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INTERDEPENDENT IMPACTS OF DISRUPTION MANAGEMENT: RISK-BASED APPLICATIONS TO PORT CLOSURES, NATURAL DISASTERS, AND OIL SPILLS

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INTERDEPENDENT IMPACTS OF DISRUPTION MANAGEMENT:
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AND OIL SPILLS

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Abstract

Recent disasters such as Hurricane Katrina, the *Deepwater Horizon* oil spill, and the 2011 earthquake and tsunami in Japan disabled production facilities, created supply shortages, disrupted business operations, and altered consumer behavior. Disruptions in one geographic area can disrupt supply chains and production on a local, regional, or global scale. Accurate models of the interdependencies between industries, countries, and regions are crucial in order to analyze and quantify the economic impacts of a disruption.

This dissertation provides multiregional input-output models and real-world simulations to analyze the direct and indirect economic impacts of disruptions on industries, countries, and regions. This research quantifies the impact of industry and government mitigation strategies, such as keeping inventory, buying from alternate suppliers, using alternate modes of transportation, and allocating resources to help industries recover from a disruption. The models incorporate industry decision making to maintain production in response to a disruption, and the optimal alternative is solved as a function of model parameters. Because of these models' complexities, simulations are constructed in which firms and suppliers act as entities that make decisions to achieve their own objectives. By modeling mitigation strategies, business decision making, and consumer behavior, this research provides a realistic and unique analysis of the economic impacts of recent disasters.

Each chapter in this dissertation applies these models and simulations to real-world applications that rely on publicly available data and media stories to estimate parameters. Case studies include the sudden closure of an inland waterway port, the macroeconomic impacts of the Japanese earthquake and tsunami, the disruption in

the automobile sector caused by the Japanese disaster, and the *Deepwater Horizon* oil spill. The numerical results and models presented in this dissertation provide new information and insights to aid policymakers and business leaders to make sound decisions to reduce economic losses caused by future disruptions.

Chapter 1

Introduction and Literature Review

Recent disasters like Hurricane Katrina, the volcanic eruptions of Eyjafjallajökull in Iceland, the *Deepwater Horizon* oil spill, the earthquake and tsunami in Japan, and the floods in Thailand temporarily changed consumer behavior, disabled production facilities, created supply shortages, and disrupted business operations. Businesses in a global environment rely on each other for supplies and serve customers around the world. Consequently, disruptions in one geographic area can disrupt supply chains and production on a local, regional, or global level.

Accurately modeling the interdependencies among industries and between countries or regions is important to analyze and quantify the economic impacts of disruptions, including natural disasters and man-made incidents. Quantifying the economic impacts of a disruption that has already occurred can lend credibility to the modeling process and help differentiate between economic impacts caused by the disruption and other events that may have affected the economy at the same time. Modeling a potential disruption can help policymakers understand the consequences of a disruption and can lead to better decision making to prepare for and respond to the disruption.

Modeling the interdependencies and quantifying the economic impacts of disruptions fall within the domain of risk analysis. Risk analysis traditionally attempts to answer the following three questions (Kaplan and Garrick, 1981):

(i) What can go wrong?

(ii) What are the chances of something going wrong?

(iii) What are the consequences if the undesirable event occurs?

Although this research touches on the first two questions, analyzing the economic and business impacts of disruptions most directly answers the third question, the consequences of disruptions. Consequence analysis can be incorporated with the likelihood of a disruption to encourage better risk management strategies that prevent and mitigate the impacts of these disruptions. This type of analysis can benefit: (i) businesses wanting to protect their supply chains, (ii) local and regional officials responsible for maintaining economic vitality in their cities and regions, and (iii) national leaders who must consider a multitude of risks facing their nations.

The goal of this dissertation is to provide modeling tools that analyze the economic and business impacts of disruptions and to understand how disruptions that directly impact some companies can affect other businesses and industries that are not initially impacted. This research links industries, regions, and countries together through multiregional input-output (I-O) models. Several disruptions are examined, including the sudden closure of an inland waterway port (a local event with regional implications), the Japanese earthquake and tsunami (a natural disaster with international effects), and the *Deepwater Horizon* oil spill (a man-made incident with regional impacts). Modeling the behavior of businesses and consumers during these disruptions increases the realism of economic impact analysis. The models quantify the impact of industry and government mitigation strategies, such as keeping inventory, buying from alternate suppliers, using alternate modes of transportation, and allocating resources to help industries recover from a disruption. This research generates a richer and more nuanced picture of the economic impact of disasters.

The remainder of this introduction reviews some of the literature and modeling approaches to interdependent risks, with a specific focus on I-O models. The introduction concludes by summarizing this dissertation's unique contributions.

1.1 Interdependence in Risk Analysis

Two entities are interdependent if each impacts or influences the performance or functionality of the other entity (Rinaldi et al., 2001). This concept of interdependence plays an important role in risk analysis because a disruptive event that directly impacts infrastructure, business, or the economy can induce partial or even total failure in other systems, markets, and businesses that are not directly impacted by the event. At least three types of interdependencies exist when analyzing risks: interdependence among critical infrastructure, supply chain interdependency, and economic interdependency. A variety of models (see U.S. Department of Energy, 2006; Medal et al., 2011) have been proposed to understand and analyze the linkages among critical infrastructure systems, such as water, energy, information technology, and transportation systems (U.S. Department of Homeland Security, 2009). Network models can quantify the vulnerability, resilience, and interdependence of infrastructure systems (Dueñas-Osorio et al., 2007; Johansson and Hassel, 2010; Johansson et al., 2011). According to network theory, critical infrastructure can be protected most effectively by focusing on the most critical nodes, and about 80% of the available resources should be used to protect 20% of the critical infrastructure (Lewis, 2006). System dynamics models attempt to capture the interdependence between infrastructure and humans who rely on infrastructure during a disruption (Conrad et al., 2006).

Interdependencies within supply chains are another important consideration in risk analysis. A supply chain is a system of people, technology, and processes that deliver a product or service from a supplier to a customer. Analyzing and managing supply chain risk means understanding the nature of modern supply chains. Today's supply chains are more vulnerable in part because of increased interdependence due to outsourcing and the global nature of these supply chains (Christopher, 2005; Jüttner, 2005). A firm who seeks to manage risk in its supply chain often needs to increase visibility into its supply chain by understanding its own suppliers' efforts to control and manage their supply chain (VanderBok et al., 2007; Lynch, 2009). Like critical infrastructure, a supply chain can be modeled as a network in which the nodes and paths are vulnerable to disruptions (Snyder et al., 2006; Song and Zipkin, 2009). Because supply chains are composed of multiple firms, each with different objectives and constraints, using a separate optimization problem to represent each firm's decision can provide insight into the interdependent nature of supply chain risk management decisions (Nagurney, 2006; Hopp et al., 2012). Levy (1994) proposes chaos theory as tool to model industry behavior to decrease the volatility in supply chains. In this dissertation, Chapter 4 focuses on supply chain disruptions.

Economic interdependence, sometimes referred to as impact analysis, serves as useful construct for quantifying and analyzing the consequences of disruptive events (Okuyama and Chang, 2004). Economic interdependence differs from critical infrastructure in a crucial way. Modeling critical infrastructure interdependence attempts to understand the cascading impacts of critical infrastructure failure by analyzing how one element of infrastructure is degraded because a different element has experienced some degree of failure. Modeling economic interdependence in the context of disruptions seeks to quantify production and demand changes that occur because of a disruptive event. Although the disruptive event may directly impact businesses by disabling production facilities and degrading critical infrastructure used by businesses, the indirect impacts analyzed by economic interdependency models are generally not physical disruptions. Businesses produce less because their customers are demanding less or their suppliers are producing less. Economic interdependency models can analyze the consequences of critical infrastructure failure, but the economic models depend on sound engineering models that translate the failure of critical infrastructure networks into direct business interruption losses (Shinozuka and Chang, 2004; Rose and Liao, 2005).

I-O and computable general equilibrium models provide the foundation for analyzing economic interdependence. Derived from the industry relationships described by I-O models, computable general equilibrium models (Shoven and Whalley, 1992) are market-based simulations that incorporate the concurrent optimizing behavior of consumers and firms in order to reach a new equilibrium (Rose and Guha, 2004). Because the research presented in this dissertation relies on I-O models to quantify the economic impacts of disruptions, the next section reviews several I-O models.

1.2 Input-Output Modeling

1.2.1 Leontief model

In the 1930s, Wassily Leontief (1936) proposed an analytical framework for measuring production changes in the economy through a linear, I-O model. Leontief's I-O model (also see Leontief, 1951, 1986) describes the amount of production needed to satisfy a given level of demand where each industry's production is used in the production of other goods and services or is consumed as final demand. Miller and Blair (2009) provide a good overview of I-O economics.

Eq. (1.1) 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 industries, $\mathbf{x}$ and $\mathbf{c}$ are vectors of length n that represent economic production and final demand, respectively, for each economic sector. The technical coefficient square matrix $\mathbf{A}$ of order n describes the interdependence of these sectors: for every dollar that industry j produces, it requires a_{ij} dollars of input from industry i.

$$\mathbf{x} = \mathbf{Ax} + \mathbf{c} \Rightarrow \mathbf{x} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{c} \tag{1.1}$$

The second half of Eq. (1.1) demonstrates how the final demand or consumption vector $\mathbf{c}$ determines total production in the economy.

The technical coefficient matrix $\mathbf{A}$ is calculated as the product of the normalized make matrix $\hat{\mathbf{V}}$ and the normalized use matrix $\hat{\mathbf{U}}$. The use matrix $\mathbf{U}$ is a commodity-by-industry matrix where the m rows represent commodities in the economy and the n columns represent industries. The element u_{ij} describes the dollar amount of commodity i that is used by industry j in its production. The make matrix $\mathbf{V}$ is an $n \times m$ or industry-by-commodity matrix, and v_{ij} describes the dollar amount of commodity j that industry i produces. Each matrix is normalized by its column sums: $\hat{\mathbf{V}} = \mathbf{V}\left[\mathrm{diag}\left(\mathbf{y}\right)\right]^{-1}$ and $\hat{\mathbf{U}} = \mathbf{U}\left[\mathrm{diag}\left(\mathbf{x}\right)\right]^{-1}$, where the vector $\mathbf{y}$ (the column sums of $\mathbf{V}$) represent total commodity output and $\mathbf{x}$ (the column sums of $\mathbf{U}$) is industry output or production. The technical coefficient matrix $\mathbf{A} = \hat{\mathbf{V}}\hat{\mathbf{U}}$ is an industry-by-industry matrix that mathematically relates industry inputs and outputs.

Several countries, including the United States, collects and publishes I-O data. The Bureau of Economic Analysis (BEA) annually publishes use and make matrices for $n = 65$ industries and $m = 65$ commodities (BEA, 2012a) in the U.S. economy and publishes benchmark I-O accounts (including the use, make, and technical coefficient matrices) for over 400 industries every five years (BEA, 2008). The annual I-O data published by the BEA are used in Chapters 2 and 5. Internationally, the Organization of Economic Cooperation and Development (OECD) collects and publishes interindustry transactions matrices (i.e., the product of $\mathbf{A}$ and $\mathbf{x}$), $\mathbf{x}$, and $\mathbf{c}$ in U.S. dollars for each of the 33 OECD member countries and for 11 non-OECD countries in Asia and South America. The most recent data come from the mid-2000s, and each national economy is divided into $n = 37$ industries (OECD, 2011). Chapter 3 relies on this OECD data to analyze the international economic impact of the Japanese earthquake and tsunami.

Table 1.1: Notation for Chapter 1

$\mathbf{A} = \{a_{ij}\}$	Technical coefficient matrix in the Leontief I-O model
$\mathbf{A}^r = \left\{a_{ij}^r\right\}$	Technical coefficient matrix for region r
$\overrightarrow{\mathbf{A}} = \{\overrightarrow{a}_{ij}\}$	Allocation coefficient matrix in the supply side I-O model
$\mathbf{A}^* = \left\{a_{ij}^*\right\}$	Interdependent matrix in the IIM
$\mathbf{A}^{*r}$	Interdependent matrix for region r in the IIM
$\mathbf{c} = \{c_i\}$	Vector of industry final demand
$\mathbf{c}^r$	Vector of industry final demand in region r
$\mathbf{c}^*$	Vector of final demand perturbation
$\mathbf{c}^{*r}$	Vector of final demand perturbation in region r
$\tilde{c}_i$	Degraded final demand for industry i
$\mathbf{K} = \{k_i\}$	Diagonal resilience matrix in the DIIM
$\tilde{\mathbf{K}} = \left\{\tilde{k}_{n(r-1)+i}\right\}$	Diagonal resilience matrix in the multiregional DIIM
l_i^r	Location quotient for industry i in region r
m	Number of commodities in the economy
n	Number of industries or sectors in the economy
p	Number of regions in the multiregional I-O model
$\mathbf{q} = \{q_i\}$	Vector of industry inoperability
$\mathbf{q}^r$	Vector of industry inoperability in region r
$\mathbf{T}$	Interregional matrix
$\mathbf{T}^{rs} = \{t_i^{rs}\}$	Matrix of trade flows from region r to region s
$\mathbf{T}^*$	Interregional matrix in the multiregional IIM
T_i	Recovery time of industry i
t	Time in the DIIM
$\mathbf{U} = \{u_{ij}\}$	Use matrix
$\hat{\mathbf{U}}$	Normalized use matrix
$\mathbf{V} = \{v_{ij}\}$	Make matrix
$\hat{\mathbf{V}}$	Normalized make matrix
x	Total production in the national economy
x^r	Total production in region r
$\tilde{x}_i$	Degraded production for industry i
$\mathbf{x} = \{x_i\}$	Vector of industry production
$\mathbf{x}^r = \{x_i^r\}$	Vector of industry production in region r
$\mathbf{y}$	Vector of commodity output
z_i^{rs}	Commodities in industry i sent from region r to region s
z_i^s	Total amount of commodity i consumed in region s
$\boldsymbol{\nu}$	Vector of industry value added

1.2.2 Multiregional I-O model

A multiregional I-O model (Leontief and Strout, 1963; Isard et al., 1998) quantifies the economic impact of demand or production changes in several states, regions, or nations. Each state or region has its own technical coefficient matrix, which ideally should be derived from surveys of regional industries (BEA, 1997). 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 or industry (see Miller and Blair, 2009, for several examples of location quotients). The location quotient l_i^r for industry i in region r is calculated in Eq. (1.2), where x_i^r is industry i's production in region r, x^r is the total economic production in region r, and x is the national economic production.

$$l_i^r = \frac{x_i^r / x^r}{x_i / x} \tag{1.2}$$

The location quotients are used to derive a regional technical coefficient matrix $\mathbf{A}^r$ from the national technical coefficient matrix $\mathbf{A}$, as shown in Eq. (1.3) (Santos and Haimes, 2004).

$$a_{ij}^r = \begin{cases} l_i^r a_{ij} & \text{if } l_i^r < 1 \\ a_{ij} & \text{if } l_i^r \geq 1 \end{cases} \tag{1.3}$$

The BEA (2012b) annually publishes Gross Domestic Product (GDP) for 63 industries for each U.S. state. (The GDP state data with 63 industries combine two separate sectors for state and local government spending and two separate sectors for federal government spending that exist in the national I-0 accounts with 65 industries.) The national GDP for industry i is equivalent to the value added amount for that industry, and x_i^r / x_i is assumed to be equal to the ratio of industry i's value added at the state level to that industry's value added at the national level.

Eqs. (1.2) and (1.3) are used to estimate technical coefficient matrices for 10 different U.S. states in Chapter 2 and the Gulf of Mexico region in Chapter 5. Because the OECD data provides technical coefficient matrices for each country, location quotients are not necessary for the multinational I-O model constructed in Chapter 3.

Knowledge about the extent to which one region trades with another region enables the estimation of changes in production in one region due to demand changes in another region. Let t_i^{rs} be the proportion of commodity i consumed by region s that originated from industry i in region r.[1]This proportion is equal to z_i^{rs}/z_i^s where z_i^{rs} is the dollar value of industry i's commodities sent from region r to region s and z_i^s is the total amount of commodity i consumed in region s (Isard et al., 1998). These numbers can be calculated for each state in the United States using the Commodity Flow Survey published by the Bureau of Transportation Statistics (2009b) and for each country in a multinational model using import and export data.

After creating these proportions for every industry and every region under consideration, the interregional matrix $\mathbf{T}$ is shown in Eq. (1.4), where $\mathbf{T}^{rs}$ is a $n \times n$ diagonal matrix composed of the proportion of commodities consumed by region s and produced in region r. The variable p represents the total number of regions.

$$\mathbf{T} = \begin{pmatrix} \mathbf{T}^{11} & \mathbf{T}^{12} & \cdots & \mathbf{T}^{1p} \\ \mathbf{T}^{21} & \mathbf{T}^{22} & \cdots & \mathbf{T}^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{T}^{p1} & \mathbf{T}^{p2} & \cdots & \mathbf{T}^{pp} \end{pmatrix} \tag{1.4}$$

The interregional matrix is incorporated into the Leontief I-O model in Eq. (1.5)

[1]Commodities follow the same classification as economic sectors. If industry i produces more than one commodity, all of these commodities are grouped together and are called commodity i.

to understand the multiregional impacts of demand changes, where $\mathbf{x^r}$ and $\mathbf{c}^r$ are production and final demand in region r, respectively.

$$\begin{pmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^p \end{pmatrix} = \mathbf{T} \begin{pmatrix} \mathbf{A}^1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^p \end{pmatrix} \begin{pmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^p \end{pmatrix} + \mathbf{T} \begin{pmatrix} \mathbf{c}^1 \\ \mathbf{c}^2 \\ \vdots \\ \mathbf{c}^p \end{pmatrix}$$
$$\Rightarrow \begin{pmatrix} \mathbf{x}^1 \\ \mathbf{x}^2 \\ \vdots \\ \mathbf{x}^p \end{pmatrix} = \left[\mathbf{I} - \mathbf{T} \begin{pmatrix} \mathbf{A}^1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^p \end{pmatrix} \right]^{-1} \mathbf{T} \begin{pmatrix} \mathbf{c}^1 \\ \mathbf{c}^2 \\ \vdots \\ \mathbf{c}^p \end{pmatrix} \tag{1.5}$$

1.2.3 Supply side I-O model

As an alternative to the demand-driven Leontief I-O model, the supply side I-O model (Ghosh, 1958) as shown in Eq. (1.6) expresses production as a function of primary inputs like labor. The $n \times n$ allocation coefficient matrix $\overrightarrow{\mathbf{A}}$ describes the output that can be produced with a given level of inputs: for every dollar that industry i produces or supplies, industry j can produce $\overrightarrow{a}_{ij}$ amount of product. The variable $\boldsymbol{\nu}$, a vector of length n, represents each industry's value added, which includes primary inputs.

$$\mathbf{x}^\intercal = \mathbf{x}^\intercal \overrightarrow{\mathbf{A}} + \boldsymbol{\nu}^\intercal \tag{1.6}$$

The supply side I-O model has been used to model disruptions by assuming the disruption impacts production and constrains supplies (Davis and Salkin, 1984; Park, 2008). Eq. (1.6) can translate this constrained supply into reduced production in the economy.

The supply side I-O model has been criticized for the underlying assumption that supply generates demand (Oosterhaven, 1998, 1989) although a simulation of a supply disruption in aluminum in the state of Washington reveals that the supply side I-O model can return realistic results (Rose and Allison, 1989). Supply side I-O models may more accurately measure price rather than production deviations (Dietzenbacher, 1997). Because of the disagreements over the supply side I-O model, this dissertation exclusively uses demand-driven I-O models.

1.2.4 Inoperability Input-Output Model

The Inoperability Input-Output Model (IIM) is a risk-based extension to the I-O model that describes the interdependent effects of inoperability (Haimes and Jiang, 2001). Inoperability, as represented by $\mathbf{q}$, a vector of length n, describes the degree to which each industry is not functioning relative to its intended output. A value $q_i = 1$ signifies that industry i is not producing at all, and $q_i = 0$ indicates the industry is functioning and producing as intended or planned. Eq. (1.7) demonstrates how initial inoperability in each industry as represented by the vector $\mathbf{c}^*$ translates into total inoperability. The $n \times n$ interdependent matrix $\mathbf{A}^*$ describes how inoperability in one industry leads to inoperability in another industry, and a_{ij}^* represents the additional amount of inoperability in industry i resulting from inoperability in industry j.

$$\mathbf{q} = \mathbf{A}^*\mathbf{q} + \mathbf{c}^* \Rightarrow \mathbf{q} = [\mathbf{I} - \mathbf{A}^*]^{-1}\mathbf{c}^* \tag{1.7}$$

In the original IIM, Haimes and Jiang (2001) propose that $\mathbf{A}^*$ can represent the degree of dependence among infrastructure systems where the partial or total failure of one type of infrastructure (e.g., electric power) results in failure in other infrastructures (e.g., finance, transportation). Reed et al. (2009) apply the infrastructure IIM to an analysis of infrastructure failure and resilience caused by Hurricane Katrina, and Wei et al. (2009) estimate $\mathbf{A}^*$ for a supply chain network by analyzing the degree of connectedness between several nodes in the supply chain.

The primary difficulty with the application of the IIM to describe physical interdependencies among infrastructure systems is the lack of available data to populate $\mathbf{A}^*$. Estimating the degree to which inoperability in one infrastructure impacts the functionality of another infrastructure generally requires specific engineering knowledge and analysis of the system. Populating $\mathbf{A}^*$ requires n^2 such estimations. A study conducted by Zimmerman and Restrepo (2006), who examine how previous electric power outages created failures on other infrastructure systems, could potentially be replicated to populate the IIM for infrastructure interdependencies. Alternatively, the same I-O data from the BEA or the OECD that populates the Leontief I-O model can be used in the IIM (Santos and Haimes, 2004; Santos, 2006). The inoperability of industry i can be defined as $q_i = (x_i - \tilde{x}_i)/x_i$ where x_i is the as-planned production of industry i and $\tilde{x}_i$ is the degraded level of production of industry i due to a disruptive event. Initial inoperability can be interpreted as a perturbation in final demand for industry i's products and services that is caused by a disruption, and $c_i^* = (c_i - \tilde{c}_i)/x_i$ where c_i is the as-planned final demand and $\tilde{c}_i$ is the reduced or degraded demand. The inoperability interdependency matrix $\mathbf{A}^*$ can thus be derived from the technical coefficient matrix $\mathbf{A}$ with $\mathbf{A}^* = [\text{diag}\,(\mathbf{x})]^{-1}\,\mathbf{A}\,[\text{diag}\,(\mathbf{x})]$.

If economic I-O data are deployed to assess parameters in the IIM, this demand-reduction IIM (Santos and Haimes, 2004) produces identical results to the Leontief I-O model to quantify the impacts from a disruption, where the disruption perturbs final demand in one or more industries. The vector $\mathbf{q}$ as calculated by Eq. (1.7) translates directly to production losses, where $\mathbf{x} - \tilde{\mathbf{x}} = [\text{diag}\,(\mathbf{x})]\,\mathbf{q}$. This lost production is identical to the changes in production that the Leontief I-O model calculates via Eq. (1.1) if the same demand perturbation is used. Although the IIM and the Leontief I-O model produce identical results, estimating the changes in demand due to a disruption as a fraction of as-planned production as the IIM requires may be easier than estimating the actual value of lost demand as required by the Leontief I-O model.

The IIM and its extensions have been used to study a number of risk-based applications, including terrorist attacks (Haimes et al., 2005a,b), cyber security (Andrijcic and Horowitz, 2006; Dynes et al., 2007), and workforce disruptions (Barker and Santos, 2010b; Orsi and Santos, 2010a). A supply-driven inoperability model based on the supply side I-O model uses the allocation coefficient matrix $\overrightarrow{\mathbf{A}}$ to calculate the interdependency among industries (Chen et al., 2009).

1.2.5 Dynamic Inoperability Input-Output Model

The dynamic Leontief (1970) I-0 model allows for some portion of inputs (i.e., capital stock) to be to used for production in future time periods. Based on the framework of the dynamic Leontief model, the Dynamic Inoperability Input-Output Model (DIIM) is a dynamic extension of the IIM to model the change in inoperability from time t to time $t+1$ (Lian and Haimes, 2006). The DIIM is shown in Eq. (1.8), where $\mathbf{K}$ is a $n \times n$ diagonal matrix and vectors $\mathbf{q}(t)$ and $\mathbf{c}^*(t)$ correspond to inoperability and demand perturbation at time t.

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}\left[\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t) - \mathbf{q}(t)\right] \tag{1.8}$$

The ith diagonal element of $\mathbf{K}$ represents the resilience of industry i, or its capability to return to full operability following a disruption.

Analyses using the DIIM often assume that $\mathbf{c}^*(t) = 0$, which means that the disruption does not perturb final demand. In this case, inoperability results exclusively from the initial impacts as represented by $\mathbf{q}(0)$. Under this assumption, an exponential model, as shown in Eq. (1.9), serves as a closed-form solution to the dynamic system of Eq. (1.8).

$$\mathbf{q}\left(t\right)=\mathbf{q}\left(0\right)e^{-\mathbf{K}\left(\mathbf{I}-\mathbf{A}^{*}\right)t} \tag{1.9}$$

The scalar form of Eq. (1.9) is provided in Eq. (1.10) for a single industry i. The diagonal entry of $\mathbf{A}^{*}$, a_{ii}^{*}, measures the dependency of an industry on itself.

$$q_{i}\left(t\right)=q_{i}\left(0\right)e^{-k_{i}\left(1-a_{ii}^{*}\right)t} \tag{1.10}$$

If the initial inoperability $q_i\left(0\right)$ and the final desired inoperability $q_i\left(T_i\right)$ at recovery time T_i are known for a disruption, Eq. (1.10) can be rearranged as shown in Eq. (1.11) to solve for the resilience coefficient k_i.

$$k_{i}=\frac{\log\left[q_{i}\left(0\right)/q_{i}(T_{i})\right]}{T_{i}\left(1-a_{ii}^{*}\right)} \tag{1.11}$$

As Eq. (1.11) suggests, an accurate estimate of the resilience coefficient matrix $\mathbf{K}$ for all n industries requires knowledge about or data describing the initial inoperability, the final desired inoperability, and recovery time for each sector or industry. If these values are known, the DIIM can serve as a useful risk management tool to help policymakers quantify the economic consequences of potential disruptions. Assessing values for these parameters, especially T_i, poses a challenge, as the time to recover from a disruption is usually unknown. Without a good estimate of either the time it takes to recover or the resilience coefficient, the DIIM may not provide accurate results for estimating the impacts from a disruption.

This difficulty with estimating $\mathbf{K}$ may limit the usefulness of the DIIM. MacKenzie and Barker (forthcoming) use regression on a data set of recovery times following electric power outages in the United States to empirically assess a value of $k_i = 0.005$ for the Utilities industry. Although the fitted regression model is statistically significant for this data set, the high variation in the data and small R^2 term shed doubt on the fitted model's accuracy. Other approaches to estimating $\mathbf{K}$ depend on assuming a disruption lasts a given number of days (Barker and Santos, 2010b), estimating resilience based on the available workforce (Santos et al., 2009), and using a forward-sensitivity approach for dynamic systems (Pant, 2012).

An alternative interpretation for $\mathbf{K}$ describes how quickly the economy reaches equilibrium as determined by Eq. (1.7). If $\mathbf{K} = \mathbf{I}$, each industry adjusts its production in a single time period to reflect perfectly changes in both intermediate and final demand. At the other extreme, if $\mathbf{K} = \mathbf{0}$, the economy will never reach equilibrium and $\mathbf{q}(t+1) = \mathbf{q}(t)$. The DIIM in Chapter 2 uses this interpretation to quantify economic impacts over time.

The DIIM has been proposed as a tool to help decision makers choose among competing risk management strategies (Lian and Haimes, 2006; Barker and Haimes, 2009) such as maintaining inventory to protect against supply chain disruptions (Barker and Santos, 2010a).

1.2.6 Multiregional IIM and DIIM

Similar to the multiregional I-O model, the multiregional IIM (Crowther and Haimes, 2010) as shown in Eq. (1.12) provides a framework to analyze the inoperability and economic impacts in each region that might be affected by a disruptive event.

$$\begin{pmatrix} \mathbf{q}^1 \\ \mathbf{q}^2 \\ \vdots \\ \mathbf{q}^p \end{pmatrix} = \mathbf{T}^* \begin{pmatrix} \mathbf{A}^{*1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{*2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^{*p} \end{pmatrix} \begin{pmatrix} \mathbf{q}^1 \\ \mathbf{q}^2 \\ \vdots \\ \mathbf{q}^p \end{pmatrix} + \mathbf{T}^* \begin{pmatrix} \mathbf{c}^{*1} \\ \mathbf{c}^{*2} \\ \vdots \\ \mathbf{c}^{*p} \end{pmatrix} \tag{1.12}$$

where

$\mathbf{q}^r$ is a vector of length n of inoperability in region r

$\mathbf{T}^* = [\text{diag}(\mathbf{x}^1, \mathbf{x}^2, \cdots, \mathbf{x}^p)]^{-1}\mathbf{T}[\text{diag}(\mathbf{x}^1, \mathbf{x}^2, \cdots, \mathbf{x}^p)]$

$\mathbf{A}^{*r} = [\text{diag}(\mathbf{x}^r)]^{-1}\mathbf{A}^r[\text{diag}(\mathbf{x}^r)]$ is region r's inoperability interdependency matrix

$\mathbf{c}^{*r}$ is a vector of length n of final demand perturbation in region r

This multiregional formulation can also be applied to the DIIM (Crowther, 2007), as shown in Eq. (1.13) where $\tilde{\mathbf{K}}$ is a $np \times np$ diagonal matrix and $\tilde{k}_{n(r-1)+i}$ represents the resilience of industry i in region r. The multiregional DIIM can measure the inoperability of industries over time and across multiple regions, and Chapter 2 uses the multiregional DIIM to analyze the economic impacts of the sudden closure of an inland waterway port.

$$\begin{pmatrix} \mathbf{q}^1(t+1) \\ \mathbf{q}^2(t+1) \\ \vdots \\ \mathbf{q}^p(t+1) \end{pmatrix} = \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} + \tilde{\mathbf{K}} \left[\mathbf{T}^* \begin{pmatrix} \mathbf{A}^{*1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{*2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^{*p} \end{pmatrix} \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} \right.$$
$$\left. + \mathbf{T}^* \begin{pmatrix} \mathbf{c}^{*1}(t) \\ \mathbf{c}^{*2}(t) \\ \vdots \\ \mathbf{c}^{*p}(t) \end{pmatrix} - \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} \right] \tag{1.13}$$

1.2.7 Economic interpretation of the IIM and DIIM

The use of economic data to populate the IIM and the DIIM carries both a blessing and a curse to the application of these models to disruptions. The economic data allow these models to be used in real-world applications without the tedious and imposing challenge of individually assessing all of the interdependencies between any two pairs of industries or economic sectors. If $\mathbf{A}^*$ is derived from the Leontief technical coefficient matrix $\mathbf{A}$, however, a_{ij}^* no longer represents the physical inoperability induced by industry or infrastructure j on industry i but rather the economic "inoperability" caused by industry j reducing its demand for industry i's goods and services. Industry i reduces its production by $x_i a_{ij}^* q_j$ dollars because industry j is producing less and consequently demanding fewer inputs. Like the Leontief I-O model, the IIM and DIIM assume "pull" systems, where the indirect impacts of a disruption are caused by industries and consumers reducing their demand for goods and services. Consequently, these models cannot easily quantify the downstream impacts of supply shortages. The pull nature exists whether the initial impacts are perturbations in final demand, as represented by $\mathbf{c}^*$, or physical disruptions to industries, as represented by $\mathbf{q}(0)$ in the DIIM.[2]

The economic nature of these models limits but does not nullify their application to infrastructure disruptions. For example, if state emergency managers are interested in understanding the economic impacts of an extended power outage due to a natural disaster, they would probably like to assess the lost production due to businesses that would be without power if 50% of the state were without power. It is tempting to assess the fraction of businesses without power in, for example, the Banking industry by multiplying $a_{ij}^* q_j$ where industry i represents Banking and industry j represents Utilities, which includes the electric power sector, and $q_j = 0.5$. However, $a_{ij}^* q_j$ actually calculates the fraction of lost demand that the Banking would suffer because of less production in Utilities and thus answers a different question than the fraction of banks without power. Assessing the number of businesses without power requires an understanding of where the power outage would occur and which business and

[2] The IIM can be used to calculate a forced reduction in final demand, $\mathbf{c}^*$, due to a supply shortage or physical disruption, $\mathbf{q}$, via $\mathbf{c}^* = (\mathbf{I} - \mathbf{A}^*)\,\mathbf{q}$. However, this calculation often results in elements of $\mathbf{c}^*$ that are negative, which implies increased demand, and it provides no information about indirect impacts on production caused by a supply shortage.

industries are located in that area. This geographic information could then be used to generate a vector of initial inoperability $\mathbf{q}$ which can be incorporated into the IIM or DIIM to calculate other production losses due to these industries reducing their demand for goods and services.

Although economic data may serve as an appropriate substitute for data that represent physical relationships among infrastructure systems (Haimes et al., 2005a; Haimes and Chittester, 2005), a closer look at $\mathbf{A}^*$ raises questions about that assumption. In the 2009 I-0 data for the United States produced by the BEA, $a^*_{ii} = 0.0012$ for Utilities. If this value represents physical interdependency, then an electric power outage would induce no power failures in any electric power businesses not initially impacted. The 2003 U.S. blackout suggests that the electric power sector is much more interdependent. Of the remaining 64 industries, only four industries (Oil and Gas, Mining, Rail Transportation, and Pipeline Transportation) have a^*_{ij} values greater than 0.01. An electric power outage would probably impact more industries than these four.

1.3 Contributions

This dissertation offers several contributions to analyze the interdependent economic impacts of disruptions. Unique methods use I-O models to evaluate the economic impacts of supply shortages and constrained production. Models incorporate industry decision making to maintain production in response to a disruption, and the optimal alternative is solved as a function of model parameters. Because of the complexity in these models, simulations are constructed in which firms and suppliers act as agents that make decisions to achieve their own objectives. Each chapter applies these models and simulations to real-world applications that rely on publicly available data and media stories to estimate parameters. Numerical results used to generate lessons learned about each model and disruption can aid policymakers and business leaders interested in understanding the economic impacts of disruptions. Finally, decision makers can use I-O models to make optimal decisions about allocating resources to help industries recover from a disruption.

This dissertation can be divided into three principal modeling activities: economic impact analysis using I-O models (Chapters 2 and 3), interdependent impacts of supply chain disruptions (Chapter 4), and optimal resource allocation for recovery of interdependent systems (Chapter 5).

1.3.1 Economic impact analysis using I-O models

The previous discussion of I-O modeling, the IIM and DIIM, and the economic interpretation of these models is important for understanding the analysis in Chapters 2 and 3. Each chapter models a specific disruption and uses I-O models to quantify the indirect economic impacts from those disruptions.

Chapter 2 models a disruption to an inland waterway port. 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 chapter examines the economic impact of suddenly closing an inland port by combining a simulation and the multiregional DIIM. The simulation models how companies may react if an inland waterway port suddenly closes, and the multiregional DIIM quantifies the interdependent effects of these decisions. A case study is developed involving the Port of Catoosa in Oklahoma, a port located on the Arkansas River. Several publicly available databases are employed to derive realistic results for the case study.

Chapter 3 quantifies the international economic impact from the 2011 Japanese earthquake and tsunami. The disaster disrupted global supply chains, which was blamed for anemic growth in the global economy. The multiregional I-O model quantifies the international impacts on production due to changes in demand from companies reducing their orders because of a disruption. The I-O model is conceptualized as a supply chain, and a unique method for calculating indirect production losses caused by disabled production facilities is proposed. Methods for calculating the possible transfer of demand to industries in other countries are also discussed. Quantifying changes in international production provides greater understanding of the global economic impacts of the Japanese earthquake and tsunami, the importance of inventory and increased imports to satisfy customer demand, and the structural features of the Japanese automotive industry.

1.3.2 Supply chain disruptions

Many firms suffered from supply disruptions due to the recent Japanese earthquake and tsunami. Chapter 4 analyzes these disruptions by developing a simulation and model in which several suppliers' production facilities are rendered inoperable. Each supplier must decide whether to move some production to an alternate facility or wait for its facility to reopen before producing. If suppliers do not produce at alternate facilities, firms may experience a supply shortage and will need to decide how to mitigate the impacts of a supply shortage.

The firm's decision process is modeled as a multi-criteria decision problem in which each firm must trade off satisfying its current demand with maximizing its profit in each period. The supplier's and the firm's optimal decisions are solved as functions of a number of parameters, including the cost of production, revenue, the cost of the mitigation option, and lost customers if production is less than what is demanded. This model and simulation is applied to a simplified representation of the disruption in the automobile sector that occurred in the wake of the Japanese earthquake and tsunami.

1.3.3 Recovery of interdependent systems

Investing in infrastructure and industry sectors can lessen the direct impacts of disruptive events. Four different decision models are presented in Chapter 5 to determine the optimal resource allocation to assist impacted sectors to recover. The first decision model minimizes direct impacts from a disruption, and the second model uses the IIM to minimize direct and indirect impacts. The third model is a discrete-time dynamic model that allows a decision maker to allocate resources over time. In the fourth model, a decision maker can allocate resources to prepare for a disruption and also allocate resources to recover from the disruption, and the IIM and Leontief I-O model quantify the benefits of these decisions. A solution for the optimal allocation in each model is described as a function of model parameters. These models are applied to a data-driven case study to analyze the economic impacts of the *Deepwater Horizon* oil spill, which adversely impacted several industries in the region such as tourism, fishing, and real estate.

1.4 Explanation of Dissertation's Structure

Because each of these chapters present different modeling approaches and study different types of disruptions, each chapter begins with its own literature review specific to the problem studied in that chapter. Each chapter is also designed to be a standalone section and can be understood without reference to the other chapters although this introduction to I-O modeling is useful for understanding Chapters 2 and 3. Although some variable definitions are common across the dissertation, each model has a unique set of variables. Therefore, each chapter contains a table detailing the notation used in that chapter. Notation in one chapter does not necessarily carry over to the other chapters.

Chapter 2

Evaluating the Consequences of an Inland Waterway Port Closure with the Dynamic Multiregional Interdependency Model

Inland waterway ports play an important role in the United States 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, traverse through inland ports (U.S. Army Corps of Engineers, 2009). 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 United States. 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 (U.S. Department of Homeland Security, 2005).

Vulnerabilities that coastal ports face have been extensively studied in the risk analysis literature (Martonosi et al., 2005; Rosoff and von Winterfeldt, 2007), 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 (Gordon et al., 2005; Park, 2008; Jung et al., 2009). Regardless of whether this assumption is valid for coastal ports (Hall, 2004), 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 (Folga et al., 2009).

If highway disruptions occur, companies will find alternate routes to deliver their products (Kim et al., 2002; Sohn et al., 2003; Ham et al., 2005a,b; Pulat et al., 2010). Rerouting cargo from a closed inland port is more difficult than finding an alternate road route if part of a highway is closed, though the likely availability of rail and truck alternatives makes finding an alternate shipping mode more plausible than if a coastal port closes. Companies who 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 product remain on a barge or at a port until the port reopens. This chapter 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 (Simchi-Levi et al., 2008; Jain et al., 2010). Incorporating these types of cost-benefit analyses into a simulation can anticipate a company's decision in the face of uncertainty over when the port may reopen.

Although companies likely make decisions without considering how their decisions impact other industries, such decisions carry interdependent ramifications for the economy. I-O models have been deployed extensively in evaluating the consequences of closing seaports, in particular the twin ports of Los Angeles-Long Beach. Jung et al. (2009) combine the IIM with GDP to estimate that the impact of not being able to import or export through those two California ports for 10 days would result in \$7.7 to \$13 billion of production losses. A different I-O model (Park, 2008) 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

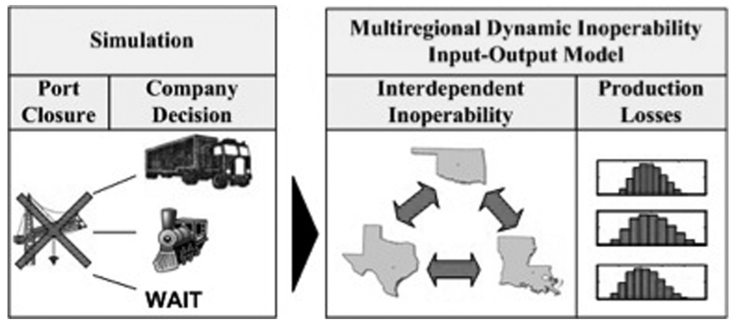

Figure 2.1: Depiction of simulation and interdependency model

al. (2005) 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 chapter also uses an I-O model, it differs because the simulation determines whether a company decides to let 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 systems modeling creates a new framework for evaluating the consequences of closing an inland port (Fig. 2.1). Explicitly modeling company behavior provides valuable insight into what might occur if an inland port closes. Companies who 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 DIIM 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 study can lead to better risk management strategies to mitigate the effect of inland port closures.

The remainder of this chapter is as follows: Section 2.1 explains the simulation of closing an inland port and company responses. Section 2.2 demonstrates how the

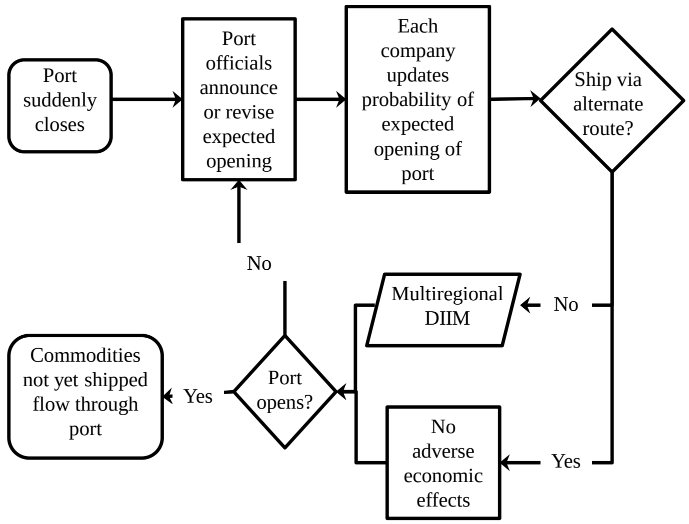

Figure 2.2: Flowchart of simulation of inland port closure

results of the simulation are incorporated into the multiregional DIIM to measure the economic impact of closing the port. In Section 2.3, this simulation and model are deployed on a case study involving an Oklahoma port on the Arkansas River. In order to derive realistic results, several publicly available databases are used to estimate a shipment schedule for this port.

2.1 Simulation of Port Closure Decision

An agent-based simulation models the reactions of companies following a disruptive event that temporarily closes an inland waterway port. Each company who planned to move product through the port acts as individual in the simulation. Fig. 2.2 illustrates 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. The actual (unknown) number of remaining days 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 Eq. (2.1).

$$\tilde{D}_t = \begin{cases} \tilde{D}_{t-1} & \text{with probability } \theta \\ \tilde{D}_{t-1} - 1 & \text{with probability } 1 - \theta \end{cases} \tag{2.1}$$

If the estimate is not revised, the number of days until officials expect to open the port decreases by one, and $\tilde{D}_t = \tilde{D}_{t-1} - 1$. 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 who normally use the port relies on the public information about the port's opening to assess when the port will actually open. This process is modeled 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 $\lambda = 0, 1, 2, ..., \lambda^*$ 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' beliefs about when the port will open differ throughout the simulation.

Each day that the port is closed, a company updates its probability distribution, $P(\lambda)$, after hearing whether or not 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

Table 2.1: Notation for Chapter 2

a_{ji}^r	Technical coefficient that industry i requires from industry j in region r
$\mathbf{A}^{*r}$	Interdependent matrix in the DIIM in region r
$\mathbf{c}^{*r} = \{c_i^{*r}\}$	Vector of final demand perturbation in region r
C_{alt}	Cost of alternate mode
C_{port}	Cost of using the port
$C(D_t)$	Penalty cost
D_t	Number of days until the port reopens if it has been closed for t days
$\tilde{D}_t$	Estimate on day t of remaining days the port will be closed
D_{uv}	Distance in miles from port u to port v
$\mathbf{e}^r = \{e_i^r\}$	Vector of exports not shipped from region r
$\tilde{\mathbf{K}}$	Matrix describing time to reach equilibrium for the multiregional DIIM
lat_u	Latitude of port u
lon_u	Longitude of port v
$\mathbf{m}^r = \{m_i^r\}$	Vector of imports not received by region r
M	Number of companies
$P(\lambda)$	Company's probability on λ
$\mathbf{q}^r = \{q_i^r\}$	Vector of industry inoperability in region r
$\tilde{\mathbf{q}}^r = \{\tilde{q}_i^r\}$	Vector of industry inoperability due to a supply shortage in region r
$\hat{\mathbf{q}}^r = \{\hat{q}_i^r\}$	Vector of industry inoperability used as an input in the DIIM
Q^r	Total production loss in region r
t	Number of days the port has been closed
$\mathbf{T}^*$	Interregional matrix in the multiregional DIIM
$\mathbf{x}^r = \{x_i^r\}$	Vector of industry production in region r
$\tilde{x}_i^r$	Degraded production for industry i in region r
z_{ji}^r	Value of industry j's production consumed by industry i in region r
$\tilde{z}_{ji}^r$	Reduced amount of industry j's production consumed by industry i in region r
β	Company's desire to deliver product on time
θ	Probability that the estimate of the port's opening is revised
λ	Number of days the port's opening will be delayed
λ^*	Maximum number of days the port's opening will be delayed
τ	Final day that delayed commodities are shipped

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, Eq. (2.2) shows how Bayes' rule can be used to calculate the posterior probability on λ given the official announcement on day t.

$$P(\lambda|\tilde{D}_t) \propto \begin{cases} \dfrac{\lambda+1}{\lambda+1+\tilde{D}_{t-1}} * P(\lambda+1) & \text{if } \tilde{D}_t = \tilde{D}_{t-1} \\ \dfrac{\tilde{D}_{t-1}}{\lambda+\tilde{D}_{t-1}} * P(\lambda) & \text{if } \tilde{D}_t = \tilde{D}_{t-1} - 1 \end{cases} \tag{2.2}$$

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 trade-offs among these different, potentially competing, objectives (Schillo and Vierke, 2000). 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 $C_{alt} > C_{port}$ 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, Wal-Mart recently imposed a 3% penalty if its suppliers were more than four days late (Painter and Whalen, 2010). Other suggestions for penalties include a 3% penalty for the first week and a 10% penalty for each additional week the shipment is late (Anjoran, 2009) and a per-unit-time penalty (Kwon et al., 1998). 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 or not 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 Eq. (2.3) 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.

$$C_{alt} * (1 - \beta) \leq C_{port} + \sum_{\lambda=0}^{\lambda^*} C(\lambda + \tilde{D}_t) * P(\lambda) \tag{2.3}$$

Each company makes this decision for the days when it is 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.

2.2 Incorporating Simulation Results into the Multiregional DIIM

The simulation 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. As discussed in Chapter 1 and given in Eq. (2.4), the multiregional DIIM calculates the interdependent inoperability and economic impacts where $\mathbf{q}^r(t)$ is a vector of industry inoperability at time t, $\mathbf{c}^{*r}(t)$ is a vector of perturbation of final demand, $\mathbf{A}^{*r}$ is the interdependency matrix in region r, $\mathbf{T}^*$ is the interregional matrix, and $\tilde{\mathbf{K}}$ is a diagonal matrix describing the time it takes for the economy to reach an equilibrium.

$$\begin{pmatrix} \mathbf{q}^1(t+1) \\ \mathbf{q}^2(t+1) \\ \vdots \\ \mathbf{q}^p(t+1) \end{pmatrix} = \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} + \tilde{\mathbf{K}} \left[\mathbf{T}^* \begin{pmatrix} \mathbf{A}^{*1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^{*2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}^{*p} \end{pmatrix} \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} \right.$$
$$\left. + \mathbf{T}^* \begin{pmatrix} \mathbf{c}^{*1}(t) \\ \mathbf{c}^{*2}(t) \\ \vdots \\ \mathbf{c}^{*p}(t) \end{pmatrix} - \begin{pmatrix} \mathbf{q}^1(t) \\ \mathbf{q}^2(t) \\ \vdots \\ \mathbf{q}^p(t) \end{pmatrix} \right] \tag{2.4}$$

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 (Jung et al., 2009). Exports are categorized as final demand in the I-O model (BEA, 2009) and a company that cannot export part of its product will see a loss in demand. Eq. (2.5) presents the loss in demand for a company in industry i that is unable to export e_i^r dollars of commodities from region r and that plans to produce x_i^r.

$$c_i^{*r} = \frac{e_i^r}{x_i^r} \tag{2.5}$$

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, a production function is used where industry i's production in region r is determined by the minimization problem in Eq. (2.6). The variable z_{ji}^r is the total dollar value of industry j's production consumed by industry

i in region r (Oosterhaven, 1998).

$$\min\left(\frac{z^r_{1i}}{a^r_{1i}},\cdots,\frac{z^r_{ji}}{a^r_{ji}},\cdots,\frac{z^r_{ni}}{a^r_{ni}}\right) \tag{2.6}$$

Because the technical coefficient $a^r_{ji} = z^r_{ji}/x^r_i$ for all j, industry i produces x^r_i as described by the Leontief I-O model under normal operations.

If region r is unable to import m^r_j dollars of commodity j, all of the region's economic sectors that use industry j's production will suffer supply shortages. The proportion of industry j's production that is used by industry i is z^r_{ji}/x^r_j. Assuming that imports are distributed according to that same proportion, the reduced amount of industry j's inputs to industry i is given by Eq. (2.7).

$$\tilde{z}^r_{ji} = (x^r_j - m^r_j)\frac{z^r_{ji}}{x^r_j} \tag{2.7}$$

By replacing z^r_{ji} with $\tilde{z}^r_{ji}$ in Eq. (2.6), Eq. (2.8) calculates $\tilde{q}^r_i$, the inoperability of industry i due to supply shortages from industry j where $\tilde{x}^r_i$ is the degraded amount of production in industry i.

$$\tilde{q}^r_i = 1 - \frac{\tilde{x}^r_i}{x^r_i} = 1 - \left(\frac{1}{x^r_i}\right)\frac{\tilde{z}^r_{ji}}{a^r_{ji}} = \frac{m^r_j}{x^r_j} \tag{2.8}$$

If commodities from multiple industries are not imported into region r, industry i's inoperability is governed by the $\tilde{z}^r_{ji}$ that minimizes Eq. (2.6) or equivalently by the m^r_j that maximizes Eq. (2.9).

$$\tilde{q}^r_i = \max\left(\frac{m^r_1}{x^r_1},\cdots,\frac{m^r_j}{x^r_j},\cdots,\frac{m^r_n}{x^r_n}\right) \tag{2.9}$$

If industry i does not use any production from industry h, i.e. if $a^r_{hi} = 0$, the corresponding term m^r_h/x^r_h is excluded from Eq. (2.9).

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. Eq. (2.5) calculates $\mathbf{c}^{*r}(t)$ from $\mathbf{e}^r(t)$, and Eq. (2.9) calculates $\tilde{\mathbf{q}}^r(t)$, a vector of length n, from $\mathbf{m}^r(t)$ where industry 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 Eq. (2.4) where $\mathbf{q}^r(t)$ is replaced on the right hand side of the equation with $\hat{\mathbf{q}}^r(t)$ as defined in Eq. (2.10).

$$\hat{q}_i^r(t) = \max\{\tilde{q}_i^r(t), q_i^r(t)\} \tag{2.10}$$

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

When the port opens, 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 product that was waiting to be moved is shipped when the port opens, demand increases for exporting industries and $c_i^{*r}(t) = -e_i^r(t)/x_i^r(t)$, where $e_i^r(t)$ now represents 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 industries in region r at time t is expressed in Eq. (2.11) as a function of the inoperability at time t and expected production in that time period.

$$Q^r(t) = [\mathbf{q}^r(t)]^\intercal \mathbf{x}^r(t) \tag{2.11}$$

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 (Barker and Haimes, 2009; Santos, 2008; Santos et al., 2008; Orsi and Santos, 2010b), the IIM and its extensions have generally been treated as deterministic models. Combining simulation with the DIIM in a multiregional context incorporates industry actions and 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.

2.3 Case Study: Port of Catoosa

This model and simulation are applied 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 3,000-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 1,000 trucks a day go through the port (Hampton, 2008).

The daily shipping activity at Catoosa is estimated from different sources of data. The U.S. Army Corps of Engineers (2008a,b,c) publishes the number of tons of specific commodities that moved through Catoosa in 2007 and the amount of each commodity that was shipped via water between states. The Tulsa Port of Catoosa (2009) releases the number of barges and tons of cargo that were shipped through Catoosa in every month of 2007. The value of each type of cargo is estimated using the Commodity Flow Survey (U.S. Bureau of Transportation Statistics, 2009a). Table 2.2 shows that approximately $937 million worth of cargo moved through Catoosa in 2007, with Chemical Products and Primary Metals representing the largest industries in terms of dollar values.

These data sources are combined to estimate the day and number of tons that

Table 2.2: Estimated value of cargo moving through Catoosa in 2007 (millions of dollars)

		INDUSTRY								
		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

each commodity is shipped through Catoosa. Although a single shipment could fill as many as 15 barges (Tulsa Port of Catoosa, 2010), most shipments probably fill no more than six barges (May, 2002). Each barge can carry approximately 1,500 tons, and it is assumed that no shipment is greater than six barges or 9,000 tons. Each shipment is assigned 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.

To calculate the distance of each shipment, the simulation assumes that the product is being shipped either to or from the state's busiest port in the Mississippi River Basin. For example, product shipped from Oklahoma to Mississippi leaves Catoosa and arrives at the Port of Vicksburg. Eq. (2.12) calculates the distance in miles D_{uv} that goods travel from port u to port v, where lon and lat represent the longitude and latitude of either port u or port v (Simchi-Levi et al., 2008).

$$D_{uv} = 69\sqrt{(lon_u - lon_v)^2 + (lat_u - lat_v)^2} \tag{2.12}$$

The simulation assumes a one-to-one correspondence between an industry's commodities shipped from one state to another state and the company. Table 2.2 contains 24 non-zero elements, and each element corresponds to a company in the simulation. Increasing and decreasing the number of companies shipping each commodity does not significantly change the results of the simulation.

If the Port of Catoosa were closed, a company could potentially transport its product by truck or rail or attempt to divert its product to a different waterway port. For the simulation, 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 (Tulsa Port of Catoosa, 2010). 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., $\beta = 0.1$). BEA data from 2007 is inputted into the model with 62 industries for each of the ten states. The simulations assume $\tilde{\mathbf{K}} = 0.5 * \mathbf{I}$, which means that an industry's inoperability at time $t+1$ is the average of its own inoperability at time t and the interdependent effects of other industries' inoperability at time t.

Table 2.3: Value of product not shipped with no penalty (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

2.3.1 No penalty

Closing the Port of Catoosa for one to two months is simulated $1,500$ times. (For the data and model, $1,500$ 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 2.3.

In Table 2.4, 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 suffer significant production losses. The interdependency model translates the initial effects of product not being shipped into production losses of almost 50 times the value of the initial effects.

Table 2.4: Production losses with no penalty (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

The distributions of lost production for Oklahoma and the entire region (Fig. 2.3) 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 2.4. 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.

Fig. 2.4 depicts the inoperability for all of Oklahoma's and Louisiana's industries for a single simulation run when the Port of Catoosa is closed for 49 days. Each line represents a single industry's inoperability at each day. Oklahoma's industries experience greater inoperability than those in Louisiana, and many industries experience high levels of inoperability even though these industries do not ship any products through Catoosa.

The step-like increases in inoperability that occur in Fig. 2.4 generally indicate that a scheduled shipment was not sent on that day. The inoperability for Oklahoma's industries is particularly high for days 22 and 23 because the amount of Food, Bever-

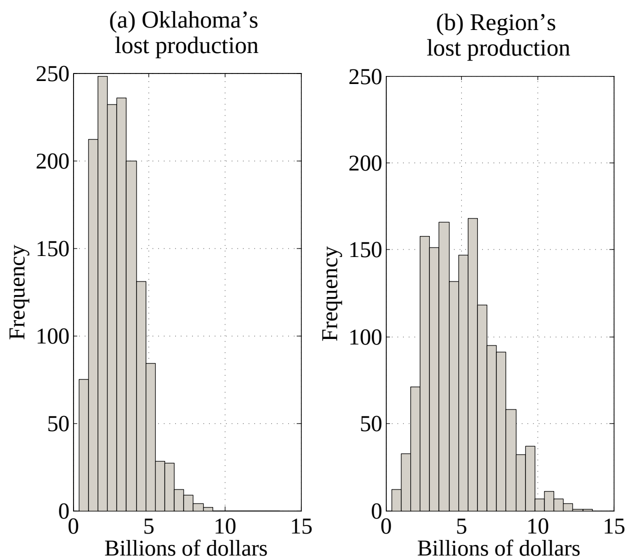

Figure 2.3: Distribution of production losses for (a) Oklahoma and (b) all ten states with no penalty

age, and Tobacco Products originally scheduled to be 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 industries experience a drop in inoperability, which signifies an increase in production. Several industries experience negative inoperability, which signifies that these industries recover a portion of the production they previously had lost.

2.3.2 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 product via train unless they expect the port to reopen in the next week or two.

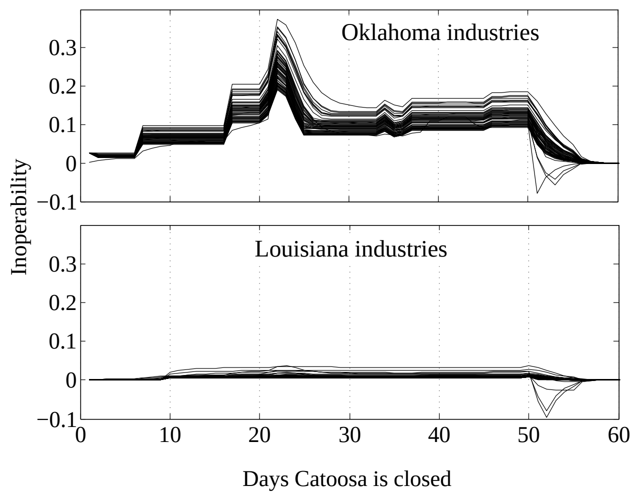

Figure 2.4: Inoperability over time for industries in Oklahoma and Louisiana with no penalty

Table 2.5 provides the results of 1,500 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. Product belonging to high-value industries, such as Primary Metals, Fabricated Metal Products, Machinery, and Manufacturing, carry such a heavy penalty that more than 96% of those commodities are transported by train.

Table 2.5: Value of product not shipped with a 0.2% penalty (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

The multiregional DIIM translates the unshipped product to average production losses of \$465 million for the ten states combined, as shown in Table 2.6. 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.

Table 2.6: Production losses with a 0.2% penalty (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

As shown in Fig. 2.5, the distributions of lost production with the 0.2% penalty are much more skewed to the right 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. 2.6 shows industry-specific inoperability for Oklahoma and Louisiana for the

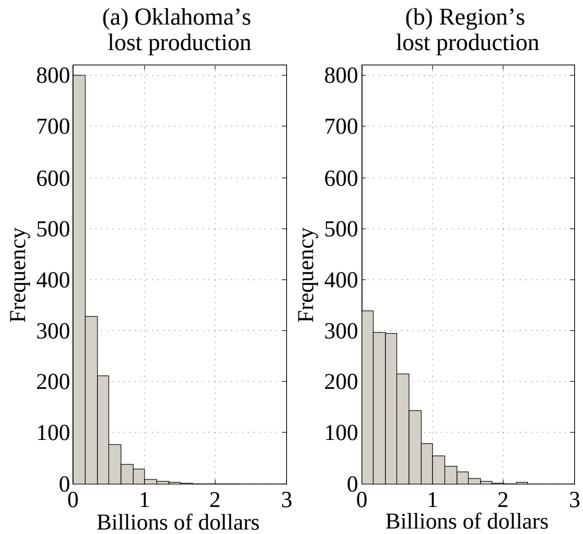

Figure 2.5: Distribution of production losses for (a) Oklahoma and (b) all ten states with a 0.2% penalty

same simulation as in the previous subsection but with the 0.2% penalty imposed. Industry 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 industries experience higher levels of inoperability than Oklahoma's industries. 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 industries, which are magnified by the interdependencies.

2.3.3 Varying the penalty

As the previous discussion implies, results from the simulation and model are highly sensitive to the value of the penalty. Fig. 2.7 provides the average production lost in Oklahoma and the region when 500 simulations were conducted for a range of

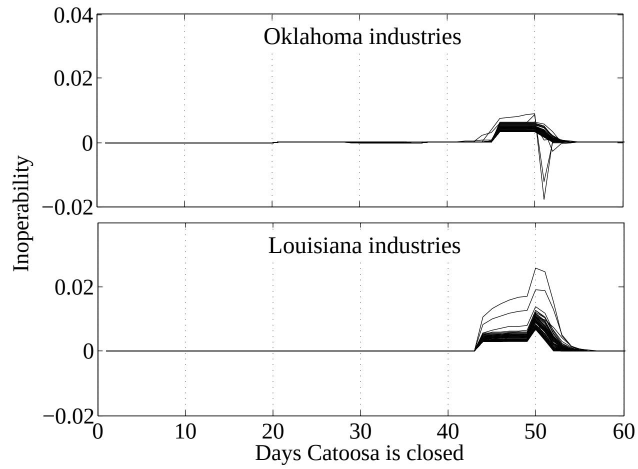

Figure 2.6: Inoperability over time for industries in Oklahoma and Louisiana with a 0.2% penalty

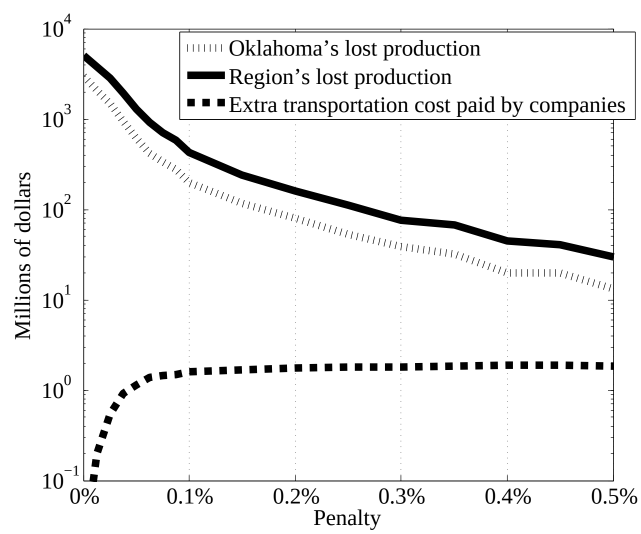

Figure 2.7: Average lost production in Oklahoma and the region with different penalties

penalties. (The margins of error for these 500 simulations are less than 17% of the sample mean for a 95% confidence interval.) The curve on the bottom of Fig. 2.7 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 always economically beneficial for commodities to be moved by train rather than wait for the Port of Catoosa to reopen.

2.3.4 Sensitivity analysis on other parameters

In addition to the penalty parameter, sensitivity analysis is performed on the number of days the port is closed and the time of year when the port is closed. In this subsection, the penalty remains at 0.2% for all simulations. Previous simulations closed Catoosa for one to two months, but new simulations vary the length of time that Catoosa is closed from 2 to 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 chapter 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, the effect of the time of year during which Catoosa is closed can be studied. Each chart in Fig. 2.8 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 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 on January 1, February 1, and March 1, and the average production

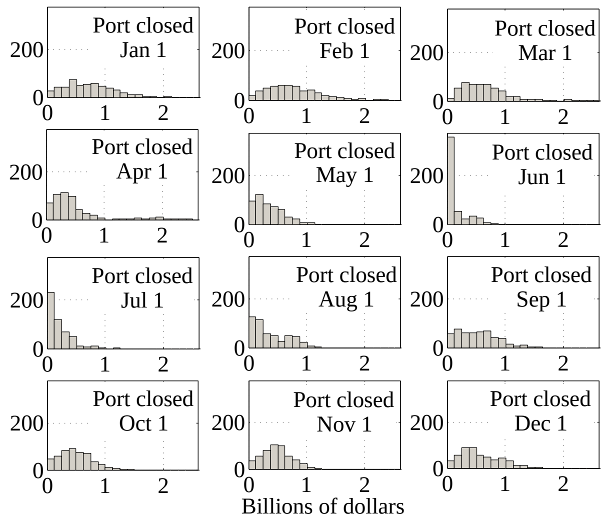

Figure 2.8: Distribution of production losses in the ten states when the first day Catoosa is closed occurs at the beginning of each month

loss is \$700 million for all ten states. The smallest production losses occur when the port is first closed on June 1 and July 1, and the average production loss is \$150 million for the region. A closure beginning on 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 (Tulsa Port of Catoosa, 2009). Simulating a port closure for a specific month can help policymakers more accurately forecast the consequences if Catoosa suddenly closed in a given month.

2.4 Conclusion

This chapter 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 provides insight into inoperability and production losses over several dimensions. First, the IIM model encapsulates the interdependencies among industries (Santos and Haimes, 2004; Santos, 2006). Second, the dynamic element of the DIIM creates a framework for examining the change in inoperability over time (Lian and Haimes, 2006). 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 (Crowther and Haimes, 2010). This chapter combines these elements into one model, and the case study provides a real-world application of examining inoperability across time, different industries, and different states.

The simulation described in this chapter can 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, the simulation models the companies as individual agents with objectives 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 chapter applies 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. Simple heuristics are developed, 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 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 (Shoven and Whalley, 1992; Rose, 2004a) have been developed to reflect the impact of fluctuating prices and substitution effects that might be brought about by a port closure.

A unique method analyzes the effects of a state not being able to import or export specific commodities. Publicly available databases provide a means 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 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 (Hall, 2004; Hedberg, 2010). Production losses on the order of hundreds of millions of dollars appear more realistic than losses in the 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 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 (Gordon et al., 2005; Park, 2008). Other studies using interdependency modeling have calculated $2 to $12 billion in production losses from a pandemic in the state of Virginia (Orsi and Santos, 2010a), a $6.5 billion loss from the August 2003 three-day blackout in the Northeast United States (Anderson et al., 2007), and a $5 billion loss from flooding the Midtown Tunnel near Hampton Roads, Virginia (Haggerty et al., 2008). 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 provide 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 provides insight into how their decisions and actions impact the economic production of an entire region.

Chapter 3

Measuring Changes in International Production from a Disruption: Case Study of the Japanese Earthquake and Tsunami

On March 11, 2011, a 9.0 magnitude earthquake and tsunami struck Japan. More than 15,000 people were confirmed dead with almost 5,000 missing people, and 120,000 homes and buildings were destroyed. The Japanese government estimated that reconstruction would cost about \$300 billion (MacLeod, 2011). In addition to the humanitarian and reconstruction costs, the disruption was blamed in part for anemic growth in the U.S. and the global economy. U.S. Treasury Secretary Timothy Geithner (interview, *Meet the Press*, July 20, 2011) stated:

> The economy absolutely slowed in the first half of the year. ... It slowed because ... gas prices went up a lot because we had a huge supply disruption in the Mideast. You saw some really terrible weather across the country which slowed construction spending. State and local governments across the country are having to cut back, tighten their belts. You saw Japan suffer catastrophic damage. A lot of concern out of Europe still. And those factors together account for a large part of the slowdown.

As Secretary Geithner suggested, several other global events occurred during the first half of 2011, and separating the economic impacts due to the earthquake and tsunami from impacts caused by other events poses a challenge for modelers. Accurately quantifying the international impacts on production caused by major natural disasters can help national and international policymakers better understand how a disruption that occurs in one country may exacerbate an economic slowdown in other countries. At a more micro level, business leaders can use this analysis to anticipate the effects on their companies or industries. This understanding can encourage better risk management at an international, national, and firm level.

Possible international economic impacts from a disaster include supply disruptions due to disabled production and transportation infrastructure, demand fluctuations because companies and people in the disrupted country order fewer goods and services, and changes in producer and consumer behavior. Many companies in other countries, especially in the automotive and electronics industries, experienced supply disruptions due to the Japanese earthquake and tsunami. When the earthquake struck, these companies quickly realized that some supplies might be scarce, and most companies who were not physically impacted worked tirelessly to ensure that any supply disruptions that might occur would not severely slow their production lines (Blackwell, 2011; Bunkley, 2011a).

Although the events in Japan adversely impacted companies by increasing their costs and delaying some production (U.S. Congressional Research Service, 2011), the companies' ability to manage disruptions within their supply chains may have limited the macroeconomic impacts of supply shortages in other countries (Lohr, 2011; Salter, 2011). The slowdown in manufacturing in European and North American countries that occurred in spring 2011 was partly due to supply disruptions caused by the earthquake and tsunami, but this slowdown did not seem to impact consumers' ability to purchase commodities. Chapter 4 focuses more concretely on the effects of supply shortages.

Unlike supply shortages, demand fluctuations caused by drops in consumer and intermediate demand may represent more permanent production changes. The earthquake and tsunami rendered many Japanese production facilities inoperable for several weeks and months. Production in many Japanese industries dropped significantly, final sales to Japanese consumers fell for some industries, and Japanese imports and exports fluctuated in the months after the earthquake (Japan, 2011c; Wassener, 2011).

Because production fell in Japan, companies in Japan and those that deliver supplies to Japanese industries may have experienced a drop in the demand for their goods and services. Changes in Japanese exports and imports reflect changes in producer and consumer behavior, as Japanese consumers and companies substituted good and services produced by foreign companies because of inoperability in domestic production.

Chapter 2 relies on the multiregional DIIM to quantify the regional economic impacts of an inland waterway port closure, and multiregional I-O models (Isard et al., 1998; Crowther and Haimes, 2010) can help policymakers understand the global impacts due to demand fluctuations and changes in consumer and producer behavior that are caused by a major disruption. I-O models produce results that demonstrate the interdependent effects on industries that are not directly impacted by the disruption. Industries in foreign countries may also increase their production if the country in which the disruption occurs increases its imports or decreases its exports because of domestic production difficulties. I-O analysis provides a richer understanding of both the positive and negative impacts of a disruption on an industry-by-industry and a country-by-country basis.

Although this chapter relies on ideas developed in several I-O models, which are reviewed in Section 3.1, this chapter advances the field in several ways. Section 3.2 presents several different manipulations of the multiregional I-O model to reflect different types of impacts, including the effects of disabled production facilities, possible mitigation impacts of inventory, changes in demand resulting from a disruption, and consumers substituting goods and services. Section 3.3 applies this model to the Japanese earthquake and tsunami and uses production and consumer data collected by the Japanese government as inputs into the multiregional model. Finally, the multiregional model is used to analyze the structural features of the Japanese automotive industry and explore how this industry's business structure influenced the international effects of the disaster.

3.1 Methodological Background

A variety of methods and models have been proposed for measuring the direct and indirect effects on production caused by disruptions (Rose, 2004b; Okuyama, 2008). In addition to econometric models (Ellson et al., 1984), I-O models have formed the core of modeling the economic impacts of disasters.

3.1.1 Literature review

As discussed previously, I-O models describe the amount of production needed to satisfy a given level of demand where each industry's production is used in the production of other goods and services or is consumed as final demand (Leontief, 1936, 1951). I-O models traditionally rely on an exogenously determined level of demand to calculate each industry's production in an economy. If changes in industry production can be converted to changes in final demand, the final demand can be incorporated within an I-O model to estimate total production losses due to a disruption (Boisvert, 1992; Rose et al., 1997). Generating demand reductions based on employment impacts due to a large-scale disruption has been another popular alternative (Gordon et al., 1998, 2005). Supply side I-O models, which were introduced in Chapter 1, can also measure the impacts of constrained supply due to a disruption (Davis and Salkin, 1984; Park, 2008; Chen et al., 2009).

Like the Leontief I-O model, the static IIM calculates production changes based on demand reductions and has been applied to terrorist attacks (Haimes et al., 2005a,b; Santos, 2006), cyber disruptions (Andrijcic and Horowitz, 2006; Dynes et al., 2007), hurricanes (Haggerty et al., 2008), trade shortfalls (Jung et al., 2009), and inland waterway port disruptions (Pant et al., 2011). In addition to inland waterway port disruptions as described in Chapter 2 (see also MacKenzie et al., 2012), the DIIM has calculated the interdependent effects of constrained production due to employees falling ill from a pandemic (Orsi and Santos, 2010a,b).

In order to more accurately incorporate industry actions before and during a disruption, I-O models have been adapted to incorporate uncertainty (Santos, 2008; Barker and Haimes, 2009), industry mitigation activities such as inventory (Barker and Santos, 2010a,b), the possibility of alternate routes during a transportation disruption (Gordon et al., 2005; MacKenzie et al., 2012), the substitution of different inputs (MacKenzie and Barker, 2011), and timing effects that differ among industries (Okuyama et al., 2004). The adaptive regional I-O model (Hallegatte, 2008, 2011) measures the impact of supply constraints and new sources of inputs on production in the wake of Hurricane Katrina.

Computable general equilibrium models (Shoven and Whalley, 1992) build on the basic I-O framework but create flexibility in the model by allowing consumers and producers to optimize simultaneously and substitute other inputs for constrained supply (Rose and Guha, 2004). Because they focus on a new long-term equilibrium after a disruption, computable general equilibrium models may underestimate the impacts on production (Rose and Liao, 2005; Okuyama, 2008). Andreoni et al. (2011) use a hybrid I-O, computable general equilibrium model (Kratena and Streicher, 2009) to reconcile the disequilibrium between demand and supply caused by the Japanese earthquake and tsunami, but it may be overly optimistic about Japanese demand transferring to other countries.

3.1.2 Multiregional I-O model for international impacts

The multiregional I-O model (Isard et al., 1998) is used to analyze the global economy by connecting countries based on international trade. In a model with p countries and n industries per country, country s produces $\mathbf{x}^s$ amount of goods and services, consumes $\mathbf{c}^s$ amount of goods as final consumption, and relies on the technical coefficient matrix $\mathbf{A}^s$ to describe the economic interdependence among industries. The OECD collects and publishes the production, final demand, and technical coefficient matrices for over 30 countries.

Let t_i^{rs} be the proportion of goods and services in industry i consumed by country s that are produced in country r, as determined by Eq. (3.1), where m_i^{rs} is the value of industry i's goods and services that are imported by country s from country r, and m_i^s and e_i^s are country s's total imports from and exports to all other countries included in the model for industry i.

$$t_i^{rs} = \begin{cases} \dfrac{m_i^{rs}}{x_i^s + m_i^s - e_i^s} & \text{if } s \neq r \\ \dfrac{x_i^s - e_i^s}{x_i^s + m_i^s - e_i^s} & \text{if } s = r \end{cases} \tag{3.1}$$

The formula for t_i^{ss} represents goods and services that are produced and consumed in the same country. Including both exports and imports in the calculation ensures that t_i^{rs} captures all the production in industry i and that $\sum_{\forall r} t_i^{rs} = 1$.

As depicted in Eq. (1.4), the interregional matrix $\mathbf{T}$ is composed of p^2 diagonal sub-matrices, where the ith element on the diagonal of $\mathbf{T}^{rs}$ is t_i^{rs}. Introduced in Chapter 1, the multiregional I-O model is shown in Eq. (3.2) (For notational simplicity, the notation $\mathbf{y}^{q:p} = \left[(\mathbf{y}^q)^\intercal, (\mathbf{y}^{q+1})^\intercal, \ldots, (\mathbf{y}^p)^\intercal\right]^\intercal$ represents a vector of length $n(p-q+1)$ for countries $q, q+1, \ldots, p$, where $\mathbf{y}^s$ is a vector of interest such as production, final demand, or changes in production.) The square matrix $\mathbf{A} = \text{diag}\left(\mathbf{A}^1, \mathbf{A}^2, \ldots, \mathbf{A}^p\right)$ is of order np.

$$\mathbf{x}^{1:p} = \mathbf{TAx}^{1:p} + \mathbf{Tc}^{1:p} \Rightarrow \mathbf{x}^{1:p} = \left(\mathbf{I} - \mathbf{TA}\right)^{-1} \mathbf{Tc}^{1:p} \tag{3.2}$$

By necessity, multiregional models include fewer countries than the total number of countries in the world. Trade between countries in the model and all the countries

Table 3.1: Notation for Chapter 3

$\mathbf{A}$	Technical coefficient matrix for all countries
$\mathbf{A}^s$	Technical coefficient matrix in country s
$\mathbf{c}^s$	Vector of final demand in country s
e_i^s	Industry i's exports in country s
l	Number of directly impacted industries
m_i^s	Industry i's imports in country s
m_i^{rs}	Industry i's imports from country r to country s
$\bar{m}_i^{1s}$	Reduced level of imports from country 1 to country s
$\mathbf{m}_{ROW}^s = \left\{m_{ROW,i}^s\right\}$	Vector of imports from the rest of the world (ROW) to country s
n	Number of industries
p	Number of countries
$\mathbf{P}$	Matrix of proportion of companies not directly impacted
$\mathbf{T}$	Interregional matrix for all countries
$\mathbf{T}^{rs} = \{t_i^{rs}\}$	Matrix of trade flows from country r to country s
$\mathbf{x}^s = \{x_i^s\}$	Vector of industry production in country s
$\bar{\mathbf{x}}_{1:l}^1$	Vector of constrained production in country 1 for industries 1 through l
$\tilde{\mathbf{x}}^s$	Vector of new industry production in country s
$\boldsymbol{\alpha} = \{\alpha_i\}$	Vector of inverse of proportion of production impacts on domestic industries
$\mathbf{B}^s = \{\beta_i^s\}$	Matrix of proportion of country 1's imports produced in country s
$\delta\mathbf{x}^1(0) = \{\delta x_i^1(0)\}$	Vector of direct impacts in country 1
$\delta\mathbf{x}^1(0:\infty) = \left\{\delta x^1(0:\infty)\right\}$	Vector of production changes for country 1 accounting for the ROW
$\delta\mathbf{x}^s = \{\delta x_i^s\}$	Vector of indirect impacts in country s without accounting for the ROW
$\delta\mathbf{x}^s(1)$	Vector of production changes for immediate suppliers to directly impacted industries in country s
$\delta\mathbf{x}^s(1:\infty) = \{\delta x^s(1:\infty)\}$	Vector of indirect impacts for country s accounting for the ROW
$\boldsymbol{\Delta} = \{\Delta_i\}$	Vector of additional imports to satisfy final consumption by country 1
$\boldsymbol{\gamma}^s = \{\gamma_i^s\}$	Vector of additional exports from country s to satisfy country 1's final consumption
$\boldsymbol{\rho} = \{\rho_i\}$	Vector of proportion of companies not directly impacted

not included in the model, which is called the rest of the world (ROW), can be used to estimate the impacts on countries not included in the model. Let $\mathbf{m}^s_{ROW}$ be a vector of length n that represents the value of imports that country s imports from the ROW. Because the final demand vector $\mathbf{c}^s$ subtracts imports from final household consumption in the original I-O model, the ROW imports are added back into the original final demand vector to preserve the equilibrium between supply and demand (Isard et al., 1998). The new multiregional I-O model that includes the ROW is given in Eq. (3.3).

$$\mathbf{x}^{1:p} + \mathbf{m}^{1:p}_{ROW} = \mathbf{TA}\left(\mathbf{x}^{1:p} + \mathbf{m}^{1:p}_{ROW}\right) + \mathbf{T}\left(\mathbf{c}^{1:p} + \mathbf{m}^{1:p}_{ROW}\right) \tag{3.3}$$

Including the ROW ensures that the model represents a complete economic system.

3.2 Changes in Production due to a Disruption

For the purposes of this chapter, a major disruption can directly impact production in two different ways. First, production facilities may be destroyed or severely damaged such that only a portion of the normal production can occur in that facility. Second, the disruption may cause an increase in the demand for certain industries, such as machinery manufacturing and construction that are necessary to rebuild the nation's infrastructure. Although the latter type of impact may be more properly considered as an indirect impact (Hallegatte and Przyluski, 2010), describing both types as direct impacts fits more appropriately with the data, as will be discussed.

Indirect impacts are defined as the changes in production among industries who supply goods and services to companies directly impacted by the disruption. For example, if a disruption disables automotive companies' facilities so that they are unable to produce the usual quantity of cars, they will be forced to order less steel. The construction industry may require more steel, however, in order to rebuild infrastructure after the disruption. Although not directly impacted by the disruption, steel production will change due to decreased demand from the automotive industry and increased demand from the construction industry. Because industries represent the aggregation of companies that produce similar goods and services, a single industry may include companies that are directly impacted, companies that are indirectly impacted, and companies that are not impacted at all.

This modeling approach assumes that data describe production in some of a country's industries for a period of time following a disruption. The available data may only record the direct impacts for those industries, or it may record both the direct and indirect impacts for those industries. Each of these cases and their implications for production losses are presented in separate subsections.

3.2.1 Data representing direct impacts

Calculating the indirect impacts resulting from constraints on production challenges I-O modelers because I-O models calculate production levels based on an exogenously determined demand. Estimating reduced levels of final demand due to constrained production (Davis and Salkin, 1984; Boisvert, 1992; Steinback, 2004) may not be appropriate for a multiregional model because production is only constrained in one country and demand may not be reduced if that country increases its imports. Based on the frameworks offered by Cronin (1984) and Oosterhaven (1998), a method is developed to calculate the indirect impacts due to disabled production facilities that explicitly uses the technical coefficient matrix (the $\mathbf{A}$ matrix) as a means of estimating how a company whose production facilities are disabled will be forced to reduce its demand to its suppliers. Conceptualizing the I-O model as a supply chain composed of producers and suppliers echoes other studies (see Lin and Polenske, 1988; Albino et al., 2002) in which a company's supply chain is modeled as an I-O process.

Without loss of generality, industries $1 \ldots l$ in country 1 are directly impacted by the disruption where $l \leq n$ and n is the number of industries in each county. The disruption does not directly impact either the remaining $n-l$ industries in country 1 or any of the industries in countries $2 \ldots p$. The direct impacts in country 1 due to a disruption are given by the vector $\delta\mathbf{x^1}(0)$ where $\delta x_i^1(0)$ is non-zero for $1 \leq i \leq l$ and is zero for $l+1 \leq i \leq n$. Eq. (3.4) derives the production loss for the immediate suppliers in the p countries due to the l directly impacted industries in country 1, where $\delta\mathbf{x}^s(1)$ is the change in production in the immediate suppliers located in country s.

$$\begin{pmatrix} \delta\mathbf{x}^1(1) \\ \delta\mathbf{x}^{2:p}(1) \end{pmatrix} = \mathbf{TA} \begin{pmatrix} \delta\mathbf{x^1}(0) \\ \mathbf{0} \end{pmatrix} \tag{3.4}$$

This first echelon of suppliers consequently reduces its demand to its suppliers, and this pattern continues *ad infinitum*. Eq. (3.5) demonstrates the total production loss, where $\delta\mathbf{x}^s$ represents the direct plus indirect impacts in country s. The impact of including the ROW imports in the model is momentarily ignored.

$$\begin{pmatrix} \delta\mathbf{x}^1 \\ \delta\mathbf{x}^{2:p} \end{pmatrix} = \sum_{k=0}^{\infty} (\mathbf{TA})^k \begin{pmatrix} \delta\mathbf{x^1}(0) \\ \mathbf{0} \end{pmatrix} = (\mathbf{I} - \mathbf{TA})^{-1} \begin{pmatrix} \delta\mathbf{x^1}(0) \\ \mathbf{0} \end{pmatrix} \tag{3.5}$$

This method might overestimate the indirect impacts in country 1, however, because some of the directly impacted companies may also be suppliers to other directly impacted companies. This could particularly be true in a country like Japan where suppliers are often located close to their customers (Mair, 1992; Pollack, 2011). Eq. (3.6) modifies Eq. (3.5) where $\boldsymbol{\rho}$ is a vector of length n representing the proportion of companies in each industry that are not directly and adversely impacted by the disruption.

$$\begin{pmatrix} \delta\mathbf{x}^1 \\ \delta\mathbf{x}^{2:p} \end{pmatrix} = \sum_{k=0}^{\infty} (\mathbf{PTA})^k \begin{pmatrix} \delta\mathbf{x}^{\mathbf{1}}(0) \\ \mathbf{0} \end{pmatrix} = (\mathbf{I} - \mathbf{PTA})^{-1} \begin{pmatrix} \delta\mathbf{x}^{\mathbf{1}}(0) \\ \mathbf{0} \end{pmatrix} \tag{3.6}$$

where

$$\mathbf{P} = \begin{pmatrix} \operatorname{diag}(\boldsymbol{\rho}) & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}$$

Calculating accurate values for $\boldsymbol{\rho}$ requires specific knowledge about the location of each industry's suppliers. If suppliers are uniformly distributed throughout the country, ρ_i can be estimated for industry i via Eq. (3.7).

$$\rho_i = \begin{cases} 1 + \dfrac{\delta x_i^1(0)}{x_i^1} & \text{if } \delta x_i^1(0) < 0 \\ 1 & \text{otherwise} \end{cases} \tag{3.7}$$

If $\delta x_i^1(0) > 0$, which represents a positive direct impact on industry i, the model assumes that no suppliers in this industry are directly impacted in an adverse manner.

The indirect impacts of the disruption are assumed to be spread proportionally between the country's domestic production and the ROW imports. Eq. (3.8) calculates the indirect impact in industry i in country s as represented by $\delta x_i^s(1:\infty)$, where $\delta x_i^s - \delta x_i^s(0)$ represents the indirect impacts in industry i in both country s and the ROW, and $x_i^s / \left(x_i^s + m_{ROW,i}^s\right)$ is the proportion of that industry's output that is produced in country s as opposed to being imported from the ROW.

$$\delta x_i^s(1:\infty) = \frac{\left[\delta x_i^s - \delta x_i^s(0)\right] x_i^s}{x_i^s + m_{ROW,i}^s} \tag{3.8}$$

After separating out the ROW imports, industry i's total production change in country s can be calculated as the summation of direct plus indirect impacts: $\delta x_i^s(0) + \delta x_i^s(1:\infty)$. If industry i is not directly impacted, $\delta x_i^s(0) = 0$.

The entire supply chain may not experience demand fluctuations because of disabled production facilities, as this I-O model assumes. The upper limit of summation k could be a finite number to represent the number of echelons that would be impacted. However, most empirical data suggest that $(\mathbf{PTA})^k$ converges to zero for $k > 4$.

3.2.2 Data representing both direct and indirect impacts

The previous subsection assumed that the direct impacts are known, but it may be easier to observe the total economic impact on industries. If information on industrial output is collected by surveying companies, the survey may ask a company for its level of production during a given time period. Aggregating output levels for an industry from company surveys will likely include both companies whose production changes due to indirect impacts as well as companies whose production is reduced due to disabled facilities. Under this formulation, the total impacts $\delta x_i^1(0:\infty) = \delta x_i^1(0) + \delta x_i^1(1:\infty)$ are known for the first l industries in country 1 but are unknown for industries $l+1 \ldots n$. The direct impacts $\delta x_i^1(0)$ are unknown for the first l industries. There are no direct impacts for industries $l+1 \ldots n$.

The change in industry i's production, δx_i^1, can be expressed as a function of the direct and indirect impacts on domestic production. After the formula for $\delta x_i^1(1:\infty)$ as given in Eq. (3.8) is substituted into the calculation of $\delta x_i^1(0:\infty)$ as shown in the previous paragraph, Eq. (3.9) calculates δx_i^1.

$$\delta x_i^1 = \left(1 - \frac{x_i^1 + m_{ROW,i}^1}{x_i^1}\right)\delta x_i^1(0) + \frac{x_i^1 + m_{ROW,i}^1}{x_i^1}\delta x_i^1(0:\infty) \tag{3.9}$$

Let $\alpha_i = \left(x_i^1 + m_{ROW,i}^1\right)/x_i^1$ represent the inverse of the proportion of total production changes that impact domestic production. The data, which measure direct and indirect impacts for industries $1 \leq i \leq l$, are represented by $\delta x_i^1\,(0:\infty)$. Eq. (3.10) is identical to Eq. (3.6) except that Eq. (3.9) is substituted for δx_i^1. (The vector $\mathbf{y}_{1:l}^1$ represents industries $1 \ldots l$ in country 1 for a quantity of interest y_i^1.)

$$\begin{pmatrix} \operatorname{diag}(\boldsymbol{\alpha}_{1:l})\,\delta\mathbf{x}_{1:l}^1\,(0:\infty) \\ \quad + [\mathbf{I} - \operatorname{diag}(\boldsymbol{\alpha}_{1:l})]\,\delta\mathbf{x}_{1:l}^1\,(0) \\ \delta\mathbf{x}_{l+1:n}^1 \\ \delta\mathbf{x}^{2:p} \end{pmatrix} = (\mathbf{I} - \mathbf{PTA})^{-1} \begin{pmatrix} \delta\mathbf{x}_{1:l}^1\,(0) \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix} \tag{3.10}$$

The total impacts in the first l industries $\delta\mathbf{x}_{1:l}^1\,(0:\infty)$ are known and observed, but the direct impacts $\delta\mathbf{x}_{1:l}^1\,(0)$ in those industries as well as the total impacts in other industries $\delta\mathbf{x}_{l+1:n}^1$ and other countries $\delta\mathbf{x}^{2:p}$ are unknown. Eq. (3.10) can be solved for the direct impacts on the first l industries and the total impacts on all other industries and countries. As shown in Eq. (3.7), $\mathbf{P}$ assumes the proportion of direct impacts to total production is known *a priori.* The matrix $\mathbf{P}$ is estimated using the results derived from assuming the data only represent direct impacts.

3.2.3 Impact on final consumption

Direct production losses in country 1 may be replaced by production from other countries or by inventory. If a company whose production is disabled uses finished goods inventory to satisfy demand, production losses may still be observed. As long as its facility is inoperable, that company is not producing, and the model assumes that a non-producing company reduces orders to suppliers. Using finished goods inventory should allow the company to recover those losses in the future once its facility is restored. The company will presumably produce more than the "normal" amount in order to replenish its final goods inventory, and its orders to suppliers will increase. Finished goods inventory might not prevent production losses in the immediate aftermath of a disruption, but because inventory can satisfy current demand, industries who rely on inventory to weather the disruption should increase their production later.

If inventory is not available, other competing companies may be able to increase their production to replace the lost production. If production is constrained within country 1 at a certain level, final consumption could transfer to other countries whose industries may increase their production to satisfy demand in country 1. As before, data describing production losses in industries $1 \ldots l$ in country 1 are available, and these losses include both direct and indirect impacts. The production levels for the other industries in country 1 and all industries in the other countries are unknown. The constrained production for industries $1 \ldots l$ is given by the vector $\bar{\mathbf{x}}^1_{1:l}$. Let β_i^s be the proportion of country 1's imports belonging to industry i that derive from country s, and let β_i^{ROW} be the proportion of country 1's imports from the ROW. These proportions can be calculated using data on country 1's imports.

Because production in industries $1 \ldots l$ in country 1 is constrained, some of country 1's final demand will not be satisfied by those industries. If customers in country 1 buy from industries in other countries, $\boldsymbol{\Delta}$ can represent this change in consumer behavior. This parameter is a vector of length l where each element Δ_i represents the additional amount of country 1's final consumption of industry i's goods and services that country 1 imports from other countries. The additional amount of final demand that country 1 imports from country s in the wake of a disruption is assumed to follow the same proportion of imports that country 1 usually receives from country s as given by β_i^s. If $\boldsymbol{\gamma}^s$ is a vector of length n representing the amount of additional exports needed from country s to satisfy country 1's final consumption, Eq. (3.11) calculates this quantity for industry i for $s = 2 \ldots p$ and $s = ROW$.

$$\gamma_i^s = \begin{cases} \Delta_i \beta_i^s & \text{if } i \leq l \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

This formula assumes that country 1 will not import additional product to satisfy final demand for industries that suffer no direct loss.

The additional imports as represented by $\boldsymbol{\Delta}$ to satisfy country 1's final demand is not known. Eq. (3.12) offers a way to estimate this vector. The constrained production $\bar{\mathbf{x}}^1_{1:l}$ is known, but $\tilde{\mathbf{x}}^1_{l+1:n}$, the new production for industries in country 1 that are not impacted, and $\tilde{\mathbf{x}}^{2:p}$, the production quantities in the other countries, are unknown vectors. The unknown change in final consumption as represented by $\boldsymbol{\Delta}$ is subtracted from final consumption in country 1 because this amount of consumption can no longer be supported by industries in country 1. The additional imports as represented by $\boldsymbol{\gamma}^s$ is added to the other countries' final consumption vector, and the additional imports from the ROW $\boldsymbol{\gamma}^{ROW}_{1:l}$ is included in both the production and final consumption vector.

$$\begin{aligned} \begin{pmatrix} \bar{\mathbf{x}}^1_{1:l} + \boldsymbol{\gamma}^{ROW}_{1:l} \\ \tilde{\mathbf{x}}^1_{l+1:n} \\ \tilde{\mathbf{x}}^{2:p} \end{pmatrix} &= \mathbf{TA} \begin{pmatrix} \bar{\mathbf{x}}^1_{1:l} + \boldsymbol{\gamma}^{ROW}_{1:l} \\ \tilde{\mathbf{x}}^1_{l+1:n} \\ \tilde{\mathbf{x}}^{2:p} \end{pmatrix} \\ &+ \mathbf{T} \begin{pmatrix} \mathbf{c}^1_{1:l} + \mathbf{m}^1_{ROW,1:l} - \boldsymbol{\Delta} + \boldsymbol{\gamma}^{ROW}_{1:l} \\ \mathbf{c}^1_{l+1:n} + \mathbf{m}^1_{ROW,l+1:n} \\ \mathbf{c}^{2:p} + \mathbf{m}^{2:p}_{ROW} + \boldsymbol{\gamma}^{2:p} \end{pmatrix} \end{aligned} \tag{3.12}$$

Because $\Delta_i = \sum_{s=2}^{p} \gamma_i^s + \gamma_i^{ROW}$, the total amount of final consumption remains the same in the global economy. There are l unknown values in the $\boldsymbol{\Delta}$ vector, which describes the level of demand that is satisfied by industries in other countries, and

$np - l$ unknown production values as represented by $\tilde{\mathbf{x}}$. As Appendix 3.A details, the np equations can be used to solve for these unknown values.

Customers in country 1 may not purchase goods and services from other countries, however. Industries in other countries may not be able increase their production, customers may not want to buy from foreign industries, or disruptions in shipping may limit the ability of country 1 to import products. If demand in country 1 is not satisfied by increased production in other countries or with inventory, purchases could be delayed and customers may increase their demand in later months. For example, an individual who does not buy a car because constrained production limits his or her options may choose to buy a car a few months later when production is restored.

Alternatively, demand may disappear and never be recaptured. This discussion of demand disappearing does not imply that demand will fail to return to pre-disaster levels. If demand rises above pre-disaster levels, demand that was not satisfied in the immediate aftermath of the disruption is being recaptured over the longer term. When lives are lost due to a major natural disaster like an earthquake or tsunami, people may decide in the wake of the accident not to purchase certain goods and items, especially if these are luxury items. There is no guarantee that they will buy more later.

3.2.4 Import substitution

A country that is not directly impacted by the disaster may replace lost imports from the disrupted country with its own domestic production. The fraction of country 1's constrained production that manifests itself as lost exports to country s can be assumed to equal the fraction of country 1's normal production that is exported to country s. Eq. (3.13) calculates the reduced level of imports $\bar{m}_i^{1s}$ that industry i in country s receives from country 1, where m_i^{1s} is the pre-disaster value of imports that industry i in country s imports from country 1 and $\bar{x}_i^1$ is the constrained production of industry i in country 1.

$$\bar{m}_i^{1s} = \begin{cases} \dfrac{m_i^{1s}\bar{x}_i^1}{x_i^1} & \text{if } \bar{x}_i^1 < x_i^1 \\ m_i^{1s} & \text{otherwise} \end{cases} \tag{3.13}$$

The second condition implies that imports from country 1 do not change if $\bar{x}_i^1 \geq x_i^1$, which signifies that production increases or is not constrained.

A new interregional matrix is constructed to reflect that countries are not importing as much from the country that has suffered a disruption. The new $np \times np$ interregional matrix $\mathbf{T}$ is calculated via Eq. (3.1) with $\bar{m}_i^{1s}$ replacing m_i^{1s} for each country s. The total imports by country s, m_i^s, is also reduced by $m_i^{1s} - \bar{m}_i^{1s}$.

When the disruption occurs, industries in countries not directly disrupted may experience conflicting impacts. They may suffer from lost demand due to industries in the disrupted country reducing their demand for production, as demonstrated in Eqs. (3.6) and (3.10). These industries' domestic customers may also substitute domestically produced goods and services in the place of imports from the disrupted country. This last impact is calculated by incorporating the new interregional matrix into Eq. (3.3) and solving for a new production vector $\mathbf{x}^{1:p}$ while keeping the final demand vector $\mathbf{c}^{1:p}$ constant.

This section has explored several different methods that extend the multiregional I-O model to estimate the international impacts of a major disruptive event. Any one of them may be appropriate to analyze a situation, but it is difficult to know which method or methods are most appropriate. Each of these methods is applied to the 2011 Japanese earthquake and tsunami, and the models' results are compared to understand which method seems to describe most accurately the impacts of this disaster.

3.3 Empirical Application: 2011 Japanese Earthquake and Tsunami

3.3.1 Data sources

The data sources used for this application derive from the OECD and the Japanese government. The OECD (2011) collects and publishes I-O data in U.S. dollars for all of the OECD countries and for 11 non-OECD countries in Asia and South America. The most recent data come from the mid-2000s, and each national economy is divided into 37 industries. The data are used to create the technical coefficient matrices and production and final consumption vectors. Using data from the mid-2000s to study the economic consequences of an disruption that occurred in 2011 assumes that the structural coefficients have not drastically changed in the years since this data was collected. This is customary in I-O modeling in the absence of more current data.

Eighteen countries in addition to Japan are included in the model: Australia, Belgium, Brazil, Canada, Chile, China, France, Germany, India, Indonesia, Italy, South Korea, Mexico, the Netherlands, Taiwan, Thailand, the United Kingdom, and the United States. These countries represent 66% of all of Japan's imports. The rest of Japan's imports that are not included in the model mostly derive from the Middle East and other Asian countries for which the OECD does not publish I-O tables. The I-O analysis includes the difference between a country's total imports and imports from the other 18 countries to estimate the impacts on the ROW, which includes these Middle Eastern and Asian countries.

The OECD also provides bilateral trade matrices for 21 of the 37 industries. The imports from 2009 (the most recent year available) are used to generate $\mathbf{T}$ for OECD countries. The 21 industries included in the bilateral trade matrices cover agriculture, mining, and manufacturing activities. In order to estimate trade data for the other

16 industries, the fraction that country s imports from country r for those industries is assumed to be equal to the overall proportion that country s imports from that country r. The total value of trade between the five non-OECD countries as published by the United Nations (2009) is used to estimate $\mathbf{T}$ for these five countries. Because the trade data are not disaggregated by industry, the proportion of trade between these non-OECD countries is assumed to be the same for all industries.

Data to estimate the impacts of the Japanese earthquake and tsunami come from the Japanese Ministry of Economy, Trade and Industry (METI), which publishes monthly production data for 14 manufacturing industries and the Mining, Food and Tobacco, and Construction industries (Japan, 2011b). For each industry, METI reports the production index (using 2005 as the base year) and the percent change in the index from the same month of the previous year. It also publishes indices and changes from the previous year for industry shipments and inventory (Table 3.2). The percent changes in production for March, April, and May 2011 become the production changes in these 17 industries that are directly impacted by the disruption. If 2010 represents as-planned production, the measured production deviations in 2011 are changes from typical production.

Comparing industry production with its shipments provides insight into how industries relied on inventory. If the negative percent change in an industry's production is less than the percent change in its shipments, it is assumed that the industry uses inventory to fill the gap between production and shipments. As Table 3.2 shows, in many of the months where industry shipments exceeded production, inventory also decreased during those months.

Japan's monthly consumer sales provide another important data source for this analysis. Monthly consumer sales published by METI (Japan, 2011e) are used to estimate changes in consumer sales for the Agriculture, Food and Tobacco, Textile, Wholesale Trade, Construction, and 10 manufacturing industries (Table 3.3).

Table 3.2: Percent change in industry production in 2011 from same months in 2010

Industry	March			April			May		
	Pro	Ship	Inv	Pro	Ship	Inv	Pro	Ship	Inv
Mining and Quarrying	1.4	-3.2	-4.5	-5.9	0.5	11.6	-1.8	1.1	-9.2
Food and Tobacco	-7.5	-2.2	-47.1	-2.4	-4.2	-36.2	1.9	1.1	-29.3
Textiles	2.3	-2.1	-5.2	-0.1	-2.1	-2.9	2.2	1.8	-3.7
Wood Products	1.8	3.8	-11.0	3.2	6.1	-11.0	5.6	8.8	-11.1
Paper Products	-6.2	-6.1	-5.9	-7.2	-5.4	-7.2	-6.5	-3.9	-8.1
Coke and Refined Petroleum Products	-10.0	-9.0	-4.6	-13.0	-13.7	5.0	-9.7	-7.0	-7.0
Chemicals	-7.5	-6.2	0.7	-9.0	-8.5	1.2	0.3	-5.3	4.6
Rubber and Plastic Products	-9.7	-11.7	1.3	-5.9	-9.0	2.4	0.6	-2.2	3.3
Other Non-Metallic Mineral Products	-2.9	-7.7	2.3	-2.2	-5.0	6.0	-2.4	-3.7	6.6
Basic Metals	-9.3	-7.2	7.5	-9.3	-8.4	6.7	-9.2	-12.2	10.6
Fabricated Metal	-6.9	-6.0	-1.9	-7.0	-6.2	-0.3	-0.9	-1.5	1.9
Machinery and Equipment	6.9	4.7	0.7	8.5	3.8	3.9	17.3	16.1	10.2
Electrical Machinery	-4.1	-2.7	30.8	-8.8	-7.3	25.6	-6.0	-5.2	32.4
Medical and Precision Instruments	-10.8	-8.5	-5.4	0.1	-11.9	3.3	3.0	3.5	5.7
Motor Vehicles	-47.7	-38.9	-51.8	-49.0	-52.6	-43.3	-26.5	-31.0	-23.2
Other Manufacturing	-7.3	-9.0	-0.9	-3.2	-3.3	-0.1	-0.2	1.9	-1.1
Construction	-1.3	-0.8	0.2	2.7	1.4	4.5	3.7	1.8	8.2

Production abbreviated as “Pro,” Shipments as “Ship,” and Inventory as “Inv.”

Table 3.3: Percent change in consumer sales in 2011 from same months in 2010

Industry	March	April	May
Agriculture, Forestry, and Fishing	-11.1	-14.1	-7.3
Food and Tobacco	-0.2	-0.6	3.0
Textiles	-7.9	-6.0	2.0
Wood Products	-1.5	1.5	2.4
Coke and Refined Petroleum Products	5.3	-1.0	1.3
Chemicals	-6.3	-2.5	-3.7
Other Non-Metallic Mineral Products	11.3	5.6	5.0
Fabricated Metal	11.3	5.6	5.0
Machinery and Equipment	-2.9	-1.0	8.3
Electrical Machinery	10.5	-2.7	3.9
Motor Vehicles	-9.3	-13.9	-10.8
Other Transport Equipment	-3.5	-2.4	3.3
Other Manufacturing	0.1	3.9	7.0
Construction	-1.5	1.5	2.4
Wholesale Trade	3.4	2.3	-1.5

The consumer sales data represent changes in the final consumption vector $\mathbf{c}^1$ for Japan and can be incorporated into Eq. (3.2) to calculate the impact on production. Using consumer sales as a proxy for changes in final consumption sheds more light onto the impacts of the earthquake and tsunami on the Japanese consumer and how the direct impacts of production are manifested in final sales.

3.3.2 Data representing direct impacts

The economic impact is calculated if the observed industry production data for the 17 industries recorded by METI represent only the direct impacts of the earthquake and tsunami. Fig. 3.1 shows the direct impacts without inventory and indirect impacts with and without inventory for March, April, and May 2011. The results are separated for the most impacted countries: Japan, China, Germany, South Korea, and the United States. Other Asia represents the Asian countries included in the model: Australia, India, Indonesia, Taiwan, and Thailand. Other Europe represents

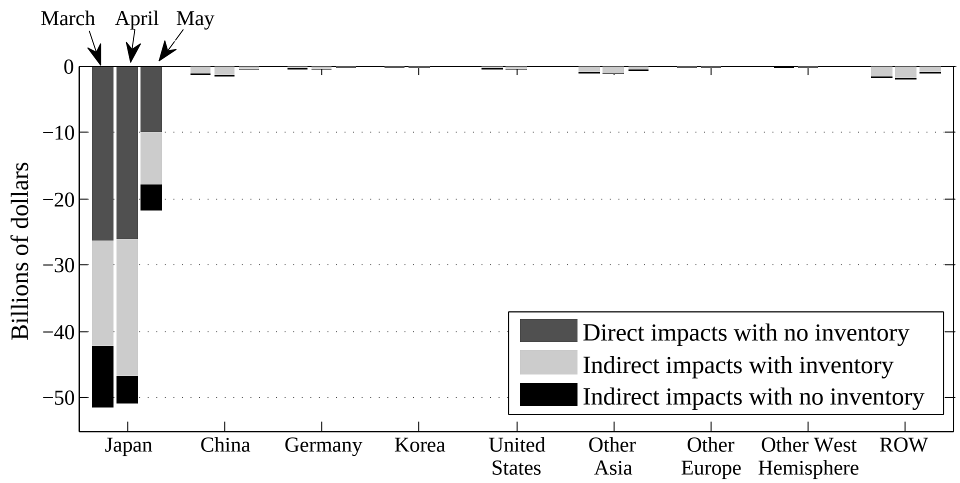

Figure 3.1: Monthly changes in production when the data represent direct impacts. Other Asia represents Australia, India, Indonesia, Taiwan, and Thailand. Other Europe represents Belgium, France, Italy, and the United Kingdom. Other West Hemisphere represents Brazil, Canada, Chile, and Mexico.

the countries of Belgium, France, Italy, and the United Kingdom; and Other West Hemisphere represents Brazil, Canada, Chile, and Mexico.

Japan's total production losses in March and April exceeded \$51.9 billion, which corresponded to 7.3% of Japan's monthly output. Production losses only totaled \$20.7 billion in May. Principal drivers behind the increased production in May include the Motor Vehicles industry whose production rose from 51.0% to 73.5% of normal in May and General Machinery that produced 17.3% more in May 2011 than it had in 2010.

These results also show that the macroeconomic impact on other countries was minimal relative to Japan. If inventory is ignored, the production loss outside of Japan was \$17.2 billion over the span of those three months. China experienced the most severe impact with losses about \$1.5 billion in March and April and \$584 million in May, but even the losses in March and April accounted for less than 0.3% of China's monthly production.

The model also demonstrates the importance of inventory. Although using fin-

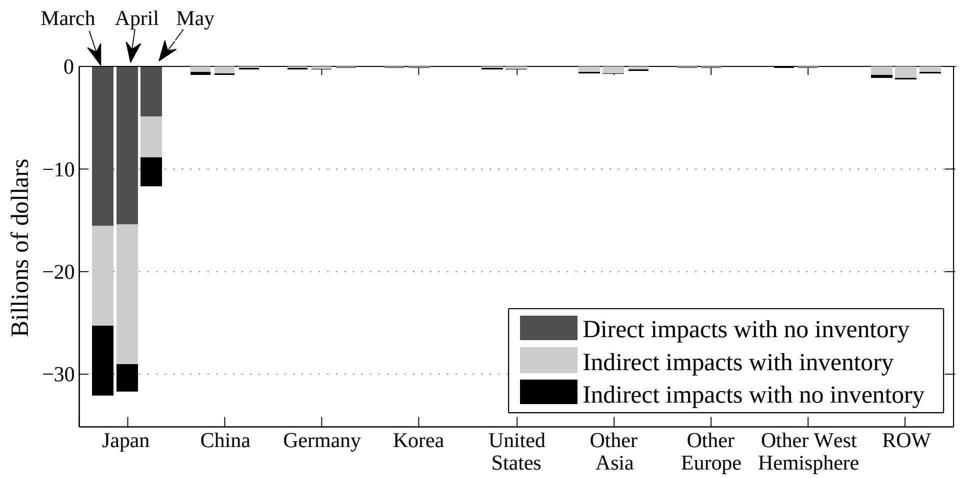

Figure 3.2: Monthly changes in production when the data represent both direct and indirect impacts

ished goods inventory may not prevent production losses if facilities are disabled, the Japanese industries that used inventory to maintain their shipments should be able to recover those production losses. Industries should produce more in order to replenish their inventory. With inventory, Japan should recover \$20.3 billion or 15.8% of its production that was lost from March to May.

3.3.3 Data representing both direct and indirect impacts

The METI production data may incorporate both direct and indirect impacts on production. As demonstrated in Fig. 3.2, assuming that the data include both direct and indirect effects significantly changes the analysis on total production losses. Japanese production losses in March and April exceeded \$32.4 billion (or about 4.6% of monthly production), and production losses in May were \$11.6 billion. Production losses in the other countries totaled \$10.8 billion over the three months. The estimate of the earthquake and tsunami's impact on production decreases by approximately 40% using a model that assumes the observed data include both types of impacts.

Comparing the analyses from Figs. 3.1 and 3.2 raises the question of which assumption is more accurate. As information on industry production is usually gathered via company surveys, answering that question depends in part on the length of time it takes for these indirect impacts to ripple through supply chains. Some industries, like Agriculture and Mining, produce months or even a year in advance to meet anticipated demand. Indirect impacts in these industries would not likely be observed for several months or more. Manufacturing industries can generally react to demand changes in weeks, and still other industries, like the service industries, can react to demand changes almost immediately (Okuyama et al., 2004). Because manufacturing industries comprise most of the observed data, indirect impacts should appear in the data within a matter of weeks as opposed to months.

The data reveal that many industries had much smaller production losses in May. If the lag time to observe the indirect impacts were larger than a few weeks, the month of May would have had greater production losses because the indirect impacts resulting from the direct effects that occurred in March and April would not have been observable until May or even later. Journalistic accounts (Lohr, 2011; Robertson, 2011; Rowley, 2011) of the earthquake and tsunami also suggest that the economic reverberations were felt within the first couple of months. It appears more reasonable to assume that the published data include both direct and indirect impacts as opposed to only direct effects.

I-O analysis provides important insight into the impacts on individual industries. The 37 industries are aggregated into 10 industries, and Fig. 3.3 depicts direct and indirect impacts in each industry in Japan both with and without inventory. These results are based on the assumption that the METI production data include both direct and indirect impacts. The Transportation and Office Equipment industry, which includes the automotive sector, suffered the greatest production losses, both in direct and in indirect impacts. The Minerals and Metals industry, which includes a lot of basic manufacturing, had $10.3 billion in indirect production losses even though the industry's direct losses only totaled $1.1 billion. Japanese service industries (Whole-

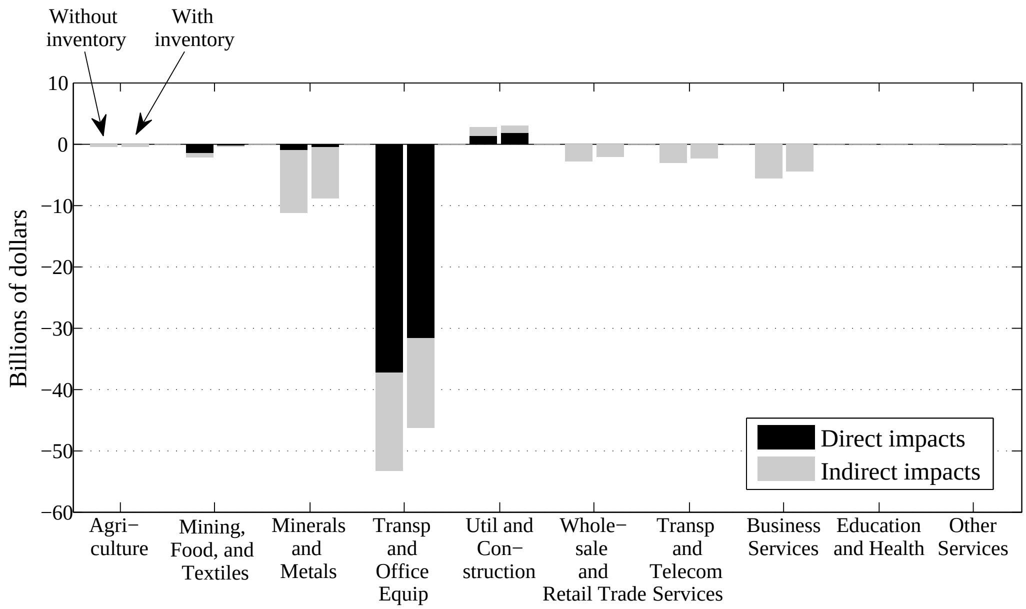

Figure 3.3: Changes in production in Japanese industries

sale and Retail Trade, Transportation and Telecommunication, and Business Services) had no direct impacts but suffered \$11.6 billion in production losses during the three months following the earthquake and tsunami. Conversely, Agriculture, Mining, Food, and Textiles only lost \$2.6 billion, of which \$1.6 billion were direct production losses. As Barker and Santos (2010b) discuss, the breakdown of industry production losses can help policymakers determine the key sectors that are impacted by a disruption. The disruption in the Japanese automotive sector led to tens of billions of dollars of production losses in the service and manufacturing sectors.

3.3.4 Impact on Japanese demand

The other data set, the commercial sales indices, demonstrates the impact of the earthquake and tsunami on the Japanese consumer. Fig. 3.4 shows the impact of demand fluctuations on production over March, April, and May. The total production loss due to demand changes was an order of magnitude less than the impact due to disabled production facilities. The largest month, April, only had production losses

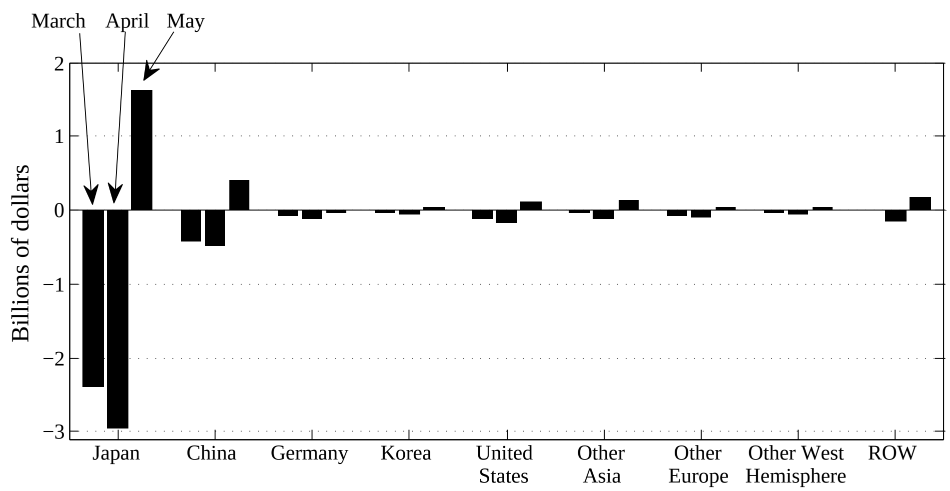

Figure 3.4: Monthly changes in production due to demand changes

of \$3.0 billion, which is less than a tenth of production losses as calculated from production losses. Final consumption increased in May beyond 2010 levels, leading to a gain of \$2.1 billion in production for Japan and minor increases in production for the other countries. These results suggest that much of the demand that was not satisfied in March and April returned in May.

How should the results based on production data be interpreted in light of the results based on commercial sales? First, Japanese demand seems to be resilient. Even though final consumption dropped during the first two months after the tsunami and the earthquake, it started to revive by the third month. Second, commercial sales data only include a fraction of the Japanese industries. Including changes in consumer demand for more of the industries might result in greater production losses for March and April, but it still would not equal the results based on METI's production data.

Third, Japanese final consumption never fell as far as Japanese production. The results derived from the production data suggest that Japanese industries were not producing enough to meet the current demand, and yet, much of that demand was actually met. For example, Motor Vehicle production in March and April fell 45% from 2010 levels, but final demand for that industry only fell 10% to 15%.

Table 3.4: Changes in production according to different models (millions of dollars)

Country	Driver of production changes: Disabled facilities	Increased exports to Japan	Import substitution
Japan	-78,068		
China	-2,230	6,774	3,350
Germany	-824	10,495	1,244
South Korea	-595	3,383	1,629
United States	-826	3,790	10,771
Other Asia	-1,991	3,771	3,401
Other Europe	-629	3,790	2,629
Other West Hemisphere	-411	1,722	2,377
ROW	-3,300	7,178	1,020

One explanation for this large difference is that Japan increased its imports to make up for lost production. According to the Japanese Statistics Bureau (Japan, 2011a), Japanese imports increased by 10.7% in March, April, and May 2011 compared to those same months in 2010. If Japan had replaced all of its lost production with imports, the multiregional I-O model predicts that Japan's imports should have increased by 14.7% during those three months. The second column of Table 3.4 depicts the increased production in other countries that could have been expected to occur if exports to Japan increased by 10.7%. This approach assumes that the fraction of Japan's total imports from each country remains constant. Germany and China benefited the most from increased imports as their industrial production should have increased by \$10.5 billion and \$6.8 billion, respectively.

Inventory in the pipeline likely substituted for the remaining production shortfall (Calunson, 2011; Shameen, 2011). The commercial sales data derive mostly from retail sales, and the stores' inventories are probably not reflected in the production, inventory, and shipment data released by METI. Because inventory enabled some Japanese demand to be met, Japanese production should rise above typical levels once facilities are restored. The inventory in the pipeline and stores' inventories would need to be replenished.

3.3.5 Import substitution

From March through May 2011, the total value of Japan's exports fell by 5% compared with 2010. Overall, 5% is not a large difference, but the lost exports were heavily concentrated in a few industries. Exports from Japan's Motor Vehicles industry fell by approximately 21% and Computer exports dropped by 17%. Some of Japan's trading partners were also impacted heavily, including the United States whose imports from Japan fell by 13% and Taiwan whose imports fell by 10% (Japan, 2011a).

It seems likely that countries' domestic industries produced more to replace some of the lost imports from Japan. For example, U.S. automobile manufacturers General Motors, Ford, and Chrysler increased their share of production in North America from 55% of total production in January to almost 59% by June 2011, whereas Toyota's share fell by 2% and Honda's share fell by 3% (Ward's AutoInfoBank, 2011). The third column in Table 3.4 shows the production changes if countries' domestic industries compensated for the loss in imports from Japan by increasing their production. According to this model described in Subsection 3.2.4, other countries benefited by increasing their domestic production: the United States increased its production by $10.8 billion, China by $3.4 billion, and South Korea by $1.6 billion.

As depicted in columns 2 and 3 in Table 3.4, increasing both exports to Japan and domestic production to replace lost imports from Japan greatly surpassed the indirect production losses that countries experienced due to disabled Japanese facilities. The multiregional I-O model separates and quantifies the changes in production resulting from these different drivers. According to the model, which aligns closely with the actual trade data, the overall impact from the Japanese earthquake and tsunami provided macroeconomic benefits to other countries.

3.3.6 Japanese automotive industry structure

Japan's motor vehicles or automotive industry suffered the most from the earthquake and tsunami. The Japanese auto industry, as exemplified by the Toyota *keiretsu*, stresses an integrated and closely coordinated supply chain (Ellram and Cooper, 1992; McMillan, 1996). Automotive companies encourage long-term relationships between suppliers and manufacturers and integrate subcontractors into their decision making and planning (Kim, 2011). If a disruption occurs, the *keiretsu* can band together by directing certain companies to produce more to replace the lost production at other facilities (Sheffi, 2005). Companies like Toyota and Honda resumed production more quickly after the disaster than many observers expected (Rechtin, 2011; Tabuchi, 2011).

Although the multiregional I-O model may not be best suited to analyze if structural and cultural features of the Japanese automotive industry enabled it to recover quickly, the I-O model can compare the interdependent effects of a disruption in this industry with similar disruptions in other countries. The disruption in the Japanese automobile industry is compared with a similar, but hypothetical, disruption in China, Germany, South Korea, and the United States.

Each country's automotive industry proportionally suffers the same impact as that of Japan's automotive industry from March through May: automotive production at 38.1% less than normal. Each situation is analyzed separately, i.e., only one country's automotive industry is directly impacted at one time. Fig. 3.5 shows the impact of each disruption where the first bar for each country assumes the 38.1% are direct impacts and the second bar assumes the 38.1% includes both direct and indirect impacts in the automotive industry.

Understanding the reasons for the differences in Fig. 3.5 is important for forecasting the interdependent effects of large disruptions that might occur in different

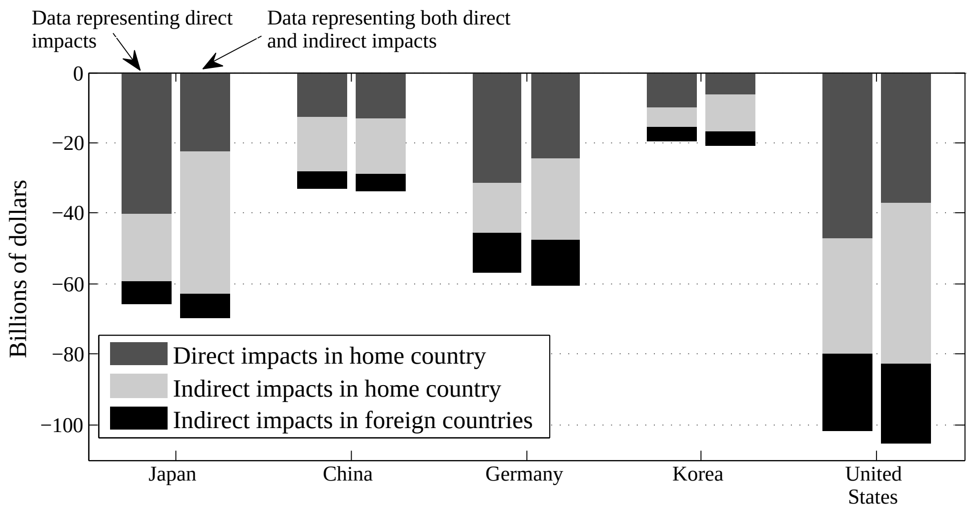

Figure 3.5: Changes in production due to impacts on the automotive industry

countries. Although the U.S. automotive industry produces about $18 billion more than the Japanese automotive industry during a three-month span, indirect production losses resulting from a disruption in the U.S. automotive industry exceed losses from a similar disruption in Japan by $21 to $29 billion. If the automotive industry in each country suffers a 38.1% shortfall in direct impacts, indirect losses are proportionally smaller in Japan than in the other countries.

Indirect losses in Japan are proportionally smaller than those in the other countries because Japan's automotive industry is very self-dependent. From the technical coefficient matrix, Japan's automotive industry requires 46 cents of production input from its own industry for every dollar of production output. None of the other countries' automotive industries require more than 40 cents of input from their own industries, and the U.S. automotive industry only needs 29 cents. If a disaster disables 38.1% of the automotive industry in Japan, many suppliers who are also part of the automotive industry will also be directly impacted. Because so many suppliers are already directly impacted, the model predicts fewer indirect production losses.

The international impacts from a disruption in Japan are smaller than if the disruption occurs in another country. The Japanese automotive industry relies more on industries within Japan than industries in foreign countries. Imports account for less than 4% of Japan's automotive production, whereas imports account for 25% of Germany's automotive production and 40% of U.S. automotive production. Because Japanese automotive industries rely on industries within its own country, the international impacts of the earthquake and tsunami were limited. If a similar disruption were to occur in the United States or a European country, the international impacts could be more significant.

3.4 Conclusion

This chapter has presented several approaches to estimate the different production impacts caused by a major disruption. The 2011 Japanese earthquake and tsunami provide an appropriate case study for this multiregional I-O modeling framework. The framework is parameterized using I-O tables and trade data from the OECD, and production and consumer sales data published by METI provide a reliable source of input data into the model.

The model does not attempt to quantify every possible international impact resulting from this disaster, and supply shortages may have caused global production to slow down, especially in the automotive and electronics industries. Other possible impacts of the disruption include international price fluctuations and changes in Japanese wages or employment (BEA, 1997). Shortages increased the prices of some consumer products, such as automobiles (Hirsch, 2011) and cameras (Lam, 2011), but employment and wages in Japan remained fairly constant from March through May (Japan, 2011d).

Without I-O tables and the Leontief economic model, understanding the differences between consumer sales and production data would be more challenging because the former involves sales to final consumers and the latter includes intermediate and final production. I-O methods translate both sets of data into a common measurement, total production losses in Japan. If the data include both direct and indirect impacts for the 17 industries, production losses in Japan totaled \$78.1 billion and Japan's GDP lost \$41.7 billion from March to May. These losses represent 3.6% of Japan's typical economic output. Disaggregating the production losses by industry reveals that Minerals and Metals Manufacturing, Transportation Equipment, and several services industries suffered the greatest indirect impacts. The consumer sales data suggest a different picture, however, as changes in final consumption only led to \$3.7 billion in production losses.

This \$74.4 billion difference generated by these two methods can be explained by increased Japanese imports from other countries and inventory in Japan's retail stores. Japanese imports increased by 10.7% during the three months following the earthquake and tsunami. This increase satisfied about 73% of the shortfall between demand and production.

The multiregional I-O model can distinguish among different impacts on production and quantify the changes in production due to losses in intermediate demand, the use of inventory, increased imports, and import substitution. The I-O model suggests that contrary to popular perception, industries in other countries may have actually benefited from the Japanese earthquake and tsunami. Japanese industries do not import enough from other countries that those countries would experience serious production losses due to a drop in intermediate demand. Japan increased its imports to replace some of its domestic production, which likely led to more production in countries like Germany and China. Some industries in other countries, especially the U.S. automotive industry, also benefited as they produced more to meet demand in their home countries. Chapter 4 explores this latter effect in more depth.

The importance of this work for planning purposes is that policymakers may not need to be concerned about the adverse economic impact of large-scale disruptions that occur in foreign countries. Certainly, the humanitarian needs of a disaster like an earthquake or tsunami require that nations and international organizations react quickly to assist in saving lives, caring for displaced people, and ensuring that basic necessities are met. Although national economies are linked together, the indirect impacts from a disruption would likely be dispersed among several different countries such that any individual country that escaped direct impacts would probably not experience large production losses. Industries in those other countries may also benefit from the disruption by increasing exports to the disrupted country and replacing imports from that country. The resilience of the global economy, the likelihood that demand will stay high or recover after a couple of months, and the ability of companies to rely on inventory can help ensure that any international production losses will be temporary and limited in scope.

3.A Appendix: Solving for Impact on Final Consumption

A solution is presented for calculating the unknown production quantities in Eq. (3.12), which describes additional imports by country 1 to satisfy final consumption when its production is constrained as described in Subsection 3.2.3. Let $\mathbf{B}^s = \text{diag}(\boldsymbol{\beta}^s_{1:l})$ be a diagonal matrix of size l and let

$$\mathbf{B}^{2:p} = \begin{pmatrix} \mathbf{B}^2 \\ \vdots \\ \mathbf{B}^p \end{pmatrix}$$

be a matrix of size $n(p-1) \times l$. Eq. (3.12) is rearranged to solve for the unknown quantities.

$$
\begin{aligned}
&(\mathbf{I}-\mathbf{TA}\ )\begin{pmatrix}\bar{\mathbf{x}}^1_{1:l}\\ \mathbf{0}\\ \mathbf{0}\end{pmatrix}-\mathbf{T}\begin{pmatrix}\mathbf{c}^1_{1:l}+\mathbf{m}^1_{ROW,1:l}\\ \mathbf{c}^1_{l+1:n}+\mathbf{m}^1_{ROW,l+1:n}\\ \mathbf{c}^{2:p}+\mathbf{m}^{2:p}_{ROW}\end{pmatrix}\\
&=(\mathbf{TA}-\mathbf{I})\begin{pmatrix}\mathbf{B}^{ROW} & \mathbf{0} & \mathbf{0}\\ \mathbf{0} & \mathbf{I} & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \mathbf{I}\end{pmatrix}\begin{pmatrix}\boldsymbol{\Delta}\\ \tilde{\mathbf{x}}^1_{l+1:n}\\ \tilde{\mathbf{x}}^{2:p}\end{pmatrix}+\mathbf{T}\begin{pmatrix}\mathbf{B}^{ROW}-\mathbf{I} & \mathbf{0} & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \mathbf{0}\\ \mathbf{B}^{2:p} & \mathbf{0} & \mathbf{0}\end{pmatrix}\begin{pmatrix}\boldsymbol{\Delta}\\ \mathbf{0}\\ \mathbf{0}\end{pmatrix}\\
&=\left[(\mathbf{TA}-\mathbf{I})\begin{pmatrix}\mathbf{B}^{ROW} & \mathbf{0} & \mathbf{0}\\ \mathbf{0} & \mathbf{I} & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \mathbf{I}\end{pmatrix}+\mathbf{T}\begin{pmatrix}\mathbf{B}^{ROW}-\mathbf{I} & \mathbf{0} & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \mathbf{0}\\ \mathbf{B}^{2:p} & \mathbf{0} & \mathbf{0}\end{pmatrix}\right]\begin{pmatrix}\boldsymbol{\Delta}\\ \tilde{\mathbf{x}}^1_{l+1:n}\\ \tilde{\mathbf{x}}^{2:p}\end{pmatrix}
\end{aligned}
\tag{3.14}
$$

Because the unknown variables, $\boldsymbol{\Delta}$ and $\tilde{\mathbf{x}}^s$, are all on the right hand side, it is trivial to solve Eq. (3.14).

Chapter 4

Modeling Severe Global Supply Chain Disruptions, with Application to the Automobile Sector Following the Japanese Earthquake and Tsunami

The earthquake and tsunami that struck Japan directly impacted over 27,000 businesses whose production, warehousing, and retail facilities were destroyed or disabled by the natural disaster. One year after the disaster, 22% of those businesses had not yet resumed operations (*Daily Yomiuri*, 2012). Several months after the Japanese earthquake and tsunami, floods in Thailand forced the closure of almost 1,000 manufacturing factories (*The Nation*, 2011). Japanese and Thai businesses deliver parts and supplies to firms and consumers throughout the globe, and these natural disasters disrupted global supply chains, especially in the automotive and electronics industries. As a result, production was temporarily halted at some facilities around the world, customer orders were delayed, and inventory in the pipeline fell dramatically (Nakata, 2011).

The supply chain disruptions caused by the Japanese earthquake and tsunami and the Thailand flood exemplify the increasing vulnerability of modern supply chains. The globalization of supply chains and the emphasis on lean and efficiency in logistics have increased the risk of disruption in those same supply chains (Christopher, 2005). A firm in one country may receive parts, supplies, and raw materials from suppliers in multiple countries. If a disruptive event strikes one of those countries and hinders a company's ability to produce or deliver supplies, supply shortages may suddenly occur. Efficient supply chains often mean less inventory and reliance on a single supplier for production inputs, which can make it more difficult for a firm if its supplier defaults on its obligations.

A severe supply chain disruption is defined in this chapter as a disruptive event that causes production difficulties for multiple suppliers and at least two of these suppliers deliver goods or services to at least two competing firms. When severe disruptions occur, companies must make decisions about maintaining operations, repairing facilities in the case of a physical disruption, possibly reducing production, obtaining supplies if their suppliers are disrupted, and recovering from the disruption. The severity of a supply chain disruption can be measured by the number of entities that encounter difficulties in receiving or delivering materials or goods due to an unplanned event (Craighead et al., 2007).

This chapter proposes a model for severe disruptions in which a disruption simultaneously impacts several suppliers and the suppliers' customers, which are called firms, may face supply shortages as a result. The model incorporates decisions made by both suppliers and firms in the midst of this disruption, including whether or not to move production to an alternate facility, using inventory to continue production and meet customer demand, and acquiring supplies from other suppliers who are not impacted.

Unlike much of the supply chain risk literature which focuses either on decisions taken by companies prior to a disruption or on the equilibrium strategies resulting from the interaction of suppliers and firms, this chapter focuses on decisions made by suppliers and firms during and after the disruption. A firm or supplier whose production is disrupted will rely on any measures it has previously taken to prepare for a disruption. If the disruption is severe and impacts several suppliers or multiple nodes in the supply chain, the entity may need to adjust its scheduling, production, and delivery of products and services beyond that foreseen by its preparedness activities. Additionally, businesses cannot plan for every possible disruption, and a disruption can render business strategies useless. For example, a Japanese company may have stocked inventory in case of supply or production difficulties, but the tsunami may have destroyed its inventory. By focusing on post-disruption decision making, the model explores what suppliers and firms can do even if they had not adequately planned for a particular disruption. The optimal decisions for suppliers and firms are solved as functions of input parameters, such as cost, revenue, and customer loyalty. These input parameters can be interpreted as decisions made prior to the disruption, which impact the businesses' abilities to maintain operations during and after the disruption.

This model can quantify the response of suppliers and firms to a disruption in terms of the level of demand that they are able to satisfy. Section 4.1 reviews the literature in supply chain risk and disruption management, the latter of which models optimal strategies for recovering from production disruptions. Section 4.2 presents the model and optimal decisions for suppliers and firms in the midst of production and supply difficulties. Section 4.3 applies this model to an example inspired by the supply chain disruption that occurred in the automobile sector as a result of the Japanese earthquake and tsunami. This application estimates several parameters based on automobile data and media stories during the disaster, and a simulation of the model with these parameters produces results realistic results.

4.1 Literature Review

Supply chain risk literature can either be qualitative or quantitative. Qualitative studies (Chopra and Sodhi, 2004; Sheffi, 2005; Tang, 2006) generally classify supply chain risk into several categories and studies or recommends best practices for companies to prevent and prepare for potential disruptions. The causes of risk in the supply chain include supply-side risk, demand-side risk, operational risk, and security or catastrophic risk (Manuj et al., 2007). This chapter models catastrophic risk, or severe disruptions, and this catastrophic risk produces supply-side disruptions.

Quantitative models of supply chain risk broadly follow one of two methodologies: (i) adapting traditional inventory or sourcing models to account for the possibility of supply shortages or (ii) developing game theoretic models to explore the interdependent decision making between suppliers and firms. Traditional supply chain and inventory models (see Hopp and Spearman, 2008) have been modified to incorporate the possibility of a firm's supplier failing to satisfy the firm's demand. A modified economic order quantity inventory policy is optimal if supply is available and then unavailable for a random amount of time (Parlar and Berkin, 1991). If disruptive events vary the supply leadtime, a discrete-time Markov process can determine the optimal inventory level (Song and Zipkin, 1996). Tomlin (2006) builds on this discrete-time Markov model to determine the optimal inventory level where a firm can also purchase raw materials from an alternate supplier if its primary supplier suffers a disruption. Further extensions include the impact on a firm's decision when it obtains more information about the reliability of a supplier (Tomlin, 2009), incorporating multiple supply sources each with variable leadtimes (Song and Zipkin, 2009), and the effect of a firm being able to produce multiple products on its ability to manage uncertainty in the supply chain (Tomlin and Wang, 2005).

Because suppliers and firms are both making decisions to mitigate risks in the supply chain, game theory provides a useful modeling construct. Babich et al. (2007) explore whether a firm should source from one or two suppliers when each supplier may suffer from a disruption. The answer depends, in part, on whether the probabilities of failure for the two suppliers are positively correlated or not. Given that contracts usually govern supplier-firm relationships, understanding the contracting process when suppliers may default on their obligation provides insight into managing supply chain risks (Swinney and Netessine, 2009; Yang et al., 2009). Other approaches include a network-based model where several suppliers, manufacturers, and distributors are simultaneously maximizing their profit and minimizing their risk (Nagurney, 2006).

In contrast to the above models, which primarily focus on decisions made prior to a disruption, disruption management models decision making during and after a disruption (Yu and Qi, 2004). Despite preventative measures, disruptions can occur in the production and distribution of goods and services. When disruptions occur, suppliers and firms must adjust their plans, and disruption management explores the optimal way to manage disruptions and return to normal operations as quickly as possible. Supply chain disruptions studied include production difficulties or operational risks (Xia et al., 2004), sudden drops in demand (Xiao et al., 2005), supply shortages (Xiao and Yu, 2006), and cost fluctuations that impact wholesale prices (Xiao and Qi, 2008). Rescheduling production (Bean et al., 1991; Adhyitya et al., 2007), moving production to other machines (Lee et al., 2006), transporting goods by alternate modes if one mode fails (MacKenzie et al., 2012), and purchasing supplies from a backup supplier (Hopp et al., 2012) are examples of disruption management strategies.

The model proposed in this chapter follows the disruption management literature approach. A disruption occurs and causes the production plans of suppliers and firms to deviate from normal operations. Quantitative models from the supply chain risk literature motivate several aspects of the modeling paradigm provided here. As in Tomlin (2006), a firm that suffers a supply shortage can buy from a more expensive alternate supplier or produce less, and its decision depends on its inventory. Although the complexity and number of entities in the model prevent an exact equilibrium solution as in a game theoretical model, both firms and suppliers are making decisions based on the decisions of the other entities. As time progresses, their optimal decisions can change. Finally, Nagurney (2006) has inspired the multitude of suppliers and firms, each of which is solving an optimization problem to maximize its objective.

4.2 Supply Chain Disruption Model

The supply chain contains N suppliers and M firms. Supplier n ($n = 1, 2, \ldots, N$) delivers product to M_n firms, and firm m ($m = 1, 2, \ldots, M$) has N_m suppliers. A firm receives a different product from each supplier, and each product is required for production. The firms compete with each other to sell their products to final consumers. Prior to a disruption, the system is in equilibrium, and each firm has constant demand.

As outlined in Fig. 4.1, a disruptive event directly impacts the N suppliers and temporarily closes each supplier's facility but does not impact the firms' production facilities. Each supplier may choose to move production to an alternate facility. If a supplier chooses not to move production, each firm who usually receives product from that supplier must deal with the lack of supplies. A firm uses inventory of raw materials, if available, to continue production. If the firm has not maintained raw material inventory—the model assumes the supplier does not maintain inventory—the firm determines its optimal production as described below by purchasing from more costly alternate suppliers.

If the firm's optimal production is less than its demand, the firm can make up the shortfall by using any finished goods inventory that it has maintained. If the sum of the firm's production and its finished goods inventory is less than demand, firm m's customers will buy from its competitors with probability τ_m. Any customers who do not purchase from the firm's competitors become backorders for the firm in the next period. At the end of the period, supplier n's production facility reopens with a constant probability, p_n. The simulation ends when all the suppliers' facilities have reopened.

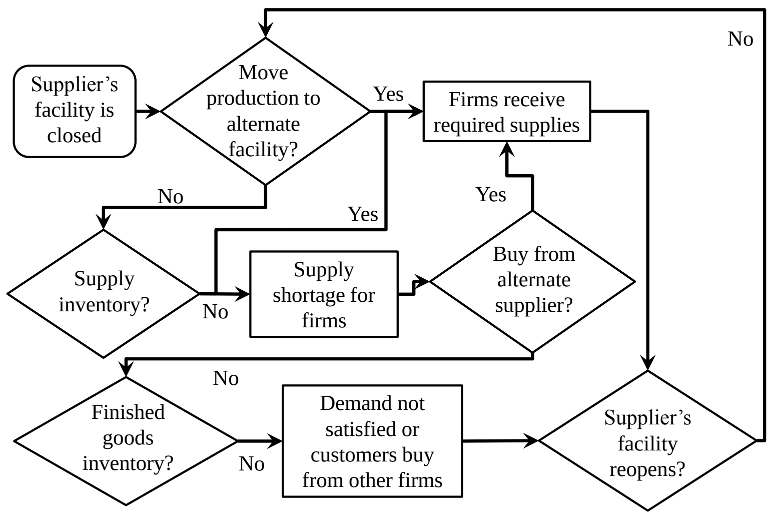

Figure 4.1: Simulation flowchart

The main decisions in the simulation are each supplier's decision about moving production to an alternate facility and each firm's decision about buying from alternate suppliers. The optimal decision for a supplier and a firm in this simulation is examined in separate subsections.

4.2.1 Supplier

Before the disruption, a supplier produces z units in each period at a per-unit cost c and receives r revenue per unit produced. In period $k = 0$, a disruption closes the supplier's facility, and the supplier's facility will reopen at the beginning of the next period with a constant probability p. (Although each parameter can differ for each supplier, the subscript n that represents a supplier is dropped for simplicity.) The decision for the supplier is whether to move its production to an alternate facility or wait for its primary facility to reopen. This decision mirrors the decision faced by several Japanese companies whose facilities were closed by the earthquake and tsunami (Eisenstein, 2011; Greimel, 2011).

If the supplier moves production to an alternate facility, the supplier incurs a

Table 4.1: Notation for Chapter 4

A, B, G	Parameters in supplier's profit function
c	Per-unit cost at primary facility for supplier
c^+	Per-unit cost at alternate facility for supplier
C	Fixed cost of moving production to alternate facility
$\bar{C}$	Fixed cost threshold
d	Firm's demand in a period
$f(x)$	Firm's objective function
i^*	Index for firm's cost function
k	Period
k^*	Optimal period to move production for supplier
M	Number of firms
M_n	Number of firms supplied by supplier n
N	Number of suppliers
N_m	Number of suppliers that firm m uses
p, p_n	Probability supplier's facility will reopen next period
$\bar{p}$	Probability threshold
r	Per-unit revenue for supplier
$\bar{w}$	Firm's per-unit cost of production before disruption
$w_1, \ldots, w_L$	Different per-unit costs of production for firm
$w(x)$	Firm's cost function after disruption
x	Firm's production quantity after disruption
$\bar{x}$	Firm's production quantity before disruption
x^*	Firm's chosen production quantity after disruption
$x_1, \ldots, x_{L-1}$	Production quantity levels for firm's cost function
z	Units produced by supplier in each period
Z	Backordered demand for supplier
α	Trade-off parameter for firm's objective function
θ	Probability supplier's customers will buy from other suppliers
$\pi(k)$	Supplier's expected profit if it moves production in k periods
ρ	Firm's per-unit selling price
τ_m	Probability firm m's customers will buy from firm's competitors

one-time fixed cost C and the supplier's per-unit cost of production is c^{+}, where $c^{+} \geq c$. The supplier is able to produce in the same period in which it decides to move production. If the supplier does not move production, the supplier cannot produce in that period, and the supplier's customers will buy from other suppliers with a time-invariant probability θ.

Eq. (4.1) describes the supplier's expected profit $\pi(k)$ if it decides to move production k periods after the current period where $k = 0, 1, 2, \ldots$. The expected profit is the sum of $\pi_{\leq k}(k)$, the expected profit if the primary production facility opens within k periods, and $\pi_{>k}(k)$, the expected profit if the primary facility opens after k periods.

$$\pi(k) = \pi_{\leq k}(k) + \pi_{>k}(k) \tag{4.1}$$

The supplier's expected profit if the facility reopens within k periods is given in Eq. (4.2) where Z represents backordered demand for the supplier. For each period that the supplier is not producing, the probability its customers wait until the next period is $1-\theta$. The period in which the original facility reopens serves as the stopping criteria for this finite-horizon time problem. After the facility reopens, the supplier moves production back to the original facility and produces at a per-unit cost of c.

$$\begin{aligned}
\pi_{\leq k}(k) &= p(1-\theta)(Z+z)(r-c)+(1-p)p\left[(1-\theta)^2(Z+z)+(1-\theta)z\right](r-c) \\
&\quad +(1-p)^2 p\left[(1-\theta)^3(Z+z)+(1-\theta)^2 z+(1-\theta)z\right](r-c)+\ldots \\
&\quad +p(1-p)^{k-1}\left[(1-\theta)^k(Z+z)+\sum_{l=0}^{k-1}(1-\theta)^l z\right](r-c) \\
&= p\sum_{i=0}^{k-1}(1-p)^i\left[(1-\theta)^{i+1}(Z+z)+\sum_{l=0}^{i}(1-\theta)^l z\right](r-c) \\
&= p\left(\frac{1-\left[(1-p)(1-\theta)\right]^k}{\theta+p(1-\theta)}\left(\frac{1-\theta}{\theta}\right)\left[\theta Z+(1-\theta)z\right]+\frac{\left[1-(1-p)^k\right]z}{p\theta}\right) \\
&\quad (r-c)
\end{aligned} \tag{4.2}$$

The supplier's expected profit if the facility reopens after the supplier moves production is given in Eq. (4.3). The expected profit is the summation of three terms: the first term represents the expected product that would still be demanded of the supplier even though it did not produce in periods 0 through $k-1$; the second term represents the expected profit of producing at the original facility after it reopens; and the third term represents the expected profit of producing at the alternate facility.

$$\begin{aligned}
\pi_{>k}(k) &= (1-p)^k\left(\left[(1-\theta)^k Z+\sum_{l=0}^{k}(1-\theta)^l z\right]\left(r-c^+\right)+p\sum_{i=0}^{\infty}(1-p)^i z(r-c)\right. \\
&\quad \left.+\sum_{i=1}^{\infty}(1-p)^i z\left(r-c^+\right)-C\right) \\
&= (1-p)^k\left(\left[(1-\theta)^k Z+\frac{\left(1-(1-\theta)^{k+1}\right)z}{\theta}\right]\left(r-c^+\right)+z(r-c)\right. \\
&\quad \left.+\frac{(1-p)z\left(r-c^+\right)}{p}-C\right)
\end{aligned} \tag{4.3}$$

Eqs. (4.2) and (4.3) can be combined into a single profit function. If the supplier wants to maximize its profit over the course of the disruption, it should choose k such that Eq. (4.4) is maximized.

$$A\left[(1-p)(1-\theta)\right]^{k} + B(1-p)^{k} \tag{4.4}$$

where

$$\begin{aligned}
A &= -\frac{p(1-\theta)[\theta(Z+z)-z](r-c)}{(\theta+p(1-\theta))\theta} + Z(r-c^{+}) - \frac{(1-\theta)z(r-c^{+})}{\theta} \\
&= \frac{\left[\theta Z-(1-\theta)z\right]\left[\theta\left(r-c^{+}\right)-p(1-\theta)\left(c^{+}-c\right)\right]}{(\theta+p(1-\theta))\theta} \\
B &= -\frac{z(r-c)}{\theta} + \frac{z(r-c^{+})}{\theta} + z(r-c) + \frac{(1-p)z(r-c^{+})}{p} - C \\
&= \frac{z\left[\theta\left(r-c^{+}\right)-p(1-\theta)\left(c^{+}-c\right)\right]}{p\theta} - C
\end{aligned}$$

This objective function serves as the basis for describing the conditions under which a supplier will choose to move production in a future period.

Proposition 1. *A supplier who wants to maximize Eq. (4.4) will move production in period k^* as given in Eq. (4.5) if and only if $A<0$, $B>0$, and $-BG/A<1$ where $G = log(1-p)/log\left[(1-\theta)(1-p)\right]$.*

$$k^{*} = \frac{log\left(-\dfrac{BG}{A}\right)}{log(1-\theta)} \tag{4.5}$$

Proof. The solution k^* is obtained by setting the first derivative in Eq. (4.4) to 0 and solving for k. Because k^* represents the period in which production is moved, a solution is needed such that $k^*>0$.

The solution $k^*>0$ if and only if $0<-BG/A<1$. This is true because $\log(1-\theta)<0$. Because G is positive, A and B must have opposite signs in order that $-BG/A > 0$.

Eq. (4.4) has at most one critical point, so the maximum profit either occurs at $k = 0$, $k = k^*$, or $k \to \infty$. Thus, to prove that k^* is a unique maximum if and only if $A < 0$ and $B > 0$, it suffices to show that the first derivative of Eq. (4.4) is greater than 0 for all $k < k^*$ and is less than 0 for all $k > k^*$ if and only if $A < 0$ and $B > 0$.

The condition $k > k^*$ is examined first. If $A < 0$, then $B > 0$. Under this assumption, if $k > \log\left(\frac{-BG}{A}\right) / \log(1-\theta)$, then

$$\begin{aligned} k\log(1-\theta) &< \log\left(\tfrac{-BG}{A}\right) \\ \Rightarrow (1-\theta)^k &< \frac{-BG}{A} \\ \Rightarrow A\log\left[(1-p)(1-\theta)\right]\left[(1-p)(1-\theta)\right]^k &< -B\log(1-\theta) \\ \Rightarrow A\log\left[(1-p)(1-\theta)\right]\left[(1-p)(1-\theta)\right]^k + B\log(1-\theta) &< 0 \end{aligned} \tag{4.6}$$

where the left-hand side of the expression is the first derivative of Eq. (4.4). Thus, if $A < 0$ and $B > 0$, the first derivative is less than 0. If $A > 0$ and $B < 0$, Eq. (4.6) results in the first derivative being greater than 0. Thus, if the first derivative is less than 0 for $k > k^*$, then $A < 0$ and $B > 0$.

Likewise, for $k < k^*$, if $A < 0$ and $B > 0$,

$$\begin{aligned} k &< \frac{\log\left(\frac{-BG}{A}\right)}{\log(1-\theta)} \\ \Rightarrow k\log(1-\theta) &> \log\left(\tfrac{-BG}{A}\right) \\ \Rightarrow (1-\theta)^k &> \frac{-BG}{A} \\ \Rightarrow A\log\left[(1-p)(1-\theta)\right]\left[(1-p)(1-\theta)\right]^k &> -B\log(1-\theta) \\ \Rightarrow A\log\left[(1-p)(1-\theta)\right]\left[(1-p)(1-\theta)\right]^k + B\log(1-\theta) &> 0 \end{aligned} \tag{4.7}$$

and the first derivative is greater than 0. Thus if $A < 0$ and $B < 0$, the first derivative is greater than 0 when $k < k^*$. If $A > 0$ and $B < 0$, Eq. (4.7) results in the first derivative being less than 0. Thus, if the first derivative is greater than 0 for $k < k^*$, then $A < 0$ and $B > 0$. □

The solution k^* is generally not an integer. Choosing the optimal period requires comparing the objective function of the two integers nearest to k^* to determine the optimal period in which the supplier will move production to an alternate facility. Rounding a solution to a continuous optimization problem in order to obtain a discrete solution (Siddall, 1982; Ringertz, 1988) can potentially lead to suboptimal and even infeasible solutions (Glover and Sommer, 1975). However, the supplier's optimization problem contains a single decision variable, and the usual problems such as determining which variables to round up and down do not apply here.

If the conditions of Proposition 1 are not satisfied, no interior maximum exists, and the supplier will compare the alternatives of moving production immediately, $k = 0$, and never moving production.

Proposition 2. *If the conditions of Proposition 1 are not satisfied, a supplier who wants to maximize Eq. (4.4) will choose to move production immediately if and only if the fixed cost C is less than $\bar{C}$ as given in Eq. (4.8).*

$$\bar{C} = \frac{(pZ + z)\left[\theta\left(r - c^+\right) - p\left(1 - \theta\right)\left(c^+ - c\right)\right]}{p\left[\theta + p\left(1 - \theta\right)\right]} \tag{4.8}$$

Proof. The expected profit evaluated at $k = 0$ is greater than expected profit as $k \to \infty$ if and only if $A + B > 0$, which is obvious by setting $k = 0$ and letting $k \to \infty$ in Eq. (4.4).

$$\begin{aligned} A + B &= \frac{\left[\theta Z - (1 - \theta)\, z\right]\left[\theta\left(r - c^+\right) - p\left(1 - \theta\right)\left(c^+ - c\right)\right]}{\left[\theta + p(1 - \theta)\right]\theta} \\ &\quad + \frac{z\left[\theta\left(r - c^+\right) - p\left(1 - \theta\right)\left(c^+ - c\right)\right]}{p\theta} - C \\ &= \frac{(pZ + z)\left[\theta\left(r - c^+\right) - p\left(1 - \theta\right)\left(c^+ - c\right)\right]}{p\left[\theta + p(1 - \theta)\right]} - C \end{aligned}$$

Clearly, $A + B > 0$ if and only if $C < \bar{C}$ as stated in Eq. (4.8). □

Table 4.2: Supplier's decision of when to move production

Conditions	$p < \bar{p}$	$p > \bar{p}$
$A < 0$, $B > 0$, and $\frac{-BG}{A} < 1$	Move in k^* periods	$\uparrow$
$A \geq 0$, $B \leq 0$, or $\frac{-BG}{A} \geq 1$		Never move
$C < \bar{C}$	Move immediately	
$C > \bar{C}$	Never move	$\downarrow$

The final element to explore in the supplier's decision is the impact of p, the probability that the original production facility will reopen in the next period.

Proposition 3. *A supplier who wants to maximize Eq. (4.4) will never move production if the probability that its facility reopens in the next period is greater than $\bar{p}$ where $\bar{p}$ is given in Eq. (4.9).*

$$\bar{p} = \frac{\theta \left(r - c^{+}\right)}{\left(1 - \theta\right)\left(c^{+} - c\right)} \tag{4.9}$$

Proof. The proof follows from Propositions 1 and 2. If $p \geq \bar{p}$, then $B \leq 0$, which means no interior optimal point exists, and $\bar{C} \leq 0$. Thus, letting $k \to \infty$ maximizes the expected profit in Eq. (4.4). $\square$

If the chances that the primary facility will reopen in the next period are high (i.e., if $p > \bar{p}$), it is optimal for the supplier to wait and choose not to move to the alternate facility. If $p = \bar{p}$, $\bar{C} = 0$ and the supplier is indifferent between moving production to the alternate facility immediately and never moving production if the fixed cost C is 0. In general, if $C = \bar{C}$ the supplier is indifferent between moving production and never moving production. Table 4.2 summarizes the supplier's optimal decision of when, if ever, to move production to an alternate facility, and Fig. 4.2 graphically depicts those conditions.

Because Z can change from period to period, the supplier's optimal decision may

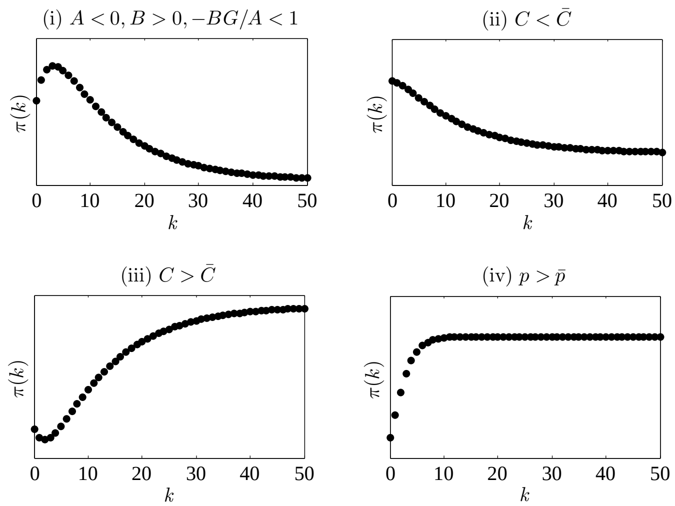

Figure 4.2: Examples of selecting k to maximize expected profit: (i) interior optimal point, (ii) move immediately, (iii) never move, and (iv) never move

change over time. For example, if the supplier has no backordered demand when the disruption initially closes its facility, the supplier may determine that never moving production is optimal because $C > \bar{C}$. As time progresses, the actual fraction of the supplier's customers that buy from other suppliers may be less than the probability θ. If Z increases in a few periods, the supplier may choose to move production to an alternate facility if $\bar{C}$ increases and $C < \bar{C}$.

4.2.2 Firm

Without loss of generality, it is assumed that one unit of product produced by firm m requires one unit from each of its N_m suppliers. Each one of these N_m supplies is also required for firm m to produce one unit.

Before the disruption, the per-unit selling price for a firm is ρ and the per-unit cost of production is $\bar{w}$ where $\rho \geq \bar{w}$. The cost of production includes both the cost of inputs and the cost of other factors of production such as labor and capital. The firm produces $\bar{x}$ amount of product in each period.

After the disruption occurs, if at least one of the firm's suppliers is unable or chooses not to move production to an alternate facility, the firm must decide how to resolve this supply shortage. It may have inventory of supplies or raw material inventory. The model assumes that the firm will use this inventory before seeking to buy supplies from an alternate supplier.

Alternate suppliers sell supplies to the firm at a higher cost than the primary suppliers, and the firm's cost function $w(x)$ becomes a piecewise linear cost function with an increasing marginal cost. The increasing marginal cost of production reflects the model's assumption that the firm buys inputs from alternate suppliers who cost more than the firm's primary suppliers. The cost function is expressed in Eq. (4.10) where $x_1 < x_2 \ldots < x_{L-1}$ are different production quantities for the firm and $\bar{w} < w_1 < w_2 \ldots < w_L$ are different per-unit costs of production corresponding to the different production quantities. For example, a firm who produces x where $x_1 < x < x_2$ has a cost of $w_1 x_1$ for the first x_1 units of production because it can buy x_1 units from one alternate supplier and a cost of $w_2(x - x_1)$ for the remaining units of production because it buys those from a different alternate supplier.

$$w(x) = \begin{cases} w_1 x & \text{if } x \leq x_1 \\ w_1 x_1 + w_2 (x - x_1) & \text{if } x_1 < x \leq x_2 \\ \vdots & \vdots \\ \sum_{i=1}^{L-2} w_i (x_i - x_{i-1}) + w_{L-1} (x - x_{L-2}) & \text{if } x_{L-2} < x \leq x_{L-1} \\ \sum_{i=1}^{L-1} w_i (x_i - x_{i-1}) + w_L (x - x_{L-1}) & \text{if } x_{L-1} < x \end{cases} \tag{4.10}$$

Because the firm's cost function is unbounded, assigning $x_0 = 0$ and $x_L = \infty$ provides a useful way to bound the cost function. Eq. (4.11) expresses the post-disruption cost function as a maximum function.

$$w(x) = \max_{1 \leq l \leq L} \left\{ \sum_{i=1}^{l-1} w_i (x_i - x_{i-1}) + w_l (x - x_{l-1}) \right\} \tag{4.11}$$

The values of w_i and x_i can change depending on how many suppliers are not delivering product to the firm. If only one of the firm's initial N_m suppliers is not delivering supplies, the firm's cost of producing $\bar{x}$, $w(\bar{x})$, will likely only be slightly greater than the firm's cost before the disruption $\bar{w}\bar{x}$. If several of the firm's primary suppliers are not producing, $w(\bar{x})$ will likely be much greater than $\bar{w}\bar{x}$.

If the firm is able to purchase product from alternate suppliers at a higher cost, the firm must decide how much to produce in each period until all of its primary suppliers are producing again. Ultimately, the firm desires to maximize its long-run profit, which is the sum of its profit in each period. However, while the firm is managing a disruption, it may not be able to accurately assess its long-run profit. A heuristic is proposed for the firm's objective of maximizing long-run profit, which seeks to mirror how a firm will actually respond to a disruption (Yu and Qi, 2004). In the model, the firm has two objectives: (i) maximize its profit in the current period and (ii) satisfy the current demand d for its product. If the cost of supplies increase due to the disruption, a firm that solely maximizes its profit in the current period may choose to produce less or even not to produce at all. However, a firm that just focuses on maximizing profit in the short term may hurt its long-run profit because its customers will buy from the firm's competitors. Therefore, a firm will also seek to meet customer demand over the course of the disruption.

As given in Eq. (4.12), the firm's objective function $f(x)$ combines these two objectives into a single objective, where $\alpha \geq 0$ is the trade-off parameter between the two objectives.

$$\begin{aligned} \text{maximize} \quad & f(x) = \rho x - w(x) - \alpha (x - d)^2 \\ \text{subject to} \quad & x \leq d \end{aligned} \tag{4.12}$$

The constraint exists because the firm never produces more than demand. The demand for the firm may fluctuate in each period because d includes not only the constant customer demand but also customers from previous periods who chose not to buy from the firm's competitors and any inventory that was used. The demand d is known by the firm when it decides how much to produce in a period.

The firm's optimal production is explored if its sole objective is to maximize profit in the current period, or if $\alpha = 0$.

Proposition 4. *If $\alpha = 0$, the firm will produce $min\,(x^*, d)$ where x^* is given in Eq. (4.13) and $i^* = argmin_{1 \leq i \leq L} \{\rho - w_i\}$ subject to $\rho - w_i \geq 0$.*

$$x^* = \begin{cases} 0 & \textit{if } \rho < w_1 \\ \textit{anywhere in the interval } [x_{i^*-1}, x_{i^*}] & \textit{if } \rho = w_{i^*} \\ x_{i^*} & \textit{if } \rho > w_{i^*} \end{cases} \tag{4.13}$$

Proof. From classical microeconomic theory, a firm produces at a level where marginal revenue equals marginal cost, and this proof demonstrates that x^* is the quantity at which marginal revenue equals marginal cost. The firm's marginal cost as given in Eqs. (4.10) and (4.11) is non-decreasing. If $\rho < w_1$, i^* is undefined because no feasible solution exists. The firm is unable to make a profit, and it will choose to produce $x^* = 0$.

If $\rho = w_{i^*}$ for some $i^* = 1, 2, \ldots, L$, then the firm's profit increases for all $x < x_{i^*-1}$ and decreases for all $x > x_{i^*}$. The firm's profit remains constant for $x_{i^*-1} \leq x \leq x_{i^*}$, and the firm is indifferent to producing any amount within this interval. The firm's profit is positive if $i^* > 1$ because $\rho > w_i$ for all $i < i^*$.

If $\rho > w_{i^*}$, no point exists where the firm's marginal cost equals its marginal revenue. Given the firm's non-decreasing marginal cost, the firm's profit decreases for all $x > x_{i^*}$. A firm that maximizes its profit will choose $x^* = x_{i^*}$.

If the chosen x^* exceeds the current demand d, the firm chooses to produce d. By producing d, the firm's marginal revenue exceeds its marginal cost, but it is unable to sell more than demand. $\square$

Although the firm desires to maximize its profit during a disruption, it may be willing to sacrifice some profit in order to satisfy the current demand. The firm's optimal production is detailed for the case where $\alpha > 0$.

Proposition 5. *If $\alpha > 0$, the firm will produce $\min(x^*, d)$ where x^* is given in (4.14) and $i^* = \mathrm{argmin}_{1\leq i\leq L}\{\rho - w_i - 2\alpha(x_i - d)\}$ subject to $\rho - w_i - 2\alpha(x_{i-1} - d) \geq 0$.*

$$x^* = \begin{cases} \dfrac{\rho - w_{i^*}}{2\alpha} + d & \text{if } \rho - w_{i^*} - 2\alpha(x_{i^*} - d) \leq 0 \\ x_{i^*} & \text{otherwise} \end{cases} \tag{4.14}$$

Proof. The objective function $f(x)$ given in Eq. (4.12) is concave because it is the summation of three concave functions: ρx is linear and $-w(x)$ and $-\alpha(x-d)^2$ are both concave. The cost function $w(x)$ is convex because it is the maximum of piecewise affine functions and the maximum of multiple convex functions is also convex (Boyd and Vandenberghe, 2004).

Because the objective function is concave, a unique maximum exists if the first derivative, when it exists, equals 0. The function is differentiable except at the points where the cost function changes, i.e., $x = x_1, x_2, \ldots, x_{L-1}$, and $f'(x) = \rho - w_i - 2\alpha(x-d)$ for all other x.

If $\rho - w_{i^*} - 2\alpha(x_{i^*} - d) \leq 0$, a point $x^* = (\rho - w_{i^*})/(2\alpha) + d$ exists within the interval $[x_{i^*-1}, x_{i^*}]$ where $f'(x^*) = 0$. This is true because $\rho - w_{i^*} - 2\alpha(x_{i-1} - d) \geq 0 \geq \rho - w_{i^*} - 2\alpha(x_{i^*} - d)$.

If $\rho - w_{i^*} - 2\alpha(x_{i^*} - d) > 0$, no point exists where the first derivative equals 0. This is true because $\rho - w_{i^*+1} - 2\alpha(x_{i^*} - d) < 0$. If $\rho - w_{i^*+1} - 2\alpha(x_{i^*} - d)$ were not less than 0, then $\rho - w_{i^*+1} - 2\alpha(x_{i^*+1} - d) < \rho - w_{i^*} - 2\alpha(x_{i^*} - d)$ because $w_{i^*+1} > w_{i^*}$ and $x_{i^*+1} > x_{i^*}$. This would contradict the definition that

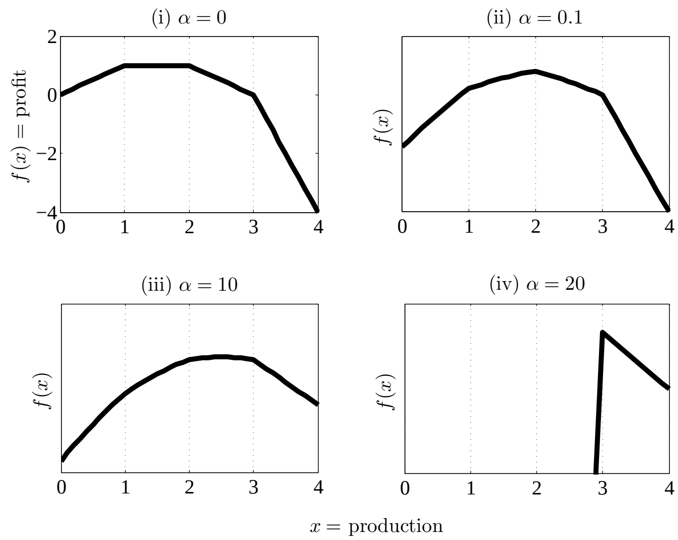

Figure 4.3: Examples of impact on α on firm's production when the current demand $d = 3$

$i^* = \text{argmin}_{1 \leq i \leq L} \{\rho - w_i - 2\alpha (x_i - d)\}$. Because of the concavity of the objective function, x_i^* maximizes the firm's objective function if $f(x_i^*) > f(x_i^* - \delta)$ and $f(x_i^*) > f(x_i^* + \delta)$ for an arbitrary small $\delta > 0$. The objective function $f(x)$ is not differentiable at $x = x_i^*$, but the left-hand derivative $f'_{\text{left}}(x_i^*) = \rho - w_{i^*} - 2\alpha(x_{i^*} - d) > 0$, and $f(x_i^*) > f(x_i^*) - \delta f'_{\text{left}}(x_i^*) > f(x_i^* - \delta)$. The right-hand derivative $f'_{\text{right}}(x_i^*) = \rho - w_{i^*+1} - 2\alpha(x_{i^*} - d) < 0$, and $f(x_i^*) > f(x_i^*) + \delta f'_{\text{right}}(x_i^*) > f(x_i^* + \delta)$.

As in the case of $\alpha = 0$, the firm will produce d if $x^* > d$. □

As illustrated in Figure 4.3, the parameter α can have a large impact on the firm's level of production during a supply shortage. If $\alpha = 0$ (chart i), the firm is solely maximizing its profit which occurs at any production level from 1 to 2. For large α (chart iv) the firm is willing to produce without any profit in order to satisfy demand, $d = 3$. Estimating α poses challenges and can depend on each firm's priorities and business model.

4.3 Application to Automobile Sector Disruption

The Japanese earthquake and tsunami impacted the automobile sector most heavily. The production of the Japanese motor vehicle industry dropped by almost 50% in March and April 2011 compared to the industry's production in the same months in 2010 (Japan, 2011b). Companies like Renesas, who manufactures electronics for the automobile industry, and Merck, who produces a chemical agent used in automobile paint, had facilities that were closed for months (Greimel, 2011). Toyota and Honda did not return to normal production until about six months after the tsunami (Bunkley, 2011c). Nissan was positioned slightly better before the disaster because it had been surging its inventory to prepare for a production increase. It was able to resume full production a couple of months before Toyota and Honda (Bunkley, 2011b; Woodyard, 2011). Automobile production difficulties in Japan impacted automobile manufacturers around the globe, leading to temporary halts in some production lines, longer waits for certain vehicles, and extremely low inventory levels.

An application of the supply chain disruption model is inspired by this disruption in the automobile sector. This application is designed to simulate automobile production in North America in the months following the Japanese earthquake and tsunami.

4.3.1 Input data

The application has $N = 4$ suppliers and $M = 3$ firms. Firm 1 receives supplies from Suppliers 1 and 2; Firm 2 receives supplies from Suppliers 1, 2, and 3; and Firm 3 receives supplies from Suppliers 1, 2, and 4. The disruption closes the four suppliers' production facilities, and Table 4.3 shows the input parameters for the suppliers.

Supplier 1 resembles Renesas, whose production facility was closed for 12 weeks (Okada, 2011). With a geometric probability distribution, the expected number of

Table 4.3: Inputs for suppliers

n	r	c	c^+	z	p	θ
1	3	1	2	84	1/12	0.221
2	3	1	2	84	1/8	0.136
3	3	1	2	21	1/26	0.315
4	3	1	2	8	1/13	0.198

periods that Supplier 1's facility will be closed is 12 if the probability of reopening in each period is 1/12. Supplier 2 represents Merck, whose production facility was closed for 8 weeks (Agence France Press, 2011). Supplier 3 represents Toyota and Honda combined, and Supplier 4 represents Nissan. Because Nissan's production resumed more quickly than that of Toyota and Honda, the probability of Supplier 4's facility reopening is twice as large as that of Supplier 3. The parameter θ which represents the probability the suppliers' customers will buy from alternate suppliers is calculated by predicting what the firms will do based on their optimal decision making as presented in Section 4.2.

Firm 1 represents Ford, General Motors, and Chrysler (the "Detroit 3") combined; Firm 2 represents Toyota and Honda in North America; and Firm 3 represents Nissan in North America. Because the Detroit 3 are less dependent on Japanese suppliers than Japanese automakers, Firm 1 only receives supplies from two of the suppliers. As shown in Table 4.4, each firm's pre-disruption production, $\bar{x}$, reflects the percentage of total production in North America in 2010: the Detroit 3 produced 55% of vehicles in North America, Toyota and Honda produced 21%, and Nissan produced 8% (Ward's AutoInfoBank, 2011). The customer loyalty parameter τ (or how likely customers will buy from a competitor) is derived from the 2012 Customer Retention Study published by J. D. Power and Associates (2010). Generally, the automotive pipeline has about eight weeks worth of inventory (Snyder, 2011), and Firms 1 and 2 have two weeks

Table 4.4: Inputs for firms

n	ρ	$\bar{x}$	$\bar{w}$	w_1	w_2	w_3	w_4	x_1	x_2	x_3	raw materials inventory	finished goods inventory	τ
1	4	55	3	5	7	8	10	25	50	55	110	330	0.48
2	5	21	4	7	10	14	17	11	21	31	42	126	0.39
3	5	8	4	7	10	14	17	4	8	12	24	48	0.46

of raw materials inventory and six weeks of finished goods inventory at the start of the simulation. Because Nissan had begun an inventory surge before the disruption, Firm 3 begins with three weeks of raw materials inventory.

Simplifying assumptions are necessary for the cost and revenue parameters for both suppliers and firms. For a supplier, the marginal cost of producing at an alternate facility is twice as much as the marginal cost of producing at the primary facility. The firms make a profit of one for each unit produced. The cost of the alternate suppliers begins at a little less than twice as much as the primary supplier and increases by a constant rate.

4.3.2 Case 1: No alternate facility and $\alpha = 0$

The first simulation is conducted where the suppliers have no alternate facility, and the firms are solely concerned with maximizing their profit. Table 4.5 and Fig. 4.4 depict the result for the four suppliers, and Table 4.6 and Fig. 4.5 show the results for the three firms, based on 10,000 simulations. With no alternate facility available, the time when the primary facility opens determines the performance of each supplier during the disruption. Supplier 2 performs the best, and Supplier 3 performs the worst. Raw materials inventory satisfies about 20-25% of the supply demanded by the firms.

Because the firms' profit margins are low and because they are solely concerned

Table 4.5: Supply results for Case 1

	Average % produced by supplier	Average % met by raw materials inventory
Supplier 1	54.7	21.6
Supplier 2	67.4	18.8
Supplier 3	27.7	24.7
Supplier 4	53.2	20.0

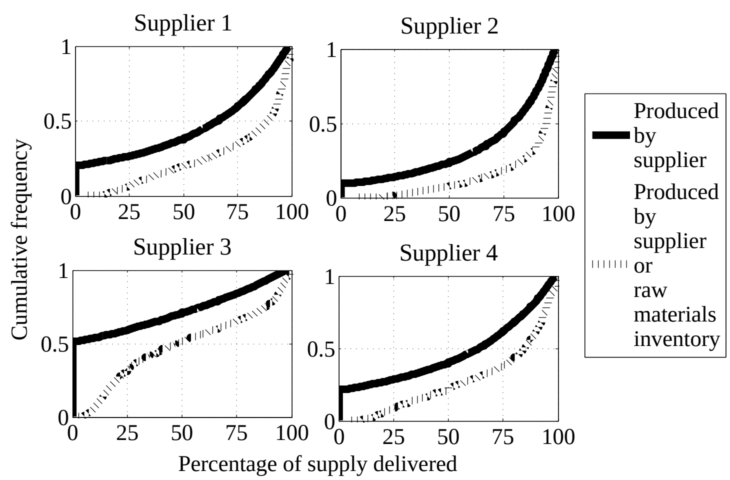

Figure 4.4: Simulation results when suppliers have no alternate facility

with maximizing profit, the supply shortage greatly hinders the firms' abilities to meet customer demand (Table 4.6). Firm 2 only satisfies on average 68% of its demand. Because it is reliant on only two suppliers, Firm 1 performs the best, and it is able to satisfy 100% of its demand in about 40% of the simulations.

The firms can also lose customers, and Firm 2 loses an average of 5% of its customers to Firms 1 and 3, and Firm 3 loses an average of 3% of its customers to Firm 1. Because Firm 1's initial production is larger than that of Firms 2 and 3, these additional customers represent an average of 2% of Firm 1's total production.

Table 4.6: Firm results for Case 1

	Avg % of demand satisfied by firm	Avg % of demand taken by another firm	Avg % of demand not satisfied	Avg % of additional demand
Firm 1	87.4	0.0	12.6	2.2
Firm 2	68.3	5.3	26.4	0.1
Firm 3	80.5	2.7	16.8	1.5

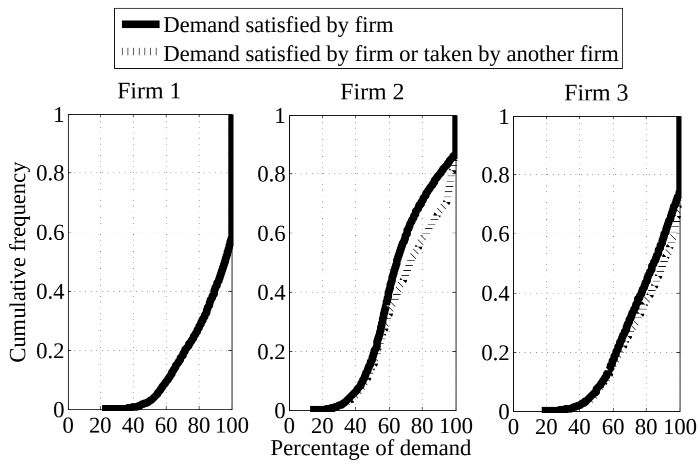

Figure 4.5: Simulation results when suppliers have no alternate facility and firms are only maximizing profit

4.3.3 Case 2: No alternate facility and $\alpha > 0$

Firms impacted by the supply shortage from Japan apparently sacrificed some short-term profit in order to maintain production levels. In the model, the parameter α determines the trade-off between the two objectives of maximizing profit and meeting current demand. Because the increased costs from purchasing supplies from alternate suppliers exceed the firms' selling prices by single digits and the objective of meeting demand squares the difference between production and what is demanded, very small values of α give a lot of importance to the second objective. Because Firm 1's demand is 55 units and Firm 3's demand is 8 units, if both firms produce half of what is

Table 4.7: Firm results for Case 2

	Avg % of demand satisfied by firm	Avg % of demand taken by another firm	Avg % of demand not satisfied	Avg % of additional demand
Firm 1	95.5	0.0	4.5	2.2
Firm 2	87.0	5.4	7.6	0.1
Firm 3	91.6	2.7	5.7	1.5

demanded of them, Firm 1 performs much worse on the second objective than Firm 3. Case 2 sets $\alpha = 0.005$ for Firm 1 and multiplies α by $55/21$ for Firm 2 and by $55/8$ for Firm 3. The values of α for Firms 1, 2, and 3 are 0.005, 0.0131, and 0.0344, respectively.

The results for the suppliers are almost the same as the results from Case 1, but the firms satisfy much more of their customer demand (Table 4.7 and Fig. 4.6). Firm 2 loses an average of 5% of its demand to Firms 1 and 3. This corresponds with Toyota and Honda's actual production, where their share of production in North America declined by about 5% following the Japanese earthquake and tsunami (Ward's AutoInfoBank, 2011). The Detroit 3's share of production increased by about 3.5%, compared to an average of 2.2% from the simulation. On average, Firm 3 loses 2.7% of its customers but gains 1.5%, which reflects reality where Nissan's share of production remained relatively constant. From the simulation, about 17% of total demand is not satisfied by any firm.

4.3.4 Case 3: With alternate facility and $\alpha = 0$

If alternate facilities are available for the four suppliers, and the fixed cost of moving production to those alternate facilities is less than the fixed cost, suppliers will choose to move production to those alternate facilities. With the values of θ as given in Table

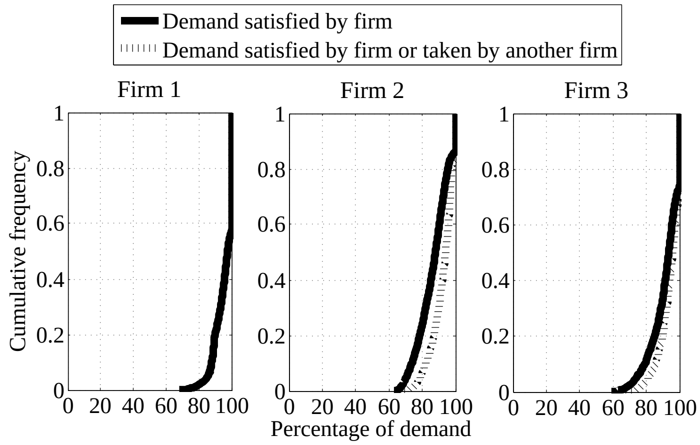

Figure 4.6: Simulation results when suppliers have no alternate facility and firms have both objectives

4.3, the fixed cost threshold $\bar{C}$ equals 550, 77, 462, and 55 for Suppliers 1, 2, 3, and 4. The fixed cost of moving production to alternate facilities, C, is set to 165, 19, 165, and 15 for the four suppliers. This incentivizes the suppliers to move production to an alternate facility but not immediately. With these parameters, a supplier moves production in period $k = 9, 10$ if its primary facility has not reopened before that period.

Table 4.8 and Fig. 4.7 show the results for the suppliers with the option of the alternate facility. On average, suppliers satisfy between 65% and 75% of the firms' requirements. If raw materials inventory is included within the calculation, supply shortages occur with much less frequency than in the previous cases. Eighty percent of supplies from Suppliers 1 and 2 are produced by those suppliers or through inventory almost 100% of the time. At least 80% of supplies from Suppliers 3 and 4 are delivered 90% of the time.

With a supply shortage occurring much less frequently, the firms, who are solely maximizing profit, are able to satisfy almost all of their customers' demand (Table 4.9 and Fig. 4.8). On average, only 2% of total customer demand is not met during

Table 4.8: Supply results for Case 3

	Average % produced by supplier	Average % met by raw materials inventory
Supplier 1	71.4	20.8
Supplier 2	74.8	18.6
Supplier 3	65.3	24.9
Supplier 4	67.6	20.2

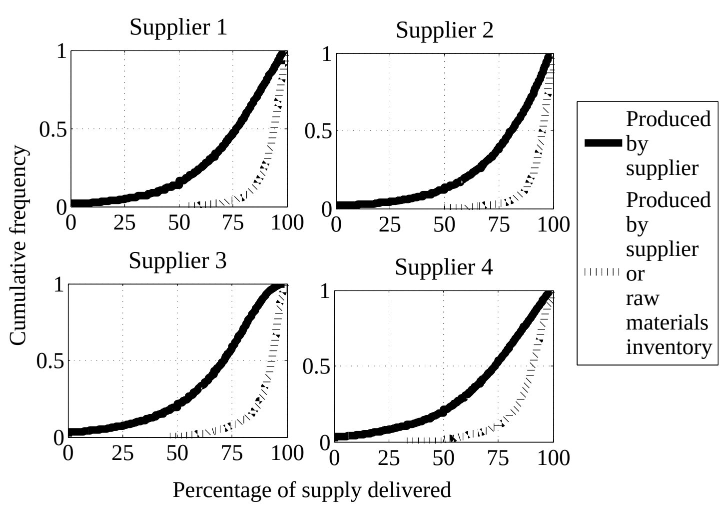

Figure 4.7: Simulation results when suppliers have alternate facility

Table 4.9: Firm results for Case 3

	Avg % of demand satisfied by firm	Avg % of demand taken by another firm	Avg % of demand not satisfied	Avg % of additional demand
Firm 1	99.2	0.0	0.8	0.6
Firm 2	97.7	1.4	1.0	0.1
Firm 3	99.0	0.7	0.3	0.5

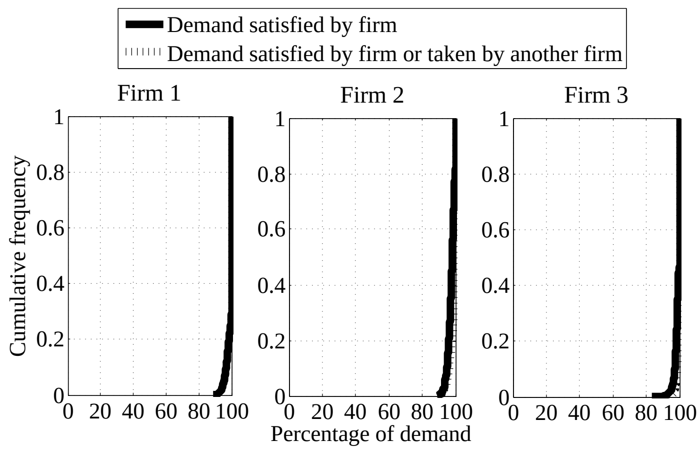

Figure 4.8: Simulation results when suppliers have alternate facility and firms are only maximizing profit

the disruption although Firm 2 still loses a little bit of demand to Firms 1 and 3. The cumulative distributions show that each firm satisfies 85 to 90% of its demand 100% of the time.

4.3.5 Sensitivity analysis

Sensitivity analysis is conducted on some of the key parameters for Supplier 1 and Firm 2. Supplier 1, which represents Renesas, is chosen because it supplies all three firms, and the insights derived from sensitivity analysis for this supplier can be applied to the other suppliers. Firm 2, which represents Toyota and Honda, is the most

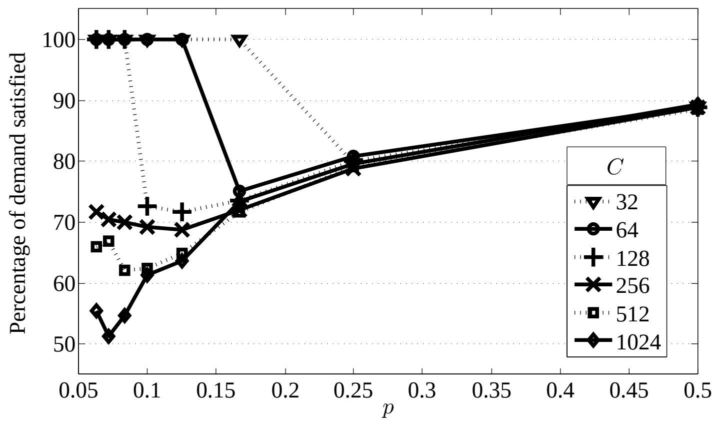

Figure 4.9: Sensitivity on probability that Supplier 1's facility reopens at different fixed costs

impacted firm in the model. Sensitivity analysis for Firm 2 can give some indication of risk management strategies for the firm.

The parameters p, the probability of the Supplier 1's primary facility reopening is varied, for different values of C, the fixed cost of moving production to an alternate facility (Fig. 4.9). For a fixed value of p, as the fixed cost increases, Supplier 1 fails to meet as much demand because larger fixed costs make moving production to an alternate facility less appealing. A relatively small value of C (less than 128) and a small likelihood of the primary facility reopening in the next period (less than 0.1) incentivize the supplier to move production to an alternate facility immediately. The supplier meets 100% of the required supplies.

However, for these relatively small values of C, as p increases, the fixed cost threshold $\bar{C}$ decreases. Thus, Supplier 1 is less likely to move production to an alternate facility. Even though its primary facility reopens more quickly as p increases, it meets less of its required supply. If p exceeds $\bar{p} = 0.28$, the supplier never moves production to an alternate facility, and it meets the same amount of demand regardless of the value of C.

Several parameters are varied for Firm 2, alternating among low, base, and high

Table 4.10: Sensitivity on parameters for Firm 2

Parameter	Symbol	Low	Base	High
Objective trade-off	α	0	0.0131	10
Finished goods inventory		0	126	252
Cost of alternate supplier	w_1, w_2, w_3, w_4	$10, 16, 23, 29$	$7, 10, 14, 17$	$4, 4, 5, 5$
Selling price	ρ	4	5	6
Probability that Supplier 3's primary facility reopens	p	1/36	1/26	1/3
Raw materials inventory		0	42	84
Probability that customers buy from competitors	τ	0.01	0.39	0.99

values for each parameter as given in Table 4.10. The base values for each parameter are identical to those given in Table 4.4 and used in the previous three cases. A value of $\alpha = 0.0131$ is chosen from Case 2. A low value in Table 4.10 means that Firm 2 will satisfy less demand than at the base level, and a high value indicates the firm will satisfy more demand.

Five thousand simulations are run with each parameter moved to its low or high level and the other parameters remaining at the base level. The tornado diagram in Fig. 4.10 depicts the average demand satisfied by Firm 2 at each value. Whether Firm 2 satisfies demand depends most heavily on the value of α, which determines the relative importance of meeting demand to maximizing profit. The firm can satisfy all of its demand if it is willing to sacrifice its profit.

This sensitivity analysis provides some insight into potential risk management strategies for Firm 2. Besides α, Firm 2 satisfies the most demand when the cost of alternate suppliers and the selling price are set to the high values. This suggests that if the firm is able to find a low-cost alternate supplier or has some flexibility in increasing its selling price without losing customers, these strategies can best help the firm maintain operations during the disruption. Another potential strategy is

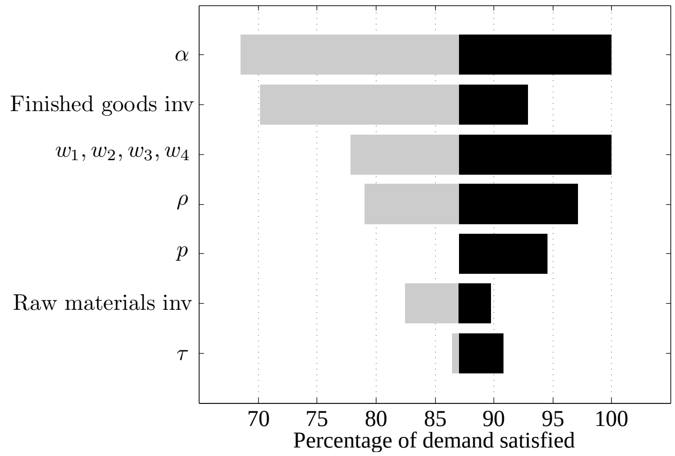

Figure 4.10: Sensitivity analysis of parameters on Firm 2's ability to meet demand

for Firm 2 to help Supplier 3 recover more quickly, which increases the value of p. Alternatively, strategies such as keeping inventory help the firm meet more demand, but eventually the inventory runs out during this lengthy disruption. Inventory may not be as effective of a risk management strategy although if Firm 2 has no finished goods inventory, it really struggles to meet customer demand. Using this sensitivity analysis as insight into the firm's risk management strategies focuses exclusively on the potential benefits of risk management and should also incorporate the cost of each strategy (e.g., cost of holding inventory or cost of keeping an alternate supplier) in order to accurately compare among risk management strategies.

4.4 Conclusion

This chapter has proposed a model of severe supply chain disruptions in which several suppliers' facilities are suddenly closed. Each supplier must decide whether or not to move production to an alternate facility. Depending on the suppliers' decisions, firms may suffer from supply shortages. If a firm has a supply shortage, it must decide whether or not to purchase goods from alternate suppliers. The firm can also use raw materials or finished goods inventory to maintain operations in the midst of a supply disruption.

The optimal decisions of both suppliers and firms are expressed as functions of the input parameters such as the revenue and cost of production as well as parameters related to the disruption, like the cost of moving production to an alternate facility, the probability of the original facility reopening, the cost of buying from an alternate supplier, and the probability that customers buy from competitors. For the supplier, as the probability that its primary facility reopens and the fixed cost of moving production to an alternate facility increase, the supplier has less incentive to move production. A supplier will never choose to move production if these two inputs are greater than the threshold parameters for these two inputs.

For the firm who decides how much product to purchase from alternate suppliers, its decision is modeled as a two-objective problem where the firm desires to maximize profit and satisfy current demand. The trade-off parameter between these two objectives plays a large role in determining the firm's optimal production level.

Inspired by the supply disruption caused by the Japanese earthquake and tsunami, a simulation of this model includes four suppliers and three firms. The firms represent the Detroit 3 automakers, Toyota and Honda, and Nissan operating in North America. Three different cases of this simulation are presented, and the results of Case 2 where the suppliers have no alternate facility and the firms have some desire to meet current demand closely reflect automobile production in the summer of 2011. Toyota and Honda lost market share but the Detroit 3 gained market share in the United States. Nissan suffered from the natural disaster but to a lesser extent than Toyota and Honda. Other important factors that contributed to this shift in market share but are not included in the model were Toyota's problems with its braking system early in 2011 and the restructuring of the U.S. automakers.

A more realistic model would include several firms, maybe as many as 15 to account for the other automobile manufacturers, and at least two to three times as many suppliers as firms. Some suppliers to the automobile manufactures may also be purchasers from other suppliers. The model and simulation could incorporate this additional complexity if parameters could be estimated for the 50 to 70 entities that would be included in such a simulation.

Sensitivity analysis for both suppliers and firms demonstrates relationships between the input variables and the results. As the likelihood that a supplier's primary facility will reopen increases, the supplier is less likely to move production to an alternate facility. This can result in fewer supplies provided. As the likelihood continues to increase, reopening the facility earlier helps the supplier meet more of its requirements. Varying input parameters for a firm can represent different risk management strategies. Strategies such as negotiating lower prices with alternate suppliers and helping the primary supplier recover more quickly can benefit a firm more than keeping inventory. For long disruptions, inventory may run out before the disruption ends.

Further extensions of this model can include the broader economic impacts of supply shortages and the impact of industry mitigation strategies. Some research has already been pursued in this direction, including the demand-driven I-O model detailed in Chapter 3 (see also MacKenzie et al. forthcoming) and the Inventory IIM (Barker and Santos, 2010a,b).

The model in this chapter provides new insights into managing supply chain disruptions. Understanding the optimal disruption management strategy can help suppliers and firms determine appropriate actions during a disruption. From a broader perspective, anticipating how businesses may react following a disruption can serve to quantify the business interruption losses from a natural disaster and supply chain disruption.

Chapter 5

Optimal Resource Allocation for Recovery of Interdependent Systems: Case Study of the *Deepwater Horizon* Oil Spill

On April 20, 2010, an explosion on the *Deepwater Horizon* offshore oil drilling rig claimed 11 lives, injured 16 other employees, and led to nearly 5 million barrels of crude oil spilling into the Gulf of Mexico over a span of three months. The loss of human life, the damage to the environment and wildlife, the loss of business to several Gulf industries, and the technical and engineering challenges of stopping the oil leak combined to make this incident the largest marine oil spill and perhaps the most devastating (Robertson and Krauss, 2010).

The *Deepwater Horizon* oil spill embodies the type of large-scale disruptive event that concerns homeland security officials in federal agencies, state and local governments, and foreign governments. The magnitude of a disruption, the complex interdependencies in the impacted ecosystem and economy, and the uncertainty involved hinder efforts to contain and recover from this type of disruption. Officials who respond to a disruptive event must quickly determine where to devote resources and the tasks that are necessary for an effective recovery.

This chapter addresses resource allocation for regional economic recovery, focusing on the interdependent economic impacts among the homeland security concerns discussed above. An optimization problem is developed to allocate resources to specific industries in order to effectively reduce the adverse impact of a disruptive event. Section 5.1 reviews previous optimal resource allocation models and outlines the unique contributions of this chapter. Section 5.2 develops and provides solutions for four optimization models: (i) a model of direct impacts from a disruption, (ii) a model of both direct and indirect impacts from a disruption, (iii) a discrete-time dynamic model where resources are allocated over time, and (iv) a model that allocates resources to prepare for and recover from a disruption. Section 5.3 applies these models to the *Deepwater Horizon* oil spill and analyzes the sensitivity of model results to key parameters. The models imply that a decision maker is allocating money from a fixed budget, but the models could incorporate any constrained resource, such as labor or raw materials, that could be used to mitigate a disruption's impacts. Concluding remarks appear in Section 5.4.

5.1 Literature Review

A resource allocation model addresses the fundamental economic question of how to satisfy unlimited wants with limited resources in a specific domain. Such resource allocation models that attempt to effectively divide a fixed budget have been developed and deployed in numerous domains, including disease prevention and treatment, engineering risk analysis, and homeland security.

Many resource allocation models are formulated as static or dynamic optimization problems with a resource budget serving as the primary constraint. Estimating parameters to accurately measure the objective function in these optimization problems and the impact of allocating resources can pose a challenge for modelers. Within the medical field, clinical studies can be used to estimate model parameters, including the type of disease, treatment options and effectiveness, and patient characteristics (Tao et al., 2002).

Allocating resources as part of an intervention strategy to fight the spread of the human immunodeficiency virus (HIV) has been modeled using linear models, dynamic models, and simulation (Alistar and Brandeau, 2012). Adapted from the economic literature, a "production function" (Kaplan, 1998) mathematically describes how allocating resources to an intervention strategy changes transmission or treatment rates. A cost-effectiveness ratio, which might be the ratio of the number of years saved by a given strategy to the cost of that strategy, can be used to compare among different allocation possibilities (Kahn, 1996; Ruiz et al., 2001). Dynamic problems can either require a single decision that impacts the spread of HIV over time (Zaric and Brandeau, 2001) or a decision in each time period (Alistar et al., 2011).

Resource allocation models in engineering risk management generally focus on reinforcing different components or building redundancy within a system in order to maximize reliability or minimize failure (Tillman et al., 1970; Misra and Ljubojević, 1973; Elms, 1997). Guikema and Paté-Cornell (2002) develop an optimization problem in which several components can be upgraded, and the decisions are whether or not to select a component for upgrading and how much money to spend on upgrading the component. A two-period model (Dillon et al., 2003) examines a problem where a decision maker designs a system that minimizes technical risk in the first period and allocates the remainder of the budget to minimize the risk of failure during the development phase. A dynamic model (Dillon et al., 2005) extends this two-period model by allowing the decision maker to allocate resources at different points in time to improve reliability.

Homeland security officials have struggled with how to allocate resources to different geographic areas based on risk or cost effectiveness. Allocating resources to urban areas to protect them from terrorism based on the risk of a terrorist attack differs from the Department of Homeland Security's allocation in fiscal year 2004 (Willis, 2007). As Willis (2007) acknowledges, the decision should be based on where the money reduces risk the most rather than on which areas carry the most risk, but no data exist to estimate the functional relationship between investing in protection and risk reduction.

One potential way to understand how allocating resources changes the risk of a terrorist attack is to employ a game theoretic model in which the terrorist's strategy changes based on the government's decisions (Major, 2002). The government or defender may choose to leave a location unprotected or even prefer more vulnerability in a certain location (Bier, 2007; Bier et al., 2007), and the cost-effectiveness of security can have a large impact on the optimal allocation of resource (Bier et al., 2008). Zhuang and Bier (2007) identify equilibrium strategies for a defender choosing to allocate investments to protect several targets from a strategic attacker (e.g., a terrorist) and a non-strategic actor (e.g., a natural disaster). Assuming that an attacker is perfectly rational or strategic may not be realistic, and another model (Hao et al., 2009) determines the optimal resource allocation where uncertainty exists about whether or not the attacker is strategic.

Specifically for oil spills, Psaraftis and Ziogas (1985) develop a resource allocation model to determine the appropriate type of equipment needed to clean up a spill. The decision maker's objective is to minimize a weighted combination of the damage costs from the spill and the costs of responding to the spill (i.e., the resource budget). Srinivasa and Wilhelm (1997) develop a model for responding to oil spills, but their model focuses on tactical decisions whereas the models in this chapter focus on strategic decision making.

The modeling approach in this chapter borrows from these resource allocation models but also develops new insights and methods. Unlike many other homeland security resource allocation models, the models in this chapter focus on post-disruption decision making in order to limit the impacts and enhance recovery. Because preparing for every possible type of disruption is practically impossible, empowering decision makers to make good decisions following a disruption is of importance in homeland security. The final model in this chapter is similar to the two-period model in Dillon et al. (2003) and incorporates both preparedness and post-disruption decision making.

The models seek to minimize the economic impact caused by a disruptive event, and similar to other studies, a resource budget serves as the primary constraint. Applying the model to an oil spill disruption also requires estimating several parameters, which is accomplished by relying on media articles, scholarly work, think-tank reports, and government data. These sources provide a way to relate the allocation decisions to the objective, which is a challenge for many of the resource allocation models. Although recovering from an oil spill provides the specific application and motivation, the models can be applied to a wide variety of disruptive events.

As discussed throughout this dissertation, disruptions can have indirect impacts as well as direct impacts. In Chapter 3, the direct impacts from the macroeconomic impacts of the Japanese earthquake and tsunami could be either positive or negative. In this chapter, direct impacts only represent production losses that result directly from final consumers reducing their demand or from facilities that are inoperable due to the disruption. Indirect impacts are production losses incurred by industries or firms who are tied economically to directly impacted industries. This chapter compares allocation decisions when only direct impacts are considered and when both direct and indirect impacts are considered. This modeling approach also compares the benefits of allocating resources that can help multiple industries recover simultaneously with the benefits of targeting individual industries for recovery. The dynamic model explores allocating resources over time where there is a single resource constraint over the entire time period.

5.2 Resource Allocation Models

Four resource allocation models measure the economic consequences from a disruption. The first model minimizes the direct economic impacts from a disruption. The second model minimizes the total production losses from a disruption, which include both direct and indirect impacts. The third model minimizes total production losses over time and allows the decision maker to allocate resources at different points in time. By incorporating the probability of a disruption and allowing a decision maker to allocate resources prior to a disruption, the fourth model seeks to minimize the expected production losses. The models assume that a disruption directly impacts m industries in an economy with n industries, where $m \leq n$. Each subsection presents the model and necessary conditions for optimal allocation.

5.2.1 Model 1: Direct impacts

For the first model, a decision maker wishes to effectively allocate resources to minimize D, the direct impacts caused by the disruption. D is the scalar product of two vectors of length m: $\tilde{\mathbf{x}}$ describes each industry's as-planned production in dollars and $\mathbf{c}$ measures the direct impact, in proportional terms, to each industry if recovery resources are allocated. Eq. (5.1) models the decision maker's problem as an optimization problem. The total budget, Z, is divided into resources allocated to each industry, $z_1, \ldots, z_m$, and to all industries simultaneously, z_0. These z_i and z_0, which serve as the decision variables in the optimization problem, are investments to promote recovery following a disruptive event.

$$\begin{aligned} \text{minimize} \quad & D = \tilde{\mathbf{x}}^\intercal \mathbf{c} & \\ \text{subject to} \quad & c_i = \hat{c}_i \exp\left(-k_i z_i - k_0 z_0^2\right) & i = 1, \ldots, m \\ & z_0 + \sum_{i=1}^{m} z_i \leq Z & \\ & z_0, z_i \geq 0 & i = 1, \ldots, m \end{aligned} \tag{5.1}$$

Because the first constraint describing the impacts on each industry can be substituted directly into the objective function, the problem has one principal constraint, the resource budget Z, which cannot be exceeded.

Table 5.1: Notation for Chapter 5

$\mathbf{A}$	Technical coefficient matrix in the Leontief I-O model
$\mathbf{A}^*$	Interdependent matrix in the IIM
$\mathbf{B}$	Square matrix translating direct impacts for all industries
$\tilde{\mathbf{B}} = \{\mathbf{b}_{*i}\}$	Matrix translating direct impacts into direct and indirect impacts
$\hat{c}_i$	Direct impacts on industry i if no resources are allocated
$\mathbf{c} = \{c_i\}$	Vector of direct impacts after resources are allocated
$\tilde{\mathbf{c}}$	Vector of final demand for all industries
C	Sum of total demand in economy
D	Economic impact due to directly impacted industries (Model 1)
$g(Z - z_p)$	Function describing benefits of not allocating resources
J	Total production losses occurring over time (Model 3)
k_0	Effectiveness of allocating resources simultaneously for all industries
k_i	Effectiveness of allocating resources to industry i
k_p	Effectiveness of allocating resources before industry
L_j	Lagrangian for Model j
m	Number of industries directly impacted by disruption
n	Number of industries or sectors in economy
p	Probability of disruptive event after resources are allocated
$\hat{p}$	Probability of disruptive event if no resources are allocated
Q	Total production losses (Model 2)
$\tilde{Q}$	Total production losses (Model 4)
t	Time in the discrete-time dynamic model
t_f	Fixed final time in the discrete-time dynamic model
$\mathbf{x}$	Vector of as-planned production for all industries
$\tilde{\mathbf{x}} = \{\tilde{x}_i\}$	Vector of as-planned production for directly impacted industries
z_0	Amount of resources allocated to simultaneously benefit all industries
z_i	Amount of resources allocated to industry i
z_p	Amount of resources allocated before disruption
z_0^*	Optimal allocation to all industries in Model 1
z_i^*	Optimal allocation to industry i in Model 1
$\hat{z}_0^*$	Optimal allocation to all industries in Model 2
$\hat{z}_i^*$	Optimal allocation to industry i in Model 2
Z	Total resource budget
λ	Lagrange multiplier for budget constraint
λ_0, λ_i, λ_p	Lagrange multipliers for nonnegative constraints
$\mu_i(t)$	Lagrange multiplier for equality constraint i in Model 3

The impact on each industry c_i is a function of the allocation amounts, the effectiveness of the resource allocation, k_i and k_0, and the direct impact if no resources are allocated, $\hat{c}_i$. Direct impacts on an industry can be assessed by (i) estimating the number of consumers that would stop purchasing from an industry because of a disruption or (ii) measuring the amount of production that would be lost if a facility were suddenly closed.

The model assumes that allocating resources reduces the impacts exponentially, which is a frequent assumption in engineering risk problems (Bier and Abhichandani, 2003; Guikema and Paté-Cornell, 2002; Dillon et al., 2005). With an exponential function, the impacts are completely eliminated only if an infinite amount of resources are allocated. As more resources are allocated to an industry, the impacts on an industry decline at a constantly decreasing rate, and investing an additional dollar to reduce risk returns less benefit than investing the first dollar. Mathematically, an exponential function is continuously differentiable, which is important for arriving at an analytical solution. For each directly impacted industry, the exponential function requires estimating a cost-effectiveness parameter, k_i. As Eq. (5.2) shows, this parameter can be assessed if z_i, the amount of resources needed to reduce the direct impacts on industry i by a given fraction $c_i/\hat{c}_i$, is known or can be estimated.

$$k_i = -\frac{\log\left(c_i/\hat{c}_i\right)}{z_i} \tag{5.2}$$

Allocating resources to simultaneously benefit all industries, as represented by the parameter z_0, could include activities such as cleaning the area and removing debris after the disruption, repairing infrastructure that all the other industries require (e.g., electric power, transportation), and engaging in risk communication efforts to inform the public that a region is safe. The model squares this allocation amount because of an assumption that if a major disruption occurs, allocating resources for these types of activities will not enhance recovery unless a significant amount of resources is allocated. Mathematically, $k_0 < 1$ and squaring z_0 reduces the impact of allocating z_0 if $\sqrt{k_0}z_0 < 1$. If $\sqrt{k_0}z_0 > 1$, squaring the term enhances the effect of this allocation.

The optimization problem can be solved by first forming the Lagrangian L_1in Eq. (5.3), where λ, λ_i, and λ_0 are the Lagrange multipliers for the budget constraint, the nonnegative constraints for z_i, and the nonnegative constraint for z_0, respectively. Eq. (5.3) replaces each element in $\mathbf{c}$ in the objective function with the equality constraint $c_i = \hat{c}_i \exp\left(-k_i z_i - k_0 z_0^2\right)$.

$$L_1 = \sum_{i=1}^{m} \tilde{x}_i \hat{c}_i \exp\left(-k_i z_i - k_0 z_0^2\right) + \lambda\left(z_0 + \sum_{i=1}^{m} z_i - Z\right) - \lambda_0 z_0 - \sum_{i=1}^{m} \lambda_i z_i \tag{5.3}$$

The first derivative of L_1 leads to the following Karush-Kuhn-Tucker (KKT) conditions (Hillier and Lieberman, 1986; Luenberger, 2003) for optimality as depicted in Eqs. (5.4) - (5.6).

$$\lambda = \left[\prod_{i:z_i>0} \left(\tilde{x}_i \hat{c}_i k_i\right)^{1/k_i}\right]^{\left(\sum_{i:z_i>0} 1/k_i\right)^{-1}} \exp\left(Z - z_0 + \sum_{i:z_i>0} \frac{k_0 z_0^2}{k_i}\right)^{-\left(\sum_{i:z_i>0} 1/k_i\right)^{-1}} \tag{5.4}$$

$$z_i = \frac{1}{k_i}\log\left(\frac{\tilde{x}_i \hat{c}_i k_i}{\lambda - \lambda_i}\right) - \frac{k_0 z_0^2}{k_i} \qquad \lambda_i z_i = 0 \tag{5.5}$$

$$-2k_0 z_0 \sum_{i=1}^{m} \tilde{x}_i \hat{c}_i \exp\left(-k_i z_i - k_0 z_0^2\right) + \lambda - \lambda_0 = 0 \qquad \lambda_0 z_0 = 0 \tag{5.6}$$

Because the parameter z_0 is squared within the exponential function, the optimization problem is non-convex in z_0, and the above conditions represent necessary but not sufficient conditions. However, if z_0 is known, the equations for λ and z_i represent both necessary and sufficient conditions. Eq. (5.6) has at most two real roots, and solving this equation generates at most two potential optimal allocations. Comparing the values of the objective function at these local minima provides a means to determine the optimal allocation of resources.

As long as some resources are allocated to industry i, the optimal allocation for that industry, z_i, monotonically increases with $\tilde{x}_i$ and $\hat{c}_i$. If an industry produces more or if the direct impacts are larger, homeland security officials should devote more resources to reducing losses in that industry. The optimal allocation to industry i increases as k_i increases for smaller values of k_i but decreases for larger values of k_i. If allocating resources to an industry becomes more effective, the industry requires fewer resources, leaving more resources available for other industries.

5.2.2 Model 2: Direct and indirect impacts

Because of the complexity and connectedness of the modern economy, direct impacts in some industries may lead to indirect impacts in all industries. Measuring those indirect impacts is important to accurately quantify the losses from a disruption and may influence decision making during the recovery phase. The $n \times n$ square matrix $\mathbf{B} \equiv (\mathbf{I} - \mathbf{A}^*)^{-1}$ translates direct impacts into direct and indirect impacts in all n industries where $\mathbf{A}^*$ is the normalized interdependency matrix for the IIM (Santos and Haimes, 2004) as described in Chapter 1. Because the disruption directly impacts m industries, $\tilde{\mathbf{B}}$ is a $n \times m$ matrix whose columns correspond to the directly impacted industries from $\mathbf{B}$. The vector $\mathbf{x}$ of length n represents as-planned economic output in the economy.

Under this model, the decision maker's goal is to minimize the total impacts or total production losses in a region, as represented by Q. The optimization problem in Eq. (5.7) is equivalent to Eq. (5.1) except for the objective function.

$$\begin{aligned} \text{minimize} \quad & Q = \mathbf{x}^{\intercal}\tilde{\mathbf{B}}\mathbf{c} \\ \text{subject to} \quad & c_i = \hat{c}_i \exp\left(-k_i z_i - k_0 z_0^2\right) \quad i = 1, \ldots, m \\ & z_0 + \sum_{i=1}^{m} z_i \leq Z \\ & z_0, z_i \geq 0 \qquad\qquad\qquad\qquad i = 1, \ldots, m \end{aligned} \tag{5.7}$$

The necessary conditions for optimality are identical to the optimality conditions given in Eqs. (5.4) - (5.6) except that the scalar product $\mathbf{x}^\intercal \mathbf{b}_{*i}$ replaces $\tilde{x}_i$, where $\mathbf{b}_{*i}$ is the ith column of the matrix $\tilde{\mathbf{B}}$. Thus, the optimal allocation of resources depends upon the interdependent impacts from the disruption of industry i rather than industry i's own production as in Model 1.

Eq. (5.8) compares the optimal allocations to industry i if the decision maker only considers direct impacts and if he or she considers both direct and indirect impacts. The parameters $\hat{z}_i^*$ and $\hat{z}_0^*$ represent the optimal allocations to industry i and to all industries, respectively, from Model 2, and z_i^* and z_0^* represent the optimal allocations from Model 1. Eq. (5.8) is only true if $\hat{z}_i^* > 0$ and $z_i^* > 0$.

$$\begin{aligned}\hat{z}_i^* - z_i^* =& \frac{1}{k_i} \log\left(\frac{\mathbf{x}^\intercal \mathbf{b}_{*i}}{x_i}\right)\left(1 - \frac{1}{k_i \sum_{j=1}^m 1/k_j}\right) \\ & - \frac{1}{k_i \sum_{j=1}^m 1/k_j} \sum_{j \neq i} \frac{1}{k_j} \log\left(\frac{\mathbf{x}^\intercal \mathbf{b}_{*j}}{x_j}\right) - \frac{1}{k_i \sum_{j=1}^m 1/k_j}\left(\hat{z}_0^* - z_0^*\right)\end{aligned} \tag{5.8}$$

The ith element of $\mathbf{b}_{*i}$ always exceeds 1, and $\mathbf{x}^\intercal \mathbf{b}_{*i} > x_i$ for all i. Numerical studies reveal that the quotient $\mathbf{x}^\intercal \mathbf{b}_{*i}/x_i$ ranges between 1 and 3 for any industry i. Because Eq. (5.8) relies on the natural logarithm of this quotient, the difference between an industry's interdependencies and the industry's own production produces relatively little change in the optimal allocation.

Although the effectiveness of allocating to industry i is equivalent in both models, the value of k_i impacts the difference in allocations between the two models. If $\sum_{j=1}^m 1/k_j > 1$, larger k_i values produce smaller changes in the optimal allocations. Smaller k_i values produce greater differences. If $\sum_{j=1}^m 1/k_j < 1$, larger values of k_i produce greater changes in the optimal allocations. If allocating resources is effective for several industries, accounting for economic interdependencies could lead to allocating more resources to those industries whose allocation is most effective.

5.2.3 Model 3: Discrete-time dynamic

Disruptions can last a period of time, and recovering from a disruption often requires allocating resources over time. A discrete-time dynamic resource allocation model is given in Eq. (5.9) where a decision maker allocates resources at fixed points in time. The disruption occurs at time $t = 0$, and $t = t_f$ is the fixed final time in the model. The decision maker seeks to minimize J the total production losses (both direct and indirect) in the time interval $[1, t_f]$ by allocating resources in the time interval $[0, t_f - 1]$. The model assumes it takes one time period for the allocated resources to reduce the industry impacts. The other variables in this model correspond to those in Model 2 except that many of the variables change over time.

$$\begin{aligned}
\text{minimize} \quad & J = \sum_{t=1}^{t_f} \mathbf{x}(t)^\intercal \tilde{\mathbf{B}} \mathbf{c}(t) \\
\text{subject to} \quad & c_i(t+1) = c_i(t) \exp\left(-k_i(t) z_i(t) - k_0(t) z_0^2(t)\right) \\
& \qquad\qquad\qquad\qquad i = 1, \ldots, m \qquad t = 0, \ldots, t_f - 1 \\
& \sum_{t=0}^{t_f - 1} \left[z_0(t) + \sum_{i=1}^{m} z_i(t) \right] \leq Z \\
& z_0(t), z_i(t) \geq 0 \qquad i = 1, \ldots, m \qquad t = 0, \ldots, t_f - 1 \\
& c_i(0) = \hat{c}_i \qquad i = 1, \ldots, m
\end{aligned} \tag{5.9}$$

Because resources allocated over the entire time interval are constrained by a single budget Z, the optimal decision may be to allocate the entire budget in the first time period, $t = 0$, wait to allocate resources, or spread the resources over time. This timing decision depends on how the effectiveness of allocation changes over time as governed by $k(t)$. If $k(t)$ remains constant over time or decreases with time, then a decision maker should allocate the entire budget Z at time $t = 0$. The optimal allocation follows the optimal allocation described in Model 2. If $k(t)$ increases with time, it may be optimal to wait to allocate some of the available resources. A trade-off exists between allocating resources so that recovery begins immediately and saving resources in order to impact recovery the most.

Eq. (5.10) presents the Lagrangian L_3 with the Lagrange variables: λ for the budget constraint, $\lambda_i(t)$ for the nonnegative constraints, and $\mu_i(t)$ for the first equality constraint in Eq. (5.9) that represents the change in direct impacts over time.

$$\begin{aligned} L_3 = \quad & J + \sum_{t=1}^{t_f}\sum_{i=1}^{m}\mu_i(t)\left[c(t) - c(t-1)\exp\left(-k_i(t-1)z_i(t-1) - k_0 z_0^2(t-1)\right)\right] \\ & + \lambda\sum_{t=0}^{t_f-1}\left(Z - z_0(t) - \sum_{i=1}^{m} z_i(t)\right) - \sum_{t=0}^{t_f-1}\lambda_0(t) z_0(t) - \sum_{t=0}^{t_f-1}\sum_{i=1}^{m}\lambda_i(t) z_i(t) \end{aligned} \tag{5.10}$$

Although the necessary conditions for optimality resemble Eqs. (5.4) - (5.6) from the static model, including the time parameters complicates the equations (Hull, 2003).

$$\begin{aligned} \lambda = & \left[\prod_{t=0}^{t_f-1}\prod_{i:z_i>0}\left(-\mu_i(t+1)c_i(t)k_i(t)\right)^{1/k_i(t)}\right]^{\left(\sum_{t=0}^{t_f-1}\sum_{i:z_i>0}1/k_i(t)\right)^{-1}} \\ & \exp\left(Z - \sum_{t=0}^{t_f-1}\left[z_0(t) + \sum_{i:z_i>0}\frac{k_0(t)z_0^2(t)}{k_i(t)}\right]\right)^{-\left(\sum_{t=0}^{t_f-1}\sum_{i:z_i>0}1/k_i(t)\right)^{-1}} \end{aligned} \tag{5.11}$$

$$z_i(t) = \frac{1}{k_i(t)}\log\left(\frac{-\mu_i(t+1)c_i(t)k_i(t)}{\lambda - \lambda_i(t)}\right) - \frac{k_0(t)z_0^2(t)}{k_i(t)} \qquad \lambda_i(t) z_i(t) = 0 \tag{5.12}$$

$$\begin{gathered} 2k_0(t)z_0(t)\sum_{i=1}^{m}\mu_i(t+1)c_i(t)\exp\left(-k_i(t)z_i(t) - k_0(t)z_0^2(t)\right) + \lambda - \lambda_0(t) = 0 \\ \lambda_0(t) z_0(t) = 0 \end{gathered} \tag{5.13}$$

$$\begin{gathered} \mu_i(t_f) = -\mathbf{x}(t)^{\intercal}\mathbf{b}_{*i} \\ \mu_i(t) = \mu_i(t+1)\exp\left(-k_i(t)z_i(t) - k_0(t)z_0^2(t)\right) - \mathbf{x}(t)^{\intercal}\mathbf{b}_{*i} \end{gathered} \tag{5.14}$$

Eq. (5.15) combines Eqs. (5.13) and (5.14) to express $z_0\left(t\right)$ as a function $z_0\left(t+1\right)$.

$$z_0\left(t\right)=\frac{\lambda_0\left(t\right)-\lambda_0\left(t+1\right)+2k_0\left(t+1\right)z_0\left(t+1\right)\sum_{i=1}^{m}\mu_i\left(t+2\right)c_i\left(t+2\right)}{2k_0\left(t\right)\sum_{i=1}^{m}\mu_i\left(t+1\right)c_i\left(t+1\right)} \tag{5.15}$$

Eq. (5.15) can be used to express Eq. (5.13) as a function of $z_0\left(t_f-1\right)$. An iterative technique like the steepest descent method or the conjugate gradient approach (Lewis et al., 2006) could be deployed to converge to a solution that satisfies the above equations.

5.2.4 Model 4: Preparedness and response allocations

The previous three models have focused exclusively on allocating resources after a disruption first occurs. Even Model 3, which allocates resources over time, does not begin assessing the situation and recommending decisions until after the disruption occurs. Risk management strategies include preparing for a disruption, but planning for a disruption should also account for the possibility that the disruption may never occur. A decision maker's goal in preparing for a disruption may be to reduce the chances of the disruption never occurring.

As presented in Eq. (5.16), Model 4 incorporates the allocation of resources prior to a disruption into the static optimization problem from Model 2. The amount of resources allocated before a disruption z_p reduces the initial probability of the disruption $\hat{p}$ to a lower probability p. An exponential function describes the function relationship between z_p and the chances of the disruption occurring, where k_p describes the effectiveness of allocating resources prior to the disruption.

If the disruption does not occur, the resources that would have been allocated to help the region recover from the disruption, $Z-z_p$, can be used on other projects or returned to taxpayers if this is a public sector allocation. A new function $g\left(Z-z_p\right)$

is introduced, which is strictly increasing in $Z - z_p$ and represents what could be done with the resources to help regional production if no disruption occurs. The solution assumes that $g(\cdot)$ is continuously differentiable. Because the decision maker desires to minimize the expected production losses if the disruption occurs and maximize the expected production gain if the disruption does not occur, minimizing the objective function $\tilde{Q}$ requires inserting a negative sign before the expected gain in production $(1-p)\, g(Z - z_p)$.

$$
\begin{aligned}
\text{minimize} \quad & \tilde{Q} = p\mathbf{x}^{\intercal}\tilde{\mathbf{B}}\mathbf{c} - (1-p)\, g(Z - z_p) & \\
\text{subject to} \quad & c_i = \hat{c}_i \exp\left(-k_i z_i - k_0 z_0^2\right) & i = 1, \ldots, m \\
& p = \hat{p} \exp\left(-k_p z_p\right) & \\
& z_p + z_0 + \sum_{i=1}^{m} z_i \leq Z & \\
& z_p, z_0, z_i \geq 0 & i = 1, \ldots, m
\end{aligned}
\tag{5.16}
$$

After the constraints for the direct impacts and the probability of a disruption are substituted into the objective function, the Lagrangian L_4 is given in Eq. (5.17). The parameter λ_p is the Lagrange multiplier for the nonnegative constraint for z_p.

$$
\begin{aligned}
L_4 = & \hat{p} \exp\left(-k_p z_p\right) \mathbf{x}^{\intercal}\tilde{\mathbf{B}}\mathbf{c} - (1-p)\, g(Z - z_p) \\
& + \lambda \left(z_p + z_0 + \sum_{i=1}^{m} z_i - Z \right) - \lambda_p z_p - \lambda_0 z_0 - \sum_{i=1}^{m} \lambda_i z_i
\end{aligned}
\tag{5.17}
$$

Solving for the parameters in L_4 requires calculating the first derivatives, and Eq. (5.18) depicts the partial derivative with respect z_p.

$$
\begin{aligned}
\frac{\partial L_4}{\partial z_p} = & -\hat{p} k_p \exp\left(-k_p z_p\right) \left[\mathbf{x}^{\intercal}\tilde{\mathbf{B}}\mathbf{c} + g(Z - z_p) \right] \\
& + \left[1 - \hat{p} \exp\left(-k_p z_p\right)\right] \frac{dg}{dz_p} + \lambda - \lambda_p = 0
\end{aligned}
\tag{5.18}
$$

The KKT necessary conditions for optimality are given in Eqs. (5.19)-(5.22).

$$
\begin{aligned}
\lambda = & \left[\prod_{i:z_i>0} \left(\hat{p} \mathbf{x}^\intercal \mathbf{b}_{*i} \hat{c}_i k_i \right)^{1/k_i} \right]^{\left(\sum_{i:z_i>0} 1/k_i\right)^{-1}} \\
& * \exp \left(Z - z_0 - z_p + \sum_{i:z_i>0} \frac{k_0 z_0^2 + k_p z_p}{k_i} \right)^{-\left(\sum_{i:z_i>0} 1/k_i\right)^{-1}}
\end{aligned} \tag{5.19}
$$

$$
z_i = \frac{1}{k_i} \log \left(\frac{\hat{p} \mathbf{x}^\intercal \mathbf{b}_{*i} \hat{c}_i k_i}{\lambda - \lambda_i} \right) - \frac{k_0 z_0^2 + k_p z_p}{k_i} \qquad \lambda_i z_i = 0 \tag{5.20}
$$

$$
-2 k_0 z_0 \hat{p} \sum_{i=1}^{m} \mathbf{x}^\intercal \mathbf{b}_{*i} \hat{c}_i \exp \left(-k_i z_i - k_0 z_0^2 - k_p z_p \right) + \lambda - \lambda_0 = 0 \qquad \lambda_0 z_0 = 0 \tag{5.21}
$$

$$
\begin{aligned}
z_p = \frac{1}{k_p} \log \left(\frac{\hat{p} \left[k_p \sum_{i:z_i=0} \mathbf{x}^\intercal \mathbf{b}_{*i} \hat{c}_i \exp\left(-k_0 z_0^2\right) + k_p g\left(Z - z_p\right) + dg/dz_p \right]}{\lambda \left(\lambda_p - k_p \sum_{i:z_i>0} 1/k_i \right) + dg/dz_p} \right) \\
\lambda_p z_p = 0
\end{aligned} \tag{5.22}
$$

These conditions demonstrate that Model 4 recommends fewer resources allocated to industry i than in Model 2 because the optimal allocation z_i is now a function of $\hat{p}$ and subtracts $k_p z_p / k_i$. Without more specificity on the function $g\left(Z - z_p\right)$, little insight into the optimal allocation of z_p can be gleaned from Eq. (5.22). In general, z_p increases as $\hat{p}$ increases but because $g\left(Z - z_p\right)$ decreases as z_p increases, there is a trade-off between the increase in $\hat{p}$ and $g\left(Z - z_p\right)$ and potentially dg/dz_p.

The function $g\left(Z - z_p\right)$ describes what happens to the resources that do not need to be allocated if the disruption does not occur. The portion of the budget originally reserved for recovery could be used to increase demand through a tax cut or by spending on public sector services like education and infrastructure. Eq. (5.23) assumes that the increase in demand for an industry is proportional to that industry's original demand, where $\mathbf{A}$ is the technical coefficient from the Leontief I-O model, $\tilde{\mathbf{c}}$ is a vector of length n describing the final demand for each industry, C is the sum of total demand in the economy, and $\mathbf{1}$ is a vector of length n of all ones.

$$g\left(Z - z_p\right) = \mathbf{1}^\intercal \left(\mathbf{I} - \mathbf{A}\right)^{-1} \tilde{\mathbf{c}} \frac{\left(Z - z_p\right)}{C} \tag{5.23}$$

As with the previous models, the above conditions represent necessary but not sufficient conditions for optimality. Modern software tools like the "fzero" program in Matlab (2012) can solve Eqs. (5.21) and (5.22) by incorporating the analytical solutions for z_i and λ.

5.3 Case Study: Recovery from *Deepwater Horizon* Oil Spill

These resource allocation models are applied to a case study examining the economic impacts of the *Deepwater Horizon* oil spill. As a result of the April 20, 2010 explosion on the *Deepwater Horizon* oil rig, almost 5 million barrels of crude oil spewed into the Gulf of Mexico until the leak was finally capped on July 15. The operator of *Deepwater Horizon*, BP, agreed to establish a $20 billion fund to pay for damage to the Gulf ecosystem, reimburse state and local governments for the cost of responding to the spill, and compensate individuals for lost business. The U.S. government imposed a six-month moratorium on deepwater drilling in the Gulf of Mexico, and it did not issue new leases for oil exploration in the Gulf until December 2011 (Fowler, 2011).

This application quantifies the economic impacts of this disaster by focusing on the spill's direct impacts on five different industries. Parameter estimation for the models derive from publicly available economic data, think-tank and government reports, journal articles, and news stories. The two models are analyzed and compared, and sensitivity analysis on key parameters is performed.

5.3.1 Assumptions and parameter estimates

The models include five Gulf states (Texas, Louisiana, Mississippi, Alabama, and Florida). Economic data collected by the BEA (2010a,b, 2011) provide information on the production of different industries or sectors in each of those states, the vector $\mathbf{x}$, and the interdependencies among sectors, $\tilde{\mathbf{B}}$. The models combine the five Gulf States into a single economy with a total of $n = 63$ economic sectors.

The models focus exclusively on business interruption losses, which are defined as production losses due to inoperable facilities or reduced demand, and ignore the severe environmental damage. The costs of stopping the oil leak or containing and removing crude oil are modeled to the extent that these activities impact demand and production in the Gulf region. Direct impacts from the oil spill include: (i) demand losses because consumers decide to buy or consume fewer goods and services as a result of the oil spill and (ii) less industry production because facilities are inoperable. Demand losses occurred because people did not travel to the Gulf for vacation or buy fish from the Gulf (and fewer fish were caught). The demand for beachfront property also declined. Firms drilled for less oil in the Gulf because of the moratorium, the lack of new leases and licenses, and the need for enhanced safety measures. The models consider that the oil spill directly impacted the Fishing and Forestry, Real Estate, Amusements, Accommodations, and Oil and Gas industries ($m = 5$).

The decision maker for this case study is a hypothetical entity responsible for limiting economic losses in the five Gulf states. The decision maker controls resources that can be used to increase demand for seafood, tourism, and real estate in the Gulf, implement new safety requirements in the offshore oil platforms, and remove crude oil from the Gulf which benefits all of the impacted industries. Although the U.S. federal government and the Department of Homeland Security have responsibility for many of these areas, in practice, the federal government, state and local entities, and

Table 5.2: Input values for *Deepwater Horizon* case study

i	Industry	k_i (per \$1 million)	$\hat{c}_i$
0	All industries simultaneously	$7.4 * 10^{-9}$	
1	Fishing and Forestry	0.074	0.0084
2	Real Estate	0	0.047
3	Amusements	0.0038	0.21
4	Accommodations	0.0027	0.16
5	Oil and Gas	0.0057	0.079
	Preparedness	$k_p = 0.0031$	$\hat{p} = 0.045$

the private sector all control resources that can be used for these types of tasks.

Table 5.2 displays the parameter estimates for the effectiveness of allocating resources, k_i, and the direct impacts for each industry, $\hat{c}_i$. Allocating resources to one of the industries directly impacted by reduced demand means better communication about the risks, safety, and cleanliness of the products and services produced by these industries. The models assume that these resources can be expressed in monetary terms. If people are not consuming fish caught in the Gulf of Mexico, resources can be devoted to testing fish for oil contamination and to a public relations campaign explaining that fish are safe for consumption. A National Resources Defense Council (2011) report is the principal source to estimate direct impacts for the Fishing and Forestry industry ($i = 1$), and the report found that fishing revenue decreased by \$63 million. The parameter k_1 is derived from two studies (Richards and Patterson, 1999; Verbeke and Ward, 2001) examining the effectiveness of positive media stories following two different food scares.

Tourism to the Gulf can be encouraged by ensuring that the beaches are free of oil and debris and demonstrating to potential tourists that the beaches are safe and open. The direct impacts for Amusements ($i = 3$) and Accommodations ($i = 4$) are based on an estimate that tourism declined in Louisiana, Alabama, Mississippi, and Florida by 30% although tourism in Texas does not appear to have been impacted

(Market Dynamics Research Group, 2010; Oxford Economics, 2010). The effectiveness parameters are derived from an Oxford Economics (2010) study that argues for a return on investment of 15 to 1 in tourism marketing. For the Real Estate industry ($i = 2$), the models assume that the demand for housing in the four states fell 10% and that increasing demand for housing depends entirely on tasks devoted to helping all industries such as stopping the oil leak and cleaning the oil. Hence, $k_2 = 0$.

Allocating resources to the Oil and Gas industry ($i = 5$) means implementing new safety measures to reduce the risk of an accident on an offshore oil platform. The federal government may have lifted the moratorium earlier and granted more licenses and leases if the oil industry had demonstrated the safety of deepwater drilling. Direct impacts are based on domestic oil production from the Gulf of Mexico in 2010 (U.S. Energy Information Administration, 2011), and k_5 is derived from an estimate that the new safety measures cost $183 million (McAndrews, 2011).

Capping the oil leak, containing the spill, and removing crude oil from the ocean can simultaneously benefit all five directly impacted industries. If less oil spills or if the oil is cleaned up more quickly, people are more likely to eat fish from the Gulf and vacation on its beaches. The Oil and Gas industry can also benefit because lifting the moratorium is less politically sensitive if the consequences of the oil spill are limited. Approximately $11.6 billion was spent on stopping the oil leak and cleaning up the oil (Trefis Team, 2011), and k_0 (per $1 million squared) is estimated by assuming that $\sqrt{k_0} * \$11600 = 1$. This assumption implies that billions of dollars must be allocated in order to reduce substantially the direct impacts on the five industries.

Calculating the probability of a large oil spill similar to the *Deepwater Horizon* oil spill in the Gulf of Mexico relies on the percentage of oil spills that are greater than 10,000 barrels (U.S. Bureau of Ocean Energy Management, 2011) and the fact that 40 oil spills occurred in the Gulf of Mexico from 2006 to 2010 (U.S. Bureau of Ocean Energy Management, 2012). Because the 5 million barrels spilled from the *Deepwater*

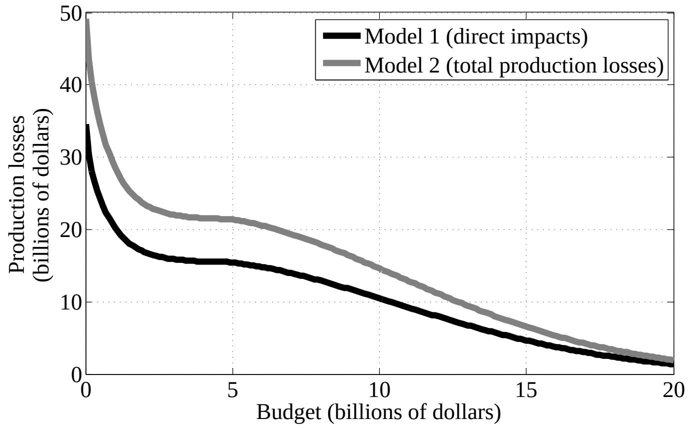

Figure 5.1: Production losses for Models 1 and 2 at different budget amounts

Horizon is much greater than the lower limit of 10,000 barrels, the initial probability $\hat{p} = 0.0445$ per year overestimates the chances of repeating a *Deepwater Horizon*-type spill. Estimating the effectiveness of allocating resources to reduce the chances of a spill poses a challenge. An assumption is made that the fiscal year 2013 budget request ($222.2 million) for the new federal Bureau of Safety and Environmental Enforcement reduces the chances of a spill by 0.5. The Bureau regulates offshore drilling, inspects offshore facilities, and prepares for oil spills. This assumption may overestimate the effectiveness of allocating resources to reduce the chances of an oil spill.

5.3.2 Model 1 and 2 results

The similarity of Models 1 and 2 facilitates analyzing them simultaneously, and the parameters are inputted into both models. Fig. 5.1 depicts the optimal resource allocation for both Model 1 and 2 for different budgets ranging from $0 to $20 billion, where $20 billion reflect the amount in BP's fund for reimbursing cleanup costs and lost business. Table 5.3 shows the allocation amounts to each industry for four different budget amounts.

According to Model 1, whose objective is to minimize direct impacts, the direct impacts total $34.5 billion if no resources are allocated. Optimally allocating a bud-

Table 5.3: Optimal allocation amounts for Models 1 and 2

i	Industry	z_i (millions of dollars)							
	Model	1	2	1	2	1	2	1	2
0	All industries	0	0	1,876	1,741	8,159	8,078	18,986	18,911
1	Fishing and Forestry	0	0	32	33	11	12	0	0
2	Real Estate	0	0	0	0	0	0	0	0
3	Amusements	251	250	927	968	519	543	255	278
4	Accommodations	359	379	1,326	1,407	742	799	365	420
5	Oil and Gas	390	372	841	850	569	567	393	391
Z	Total budget	1,000	1,000	5,000	5,000	10,000	10,000	20,000	20,000

get of \$20 billion reduces the direct business losses to \$1.4 billion. A decision maker concerned about the economic vitality of the region may want to consider the interdependent impacts, and Model 2 seeks to minimize total production losses in the Gulf region. Losses increase by about 40% if the model includes indirect as well as direct impacts. Total production losses are \$49.1 billion if no resources are allocated and drop to \$2.0 billion if the budget is \$20 billion.

If the budget is less than \$4.8 billion in either model, the decision maker should not devote any resources to simultaneously help all industries because these industries do not benefit as much as they do from targeting individual industries. If the budget is less than \$4.8 billion, dividing resources roughly equally among Amusements, Accommodations, and Oil and Gas is ideal. Because the direct impacts in Fishing and Forestry are less than those in the other industries and because allocating resources to this industry is the most effective, only allocating about \$50 million for this industry is optimal if the budget is \$4 billion.

The decision maker should spend \$1.88 billion (Model 1) or \$1.74 billion (Model 2) to benefit all the industries if the budget is \$5 billion. Proportionally more resources should be allocated to help all industries as the budget increases. Almost 95% of a \$20 billion budget should be spent on this category. Ensuring that the oil leak is capped and that crude oil is removed from the Gulf benefits the economy more than

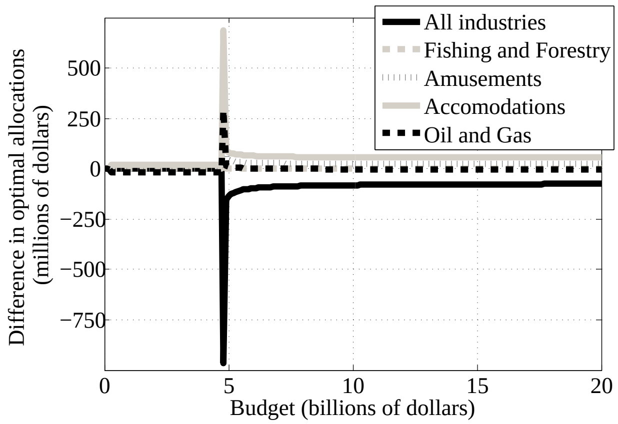

Figure 5.2: Model 1 optimal allocation amounts subtracted from Model 2

increasing demand by targeting individual industries through a media campaign.

Comparing the optimal allocations from Model 1 and Model 2 reveals that including interdependencies does not substantially change the optimal division of a budget (Fig. 5.2). The largest difference between the two models occurs if the budget is \$4.8 billion, which is the smallest budget amount at which it is optimal to allocate resources for all industries. If the model only considers direct impacts, \$1.47 billion should be allocated for all industries, but \$505 million should be allocated for all industries if the model incorporates an interdependent framework. However, if the decision maker follows the optimal allocation suggested by Model 1, total production losses are only \$51 million greater than the production losses if the decision maker follows the optimal allocation suggested by Model 2.

The differences in the two models' solutions are similar for any budget that exceeds \$10 billion. Model 2 recommends allocating \$56 million more to Accommodations than Model 1 because this industry has the least effectiveness (i.e., the smallest k_i value) and $\sum_{j=1}^{m} 1/k_j > 1$. Although Model 2 recommends a similar division of the budget to that of Model 1, the losses in Model 2 are almost 1.5 times greater than those of Model 1. The larger losses may influence a decision maker using Model 2 to spend more, or request a larger budget, than if he or she uses Model 1.

5.3.3 Model 3 results

The effects from major disruptions can last several months or even years, and the Coast Guard and BP engineers worked to stop the oil leak for almost three months. Homeland security officials working to contain and recover from disruptions need to make decisions at different points in time. The discrete-time dynamic model discussed previously can provide guidance on the optimal way to allocate resources over time. The model analyzes the oil spill for one year and divides the year into 12 months, and $t_f = 12$. Regional production is assumed to be constant in each month, and $\mathbf{x}(t) = \mathbf{x}/12$.

If the effectiveness of allocating resources, $k_i(t)$ and $k_0(t)$, decreases or remains constant with time, the decision maker should allocate all resources at time $t = 0$ according to the optimal division suggested by the results from Model 2. Tasks such as capping the oil leak and removing crude oil from the Gulf may not get easier as time passes, and $k_0(t) = k_0$ for all t. However, encouraging people to eat fish caught in the Gulf and to vacation on the beaches may become more effective with time because people will worry less about the risks. The effectiveness of allocating resources to individual industries is assumed to increase linearly with time, and $k_i(t) = (t+1)k_i$ for $t = 0, \ldots, t_f - 1$ and $i = 1, \ldots, 5$.

Results from the dynamic model for four different budgets ($1 billion, $5 billion, $10 billion, and $20 billion) reveal that most of the resources should be allocated to benefit all industries simultaneously at time $t = 0$ if the budget is $5 billion or more (Fig. 5.3). If the budget is $1 billion, no resources should be allocated to help all industries because the amount of money that could be spent is too small to make a difference.

Proportionally more money should be spent to benefit all industries as the budget increases, and this category should receive 96% of a $20 billion budget. The remainder

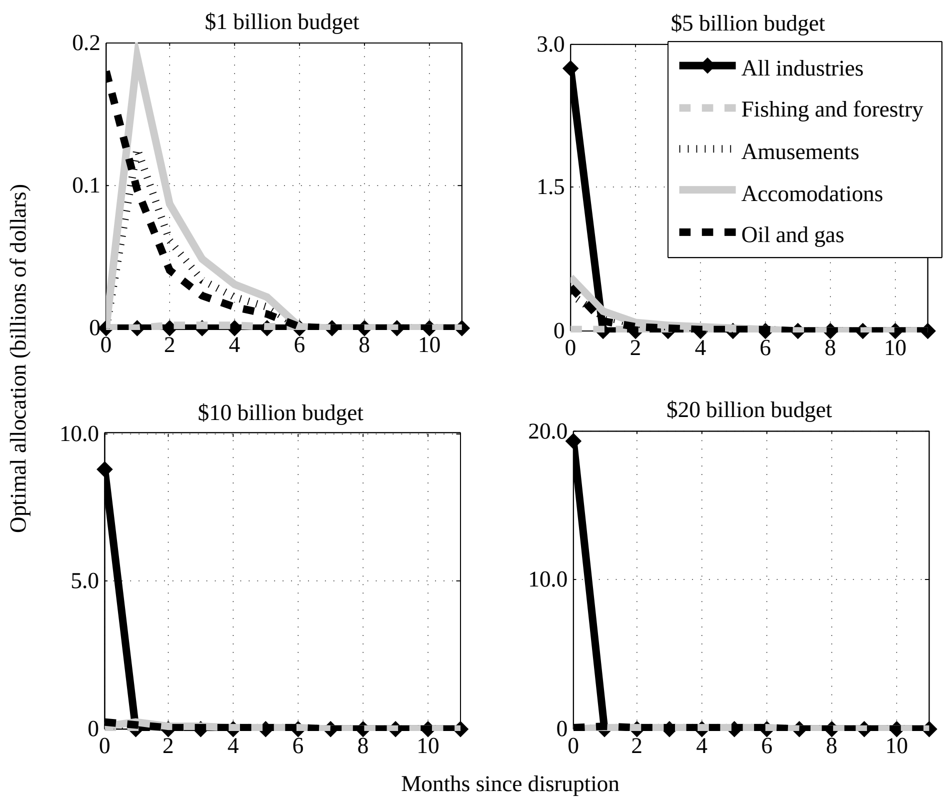

Figure 5.3: Optimal allocation for discrete-time dynamic model

of the budget should be spent on Amusements, Accommodations, and Oil and gas during the first five or six time periods, with most of the money allocated during the first two time periods.

These results demonstrate the importance of stopping and containing the oil spill as the top priority. When a disruption occurs, allocating resources to help individual industries recover is sub-optimal if the disruption like a spill is worsening. Although the decision maker should spend most of the budget immediately to contain and clean up the spill, some resources should remain in reserve to help specific industries recover once the primary disruption or spill is contained.

5.3.4 Model 4 results

Resources can be allocated to prepare for and reduce the probability of an oil spill, and Model 4 incorporates preparedness activities, and the function $g\left(Z - z_p\right)$ follows Eq. (5.23) to represent the benefits if no oil spill occurs. As Table 5.4 shows, the optimal allocation recommends spending approximately \$300 million to reduce the probability of an oil spill, which remains fairly constant over the different budgets. After the probability of an oil spill is reduced to approximately 0.018, spending money to increase regional demand as given by Eq. (5.23) is better than investing more to reduce the chances of an oil spill.

Overall, these results suggest that a relatively small portion of the budget should be spent on preventing a large oil spill. The probability of such a large oil spill is fairly small, and the model assumes that money not spent on preparedness activities can be used to increase regional production. Although spending billions of dollars to prevent a large oil spill is sub-optimal, this model is not considering small and medium oil spills. Although the economic consequences of those spills are smaller than the *Deepwater Horizon* oil spill, spending money to reduce the chances of a large oil spill also reduces the probability of a small or medium oil spill and thus

Table 5.4: Optimal allocation amounts for Model 4

i	Industry	z_i (millions of dollars)			
p	Preparedness	299	301	313	347
0	All industries	0	0	7,724	18,544
1	Fishing and Forestry	0	57	12	0
2	Real Estate	0	0	0	0
3	Amusements	153	1,426	556	285
4	Accommodations	241	2,062	818	429
5	Oil and Gas	307	1,155	576	395
Z	Total budget	1,000	5,000	10,000	20,000

carries environmental and economic benefits.

5.3.5 Sensitivity analysis

Sensitivity analysis on a few key parameters provides insight into how these parameters affect the optimal allocation of resources. Sensitivity analysis is explored on the effectiveness of allocating resources to all industries, the direct impacts and the effectiveness of allocating resources to the Fishing and Forestry industry, and the probability and effectiveness of reducing the probability of an oil spill.

One of the most important parameters in the model is the effectiveness of allocating to all industries, k_0, which determines the amount that should be allocated to stop the oil spill and clean up the the oil. The proportion of resources allocated to all industries in Model 2 is highly sensitive to small changes in k_0 (Fig. 5.4). Increasing k_0 by 1×10^{-8} can increase the resources allocated to all industries by 20% or more. For large values of k_0, the entire budget should be allocated to all industries, especially when the budget is greater than \$10 billion. As such, the larger the k_0, the more effective it is to invest in industry-wide efforts. Because the optimal allocation is highly sensitive to very small changes in k_0, a more careful estimation of this parameter should be undertaken before the model is used as a practical aid in

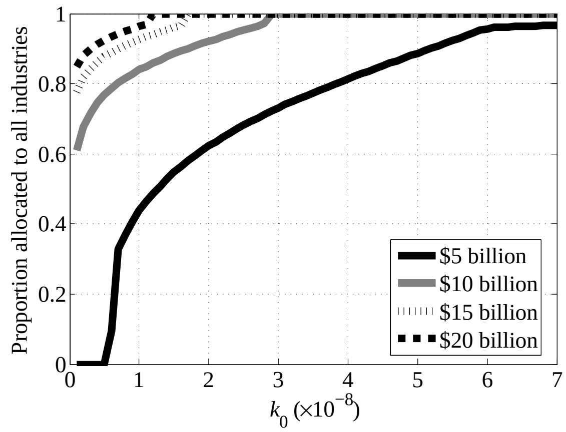

Figure 5.4: Sensitivity analysis on effectiveness of allocating resources to all industries responding to an oil spill.

The base case results in Model 2 recommend allocating less than \$50 million to the Fishing and Forestry industry ($i = 1$). Sensitivity analysis can reveal if this recommendation remains valid if the allocation effectiveness, k_1, and direct impacts, $\hat{c}_1$, change (Fig. 5.5). The optimal allocation to this industry increases as $\hat{c}_1$ increases. As k_1 increases, the optimal allocation initially increases but then decreases. If the budget is \$10 billion, the most the industry should receive is \$300 million at $k_1 = 0.01$ and $\hat{c}_1 = 0.5$. This extreme level of direct impacts is very unlikely, however, and \$300 million still only represents 3% of the entire budget. As the effectiveness increases, even less money needs to be allocated to the Fishing and Forestry industry even if the direct impacts are very large. Although the recommended allocation for this industry varies with k_1 and $\hat{c}_1$, the optimal solution is much less sensitive to these parameters than it is to k_0.

The probability of an oil spill, $\hat{p}$, and the effectiveness of reducing the probability, k_p, play an important role in Model 4, which divides the budget into preparedness and response allocations. Fig. 5.6 shows how the resources allocated to preparedness as a proportion of a \$10 billion budget vary with $\hat{p}$ and k_p. As $\hat{p}$ increases, more money should be allocated to reduce the probability of an oil spill, but even if $\hat{p} = 0.3$, which

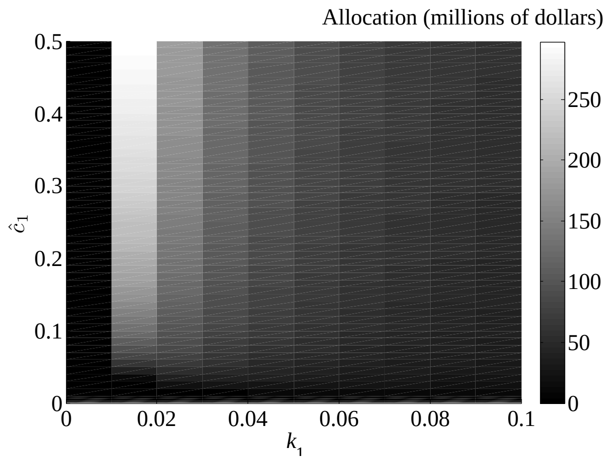

Figure 5.5: Sensitivity analysis on allocation effectiveness and direct impacts for Fishing and Forestry with a budget of \$10 billion

is extremely high, only 20% of the budget should go toward preparedness activities. The optimal allocation's sensitivity to k_p is similar to the sensitivty analysis of k_1. As k_p increases, the amount allocated to reduce the probability initially increases but then decreases. If the allocation of resources to reduce the probability is effective, 4% or less of the budget should be allocated for preparedness, even if the initial probability of an oil spill is large.

Model 4 recommends \$313 million for preparedness for the base values of $\hat{p} = 0.045$ and $k_p = 0.003$. If these values overestimate these two parameters, sensitivity analysis demonstrates that even less money should be allocated toward preparedness. If $\hat{p} \leq 0.04$ and $k_p \leq 0.001$, no money should be spent to reduce the probability of a large oil spill. Both the chances an oil spill and the effectiveness of preventing one provide less benefit than using the money to increase regional production as represented by the function $g(Z - z_p)$.

5.4 Conclusion

The four different models presented in this chapter can help homeland security officials determine how to allocate resources prior to and following a disruption. The first

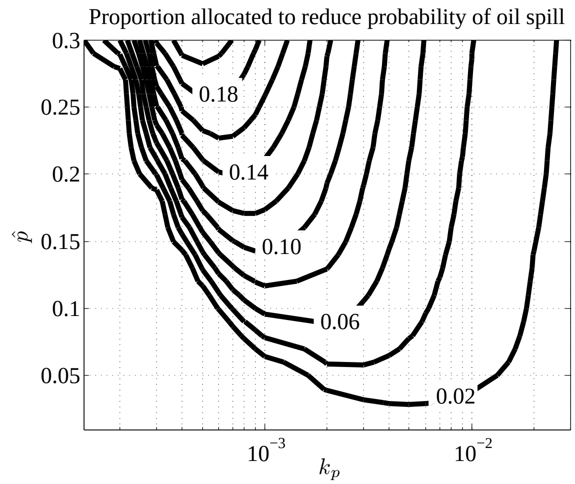

Figure 5.6: Sensitivity analysis on allocation effectiveness and probability of oil spill with a budget of $10 billion

model minimizes direct impacts; the second model minimizes direct and indirect impacts, or total production losses; the third model minimizes total production losses over time; and the fourth model incorporates preparedness decision making. The KKT conditions for optimality enable the expression of optimal resource allocations as functions of model parameters, such as the initial impact, the effectiveness of allocating resources, an industry's production or interdependent effects in an economy, and the probability of a disruption.

Newspaper accounts, think-tank reports, journal articles, and government data provide information to estimate parameters in order to apply these models to the 2010 *Deepwater Horizon* oil spill. If no money is spent on economic recovery after the Gulf spill, the direct impacts equal $34.5 billion and total production losses equal $49.1 billion. Several financial institutions estimated damages from the oil spill between $10 and $20 billion (Aldy, 2011), and the Oxford Economics (2010) study proposes that tourism revenues could decline by as much as $23 billion over a three-year span. If the total budget for recovering from the spill is $11.6 billion (the amount that BP spent to stop the spill), the direct impacts and total production losses are $8.8 billion and $12.3 billion, respectively, if the decision maker chooses the optimal allocation.

These estimates align closely with the other estimates.

The discrete-time dynamic allocation model reinforces the recommendation from Model 1 and 2 that tasks to benefit all industries (e.g., stopping the oil spill and cleaning the oil) should be the immediate focus of decision makers. If the budget is \$5 billion, 55% of the budget should be allocated immediately to help all industries recover, and this percentage increases to 96% as the budget increases. If the effectiveness of allocating resources for individual industries increases with time, some portion of the resources—between \$720 million and \$2.2 billion, depending on the budget—should be allocated in the four or five periods following the disruption to help individual industries recover.

A decision maker can use Model 4 to allocate resources prior to a disruption and following a disruption. The application to an oil spill suggests that \$300 million should be spent to reduce the probability of a large oil spill. Sensitivity analysis demonstrates that allocating even \$300 million may be too large if either the probability of an oil spill or the effectiveness of allocating money to reduce the probability are smaller than the base values. Model 4 assumes that any resources not allocated to prevent an oil spill can be used to increase economic production in the Gulf Region if an oil spill does not occur. If the opportunity cost of spending money to lessen the chances of an oil spill is less efficient than the model's assumption, a decision maker may want to spend more on prevention.

The conclusions derived from the models in this chapter and the case study can guide federal and state officials in making decisions about recovering from future disruptions. First, considering both direct and indirect impacts may not substantially change the optimal allocation from the allocation if just direct impacts are considered. However, the interdependent effects lead to larger estimates of the economic consequences, and understanding these interdependencies may help determine the total budget that should be available for recovery. Second, the budget for recovering from a disruption should be large enough to repair physical damage and limit environmental damages. These activities can benefit all of the directly impacted industries simultaneously and accomplish more than engaging in a risk communication campaign to help specific industries recover.

Third, a dynamic resource allocation model can guide a decision maker in allocating resources at different points in time while recovering from a disruptive event. Finally, modeling preparedness decisions requires allocating some resources to prepare for a disruption, which reduces the likelihood of a disruption. Modeling allocation in advance of a disruption allows a decision maker to trade off investing in preparedness activities with holding resources in reserve to help with recovery.

Chapter 6

Concluding Remarks

This dissertation has explored several disruptions and modeled the interdependent economic impacts of those disruptions. A different model is created for each disruption in order to quantify production changes resulting from a disruption. The models and simulations are applied to real-world case studies that integrate publicly available data from several sources. The contributions of this research include unique modeling approaches and important insights derived from the case studies that can benefit government organizations and businesses concerned about the effects of disruptions.

6.1 Significant Insights

6.1.1 Modeling insights

New simulations are created to depict the sudden closure of an inland waterway port (Chapter 2) and a severe supply chain disruption that causes supply and production difficulties (Chapter 4). These simulations model the behavior and actions of businesses that are impacted by the disruption. Each business acts as a separate entity and makes decisions based on its own objective, the constraints of the simulation, and the actions of other companies. Because the businesses are not static actors, a more accurate and nuanced picture of the disruption emerges from these simulations. Each simulation contains several parameters and uncertainties that can be tuned to reflect different situations. Simulations provide insight into the relationship between model inputs and outputs, such as how the length of a disruption affects production changes. These simulations can also be modified to address similar disruptions.

The simulations and models quantify the actions and decisions made by businesses in the midst of disruptions. During a disruption, impacted businesses attempt to maintain or resume operations, and modeling the economic impacts of these disruptions should account for these industry efforts. In Chapter 2, the model of a sudden closure of inland waterway port quantifies the effect of companies moving their commodities by alternate modes of transportation. Chapter 3 measures the impact of inventory, increasing imports to replace lost domestic production, and substituting domestic production in the place of imports. In Chapter 4, several mitigation strategies are modeled, including moving production to an alternate facility, using inventory, purchasing supplies from an alternate supplier, and assisting a primary supplier to recover more quickly.

Solving for the optimal decision for suppliers and firms during a supply disruption (Chapter 4) and for the optimal allocation of resources to help a region recover from a disruption (Chapter 5) instructs business and government officials on optimal disruption management strategies. For example, a supplier whose facility is disabled should not move to an alternate facility if either the probability that its primary facility reopens or the fixed cost of moving production is above the threshold parameters. The resource allocation model can instruct a decision maker on how to allocate resources among preparing for a disruption, assisting individual industries to recover, and helping all industries recover simultaneously.

This research proposes new approaches to the traditional I-O models in order to calculate the impact of supply shortages and production constraints. Chapter 2 relies on the assumption of fixed technical coefficients to calculate the inoperability among industries when they do not receive product originally expected to be shipped through an inland waterway port. This initial inoperability is incorporated into the multiregional DIIM to quantify the broader economic impacts of these supply shortages. Chapter 3 manipulates the Leontief I-O model in order to calculate the total production changes when data describe the direct impacts and when the data describe both direct and indirect impacts. The I-O model is extended to include the possibility of a country increasing its imports to satisfy customer demand and another country increasing its domestic production to replace lost imports. Chapter 5 creates a resource allocation model in which the decision maker desires to minimize both the direct and indirect impacts from a disruption, as calculated by the IIM.

6.1.2 Application insights

In addition to these theoretical contributions, much of this research emphasizes applying the models and simulations to real-life disruptions that either have occurred or that could potentially occur. These applications require estimating several parameters, which is achieved by using publicly available databases, gleaning information from media stories, and relying on studies previously published in journal articles.

The first application is a hypothetical closure of the Port of Catoosa in Oklahoma. From the simulation, if the port is closed for one to two months, the ten states that use the port would suffer $5 billion in production losses on average if product remains at the port. If companies transport most of the product by train, production losses would be reduced by about 90%. The results demonstrate the importance of businesses taking action to ensure their customers receive their product. From a policy perspective, if officials notice that product is staying at the port during a lengthy closure, they should incentivize companies to move product by an alternate mode.

Second, the multiregional I-O model analyzes the macroeconomic impacts of the Japanese earthquake and tsunami. Based on data from the Japanese government and international trade data, Japanese production suffered very large losses in the three months following the natural disaster. However, international production losses were relatively small, and no country lost more than 0.3% of its production due to the interdependent effects. Non-Japanese businesses benefited from the disruption because they were able to replace Japanese businesses whose production was degraded.

Following this macroeconomic case study of the Japanese earthquake and tsunami is a microeconomic model inspired by the disruption in the automobile sector caused by the Japanese disaster. If no alternate production facilities are available and firms only maximize their profit, firms fail to satisfy 12 to 27% of their customer demand on average. If firms are willing to sacrifice some profit in order to satisfy customer demand, each firm satisfies between 87 to 96% of its demand. Firm 1, which represents the Detroit 3 automakers, increases its market share because it relies less on suppliers whose production facilities are disabled. Firm 2, which represents Toyota and Honda, loses about 5% of its market share. These results mirror automobile production in North America. Sensitivity analysis on parameters for Firm 2 suggests that buying from a low-cost alternate supplier, helping suppliers recover more quickly, and raising the selling price to customers are better disruption management strategies than relying on inventory.

Finally, the resource allocation model is applied to recovery from the *Deepwater Horizon* oil spill. If the budget for recovery is larger than \$5 billion, a decision maker should allocate most of the budget to help all industries recover, which highlights the importance of the stopping the oil spill and cleaning up the oil. If the decision problem includes the option of allocating resources to reduce the probability of a disruption, a decision maker should spend approximately \$300 million in preparing for the disruption. This recommended allocation rests on the assumption that money not spent on preparation can be used to increase regional production if the disruptive event does not occur.

6.2 Future Work

Any major research project will raise further questions and can be extended in other directions, and this dissertation is no exception. Future research based on this dissertation include increasing the realism of the case studies, carefully analyzing the costs and benefits of risk management strategies, and developing a better dynamic I-O model.

6.2.1 Increasing realism of case studies

Parameters for the case studies and applications are estimated from media stories, journal articles, and government reports. Additionally, the models and simulations used for these case studies are simplifications of what actually occurred or what might occur. Including more parameters within the model and more alternatives for businesses can increase the realism of these applications. A more accurate model of business reactions during a supply chain disruption will likely involve discussions with firms and suppliers about their objectives and risk management strategies. Sensitivity analysis on the *Deepwater Horizon* case study in Chapter 5 reveals that the numerical results are very dependent on some of the parameters, especially the effectiveness of allocating resources. Developing more accurate methods to estimate these parameters would help strengthen the case study's conclusions.

6.2.2 Cost-benefit comparisons of risk management strategies

This research focuses on specific actions that can be taken to reduce the impacts of a disruption. Chapter 2 explores the possibility of companies transporting their product by alternate modes of transportation in the event of a port closure. Chapter 4 models decisions made by suppliers to move their production to alternate facilities and includes several different mitigation options for firms (raw materials inventory, finished goods inventory, buying from alternate suppliers, raising prices, and helping suppliers recover more quickly). The models and case studies quantify the benefit of these risk mitigation strategies.

In order to accurately compare different risk management strategies and recommend one strategy over another, the cost of each strategy should be incorporated into the model. Chapter 4 can be enhanced to include the cost of keeping inventory, the cost of having an alternate supplier ready to supply the firm in case of a disruption, and the cost of helping the primary supplier recover. Understanding whether these are good risk management strategies and comparing these strategies require incorporating the cost as well as the benefits in order to help a firm determine the optimal course of action. Chapter 2 incorporates the additional cost of moving product via an alternate mode, and further extensions could compare the cost and benefits of this strategy with the costs and benefits of maintaining inventory.

Integrating disruption management strategies with preparedness strategies can also provide a more realistic picture of the impact of industry strategies and offer greater insight to businesses who want to minimize the risk of supply chain disruptions. Preparedness strategies include building up inventory as safety stock, purchasing the same supply from multiple suppliers, and building facilities and warehouses in different locations to avoid a single disruptive event rendering all facilities inoperable. Incorporating the allocation of resources as a preparedness strategy is one of the significant contributions of Chapter 6. That type of resource allocation model could potentially be applied to a firm's decision making process about preparing for a supply chain disruption.

6.2.3 Improving the dynamic I-O model for disruptions

The DIIM used in Chapter 2 to quantify the economic impacts of a disruption over time has some shortcomings that could be addressed by a more accurate dynamic model. Because the DIIM is usually populated with economic data designed for the Leontief I-O model, the DIIM should be interpreted as an economic interdependency model, as discussed in Chapter 1. If the vector $\mathbf{q}(0)$ represents directly impacted industries, the matrix-vector product $\mathbf{A}^*\mathbf{q}(0)$ calculates the inoperability in the immediate suppliers to the directly impacted industries, where $\mathbf{A}^*$ is the normalized interdependency matrix. These suppliers produce less because the industries contained in $\mathbf{q}(0)$ reduce their demand.

The DIIM as given in Eq. (1.8) can be rearranged as in Eq. (6.1), where $\mathbf{K}$ is a diagonal matrix describing the resilience and $\mathbf{c}^*(t)$ represents the perturbation in final consumption.

$$\mathbf{q}(t+1) = (\mathbf{I} - \mathbf{K})\,\mathbf{q}(t) + \mathbf{K}\left[\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t)\right] \tag{6.1}$$

The first part of the right-hand side $(\mathbf{I} - \mathbf{K})\,\mathbf{q}(t)$ implies that industries that are inoperable at time t recover some operability at time $t+1$ by a factor of $\mathbf{I} - \mathbf{K}$.

The second part of the right-hand side describes the interdependencies. Pre-multiplying $\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t)$ by $\mathbf{K}$ implies that lost demand is reduced by a factor of $\mathbf{K}$, where $\mathbf{K} < \mathbf{I}$. This lost demand includes both intermediate demand as represented by $\mathbf{A}^*\mathbf{q}(t)$ and final consumption as represented by $\mathbf{c}^*(t)$.

The implication that lost demand is not as large as it should be due to the resilience matrix $\mathbf{K}$ is problematic from an economic point of view. If the demand for a firm's product decreases, the firm should produce less, or it will be producing more than it can sell. The firm's resilience as described by $\mathbf{K}$ should not empower the firm with an ability to produce more than what is demanded of it.

Future work on creating a more accurate dynamic model should account for at least three different effects. First, directly impacted industries recover from a physical disruption, which can be described by a resilience parameter. Unlike the current

DIIM, this resilience parameter should only be applied to directly impacted industries.

Second, some industries may not experience the indirect impacts calculated by $\mathbf{A}^*\mathbf{q}(0)$. These industries may represent fixed inputs that other industries must order regardless of the latter's production. This modeling approach violates a key assumption of the Leontief I-O model, namely the idea of fixed technical coefficients, but it seems realistic especially if the disruption is of limited duration. An automobile industry who suffers a disruption and recovers in two or three months may still need the same level of financial services.

Finally, as discussed in Chapter 3, some industries may feel the indirect impacts more quickly than other industries. For example, manufacturing industries can change their production schedule relatively quickly to reflect changes in intermediate demand, but agriculture industries may not be able to change its production schedule for several months or a year. A model seeking to measure the temporal impacts of a disruption should account for the different timing elements that industries would experience.

Including these elements within a dynamic I-O model would increase the realism of the DIIM and better measure the temporal impacts of a disruption. Other dynamic models, like the sequential interindustry model (Romanoff and Levine, 1981, 1986; Levine and Romanoff, 1989; Okuyama et al., 2004; Okuyama, 2008) and the adaptive regional I-O model (Hallegatte, 2008, 2011), currently address some of the above elements. A difficulty with adding this complexity to the dynamic model is the increased number of parameters that would need to be estimated.

6.3 Lessons Learned from Studying the Economic Impacts of Disruptions

By modeling different disruptions, this research can offer general insights into the economic impacts of disruptions. Although the direct economic impacts of a disruption can be quite large, firms and industries will likely take steps to minimize impacts and maintain operations. Other businesses who are not affected may step into the void left by firms whose production is degraded. Consequently, individual firms and businesses may suffer supply shortages and reduced demand due to disruptive events, but the overall macroeconomic impacts due to economic interdependencies may be relatively small. If consumer demand does not significantly fall, the long-term indirect economic impacts from a disruption may be minimal.

Industry behavior during a disruption is important for policymakers to consider when preparing for and responding to disruptions. The behavior of industries, such as transporting goods via alternate modes or buying from alternate suppliers, can substantially reduce the economic impacts of a disruption. If a disruption occurs, government officials worried about the economic consequences should focus on taking steps that will assist businesses to implement their own disruption management strategies. These steps may include actions like rebuilding damaged infrastructure that industry uses and containing and limiting the direct impacts of a disruption.

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