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Risk-Based Input-Output Analysis of Influenza Epidemic Consequences on Interdependent Workforce Sectors

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Abstract

Outbreaks of contagious diseases underscore the ever-looming threat of new epidemics. Compared to other disasters that inflict physical damage to infrastructure systems, epidemics can have more devastating and prolonged impacts on the population. This paper investigates the interdependent economic and productivity risks resulting from epidemic-induced workforce absenteeism. In particular, we develop a dynamic input-output model capable of generating sector-disaggregated economic losses based on different magnitudes of workforce disruptions. An ex post analysis of the 2009 H1N1 pandemic in the National Capital Region (NCR) reveals the distribution of consequences across different economic sectors. Consequences are categorized into two metrics: (i) economic loss, which measures the magnitude of monetary losses incurred in each sector, and (ii) inoperability, which measures the normalized monetary losses incurred in each sector relative to the total economic output of that sector. For a simulated mild pandemic scenario in NCR, two distinct rankings are generated using the economic loss and inoperability metrics. Results indicate that the majority of the critical sectors ranked according to the economic loss metric comprise of sectors that contribute the most to the NCR's gross domestic product (e.g., federal government enterprises). In contrast, the majority of the critical sectors generated by the inoperability metric include sectors that are involved with epidemic management (e.g., hospitals). Hence, prioritizing sectors for recovery necessitates consideration of the balance between economic loss, inoperability, and other objectives. Although applied specifically to the NCR region, the proposed methodology can be customized for other regions.

Keywords

Pandemic; Input-Output Model; Critical Workforce; Disaster Preparedness; Prioritization

1.0 Background

Influenza is a highly transmissible virus that causes significant morbidity and mortality during yearly seasonal winter epidemics, particularly to the elderly and those with underlying medical conditions. During a pandemic, which occurs when a novel strain of Influenza A transmits widely to a highly susceptible previously non-immune population, influenza can have more devastating impacts on the population, including significant economic losses from direct healthcare costs as well as workforce absenteeism.

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The incubation period for influenza is approximately 1 to 3 days, with the duration of infectivity being up to seven days. Airborne transmission, or respirable droplets, are the primary mode of transmission in longer term epidemics, whereas the inspirable route is most important for short term epidemics with a high attack rate⁽¹⁾. The term “attack rate” is defined as the percentage of people infected relative to the total number of exposed people. Stochastic and computational models to predict influenza epidemics have been developed. In one publicly available model that simulates the propagation of an influenza epidemic nationwide, secondary attack rates for influenza range from 9 to 35%, depending upon transmissibility and whether the index case is a child or an adult. On average, the attack rate in an urban center is estimated to be 33%⁽²⁾. For a moderate epidemic, up to 55% of the population would be infected with a cumulative attack rate of 28% and a peak at 60 days⁽³⁾. Cumulative attack and peak daily rates depend on the expected number of secondary cases an individual will produce in a susceptible population, or R_0 , and thus the true economic impact of a pandemic may also be difficult to predict⁽³⁾.

In the United States, it is estimated that during an epidemic of influenza, 30% of transmission will occur within households, whereas 33% will occur in the community and 37% at school or in the workplace⁽³⁾. Employee absenteeism rates during a pandemic have been reported from 10 to 40%, with worker absenteeism as high as 7 workdays lost per symptomatic case. For an influenza epidemic with moderate transmission, approximately 9% of workers would be absent⁽³⁾, although this will vary according to the severity of the pandemic and public perception of risk. Using the FluWorkLoss⁽⁴⁾ program, it was estimated that 3.4% of available workdays would be lost during an 8-week pandemic wave with an attack rate of 35%⁽⁵⁾.

The 2009 H1N1 pandemic, which was milder than expected, provides a unique “real-life” opportunity to study the economic impacts of a pandemic on workforce inoperability. In April 2009 a novel strain of influenza A virus, or novel A H1N1, emerged in North America and spread throughout the world. Compared to seasonal influenza, the H1N1 strain disproportionately affected children, pregnant women, and younger adults with chronic medical conditions such as diabetes, asthma, and cardiovascular disease. Declared a pandemic in June 2009, the official pandemic period lasted until August 2010, with the virus continuing to circulate around the world⁽⁶⁾⁽⁷⁾. The age distribution of H1N1 deviated from typical patterns for seasonal influenza strains, and the 2009-2010 influenza season had increased rates of hospitalizations in children and young adults than in previous years⁽⁸⁾. The R_0 of H1N1 was estimated to range from 1.4 to 1.6, at the moderate end, with attack rates ranging from 27 to 37% of the population. The final attack rate was calculated at 32.5% with a peak ill population of 6.6% and a peak epidemic at 45 days⁽⁹⁾.

Schanzer et al.⁽¹⁰⁾ conducted a study about the effect of seasonal and pandemic influenza on absenteeism based on published labor statistics. The study was conducted using a regression model to account for seasonal baseline, secular trends, and the impact of influenza. The goal of the study was to evaluate and compare the absenteeism rates and hours lost between seasonal influenza and the two pandemic waves of the 2009 H1N1 season. Intuitively, the hours lost due to the H1N1 pandemic waves were greater than the hours lost due to the seasonal influenza. The H1N1 pandemic waves caused a loss of 0.2% of the annual working hours, while the seasonal influenza accounts for only 0.08%. On the hand, absenteeism rates were 13% for the H1N1 pandemic waves compared to 12% for the seasonal influenza. On average, employees took 25 hours off during the pandemic waves of H1N1 compared to 14 hours off in the case of the seasonal influenza. The study also found that the hours lost due to illness increase with age.

The current paper focuses specifically on the interplay between epidemic transmission modeling and analysis of resulting interdependent workforce consequences. Figure 1 depicts the main components of the proposed integrated models. The models are applied to an *ex post* analysis of the 2009 H1N1 pandemic in the National Capital Region. The modeling framework in Figure 1 features several key indicators that affect the total number of people infected. It comprises three sections, namely mitigation, infectivity, and recovery. The mitigation section is concerned with the treatment of ill persons and preventive measures to decrease the rate of infection and epidemic propagation. The infectivity section describes the initial number infected, the infection rate, and the duration of the effect of the pandemic. The recovery section attempts to analyze the recovery behavior and the efficacy of preparedness. The model parameters are based on the FluWorkLoss⁽⁴⁾ software, which is a tool used to estimate the workforce hours lost during an epidemic wave. This tool is useful particularly in performing further analysis of critical sectors that are prone to disruptions, and therefore need an efficient emergency management plans. The software offers the users the flexibility of adjusting the input parameters such as the workdays lost when a worker is sick, or worker absenteeism due to caring for another member of the family. The software can generate graphical illustrations of the total days lost based on the magnitude and duration of the epidemic waves.

The design used to structure the epidemic model is the Inoperability Input-Output Model (IIM), which provides a framework to account for cascading effects and derivative losses in light of initial workforce disruptions and sector interdependencies. The IIM also enables us to perform risk analysis to identify the as-planned output, the degraded output, the consequences, and the prioritization of critical sectors. The objective of the IIM is to assess the varying consequences on interdependent sectors. The IIM model and its components are further explained in Section 2 with supporting mathematical formulations. The resulting integrated model uses two metrics to assess the impact of epidemic transmission on interdependent sectors, namely inoperability level and economic loss. These two metrics give different but related information about the impact of an epidemic wave. The inoperability level is estimated from absenteeism rates and interdependencies among sectors. On the other hand, the estimated economic loss gives information about the monetary value of labor for sectors, and the associated degraded production of goods and services. Both direct and indirect consequences describe the significant ripple effects of an epidemic on the affected region. The dependence of economic sectors on workforce productivity directly impacts the inoperability level, whereas the interdependencies between sectors indirectly propagate the initial perturbation into other sectors. However, the overall impact depends on the sector recovery rate or its resilience, which is the degree to which a given sector can absorb the impact of an epidemic and recover to the pre-disaster state.

In this paper we model the impacts of a mild pandemic of influenza, using data from 2009 H1N1, on workforce inoperability, including economic losses, for the National Capital Region (NCR), a large metropolitan region with significant interdependence and of special biosecurity concern. The NCR analysis presented in this paper provides more detailed estimates of economic losses due to the H1N1 pandemic, which could guide disaster preparedness efforts for future pandemics.

2.0 Supporting Models

2.1 Input-Output Analysis

At the core of the epidemic risk model developed in this paper is the concept of input-output (I-O) modeling. The I-O model structures the economy as a set of interconnected sectors, which both produce goods as well as consume goods in the process of production. When the intermediate consumption is combined with the final consumer demand for products, the

result is a model useful for understanding the interdependent nature of an economy⁽¹¹⁾. Leontief's model has been extended and applied to myriad problems, including the effect of new technologies or taxes on the energy industry, and pollution creation and elimination⁽¹²⁾. Leontief's model has also been used by Jiang and Haines⁽¹³⁾ to minimize the total loss or inoperability of the set of interdependent sectors. This minimization process is done by mitigating the *cascading effect*, which causes the initial perturbation to develop into a far greater *derivative loss* due to the interconnectedness of the complex systems of the economy. Understanding the interdependencies and resulting cascading impacts from an emergency event is essential to developing an effective security plan⁽¹⁴⁾. The I-O model is a method for modeling interdependencies across multiple sectors of a given regional economy⁽¹²⁾⁽¹⁵⁾. The National Cooperative Highway Research Program⁽¹⁶⁾ recognizes the I-O method in its guidebook for assessing the social and economic factors in infrastructure management domain. Extensions and current frontiers on I-O analysis can be found in Dietzenbacher and Lahr⁽¹⁷⁾.

Geographic modeling and decomposition enable a more focused and hence a more accurate analysis of regional characteristics as well as associated regional interactions. Interdependencies across regions are becoming more and more prevalent due to the increasing trend in interregional transportation and trading activities. Significant segments of the working population commute across regions, as evidenced from the Journey to Work and Place of Work data⁽¹⁸⁾. The increasing number of commodity shipments across regions bolsters the activities of the freight and trade sectors based on the Commodity Flow Survey⁽¹⁹⁾. Several input-output model derivatives are available for analysis of disruptions and their adverse effects on workforce and supply chains⁽²⁰⁾. The benefits of I-O models are many, particularly with respect to modeling the effect of disruptive events on interdependent regional sectors. I-O data published by the Bureau of Economic Analysis (BEA) describe the relationships among interdependent different sectors of the economy. Furthermore, I-O data are essential components within the larger social accounting matrices used in computable general equilibrium modeling⁽²¹⁾.

The Leontief I-O model is formulated as follows:

$$\mathbf{x} = \mathbf{Ax} + \mathbf{c} \quad \text{Eq. (1)}$$

Where:

- $\mathbf{x}$ is the production output vector (i.e., the element, x_i , denotes the output of sector i)
- $\mathbf{A}$ is the Leontief technical coefficient matrix (i.e., the element a_{ij} denotes the input requirement of sector j from sector i , with respect to the total input requirements of sector j)
- $\mathbf{c}$ is the final demand vector (i.e., the element, c_i , denotes the final demand for sector i)

One of the advantages of the Leontief model is that it is supported by detailed data collected and compiled by national census and statistical agencies. In the United States, for example, extensive I-O data are published by the Bureau of Economic Analysis (BEA) to generate the technical coefficient matrix⁽¹²⁾. This methodology is coupled with the BEA's Regional Input-Output Multiplier System (RIMS II) to provide a useful framework for evaluating economic interdependencies⁽²²⁾. These data are available from BEA for the nation as a whole, each state, metropolitan regions (using the U.S. Census definitions), and counties. The availability of high-resolution economic data and social accounting matrices enables the

application of I-O model and computable general equilibrium for analysis of relatively small regions (e.g., analysis of infrastructure disruptions in Portland⁽²³⁾).

Haimes and Jiang⁽²⁴⁾ revisited the Leontief model and expanded it to account for *inoperability*, or the inability for sectors to meet demand for their output. This model, the Inoperability Input-Output Model (IIM), has been featured in several applications. Examples include modeling of infrastructure interdependencies and risks of terrorism⁽²⁵⁾⁽²⁶⁾, multi-state regional electric power blackouts⁽²⁷⁾, inventory management⁽²⁸⁾, and hurricane scenarios⁽²⁹⁾⁽³⁰⁾. The IIM has also been applied to problems with sequential decisions and multiple objectives, such as the biofuel subsidy analysis explored by Santos et al.⁽³¹⁾. A conceptual framework for bridging I-O analysis with agent-based simulation of interdependent infrastructure systems was also formulated by Santos et al.⁽³²⁾. The IIM has been used in many applications for risk assessment of interdependent systems within a macroeconomic context. Other recent applications have further extended its use. Wei et al.⁽³³⁾ used the IIM model to study the impact of a perturbation event to supply chain networks.

2.2 Parameters of the Inoperability Input-Output Model (IIM)

The IIM is structurally similar to the Leontief I-O model. Eq. (2) shows the mathematical formulation of the IIM. The parameters of the IIM are summarized below. Details of model derivation and an extensive discussion of model components are found in Santos et al.⁽³¹⁾ and also in Santos and Haimes⁽³⁴⁾. Table I summarizes the sector classifications used in the regional model and case study.

$$\mathbf{q} = \mathbf{A}^* \mathbf{q} + \mathbf{c}^* \quad \text{Eq. (2)}$$

- $\mathbf{q}$ is the inoperability vector (i.e., the element, q_i , denotes the inoperability of sector i)
- $\mathbf{A}^*$ is the interdependency matrix (i.e., the element a_{ij}^* denotes the input requirement of sector j that comes from sector i , normalized with respect to the total input requirements of sector j)
- $\mathbf{c}^*$ is the demand perturbation vector (i.e., the element, c_i^* , denotes the demand perturbation to sector i)

In addition, the dynamic formulation of the IIM takes into account the economic resilience of each sector, which influences the pace of recovery of the interdependent sectors in the aftermath of a disaster. A key motivation that led to the development of the dynamic IIM is the need for linking the concept of economic resilience with disaster recovery. In general, resilience is defined as the ability or capability of a sector to absorb or cushion against damage or loss⁽³⁵⁾⁽³⁶⁾. Rose and Liao⁽²³⁾ suggest that 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, among others. Rose⁽³⁷⁾ provides comprehensive definitions and categories of economic resilience including static, dynamic, inherent, and adaptive. The formulation of the dynamic IIM is as follows:

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K} [\mathbf{A}^* \mathbf{q}(t) + \mathbf{c}^*(t) - \mathbf{q}(t)] \quad \text{Eq. (3)}$$

The term, $\mathbf{K}$, is a sector resilience coefficient matrix that represents the rates with which sectors recover to their nominal levels of production following a disruption⁽³⁸⁾. The model

dictates that the inoperability level at the following time step, $q(t+1)$, is equal to the inoperability at the previous stage, $q(t)$, plus the effects of the resilience of the sector. The values of $\mathbf{K}$ tend to be negative or zero, thereby detracting from the overall level of inoperability. As seen in Eq. (3), $\mathbf{K}$ is multiplied with the indirect inoperability resulting from other sectors, $\mathbf{A}^*q(t)$, plus the degraded final demand, $c^*(t)$, minus the current level of inoperability, $q(t)$. The resilience coefficient, $\mathbf{K}$, is assumed to be an inherent characteristic of a particular sector, but multiplying it with the inoperability product term, $\mathbf{A}^*q(t)$, will result in coupled resilience across directly related sectors. This is relevant when analyzing a sector that heavily depends on another sector for achieving its as-planned productivity levels. Regardless of how a sector is inherently resilient, its productivity will be compromised when another sector it depends on becomes inoperable in the aftermath of a disaster.

The dynamic extension Eq. (3) answers one of the fundamental limitations of the basic IIM Eq. (2), which is the ability to capture time varying recovery that adapts to some *a priori* and current levels of inoperability within the perturbation and recovery period. Barker and Haimes⁽³⁹⁾ used the dynamic inoperability input-output model (DIIM) with a multi-objective approach, which enables structural changes in the interdependencies. The objective of the proposed approach is to measure the efficacy of preparedness strategies for interdependent sectors of the economy, allowing prioritization of sectors according to how sensitive they are to changes in their interdependencies. For the dynamic extension to the IIM, Lian and Haimes⁽³⁸⁾ provide the formulation to estimate the sector resilience coefficient of each sector. This resilience coefficient is a function of: (i) sector inoperability, (ii) sector interdependencies, (iii) recovery period, and (iv) the desired level of inoperability reduction for the target recovery period. Economic resilience is inversely proportional to the recovery period. This is because resilience is a desired attribute of any system and, hence, a higher level of resilience is preferred. On the other hand, recovery period (i.e., the time it takes to reach full recovery) is desired to be at minimum to the extent possible. Lian et al.⁽⁴⁰⁾, Santos⁽²⁵⁾, Lian and Haimes⁽³⁸⁾, and Haimes et al.⁽⁴¹⁾ applied the model to various regional disaster scenarios to analyze the recovery behaviors of critical economic sectors and infrastructure systems.

3.0 Scope of Data Used in the Study

In this paper, we specifically analyze an epidemic scenario for the Washington-Arlington-Alexandria, DC-VA-MD-WV metropolitan statistical area. For brevity, we refer to this study site as the National Capital Region (NCR).

3.1 Sector Classifications

This paper configures the data collection methodology using the North American Industry Classification System (NAICS). RIMS II adopts an aggregated version of the detailed sector classification⁽²²⁾—comprised of 65 sectors (see Table I).

3.2 Input-Output Matrices

In a simplified I-O model formulation, each industry is assumed to produce a distinct commodity. The term “commodity” in this paper refers to the output of an industry, which can take the form of goods or services. Realistically however, it is possible that a given industry produces more than one commodity. In addition, a given commodity may not be a unique output of an industry. The BEA makes the distinction between an industry and a commodity in its published I-O data via the “industry-by-commodity” and “commodity-by-industry” matrices.

3.3 Gross Domestic Product

Gross Domestic Product (GDP) consists of final consumption—other than those used as intermediate production inputs to the endogenous sectors. As such, GDP is also interpreted as the value of final uses (or consumptions), which includes personal consumption expenditure, gross private domestic investment, government purchases, and net foreign exports (i.e., difference in exports and imports)⁽¹²⁾. GDP is also defined by BEA as “the market value of goods and services produced by labor and property in the United States, regardless of nationality; GDP replaced gross national product (GNP) as the primary measure of U.S. production in 1991.”¹ GDP data is also available for all states and metropolitan areas within the United States.

3.4 Local Area Personal Income

Local Area Personal Income (LAPI) refers primarily to the wages paid to the workers in a given region. Other components of LAPI include “supplements to wages and salaries, proprietors' income with inventory valuation adjustment (IVA) and capital consumption adjustment (CCAdj), rental income of persons with CCAdj, personal dividend income, personal interest income, and personal current transfer receipts, less contributions for government social insurance.”² LAPI data are available for each of the 65 sectors. To convert the output of disaster impact into a measure of workforce sector inoperability, there needs to be a way to translate a percentage decrease in workforce availability into a measure of sector inoperability. Arnold et al.⁽⁴²⁾ accomplished this through estimates of worker productivity. To generate worker impact for the RIMS II sectors, the ratio of Local Area Personal Income (LAPI) to industry output is computed⁽⁴³⁾. The LAPI provides the value of workforce to the industry (the market value of the laborers' work) and dividing this by the industry output gives the proportion of output that is dependent on the workforce. The calculation of inoperability for a given sector is shown in Eq. (4).

$$\frac{\text{Unavailable\_Workforce}_i}{\text{Size\_of\_Workforce}_i} \times \frac{\text{LAPI}_i}{x_i} = \text{Sector\_Inoperability}_i \quad \text{Eq. 4}$$

The impact on workers is then multiplied with the number of workers in that sector that are unavailable divided by the number of workers in that sector (giving percentage of workers missing) to determine overall sector inoperability. The LAPI-based approach for assessing workforce inoperability is consistent with the commonly used metrics for measuring workforce input, which are number of hours, number of jobs, and number of employed people⁽⁴⁴⁾. Historical epidemic trends and wave functions such as those suggested by Chowell et al.⁽⁴⁵⁾ can be used to formulate the time varying resilience function.

3.5 Employment by Industry

Employment data are available for different states and metropolitan areas. For example, BEA publishes annual estimates of the total full-time and part-time employment by NAICS industry. These employment numbers are available only for a subset of the 65 sectors in the IIM. Hence, the regional *per capita income* can serve as a basis for estimating the number of workers in sectors with missing data. These sector-specific employment numbers are used in determining the equivalent number of jobs lost (due to workforce absenteeism) within the disaster horizon.

¹BEA Glossary: http://www.bea.gov/glossary/glossary_g.htm

²BEA Glossary: http://www.bea.gov/glossary/glossary_l.htm

3.6 Epidemic Scenarios

The Centers for Disease Control and Prevention (CDC) has developed a set of tools to estimate epidemic consequences such as deaths, hospitalizations, outpatient visits, and the resulting workdays lost aggregated throughout a region⁽⁴⁶⁾. In particular, the FluWorkLoss program⁽⁴⁾, which provides the trajectory of workdays lost within the duration of an epidemic, was used to generate the sector inoperability parameters in the IIM.

4.0 Decision Support System

The decision support tool utilized in this research comprises a front-end graphical user interface (GUI) developed in Microsoft Excel™. The spreadsheet tool comprises several modules as follows: (i) scenario generation, (ii) computation, (iii) visualization, and (iv) prioritization and sensitivity analysis. These modules are described below.

4.1 Scenario Generation Module

The scenario generation module enables the user to provide the model scenario inputs. The user is asked to enter the initial inoperability for each of the sectors, as well as the time it takes to achieve full recovery. Initial inoperability (denoted by q_0) is a number between 0 and 1, which describes the extent to which a given sector's production capacity is affected initially (i.e., 0.1 means that 10% of the production capacity is rendered inoperable by a disaster). On the other hand, the time to recovery (denoted by T) is the time that a sector is expected to take to recover to its pre-disaster production level. In the model, the time to recovery is measured in days.

4.2 Computation Module

The computational module is the computing engine of the program containing the codes for the IIM. This module stores the simulation rules and algorithms needed for executing the IIM and its dynamic recovery model extensions. This module also includes the algorithms for visualizing the model results, namely the inoperability and economic loss for each sector and for each day within the recovery period.

4.3 Visualization Module

The visualization module enables the user to view the recovery behaviors of the critical sectors given the parameter values entered in the scenario definition stage. The critical sectors are selected as the top-10 sectors (out of 65) with respect to the two primary metrics, which are *inoperability* and *economic loss*. The sector rankings generated from these two metrics are generally different. The actual visualization of the key sectors generated by each objective is deferred to the NCR case study in a subsequent section.

4.4 Prioritization Sensitivity Analysis Module

The prioritization sensitivity analysis module requires two categories of user inputs: (i) preference structure for economic loss and inoperability objectives, and (ii) prioritization scope to determine the size of the prioritization filter⁽⁴⁷⁾. The process and descriptions of these inputs are described as follows. First, the user is asked for the economic loss weight, or the relative importance of the economic loss objective with respect to inoperability. A scale of 0 to 1 is used, with the following sample interpretations:

- A value of 1 means economic loss is the only objective that matters
- A value of 0.5 means economic loss is equally preferred to inoperability
- A value of 0 means inoperability is the only objective that matters

In addition, the tool requires the user to enter a prioritization scope—a positive integer that can be adjusted to set the size of the prioritization area. This integer is increased when more sectors are to be prioritized, and decreased when fewer sectors can be prioritized (e.g., a budget constraint). Figure 2 shows a sample output of the prioritization sensitivity analysis module depicting the case of equal preference assignments to the economic loss and inoperability minimization objectives.

5.0 Epidemic Scenario Analysis for NCR

Epidemic consequences include workforce absenteeism, loss of lives, and regional economic losses. Losses due to workforce absenteeism can significantly decrease a sector's output regardless of the efficiency of other production factors. Regional economies, like the NCR, have limited resources to manage disaster consequences. The objective of the case study is to manage impacts of an epidemic scenario in the NCR using available economic and survey data. This section demonstrates the use of the IIM and its dynamic extensions to assess the impacts of disaster scenarios on the interdependent economic sectors. Data sets assembled from various economic and census agencies include input-output matrices, gross domestic product data, local area personal income data, and employment numbers, among others. These data sets are coupled with the epidemic scenarios derived from FluWorkLoss.

The following sections demonstrate the application of the IIM using an epidemic scenario based on an *ex post* analysis of the 2009 influenza season. This case is introduced with scenario descriptions, as well as a summary of the different loss categories that could be of interest to regional policymakers. Recall that the two primary consequence categories provided by the IIM are *inoperability* and *economic loss*. The economic losses are computed by the IIM for each of the 65 sectors.

In addition, the rankings of the critical sectors according to the inoperability and economic loss metrics are shown, along with the associated visualization outputs of the IIM. The DCP tool also provides sample prioritization of key sectors based on priority assignments to the inoperability and economic loss objectives. The DCP results can identify the economic sectors that are expected to receive the greatest consequences from an epidemic scenario and can help in formulating policies for enhancing regional resilience.

5.1 Modeling Workforce Disruption

Consider an epidemic scenario in the NCR region with workforce absenteeism rates similar to what occurred during the 2009 season. Figure 3 describes the epidemic curve of the 2009 H1N1 pandemic. The influenza season typically lasts from week 40 through week 20 of the next year (early October through mid May), which corresponds to the period of influenza surveillance. The number of positive laboratory specimens reflects the number of cases of influenza and these plotted over time form the epidemic curve. The 2009-2010 influenza season demonstrates an atypical pattern; in April of 2009, when the number of positive influenza tests was decreasing, an unexpected rapid uptick subsequently occurred leading to a second epidemic curve that represents the new pandemic. Workforce disruption due to influenza is expected to be highest during the winter season; however, in this case the model needs to be extended beyond the expected influenza season due to the aberrant pattern exhibited by the occurrence of the H1N1 pandemic during the expected off season for the virus.

The parameters that describe the initial effects of the disaster scenario are entered into the dynamic IIM and generated the charts for inoperability (Figure 4) and economic loss (Figure 5). The total economic loss for the simulated scenario is approximately \$6.7 billion.

5.2 Results

The top 10 sectors that suffer the highest inoperability in this scenario (Figure 4) are: Social assistance (*S56*); Hospitals and nursing and residential care facilities (*S55*); Ambulatory health care services (*S54*); Construction (*S7*); State and local government enterprises (*S64*); Primary metals (*S18*); State and local general government (*S65*); Transit and ground passenger transportation (*S33*); Securities, commodity contracts, and investments (*S42*); and Warehousing and storage (*S36*).

For the same scenario, the top 10 sectors with highest economic losses (Figure 5) are: Federal government enterprises (*S62*); Miscellaneous professional, scientific, and technical services (*S49*); Legal services (*S47*); State and local general government (*S65*); Other services, except government (*S61*); Administrative and support services (*S51*); Hospitals and nursing and residential care facilities (*S55*); Real estate (*S45*); Federal Reserve banks and credit intermediation (*S41*); and Retail trade (*S28*).

The inoperability and economic loss rankings are different because the production outputs of the sectors could vary by orders of magnitude. As such, a sector that suffers a relatively low economic loss value can have a critical ranking in inoperability if its total production output is also lower relative to other sectors. By the same token, a sector with a relatively low inoperability value can have a critical ranking in economic loss if its total production output is significantly higher compared to the other sectors.

The dynamic cross prioritization plot (DCPP) tool enables the users to perform sensitivity analysis with respect to how they structure their preference between the economic loss and inoperability objectives. Two sample scenarios are presented in the following figures. The vertical region (Figure 6) corresponds to a preference strategy that gives importance to economic loss only, while the horizontal region (Figure 7) corresponds to assigning the full weight to the inoperability objective. For a purely economic loss minimizing strategy, there is a risk to exclude sectors that have critical ranking with respect to inoperability (e.g., Social assistance and Ambulatory health care services). Nevertheless, there is also a risk of excluding sectors with critical economic loss rankings in this equal weighting strategy (e.g., Federal Government and Legal Services). Hence, prioritizing sectors for recovery requires consideration of the balance between economic loss and inoperability.

6.0 Analysis and Discussion

Pandemic preparedness has traditionally focused on maintenance of the health sector and impacts on population health rather than on indirect economic impacts⁽⁴⁹⁾. The cost of influenza, however, includes not only complications directly due to medical illness but high rates of absenteeism lead to significant costs of sick leave. Workforce absenteeism leads to important economic losses during a pandemic as well as significant productivity losses during seasonal epidemics⁽⁵⁰⁾. While prior studies have demonstrated the macroeconomic impact of pandemic influenza on multi-sector single country models⁽⁵¹⁾, our study is novel in demonstrating the significance of regional workforce inoperability during a pandemic, providing evidence of significant regional ripple effects that impact multiple sectors. The analysis presented in this paper shows a total estimated \$6.7 billion economic loss in the NCR region using the H1N1 pandemic scenario as a model. Given that the H1N1 pandemic was relatively mild compared to previous pandemics, including the 1918 pandemic which decimated approximately 50% of the workforce, this figure is likely an underestimate of the potential impact of a more severe pandemic. Our estimates are significantly higher than prior study using data from the District of Columbia using the MIDAS model, which estimated a nationwide economic impact of 112.6 million dollars for a 15% attack rate, and 193.8 million for a 25% attack rate⁽⁵²⁾. Such differences in estimates can be attributed to our

inclusion of (i) the ripple effects of workforce absenteeism and associated productivity losses across interdependent economic sectors, and (ii) the losses spanning a one-year horizon comprised of the two epidemic waves.

Among the sectors with the highest inoperability in our model include social assistance, the healthcare sector, and the local and federal government. The impact on the federal government enterprises in particular represents a significant national biosecurity concern. While we did not model the impact of the influenza pandemic beyond the NCR region, it can be assumed that any increase in inoperability in the federal sector due to the effect of the epidemic on the NCR region would have nationwide repercussions. There are particular concerns with regards to the healthcare sector and social assistance, as disruption of these services in the NCR might disproportionately affect underserved regions and disadvantaged populations that rely heavily on federal government resources, including Native Americans (Indian Health Service), rural areas and the urban poor (Medicare/Medicaid services), and those who depend on social security benefits. The economic disruption to disadvantaged populations will be the subject of future study using this model. Our results also emphasize the importance of further study of the resilience of the NCR in the face of pandemics and other disasters given the need for special preparedness efforts for this region.

According to Figure 4, social assistance services are the most affected sectors in terms of inoperability levels. Such sectors show the lowest GDP figures. For example, the social assistance sector GDP in 2009 was estimated to be just 0.68 billion dollars⁽⁵³⁾; however, it shows the highest inoperability level. Two reasons seem to account for the social and health services being the most affected. First, due to the epidemic wave, many individuals become sick and require health care, which overwhelms the capacities of health care centers. The effect of many incoming sick cases and limited capacity creates a state of inoperability. Second, the inoperability of social services could be traced to the direct interactions between the health care personnel and the infected people. Health care facilities and social assistance centers pose a unique setting not only because a higher than average expected risk for influenza transmission but also due to the impacts of workforce absenteeism in these sectors on the provision of care, therefore leading to an increase in the inoperability of the respective sector.

According to Figure 6, the most impacted sector in terms of economic loss is the federal government enterprises. Although its inoperability ranking is low compared to other sectors, the peak monetary value loss was estimated to be 1.3 billion dollars. Such result could be explained by the fact that the production output of this sector is significant enough that even a negligible inoperability level can generate huge economic losses. Specifically, the GDP figure of the federal government enterprises was estimated to be \$30 billion dollars in 2009⁽⁵³⁾. The same reasoning can be applied on the legal services sector, whose GDP was estimated to be 10 billion dollars in spite of its low inoperability ranking. However, the miscellaneous professional, scientific, and technical services sector was not expected to be ranked the second most impacted sector in terms of economic loss. With a GDP of 8 billion dollars in 2009, the sector incurred a loss of around 0.6 billion dollars, which is significant compared to the overall GDP of the sector. This finding might be attributable to this sector's substantial interdependence with all other sectors, and therefore any major disruption in any of the sectors would have a much larger negative impact on the miscellaneous professional, scientific, and technical services sector.

The DCPG graphs (Figures 6 and 7) provide a different way of looking at the inoperability and economic loss metrics. Particularly, the DCPG tool allows prioritizing the critical objective. For example, Figure 6 highlights critical sectors with respect to the overall economic loss by assigning a maximum weight to the economic loss metric. Therefore, we

can read from the vertical region that federal government, computer systems, and legal services are the top 3 sectors in terms of economic loss. On the other hand, Figure 7 shows the most impacted sectors in terms of inoperability by giving it the maximum weight. These sectors are social assistance, hospitals, and ambulatory health care services. It is clear that different results are achieved as far as how the critical sectors are prioritized when different levels of importance are assigned to the two metrics. The two graphs may have approached the overall picture from a reductionist perspective; however, assigning balanced weights to both metrics and adjusting the prioritization scope can provide an integrated view of the distribution of the different sectors. The weights can be assigned depending on the significance given to each metric dimension in the analysis. Also, adjusting the prioritization scope enables to filter the number of sectors to include in the analysis. For example, Figure 2 shows a quarter circle obtained when giving each metric an equal weight of 0.5.

The results on inoperability in the healthcare sector, both for the healthcare facility based setting and the ambulatory setting, likely represent an underestimation of the true impact. Influenza can be transmitted in the healthcare setting and hospital-acquired outbreaks of influenza have been reported⁽⁵⁴⁾. We did not expect the results for high inoperability of primary metals sector in our region; however, this may be due either to (i) the sector's interdependencies to the US Mint and energy sectors in the NCR, or (ii) some unforeseen external effects of the mining industries proximate to the study region.

Although the education sector does not figure in the top ten sectors impacted using the I-O model described here, our model is limited in that it does not take into account the particular age distribution of the population affected by H1N1, including children and healthy working parents who may have been caregivers for sick children during the pandemic. Furthermore, we cannot adequately estimate the added impact on workforce inoperability of multiple school closures for up to two weeks during the peak of the pandemic. However, this may be mitigated by the fact that the educational sector may “produce” less in terms of economic output, at least in the short term.

Additional model limitations include the inability to address the effects of specific pandemic interventions such as vaccination, the use of antiviral medication, or school closures both generally and in specific sectors. For example, prior study of the impact of the H1N1 pandemic demonstrated workforce absenteeism related to seven-day school closure was 27%, with 18% reporting lost wages⁽⁵⁵⁾. A similar study in North Carolina⁽⁵⁶⁾ found that 24% of households reported missing work. Prior study has shown through sensitivity analyses that there may be less variability with regards to fluctuations in disease parameters than with policies such as school closure and recommendations to stay home⁽⁴⁹⁾. In fact, CDC policy recommended ill persons to stay home for up to 7 days during the H1N1 pandemic.

Interventions could thus significantly reduce the economic impacts of the pandemic, with targeted antivirals and prevaccination where available being the least costly, and school closure increasing cost by \$2700 per capita⁽⁵⁷⁾. Furthermore, as previously indicated for the health sector, the rate of transmission and subsequent infection is not distributed evenly across sectors, and risk perception plays an important role in absenteeism beyond symptomatic illness rates alone. Absenteeism may vary by student or worker type, with health care students and professionals reporting lower than expected rates of absenteeism when ill with influenza like illness during 2009 H1N1; nine percent of medical students and 61% of medical residents reported to class or work when ill in one institution in Washington DC despite CDC and School of Medicine recommendations to stay home when ill⁽⁵⁸⁾. In a study that surveyed six essential workgroups, the group that was most likely to be willing and able to report to work during a pandemic was the healthcare workers; however, more

than 50% of workers might be absent due to non-illness related factors, including caregiving for sick family members and fear of becoming ill⁽⁵⁹⁾. In the case of H1N1, school closures may have led to increased absenteeism for working parents, especially in the health and social sectors⁽⁶⁰⁾. A study in Spain that employed time series analysis of worker absenteeism due to influenza like illness (ILI) found that the highest impact was in women and in the education, health and social activities sectors⁽⁶¹⁾.

There is also evidence from models evaluating the macroeconomic impacts of influenza pandemics that policies of school closure and recommendations to stay home from work may triple the effects of GDP losses. Increasing school closures from four weeks at the peak to entire pandemic closure nearly doubles the cost, but antivirals and vaccination may mitigate the effects⁽⁵¹⁾. Thus, future models will attempt to provide more detailed estimation of the impact of pharmaceutical and nonpharmaceutical interventions on workforce inoperability and economic losses. A more detailed analysis using the I-O model at the county level could identify inequalities in economic disruption impacting vulnerable populations and help guide future preparedness and response to a pandemic.

7.0 Conclusions and areas for future model improvements

The economic consequences of disruptive events such as influenza epidemics can cascade across interdependent economic sectors, further delaying recovery. This paper develops a recovery model to estimate sector inoperability and economic losses for a disaster scenario in the example region. Two primary IIM metrics for determining critical sectors are presented—namely inoperability and economic loss. Inoperability measures the percentage reduction relative to the total output of the sector. Economic loss, on the other hand, corresponds to the decrease in the value of economic output due to the productivity disruptions. From the economic loss values computed by the IIM, other loss categories could be derived such as tax loss, income loss, and equivalent number of jobs lost. Sensitivity analysis of inoperability and loss reduction objectives can provide insights on identification and prioritization of critical sectors. Based on the simulated scenarios, the 10 most critically affected sectors (out of 65) account for more than half of the estimated losses. This observation will be particularly useful in informing the regional decision-makers just who will bear the greatest losses.

The simulated scenarios for the example region showed that the majority of the top-10 sectors based on the economic loss metric are typically those that contribute the most to the NCR's gross domestic product (e.g., Federal government enterprises, Miscellaneous professional, scientific, and technical services, Legal services, and State and local general government). In contrast, the majority of the top-10 sectors based on the inoperability metric include combinations of sectors that are involved with health care provision or sectors that are significantly more labor-intensive (e.g., Social assistance, Hospitals and nursing and residential care facilities, Ambulatory health care services). Hence, a careful balance must be sought in prioritizing key sectors as different performance measures may indicate a different set of rankings.

There are several opportunities to improve and build on the workforce-based epidemic model explored in this paper. Given decision-maker preferences, there exists an opportunity to use preference elicitation methods to guide in the prioritization of the key sectors. Although applied specifically to the NCR region, the same methodology can be implemented in other regions. The methodology and decision analysis tool developed in this paper can be integrated with other disaster models. Currently available models typically lack explicit inclusion of societal factors and behavioral changes in response to an outbreak, which are critical to the evolution of an epidemic⁽⁶²⁾. Therefore, future modeling concepts

could be extended through the application of diverse approaches, including risk theories, human capital approaches, and macro-economic modeling ⁽⁶³⁾.

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Figure 1. Input-Output Framework for Assessing Epidemic-Induced Workforce Losses

Figure 2. Prioritization with equal weights for economic loss and inoperability objectives

Figure 3. Influenza positive tests reported to CDC⁽⁴⁸⁾

S56	Social assistance
S55	Hospitals and nursing and residential care facilities
S54	Ambulatory health care services
S7	Construction
S64	State and local government enterprises
S18	Primary metals
S65	State and local general government
S33	Transit and ground passenger transportation
S42	Securities, commodity contracts, and investments
S36	Warehousing and storage

Figure 4. Top-10 critical sectors ranked according to inoperability

Figure 5. Top-10 critical sectors ranked according to economic losses

Scenario:

Economic Loss Weight	1.0
Prioritization Scope	20

A weight of 1 to economic loss means inoperability is ignored.

Prioritization scope selects the sectors based on economic loss metric alone, and hence the threshold is shown as a vertical line.

Figure 6. Prioritization with maximum weight to economic loss

Figure 7. Prioritization with maximum weight to inoperability

Sector Classification

Table I

Sector	Description
S1	Farms
S2	Forestry, fishing, and related activities
S3	Oil and gas extraction
S4	Mining, except oil and gas
S5	Support activities for mining
S6	Utilities
S7	Construction
S8	Wood products
S9	Nonmetallic mineral products
S10	Primary metals
S11	Fabricated metal products
S12	Machinery
S13	Computer and electronic products
S14	Electrical equipment, appliances, and components
S15	Motor vehicles, bodies and trailers, and parts
S16	Other transportation equipment
S17	Furniture and related products
S18	Miscellaneous manufacturing
S19	Food and beverage and tobacco products
S20	Textile mills and textile product mills
S21	Apparel and leather and allied products
S22	Paper products
S23	Printing and related support activities
S24	Petroleum and coal products
S25	Chemical products
S26	Plastics and rubber products
S27	Wholesale trade
S28	Retail trade
S29	Air transportation
S30	Rail transportation
S31	Water transportation
S32	Truck transportation
S33	Transit and ground passenger transportation
S34	Pipeline transportation
S35	Other transportation and support activities
S36	Warehousing and storage
S37	Publishing industries (includes software)
S38	Motion picture and sound recording industries
S39	Broadcasting and telecommunications

Sector	Description
S40	Information and data processing services
S41	Federal Reserve banks, credit intermediation, and related activities
S42	Securities, commodity contracts, and investments
S43	Insurance carriers and related activities
S44	Funds, trusts, and other financial vehicles
S45	Real estate
S46	Rental and leasing services and lessors of intangible assets
S47	Legal services
S48	Computer systems design and related services
S49	Miscellaneous professional, scientific, and technical services
S50	Management of companies and enterprises
S51	Administrative and support services
S52	Waste management and remediation services
S53	Educational services
S54	Ambulatory health care services
S55	Hospitals and nursing and residential care facilities
S56	Social assistance
S57	Performing arts, spectator sports, museums, and related activities
S58	Amusements, gambling, and recreation industries
S59	Accommodation
S60	Food services and drinking places
S61	Other services, except government
S62	Federal general government
S63	Federal government enterprises
S64	State and local general government
S65	State and local government enterprises

Source: Bureau of Economic Analysis