Estimating production losses from disruptions based on stock market returns: Applications to 9/11 attacks, the *Deepwater Horizon* oil spill, and Hurricane Sandy

by

Aditya Kiran Pathak

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Industrial and Manufacturing Systems Engineering

Program of Study Committee:
Cameron A. MacKenzie, Major Professor
Michael S. Helwig
Mark Mba –Wright

Iowa State University

Ames, Iowa

2017

DEDICATION

To my parents, Sandhya and Kiran Pathak, and my sister Sheetal Pathak.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

VUCA	Volatile, Uncertain, Complex and Ambiguous
IO	Input – Output
IIM	Inoperability Input – Output Model
CGE	Computable General Equilibrium
DIIM	Dynamic Inoperability Input – Output Model
BEA	Bureau of Economic Analysis
NAICS	North American Industry Classification System
G-7	Group of Seven
DJUSEN	Dow Jones U.S. Oil & Gas Index
DJUSUT	Dow Jones U.S. Utilities Index
DJUSTS	Dow Jones U.S. Transportation Services Index
DJUSTC	Dow Jones U.S. Technology Index
DJUSFN	Dow Jones U.S. Financials Index
HMM	Hidden Markov Model

ACKNOWLEDGMENTS

I would like to thank my committee chair, Dr. Cameron MacKenzie, who has consistently supported and helped me whenever I faced difficulties and had questions about my research or writings. I would also like to thank my committee members, Dr. Michael Helwig, and Dr. Mark Mba – Wright, for their guidance and support throughout the course of this research.

In addition, I would also like to thank my colleagues, the IMSE department faculty, and staff for making my time at Iowa State University a wonderful experience. I would like to thank my friends for their valuable advice and support throughout my career and henceforth.

Finally, I express my deep gratitude to my parents and my sister for their continuous encouragement and constant support throughout my years of my study and the course of this research.

This accomplishment would not have been possible without all of them. *Thank you.*

ABSTRACT

The threats to human life and infrastructure are ever growing due to global terrorism, conflicts and climate change as well as the omnipresent threat of natural disruptions like earthquakes, volcanos, tsunamis etc. Disruptions or disasters lead to sudden changes in demand, production and supply. In case of such scenarios it is essential to optimize the utilization of available resources and avoid further wastage. In this study a model is presented to measure the changes in production due to changes in supply and demand of goods and services, and measure possible losses to industries during such disruptions. It is anticipated that there is a strong economic correlation of growth among the industries and there is a ripple effect causing losses to interdependent industries and economies in such scenarios. It is believed that, variability in the economy is preceded by stock market price fluctuations. The trend of any economy is reflected in the stock markets that it encompasses and these markets provide instantaneous feedback to changes in a state of normalcy. These stock markets have been used to study the variability in economic output of industries, and measure the dynamic changes in production or output of industries. The results of the study justify the existence of such a correlation between the gross output of industries and the stock indices that are related to these industries. Study of past disruptions is performed through a deterministic model and a stochastic model and the results obtained resonate with the existing estimates published by studies measuring the economic impacts of these disruptions. Such a study would enable governments, corporations and individual businesses to make informed decisions regarding the allocation of resources and contingency plans in case of such a disruption. The risk of monetary and market losses can be substantially reduced thus enabling faster recovery and higher resilience.

CHAPTER 1. INTRODUCTION

The world has experienced disruptions and threats of potential disruptions regularly in the recent past. The number of disruptions have increased exponentially (Coleman, 2006; Guha-Sapir, et al., 2013). A disruption is a state of unbalance or disturbance that affects a system. When it comes to the economy or a nation, a disruption could be an event or a series of events causing damage to the normal functioning of these systems. Disruptions can be defined as an event that causes diversion from a state of the usual or expected. These can range from a wide selection of natural disasters or man-made disruptions like terrorism or war. These disruptions cause loss of life, damages to private and public property, our environment and our day-to-day lives. This study deals with the effects of such disruptions on economies, businesses and industries.

In this study we deal with the economic impacts of such events and hence the focus would be towards economies and industries. Such events pose a threat of potential loss to economies and industries that may be affected directly or indirectly. Potential threats can be analyzed using principals of 'risk analysis.' Risk analysis or risk management has been defined in multiple concepts, one such definition is "The identification, assessment, and prioritization of risks followed by coordinated and economical application of resources to minimize, monitor, and control the probability and/or impact of unfortunate events" (Hubbard, D., 2009). A complete study of a risk analysis problem broadly should report comprehensive solutions to three questions "1. What can go wrong? 2. How likely is it that such a situation will occur? 3. What are the consequences if it occurs?" (Kaplan, S., & Garrick, B., 1981). This study is associated with the economic risks of unwanted events or disruptions to interdependent industries and the effect of inter – industry dependence on these risks.

Stiehm described the post-cold war world as a more Volatile, Uncertain, Complex and Ambiguous or VUCA (Stiehm, J. H., 2010). The world is constantly under threats of disruptions to a normal way of life

Global economies and nations continuously strive to grow. With growth in the industrial sector arises a greater interdependence among industries and international economies. Interdependence aids in swift and stable growth but also is a weakness because such systems are more susceptible to loss if any of the entities face damages due to disruptions. The average cost of natural disruptions has increased from $50 billion in the 1980s to $200 billion in the recent years and approximate losses worth $1.5 trillion were incurred during 2003 to 2013 (Al Kazimi, A. & MacKenzie, C., 2016; Associated Press, 2014).

With such catastrophic consequences it is essential that governments and corporations make efforts towards mitigating the risks of such events in order to reduce the losses and safeguard life. In this study, we put forth a statistical model to predict the losses incurred by industries due to direct and indirect impacts of disruptions. The model will enable stakeholders to make better and informed decisions for resource allocation and preventive measures. A unique approach of quantifying future losses in output of industries that might be incurred after the occurrence of such an event using the stock market returns as an indicator has been employed.

Hence motivation of this study is to identify and exploit the relation between the stock market prices and industrial production to better predict losses due to disruptions and reduce the recovery period and costs. Chapter 2 of this thesis introduces the model with case examples of past disruptions. Chapter 3 discusses the summary of the research and future work.

REFERENCES

A. A. Kazimi and C. A. MacKenzie, "The economic costs of natural disasters, terrorist attacks, and other calamities: An analysis of economic models that quantify the losses caused by disruptions," 2016 IEEE Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, 2016, pp. 32-37. DOI: 10.1109/SIEDS.2016.7489322

Associated Press. 2014. Official: disaster cost quadrupled in past decades. Daily Mail, 5 June. Available at http://www.dailymail.co.uk/wires/ap/article-2649515/Official-Disaster-cost-quadrupled-past-decades.html, Accessed on February 9, 2017.

Coleman, L. (2006), Frequency of Man-Made Disasters in the 20th Century. Journal of Contingencies and Crisis Management, 14: 3–11. doi:10.1111/j.1468-5973.2006.00476.x

Guha-Sapir, D., Santos, I., & Borde, A. (2013). The economic impacts of natural disasters / edited by Debarati Guha-Sapir, Indhira Santos, Alexandre Borde. Oxford ; New York: Oxford University Press.

Hubbard, D. (2009). *The failure of risk management: Why it's broken and how to fix it / Douglas W. Hubbard.* Hoboken, N.J.: Wiley.

Kaplan, S., & Garrick, B. (1981). On The Quantitative Definition of Risk. Risk Analysis, 1(1), 11-27.

Stiehm, J. H. (2010). U.S. Army War College. Philadelphia: Temple University Press. Retrieved from http://ebookcentral.proquest.com/lib/iastate/detail.action?docID=616015

CHAPTER 2. ESTIMATING PRODUCTION LOSSES FROM DISRUPTIONS BASED ON STOCK MARKET RETURNS: APPLICATIONS TO 9/11 ATTACKS, THE *DEEPWATER HORIZON* OIL SPILL, AND HURRICANE SANDY

1. Introduction

We live in a world threatened by various disruptions, both natural and manmade. These disruptions can cause fatalities, injuries, infrastructure and environmental damage, and lost business. Unfortunately, the frequency and damages from these disruptions seem to be increasing. The global cost of natural disasters has risen from approximately $50 billion in the 1980s to $200 billion per year in the 2010s (Al Kazimi, A. & MacKenzie, C., 2016; Associated Press, 2014). The global economy is an interconnected web of industries, governments, businesses, and people, and it functions by exchanging goods, services, and money among these parties. Consequently, when a disruption strikes a specific region or directly impacts a specific sector or industry, the economic impacts of the disruption can extend beyond that region or that sector of the economy. Developing models that quantify and predict the interdependent economic impacts of a disruption is important in order to understand the total cost of these disruptions. Quantifying the cost from a disruption can be used to determine what mitigation actions should be taken and how much should be spent in order to prepare and respond to the disruption.

Disruptions can affect both the production or output and demand for industries or sectors in the economy. Interdependent industries can also be affected even if they do not suffer physical damages. The economic input-output (IO) model developed by Leontief (1951ab) is one of the most popular frameworks for quantifying the economic impacts of disruptions (Van der Veen and Logtmeijer, 2005; Santos, 2006; Lian and Haimes, 2006; Hallegatte, 2008; Okuyama, 2010;

Rose and Wei, 2013). The loss in output from sectors that are directly impacted by disruptions (e.g., physical damage to buildings) spreads to interdependent sectors through forward or backward linkages which intensifies the original loss (Rose, 2004; Okuyama and Santos, 2014). The cost of a disruption can be divided into two parts direct losses and indirect losses also known as higher order effect. These are calculated mostly using macroeconomic multipliers for both direct and indirect effects, which are quantified using empirical relations estimating the economic activity.

Several models have extended the basic demand-driven IO model to quantify the impact of disasters. The Inoperability IO Model (IIM) quantifies the loss in production or output of each industry by calculating the inoperability of an industry (Haimes and Jiang, 2001; Santos and Haimes, 2004). In addition to IO models, computable general equilibrium models and social-accounting matrices have also been used to assess the economic impacts from disruptions.

One challenge with these economic impact models has been to quantify the dynamic impacts of a disruption by correctly analyzing the length of time for the indirect impacts to flow throughout the economy. The Dynamic Inoperability IO Model (DIIM) uses a “resilience” matrix that describes how quickly the economic industries recover from a disruption (Lian and Haimes, 2006) or how quickly the economy reaches equilibrium (MacKenzie et al., 2012a). Many economic disaster impact studies based on IO models also assume the same underlying supply and demand mechanisms that exist at the equilibrium state before a disruption remain constant during and after disruption. For example, if an industry requires 20 cents in goods and services from a second industry for every dollar that the first industry produces at equilibrium, then IO models assume this relationship remains the same during the disruption. CGE models, discussed in the following section, provide more flexibility by allowing for price changes and substitution effects, but estimating the parameters for a CGE model can be very difficult and the CGE model might overestimate the ability of consumers and producers to substitute other goods and services during a disruption (Rose and Liao, 2005; Okuyama, 2008). Other studies allow a region to use imports to replace lost production during a disruption (MacKenzie et al., 2012b).

This paper proposes a new model to quantify the dynamic economic impacts that does not rely on equilibrium assumptions that may not be valid during a disruption. The model estimates production losses due to a disruption based on stock market activity following a disruptive event. The model assumes the stock market indices for specific industries reflects production in those industries. Fama (1990), Choi et al. (1999), Barro (1990), Ferson and Harvey (1991), Schwert (1990) discuss the relation of the stock market with the gross output or revenue of any industry especially in the United States market as well as in the international markets.

The model uses regression analysis to model the relationship between stock market activity and each industry in the U.S. economy. The stock market reacts to a large disruptive event, such as a terrorist attack, a large-scale industrial accident, or a natural disaster. If the stock market reflects to some extent the economic activity, such as production or demand (Fama, 1990; Choi et al., 1999; Barro, 1990; Ferson and Harvey, 1991; Schwert, 1990), after the disruption, then using stock market prices to assess the impact on production in the economy is justified. This paper introduces two new modeling approaches for disaster impact studies. The first model uses five stock market indices to predict weekly production for each industry in the U.S. economy. The weekly production for each industry following three recent disruptions is calculated based on the regression model. The second model focuses on the production for each industry for which a stock market index exists. After using regression to predict the production for each industry based on the industry's own stock market index, Monte Carlo simulation is used to analyze the uncertainty in production after a disruptive event. This model calculates the correlation in the stock market indices to induce correlation (i.e., interdependence) in the simulated production output.

The uniqueness of this approach is the use of stock market returns to estimate economic losses from a disruption. Many studies like Chen et al. (1986), Cheug and Ng (1997), Rappaport (1987), Fama (1981), and Choi et al. (1999) discuss the relation among the stock market and the industrial output or put forth forecasting models. The model uses weekly stock market prices, and the output is weekly production of national industries. Thus, the model inherently captures dynamic elements and can be used to examine how long industries recover after a disruption, which is a difficult modeling challenge. Since the model predicts economic activity for multiple industries, the model can be used to explore the interdependent economic impacts from the disruption. Using correlation in industrial stock market indices to represent the interdependence among industrial sectors represents a novel contribution. The model is applied to three recent disruptions: the 9/11 attacks, the *Deepwater Horizon* oil spill, and Hurricane Sandy. First, the five stock market indices quantify the national economic losses for each of the 15 industries in the U.S. economy. Second, the model uses these disruptions to measure the interdependence among a subset of industrial sectors. It simulates the relationship for these industries for the three disruptions in order to understand the range of possible impacts for similar disruptions.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature including economic impact models and interpretations of the stock market. Section 3 introduces the methodology used for the deterministic approach and the stochastic approach. Section 4 discusses the data collection techniques and the data structure. Section 5 put forth the analysis of pilot studies of past disruptions using both techniques. Section 6 is a discussion section for the results of the analysis followed by section 7 which concludes the findings and discusses the further scope of the study.

2. Literature Review

The economic IO model developed by Leontief (1951ab) describes the economic interdependence among industries by determining the amount of goods and services required by each industry. The original IO model is demand driven. For each dollar of good or service demanded by the final consumer, an industrial sector requires inputs and supplies from other sectors in the economy. If demand for one industry decreases, the industrial sector requires fewer inputs from other industrial sectors, and consequently, the entire economy produces less (Miller and Blair, 2009). IO models are widely support by data collection efforts across the globe. In the United States, the Bureau of Economic Analysis (BEA) is responsible for collecting and publishing national IO data, and private corporations provide local and state IO data. The BEA data represents the IO accounts of industries classified under the North American Industry Classification System (NAICS) code.

The basic structure of the IO model has been extended in a variety of ways to capture time and different regions (Miller and Blair, 2009). Regional IO multipliers quantify the impact of demand changes within a region (Isard et al., 1998; Bess, Ambargis, 2011). IO models have been used frequently to assess the economic impacts from disruptions (MacKenzie et al., 2012b; Hallegatte 2008, 2014). As discussed earlier the IIM defines the industry's inoperability as the degree to which an industry is not producing compared to its normal operations or production. The IIM is a linear model that calculates the inoperability in each industry based on the initial inoperability induced by a disruption (Haimes and Jiang, 2001). This model and its modifications have a varied set of risk analysis applications like terror attacks (Haimes et al., 2005a, b), workforce disruptions (Orsi and Santos, 2010a; Barker and Santos, 2010b), cyber security (Andrijcic and Horowitz, 2006; Dynes et al., 2007), oil spills (MacKenzie et al., 2016), and the closure of inland waterway ports (Pant et al., 2011; MacKenzie et al., 2012a).

A variation of the IIM is the Dynamic Inoperability Input – Output Model (DIIM) which is based on the dynamic Leontief (1970) IO model (Lian and Haimes, 2006) considers the dynamic changes in production from a disruption by relating production in one time interval to production in the next time interval. The model quantifies changes in demand and the time required by industrial sectors to recover from a disruption. The model considers the resilience of industrial sectors to disruptions as a key parameter of the recovery period. These coefficients are computed using historical data and expert opinions (Lian and Haimes, 2006). Studies researching the varied applications of the DIIM have been published since the inception of the model. the recent studies include modelling of economic losses due to man-made attacks on the IT sector (Ali and Santos, 2015), the use of the DIIM to model the losses in regions affected by water shortages and droughts and to identify critical sectors affect due to water shortages (Pagsuyoin and Santos, 2015) and economic losses to industrial sectors and inoperability of sectors due to influenza epidemics causing shortages in the workforce (Santos, May & Haimar, 2013). However, estimating parameters for this resilience matrix is difficult, and the suggested mathematical methods (MacKenzie and Barker, 2013; Pant et al., 2014) rely on assumptions that are difficult to validate.

The Computable General Equilibrium (CGE) uses some of the principles of IO modeling but allows for non-linear relationships due to price changes, import substitutions, and supply constraints (Okuyama and Santos, 2014; Rose and Liao, 2005). The Social Account Matrix has fixed coefficients which result in relationally higher estimates for disasters (Okuyama, 2007;

Cole, 1995, 1998, 2004). The Adaptive Regional IO model (Hallegatte, 2008; 2014) measures changes in production capacity over time based on capital losses and bottlenecks in the production process, but the dynamic element in this model is driven by the change in demand over time and does not seem to account for possible lags in the indirect impacts.

According to Chen et al. (1986), stock markets are representations of “systematic economic news” and their behavior is based on the outcomes in these news findings. The news can be quantified in terms of few driving variables to analyze the behavior of stock process. These variables include industrial production, risk premiums, inflation and changes in inflation levels (Chen et al., 1986). Cheug and Ng (1997) prove an empirical relation between the stock market indexes and variables like output of an industry. The efficiency of a stock market is the its ability to represent the real economic activity. It is believed that even though markets do respond to investor sentiments, the core driving force of the stocks are the news about the real activity. The investments made by traders based on sentiment, also known as ‘noise traders’ is often compensated by the investments made due to mistaken judgements. Thereby suggesting that the market is not affected by sudden noise but by informed investment decisions (Morck et al., 1990). Alfred Rappaport suggests that the stock market price is a representation of the investors’ expectations of a company, and whether they have been fulfilled or not, which are based on the information that the company makes available (Rappaport, A., 1987). This paper analyzes the economic effects of disruptions on industries based on the variation in the stock prices according to sector indices. Other papers analyze the relation between the stock market and economic production. According to Fama (1981), the variations in stock returns show a strong relation to the growth rate of industrial production and anticipated growth rates in the near future. Choi et al. (1999) suggest that log levels of production output and stock prices are correlated in G-7 nations over a short time period. Santos and Haimes (2008) demonstrate that diversifying a stock portfolio using a model based on the interdependencies among the industries as given by the IO model is more resilient to aberrant markets due to some anomaly.

This paper diverts from the traditional IO model of measuring the interdependent economic impacts from disruptions based on social accounting matrices. By statistically measuring the relationship between stock market indices and industrial production, we allow the model to capture the interdependence of industries through the correlation in stock market indices. Stock market prices provide a rich source of data that can supplement annual BEA production data. Since the interdependence among industries and the changes over time are driven by the stock market indices, the model is inherently interdependent and dynamic. Since the model is based on a linear regression, it alleviates the need to estimate many parameters which is necessary for CGE and some IO models such as the Adaptive Regional IO model (Hallegatte, 2008; 2014).

3. Methodology

The methodology presents two models based on stock market prices. The first model is a deterministic model in which weekly prices from industrial stock market indices are used to calculate weekly production for each industry in the economy. The second model is a stochastic model in which the weekly production for a subset of industries follow a multivariate normal distribution in which the parameters of the multivariate distribution are calculated based on the prices of each stock market index. Each model is derived using linear regression.

3.1 Deterministic model

To predict the loss in production based solely on the historical output data and input stock prices the use of a deterministic method is considered. The relation between the production or output of any one industrial sector and its corresponding stock market prices is established. As discussed earlier, many studies suggest a strong correlation of the stock price with the production output of an industry. Studies like Fama (1981), make use of regression models to justify the relation between stock prices and real variables like production, cash flows, gross national product and the growth rates of these variables. Fama (1990) defines a linear relationship between weighted lagged stock market returns and the production. While, Choi et. al. (1999) define a log – linear relationship between the stock prices and industrial production. It was found that linear regressions were better fits than log – linear regression. Thus this model makes use of linear regression method to justify the hypothesis.

Consider an industrial sector *i* among n industrial sectors, and let the production output for sector *i* for time period *t* be denoted by X_{it}. The production X_{it} is a linear function of the stock market index prices for *l* industries where p_{jt} is the stock market index price at time *t* for sector *j*, where $j = 1,2, \dots, m$. The linear coefficient relating the stock market price index of sector *j* to the production in sector *i* is a_{ij} and b_i is the intercept. The production is sector *i* at time period *t* is:

$$X_{it} = \sum_{j=1}^{m} (a_{ij}\, p_{jt}) + b_i \tag{1}$$

The regression coefficients a_{ij} and b_i will be calculated based on the historical index prices of the *m* sectors and the annual production of sector *i*.

Industry *i*'s production may decline after a disruptive event. We assume the production at the time step immediately before the disruptive event, $t = 0$, represents the baseline production, and the loss in production at time t for industry i L_{it} is the difference in production at time t and time 0:

$$L_{it} = X_{i0} - X_{it} \tag{2}$$

This formulation enables us to calculate the loss in production for industry i at each time increment.

It is also necessary to estimate the time when the industry has recovered from the industry. Recovery could be defined as the first time period for which $X_{it} > X_{i0}$. However, since production for each industry is a function of the stock market index prices and these indices can fluctuate wildly, production in industry *i* can be more than X_{i0} for one period and then decrease. Thus, we decide to require more stability in the definition of recovery, and calculate the recovery time as the number of time periods until $X_{it} > X_{i0}$ for three consecutive time periods. This is a model choice that influences the total production losses. The numerical example shows how the total production losses changes if recovery is defined as one consecutive period and two consecutive periods for which $X_{it} > X_{i0}$.

3.2 Stochastic model

Since stock market index prices are obviously an imperfect predictor of actual industry production, the second model is a stochastic model to depict the uncertain relationship between the stock market and industry production. The stochastic model also explicitly models the interdependence between industries through a covariance matrix as estimated from the stock market index prices.

The stochastic model contains *m* industries and a stock market index price is available for each of the *m* industries. Due to this requirement, the stochastic model has fewer industries than the deterministic model because not every industry in the economy has a corresponding stock index price. The production of all *m* industries at time *t*, $\mathbf{X}_t$ (an *m*-dimensional vector) follows a multivariate normal distribution

$$\mathbf{X}_t \sim N(\text{diag}(\mathbf{a})\mathbf{p}_t + \mathbf{b}, \Sigma) \tag{3}$$

Where $\mathbf{p}_t$ is a *m*-dimensional vector of stock market prices at time *t*; **a** and **b** are vectors of length *m* in which a_i is the slope and b_i is the intercept; and Σ is the covariance matrix. The parameters a_i and b_i are calculated via least-squares estimation of the following relation:

$$X_{it} = \ a_i p_{it} + b_i + e_i \tag{4}$$

Where $e_i \sim N(0, \sigma_i^2)$ is the error term. Since a_i and b_i are estimated using least-squares regression, the variance around observed values of production is equal to σ_i^2 and the standard error from the regression results is the estimated value of σ_i. A predicted value of production at time t for an individual observation will have variance (Draper and Smith, 1998):

$$\sigma_i^2 \left\{ 1 + \frac{1}{T} + \frac{(p_{it} - \bar{p}_i)^2}{\sum_{\tau\,=\,1}^{T} (p_{i\tau} - \bar{p}_i)^2} \right\}$$

Where T is the total number of data points used in the least-squares model and $\overline{p}_i$ is the average stock price over the time period . Since T is very large in the model and each p_{it} makes a very small contribution to the overall sum of squares, the equation for variance for a predicted value is approximately equal to σ_i^2. For simplicity, we use σ_i^2 as the variance around the predicted production values.

We assume the correlation between production values equals the correlation between the stock market index prices. If stock market indices i and j have correlated prices equal to ρ_{ij}, the production values for industries i and j have correlation ρ_{ij}. The covariance between industries i and j is $\sigma_{ij} = \ \rho_{ij}\sigma_i\sigma_j$. This provides the necessary estimation for the covariance matrix Σ. The stochastic model is used to simulate a large number of possible production values given a set of stock market index prices.

4. Application

Both of the deterministic and stochastic models are applied to three recent disruptions in the United States: the 9/11 terrorist attacks in New York city on September 11, 2001, the *Deepwater Horizon* oil spill in the Gulf of Mexico on April 20, 2010, and Hurricane Sandy, which struck the East coast of the United States in August 2012. This section outlines the data used for each models, the parameter estimation, and results. The 9/11 attacks, had implications on the industrial productivity of the United States as more efforts and capital was invested towards security efforts (Makinen, 2002). The attacks amounted to a $10 billion to $13 billion cost to the infrastructure industry which includes the cost of restoring and rebuilding, $40 billion to the insurance companies, $10 billion to the airline industry and $40 billion in federal emergency funds were among the significant losses that are related to this study ("How much did the September 11 terrorist attack cost America?", 2004). The *Deepwater Horizon* oil spill in the Gulf of Mexico is regarded among the most devastating, in terms of the aftermath and the volume, marine oil spills in history (Robertson and Krauss, 2010) amounting to an estimated economic loss of $90 billion in containment, market share and settlements to the affected families to British Petroleum, local businesses, and the government (Park et al., 2014). Hurricane Sandy is considered to be among the worst disasters affecting the eastern coast of the US causing losses in the range of $85 billion ("Economic Impact of Hurricane Sandy.", 2013). While another study estimates the losses due to Hurricane Sandy in the range of $30 to $50 billion (Holm and Scism, 2012).

4.1 Data

The data for both the deterministic and stochastic models consist of the gross output or production of industrial sectors in U.S. dollars and the stock market index prices of corresponding sectors. The data for the gross output of industries comes from the BEA. The BEA publishes the annual production of 71 industries, and the industries can be aggregated into 15 sectors as represented in Table 1. The division of the industries follows the North American Industry Classification System (NAICS). The stock market data, for years 2002 to 2015, is collected from websites: Google Finance (www.google.com/finance) and ADVFN (www.advfn.com) which publish historical and current stock prices of indices. Stock market indices, as shown in Table 1, are only available for five sectors: mining, utilities, transportation, information, and finance.

Table 1: NAICS industry classification & stock market indices

Sector	Common Name	Stock Index
Agriculture, fishing, and hunting	Agriculture	--
Mining	Mining	Dow Jones U.S. Oil & Gas Index (DJUSEN)
Utilities	Utilities	Dow Jones U.S. Utilities Index (DJUSUT)
Construction	Construction	--
Manufacturing	Manufacturing	--
Wholesale trade	Wholesale Trade	--
Retail trade	Retail Trade	--
Transportation and warehousing	Transportation	Dow Jones U.S. Transportation Services Index (DJUSTS)
Information	Information	Dow Jones U.S. Technology Index (DJUSTC)
Finance, insurance, real estate, rental, and leasing	Finance	Dow Jones U.S. Financials Index (DJUSFN)
Professional and business services	Professional Services	--
Educational services, health care, and social assistance	Educational Services	--
Arts, entertainment, recreation, accommodation, and food services	Arts	--
Other services, except government	Other	--
Government	Government	--

These indices are selected from the Dow Jones U.S. Indices which correspond to the classification of businesses followed by the NAICS. The data for the stock index corresponding to the transportation industry is available from the year 2002 and hence in this study the transportation stock index has not been considered for the 9/11 attacks.

The time increment in this study is one week in order to capture variations in the stock price, which the model translates into production losses in the 15 industrial sectors. The weekly closing prices are collected for the five stock market indices. The BEA publishes annual production data, and weekly production is unavailable (which is why the model relies on the stock market). In order to determine the parameters for the regression models, we assume that weekly production for each industry is the annual production divided by 52 weeks. Other assumptions might also be appropriate such as a linear interpolation between production amounts in each year.

The industry stock market index prices generally dropped after each disruption and gradually returned to their pre-disruption prices. We argue the time required to recover economically depends on the resilience of the industry and the interdependent production effects among industries. For example, Figure 1a represents the stock index price of the Dow Jones Oil & Gas Index and Figure 1b represents the Dow Jones Transportation Services Index during the *Deepwater Horizon* Oil Spill which occurred on April 20, 2010. The closing weekly price of the mining sector dropped on April 22—immediately when the oil spill occurred—but the closing weekly price of the transportation index did not drop until a week after the oil spill on April 29. The decrease in the transportation index price could be because of the cascading impacts from the oil spill and due to investors believing that the transportation sector would encounter problems if the oil industry produced less.

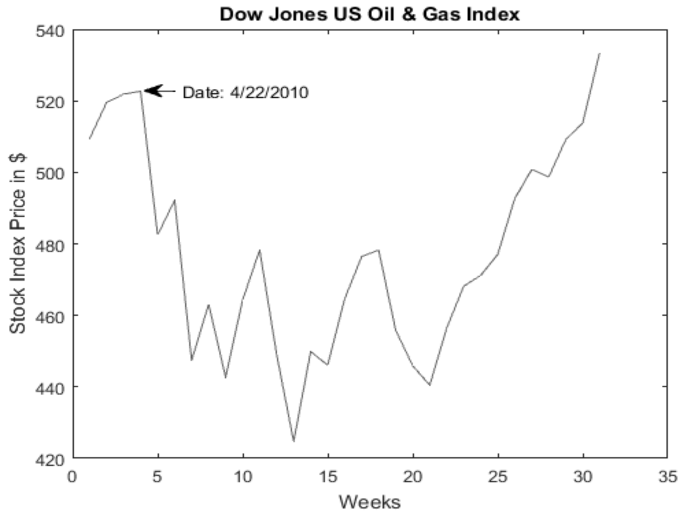

Figure 1a: Dow Jones US Oil & Gas Index after the *Deepwater Horizon* oil spill

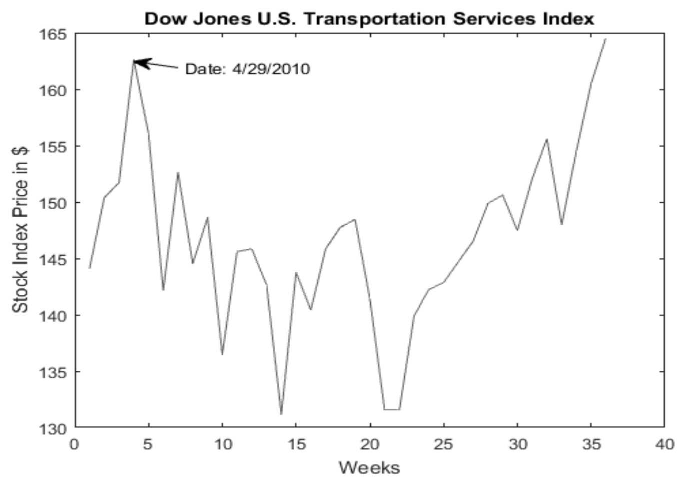

Figure 1b: Dow Jones U.S. Transportation Services Index after the *Deepwater Horizon* oil spill

According to Roll (1992), correlation and lagged response to variability in stock returns, especially in indices, is dependent on the composition of these indexes in the international market. While Roll (1992) discusses about the effect on the international market it can be assumed that similar effects are seen in the national market like the United States as the national market is composed of almost all the global multinational companies, but in such a case such an assumption is dependent on the configuration of the indices in consideration. Markets in countries which are highly dependent on industrial production are more volatile and susceptible to international market disruptions than those which have a diversified economy (Roll, 1992). Hence a disruption occurring outside the United States may have a lasting impact on the local economy but also will cause a reaction from the United States market.

The five industry price indices: mining, utilities, transportation, information, and finance generally show reaction to the disruptive events even if an industry does not seem to be directly affected. For about 20 weeks after the *Deepwater Horizon* oil spill, the transportation sector lost 26% in share value, the utilities sector lost 37%, the finance sector lost 25%, and the mining sector lost 22% in points in the stock market.

4.2 Deterministic model

As discussed earlier, the weekly production of each of the 15 industries is estimated using the simple linear regression equation (1), based on 4 industry stock market indices for 9/11 and 5 industry stock market indices for *Deepwater Horizon* and Hurricane Sandy. Both regression models estimate the slope and intercept parameters using the same stock market data from years 2000 to 2013 for the 9/11 attacks and years 2002 to 2013 for the *Deepwater Horizon* oil spill and Hurricane Sandy. Table 2 depicts the regression results for each of the 15 industries for the 9/11 attacks, and Table 3 depicts the regression results for *Deepwater Horizon* and Hurricane Sandy. The regression models are significant at the 0.01 level with p-values of the F-statistics test smaller than 0.01 in all cases of the three disruptions. The R^2 values for the latter two disruptions range from 0.71 to 0.96, with many of the models greater than 0.96. While the R^2 values for the 9/11 attacks regression ranges from 0.49 to 0.92, with a mean of 0.85. These large R^2 values indicate the regression models capture a substantial portion of the variation in the BEA production for each industry. Many of the coefficients are highly significant and have been tabulated in the Tables 2 and 3.

Table 2: Regression coefficients for different sectors and their significance: 9/11 attacks

Output	Intercept	Mining	Utilities	Information	Finance	R^2
Agriculture	5083.81 ***	8.94 ***	-3.62	0.22 ***	-3.21 *	0.86
Mining	1420.38 ***	9.65 ***	-0.08	-0.69 ***	-0.65 ***	0.49
Utilities	5287.78 ***	-2.43 ***	11.75	-1.39 ***	-0.88	0.91
Construction	13738.48 ***	6.63 ***	6.16 *	-5.67 **	15.16 ***	0.90
Manufacturing	59955.99 ***	70.47 ***	2.78	3.22 ***	-0.63	0.87
Wholesale Trade	14559.43 ***	24.30 ***	-4.90 ***	-0.53	-2.00 ***	0.87
Retail Trade	19220.04 ***	20.51 ***	-9.76	-1.10 **	0.18	0.88
Transportation	9868.95 ***	15.94 ***	-0.99 ***	-0.92 ***	-2.23 ***	0.75
Information	19904.39 ***	13.96 ***	-2.43 ***	-0.49 ***	-5.49	0.82
Finance	61712.07 ***	66.90 ***	-5.32 **	-13.12	0.12 ***	0.89
Professional Services	35568.49 ***	46.41 ***	0.21	-3.81 ***	-17.78 ***	0.92
Educational Services	30407.53 ***	42.51 ***	-12.35 ***	-5.00 ***	-20.88 ***	0.91
Arts & Entertainment	13862.65 ***	16.45 ***	-3.59 ***	-1.69 ***	-4.19 ***	0.90
Other	8776.28 ***	6.13 ***	-1.64 *	-0.79 ***	-1.23 ***	0.91
Government	50764.47 ***	53.63 ***	-7.65 ***	-10.46 ***	-28.30 ***	0.89

* represents significant at 5%

** represents significant at 1%

*** represents significant at 0.1%

Table 3: Regression coefficients for different sectors and their significance: *Deepwater Horizon* oil spill and Hurricane Sandy

Output	Intercept	Mining	Utilities	Transportation	Information	Finance	R^2
Agriculture	3856.1 ***	0.89 *	1.84 **	8.15 ***	4.67 ***	-5.24 ***	0.93
Mining	1164.3 ***	4.51 ***	5.44 ***	7.62 ***	-0.4	-2.55 ***	0.83
Utilities	6455.4 ***	4.55 ***	5.99 ***	-1.28	-5.94 ***	0.39 ***	0.71
Construction	14725 ***	-0.08	21.97 ***	4.72	-11.65 ***	11.97 ***	0.85
Manufacturing	52796 ***	9.99 *	59.55 ***	56.71 ***	24.53 ***	-17.56 ***	0.89
Wholesale Trade	11732 ***	1.43	16.08 ***	19.55 ***	8.43 ***	-8.17 ***	0.92
Retail Trade	16166 ***	-4.23 ***	12.51 ***	20.02 ***	9.08 ***	-6.32 ***	0.91
Transportation	8394.9 ***	2.14 **	12.59 ***	12.51 ***	3.42 ***	-6.19 ***	0.93
Information	17885 ***	0.88	7.95 ***	9.96 ***	6.51 ***	-8.63 ***	0.94
Finance	56015 ***	-1.78	71.82 ***	54.28 ***	1.63	-20.3 ***	0.91
Professional Services	30601 ***	4.35 **	40.74 ***	31.22 ***	12.06 ***	-28.94 ***	0.96
Educational Services	25021 ***	0.05	25.52 ***	33.43 ***	13.18 ***	-32.02 ***	0.96
Arts & Entertainment	11953 ***	0.43	11.91 ***	10.84 ***	4.55 ***	-8.34 ***	0.94
Other	8019.1 ***	0.33	3.84 ***	3.42 ***	1.76 ***	-2.65 ***	0.93
Government	46180 ***	4.49	43.48 ***	42.11 ***	2.88 *	-42.87 ***	0.94

* represents significant at 5%

** represents significant at 1%

*** represents significant at 0.1%

The largest coefficient for the production models for *Deepwater Horizon* and Hurricane Sandy correspond to the either the utilities or transportation stock market index. The coefficient for the finance stock market index is often negative. Thus, the deterministic models for production will depend mostly on the utilities and transportation stock prices, and the finance market index has an inverse effect on the assessment of actual production.

The deterministic regression results are depicted in Table 4. Total production losses for each of the 15 industries is calculated based on when the industry recovered. Recovery time is defined as the time period when the production level is greater than that of the first time period of the disruption and is constantly above this level for the next consecutive two time periods, thus making it three consecutive time periods.

Table 4: Estimated production losses during disruptions

Sector	9/11 Attacks		*Deepwater Horizon* Oil Spill		Hurricane Sandy	
	Recovery Period (weeks)	Production Loss (Million $)	Recovery Period (weeks)	Production Loss (Million $)	Recovery Period (weeks)	Production Loss (Million $)
Agriculture	3	271	24	3,918	4	233
Mining	2	149	25	5,516	6	665
Utilities	52*	27,014	12	1,596	11	1,540
Construction	0	0	12	1,624	12	5,295
Manufacturing	2	1,248	24	38,894	9	9,981
Wholesale Trade	3	404	23	9,195	9	2,207
Retail Trade	2	295	22	3,622	9	1,218
Transportation	3	288	22	5,192	9	1,796
Information	3	419	22	4,245	9	1,037
Finance	2	769	12	8,372	11	11,352
Professional Services	52*	25,553	19	8,521	11	6,402
Educational Services	36	20,853	13	3,606	9	2,220
Arts & Entertainment	3	373	20	2,628	11	1,680
Other	3	122	26	5,200	10	1,277
Government	37	46,112	12	3,519	11	4,726
Total		123,870		105,649		51,630

* Indicates that the calculations have been stopped before the industry recovers.

From this model, the vast majority of industries recover from the 9/11 attacks in only 3 weeks or less, except for utilities, professional services, educational services and government. Thus, the largest production losses occur in these industries. Losses in industries that do not seem intuitive can be due to the interdependence among industries that affects the output. For example, according to the IO model, the manufacturing sector needs to provide $0.10 to the education sector, for the education sector to produce a $1 output in the year 2000. If the disruption affects the manufacturing sector it would lead to an effect on the education sector as well.

In the *Deepwater Horizon* models, industries recover between 12 and 26 weeks, and the assessed production losses are spread out more evenly among all 15 industries. Results from the Hurricane Sandy models suggest that most industries recover between 9 and 12 weeks, and production losses are fairly evenly spread out among the 15 industries. The production losses attacks total $124 billion for the 9/11 attacks (due primarily to those 4 industries), $106 billion for *Deepwater Horizon*, and $52 billion for Hurricane Sandy. Thus, the model assess that the 9/11 attacks were economically costliest among the three, which corresponds with other studies.

Figures 2-4 present weekly production losses for each industry for the three disruptions studied. The vertical axis in each chart represents production losses, and negative production losses signify production gains. The 9/11 attacks in Figure 2 show that the utilities industry does not suffer production losses until 2 weeks after 9/11, but once it begins to exhibit losses, the losses for that industry continue for the rest of the time period. Professional services exhibit significant losses in weeks 10 through 20 and recovers slightly before suffering more losses beginning in week 40. Most of the other industries suffer losses for 2 to 3 weeks and then exhibit positive production gains for at least 3 weeks.

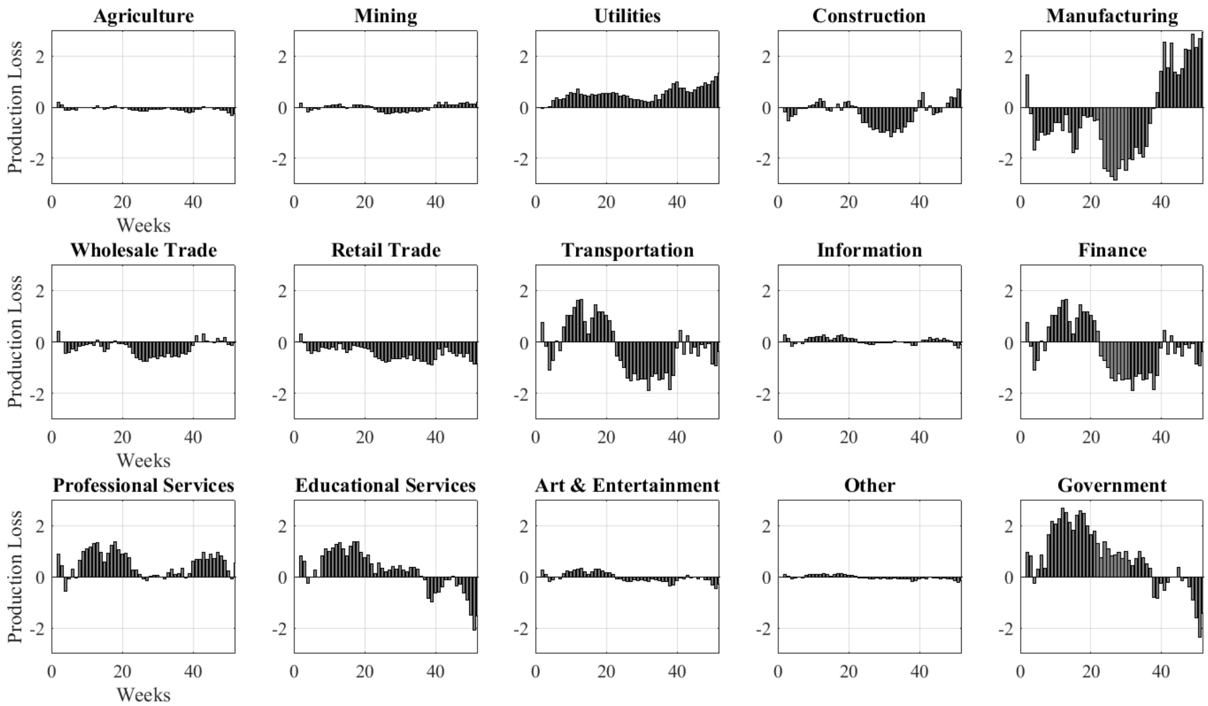

Figure 2: 9/11 Terror attacks – Weekly production loss in billions of dollars

The Deepwater Horizon oil spill production losses, depicted in Figure 3, are evenly spread out among all the industries. The manufacturing industry shows losses beginning from week 3 till week 24 and constitutes for majority of the losses. The manufacturing, wholesale trade, professional services, and finance account for 72% of the total losses of which 38% belongs to the manufacturing sector alone, while ther rest individually account for 5% or less of the total losses. The concentration of the losses to four industries, eventhough the recovery times are similar, can be attributed to the large market caps of these industries which can be clearly observed with the finance industry. As discussed earlier, the mining sector and the mining sector begins to show losses from week 2 and has momentary gain in week 3 followed by loss and the transportation sector begins to show losses from week 3 onwards which resonates with Figure 1a,b.

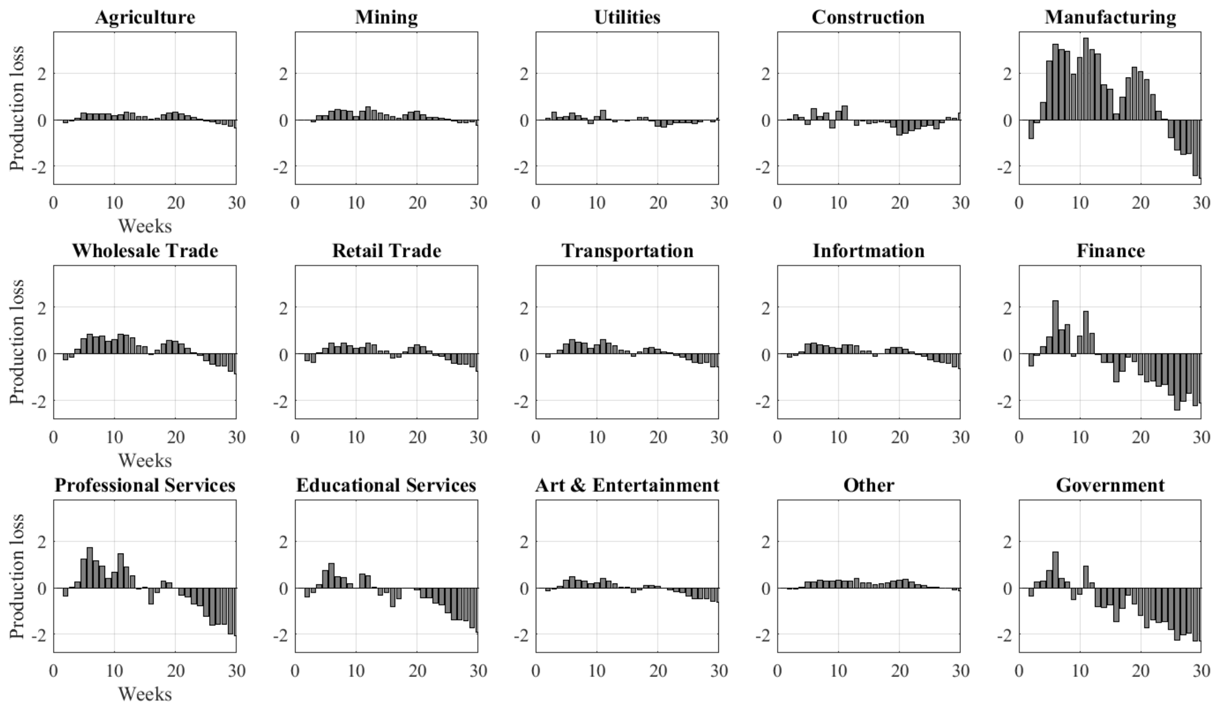

Figure 3: *Deepwater Horizon* oil spill – Weekly production loss in billions of dollars

The models suggest that Hurricane Sandy led to smaller production losses than the *Deepwater Horizon* oil spill. Industries generally recover within 9 to 12 weeks for Hurricane Sandy, but many industries do not recovery until 22 weeks after the *Deepwater Horizon* oil spill. The analysis does show a change in behavior of fits due to the financial recession that hit the United States economy from 2008 to 2009. Which could be the reason for a longer recovery as the Deepwater Horizon oil spill occurred recently after. During Hurricane Sandy, sectors like construction, manufacturing, finance, professional services, and government show higher losses as compared to the rest. These industries account for 73% of the total losses. The agriculture industry shows almost negligible losses due to the hurricane. The wholesale and retail trade industries show maximum losses in the same two weeks and then recovers within the next 5 weeks which account for very less losses. Almost all industries show maximum losses in the week 3 and 4 as in case of the retail and wholesale trade industries and then recover with comparatively lesser loss, which indicates an overall economy recovery after week 4.

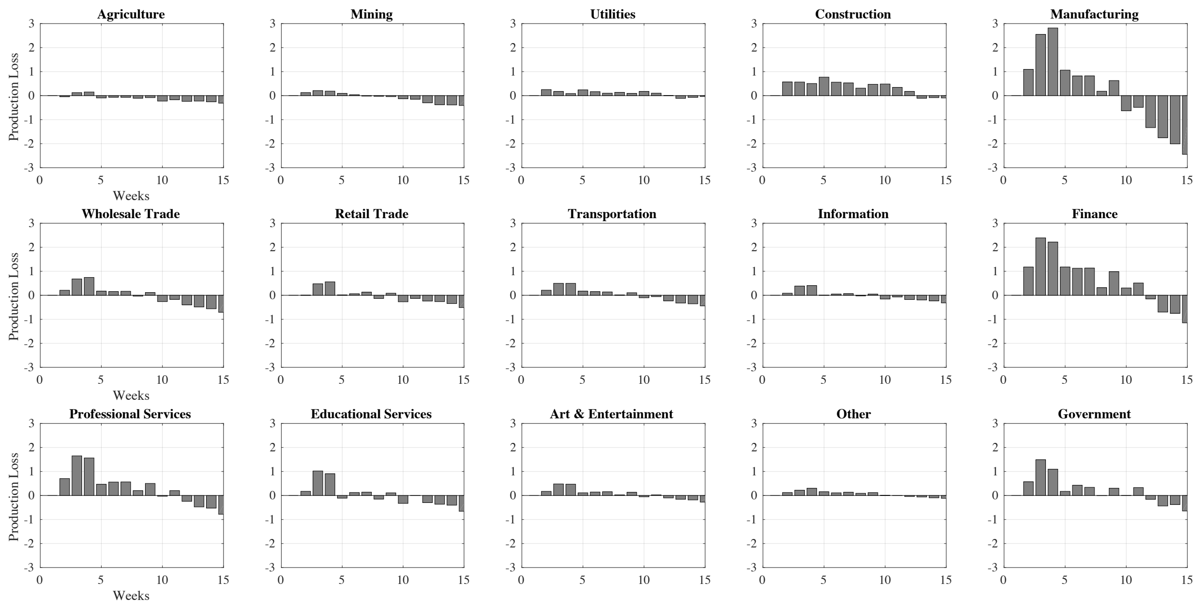

Figure 4: Hurricane Sandy – Weekly production loss in billions of dollars

We compare the results of the deterministic model to other economic impact studies in order to assess the validity of this approach. Estimation of total losses in the gross domestic production 9/11 attacks range between $23 billion and $ 246 billion with an average total loss of $ 109 billion (Rose and Bloomberg, 2010). The deterministic estimation of $124 billion from the 9/11 attacks aligns closely with these other estimates. Park et al. (2014) calculate that the *Deepwater Horizon* oil spill caused about $45 billion worth of damages to the oil, seafood, and tourism industries, and MacKenzie et al. (2016) estimate that the economic losses in the Gulf region ranged from $12 to $49 billion, depending on how resources were allocated to respond to the oil spill. The settlement for damages for BP may reach as much as $90 billion (Park et al., 2014). The estimate of $106 billion in production losses for the *Deepwater Horizon* spill in this paper may be too high compared to these other studies although the study in this paper reflects national rather than regional losses. According to a report from the U.S. Department of Commerce (2013), the economic impact of Hurricane Sandy was $84 billion. Whereas a private firm estimated losses from $30 to $50 billion (Holm and Scism 2012). Our paper estimates $52 billion in losses for Hurricane Sandy, which is similar to these other studies.

4.3 Stochastic model

The deterministic model generates production losses for each industry from which total production losses can be calculated, but all of these numbers are expressed with certainty. Considering the assumptions embedded in the model, we should be cautious about expressing results with certainty. As presented in Equations (3) and (4), the stochastic model captures the standard error in the regression results and the correlation between the stock market indices to generate a multivariate random variable representing production losses in each week. The same 5 stock market indices are used in the stochastic model as in the deterministic model. In this study the stochastic model, unlike the deterministic model, does not take into consideration any available stock market price after disruptions that have been analyzed. The regression calculations are performed beginning February 18, 2000 till September 12, 2001 for the 9/11 attacks, May 27, 2002 till April 15, 2010 for the *Deepwater Horizon* oil spill, and May 27, 2002 till October 25, 2012. The start dates are selected based on the availability of data.

Ten thousand simulations are run to estimate losses for each industry for the three disruptions based on the stock market index. The method used to calculate the loss in production is similar to that of the deterministic model, by subtracting the simulated production from the production level in the time period when the disruption occurs. The detailed regression and covariance results are listed in appendix A which explains the relationships between the industries and the error values. A negative slope indicates inverse relations while higher the root mean squared values, larger values are seen in the covariance matrix which denote large variability in the simulation. Figures 5, 6, and 7 depict the simulated results for each of the three

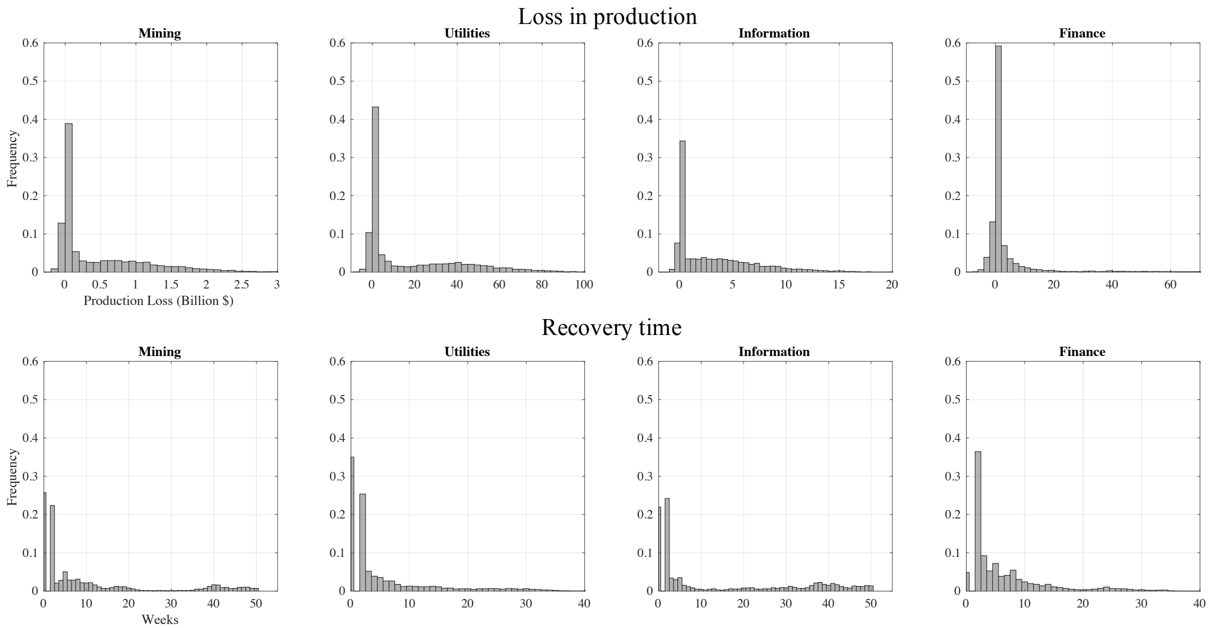

Figure 5: 9/11 Attacks – Simulated production loss and recovery time

disruptions. The 9/11 attacks do not include the transportation sector because no transportation stock market index was available in 2001. The recovery time for the 9/11 attacks ranges from 0 to 120 weeks with most of the recovery times occurring in less than 20 weeks. These recovery times result in production losses on the order of hundreds of millions of dollars for mining and billions of dollars for utilities, information, and finance.

However, scenarios occur when the industries do not recovery for more than 100 weeks, resulting in production losses on the order of tens of billions for utilities, information, and finance. Due to the correlation, if one of the industries experiences very long recovery times and severe production losses, it is more likely the other industries will also suffer severe production losses. The results for this analysis are presented in Table 5.

The magnitude of losses in during the 2001 attacks seem considerably low as compared to the more recent disruptions, this could be due to the market value of industries being lower than the recent times.

Table 5: Predicted production losses and recovery time from stochastic model

Sector	9/11 Attacks		*Deepwater Horizon* Oil Spill		Hurricane Sandy	
	Average Recovery Period (weeks)	Average Production Loss (Million $)	Average Recovery Period (weeks)	Average Production Loss (Million $)	Average Recovery Period (weeks)	Average Production Loss (Million $)
Mining	10.64	448	24.04	20,663	12.10	5,980
Utilities	5.33	16,284	23.58	9,970	10.50	10,816
Transportation	--	--	18.17	40,812	8.73	9,059
Information	14.93	3,098	26.38	31,508	15.05	12,645
Finance	6.45	3,476	--	--	--	--

Figure 6 depicts the simulated loss in production and the time for recovery for the mining, utilities, transportation, and information industries after the *Deepwater Horizon* oil spill in 2010 and the probability of occurring.

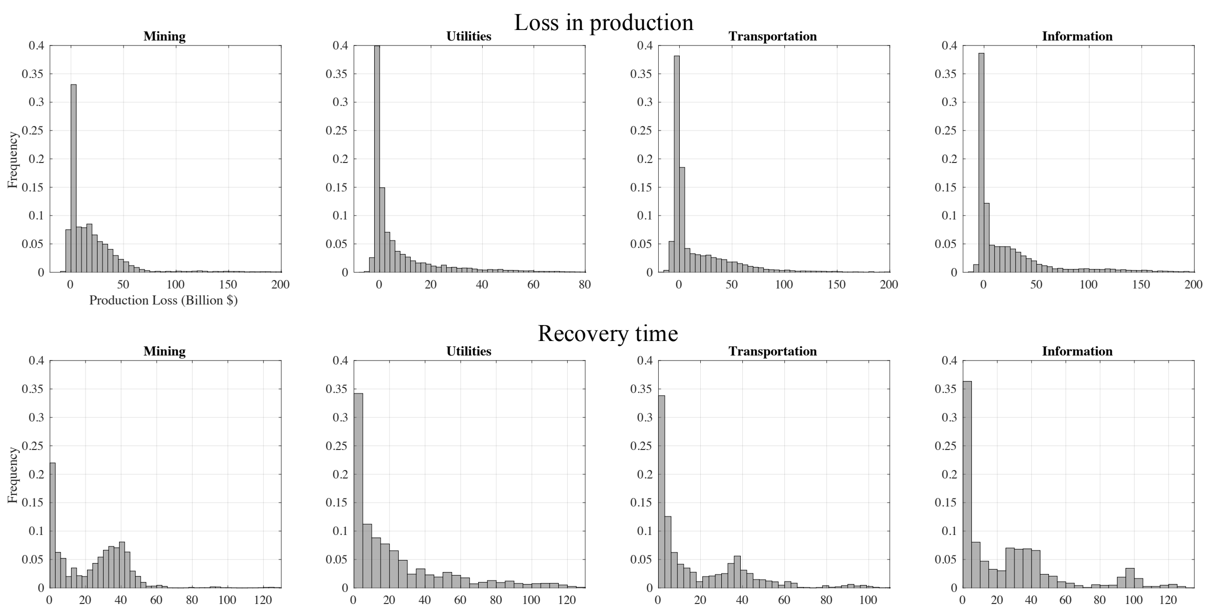

Figure 6: *Deepwater Horizon* oil spill – Simulated production loss and recovery time

The analysis of the finance sector shows irregular results in the regression fits, which is believed to be due to the financial recession that affected a sudden drop in stock market price in the years 2008 and 2009. Similar is the case with Hurricane Sandy. As both *Deepwater Horizon* oil spill and Hurricane Sandy occurred recently after the recession the results for this sector affected the production estimates by a large margin by producing large root mean squared error terms. The analysis of this sector caused unbalanced results in the stochastic model and hence have been omitted for the two disruptions.

As in case of the deterministic model the stochastic model shows that similar recovery times for the four industries, which are higher than Hurricane Sandy, even though both the disruptions were fairly regional calamities affecting the local economy. This could be caused as the economy was recovering from a recession at the time of the *Deepwater Horizon* oil spill.

Similarly, Figure 7 represents stochastic results after the Hurricane Sandy and the results are documented in Table 5.

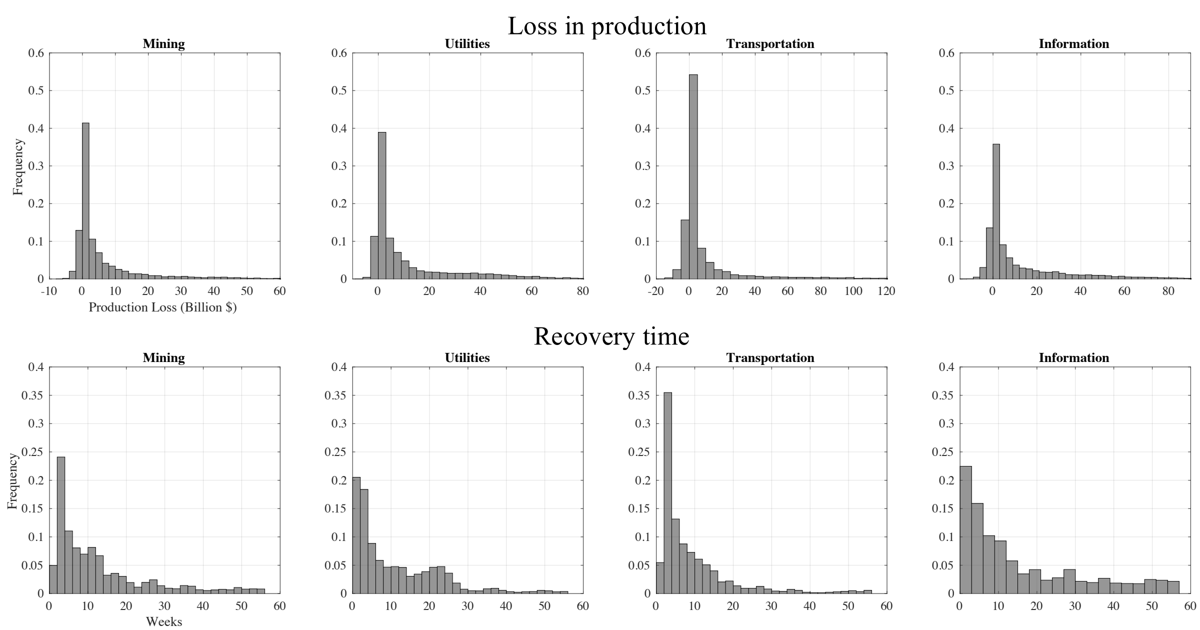

Figure 7: Hurricane Sandy – Simulated production loss and recovery time

These results indicate that the severity in terms of monetary losses of the Hurricane Sandy was much less than that of the *Deepwater Horizon* oil spill. The results from the stochastic model resonate with those of the deterministic model. Recovery periods, as in the deterministic model are in the range of 8 to 15 weeks and the losses seem to concentrated to few industries rather than the entire economy.

5. Conclusion

This study puts forth a model that aims at estimating direct and indirect losses due to disruptions in production or output of sectors of the economy. It makes use of the stock market as an indicator of the potential loss due to catastrophic events. The model has been divided into two sub – models: the deterministic approach and the stochastic approach. The deterministic model is based on linear relationships between the industry output and the stock market, and the stochastic model takes a step further by including variance in this relationship caused by the error in the regression analysis. Both these model have estimated the losses due to past disruptions with fair accuracy especially in the case of the 9/11 attacks and Hurricane Sandy.

This model as a whole is beneficial in estimating economic losses due to a decrease in production levels based on rich data for output and growth trends in the stock markets. The use of a time based approach makes it unique as it enables the study of changes in production levels for each time period thus enabling industries to adjust their approach. The results of this analysis are obtained in monetary terms which are easy to understand and universal for any organization. Also, it benefits simplified comparisons between losses due to different disruptions and industries and the use of the same metrics for these studies helps to find striking resemblances and disparities among disruptions and industrial response.

Few assumptions are made while formulating the model, of which the main assumption is the belief that the stock market prices are a reflection of the production or output of an industry. Even though few studies discussed earlier have established this relationship it is not evident in all cases of an economy. Another assumption is the use of annual gross output values to estimate the weekly production values by dividing them equally. This assumption is not applicable to the real world as production values fluctuate on a daily basis and cannot be constant over a period of one year, but the assumption can be eliminated with the use rich data from industries. A third assumption for defining recovery in the model has been made, it is assumed that recovery occurs after the production level is above the base level before the disruption for three time periods (weeks). This assumption changes the loss estimates and can be observed clearly in case of the 9/11 attacks where a lower recovery period would have reduced the estimated recovery time and loss by a large margin. These assumptions can be realistically tackled with rich data from industries and insight from stakeholders.

Further studies or extensions to the model could include the use of this model along with models that predict the stock prices in the future so as make accurate forecasts of production in the near future even if the actual stock market price is unknown. Studies like Ping-Feng and Chih-Sheng (2005) make use of the ARIMA model to predict stock prices, Hassan and Nath (2005) discussed the use of hidden Markov models (HMM) to predict stock prices of interrelated sectors, or studies like Cao, et al. (2005) which make use of univariate and multivariate neural network model to predict stock market prices in the Shanghai stock exchange could provide as a base for incorporating a stock price predictive model along with the model presented in this study. Further studies can also include methods to enhance the correlation between stock prices and production by analyzing effects of disruptions to specific entities or organizations. The process can be streamlined to suit specific needs of organizations based on the thoughts of stakeholders. Another avenue to explore with the model would be to study the methods to influence the results of the model with those of the IO model so as to capture the interdependency of the economy while maintaining the dynamic nature of this model.

This paper introduces a new concept to study the economic impacts of disruptions and helps understand the dynamic behavior of industrial losses. Applications of this model can be wide spread for the government as well as the private sector. The model can provide as a decision making tool for the stakeholders and thus enable better allocation of resources towards post disaster recovery efforts. An example for such resource allocation could be that if the government allows taxation breaks or policy relaxation for certain period of time to sectors that are highly interdependent and cause a ripple effect in the economy, the recovery of the entire economy could be expedited. The model can also provide as a forecasting tool for preventive resource allocation by simulating potential disasters. The dynamic or time based approach is essential whilst dealing with disasters, as it extremely important to initiate recovery plans in order to reduce the total loss. Such a model would be helpful in simulating data for recovery plans and prioritizing multiple recovery efforts to reduce the total impact.

REFERENCES

Ali, J. and Santos, J. R. (2015), Modeling the Ripple Effects of IT-Based Incidents on Interdependent Economic Systems. Syst. Engin., 18: 146–161. doi:10.1002/sys.21293

Andrijcic, Eva, and Barry Horowitz. 2006. A macro-economic framework for evaluation of cyber security risks related to protection of intellectual property. Risk Analysis 26, no. 4 (August):907-923.

Associated Press. 2014. Official: disaster cost quadrupled in past decades. Daily Mail, 5 June. Available at http://www.dailymail.co.uk/wires/ap/article-2649515/Official-Disaster-cost-quadrupled-past-decades.html, Accessed on February 9, 2017.

Barker, Kash, and Joost R. Santos. 2010b. A risk-based approach for identifying key economic and infrastructure sectors. Risk Analysis 30, no. 6 (June):962-974.

Barro, R. J. (1990). The stock market and investment. Review of Financial Studies, 3, 115-131.

Bess R, Ambargis ZO (2011) Input-Output models for impact analysis: suggestions for practitioners using RIMS II multipliers. In: 50th Southern Regional Science Association Conference, New Orleans, Louisiana

“BP leak the world's worst accidental oil spill". The Daily Telegraph. London. 3 August 2010. Retrieved 15 August 2010.

Cao, Q., Leggio, K. B., Schniederjans, M. J., (2005). A comparison between Fama and French's model and artificial neural networks in predicting the Chinese stock market, Computers & Operations Research, Volume 32, Issue 10, October 2005, Pages 2499-2512, ISSN 0305-0548, https://doi.org/10.1016/j.cor.2004.03.015.

Chen, N., Roll, R., & Ross, S. (1986). Economic Forces and the Stock Market. The Journal of Business, 59(3), 383-403. Retrieved from http://www.jstor.org/stable/2352710

Choi, J., Hauser, & Kopecky. (1999). Does the stock market predict real activity? Time series evidence from the G-7 countries. Journal of Banking and Finance, 23(12), 1771-1792.

Cole, S. (1995) Lifeline and livelihood: a social accounting matrix approach to calamity preparedness, Journal of Contingencies and Crisis Management, 3, pp. 228–240.

Cole, S. (1998) Decision support for calamity preparedness: socioeconomic and interregional impacts, in: M. Shinozuka, A. Rose and R.T. Eguchi (Eds) Engineering and Socioeconomic Impacts of Earthquakes, pp. 125–153 (Buffalo, NY: Multidisciplinary Center for Earthquake Engineering Research).

Cole, S. (2004) Geohazards in social systems: an insurance matrix approach, in: Y. Okuyama and S.E. Chang (Eds) Modeling Spatial and Economic Impacts of Disasters, pp. 103–118 (New York: Springer).

Draper, Norman Richard, & Smith, Harry. (1998). Applied regression analysis / Norman R. Draper, Harry Smith. (3rd ed., Wiley series in probability and statistics. Texts and references section). New York: Wiley.

Dynes, Scott, M. Eric Johnson, Eva Andricic, and Barry Horowitz (2007). Economic costs of firm-level information infrastructure failures: Estimates from field studies in manufacturing supply chains. The International Journal of Logistics Management 18, no. 3:420-442.

“ECONOMIC IMPACT OF HURRICANE SANDY." States News Service, 18 Oct. 2013. Biography in Context, link.galegroup.com/apps/doc/A346010102/BIC1?u=iastu_main&xid=1d3e8f22. Accessed 16 May 2017.

Fama, E. (1981). Stock Returns, Real Activity, Inflation, and Money. The American Economic Review, 71(4), 545-565.

Fama, E. (1990). Stock returns, expected returns, and real activity. Journal of Finance, 45(4), 1089-1108.

Ferson, Wayne and Harvey, Campbell, (1991), The Variation of Economic Risk Premiums, Journal of Political Economy, 99, issue 2, p. 385-415.

Haimes, Y., Horowitz, B., Lambert, J., Santos, J., Crowther, K., & Lian, C. (2005). Inoperability Input-Output Model for Interdependent Infrastructure Sectors. II: Case Studies. *Journal of Infrastructure Systems, 11*(2), 80-92.

Haimes, Y., Horowitz, B., Lambert, J., Santos, J., Lian, C., & Crowther, K. (2005). Inoperability Input-Output Model for Interdependent Infrastructure Sectors. I: Theory and Methodology. Journal of Infrastructure Systems, 11(2), 67-79.

Haimes, Yacov Y., and Pu Jiang (2001). Leontief-based model of risk in complex interconnected infrastructures. Journal of Infrastructure Systems 7, no. 1 (March):1-12.

Hallegatte, S. (2008) An Adaptive Regional Input–Output Model and Its Application to the Assessment of the Economic Cost of Katrina. Risk Analysis, 28, 779–799.

Hassan, M. R., and Nath, B. (2005). "Stock market forecasting using hidden Markov model: a new approach," 5th International Conference on Intelligent Systems Design and Applications (ISDA'05), 2005, pp. 192-196

Historical prices, Dow Jones Indices. Retrieved November 15, 2016 from http://www.advfn.com

Historical prices, Dow Jones Indices. Retrieved November 15, 2016 from https://www.google.com/finance

Holm, E. and Scism, L. (2012, November 2). Sandy's Insured-Loss Tab: Up to $20 Billion. The Wall Street Journal. Retrieved from https://www.wsj.com

“How much did the September 11 terrorist attack cost America?". 2004. Institute for the Analysis of Global Security. Retrieved April 30, 2014.

Isard, W., Azis, I. J., Drennan, M. P., Miller, R. E., Satlzman, S., & Thorbecke, E. (1998). Methods of Interregional Regional Analysis. Aldershot, U.K.: Ashgate Publishing.

Leontief, W., Input-output economics, Scientific American, October (1951a), 15–21.

Leontief, W., The structure of the American economy, 1919–1939: An empirical application of equilibrium analysis, 2nd Edition, International Arts and Sciences Press, New York, 1951b.

Lian, C., & Haimes, Y. (2006). Managing the risk of terrorism to interdependent infrastructure systems through the dynamic inoperability input–output model. Systems Engineering, 9(3), 241-258.

MacKenzie, C. A., & Barker, K. (2013). Empirical data and regression analysis for estimation of infrastructure resilience, with application to electric power outages. Journal of Infrastructure Systems, 19(1), 25-35.

MacKenzie, C. A., Barker, K., & Grant, F. H. (2012a). Evaluating the consequences of an inland waterway port closure with a dynamic multiregional interdependence model. IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Humans, 42(2), 359-370.

MacKenzie, C. A., Baroud, H., & Barker, K. (2016). Static and dynamic resource allocation models for recovery of interdependent systems: Application to the Deepwater Horizon oil spill. Annals of Operations Research, 236(1), 103-129.

Makinen, Gail (September 27, 2002). "The Economic Effects of 9/11: A Retrospective Assessment" (PDF). Congressional Research Service. Library of Congress. p. 5. Retrieved September 4, 2011.

Miller, R., & Blair, P. (2009). Input-output analysis: Foundations and extensions / Ronald E. Miller and Peter D. Blair. (2nd Ed.). Cambridge [England]; New York: Cambridge University Press.

Morck, Randall, Andrei Shleifer, and Robert W Vishny (1990). “The Stock Market and Investment: Is the Market a Sideshow?.” Brookings Papers on Economic Activity 21 (2): 157-216.

Okuyama, Y. (2007). Economic modeling for disaster impact analysis: past, present, and future. Economic Systems Research, 19(2), 115-124.

Okuyama, Y. (2008). Critical Review of Methodologies on Disaster Impacts Estimation. Background paper for the World Bank - UN Assessment on the Economics of Disaster Risk Reduction. Retrieved from http://gfdrr.org/gfdrr/node/284

Okuyama, Y. (2010) Globalization and Localization of Disaster Impacts: An Empirical Examination. CEFifo Forum, 11, 56–66.

Okuyama, Y., & Santos, J. (2014). Disaster Impact and Input-Output Analysis. Economic Systems Research, 26(1), 1-12.

Orsi, M.J., & Santos, J.R. (2010). Estimating workforce-related economic impact of a pandemic on the Commonwealth of Virginia. (Technical report). IEEE Transactions on Systems, Man, and Cybernetics--Part A: Systems and Humans, 40(2), 301.

Pagsuyoin, S., & Santos, J. (2015). Modeling the Effects of Drought in Urban Economies Using Regional Input-Output Analysis. British Journal of Environment and Climate Change, 5(2), 134-146.

Pant, R., Barker, K., Ramirez-Marquez, J. E., & Rocco, C. M. (2014). Stochastic measures of resilience and their application to container terminals. Computers & Industrial Engineering, 70, 183-194.

Park, J., Harry W. Richardson, Peter Gordon, James E. Moore and Qisheng Pan, (2014). The Gulf oil spill (FlexNIEMO). In *National Economic Impact Analysis of Terrorist Attacks* *and Natural Disasters* (pp. 180-191). Edward Elgar, Northampton, MA, USA. Published in print: 28 Nov 2014, ISBN: 9781783475858.

Ping-Feng Pai, Chih-Sheng Lin (2005). A hybrid ARIMA and support vector machines model in stock price forecasting, Omega, Volume 33, Issue 6, December 2005, Pages 497-505, ISSN 0305-0483, https://doi.org/10.1016/j.omega.2004.07.024.

Rappaport, Alfred. (1987). Stock market signals to managers. Harvard Business Review, 65(6), 57.

Robertson, C. and Krauss, C., August 2, 2010. "Gulf Spill Is the Largest of Its Kind, Scientists Say." The New York Times. Retrieved on May 2, 2017.

Roll, R. (1992). Industrial Structure and the Comparative Behavior of International Stock Market Indices. The Journal of Finance, 47(1), 3-41. doi:10.2307/2329089

Rose, A. (2004) Economic Principles, Issues, and Research Priorities in Hazard Loss Estimation. In:Y. Okuyama and S.E. Chang (eds.) Modeling Spatial and Economic Impacts of Disasters. NewYork, Springer, 13–36.

Rose, A. and Liao, S.-Y. (2005), Modeling Regional Economic Resilience to Disasters: A Computable General Equilibrium Analysis of Water Service Disruptions*. Journal of Regional Science, 45: 75–112. doi:10.1111/j.0022-4146.2005.00365.x

Rose, A. and Wei, D., (2013) Estimating the Economic Consequences of a Port Shutdown: The Special Role of Resilience. Economic Systems Research, 25, 212–232.

Rose, Adam Z. and Blomberg, Brock S., "Total Economic Consequences of Terrorist Attacks: Insights from 9/11" (2010). Published Articles & Papers. Paper 190.

Santos, J. (2006). Inoperability input-output modeling of disruptions to interdependent economic systems. Systems Engineering, 9(1), 20-34.

Santos, J. R., & Haimes, Y. Y. (2004). Modeling the demand reduction input-output (IO) inoperability due to terrorism of interconnected infrastructures. Risk Analysis, 24(6), 1437-1451.

Santos, J., & Haimes, Y. (2008). Portfolio Risk Partitioning with Leontief-type Diversification. Finance Letters, 117-123.

Santos, Joost R., May, Larissa, & Haimar, Amine El. (2013). Risk-Based Input-Output Analysis of Influenza Epidemic Consequences on Interdependent Workforce Sectors. Risk Analysis, 33(9), 1620-1635.

Schwert, G. W. (1990). Stock Returns and Real Activity: A Century of Evidence. Journal of Finance, 45(4), 1237-1257.

Stone, Chad (2012, November 2). The Economic Impact of Hurricane Sandy. U.S. News. Retrieved from https://www.usnews.com

U.S. Bureau of Economic Analysis, “Gross Output, 1947-2016: up to 71 industries” in Gross-Domestic-Product-(GDP)-by-Industry Data. Retrieved from https://www.bea.gov/industry/gdpbyind_data.htm (accessed [November 15, 2016]

Van der Veen, A. and C. Logtmeijer (2005) Economic Hotspots: Visualizing Vulnerability to Flooding. Natural Hazards, 36, 65–80.

Yin-Wong Cheung, Lilian K. Ng, International evidence on the stock market and aggregate economic activity, Journal of Empirical Finance, Volume 5, Issue 3, September 1998, Pages 281-296, ISSN 0927-5398, https://doi.org/10.1016/S0927-5398(97)00025-X.

CHAPTER 3. CONCLUSION

This study presents a model that will significantly improve decision making techniques and enable industries or governments to expedite recovery by providing rich and informative data, efficient resource allocation, and support decision making. The preceding chapter discusses in detail the formulation, case studies and associated results for the proposed model. Even though there have been multiple models that measure the impacts of disruptions, this model helps in understanding the ripple effect and time based impacts to industries. Stock markets have been known to represent the interpretation of an industry's growth or loss through a point of view of the investors, who rely on news about the fundamentals like the real activity. It is evident that managers make decisions based on the stock market position of the company as a feedback of their performance (Rappaport, A., 1987). Studies discussed in the previous chapter, and the presented analysis that the stock market is a correlated variable reflecting the industrial output.

The model acts as an essential tool for stakeholders in various ways. It can be used as a predicting tool during disruptions to quantify the effects of losses incurred or the possibility of losses. It can be used as a feedback tool to make sure that bearish trends are reversed in scenarios where corrective action is placed. A time based study like this can enable quick decision making thus reducing losses. Losses due to disruptions are increasing in the recent past and it essential to manage the available scarce resources to their best potential in order to reduce these losses. The risk of any organization getting affected by the increasing number of threats is also increasing and it is essential that these organizations make efforts towards reduction of this risk. Risk mitigation can be done by a preventive measures and plans for disaster preparedness. This model can be used to study possible effects of events that may happen in the future which might affect the supply and/or demand of goods produced or services rendered. According to Kristalina Georgieva, the European Commissioner for Humanitarian Aid and Crisis Response, suggested that as of 2014 of all the investment made towards natural disasters, a mere 4% is used for preventive measures while the rest is used for recovery (Associated Press, 2014). Such a model can be used towards balancing out this disparity in investment and reduce the effects by analyzing pseudo disruptions closely linked with the industry. She also suggests that any investment made towards preventive measures for losses due to disruptions provides minimum savings of four times the investment (Associated Press, 2014). Which makes it evident that studies like this can help in better analysis and distribution of resources and reduce risk of loss.

Future scope of the study could be to reduce the discrepancies in the data to achieve better predictions. Pilot studies with real time data of production output and stock prices from industries and their suppliers and customers could help as a proof of concept. Further studies can be made to find the optimum time periods to analyze the effects of disruptions and optimize the results of the model.

REFERENCES

Associated Press. 2014. Official: disaster cost quadrupled in past decades. Daily Mail, 5 June. Available at http://www.dailymail.co.uk/wires/ap/article-2649515/Official-Disaster-cost-quadrupled-past-decades.html, Accessed on February 9, 2017.

Rappaport, Alfred. (1987). Stock market signals to managers. Harvard Business Review, 65(6), 57.

APPENDIX A

STOCHASTIC MODEL PARAMETERS

The parameters estimated from the stochastic model have been listed below for each of the disruptions analyzed. Negative slopes indicate inverse relations.

1. **9/11 attacks**

Regression estimates:

Sector	Slope	Intercept	RMSE
Mining	-0.39	2864.40	20.58
Utilities	6.98	5089.40	658.21
Information	-0.73	20174.00	120.30
Finance	17.00	55062.00	832.73

Covariance matrix:

423.49	11243.37	-946.29	12143.94
11243.37	433235.11	-35459.45	412609.81
-946.29	-35459.45	14471.79	-54820.40
12143.94	412609.81	-54820.40	693446.54

2. ***Deepwater Horizon* oil spill**

Regression estimates:

Sector	Slope	Intercept	RMSE
Mining	8.19	1419.00	759.79
Utilities	8.84	4378.30	492.39
Transportation	36.25	9667.90	1452.00
Information	9.92	17241.00	1096.50

Covariance matrix:

577281.87	355986.13	753776.48	664295.68
355986.13	242452.54	565617.78	445067.25
753776.48	565617.78	2108166.65	1210361.53
664295.68	445067.25	1210361.53	1202392.79

3. Hurricane Sandy

Regression estimates:

Sector	Slope	Intercept	RMSE
Mining	8.29	1415.30	682.93
Utilities	7.36	4808.40	589.93
Transportation	44.51	8977.70	1574.70
Information	13.36	15726.00	1059.10

Covariance matrix:

466397.07	373102.12	782570.83	592851.53
373102.12	348020.20	733629.38	472670.60
782570.83	733629.38	2479826.70	1201578.88
592851.53	472670.60	1201578.88	1121599.50