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Evaluating the consequences of an inland waterway port closure with a dynamic multiregional interdependence model

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Evaluating the Consequences of an Inland Waterway Port Closure With a Dynamic Multiregional Interdependence Model

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***Abstract*—As intermodal hubs connecting barge, train, and truck transportation modes, inland ports play an important role in U.S. and global commerce. Like coastal ports, inland ports face the risk of malevolent attacks, man-made accidents, and natural disasters. However, most port impact studies focus on the consequences of one of these disruptive events suddenly closing a coastal port. This paper examines the economic impact of suddenly closing an inland port by combining a simulation and a multiregional input–output model. The simulation models how companies may react if an inland waterway port suddenly closes, and the multiregional dynamic inoperability input–output model quantifies the interdependent effects of these decisions. We deploy this simulation and model on a case study involving an Oklahoma port on the Arkansas River. The case study indicates that, if a financial penalty is imposed on companies for delivering their commodities late, companies will move their products by train rather than wait for the port to reopen. These decisions save billions of dollars in production losses for the states that use the port. We discuss the implications of these results for policymakers concerned about limiting the consequences of port closures.**

***Index Terms*—Economic interdependence, input–output model, port security, simulation.**

I. Introduction

INLAND waterway ports play an important role in the U.S. economy. These ports serve as hubs that connect components of multimodal transportation systems, including barge, train, and truck transportation modes. Approximately one billion tons of cargo or 40% of U.S. waterway commerce traverses through inland ports [1]. Ninety percent of this cargo consists of coal and petroleum products and crude materials, all of which are important commodities for U.S. manufacturing and production. Disruptive events, such as malevolent attacks, man-made accidents, and natural disasters, that close or reduce the operations of an inland port could significantly impact the flow of commodities and hamper production in the U.S. Because waterway ports are key nodes within the transportation network and because of their closeness to metropolitan areas, a disruptive event at a port could create considerable reverberations throughout the economy [2].

Vulnerabilities that coastal ports face have been extensively studied in the risk analysis literature [3], [4], but relatively little attention has been paid to inland ports. If a seaport is closed, it is usually assumed that commodities will remain on ships until the port reopens [5]–[7]. Regardless of whether this assumption is valid for coastal ports [8], commodities scheduled to be transported through an inland port could be rerouted, such as through a different port or via truck or rail. A realistic model of an inland port closure should include and account for the possibility of these alternate modes [9].

If highway disruptions occur, companies will find alternate routes to deliver their products [10]–[12]. Rerouting cargo from a closed inland port is more difficult than finding an alternate road route if part of a highway is closed, although the likely availability of rail and truck alternatives makes finding an alternate shipping mode more plausible than if a coastal port closes. Companies that planned to use a suddenly closed inland port may seek alternate modes of transportation such as rail or truck to move their products, but they may also let their product remain on a barge or at a port until the port reopens. This paper uses simulation to model the complex decision-making process of companies in such a situation. Companies typically seek to minimize total transportation cost while satisfying service-level requirements, such as on-time shipping [13]. By incorporating these types of cost–benefit analyses into a simulation, we anticipate a company's decision in the face of uncertainty in when the port may reopen.

Although companies likely make decisions without considering how those decisions impact other industries, such decisions carry interdependent ramifications for the economy. We deploy the dynamic inoperability input–output model (DIIM) [14] to model how commodities that fail to reach their destination lead to greater economic losses in the region. Based on Leontief's economic input–output (I–O) framework [15]–[17], the DIIM measures how inoperability in a few industries reverberates into production losses in many industries and subsequently dissipates over time. The DIIM has been proposed as a tool to help decision makers choose among competing risk management strategies [14], [18] such as maintaining inventory to protect against supply chain disruptions [19]. We integrate the DIIM with the multiregional inoperability input–output model (IIM) [20] to evaluate the impacts of an inland port closure across different regions.

I–O models have been deployed extensively in evaluating the consequences of closing seaports, particularly the twin ports of Los Angeles–Long Beach. Jung *et al.* [5] combine the IIM with gross domestic product to estimate that the impact of not being

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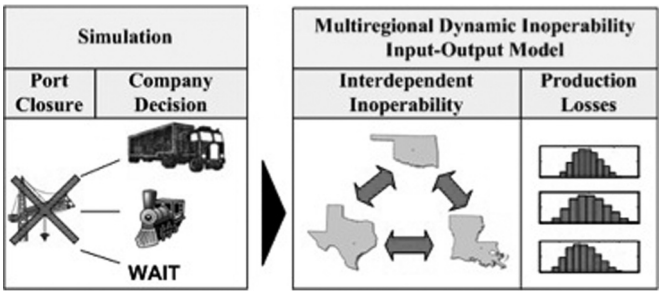

Fig. 1. Depiction of simulation and interdependence model.

able to import or export through those two California ports for ten days would result in \$7.7–13 billion of production losses. A different I–O model [6] separately calculates losses from imports (supply disruption) and exports (demand disruption) due to a 30-day shutdown of the ports. Supply shortages would lead to \$27 billion in lost production, and reduced demand would lead to \$9 billion in losses. Gordon *et al.* [7] incorporate a model of the Los Angeles area transportation network into a regional I–O model to analyze the consequences of a bomb attack that closes the ports and destroys key bridges connecting the ports. The business interruption and employment losses resulting from a four-month closure would lead to \$34 billion in losses.

Although this paper also uses an I–O model, our approach differs because the simulation determines whether a company decides to let its product remain at the port or chooses an alternate mode of transportation. Stochastic simulation can generate a wide range of production losses, and key parameters can be changed to reflect different situations.

This type of system modeling creates a new framework for evaluating the consequences of closing an inland port (Fig. 1). Explicitly modeling company behavior provides valuable insight into what might occur if an inland port closes. Companies that depend on ports to transport their products can understand how operations might be impacted by a port closure and how their decisions will affect the region's economy. Combining the simulation with the multiregional I–O model can serve as a useful planning tool for port officials and policymakers who are concerned about the security and safety of inland ports. The insights gained from this paper can lead to better risk management strategies to mitigate the effect of inland port closures.

The remainder of this paper is as follows. Section II explains the simulation of closing an inland port and company responses. Section III demonstrates how the results of the simulation are incorporated into the multiregional DIIM to measure the economic impact of closing the port. In Section IV, we deploy this simulation and model on a case study involving an Oklahoma port on the Arkansas River. In order to derive realistic results, we rely on several publicly available databases to estimate a shipment schedule for this port.

II. Simulation of Port Closure Decision

We create an agent-based simulation to model the reactions of companies following a disruptive event that temporarily

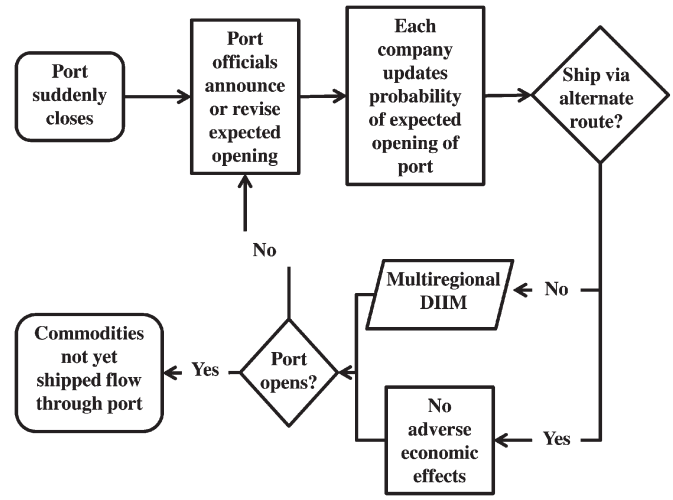

Fig. 2. Flowchart of the simulation of inland port closure.

closes an inland waterway port. Each company that had planned to move its product through the port acts as individual in the simulation. Fig. 2 shows the simulation of the inland port closure and subsequent decision process. Each step is explained in detail subsequently.

First, an unexpected event closes an inland waterway port at time $t = 0$, and port officials initially estimate that the port will reopen in $\tilde{D}_0$ days. The variable t represents the number of days that the port has been closed, and $\tilde{D}_t$ represents the officials' estimate of the number of remaining days that the port will be closed. The subscript t refers to the estimated days remaining being announced on day t. At the beginning of each day that the port is closed, port officials reevaluate their estimate based on the previous day's estimate. We assume that the actual (unknown) number of remaining days that the port will be closed is never overestimated, but it may be underestimated. Each day, there is a θ probability that officials will revise their estimate by one day, as in

$$\tilde{D}_t = \begin{cases} \tilde{D}_{t-1} & \text{with probability } \theta \\ \tilde{D}_{t-1} - 1 & \text{with probability } 1-\theta. \end{cases} \tag{1}$$

If the estimate is not revised, the number of days until officials expect to open the port decreases by one from day $\tilde{D}_{t-1}$ to day $\tilde{D}_t$. Assuming that port officials can only revise the estimate by at most one day enables the companies to use this estimate to assess when they believe the port will reopen.

Each of the M companies that normally use the port relies on the public information about the port's opening to assess when the port will actually open. We model that process by assuming that each company follows a Bayesian updating rule to incorporate the official announcement into its own belief about when the port will open. In the simulation, the companies hear port officials announce $\tilde{D}_t$ but do not know θ. Each company has a prior probability that the opening of the port will be delayed by $\lambda = 0, 1, 2, \ldots, \lambda^*$ days beyond the official announcement of $\tilde{D}_t$ days, where λ^* is the maximum number of days the port's opening will be delayed. Because each company begins with a different prior distribution on λ, the companies'

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beliefs about when the port will open differ throughout the simulation.

For each day that the port is closed, a company updates its probability distribution $P(\lambda)$ after hearing whether port officials have decided to revise $\tilde{D}_t$. If a company believes the port's opening will be delayed λ days, the company calculates that the port will be closed for $\lambda + \tilde{D}_{t-1}$ days, where $\tilde{D}_{t-1}$ is the official announcement from the previous day. Day t can be one of the λ times when the port's opening is delayed, and the company's probability or likelihood that a delay will be announced on day t is $P(\tilde{D}_t = \tilde{D}_{t-1}|\lambda) = \lambda/(\lambda + \tilde{D}_{t-1})$. Or, day t can be one of the $\tilde{D}_{t-1}$ times when there is no delay, and the probability that no delay will be announced is $P(\tilde{D}_t = \tilde{D}_{t-1} - 1|\lambda) = \tilde{D}_{t-1}/(\lambda + \tilde{D}_{t-1})$. Because λ follows a probability distribution rather than a single number, the following equation shows how Bayes' rule can be used to calculate the posterior probability on λ given the official announcement on day t:

$$P(\lambda|\tilde{D}_t) \propto \begin{cases} \frac{\lambda+1}{\lambda+1+\tilde{D}_{t-1}} * P(\lambda+1) & \text{if } \tilde{D}_t = \tilde{D}_{t-1} \\ \frac{\tilde{D}_{t-1}}{\lambda+\tilde{D}_{t-1}} * P(\lambda) & \text{if } \tilde{D}_t = \tilde{D}_{t-1} - 1. \end{cases} \tag{2}$$

As stated earlier, λ represents the number of additional days beyond $\tilde{D}_t$ that a company believes the port will be closed. If port officials delay the port's opening, the number of additional delays decreases by one, which explains why the prior of $P(\lambda + 1)$ translates to the posterior of $P(\lambda)$. Also, the posterior on λ on day t becomes the company's prior on day $t + 1$.

After updating its beliefs on how long the port will be closed, a company must decide whether it should choose to use an alternate mode to transport its product or wait for the port to open. It is assumed that the company makes decisions about freight that is scheduled to move through the port on the current day. It does not make any decisions about freight that is scheduled to ship in the future, but it can reexamine previous decisions where product was allowed to wait at the port.

Companies transporting product can have several objectives, and the decision may necessitate them making tradeoffs among these different, potentially competing, objectives [21]. The simulation considers three factors: a company's transportation cost, a penalty cost for waiting for the port to open, and the company's desire to deliver its product on time. Each company has a cost for using the port C_{port} and a cost for moving product via an alternate mode C_{alt}. The realistic assumption that $C_{\text{alt}} > C_{\text{port}}$ is made such that the company will opt to transport its freight via the port if open.

The company may also need to pay a penalty cost if it decides to let its product sit at the port until the port reopens. This penalty cost could be imposed by the customer for a late delivery or could represent the perishability of the company's products. For example, Walmart recently imposed a 3% penalty if its suppliers were more than four days late [22]. Other suggestions for penalties include a 3% penalty for the first week and a 10% penalty for each additional week the shipment is late [23] and a per-unit-time penalty [24]. In the simulation, the penalty cost is a function of the number of days until the port opens: $C(D_t)$, where D_t is the unknown number of days until the port reopens if the port has been closed for t days.

The company also desires to deliver its product on time to its customer regardless of whether it has to pay a penalty cost. This desire is represented by β, which is a fraction of the cost of shipping that a company is willing to pay to be on time. If an alternate mode (e.g., rail) will deliver the product on time, a company will choose the alternate mode if (3) holds: the cost of using the alternate mode accounting for the company's desire to be on time is at most the cost of shipping through the port plus the expected penalty cost, where $\lambda + \tilde{D}_t$ represents the company's estimated number of days until the port opens

$$C_{\text{alt}} * (1 - \beta) \leq C_{\text{port}} + \sum_{\lambda=0}^{\lambda^*} C(\lambda + \tilde{D}_t) * P(\lambda). \tag{3}$$

Each company makes this decision for the days when it was scheduled to use the port, and all of these parameters can vary for each shipping company.

This simulation runs until the port reopens, i.e., when $\tilde{D}_t = 0$. When the port reopens, it can take several days to ship the product that was waiting at the port.

III. Model of Interdependent Impacts of Closure Decisions

The simulation model provides a measure of the time the port was closed and the contingency shipping decisions made by each company. From these measures, a picture of inoperability, or the extent to which production is not occurring as a result of a disruptive event, emerges. If product is shipped via an alternate mode, it is assumed that the product reaches its customer (i.e., another industry for intermediate production), and there are no adverse economic effects. However, if a company decides to wait for the port to open, the product that sits at the port leads to inoperability that is experienced in other interdependent industries. We use a multiregional extension of the DIIM to calculate the interdependent inoperability and economic impacts.

A. Foundations of the IIM

The IIM and its extensions are based on Leontief's I–O model which describes the interdependent nature of commodity flows among the various industries or sectors of the economy within a national or regional economy [15]–[17]. Equation (4) describes the total output $\mathbf{x}$ of goods and services as a function of intermediate production $\mathbf{Ax}$ used by other industries and sectors and final consumer demand $\mathbf{c}$, all in dollars. For an economy with n sectors, $\mathbf{x}$ and $\mathbf{c}$ are vectors of length n that represent economic production and final demand, respectively, for each economic sector. The $n \times n$ matrix $\mathbf{A}$ describes the interdependence of these sectors: for every dollar that sector j produces, it requires a_{ij} dollars of sector i's production

$$\mathbf{x} = \mathbf{Ax} + \mathbf{c} \Rightarrow \mathbf{x} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{c}. \tag{4}$$

The Bureau of Economic Analysis collects and publishes I–O commodity flow data for the U.S. [25]. Miller and Blair [26] provide a good overview of I–O economics.

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The IIM is a risk-based extension to the I–O model that describes the interdependent effects of inoperability [27], [28]. The inoperability of economic sector i is defined as $q_i = (x_i - \tilde{x}_i)/x_i$, where x_i is the production of sector i under normal circumstances and $\tilde{x}_i$ is the reduced level of production of sector i due to a disruptive event. The perturbation in demand of economic sector i caused by a disruption is defined as $c_i^* = (c_i - \tilde{c}_i)/x_i$, where c_i is the final demand for sector i under normal circumstances and $\tilde{c}_i$ is the reduced demand. The inoperability interdependence matrix $\mathbf{A}^*$ is derived from the economic interdependence matrix $\mathbf{A}$, with $\mathbf{A}^* = [\mathrm{diag}(\mathbf{x})]^{-1}\mathbf{A}[\mathrm{diag}(\mathbf{x})]$. The IIM equilibrium equation is found in the following, where $\mathbf{q}$ and $\mathbf{c}^*$ are vectors of length n that represent economic inoperability and perturbation in final demand, respectively:

$$\mathbf{q} = \mathbf{A}^*\mathbf{x} + \mathbf{c}^* \Rightarrow \mathbf{q} = [\mathbf{I} - \mathbf{A}^*]^{-1}\mathbf{c}^*. \tag{5}$$

The DIIM is a dynamic extension of the IIM which models the change in inoperability from time t to time $t+1$ [14]. The DIIM is shown in the following equation, where $\mathbf{K}$ is an $n \times n$ diagonal matrix:

$$\mathbf{q}(t+1) = (\mathbf{I} - \mathbf{K})\mathbf{q}(t) + \mathbf{K}\left[\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t)\right]. \tag{6}$$

Although the ith diagonal element of $\mathbf{K}$ usually represents the capability of economic sector i to return to full operability [14], we suggest an alternative interpretation where $\mathbf{K}$ describes how quickly the economy reaches equilibrium as determined by (5). If $\mathbf{K} = \mathbf{I}$, each economic sector adjusts its production in a single time period to reflect perfectly changes in both intermediate and final demands. At the other extreme, if $\mathbf{K} = \mathbf{0}$, the economy will never reach equilibrium, and $\mathbf{q}(t+1) = \mathbf{q}(t)$.

The IIM and it extensions have been used to study a number of risk-based applications, including terrorist attacks [29], cyber security [30], and workforce disruptions [31], [32], among many others.

B. Building a Multiregional DIIM

The multiregional IIM [19] provides a framework to analyze the inoperability and economic impacts in each of several regions that might be affected by a disruptive event, accounting for cross-regional interdependences. Each state or region has its own interdependence matrix, which ideally should be derived based on surveys of regional industries [33]. Because these surveys are costly, economists often use location quotients which measure how regional production, consumption, or wages compare to those at the national level for a given economic sector (see [26] for several examples of location quotients). We calculate the location quotient l_i^r for sector i in region r in the following equation, where x_i^r is sector i's production in region r, x^r is the total economic production in region r, and x is the national economic production:

$$l_i^r = \frac{x_i^r/x^r}{x_i/x}. \tag{7}$$

The location quotients are used to derive a regional interdependence matrix $\mathbf{A}^r$ from the national interdependence matrix $\mathbf{A}$, as shown in the following [27]:

$$a_{ij}^r = \begin{cases} l_i^r a_{ij} & \text{if } l_i^r < 1 \\ a_{ij} & \text{if } l_i^r \geq 1. \end{cases} \tag{8}$$

The regional interdependence matrix and production can be used in the Leontief I–O model in (4), the IIM in (5), and the DIIM in (6) to analyze the inoperability and economic effects in a given region or state.

Knowledge about the extent to which one region trades with another region enables the estimation of the economic impact in one region due to a loss in production or demand in another region. Let T_i^{rs} be the proportion of commodity i consumed by region s that originated from sector i in region r.[1] This proportion is equal to z_j^{rs}/y_i^s, where z_j^{rs} is the dollar value of sector i's commodities sent from region r to region s and y_i^s is the total amount of commodity i consumed in region s [34]. These numbers can be calculated for each state in the U.S. using the Commodity Flow Survey published by the Bureau of Transportation Statistics [35].

After creating these proportions for every economic sector and every region under consideration, we create the interregional matrix $\mathbf{T}$, shown in the following equation, where $\mathbf{T}^{rs}$ is an $n \times n$ diagonal matrix composed of the proportion of a commodity consumed by region s that is produced in region r and p is the total number of regions:

$$\mathbf{T} = \begin{pmatrix} \mathbf{T}^{11} & \mathbf{T}^{12} & \cdots & \mathbf{T}^{1p} \\ \mathbf{T}^{21} & \mathbf{T}^{22} & \cdots & \mathbf{T}^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{T}^{p1} & \mathbf{T}^{p2} & \cdots & \mathbf{T}^{pp} \end{pmatrix}. \tag{9}$$

Extending this interregional matrix to the IIM in (5), the multiregional IIM is found in the following [20]:

$$\begin{pmatrix} \mathbf{q}^1 \\ \mathbf{q}^2 \\ \vdots \\ \mathbf{q}^p \end{pmatrix} = \mathbf{T}^* \begin{pmatrix} \mathbf{A}^{*1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{*2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^{*p} \end{pmatrix} \begin{pmatrix} \mathbf{q}^1 \\ \mathbf{q}^2 \\ \vdots \\ \mathbf{q}^p \end{pmatrix} + \mathbf{T}^* \begin{pmatrix} \mathbf{c}^{*1} \\ \mathbf{c}^{*2} \\ \vdots \\ \mathbf{c}^{*p} \end{pmatrix} \tag{10}$$

where

$\mathbf{q}^r$ a vector of length n of inoperability in region r;
$\mathbf{T}^*$ $= [\mathrm{diag}(\mathbf{x}^1, \mathbf{x}^2, \cdots, \mathbf{x}^p)]^{-1}\mathbf{T}[\mathrm{diag}(\mathbf{x}^1, \mathbf{x}^2, \cdots, \mathbf{x}^p)]$;
$\mathbf{x}^r$ a vector of length n of production in region r;
$\mathbf{A}^{*r}$ $= [\mathrm{diag}(\mathbf{x}^r)]^{-1}\mathbf{A}^r[\mathrm{diag}(\mathbf{x}^r)]$ is region r's inoperability interdependence matrix;
$\mathbf{A}^r$ regional interdependence matrix described in (8);
$\mathbf{c}^{*r}$ a vector of length n of final demand perturbation in region r.

[1]Commodities follow the same classification as economic sectors. If sector i produces more than one commodity (which is usually the case), we group all of these commodities together and call them commodity i in this paper.

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This multiregional formulation can also be applied to the DIIM [36], as shown in (11), where $\tilde{\mathbf{K}}$ is an $np \times np$ diagonal matrix and $\tilde{k}_{ii}^r$ represents how quickly sector i in region r reaches equilibrium. The multiregional DIIM allows us to measure the inoperability of sectors over time and across multiple regions

$$\begin{pmatrix} \mathbf{q}^1(t+1) \\ \mathbf{q}^2(t+1) \\ \vdots \\ \mathbf{q}^p(t+1) \end{pmatrix} = (\mathbf{I} - \tilde{\mathbf{K}}) \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} + \tilde{\mathbf{K}}\mathbf{T}^* \left[\begin{pmatrix} \mathbf{A}^{*1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{*2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^{*p} \end{pmatrix} \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} + \begin{pmatrix} \mathbf{c}^{*1}(t) \\ \mathbf{c}^{*2}(t) \\ \vdots \\ \mathbf{c}^{*p}(t) \end{pmatrix} \right]. \tag{11}$$

C. Incorporating Simulation Results into the Multiregional DIIM

In the case of a port closure, the economic impacts in each state are due to industries not being able to import or export commodities out of their regions [5]. Exports are categorized as final demand in the I–O model [37], and a company that cannot export part of its product will see a loss in demand. Mathematically, the loss in demand for a company in sector i that is unable to export e_i^r dollars of commodities from region r is given by

$$c_i^{*r} = \frac{e_i^r}{x_i^r}. \tag{12}$$

Customers in region r expecting to receive commodities could become inoperable if they do not receive their expected supplies. In order to analyze the reduced production because of supply shortages, we assume a production function where sector i's production in region r is determined by the minimization problem in (13), where z_{ji}^r is the total dollar value of sector j's production consumed by sector i in region r [38]

$$\min \left(\frac{z_{1i}^r}{a_{1i}^r}, \cdots, \frac{z_{ji}^r}{a_{ji}^r}, \cdots, \frac{z_{ni}^r}{a_{ni}^r} \right). \tag{13}$$

Because $a_{ji}^r = z_{ji}^r / x_i^r$ for all j, sector i produces x_i^r, as described by the Leontief I–O model under normal operations.

If region r is unable to import m_j^r dollars of commodity j, all of the region's sectors that use sector j's production will suffer supply shortages. The proportion of sector j's production that is used by sector i is z_{ji}^r / x_j^r. Assuming that imports are distributed according to that same proportion, the reduced amount of sector i's inputs to sector j is given by

$$\tilde{z}_{ji}^r = \left(x_j^r - m_j^r \right) \frac{z_{ji}^r}{x_j^r}. \tag{14}$$

Replacing z_{ji}^r with $\tilde{z}_{ji}^r$ in (13), the following equation provides the inoperability of sector i due to supply shortages from sector j

$$\tilde{q}_i^r = 1 - \frac{\tilde{x}_i^r}{x_i^r} = 1 - \left(\frac{1}{x_i^r} \right) \frac{\tilde{z}_{ji}^r}{a_{ji}^r} = \frac{m_j^r}{x_j^r}. \tag{15}$$

If commodities from multiple sectors are not imported into region r, sector i's inoperability is governed by $\tilde{z}_{ji}^r$ that minimizes (13) or equivalently by the m_j^r that maximizes

$$\tilde{q}_i^r = \max \left(\frac{m_1^r}{x_1^r}, \cdots, \frac{m_j^r}{x_j^r}, \cdots, \frac{m_n^r}{x_n^r} \right). \tag{16}$$

If sector i does not use any production from sector h, i.e., if $a_{hi}^r = 0$, the corresponding term m_h^r / x_h^r is excluded from (16).

For every day that the port is closed, the simulation returns $\mathbf{m}^r(t)$ and $\mathbf{e}^r(t)$, which are vectors of length n representing imports not shipped into region r and exports not shipped from region r on day t. We use (12) to calculate $\mathbf{c}^{*r}(t)$ from $\mathbf{e}^r(t)$ and (16) to calculate the $n \times 1$ vector $\tilde{\mathbf{q}}^r(t)$ from $\mathbf{m}^r(t)$, where sector i's daily production $x_i^r(t)$ is used instead of x_i^r. Daily production is estimated by dividing the annual production by 365.

The multiregional DIIM calculates inoperability as given in (11), where we replace $\mathbf{q}^r(t)$ on the right hand side of the equation with $\hat{\mathbf{q}}^r(t)$ as defined in

$$\hat{q}_i^r(t) = \max \left\{ \tilde{q}_i^r(t), q_i^r(t) \right\}. \tag{17}$$

If the multiregional DIIM has already forced sector i in region r to reduce its production as reflected in $q_i^r(t)$, the sector does not need as many inputs and might not be impacted by a supply shortage.

When the port opens, we assume that supply shortages are resolved so that $\tilde{\mathbf{q}}^r(t) = \mathbf{0}$ and $\hat{\mathbf{q}}^r(t) = \mathbf{q}^r(t)$ when t is greater than the length of time that the port was closed. Because the product that was waiting to be moved is shipped when the port opens, demand increases for exporting sectors, and $c_i^{*r}(t) = -e_i^r(t)/x_i^r(t)$, where $e_i^r(t)$ now represents the product that was shipped on day t that had been waiting at the port. Whatever demand was lost while the port is closed is satisfied in the days following the port's reopening, and $\sum_{t=0}^{\tau} c_i^{*r}(t) = 0$, where τ is the day on which the last commodity held over from when the port was closed is shipped.

Production losses across all n sectors in region r at time t are expressed in (18) as a function of the inoperability at time t and expected production in that time period

$$Q^r(t) = [\mathbf{q}^r(t)]^{\mathbf{T}} \mathbf{x}^r(t). \tag{18}$$

The total production loss across the τ prescribed time periods is $Q^r = \sum_{t=0}^{\tau} Q^r(t)$.

Except for a few notable examples [18], [39]–[41], the IIM and its extensions have generally been treated as deterministic models. Combining simulation with the DIIM in a multiregional context not only allows us to incorporate industry actions but also allows us to analyze the impact of uncertainty on key parameters, such as the length of time the port is closed, and its relationship to each region's economic loss.

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TABLE I
ESTIMATED VALUE OF CARGO MOVING THROUGH CATOOSA IN 2007 (IN MILLIONS OF DOLLARS)

		ECONOMIC SECTOR								
		Food, Beverage, and Tobacco Products	Petroleum and Coal Products	Chemical Products	Non-metallic Mineral Products	Primary Metals	Fabricated Metal Products	Machinery	Misc. Manu-facturing	Total
From Oklahoma	Alabama	9								9
	Illinois				3					3
	Kentucky			18						18
	Louisiana	131	49					30		210
	Mississippi			71						71
	Texas		8					78	6	92
To Oklahoma	Alabama					165	38			203
	Arkansas				1					1
	Illinois	1		2						4
	Iowa	2								2
	Louisiana	3	9	131		93	21			257
	Mississippi			2						2
	Ohio					55	12			67
Total		146	66	223	4	313	71	108	6	937

IV. CASE STUDY: PORT OF CATOOSA

We apply this model and simulation to the case study of the Port of Catoosa in Oklahoma on the McClellan-Kerr Arkansas River Navigation System. The Port of Catoosa is a 3000-acre manufacturing and shipping complex that handles two million tons of cargo annually, and it serves as a node for railroad, highway, and waterway. In 2007, over 10 500 rail cars went through the port, and 1000 trucks a day go through the port [42].

We estimate the daily shipping activity at Catoosa using different sources of data. The U.S. Army Corps of Engineers publishes the number of tons of specific commodities that moved through Catoosa in 2007 [43] and the amount of each commodity that was shipped via water between states [44], [45]. The Tulsa Port of Catoosa [46] releases the number of barges and tons of cargo that were shipped through Catoosa in every month of 2007. We estimate the value of each type of cargo using the Commodity Flow Survey [47]. As Table I shows, we calculate that $937 million worth of cargo moved through Catoosa in 2007, with chemical products and primary metals representing the largest economic sectors in terms of dollar values.

We combine these data sources to estimate the day and number of tons that each commodity is shipped through Catoosa. Although a single shipment could fill as many as 15 barges [48], most shipments probably fill no more than six barges [49]. Each barge can carry approximately 1500 tons. After ensuring that no shipment is greater than six barges or 9000 tons, we assign each shipment to a specific day through a combination of randomly picking the day and trying to ensure that each day in a single month has the same number of shipments.

We estimate the distance that each product is shipped. For each of the nine states that use Catoosa, in addition to Oklahoma, we assume that the product is being shipped either to or from the state's busiest port in the Mississippi River Basin. For example, the product shipped from Oklahoma to Mississippi leaves Catoosa and arrives at the Port of Vicksburg. We calculate the distance in miles D_{uv} that goods travel from port u to port v through the following equation, where lon and lat represent the longitude and latitude of either port u or port v [13]:

$$D_{uv} = 69\sqrt{(lon_u - lon_v)^2 + (lat_u - lat_v)^2}. \tag{19}$$

We also assume a one-to-one correspondence between a sector's commodities shipped from one state to another state and the company. Table I contains 24 nonzero elements, and each element corresponds to a company in the simulation. Increasing and decreasing the number of companies shipping each commodity do not significantly change the results of the simulation.

When the Port of Catoosa is closed, a company can transport its product by truck or rail or attempt to divert its product to a different waterway port. For the simulation, we assume that the alternate route considered by each company is railroad because rail is a cheaper alternative to truck, and it is difficult to know whether diverting product to a different port is feasible. The cost of transporting product via rail is 2.53 cents per ton-mile compared with 0.97 cents per ton-mile for waterway transportation [48]. We assume that there are no capacity constraints on the train, and a train will always be available for a company if it chooses to transport its product via rail.

Other assumptions in the case study include a linear penalty cost where a company is fined a percentage of the value of the shipment for each day that the product is late and that each company is willing to pay 10% of the cost of shipping to deliver product on time (i.e., $\beta = 0.1$). We use BEA data from 2007 and run the model with 62 sectors for each of the ten

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TABLE II
VALUE OF PRODUCT NOT SHIPPED WITH NO PENALTY (IN MILLIONS OF DOLLARS)

Industry	Mean	Standard Deviation
Food, Beverage, and Tobacco Products	17.1	7.4
Petroleum and Coal Products	7.8	3.5
Chemical Products	26.2	10.4
Nonmetallic Mineral Products	0.5	0.4
Primary Metals	36.5	13.6
Fabricated Metal Products	8.2	4.0
Machinery	12.7	13.7
Misc. Manufacturing	0.7	2.0
Total	109.8	36.0

TABLE III
PRODUCTION LOSSES WITH NO PENALTY (IN MILLIONS OF DOLLARS)

State	Mean	Standard Deviation
Alabama	68	31
Arkansas	61	28
Illinois	116	70
Iowa	32	14
Kentucky	60	32
Louisiana	798	391
Mississippi	277	135
Ohio	132	60
Oklahoma	2 993	1 449
Texas	525	277
Total	5 061	2 206

states. Our simulations assume $\tilde{\mathbf{K}} = 0.5 * \mathbf{I}$, which means that a sector's inoperability at time $t+1$ is the average of its own inoperability at time t and the interdependent effects of other sectors' inoperability at time t.

A. No Penalty

We ran 1500 simulations of the Port of Catoosa being closed for one to two months (for our data and model, 1500 simulations produce margins of error of less than 8% of the sample mean for a 95% confidence interval). If companies are not penalized for late delivery, they have no incentive to transport their products via train. In these simulations, all commodities sit at the port until it opens. The simulations reveal that an average of $110 million worth of product is not shipped while the port is closed, as shown in Table II.

In Table III, the multiregional DIIM shows that this $110 million of unshipped product becomes $5.1 billion worth of lost production on average for the ten states that use Catoosa. With $3.0 billion in lost production, Oklahoma accounts for almost 60% of these losses. The multiregional nature of the model also demonstrates that states with very little trade through Catoosa, such as Illinois and Kentucky, could also suffer significant production losses. The interdependence model translates the initial effects of product not being shipped into production losses of almost 50 times the value of the initial effects.

The distributions of lost production for Oklahoma and the entire region (Fig. 3) both exhibit some positive skewness which indicates that production losses are a little more likely to be less than the mean values reported in Table III. The right tails of these distributions provide some insight into the maximum production loss. There is a 5% chance that production losses in Oklahoma will exceed $5.6 billion and that production losses in all ten states will exceed $8.9 billion.

We examine how specific sectors are impacted by Catoosa closing. Fig. 4 shows the inoperability for all of Oklahoma's and Louisiana's sectors for a single simulation run when the Port of Catoosa is closed for 49 days. Each line represents a single sector's inoperability at each day. Oklahoma's sectors experience greater inoperability than those in Louisiana, and many sectors experience high levels of inoperability even though these sectors do not ship any products through Catoosa.

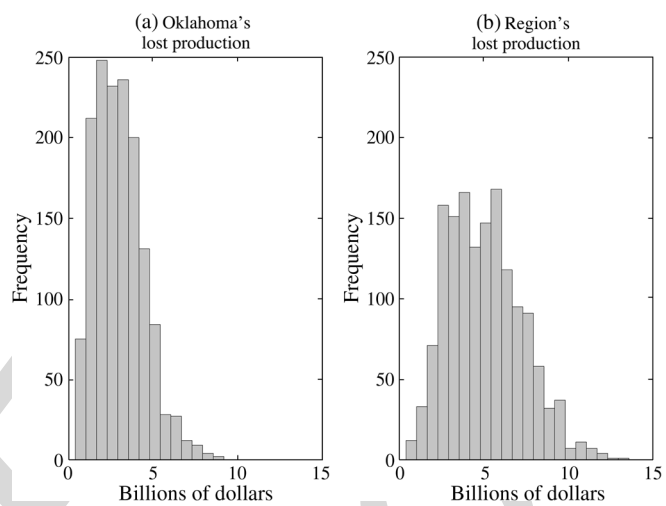

Fig. 3. Distribution of production losses for (a) Oklahoma and (b) all ten states with no penalty. (a) Oklahoma's lost production. (b) Region's lost production.

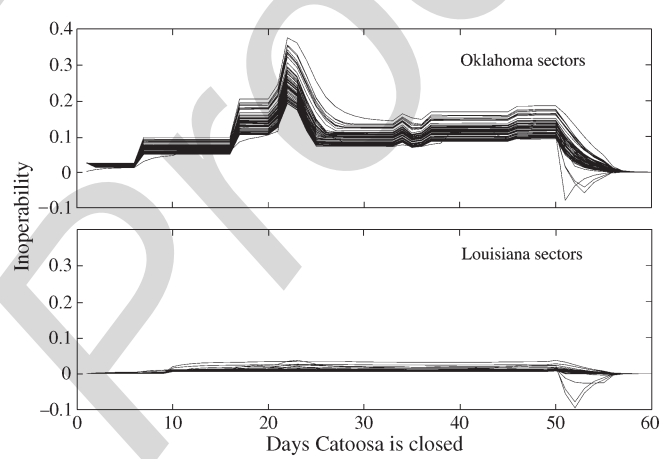

Fig. 4. Inoperability over time for sectors in Oklahoma and Louisiana with no penalty.

The step-like increases in inoperability that occur in Fig. 4 generally indicate that a scheduled shipment was not sent on that day. The inoperability for Oklahoma's sectors is particularly high for days 22 and 23 because the amount of food, beverage, and tobacco products originally scheduled to be

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TABLE IV
VALUE OF PRODUCT NOT SHIPPED WITH 0.2% PENALTY (IN MILLIONS OF DOLLARS)

Industry	Mean	Standard Deviation
Food, Beverage, and Tobacco Products	3.9	2.8
Petroleum and Coal Products	1.1	1.2
Chemical Products	4.3	3.0
Nonmetallic Mineral Products	0.2	0.3
Primary Metals	2.0	2.9
Fabricated Metal Products	0.2	0.9
Machinery	0.0	0.0
Misc. Manufacturing	0.0	0.0
Total	11.8	6.3

TABLE V
PRODUCTION LOSSES WITH 0.2% PENALTY (IN MILLIONS OF DOLLARS)

State	Mean	Standard Deviation
Alabama	7	6
Arkansas	5	4
Illinois	27	36
Iowa	3	2
Kentucky	6	11
Louisiana	137	131
Mississippi	23	34
Ohio	10	36
Oklahoma	218	232
Texas	29	57
Total	465	360

shipped to Oklahoma accounts for a large proportion of this product needed for production in Oklahoma during those two days. When the port opens on day 50 and commodities start flowing through the port, all sectors experience a drop in inoperability, which signifies an increase in production. Several sectors experience negative inoperability, which signifies that these sectors recover a portion of the production they previously had lost.

B. Imposing a Penalty of 0.2%

If the Port of Catoosa were closed for one to two months, it would be very unlikely that companies would allow their product to just sit at the port. Forcing companies to pay a penalty of 0.2% on the value of their shipment for every day that the product is late highly incentivizes companies to transport their product via train. The simulations reveal that, in general, companies facing such a penalty will transport all of their products via train unless they expect the port to reopen in the next week or two.

Table IV provides the results of 1500 simulations, showing that the total value of product not shipped averages $12 million or a little more than 10% of what was not shipped when no penalty existed. Products belonging to high-value industries, such as primary metals, fabricated metal products, machinery, and manufacturing, carry such a heavy penalty so that more than 96% of those commodities are transported by train.

The multiregional DIIM translates the unshipped product to average production losses of $465 million for the ten states combined, shown in Table V. Oklahoma's production loss averages $218 million, although the production loss is quite variable—the coefficient of variation is 1.06. In relative terms, Texas benefits the most from the penalty because most of its trade through Catoosa consists of machinery, which is always transported by train in this simulation. Louisiana, whose trade through Catoosa is mainly food, beverage, and tobacco and chemical products, bears a higher percentage of the total production losses with the penalty than without the penalty.

The distributions of lost production with the 0.2% penalty are much more skewed to the right in Fig. 5 than the distributions without a penalty. Although the most likely outcome with the 0.2% penalty is a few hundred million dollars in lost production, the right tails indicate that losses could be much greater than the mean values.

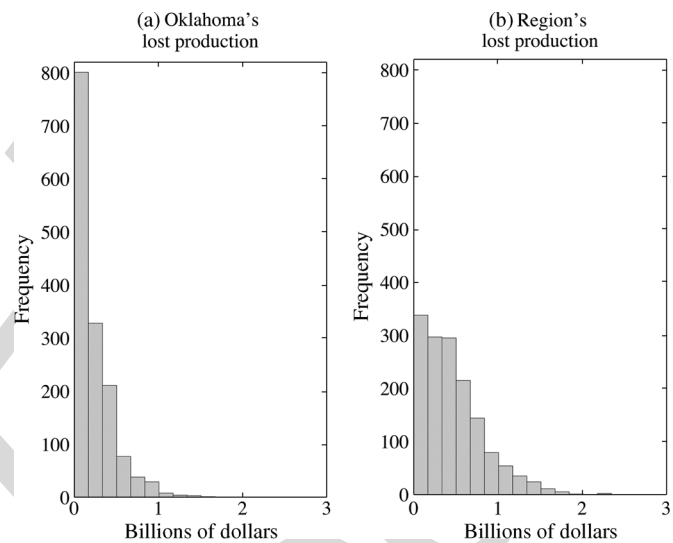

Fig. 5. Distribution of production losses for (a) Oklahoma and (b) all ten states with a 0.2% penalty. (a) Oklahoma's lost production. (b) Region's lost production.

Fig. 6 shows sector-specific inoperability for Oklahoma and Louisiana for the same simulation as in the previous section but with the 0.2 penalty imposed. Sector inoperability, which does not really begin until Catoosa has been closed for more than a month, is less severe and of shorter duration than the inoperability when no penalty was imposed. With the penalty, some of Louisiana's sectors experience higher levels of inoperability than Oklahoma's sectors. In this simulation, Louisiana was scheduled to receive food, beverage, and tobacco and petroleum and coal products, but it is not cost effective for the companies to transport these commodities by train beginning on day 43 (during the first six weeks of the simulation, the companies choose to transport these commodities by train). This causes supply shortages in Louisiana sectors, which are magnified by the interdependences.

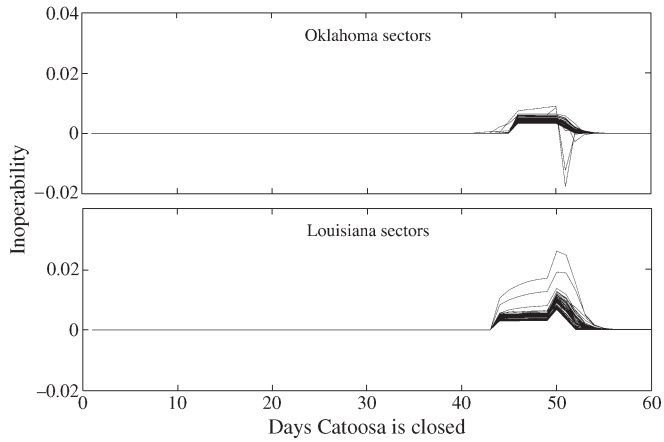

Fig. 6. Inoperability over time for sectors in Oklahoma and Louisiana with a 0.2% penalty.

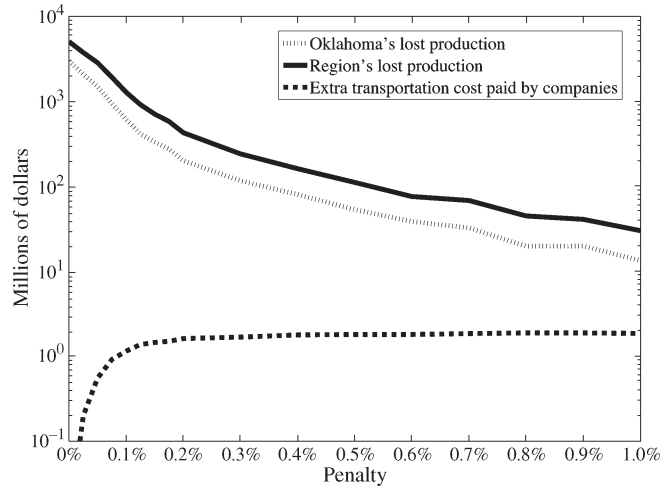

Fig. 7. Average lost production in Oklahoma and the region as a function of the penalty.

C. Varying the Penalty

As the previous discussion implies, results from the simulation and model are highly sensitive to the value of the penalty. Fig. 7 shows the average production lost in Oklahoma and the region when 500 simulations were conducted for each of a range of penalties (the margins of error for these 500 simulations are less than 17% of the sample mean for a 95% confidence interval). The curve at the bottom of Fig. 7 is the additional cost companies pay to transport their commodities by train rather than by barge.

As the penalty increases from 0% to 0.1%, the average lost production decreases from \$5.1 billion to \$1.3 billion for the region and from \$3.0 billion to \$610 million for Oklahoma. The extra transportation cost necessary to achieve these production gains is only \$1.1 million. As the penalty cost rises, the loss in production continues to fall but at a much slower rate. The results from these simulations suggest that it is always economically beneficial for commodities to be moved by train rather than wait for the Port of Catoosa to reopen.

D. Sensitivity Analysis on Other Parameters

In addition to the penalty parameter, we perform sensitivity analysis on the number of days the port is closed and the time of year when the port is closed. In this section, we set the penalty at 0.2% for all simulations. Previous simulations closed Catoosa for one to two months, but now, we explore how the length of time that Catoosa is closed impacts lost production by allowing Catoosa to be closed for 2–140 days. Production losses generally increase as Catoosa is closed for more days, but there is a lot of variability in the amount of production lost. The slope of a best-fine line indicates that production losses in the ten states increase on average by \$5.6 million for each day that the port is closed. However, the R^2 term is only 0.25, and the linear model is not a very good predictor of production losses.

The previous simulations discussed in this paper randomly selected a day in the calendar year for the first day that the Port of Catoosa is closed. By fixing the day when the port is first closed, we can understand how the time of year during which Catoosa is closed impacts production losses for the region. Each chart in Fig. 8 shows production losses for 500 simulation runs when the first day that the port is closed occurs on the first day of a given month. Although the starting date for closing the port is fixed in these simulations, the length of time that the port is closed varies between one and two months.

The Port of Catoosa is busiest during the late winter and early spring months and less busy during the summer months. The largest production losses occur when the port is first closed in January 1, February 1, and March 1, and the average production loss is \$700 million for all ten states. The smallest production losses occur when the port is first closed in June 1 and July 1, and the average production loss is \$150 million for the region. A closure beginning in April 1 exhibits the greatest variability in production losses because April is a very busy month for the port but May is much less busy [46]. Simulating a port closure for a specific month can help policymakers more accurately forecast the consequences if Catoosa suddenly closed in a given month.

V. Conclusion

This paper has demonstrated how integrating simulation with the multiregional DIIM can be deployed to evaluate the consequences of closing an inland port. Deploying the multiregional DIIM to a specific problem such as inland ports enables us to examine inoperability and production losses over several dimensions. First, the IIM model encapsulates the interdependences among industries [27], [28]. Second, the dynamic element of the DIIM creates a framework for examining the change in inoperability over time [14]. As the case study on the Port of Catoosa reveals, inoperability rises quickly when commodities do not reach the customers and falls once commodities flow through the port again. Finally, the multiregional model provides insight into the impacts of a disruptive event on individual states [20]. This paper has combined these elements into one model, and the case study provides a real-world application of examining inoperability across time, different industries, and different states.

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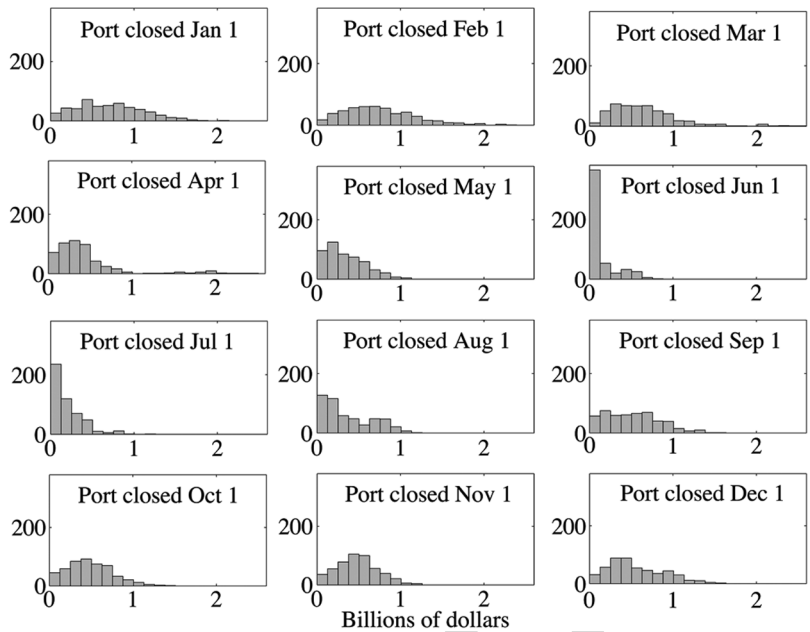

Fig. 8. Distribution of production losses in the ten states when the first day Catoosa is closed occurs at the beginning of each month.

The simulation described in this paper allows us to anticipate how companies might react to disruptions in their supply chains. Explicitly modeling the decision-making processes of companies following a disruptive event represents an improvement on previous transportation and port impact studies. Rather than assuming that companies will always choose alternate modes to ship their products or that companies will let their products sit until the port reopens, we have established some objectives for companies and have modeled the companies as individual agents within the simulation that make decisions based on those objectives and the uncertainties inherent in the situation.

Modeling human behavior increases the realism and accuracy of risk analysis studies, and this paper has applied this principle to a supply chain disruption. Further work needs to be done to model more accurately the behavior of companies moving commodities through a port. We have developed some simple heuristics such as an expected cost of waiting for the port to open based on a company's belief about when the port would open and on parameters to motivate a company to deliver its product on time. While these assumptions seem reasonable, more insight into how a company determines whether to wait or use an alternate mode of transportation would improve the simulation.

Including the effects of price changes would be an additional component to add to the model and simulation. If a supply shortage occurs because products have not been transported through the port, those commodities' prices will likely rise. Also, if companies are paying more to transport their products by train rather than barge, these companies may pass some of the additional costs off to their customers. Rising prices might lead customers to purchase different types of products or industries to substitute other inputs for the constrained supply. Some industries might be able to continue producing, and other industries could benefit from their competitors' higher prices. Computable general equilibrium models [51], [52] have been developed to reflect the impact of fluctuating prices and substitution effects that might be brought about by a port closure.

We have developed a unique method to analyze the effects of a state not being able to import or export specific commodities and have relied on publicly available databases to apply the simulation and model to the Port of Catoosa. Simulation results reveal that closing the port for one to two months could lead to $5.1 billion in lost production if companies allow $110 million worth of product to sit at the port. A penalty parameter incentivizes companies to transport their commodities by train, which limits production losses to $465 million. Although the penalty parameter in the simulation is a fine levied on companies for delivering the product late, this parameter can be interpreted more broadly as a motivating factor for companies to seek alternate transportation routes. When ports do close, companies often make alternative transportation arrangements [8], [50]. Production losses on the order of hundreds of millions of dollars appear more realistic to us than losses in billions of dollars.

These results suggest that it may be economically beneficial for policymakers to explore how they could incentivize companies to move commodities by more expensive transportation modes if a port were suddenly closed. If companies are inclined to wait for the port to open, paying an additional $1–2 million in transportation costs could avoid hundreds of millions of dollars or even billions of dollars in production losses.

Comparing the likely consequences of different types of disruptive events can help homeland security officials prioritize among different types of risks and can serve as a basis for allocating funding to protect against these risks. Although the consequences of closing an inland port the size of Catoosa would be severe, it pales in comparison with a closure of a coastal port the size of Los Angeles–Long Beach, where production losses have been estimated to be about $30 billion

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[6], [7]. Other studies using interdependence modeling have calculated $2–12 billion in production losses from a pandemic in the state of Virginia [32], a $6.5 billion loss from the August 2003 three-day blackout in the Northeast U.S. [53], and a $5 billion loss from flooding the Midtown Tunnel near Hampton Roads, Virginia [54]. Closing the Port of Catoosa for one to two months would result in similar production losses if companies did not transport their cargo by other modes. However, if companies moved their product by train, the production losses would be much less than these other disasters.

The simulation and model presented here have provided a good framework for analyzing the effects of temporarily closing an inland waterway port. Applying this simulation and model to other inland ports is straightforward and would reveal interesting results to understand which inland ports have the greatest impact on the U.S. economy. The basic structure could be applied to coastal ports where an alternate route could be a different coastal port, or it could be modified to study any multimodal response to a disruptive event. Explicitly modeling company decision-making process in the simulation results in realistic scenarios where some companies choose alternate routes and others wait for the port to reopen. Incorporating the results of the simulation into the multiregional DIIM enables us to see how their decisions and actions impact the economic production of an entire region.

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