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Pandemic Recovery Analysis Using the Dynamic Inoperability Input-Output Model

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Economists have long conceptualized and modeled the inherent interdependent relationships among different sectors of the economy. This concept paved the way for input-output modeling, a methodology that accounts for sector interdependencies governing the magnitude and extent of ripple effects due to changes in the economic structure of a region or nation. Recent extensions to input-output modeling have enhanced the model's capabilities to account for the impact of an economic perturbation; two such examples are the inoperability input-output model(1,2) and the dynamic inoperability input-output model (DIIM).(3) These models introduced sector inoperability, or the inability to satisfy as-planned production levels, into input-output modeling. While these models provide insights for understanding the impacts of inoperability, there are several aspects of the current formulation that do not account for complexities associated with certain disasters, such as a pandemic. This article proposes further enhancements to the DIIM to account for economic productivity losses resulting primarily from workforce disruptions. A pandemic is a unique disaster because the majority of its direct impacts are workforce related. The article develops a modeling framework to account for workforce inoperability and recovery factors. The proposed workforce-explicit enhancements to the DIIM are demonstrated in a case study to simulate a pandemic scenario in the Commonwealth of Virginia.

KEY WORDS: Input-output; pandemic; resilience

1. INTRODUCTION

According to disease control experts, a pandemic—an infection that spreads widely and affects a significant proportion of the population—is inevitable. With the rise of new infections such as SARS and the avian flu, as well as the threat of bioterrorism, experts from the General Accounting Office(4) believe it is imminent. In a pandemic, propagating effects endanger the general population, including those who are not yet sick. For example, pandemic-related risk scenarios include large-scale disruption to workforce sectors, which can lead to further illnesses and mortalities caused by the pandemic's cascading effects. Possible pandemic viruses include anthrax, Ebola hemorrhagic fever, and influenza.(5) Influenza viruses are the most threatening because they may mutate, overcome vaccines, and migrate rapidly. A current influenza strain, called H1N1, spreads through populations, which enables the virus to spread quickly across regions.(6) The World Health Organization (WHO)

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is monitoring various influenza strains, including H1N1, across the globe.(7)

Pandemic experts estimate that the next pandemic will infect 15–35% of the world population and last four weeks to 18 months with multiple waves.(6) Each wave lasts about eight weeks, and then repeats in the same geographic regions, infecting new people. Health experts project average illness length at two days, with a minimum of one day and maximum of 10 days.(5) They recommend 5–10-day quarantine from the onset of symptoms. Consequently, experts anticipate that 10–25% of the workforce will be absent at any given time due to illness or caring for ill family members. Furthermore, they estimate that 35% of utility (electricity, gas, and water), waste management, mortuary, transport, and healthcare workers who do not have direct patient contact will develop some form of illness. In a severe pandemic with a 40% attack rate, experts estimate at most 85% availability of normal workforce throughout the duration and 50–65% workforce availability for the peak three weeks.(8)

Pandemic risks are documented in the literature. For example, the studies developed by the Centers for Disease Control and Prevention (CDC)(9) provide insightful risk assessment information; however, opportunities exist toward developing and implementing sound risk management programs capable of protecting essential workforce and critical systems. A variety of federal and state-level initiatives seeks to solve this problem. Because of the current disparities between risk assessment and risk management efforts, the Department of Homeland Security (DHS) drafted the National Infrastructure Protection Plan.(10) The program provides funding for natural disaster risk management. In the Commonwealth of Virginia, for example, Executive Order 44 has been issued to require state agencies to develop risk management plans that would enable them to continue to provide essential services in the event of a large-scale emergency, such as a pandemic.(11)

This article seeks to provide understanding of the cascading economic effects resulting from the time-varying workforce unavailability, such as what would occur during a pandemic. Toward that end, this research uses the dynamic inoperability input-output model (DIIM), first proposed by Lian and Haimes.(3) The DIIM is based on economic input-output analysis that incorporates the interconnectedness of industries in estimating both the ability to meet as-planned production levels as well as the effects of demand and supply side perturbations.(12,13) The DIIM further extends the capabilities of input-output modeling by incorporating resilience parameters to model sector recovery rates. The resulting model output allows decisionmakers to understand what sectors will be most affected in terms of inoperability levels and economic impact.

Fig. 1 outlines this research in the context of the overarching problem. While this represents a simplified view of the problem, it serves to define the scope of the article and highlights the major contributions of this work, which can be summarized into two major areas: (1) incorporating time-varying inoperability levels that correspond to workforce unavailability into the DIIM formulation (represented in Fig. 1 by the dynamic nature of the *Available Workforce*), and (2) modeling the impact of unavailable workforce as a sector inoperability metric (represented by *Distribution of Workforce Among Sectors* and *Sector Dependency on Workforce*). The figure illustrates the myriad factors that contribute to the unavailable workforce levels resulting from a pandemic, which provide motivation to this article.

2. REVIEW OF LITERATURE

This section describes the problem context and provides discussions on existing literature covering the underlying theory and methods supporting this article.

2.1. Problem Context

Influenza claims about 20,000 American lives annually.(4) Evolving viral strains cause significant discrepancies in the intensity and severity of illness from one to the next. Periodically, but unpredictably, a genetic variation creates a potent strain that triggers widespread illnesses and deaths. As the virus spreads through the general population, the direct consequences can create additional risk scenarios. Risk scenarios include large-scale disruption to all workforce sectors, which can lead to additional illnesses and mortalities.(14) Historical global epidemics—or pandemics—disrupted 20th-century civilization on three occasions (1918, 1957, and 1968). According to the *Scientific American*, the Spanish flu of 1918 marked the beginning of the deadliest, which eradicated more than 25 million lives worldwide and 500,000 nationwide.(15) About 28% of the U.S. population contracted the virus. Consequently, mass transit refused passengers, towns closed their storefronts,

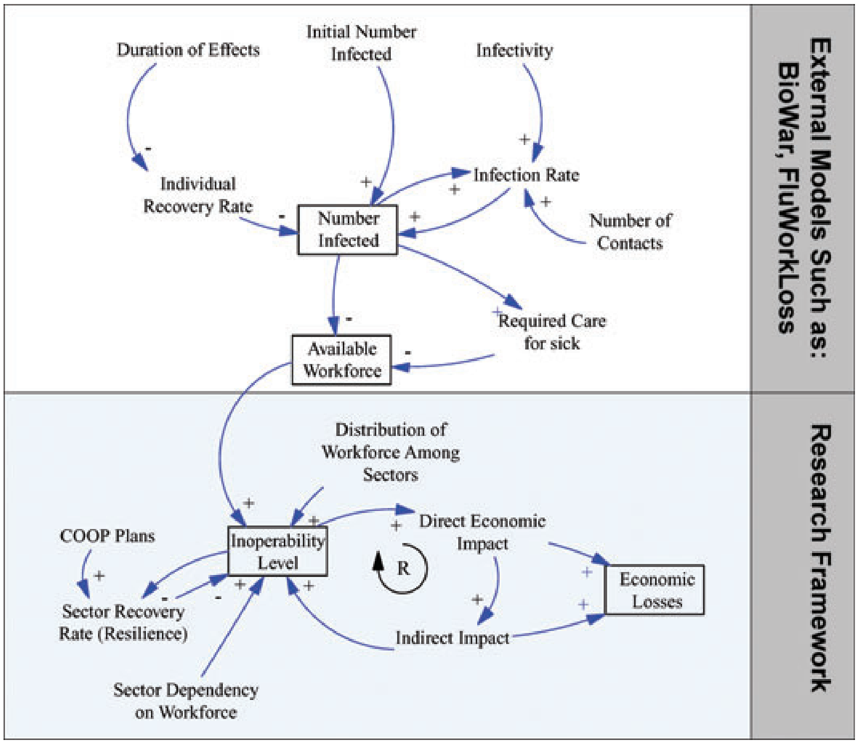


Fig. 1. Scope of article in reference to systems dynamics view of the overall problem.

and provisions grew scarce. Pandemic effectively immobilized society.

Pandemic threatens to disrupt modern civilization as it did almost a century ago. Predictive technologies cannot determine when the next killer outbreak will be, how severe it will be, or from which virus the strain will deviate.(16) Experts from the GAO speculate that an unknown flu variant will induce the next pandemic.(4) If such a virus strikes, CDC projects that 89,000–207,000 people will die in the United States alone. Hospitals will admit 314,000–734,000 patients with 18–42 million outpatient visits. Twenty to 47 million others will fall ill. The CDC estimates that it will cost the economy between \$71.3 and \$166.5 billion, excluding disruptions to commerce and society.(9) Although the CDC has assessed risks, effects to specific entities remain uncertain. Moreover, gaps appear between existing and essential risk management planning in order to mitigate consequences from a plausible pandemic scenario.

2.2. Risk Analysis

Risk analysis identifies an imminent incident, assesses the associated risks, develops and evaluates management alternatives with respect to assessed risks, and provides recommendations according to the perceived efficacy of alternatives. To implement risk analysis systematically, one must break it into its component parts, risk assessment and risk management.

What can go wrong? (e.g., a pandemic in a densely populated US region)

What is the likelihood? (e.g.,very rare but plausible)

What are the consequences? (e.g., mortalities and illnesses that adversely impact economic productivity and continuity of government)

Fig. 2. Risk assessment questions applied to a pandemic scenario.

The triplet of questions in Fig. 2 illustrates the process and concept of risk assessment as described by Kaplan and Garrick.(17)

The risk assessment questions identify a scenario, the likelihood, and the consequences. Correspondingly and in probabilistic terms, the questions attempt to identify a random variable that measures a consequence from a scenario, X, a particular realization $x \in X$, and an associated probability $P(x)$. However, one cannot address these questions directly or confidently because uncertainties are inherent and may further require supplementary data collection and expert elicitation.

What can be done and what options are available?
(e.g., immunization, backup resources, and availability of essential functions through remote access capability)

What are the tradeoffs in terms of all costs, benefits, and risks?
(e.g., challenges in containing the pandemic, recovery effort and cost, political agenda)

What are the impacts of current decisions on future options?
(e.g., preparedness policies that influence recovery horizons)

Fig. 3. Risk assessment questions applied to a pandemic scenario.

According to Haimes,[18] the risk management component of a sound risk analysis process must be cognizant of the triplet of questions listed in Fig. 3.

Risk management relies upon systematic information gathering from which an analyst can develop and evaluate alternatives. Historical and expert-elicited data provide the basis for addressing risk management questions to determine the effectiveness of available alternatives wherein a reasonable balance is achieved among multiple cost, benefit, and risk objectives.

2.3. Modeling of System Interdependencies

The Infrastructure Security Partnership (TISP) describes that understanding interdependencies and resulting cascading impacts from an impact is essential to develop an effective security plan.[19] The dependence of many, if not all, economic sectors on the workforce makes interdependency modeling a key component in assessing the likely cascading effects of disasters on economic productivity. The Leontief input-output (I-O) model is a particular method for modeling interdependencies across multiple sectors of a given regional economy.[20,21] The National Cooperative Highway Research Program[22] identifies the I-O method in its guidebook for assessing the social and economic effects of transportation projects. Extensions and current frontiers on I-O analysis can be found in Lahr and Dietzenbacher[23] and Dietzenbacher and Lahr.[24] It is worth noting that the traditional use of input-output analysis for estimating the effects of economic shifts (e.g., changes in consumption) has been extended to other applications such as disaster risk management, environmental impact analysis, and energy consumption, among others. Various studies for estimating losses pursuant to disasters have employed traditional I-O analysis and extended approaches such as computable general equilibrium (CGE) models. Rose and Liao[25] conducted a case study of water supply disruption scenarios in Portland; they used CGE to account for resilience factors (e.g., substitution and conservation) that business sectors typically consider in order to minimize potential losses. Rose[26] describes that CGE is an extension rather than a replacement of the traditional I-O model. Other methods for analyzing infrastructure interdependencies include system dynamics modeling[27] or standard statistical regression approaches.[28]

2.4. Inoperability Inoperability Model (IIM) and Dynamic IIM (DIIM)

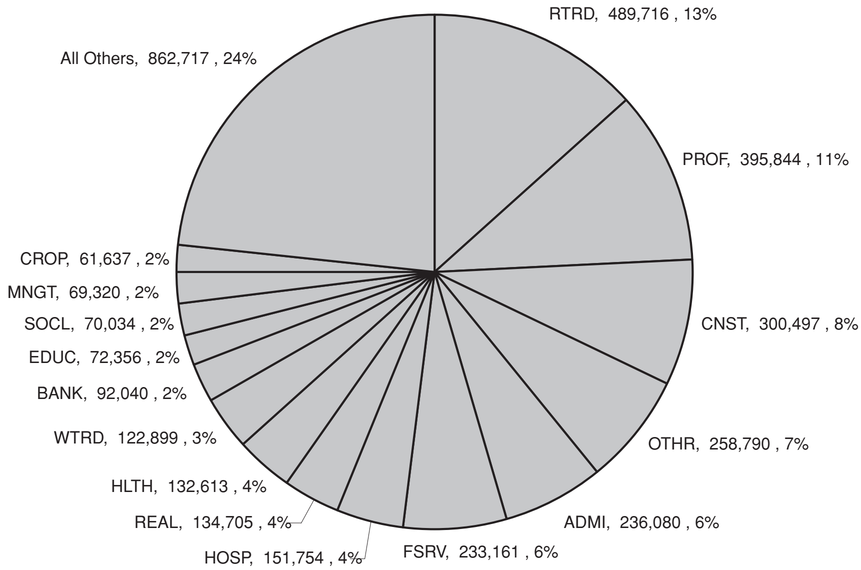
This article uses the inoperability IIM to estimate the cascade of impact from the interdependency among the sectors of the economy pursuant to a disaster.[1,2] The interdependency modeling feature of the IIM can provide insights into the distribution of the likely cascading effects of a disaster to a set of directly and indirectly affected sectors. Sectors are defined as the basic units of operation in an economy and in most cases are considered either broad economic industries or infrastructure systems. If the operations of some sectors of the economy are disrupted by a disaster such as a pandemic, the IIM can be utilized to quantify the cascading effects on other sectors. Consequences of the attacks or disasters can be measured in the model by the inoperability and the quantity of economic loss, in monetary values. The term inoperability in this article is defined as the inability of a sector(s), measured in percentage values, relative to the as-planned production level.

The DIIM describes the temporal nature of sector recoveries pursuant to a disaster. In particular, the purpose of implementing dynamic analysis in this article is to model the recovery process for workforce sectors and pursuant to a pandemic scenario. Given the initial inoperabilities caused by a disaster, the dynamic extension gives the trajectory of recovery based on the interdependence and resilience characteristics of the industry sectors. The formulation is given as follows:[3]

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

where $\mathbf{q}(t)$ and $\mathbf{q}(t+1)$ are the inoperability vectors at time t and $t+1$, respectively, $\mathbf{K}$ is the resilience matrix, $\mathbf{A}^*$ is the matrix of sector interdependencies, and $\mathbf{c}^*(t)$ is the vector of initial perturbations.

The resilience matrix generated through the dynamic extension can provide insights for describing



RTRD	Retail trade
PROF	Professional, scientific, and technical services
CNST	Construction
OTHR	Other services*
ADMI	Administrative and support services
FSRV	Food services and drinking places
HOSP	Hospitals and nursing and residential care facilities
REAL	Real estate
HLTH	Ambulatory health care services
WTRD	Wholesale trade
BANK	Federal Reserve banks, credit intermediation, and related services
EDUC	Educational services
SOCL	Social assistance
MNGT	Management of companies and enterprises
CROP	Crop and animal production

Fig. 4. Virginia workforce count and percentage per sector.

the recovery of the affected sectors. A higher value of the resilience for a particular sector corresponds to a faster pace of recovery from a disaster. Hence the resilience matrix relates to the current state of the system within the recovery process. Resilience is assessed using estimates of recovery period, which is the length of time needed for a sector to recover to normalcy. Dynamic analysis facilitated the assessment of the potential effects of a disaster such as a pandemic in terms of both the direct effects to the initially disrupted sectors and cascading effects to other interdependent economic sectors. Further discussion and examples of the DIIM can be found in Lian and Haimes,[(3)] Santos,[(29)] and Haimes *et al*.[(30)]

3. EXTENDING THE DIIM FORMULATION

3.1. Accounting for Workforce Distribution

In performing the analysis of a pandemic scenario in Virginia, we also performed an analysis of the effect of reduced workforce levels across different sectors and how their unavailability can adversely affect the productivity of the region. The preliminary step is to generate a distribution of the number of workers per sector to determine those economic sectors that employ the greatest number of manpower. The workforce count per sector and their corresponding percentage values are depicted in Fig. 4 (processed from raw data available from Bureau of Economic Analysis[(31)]). The next step is to determine the ratio with which workforce accounts for the total production requirements of each sector (i.e., production requirements include commodity, labor, capital, and energy inputs). This ratio varies significantly from sector to sector, as depicted in Fig. 5. The subsequent case study performed in this article assumes a certain level of workforce perturbation for a given period of time. The level of workforce perturbation is then distributed as initial inoperability inputs to multiple sectors, using the collected and

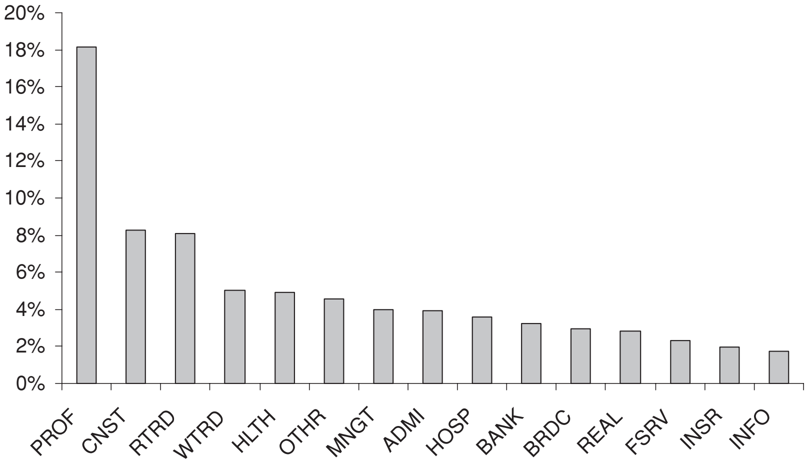


Fig. 5. Virginia top-15 sectors with largest dependence on workforce.

PROF	Professional, scientific, and technical services
CNST	Construction
RTRD	Retail trade
WTRD	Wholesale trade
HLTH	Ambulatory health care services
OTHR	Other services*
MNGT	Management of companies and enterprises
ADMI	Administrative and support services
HOSP	Hospitals and nursing and residential care facilities
BANK	Federal Reserve banks, credit intermediation, and related services
BRDC	Broadcasting and telecommunications
REAL	Real estate
FSRV	Food services and drinking places
INSR	Insurance carriers and related activities
INFO	Information and data processing services

sector-processed workforce data. Two types of analyses can be implemented. The first assumes that the perturbation is sustained at the same level for the entire duration of the recovery, which we refer to as the static model. The second assumes a resilience factor for each sector that would allow the recovery from the initial perturbation level to an improved value. We refer to the latter as the dynamic model, which extends the previously developed IIM through incorporation of temporal factors such as sector resilience, recovery time, and interdependent effects of risk management to one or multiple sectors. The analysis of workforce resilience reveals potential significant reductions in expected economic losses, which can be explored further for developing risk management efficacy metrics.

3.2. Regional Input-Output Multiplier System for Workforce Accounting

In order to quantify the impact of reduced workforce levels on the economy of Virginia, we first need to collect employment statistics for each sector of the region. We configured our data collection methodology using the North American Industry Classification System; that is, we account for the total number of workers in the region and determine their distribution according to the various sectors. The Regional Input–Output Multiplier System (RIMS II)[32] adopts an aggregated version of the detailed sector classification—comprising of 59 sectors as enumerated in Table I. Workforce accounting is performed to quantify the contribution of the workforce factor to the production requirements of each sector.

3.3. Workforce Impact Analysis of a Pandemic Using the Dynamic Interdependency Modeling

The dynamic interdependency model is capable of incorporating the workforce element into a pandemic scenario under consideration. Since the dynamic interdependency model can directly use workforce statistics as perturbation inputs, several approaches were considered to forecast the “inoperability” of the workforce across all sectors. Our approach has been to determine the workforce

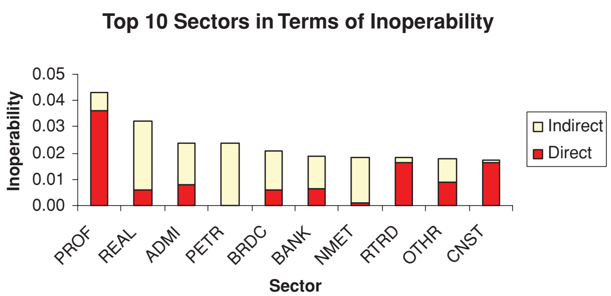
Table I. Sectors Used for Inoperability Input-Output Modeling of Cascading Effects

Code	Sector Description	Code	Sector Description
CROP	Crop and animal production	WATR	Water transportation
FRST	Forestry, fishing, and related activities	TRCK	Truck transportation
OILG	Oil and gas extraction	GRND	Transit and ground passenger transportation
MING	Mining, except oil and gas	PIPE	Pipeline transportation
MINS	Support activities for mining	TRNM	Other transportation and support activities
UTIL	Utilities	WRHS	Warehousing and storage
CNST	Construction	PUBL	Publishing including software
WOOD	Wood product manufacturing	MPIC	Motion picture and sound recording industries
NMET	Nonmetallic mineral product manufacturing	BRDC	Broadcasting and telecommunications
PMET	Primary metal manufacturing	INFO	Information and data processing services
FMET	Fabricated metal product manufacturing	BANK	Federal Reserve banks, credit intermediation, and related services
MACH	Machinery manufacturing	SECU	Securities, commodity contracts, investments
COMP	Computer and electronic product manufacturing	INSR	Insurance carriers and related activities
ELEC	Electrical equipment and appliance manufacturing	FUND	Funds, trusts, and other financial vehicles
MOTR	Motor vehicle, body, trailer, and parts manufacturing	REAL	Real estate
TREQ	Other transportation equipment manufacturing	RENT	Rental and leasing services and lessors of intangible assets
FURN	Furniture and related product manufacturing	PROF	Professional, scientific, and technical services
MFGM	Miscellaneous manufacturing	MNGT	Management of companies and enterprises
FOOD	Food, beverage, and tobacco product manufacturing	ADMI	Administrative and support services
TEXT	Textile and textile product mills	WSTE	Waste management and remediation services
APPR	Apparel, leather, and allied product manufacturing	EDUC	Educational services
PAPR	Paper manufacturing	HLTH	Ambulatory health care services
PRNT	Printing and related support activities	HOSP	Hospitals and nursing and residential care facilities
PETR	Petroleum and coal products manufacturing	SOCL	Social assistance
CHEM	Chemical manufacturing	PERF	Performing arts, museums, and related activities
PLAS	Plastics and rubber products manufacturing	AMST	Amusements, gambling, and recreation
WTRD	Wholesale trade	ACCO	Accommodation
RTRD	Retail trade	FSRV	Food services and drinking places
AIRT	Air transportation	OTHR	Other services
RAIL	Rail transportation		

requirements for every sector, and make subsequent adjustments to customize the analysis for a pandemic scenario in Virginia. Note that we posit that workforce unavailability translates to direct sector productivity effects, which is a reasonable assumption for a pandemic scenario. Furthermore, these direct workforce effects cause other higher-order effects in the productivity/output of interdependent sectors. The local area personal income (LAPI) data provided by the Bureau of Economic Analysis (BEA) allows us to accomplish this analysis. The underlying assumption in using LAPI is that it reflects the workforce component of a sector's production, which is defined by BEA "as the sum of wage and salary disbursements, supplements to wages and salaries, proprietors' income with inventory valuation and capital consumption adjustments, rental income of persons with capital consumption adjustment, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance."(31) To determine how much LAPI would be affected by the inability to work, we considered how much of each sector is dependent on the workforce. We examined each sector's workforce input requirement to estimate how it will be affected by a perturbation due to a pandemic. Calculating such workforce percentages (i.e., the ratio of LAPI to total sector production) gives valuable insights in decomposing a workforce "shock" across the economy. Furthermore, workforce decomposition enables us to translate the inoperability resulting from a disruption into varying perturbation inputs to multiple sectors. Our assumption is that the way a sector is affected by a disruption of the workforce is directly correlated with the magnitude of its LAPI. A more sophisticated approach for decomposing workforce income effects uses Miyazawa multiplier analysis wherein economic-demographic coefficients are augmented to the basic Leontief technical coefficient matrix (see Okuyama *et al.*[33] for implementation of this method in the context of unscheduled economic disruptions). In the current analysis, we have simplified the analysis of workforce unavailability and its direct impact on the productivity of each sector by converting the given output (supply) constraints into equivalent demand reductions. This process is consistent with the mixed I-O models discussed in Miller and Blair.[13]

3.4. Interdependency Analysis of Economic Ripple Effects

Using the processed workforce-by-sector data, a percentage reduction to the general workforce is considered (e.g., 20%) and decomposed into multiple sector perturbations. These perturbations are then entered to the dynamic model to determine the cascading effects throughout the assumed duration of the pandemic scenario. Consider a 30-day pandemic scenario that causes a 20% reduction of the available workforce in Virginia. This 20% reduction is decomposed into direct perturbations to different sectors of the region, using information on the number of workers employed in each sector (Fig. 4), and the contribution of workforce to the overall production requirements of each sector (Fig. 5). The resulting sector ranking in terms of inoperability is depicted in Fig. 6. Similar analysis is performed to generate the corresponding sector ranking in terms of economic loss, as shown in Fig. 7.



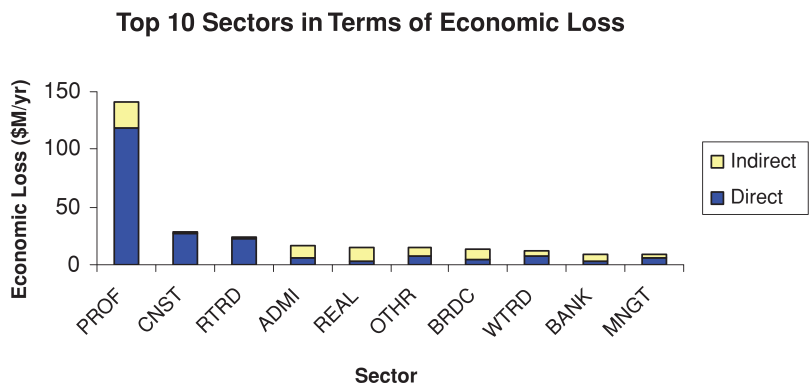
Sector	Description
PROF	Professional, scientific, and technical services
REAL	Real estate
ADMI	Administrative and support services
PETR	Petroleum and coal products manufacturing
BRDC	Broadcasting and telecommunications
BANK	Federal Reserve banks, credit intermediation, and related services
NMET	Nonmetallic mineral product manufacturing
RTRD	Retail trade
OTHR	Other services*
CNST	Construction

Fig. 6. Top-10 sectors with largest inoperability values for a 30-day pandemic scenario.

In particular, the top-10 sectors in terms of inoperability (as shown in Fig. 6) are further decomposed into direct and indirect effects. Inoperability is similar to the concept of unreliability where a value of 0.01 would connote 1% unreliability or, conversely, 99% reliability. Some sectors have significantly higher direct effects, such as professional, scientific, and technical services (PROF) and construction (CNST). Some sectors have evenly distributed direct and indirect effects, such as administrative and support services (ADMI), broadcasting and telecommunications (BRDC), Federal Reserve banks, credit intermediation, and related services (BANK), and other services (OTHR). Some sectors such as petroleum and coal products manufacturing (PETR) and nonmetallic mineral product manufacturing (NMET) are predominantly, if not purely, composed of indirect effects. Hence, our analysis reveals important "hidden" results that can be easily overlooked had the focus been on direct perturbations only. Our analysis suggests that sector prioritization should not be based solely on the direct effects of workforce unavailability, but also the cascading effects on interdependent sectors across Virginia.

Another sector prioritization scheme can be based on the actual monetary losses incurred by multiple sectors due to their reduced workforce levels. Fig. 7 shows the top-10 sectors that can potentially suffer the greatest economic losses, which are: PROF, CNST, retail trade (RTRD), ADMI, real estate (REAL), OTHR, BRDC, wholesale trade (WTRD), BANK, and management of companies and enterprises (MNGT).

It can be observed that the sector rankings in terms of inoperability and economic loss vary. Hence, integrating the inoperability and economic loss metrics offers additional insights into the IIM analysis. Specifically, these metrics generate different sector rankings, which may be attributable to the sectors' different production scales. For example, PETR and NMET are two of the top-10 most inoperable sectors, but they are not included in the top-10 sectors with highest economic losses. In contrast, WTRD and MNGT belong to the top-10 sectors in terms of economic loss, but they are not among the top-10 sectors with highest inoperability values. Therefore, both the IIM metrics of inoperability and economic loss need to be considered when conducting sector risk assessments because they yield different criticality rankings of sector effects. The effects can either be prioritized in terms of the magnitude of



Sector	Description
PROF	Professional, scientific, and technical services
CNST	Construction
RTRD	Retail trade
ADMI	Administrative and support services
REAL	Real estate
OTHR	Other services*
BRDC	Broadcasting and telecommunications
WTRD	Wholesale trade
BANK	Federal Reserve banks, credit intermediation, and related services
MNGT	Management of companies and enterprises

Fig. 7. Top-10 sectors with largest economic losses for a 30-day pandemic scenario.

monetary loss versus the "normalized" loss relative to a sector's total production. Logically, different sets of priority sectors are generated depending upon the type of objective being considered (i.e., minimizing inoperability versus minimizing economic loss).

3.5. Analysis of Sector Recovery and Resilience

Another layer of analysis in the workforce element of the model is the concept of resilience. Here, we define the recovery metric as the number of days to achieve 99% normalcy (we assume that 100% normalcy is difficult, if not impossible to achieve). In general, economic resilience is defined as the ability or capability of a system to absorb or cushion against damage or loss.[34,35] Increasing the resilience of a sector reduces its recovery time as well as the associated economic losses. Resilience can be enhanced through: (i) expedited restoration of the damaged capability; (ii) using an existing back-up capability; (iii) conservation of inputs to compensate for supply shortfalls; (iv) substitution of inputs; or (v) shifting of production locations.[26]

The DIIM is formulated previously in Equation (1), where $\mathbf{q}$ denotes the vector of inoperability for the economic sectors, t denotes time, $\mathbf{K}$ denotes the matrix of resilience coefficients, $\mathbf{I}$ is the identity matrix, and $\mathbf{A}^*$ is the interdependency matrix that represents the extent to which a sector is dependent upon another. The initial condition, i.e., the initial inoperability of the sectors at $t = 0$, is denoted by $\mathbf{q}(0)$.

$$\mathbf{q}(t) = e^{-\mathbf{K}(\mathbf{I}-\mathbf{A}^*)t}\mathbf{q}(0). \tag{2}$$

Lian and Haimes[3] provide a formula for estimating the *industry resilience coefficient* for ith sector in diagonal matrix $\mathbf{K}$ as follows:

$$k_i = \frac{\ln\left[\dfrac{q_i(0)}{q_i(T_i)}\right]}{T_i(1 - a^*_{ii})} = \frac{\omega_i}{T_i}. \tag{3}$$

In the above equation, T_i is the time that industry i recovers from its initial inoperability $q_i(0)$ to a desired level $q_i(T_i)$ (e.g., 1%). The notation a^*_{ii} represents the ith diagonal element of the interdependency matrix $\mathbf{A}^*$. The notation ω_i is a proportionality constant for sector i, which can be used for a more compact representation of the above equation. It is important to note that the initial condition $q_i(0)$ represents the direct disruption to a particular sector. In our current analysis, it describes the extent to which the reduced level of workforce in that particular sector translates to direct productivity loss. The initial loss in productivity will increase depending on the duration of the recovery, as well as the interdependencies among the sectors.

To demonstrate how to apply the above dynamic equations, consider the professional services sector as our sector i. Further, suppose that inoperability is defined as the percentage of professional services sector offices that are closed. Hence, when all offices are open, inoperability is 0%, and when all offices are closed, inoperability is 100%. In Equation (3), the notation T_i is defined as the time for the professional services sector to recover from some initial inoperability level to a desired inoperability level. Clearly, T_i will depend on (i) the initial inoperability level, (ii) the desired operability level, and (iii) the type and intensity of the disaster being considered.

If the initial inoperability level is defined as 20%, this will then be the value of $q_i(0)$. Suppose that a decisionmaker desires to improve the inoperability level to 5%—this value will now represent $q_i(T_i)$. Suppose further that a domain expert believes that it takes about 10 working days to get most professional services sector offices back to work from a 20% inoperability level to a 5% inoperability level—this means that the value of T_i is 14 days. Finally, suppose that about 70% of the professional services sector workforce is dependent on some other workforces classified within the professional services sector—this means that $a_{ii} = 0.7$. Hence, application of Equation (3) will reveal the following industry resilience metric (k_i):

$$k_i = \frac{\ln\left[\dfrac{q_i(0)}{q_i(T_i)}\right]}{T_i(1 - a_{ii}^*)} = \frac{\ln\left[\dfrac{20\%)}{5\%}\right]}{14(1 - 0.7)} = 0.33. \qquad (4)$$

This means that for the professional services sector, the industry resilience coefficient is 0.33. If the recovery time information is updated from 14 to 30 days then k_i would shrink by about half to 0.15.

3.6. Dynamic Analysis of a Pandemic Scenario

In the 30-day analysis of a pandemic scenario previously discussed (see Figs. 6 and 7), we assumed that the 20% reduction in workforce is static; that is, the 20% initial inoperability value is sustained for the entire month. The advantage of using a dynamic model beyond the static version is that it allows the incorporation of a recovery process within the period of analysis, where the initial inoperability due to workforce disruption is assumed to improve to some percentage (e.g., 1%) of the original value. To better distinguish the static from the dynamic model, we illustrate the concept using a 20% initial inoperability value. For the static model, the 20% value is held constant for the entire 30 days of analysis. In the dynamic model, this initial value of 20% is reduced exponentially to 0.2% (i.e., 1% of 20%) at $t = 30$ days. The resulting trajectories of inoperability and economic loss for the 30 days of recovery are shown in Figs. 8 and 9.

In Fig. 8, we observe that PROF started with the highest inoperability value, but it ended up with the lowest final value of inoperability, relative to the top-5 most inoperable sectors. Another interesting case is that of PETR—it is initially inoperable but spiked at some point and ended up with the worst inoperability value. This is compatible with the result from

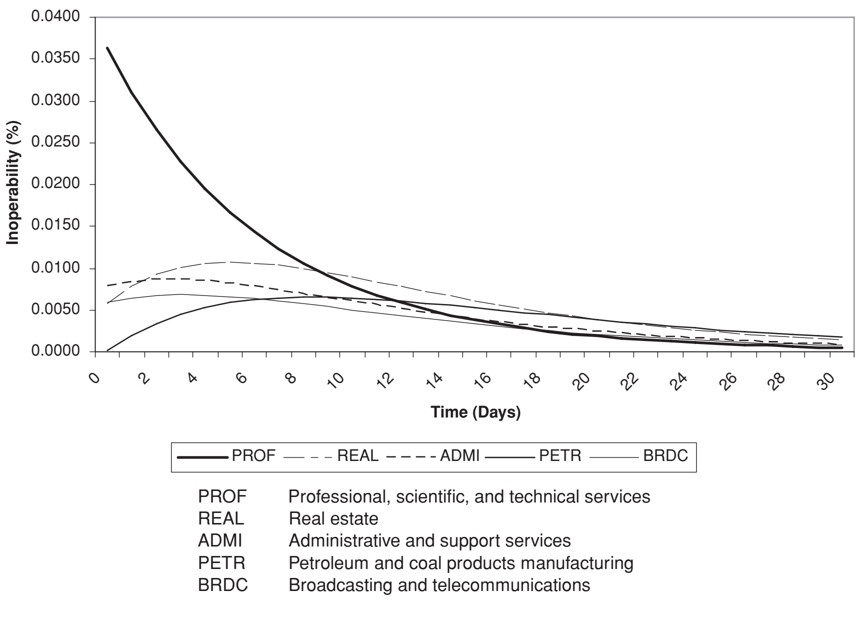


Fig. 8. Dynamic analysis of inoperability for a 30-day pandemic scenario recovery period.

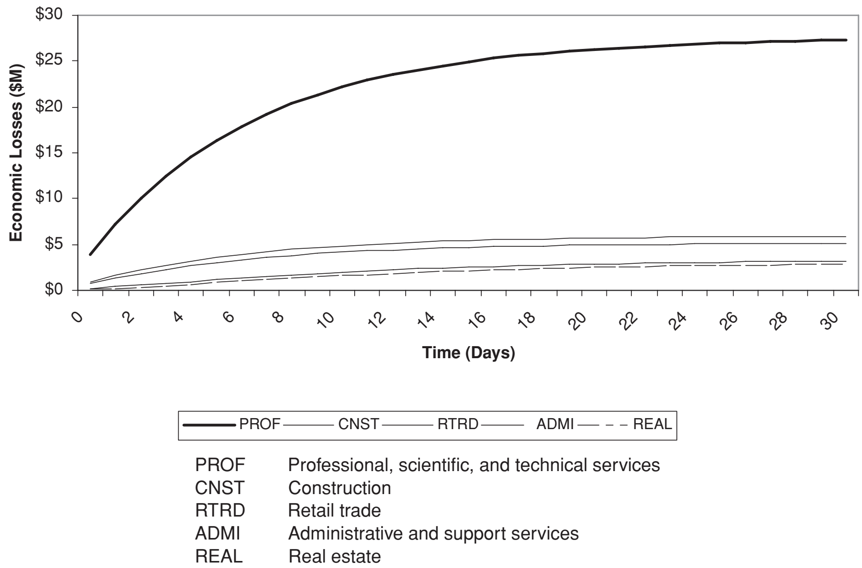


Fig. 9. Dynamic analysis of economic loss for a 30-day pandemic scenario recovery period.

Fig. 6 indicating that the inoperability of PETR is predominantly caused by indirect sources or cascading effects. Fig. 9, on the other hand, shows the accumulation of economic loss within the 30-day recovery period. The results in terms of the sectors with highest economic losses are consistent with those of Fig. 7. Nevertheless, the magnitudes of the economic losses are significantly different. For example, the economic loss using the static assumption for PROF sector is about $150 million (see Fig. 7); however, the economic loss for the same sector is reduced to approximately $25 million (see Fig. 9) when a resilience element is incorporated into the analysis. This type of dynamic analysis is useful when determining the efficacy of options that seek to expedite the recovery of different sectors.

It should be noted that the analysis of recovery is simplified to take into account only the peak of the pandemic scenario (which corresponds to the 20% initial inoperability). More sophisticated analyses can be combined with the current dynamic model deployed in this case study to assess additional complexities to the pandemic scenario such as: (i) transient effects prior to reaching the peak; and (ii) the possibility of wave-like recurrence.[36] Tools developed by the CDC[37] could provide information about flu epidemics, including their extent of spread and the ability of medical facilities to handle vaccination and other care activities. The following section demonstrates the application of DIIM to simulate the wave-like trajectory of workforce inoperability due to a pandemic.

4. VIRGINIA PANDEMIC CASE STUDY

While the problem to be addressed and methodology of this article have been discussed in the previous sections, application of the model using pandemic-specific data has not been demonstrated. This section discusses the usage of Bureau of Economic Analysis and CDC data and models to determine the impact of a pandemic on the economy of Virginia. Results of the model and implications on risk management decisions are presented and discussed.

4.1. Overview

This case study focuses on a four-week pandemic in the Commonwealth of Virginia. It explores three potential attack rate scenarios as defined by FluWorkLoss: 15, 25, and 35%. Each attack rate was run with 10,000 simulations. With a run time of roughly two seconds per simulation, this makes total run time for each simulation about 5.5 hours. For brevity, only the details of the 15% attack rate scenario are shown. Nevertheless, a tabular summary of regional losses for all three scenarios is presented at the end of this section.

4.2. Simulations and Results

The first scenario is a 15% attack rate during a four-week period. Fig. 10 shows a summary of the inoperability for all sectors over the duration of the

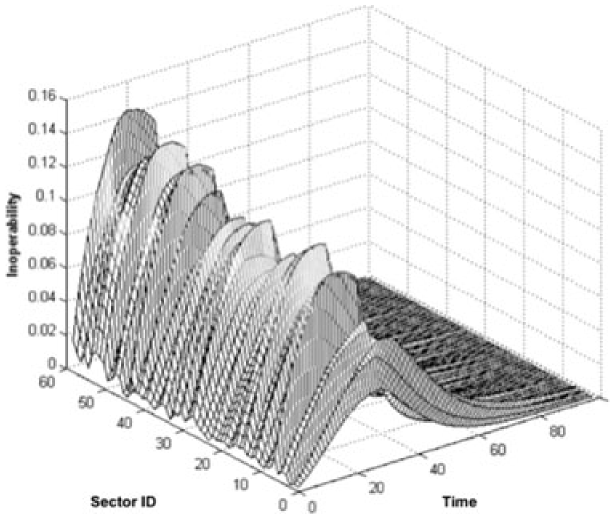


Fig. 10. Inoperability for all sectors, 4-week, 15% attack rate pandemic.

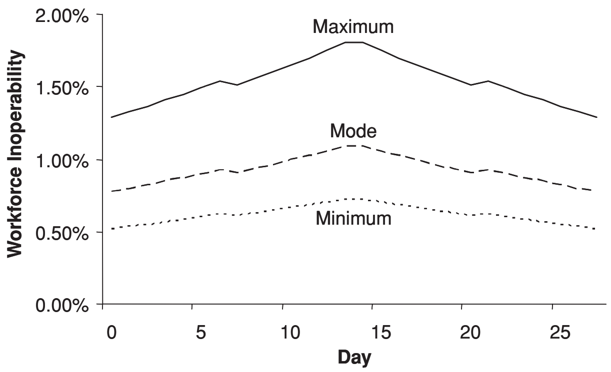


Fig. 11. FluWorkLoss inputs for scenario 1—4-week, 15% attack rate.

pandemic and time to recover to 1% of maximum inoperability. An interesting behavior of the graph is that the peak inoperability of any sector at any time is around 14%. While this seems to map to the 15% attack rate, taking a closer look at the graph in Fig. 11 reveals the peak proportion of days lost due to the pandemic is closer to 3.5% (on average). This means the 14% inoperability level instead reflects the building inoperability in the sector due to sustained levels of absent workforce, as opposed to the inputs.

Another interesting behavior is the relatively steep recovery beginning at day 28. This is seen more clearly in Fig. 12; right at day 28 (the end of the pandemic), the inoperability begins to recover very rapidly, especially relative to its previous behavior. These results can again be traced back to the Flu-

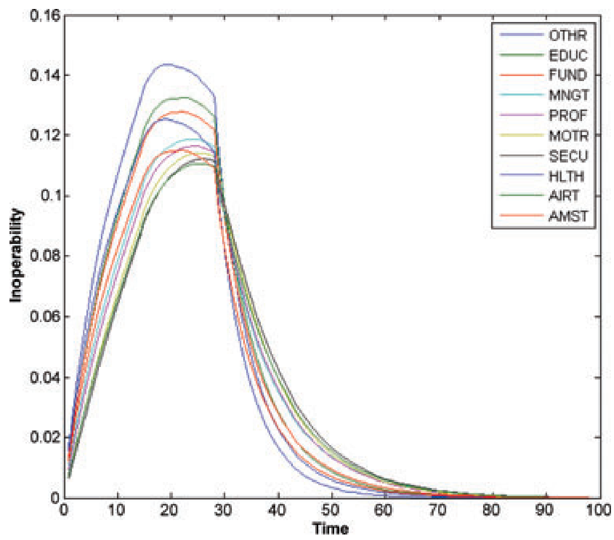


Fig. 12. Inoperability levels of the top 10 sectors most impacted in terms of inoperability.

WorkLoss inputs, which drop from 2% inoperability to 0 instantaneously. Thus at that point, the model begins to recover as it would if every person returned to work.

In terms of sectors most impacted by the pandemic, Fig. 12 illustrates that the top 10 sectors in terms of inoperability are, in order, (1) other services, (2) educational services, (3) funds, trusts, and other financial vehicles, (4) management of companies and enterprises, (5) professional, scientific and technical services, (6) motor vehicle, body, trailer and parts manufacturing, (7) securities commodity contracts and investments, (8) ambulatory health care services, (9) air transportation, and (10) amusements, gambling, and recreation.

If the same 10 sectors are viewed in terms of their economic losses, it begins to give a clearer picture of the actual impact. Although all 10 sectors had the highest inoperability, only two, other services and professional services, had a significant economic impact. Other services had average economic losses totaling \$850M (1.2% of annual GDP) and professional services had average economic losses totaling \$696M (1.8% of annual GDP). Due to the high impact of lost workforce on these sectors, they are the most impacted in terms of inoperability and economic loss, as is further demonstrated by looking at the sectors just in terms of economic loss (Fig. 13).

The summary of the 59 sectors' economic losses is shown in Fig. 14. In a fairly sharp contrast to the plot of inoperability, there are two sectors that

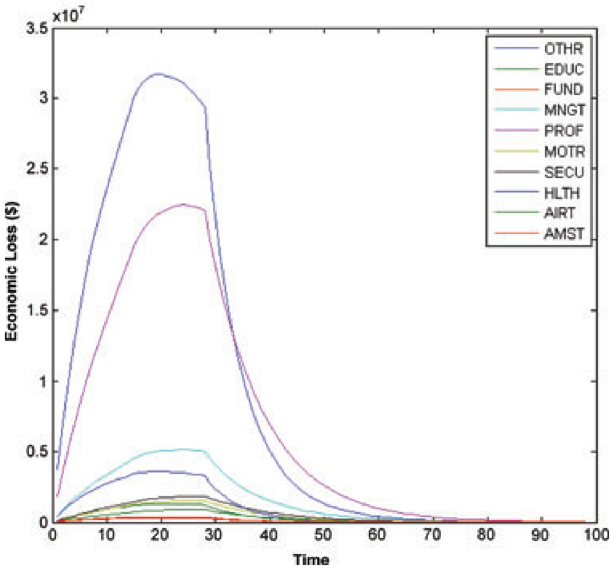


Fig. 13. Economic loss of the top 10 *inoperable* sectors.

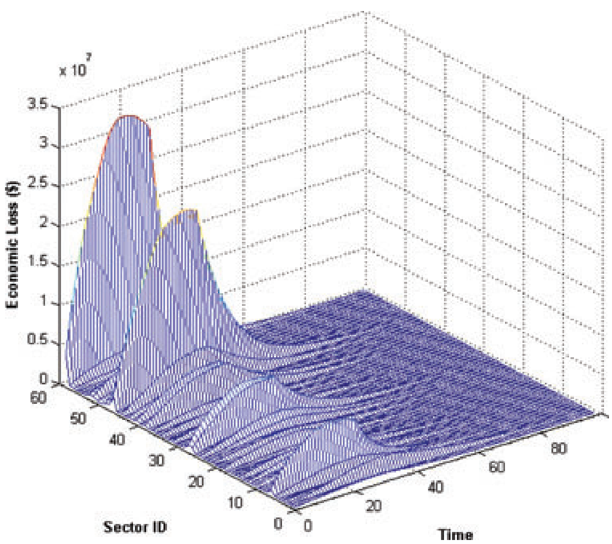


Fig. 14. Economic loss of the 59 sectors for a 4-week 15% attack rate pandemic.

clearly stand out among the rest. These two sectors are again the other services and the professional services sectors. Looking at the top 10 sectors in terms of economic loss, Fig. 15, these two sectors clearly dominate the others in terms of economic loss. The other sectors that appear in the top 10 are, in order, (3) wholesale trade, (4) construction, (5) administrative and support services, (6) retail trade, (7) real estate, (8) management of companies and enterprises, (9) broadcasting and telecommunications, and (10)

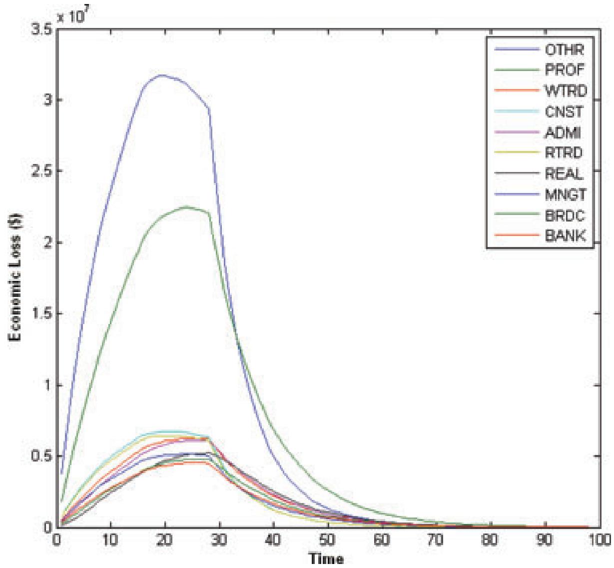


Fig. 15. Economic loss for top 10 sectors most affected in terms of economic loss.

federal reserve banks, credit intermediation, and related services.

Only 3 sectors appeared in the top 10 for both economic loss and inoperability: other services, professional services, and management of companies and enterprises. Overall, the four-week pandemic with 15% attack rate had an expected economic loss for all sectors of \$4.6B (1.3% of GDP) with a minimum of \$3.9B (1.1% of GDP) and a maximum of \$5.5B (1.6% of GDP). It took 91 days for every sector to recover to 1% of its maximum inoperability.

4.3. Summary of Three Scenarios

Similar trends that occurred in Scenario 1 (15% attack rate) also apply to Scenario 2 (25% attack rate) and Scenario 3 (35% attack rate). The shapes of the plots look similar, as well as the relative impact to sectors. The peak inoperability of all sectors is around 34%. A summary of the economic impact from the three scenarios is shown in Table II.

Lastly, Table III shows the absolute change in impact for each statistical measure when going from one scenario to the next.

The dominance of the other services and professional services sectors in terms of overall economic loss leads to some questions such as why those two are the most heavily impacted and what are the implications of this in terms of risk management. To

Table II. Economic Impact of the Three Scenarios of the Case Study (in billion U.S. dollars)

	Scenario 1	Scenario 2	Scenario 3
Minimum	3.9	6.6	9.0
Expected Value	4.6	7.7	10.8
Maximum	5.5	9.1	12.9

Table III. Change in Economic Impact Between Scenarios (in billion U.S. dollars)

	Scenario 1 to Scenario 2	Scenario 2 to Scenario 3
Minimum	2.7	2.4
Expected Value	3.1	3.1
Maximum	3.6	3.8

address why those two sectors have the greatest economic losses (despite not having such a high relative level of inoperability), it is useful to look back at the input data.

A large piece of the puzzle can be traced back to the relative size of these sectors, especially in terms of GDP. The other services sector, which in the RIMS II classification includes all of the federal employees sectors of the NAICS classification, accounts for nearly 20% of the GDP of the Virginia economy. Similarly, the professional services sector accounts for 11% of the total GDP. This explains why these two sectors would have such large economic losses relative to the other sectors; they are a larger scale than the other sectors.

However, these are not the two largest sectors. For example, the real estate sector accounts for 12% of the GDP. The question then becomes why this sector is not as heavily impacted as the other two. The answer is found in the impact of the workforce on these sectors. The professional services sector and other services sector have higher reliance on workforce than the real estate sector, as depicted previously in Fig. 5.

This realization has a significant impact on formulating risk management strategies. On the one hand, it would appear that these sectors should be prioritized to minimize the economic impact of the economy. However, upon closer inspection, this recommendation should be carefully assessed. One of the major reasons these sectors are so heavily impacted is their relative size of output, this would tend to indicate these sectors should receive no special treatment. Additionally, many of the sectors have reliance on workforce values that are similar or higher than these two sectors. Thus this research provides just one of the pieces in determining how to prioritize the protection of sectors. Many other factors need to be considered as well, for example, the health and hospital sectors will probably play a very large role in containing the outbreak and minimizing the number of infections and death rate. All of these factors need to be considered by the decisionmakers when coming up with risk mitigation policies.

5. CONCLUSIONS

This article has identified the criticality of workforce availability in the aftermath of a pandemic. Since the workforce supports different economic sectors, our analysis reveals the importance of accounting for the distribution of the workforce throughout the region. Partial availability of the workforce can result in at least two broad categories of economic impact. First, the temporary reduction of available workforce in various economic sectors can translate to productivity and income reductions. Second, problems relating to cascading impacts of workforce unavailability can exacerbate productivity losses of the affected regional economy due to interdependencies. The results in the study are preliminary and we recommend making further enhancements to the dynamic interdependency model to solidify the "supply" and "demand" concepts surrounding the availability of workforce and the functionality of infrastructure and economic sectors pursuant to a disaster. Another improvement to the model parameterization, not included in the current analysis, is an explicit accounting of specialized workforce sectors that are difficult to "substitute" when they become unavailable.

The interdependency model presented in this article is capable of assessing the magnitude of losses across different sectors; hence it provides policymaking insights on identifying the vulnerable sectors according to direct losses, as well as the indirect losses due to unmanaged recovery. Since the interdependency model is capable of evaluating the efficacy of multiple risk management options, the economic loss and inoperability estimates generated from the model can be compared with the "investment" requirements for managing recovery. Integrating the workforce loss impacts with loss estimates resulting from a catastrophic disaster, like a pandemic, can strengthen the justification for investment in protection and resilience.

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