Although the inoperability measure has been used in modeling infrastructure functionality, the dynamic behavior of workforce inoperability (i.e., degraded levels of workforce availability) and its coupling with sector resilience will be the focus of this paper. Just like the traditional definition of inoperability, workforce inoperability is defined as the percentage of loss in workforce availability relative to the ideal level. It is further normalized relative to the total production input of a sector, since a sector has other input requirements to fulfill its production including materials, machines, and other value adding inputs, in addition to labor. Coupled with publicly available epidemic curves, discussed further in the next section, workforce inoperability can be modeled as a time-varying function using the dynamic model shown in Eq (1).

Evidently, the dependence of each sector on the workforce can vary significantly. Sectors that typically leverage information technology and automation have the tendency to have relatively lower reliance on labor. The following illustrative examples further explain the impact of workforce dependence and its relevance when analyzing workforce-debilitating events. Suppose that the total production input of a hypothetical sector is \$100 of which \$10 goes to workforce, then the labor dependency ratio of that sector is 10%. In contrast, suppose that the total production input of another sector is also \$100 of which \$50 goes to workforce, then the labor dependency ratio of that sector is 50%. Hence, even if the two sectors have the same total production input, the difference in labor dependence will trigger disproportionate impacts when the workforce is perturbed. Another consideration that can cushion the impact of workforce unavailability in the aftermath of disasters is the implementation of workforce resilience strategies ([Acemoglu and Autor, 2010](#)). For example, it is possible for some labor-intensive sectors to implement “work from home” practices (or teleworking) as well as “offshoring” of business operations to minimize the production loss due to work closures ([Firpo et al., 2011](#)). In the next section, the model shall be applied to various workforce inoperability scenarios in the context of a pandemic, taking into account labor dependence ratios specific to each economic sector.

3. Results and discussion

In this section, we will explore several scenarios to gain insights on the extent to which mitigation and suppression measures can “flatten the curve” and consequently alter the trajectory of economic losses. Various studies have asserted that mitigation and suppression measures, if implemented in a timely manner, can effectively reduce the peak of the epi curve and delay the propagation of the disease. Hence, it is possible to evaluate the efficacy of various pharmaceutical and nonpharmaceutical interventions in flattening the curve for outbreaks with different R_0 ([Germann et al., 2006](#)). More recently, [Pueyo \(2020\)](#) has emphasized the urgency of implementing mitigation and suppression measures to dramatically reduce the expected number of mortalities from the magnitude of millions to hundreds of thousands. While there are ethical issues and other controversies, a significant number of research articles have reached a consensus on the efficacy of implementing such measures.

² A Web of Science search conducted on May 28, 2020 showed a disproportionate balance amongst articles that contained the keywords “workforce” and “infrastructure” in the context of disasters. To wit, Web of Science returned a total of 88,045 articles with the word *disaster*. Combining *disaster* with *infrastructure* returned 5,865 articles. On the other hand, 299 articles were returned after combining *disaster* with *workforce*, which is one order of magnitude lower than the previous keyword combination.

Table 1
Summary of epi curve parameters for the baseline, mitigation, and suppression scenarios

	Scenario 1: Baseline	Scenario 2: Mitigation	Scenario 3: Suppression	Scenario 4: Suppression + Continuity
Start (Day)	0	0	0	0
Peak (Day)	30	40	50	50
End (Day)	60	90	120	120
Peak Attack Rate	50%	25%	10%	10%

The four scenarios presented in subsequent discussions feature hypothetical epi curves that correspond to various levels of mitigation and suppression measures. The underlying economic data used in the analysis is based on the 2018 annual IO data for the USA, which comprises of 71 sectors³. On the other hand, the epi curves can be extracted from data published by several research institutes and health agencies⁴. The horizontal axis of an epi curve corresponds to time (in days), while the vertical axis gives the count of new recorded infections (usually normalized per 100,000 population). Further, when the daily number infections is expressed as a percentage of the population, it generates what epidemiological literature refers to as “attack rate” for each day of the pandemic wave⁵.

The attack rate also sheds information on the extent to which the workforce is affected by a disease outbreak. As described in the previous section, each sector has varying dependence on the workforce, which can be measured using the ratio of the sector's payments to labor with respect to its total production input. For example, a ratio of 0.1 means that workforce compensation accounts for 10% of the production input. This ratio can be calculated directly from supply and use tables in the IO accounts of national statistical agencies, such as the US Bureau of Economic Analysis (see footnote 3).

The model presented in Eq (1) was used to simulate the interdependent effects of mitigation and suppression measures. A baseline scenario (Scenario 1) was set as the reference scenario that corresponds to minimal intervention. Scenario 2 assumes that mitigation measures are implemented (e.g., some social distancing, targeted quarantine, and isolation of at-risk populations). On the other hand, Scenario 3 assumes suppression measures are enforced (e.g., mandated quarantine, border closure, mass testing, travel bans, suspension of large gatherings, and school/business closures). Finally, Scenario 4 is a hybrid of Scenario 3, taking into account the ability of each economic sector to implement strategies that can decrease the impact of workforce unavailability (e.g., teleworking, offshoring, or automation). The key model inputs associated with the four scenarios are summarized in Table 1. Furthermore, the workforce dependence ratios, which are also necessary model inputs, are computed from publicly available data (i.e., workforce compensation divided by the total production input requirements of the economic sectors). The primary data sources for the subsequent case study are described in footnotes 3–5.

Given the hypothetical parameters shown in Table 1, the economic loss trajectories of the sectors are presented in Fig. 2. Scenario 1, which is the baseline has the highest peak attack rate, albeit its realization is earlier than the subsequent scenarios. The mitigation scenario (Scenario 2) not only delayed the arrival of the peak, but also flattened the curve. In contrast, suppression scenario

(Scenario 3) further delays the peak and is also successful in flattening the curve. Finally, Scenario 4 is a re-simulation of Scenario 3, considering workforce continuity strategies in the sectors. The peak did not change, but workforce continuity strategies further contribute to flattening the curve since healthy workers who are abiding by the mandated “stay at home” directives could still work virtually despite closure of non-essential businesses. The model inputs for Scenarios 3 and 4 in Table 4 are the same; nonetheless the values of the workforce dependence for each sector (see discussion in Section 2) has been altered in Scenario 4 to take into account the application of workforce resilience strategies (e.g., teleworking, offshoring, and leveraging of information technology to continue operations in the midst of government-mandated business closures).

Due to the linearity of the model, Scenarios 1–3 have similar rankings of critically affected sectors based on economic loss. These include: State and local general government; Miscellaneous professional, scientific, and technical services; Ambulatory health care services; Wholesale trade; Construction; Administrative and support services; Hospitals; Management of companies and enterprises; Other services, except government; and Food services and drinking places. The results appear to indicate that the magnitude of losses depend on the size of the sector (measured in GDP), as well as the labor-dependence of the sectors. In the US, the State and local government; Wholesale trade; and Construction are among the highest contributors to the GDP hence their inclusion in the ranking is quite intuitive. Furthermore, the prevalence of labor-dependent sectors can also be observed in the rankings albeit their moderate contribution to the GDP such as Administrative and support services; Hospitals; Management of companies and enterprises; and Food services and drinking places.

Furthermore, it can be deduced that the sector rankings have significantly changed in Scenario 4 (see last panel of Fig. 2), when compared with the first three scenarios. Such changes in rankings can be attributed to the capability of the sectors to have workforce continuity plans, hence enabling them to further reduce their projected losses. The rankings are as follows: Ambulatory health care services; Construction; Wholesale trade; Hospitals; Other retail; Food services and drinking places; Miscellaneous professional, scientific, and technical services; Other services, except government; State and local general government; Administrative and support services. Note that, for example, the impact on State and local general government has improved (i.e., ranking has changed from 1 to 5). In contrast, the impact on Wholesale trade has worsened (i.e., ranking has changed from 7 to 2). Furthermore, new sectors emerged in the new rankings such as Other retail; and Administrative and support services.

Table 2 summarizes the economic losses for each of the four scenarios, aggregated for all the 71 sectors and also for the epi curve duration associated with each scenario. The baseline scenario reported a loss of \$1.3 trillion. In contrast, the loss associated with Scenario 2 is \$714 billion, which is nearly half (47%) of the baseline. Furthermore, the loss associated with Scenario 3 is \$381 billion, which is a 74% improvement relative to the baseline. Finally, the loss for Scenario 4 is \$187 billion, an 86% reduction when compared with the baseline. The % GDP loss was also calculated. For

³ In the US, the agency responsible for publishing IO data for different sectors and regions is the [US Bureau of Economic Analysis \(2020\)](#).

⁴ [The Johns Hopkins University and Medicine \(2020\)](#) provides publicly available reports and infographics on the current number of active COVID-19 cases and mortalities.

⁵ The term “incidence proportion” is the more formal term for “attack rate” according to [CDC \(2012\)](#).

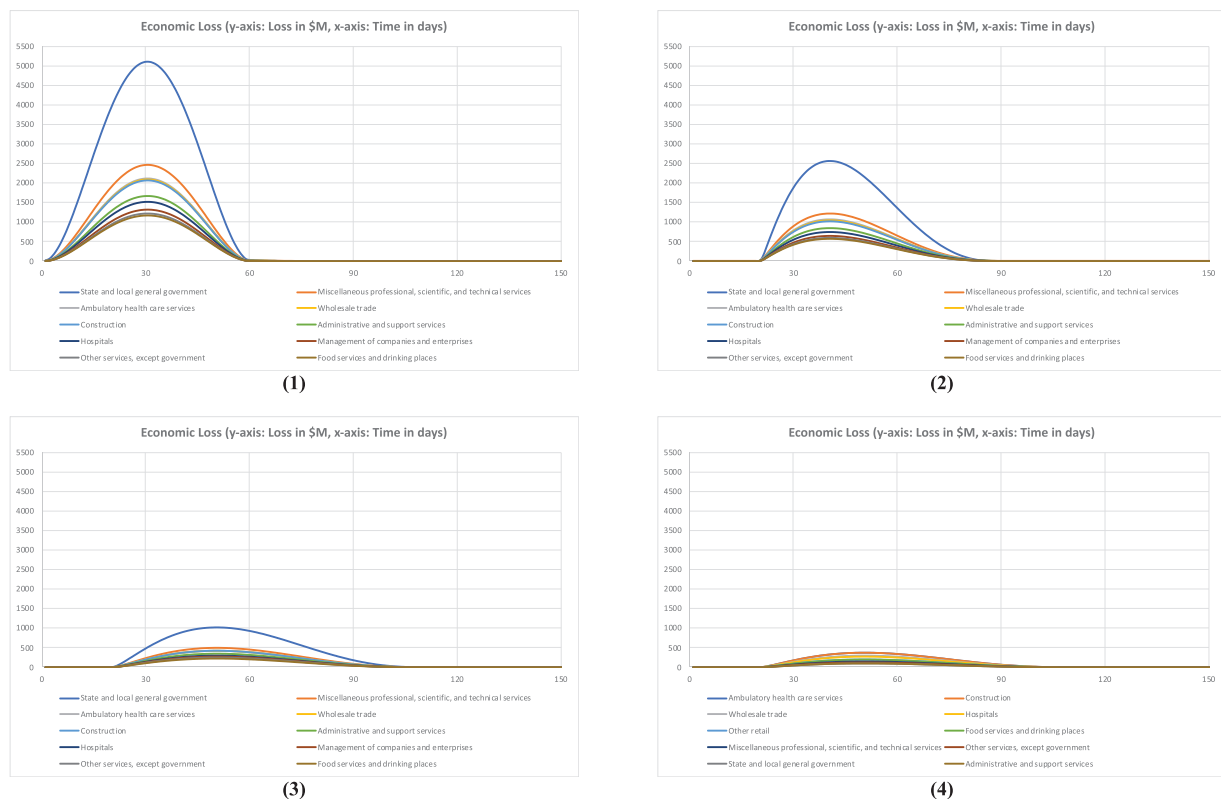


Fig. 2. Economic Loss Curves for: (1) Baseline Scenario, (2) Mitigation, (3) Suppression, (4) Suppression + Workforce Continuity

Table 2

Summary of economic losses for the baseline, mitigation, and suppression scenarios

	Scenario 1: Baseline	Scenario 2: Mitigation	Scenario 3: Suppression	Scenario 4: Suppression + Continuity
Loss (\$M)	1,336,565	714,890	380,711	186,932
% GDP Loss	7%	4%	2%	1%
% Reduction from Scenario 1	0%	47%	72%	86%

the baseline, the GDP loss is 7%, and this percentage reduces when mitigation and suppression measures are implemented. It is worth noting that the spread of the GDP loss values computed in this paper are in the same order of magnitude relative to estimates from other sources⁶.

Fig. 3 provides a visualization of the extent to which the mitigation and suppression scenarios can potentially flatten the curve. It can be observed that while mitigation flattens the curve, suppression measures (Scenarios 3 and 4) are found to be more effective in further reducing and delaying the peak of the curve. Opportunities for flattening the curve to the maximum possible extent are urgently needed to reduce the strain on the capacity of the health-care system. The final section of this paper provides reflections on the challenges associated with mitigation, suppression, and NPIs in general and provides a few areas for future research.

4. Conclusions

This paper utilizes economic IO data from the US Bureau of Economic analysis to analyze how nonpharmaceutical interventions can help in flattening the curve associated with a pandemic, like COVID-19. It has been found from hypothetical simulations of 4

scenarios that mitigation and suppression measures can dramatically decrease the height of the curve's peak and also delay its occurrence. Such ability to flatten the curve is particularly crucial in reducing the pressure off the already severely constrained health-care system. Results from this paper, expressed in monetary losses, appear to indicate that suppression measures have the highest efficacy in curbing the economic losses. This may be counterintuitive at first since such measures also drastically degrade the operability of the economic sectors due to enforced business/school closures. Nonetheless, even if the baseline scenario (Scenario 1) involves fewer business closures, the peak attack rate is significantly higher at 50% and its realization is much quicker than the other scenarios. Furthermore, countries that have implemented relaxed mitigation measures with minimal testing and contact tracing have experienced higher infection and mortality rates amongst their populations, and consequently their workforce (see, for example, Cohen, 2020). Hence, this explains why the baseline scenario could potentially lead to higher GDP loss. Severe outbreaks with high transmissibility and mortality rates further exacerbate the problem. It is worth noting that a study by Correia et al (2020), revealed that US cities that enforced stricter measures have generally emerged with higher employment growth years after the Spanish Flu pandemic of 1918.

Governments across the world however do not find it easy to implement suppression and mitigation measures since the associated controversies are quite evident. First is the issue of per-

⁶ A case in point, Morningstar (2020) predicts that the US GDP will shrink by about 2.9%.

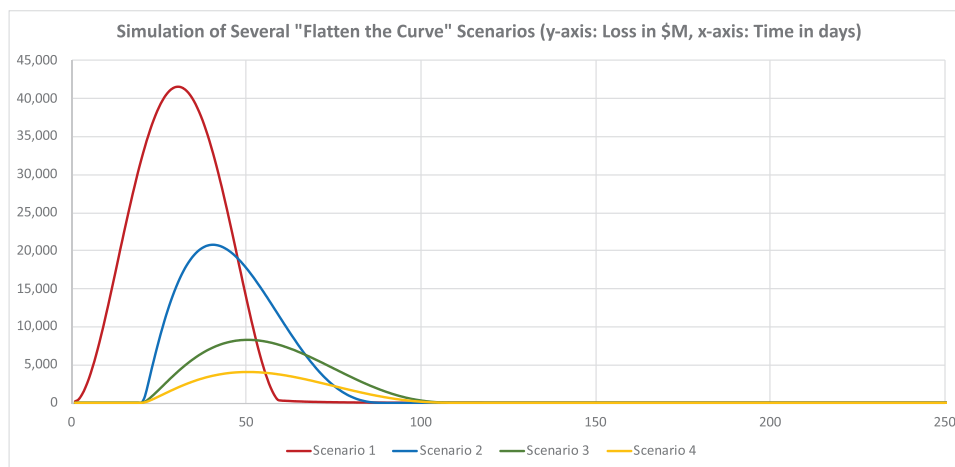


Fig. 3. Summary of Economic Loss Curves for: (1) Baseline Scenario, (2) Mitigation, (3) Suppression, (4) Suppression + Workforce Continuity

sonal liberty. Arguably, lockdown or stay at home directives could encroach on the rights of each individual notably for democratic societies. Second is the impact of isolation on mental health. Hawkley and Capitanio (2015), for example, have shown correlations between social isolation and manifestations of mental health issues such as anxiety, depression, as well as substance use. A case in point, M. Alafrangy (personal communication, April 5, 2020) who participated in 45-day confined environment in NASA's Human Exploration Research Analog project suggested that planning and maintaining of a strict schedule of activities could help reduce the impact of isolation on mental health. Third is the disproportionate effects of pandemics and disasters in general on various socioeconomic groups.

Hence, a difficult tradeoff analysis needs to be made between the consequences of social isolation and the magnitude of mortalities notably for highly transmissible and deadly pandemics like COVID-19. Articles by Pueyo (2020), Cheney (2020), Yong (2020), among others have strongly cautioned that inadequate implementation of suppression and mitigation measures could lead to astronomical number of deaths. Hence, governments need to carefully evaluate the appropriate portfolios and levels of implementing suppression (broad testing, contact tracing, and case isolation) and mitigation measures (face coverings, social distancing, and hand hygiene), especially prior to the discovery of effective vaccines.

As with any disasters, uncertainty is ubiquitous more so for events with meager historical precedence like the COVID-19 pandemic. The paper utilizes economic IO modeling leveraging the existence of economic datasets coupled with epi curves to simulate the impact of nonpharmaceutical interventions on various workforce sectors. The paper focuses only on the workforce dimension and future opportunities are called for to investigate the other consequences due to the COVID-19 pandemic such as mental health and disproportionate impact on different socioeconomic groups. Furthermore, the case study implemented in this paper is for the US and as such it does not directly provide state- or city-specific concentrations of the loss distributions. However, the method proposed on this paper could be customized to any regions pending the availability of location-specific IO and epi curve data. Additionally, information sharing, coordination of policies, and supply chain management across different regions can enhance the efficiency of disaster risk management (Yu and Aviso, 2020). Indeed, the COVID-19 has exposed many serious challenges and shortcomings in economic and infrastructure systems across the globe, and it also serves as a reminder of the importance of continuously reviewing and coordinating effective disaster risk management prac-

tices to ensure the health and functionality of critical infrastructure and socioeconomic systems in our highly interdependent global society.

Declaration of Competing Interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.spc.2020.06.001](https://doi.org/10.1016/j.spc.2020.06.001).

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