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Disaster Management and Recovery: Estimating the Disaster Impacts on Construction Costs and Evaluating the Policy Effects on Disaster Recovery

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Disaster Management and Recovery:
Estimating the Disaster Impacts on Construction Costs and
Evaluating the Policy Effects on Disaster Recovery

by

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Dedicated to

My family and my precious soul-sister, Suh Park, for their endless support, encouragement, patience, and unconditional love.

DISCLAIMER

Any opinions, findings, conclusions, and/or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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ABSTRACT

Disaster Management and Recovery: Estimating the Disaster Impacts on Construction Wages and Evaluating the Policy Effects on Post-disaster Recovery

Sooin Kim

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A rapidly increasing number of natural hazards pose an inevitable threat to communities. More than a hundred natural hazards strike the United States every year, causing numerous fatalities and billions of dollars of property and infrastructure damage. The total cost of U.S. weather and climate disasters since 1980 has already exceeded 2 trillion dollars. As the number of U.S. county-level disasters has approximately tripled in recent decades due to rapid climate change, a greater share of the population is now more likely to expose to natural disasters.

Adequate and timely reconstruction and recovery in post-disaster situations are essential for the safety, survival, and long-term resilience of a community. However, the unexpected reconstruction cost increases in the aftermath of a disaster often impede post-disaster recovery due to limited budgets and amplify direct and indirect economic losses. A better understanding of the spatiotemporal effect of a disaster on reconstruction costs can improve disaster loss evaluations and post-disaster recovery planning.

Local and federal governments have enacted various disaster policies to accelerate post-disaster recovery and strengthen the resilience of a community. For example, thirty-seven states out of fifty in the U.S. have anti-price gouging legislation that regulates exorbitant pricing, denouncing it as an unfair or deceptive trade practice during a time of disaster or emergency. One of the intended purposes of this legislation is to stabilize the reconstruction costs increased by post-disaster demand surge and ration resources for a swift recovery from disasters. Federal Motor Carrier Safety Administration (FMCSA) waives certain federal safety regulations during a time of disaster declared by the President, Governors of States, or FMCSA. The U.S. Environmental Protection Agency (EPA) has temporarily waived fuel regulations to facilitate the fuel supply in the aftermath of disasters.

According to the consensus of climate scientists, it is expected that the occurrence and intensity of disasters will increase further in the coming decades. Measuring the post-disaster demand surge for reconstruction and examining the effects of various disaster policies are critical for a better disaster response system in the trend of increasing risks of disasters.

This research aims to understand the dynamic process of the post-demand surge in the reconstruction market by estimating the spatiotemporal effects of a disaster on construction wages in different quarters after a disaster using spatial panel data models. Furthermore, this research extends its framework to quantify the effects of various local and federal disaster policies on post-disaster recovery using difference-in-differences econometric techniques.

To achieve these research objectives, first, spatial panel data models with a difference-in-differences (DID) approach were developed to determine the spatiotemporal impacts of disasters on reconstruction wages in disaster-affected counties compared to the wages in non-disaster-affected counties. Then, spatial panel data models with DID approach were implemented to estimate the effects of disaster-related policies on the post-disaster reconstruction process by quantifying the difference in dependent variables (e.g., reconstruction costs and speed) between pre-policy and post-policy periods.

The findings of this study identified and estimated the spatiotemporal impacts of disasters on reconstruction wages and evaluated the various policy effects on the post-disaster recovery process. Reconstruction capacity gaps that cause reconstruction cost inflation were revealed one quarter after a disaster occurred. Also, statistically significant impacts of a disaster on reconstruction wages in the neighboring counties were found and quantified. Moreover, it is found that anti-price gouging laws, federal motor carrier safety regulation waivers, and environmental regulation waivers statistically significantly affected the post-disaster reconstruction process.

This research contributes to the body of knowledge by developing econometric measurement methods to estimate disaster impacts and evaluate policy effects in the post-disaster reconstruction management and recovery process. This research addressed fundamental limitations of existing demand surge models by (1) solving missing data problems with spatial multiple imputation methods, (2) creating spatiotemporal econometric models for quantifying post-disaster construction cost escalations and understanding a dynamic process of post-disaster reconstruction demand surge, and (3) evaluating and quantifying the impacts of disaster-related policies on the post-disaster reconstruction process. The findings of this research are expected to generate new knowledge at the nexus of three critical disciplines: Post-disaster Construction, Economics, and Policy Analysis. The proposed approach and discovery of this research will aid disaster mitigation and recovery agencies in better understanding a post-disaster reconstruction process, developing a greater construction capacity, setting effective reconstruction goals, initiating risk mitigation and resourcing strategies, and enforcing effective regulations and policies.

TABLE OF CONTENTS

DISCLAIMER ... i
ACKNOWLEDGMENTS ... ii
ABSTRACT ... iii
TABLE OF CONTENTS ... vi
LIST OF TABLES ... viii
LIST OF FIGURES ... ix
CHAPTER 1 INTRODUCTION ... 1
CHAPTER 2 RESEARCH BACKGROUND ... 4
2.1. Post-Disaster Demand Surge ... 4
2.2. Disaster Policies ... 6
2.2.1. Anti-Price Gouging Law ... 6
2.2.2. Federal Motor Carrier Safety Regulation Waiver ... 8
2.2.3. Environmental Regulation Waiver ... 9
2.3. Gaps in Knowledge ... 10
2.4. Research Objectives ... 11
CHAPTER 3 ESTIMATING THE SPATIOTEMPORAL EFFECTS OF A DISASTER ON CONSTRUCTION WAGES ... 11
3.1. Methodology ... 12
3.1.1. Data Collection ... 12
3.1.2. Missing Data Handling ... 15
3.1.3. Difference-in-Differences (DID) Technique ... 16
3.1.4. Panel Data Models ... 17
3.2. Results ... 23
3.2.1. Results of the Base Models ... 23
3.2.2. Results of the Spatial Durbin Models ... 25
3.2.3. Results of the Spatial Durbin Models with Lagged Disaster Variables ... 30
3.3. Discussions of Results ... 37

CHAPTER 4 EVALUATING THE IMPACTS OF ANTI-PRICE GOUGING LAW ON POST-DISASTER RECOVERY 41
4.1. The Impact of Anti-Price Gouging Law on Housing Recovery Speed 42
4.1.1. Methodology 43
4.1.2. Results 52
4.1.3. Discussions of Results 57
4.2. The Impacts of Anti-Price Gouging Law on Reconstruction costs 60
4.2.1. Methodology 60
4.2.2. Results 64
4.2.3. Discussions of Results 66
CHAPTER 5 ASSESSING THE IMPACT OF FMCSA SAFETY REGULATION WAIVERS ON POST-DISASTER FUEL PRICE 68
5.1. Methodology 68
5.1.1. Data Collection 68
5.1.2. Panel Data Model with Difference-in-Differences Technique 73
5.2. Results 74
5.3. Discussions of Results 78
CHAPTER 6 ASSESSING THE IMPACT OF EPA FUEL WAIVERS ON POST-DISASTER AIR QUALITY 82
6.1. Methodology 84
6.1.1. Data Explanation 84
6.1.2. Panel Data Model with Difference-in-Differences Technique 88
6.2. Results 89
6.3. Discussions of Results 92
CHAPTER 7 POLICY IMPLICATIONS FOR EFFECTIVE DISASTER MANAGEMENT AND RECOVERY 95
7.1. Demand Surge 95
7.2. Anti-Price Gouging Law 98
7.3. Federal Motor Carrier Safety Regulation Waiver 100
7.4. Environmental Regulation Waiver 103
CHAPTER 8 CONCLUSIONS 106
REFERENCES 110

LIST OF TABLES

Table 3-1. Data Collection of Construction Industry Variables 13
Table 3-2**.** Direct and indirect effects of a disaster on construction wages in the short-run and long-run estimated by dynamic SDM 22
Table 3-3. The results from the OLS models combined with missing data handling methods 23
Table 3-4. The results of the Spatial Durbin fixed effects models combined with missing data handling methods 25
Table 3-5. Direct, Indirect, and Total Effects from Spatial Durbin Models (Imputed Datasets) . 27
Table 3-6. Direct, Indirect, and Total Effects from Spatial Durbin Models with First Lagged Disaster Variable (Imputed Datasets) 30
Table 3-7. Direct, Indirect, and Total Effects from Spatial Durbin Models with Second Lagged Disaster Variable (Imputed Datasets) 33
Table 3-8. Direct, Indirect, and Total Effects from Spatial Durbin Models with Third Lagged Disaster Variable (Imputed Datasets) 35
Table 3-9. The disaster effects on construction wages over time 38
Table 4-1. Data Collection 45
Table 4-2. Sample Design and Descriptive Statistics 46
Table 4-3. Results of the Non-Parametric DID Analysis 53
Table 4-4. Results of the Parametric DID analyses 54
Table 4-5. Results of the Breusch-Pagan Test (Pooled OLS vs. Fixed Effects) 56
Table 4-6. Results of the Breusch-Pagan Test (Pooled OLS vs. Random Effects) 56
Table 4-7. Results of the Hausman Test 57
Table 4-8. Data Collection 61
Table 4-9. Sample Design and Descriptive Statistics 62
Table 4-10. Results of the Panel Data Model Estimation 65
Table 5-1. Data Collection 69
Table 5-2. Time Windows 70
Table 5-3. Sample Design and Descriptive Statistics 72
Table 5-4. Variance inflation factors (VIFs) for Texas and Louisiana datasets 74
Table 5-5. Results of the OLS Method Estimation 76
Table 6-1. Data Collection 84
Table 6-2. Difference-in-differences Technique 85
Table 6-3. Time Windows 86
Table 6-4. Summary Statistics 87
Table 6-5. Variance Inflation Factors (VIFs) for Independent Variables 89
Table 6-6. Results of the Panel Data Models for Air Quality 91
Table 6-7. Results of the Hausman Test 91

LIST OF FIGURES

Figure 3-1. Major Disaster Declarations of Hurricanes from 2015 to 2019 in the Gulf Coast States (TX, LA, and FL) ... 14
Figure 3-2. Difference-in-differences specification ... 17
Figure 3-3. The spatiotemporal dynamic effects of a disaster on construction wages ... 39
Figure 4-1. Difference-in-differences framework for estimating the effect of the anti-price gouging law on building permits ... 44
Figure 4-2. Framework for DID parametric model selection ... 51
Figure 4-3. Economic Theoretical Explanation for the Empirical Evidence of the Anti-Price Gouging Law (APGL) Effects on the Reconstruction Process ... 67
Figure 5-1. Regional Fuel Price Changes in South Texas and Louisiana ... 71
Figure 5-2. Economic Theoretical Explanation for the Empirical Evidence of FMCSA Regulation Waivers on Fuel Price Stabilization ... 80
Figure 6-1. Economic Theoretical Explanation for the Empirical Evidence of EPA Environmental Regulation Waivers on SO_2 Concentration ... 93

CHAPTER 1 INTRODUCTION

An increasing number of natural disasters pose an inevitable threat to communities (Smith & Matthews, 2015). More than a hundred natural disasters strike the United States every year, causing numerous fatalities and billions of dollars of property and infrastructure damages (Boustan et al., 2020). The total cost of U.S. weather and climate disasters since 1980 has already exceeded 2 trillion dollars (Smith, 2020). As the number of U.S. county-level disasters has approximately tripled in recent decades due to rapid climate change, a greater share of the population is now more likely to expose to natural disasters (Boustan et al., 2020; IPCC, 2012).

Adequate and timely reconstruction and recovery in post-disaster situations are essential for the safety, survival, and long-term resilience of a community (Chowdhooree et al., 2019; Kim & Shahandashti, 2022a). However, the unexpected reconstruction cost increases in the aftermath of a disaster often impede post-disaster recovery due to limited budgets and amplify direct and indirect economic losses (Olsen & Porter, 2011; Pradhan & Arneson, 2021). Large-scale disasters often lead to a significant surge in the demand for reconstruction resources, which in turn inflates the costs associated with the rebuilding process (Babcicky & Seebauer, 2021). This socioeconomic phenomenon, commonly referred to as a demand surge, occurs when the heightened demand for reconstruction resources creates a relative scarcity, resulting in substantial cost increases over six months following the disaster (Olsen & Porter, 2013). Following Hurricane Katrina, more than 60 percent of construction material prices, as reported by Engineering News-Record, experienced statistically significant increases (Khodahemmati & Shahandashti, 2020). Similarly, the demand surge after Hurricane Katrina and Rita led to higher unit price bids for asphalt line items in the affected areas (Baek & Ashuri, 2018). In the aftermath of Hurricane Harvey, average weekly wages in the construction sector in the Houston metropolitan area rose by 20 percent (Billings et al., 2019). Puerto Rico also experienced a surge in demand for residential roofing services following Hurricane Irma (Arneson, 2019). Additionally, after the 2021 Texas winter storm, 61 percent of pipe material costs, represented by 11 line items, showed statistically significant increases (Kim & Shahandashti, 2022b). Measuring the spatiotemporal effect of a disaster on reconstruction costs can improve disaster loss evaluations and post-disaster recovery planning (Burton et al., 2018).

Local and federal governments have enacted various disaster policies to accelerate post-disaster recovery and strengthen the resilience of a community (Dzigbede et al., 2020). For example, thirty-seven states out of fifty in the U.S. have anti-price gouging legislation that regulates exorbitant pricing, denouncing it as an unfair or deceptive trade practice during a time of disaster or emergency. One of the intended purposes of this legislation is to stabilize the reconstruction costs increased by post-disaster demand surge and ration resources for a swift recovery from disasters (Cabral & Xu, 2021; Parsons, 2022; Tabe, 2019). Federal Motor Carrier Safety Administration (FMCSA) waives certain federal safety regulations during a time of disaster declared by the President, Governors of States, or FMCSA. Drivers that provided direct assistance to Texas and Louisiana in the aftermath of Hurricane Harvey were exempt from safety regulations such as twelve-hour limitations of Hours of Service and overweight restrictions on their route to the emergency (Azanza, 2017; Kingston, 2022). After Hurricane Katrina, there was a relaxation of the federal landfill waste acceptance standard to ensure a greater number of disposal sites were available, which helped accelerate the cleanup operations (Brown et al., 2011). To facilitate the fuel supply during post-disaster situations, the U.S. Environmental Protection Agency (EPA) has granted temporary fuel waivers (EPA, 2023).

According to consensus climate change projections, it is expected that the frequency and severity of disasters will continue to increase in the coming decades (Wuebbles et al., 2017). Measuring the post-disaster demand surge for reconstruction and examining the effects of various disaster policies are critical for a better disaster response system in the trend of increasing risks of disasters (Wang & van de Lindt, 2021)

This research aims to understand the dynamic process of the post-demand surge in the reconstruction market by estimating the spatiotemporal effects of a disaster on construction labor wages in different quarters after a disaster using spatial panel data models. Furthermore, this research will examine the effects of various local and federal disaster policies on post-disaster recovery using difference-in-differences econometric techniques.

Chapter 2 provides a comprehensive review of the literature on post-disaster demand surge and disaster policies. Chapter 2 also describes the gaps in knowledge and research objectives. Chapter 3 discusses the methodology of creating econometric models to measure the spatiotemporal effects of a disaster on construction wages. Then, the empirical results of the developed econometric models that measure the disaster effects on construction wages in Texas, Louisiana, and Florida are presented in Chapter 3. Chapter 4 proposes a methodology to assess the effects of various disaster policies on post-disaster recovery. Chapter 5 presents the conclusions.

CHAPTER 2 RESEARCH BACKGROUND

2.1. POST-DISASTER DEMAND SURGE

Post-disaster demand surge for reconstruction has been discussed in the literature (Pradhan & Arneson, 2021). The demand for reconstruction resources increases dramatically after large-scale disasters, inflating reconstruction costs (Babcicky & Seebauer, 2021). This socioeconomic phenomenon is known as a demand surge; a significant excess of demand over supply following a disaster triggers a relative scarcity of reconstruction resources and substantially inflates their costs over six months after the disaster (Olsen & Porter, 2013). Unexpected cost escalation caused by a demand surge is considered one of the most significant factors that amplify socioeconomic losses in large-scale disasters (Pradhan & Arneson, 2021). Demand surge primarily affects the process and performance of post-disaster reconstruction, increasing the probabilities of cost and schedule overruns in projects (Döhrmann et al., 2017; Kim et al., 2022c). For example, due to a 67 to 100 percent increase in construction wages by demand surge, the post-disaster reconstruction process was delayed during the 2004 hurricane season in Florida (Olsen & Porter, 2011). During the 2010-2011 earthquakes in New Zealand, the demand surge was a critical constraint for providing post-disaster reconstruction resources (Chang-Richards et al., 2017).

Since the post-disaster reconstruction of a community is closely related to the magnitude of the demand surge, it is crucial to measure and understand the demand surge in the disaster recovery process (Moradi & Nejat, 2020). The magnitude of the demand surge has been estimated by the amount of post-disaster increases in reconstruction costs such as labor wages and material costs compared to the pre-disaster level (Khodahemmati & Shahandashti, 2020; Olsen & Porter, 2013). The average weekly wages in construction for the Houston metropolitan area increased by

20 percent after Hurricane Harvey (Billings et al., 2019). Hurricane Irma resulted in a 41 percent demand surge for residential roofing services in Puerto Rico (Arneson, 2019). More than 60 percent of construction material prices published by Engineering News-Record have faced a statistically significant increase in the aftermath of recent disasters (Khodahemmati & Shahandashti, 2020). After Hurricane Katrina and Rita, the demand surge increased the unit price bids for asphalt line items in the hurricane-affected area (Baek & Ashuri, 2018). Sixty-one percent of pipe material costs (11 out of 18 line-items) have experienced a statistically significant increase after the 2021 Texas winter storm (Kim & Shahandashti, 2022b).

Labor wages are particularly one of the most sensitive factors to demand surge (Chang-Richards et al., 2017; Olsen & Porter, 2013). This is perhaps because the construction labor market is less flexible to market changes than the material market due to several reasons, such as annual labor contracts and relocation costs (Kim et al., 2022b). Although several cost factors impact the demand surge, including material and equipment costs, most studies agree that construction labor wage increases are one of the major driving factors of the demand surge (Ahmadi Esfahani & Shahandashti, 2020).

Demand surge is a dynamic process affected by several factors, including the total amount of repair works; general economic conditions; insurance claims handling; and spatial relationships between communities (Olsen & Porter, 2013). Xiao and Nilawar (2013) showed that the geographical closeness to the disaster-stricken communities influences the demand surge in employment and personal income after Hurricane Katrina. Ahmadi and Shahandashti (2020) reported a spatiotemporal autocorrelation in post-disaster construction wage changes between the disaster-stricken county and its neighboring counties.

2.2. **DISASTER POLICIES**

The resource availability for post-disaster reconstruction highly depends on multi-stakeholder collaboration and policies in a community (Chang et al., 2011). Wang and van de Lindt (2021) found that policies and mitigation strategies can expedite the overall recovery process of a community. Disaster policies that can be relevant to post-disaster recovery are discussed below:

2.2.1. Anti-Price Gouging Law

Lots of reconstruction resources are subject to significant price inflation resulting from demand surge in the aftermath of natural catastrophes (Olsen & Porter, 2013). The construction material costs increased up to 30 percent after Hurricane Katrina (Khodahemmati & Shahandashti, 2020). This sudden price inflation in the wake of an emergency is often denounced as price gouging (Lee, 2015). Price gouging occurs when a seller sharply increases the prices of necessary goods, services, or commodities beyond the reasonable level that covers increased costs after demand shocks, following a natural disaster or other emergencies (Zwolinski, 2008). Seventy-two percent of respondents in a *Washington Post* poll answered that oil companies were gouging following Hurricane Katrina (Rapp, 2005).

State legislators enacted anti-price gouging laws to stabilize post-disaster price spikes and protect consumers from significantly increased costs (Bae, 2009). Anti-price gouging laws become only in effect during a time of disaster or emergency upon the disaster declaration by state governors, authorized local officials, or the president of the U.S. (Brewer, 2006). Thirty-seven states, Guam, Puerto Rico, the U.S. Virgin Islands, and the District of Columbia, have statutes or regulations against price gouging during disaster or emergency. However, some states, including Alaska, Arizona, Maryland, Minnesota, Montana, Nebraska, Nevada, New Hampshire, New Mexico, North Dakota, South Dakota, Washington, and Wyoming, do not have anti-price gouging statutes, allowing the free market to handle the post-disaster recovery process. There are controversies over the effectiveness and effects of anti-price gouging laws.

Price gouging during times of emergency easily evokes a reactive and emotional outrage from people (Culpepper & Block, 2008). The vast majority have often condemned price gouging, arguing that it is unfair, immoral, exploitative, and impermissible (Zwolinski, 2008). Snyder (2009) argued that price gouging undermines equitable access to the goods and services essential to minimal human functioning and hit the poorest of a community the hardest. In the wake of disasters, substantial increases in construction costs can reduce the reconstruction speed in economically marginalized communities (Kim & Shahandashti, 2022a). Reconstruction cost increases are often identified as a major cause of project delay (Gebrehiwet & Luo, 2017). Cumulative price increases of more than 20 percent over the insurance policy limit following catastrophes can delay post-disaster repairs since the policyholders need to afford the extra repair costs by themselves (Döhrmann et al., 2017). Kim and Choi (2013) discussed that the increased costs following floods can delay the scheduled project delivery in the vicious cycle of post-disaster rebuild projects. The National Association of Home Builders called on the federal government to protect consumers against the price gouging of lumber since the reliable supply of reasonably priced construction materials is essential for a swift recovery from Hurricane Harvey (Wallisch, 2017).

Rapp (2005) reviewed the existing APG legislation and argued that the enforcement of the APG laws can enhance economic efficiency by correcting the failure of the pricing mechanism. The APG laws could counteract the gasoline price bubbles that cannot be attributed to market fundamentals after hurricanes (Oladosu, 2022). Warkentin (2021) highlighted the benefits of the APG law and insisted that the APG law should protect consumers against artificially high predatory pricing in times of crisis and emergency. Chang et al. (2011) discussed that post-disaster price control can stabilize the price of building materials and facilitate reconstruction projects in earthquake-affected regions.

However, many economists consider that such price hikes condemned as price gouging following unexpected disasters are a natural and appropriate market response to the shortage of essential goods and services (Wilson, 2014). Culpepper and Block (2008) insisted that price working as the ‘invisible hand’ in the free market can efficiently and effectively distribute scarce resources in the aftermath of disasters. Shannon (1989) argued that price controls can hinder post-disaster recovery, thwarting the work of the free market and discouraging favorable supply responses to increased demand. Tarrant (2015) investigated that the APG laws did not statistically significantly affect the wages in the construction contracting industry and building material supply stores. The APG laws can rather damage the retail markets, especially where the retail prices tend toward fixity (Richards, 2022).

2.2.2. Federal Motor Carrier Safety Regulation Waiver

Emergency declarations by the President, Governors of States, or the Federal Motor Carrier Safety Administration (FMCSA) trigger the temporary suspension of certain Federal safety regulations. For example, drivers that provide "direct assistance" to an "emergency" declared by FMCSA or a governor are exempt from applicable safety regulations such as federal Hours of Service (HOS) on their route to the emergency. Policymakers expect that these temporary safety regulation waivers assist to facilitate the supply of essential items such as fuel and food for demand surge in the aftermath of disasters.

2.2.3. Environmental Regulation Waiver

Federal and local governments have waived many environmental regulations in the aftermath of major disasters. For example, following Hurricane Katrina in 2005, the Environmental Protection Agency (EPA) and the Louisiana Department of Environmental Quality granted relief from the many environmental regulations. Recently, Texas Governor Abbott suspended several environmental regulations after Hurricane Harvey in 2017. The US Environmental Protection Agency (EPA), working with the Department of Energy, responds quickly to address fuel supply disruptions caused by, for example, refinery or pipeline infrastructure damage as the result of a hurricane or other natural disaster, by issuing emergency waivers of certain fuel standards in affected areas. On November 2, EPA waived the requirement for the use of Ultra Low Sulfur Diesel in emergency response vehicles and equipment in the five boroughs of New York City and Nassau, Suffolk, Rockland, and Westchester counties in New York, all the counties in New Jersey, and all the counties in the Commonwealth of Pennsylvania, as the result of Hurricane Sandy through November 20, 2012.

2.3. **GAPS IN KNOWLEDGE**

Although the existing studies provide valuable insights for post-disaster demand surge and disaster policies, there are significant gaps in knowledge related to the spatiotemporal analysis of the dynamics of demand surge and the quantitative evidence on the effects of various disaster policies on the recovery process. The following gaps were identified from the literature.

(1) Despite the significance of the effect of a disaster on the construction market, the effects of a disaster on the construction market have not been clarified accounting for the spatiotemporal interactions between communities.

(2) The effects of various disaster policies on post-disaster recovery have not been elucidated based on the empirical quantitative analysis using the macroeconomic and socioeconomic variables.

2.4. **RESEARCH OBJECTIVES**

The objectives of this research are to:

(1) Estimate the spatiotemporal effects of a disaster on construction wages for understanding the dynamics of demand surge in the post-disaster reconstruction labor market

(2) Identify and assess the effects of various disaster management policies on the post-disaster reconstruction process using macroeconomic and socioeconomic variables

CHAPTER 3 ESTIMATING THE SPATIOTEMPORAL EFFECTS OF A DISASTER ON CONSTRUCTION WAGES

Policymakers and reconstruction engineers need to understand the spatiotemporal dynamics of post-disaster demand surge for a timely and equitable disaster recovery under budget constraints (Smith & Matthews, 2015). Therefore, this study adopted the construction labor wage fluctuations to quantitatively estimate the spatiotemporal magnitude of the demand surge. Construction market variables were included as control variables to control for the other determinants of construction wage fluctuations (Ahmadi & Shahandashti, 2018; Farooghi et al., 2021; Kim et al., 2021).

3.1. **METHODOLOGY**

3.1.1. Data Collection

3.1.1.1. Construction Industry Variables

The magnitude of the demand surge has been estimated by the amount of post-disaster increases in reconstruction costs such as labor wages and material costs compared to the pre-disaster level (Ahmadi & Shahandashti, 2018; Khodahemmati & Shahandashti, 2020; Kim et al., 2021a; Olsen & Porter, 2013). Labor wages are particularly one of the most sensitive factors to demand surge (Chang-Richards et al., 2017; Olsen & Porter, 2013). This is perhaps because the construction labor market is less flexible to market changes than the material market due to several reasons, such as annual labor contracts and relocation costs (Kim et al., 2022b). Construction wage increases are one of the major driving factors of reconstruction cost increases caused by demand surge (Ahmadi Esfahani & Shahandashti, 2020).

Therefore, the average weekly wages in the construction industry were selected as a dependent variable for spatiotemporal analysis to estimate the disaster effect on construction wages. Table 3-1 shows the data collection of construction industry variables. The employment and establishment count data were included in the analysis as control variables to control for their confounding effects on construction wages (Barth & Dale-Olsen, 2011; Blanchflower & Oswald, 1995; Green et al., 2021).

Table 3-1. Data Collection of Construction Industry Variables

Data	***Definition***	***Period***	***Source***
Dependent variable:			
Construction wages	Average weekly wages paid during the calendar quarter in the construction industry	Q1 2015 – Q4 2019	Bureau of Labor Statistics
Control variables:			
Employment	Quarterly number of employees in the construction industry	Q1 2015 – Q4 2019	Bureau of Labor Statistics
Establishment Count	Quarterly number of establishments in the construction industry	Q1 2015 – Q4 2019	Bureau of Labor Statistics

3.1.1.2. Disaster-related Data

The independent dummy variable for representing a disaster occurrence was selected based on the major disaster declarations by Federal Emergency Management Agency (FEMA). Figure 3-1 describes all the major disaster declarations of hurricanes from 2015 to 2019 in three Gulf Coast states (Texas, Louisiana, and Florida) that are prone to hurricane strikes. A list of counties in three Gulf Coast states (Texas, Louisiana, and Florida) that received a major disaster declaration of hurricanes between 2015 and 2019 was obtained from FEMA.

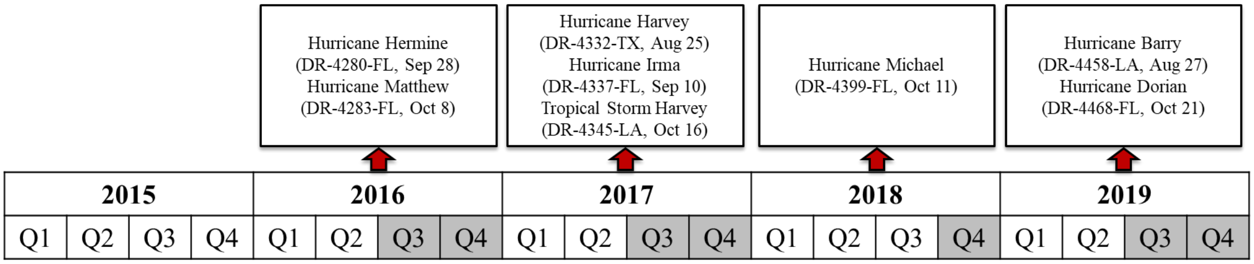


Figure 3-1. Major Disaster Declarations of Hurricanes from 2015 to 2019 in the Gulf Coast States (TX, LA, and FL)

3.1.1.3. Spatial Weight Matrices

For creating spatial econometrics models, every single observation in datasets needs to be geocoded. The spatial weight matrix defines the neighbors and describes which observations are spatially close and how much they influence each other. The spatial weight matrix in the panel data model is specified as *W* with elements w_{ij} , specifying whether county *i* and *j* are spatially correlated. Each element of *i* and *j* (w_{ij}) is defined as one if *i* and *j* are neighbors and zero otherwise. Following the standard convention, "self-influence" of county *i* on itself is excluded by assuming that w_{ii} = 0 for all *i* = 1,2, 3,…, n. Thus, the matrix of *W* has zero diagonal elements (Smith, 2014). The spatial contiguity weight matrix used in this research is represented by Eq. 3-1.

$$w_{ij} = \begin{cases} 1, & boundry(i) \cap \ boundry(j) \neq \emptyset \\ 0, & boundry(i) \cap \ boundry(j) = \emptyset \end{cases} \qquad \text{Eq. 3-1}$$

3.1.2. Missing Data Handling

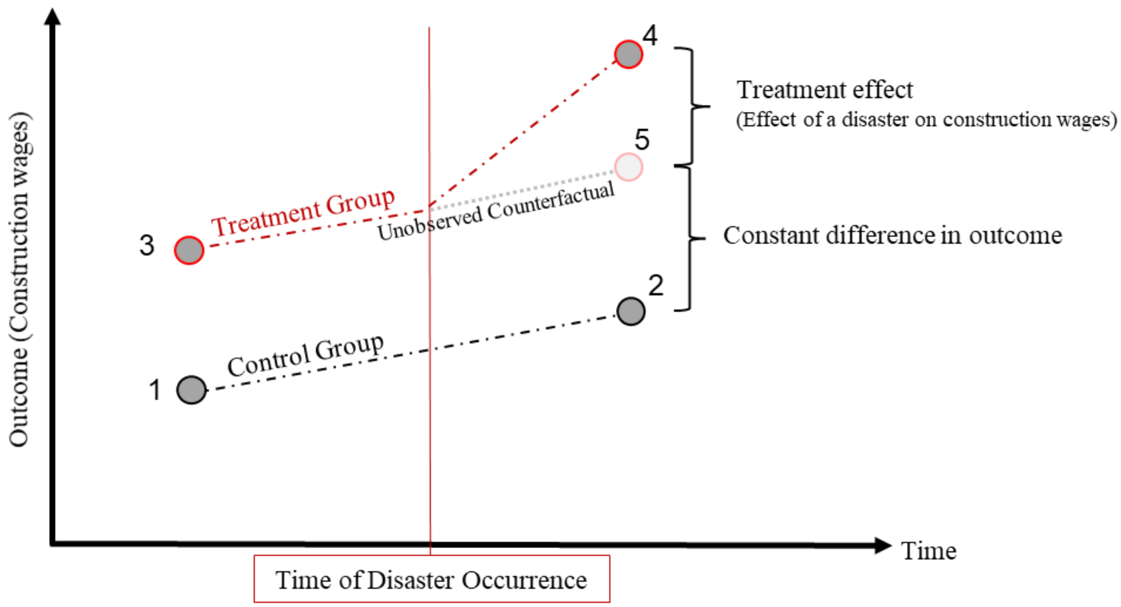
Data imputation methods have been implemented to resolve missing data problems in quantitative studies. The current study utilized two different missing data handling methods including spatial multiple imputation and missing data deletion which is a non-spatial method. The spatial multiple imputation method is used to impute a missing observation to create a complete data matrix for analysis while the missing data deletion method is used to simply omit some or all the missing observations (Jadhav et al., 2019).

The spatial multiple imputation method is implemented to replace a missing observation with a plausible value based on the maximum likelihood estimation (Spiess & Augustin, 2021). The spatial multiple imputation method is carried out in three sequential steps: (1) creating several complete sets by imputing plausible estimates to the missing observations, (2) analyzing the multiple complete datasets using a joint spatial distribution, and (3) aggregating the results from the multiple analyses (Lee et al., 2019).

The missing data deletion method is removing the missing observations from the dataset (Xie et al., 2020). While the spatial characteristics of data are not considered in the missing data deletion method, the spatial characteristics of data are considered in the spatial multiple imputation methods (Chandra et al., 2015; Yozgatligil et al., 2013). Particularly, spatial multiple imputation methods are developed for spatiotemporal analysis of panel datasets (Matthews, 2020).

3.1.3. Difference-in-Differences (DID) Technique

The difference-in-differences (DID) specification is widely used to estimate the effect of a treatment on an outcome variable by comparing the differences between the control and treatment groups before and after an intervention (Card & Krueger, 1993; Papke, 1994). The DID specification typically requires four groups: the control group before and after the intervention and the treatment group before and after the intervention. Figure 3-2 illustrates the DID specification to estimate the disaster effects on construction wages.



County-level panel data are classified into four groups as follows:

1. The control group (counties) before a disaster
2. The control group (counties) after a disaster
3. The treatment group (counties) before a disaster
4. The treatment group (counties) after a disaster

Figure 3-2. Difference-in-differences specification

The DID specification allows us to control for the unobserved time-invariant county-specific factors. The DID specification can estimate the effects of a disaster on heterogenous county-level construction wages using the one-stage modeling without the separate measurement stage, avoiding measurement errors. Spatial panel data models were utilized in this study for implementing the DID specification to examine the spatial spillover effects or the spatial dependencies between counties (Elhorst, 2014).

3.1.4. Panel Data Models

3.1.4.1. Base Models

Ordinary Least Squares (OLS) were used to estimate Eq. 3-2.

$$lnWAGE_{it} = \beta_0 + \beta_1 DIS_{it} + \beta_2 EMP_{it} + \beta_3 EST_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \qquad \text{Eq. 3-2}$$

where $WAGE_{it}$ is average weekly wages in the construction industry in county *i* and time t; DIS_{it} is a dummy variable that is equal to one if county *i* at time *t* experienced Hurricane declared as a major disaster by FEMA, and zero otherwise; EMP_{it} is the number of employees in the construction industry in county *i* and time *t*; EST_{it} is the number of establishments in the construction industry in county *i* and time *t*; α_i is the unobservable time-invariant county fixed-effects; α_t is the unobservable county-invariant time fixed-effects; and ε_{it} is the time-varying idiosyncratic error.

The estimators obtained from the OLS model do not control for the unobserved time-invariant county effects (α_i), so the results are biased and inconsistent (Kim et al., 2020). The fixed-effects model helps to mitigate the bias due to time-invariant factors (α_i) that are correlated with independent variables. A fixed-effect model can control for unobservable specific characteristics of each county, which is related to a disaster; for example, geographical features of each county that may affect natural disaster occurrence. The Lagrange multiplier test proposed by Breusch and Pagan (1980) was used to see whether unobserved time-invariant county fixed-effects (α_i) exist. The rejection of the null hypothesis shows that the OLS estimators are not appropriate, so random-effect or fixed-effect models are more appropriate.

Since the OLS model does not take spatial dependencies among counties into account, the base OLS model is not appropriate to examine the spatial spillover effects of a disaster (Kim et al., 2022a). A disaster in one county *i* can not only affect the construction wages in the county *i* directly (direct effects) but also potentially affect the construction wages in other counties indirectly based on the spatial dependencies among the counties (indirect spillover effects). This phenomenon is called *interactive heterogeneity* or *multi-county interaction* (LeSage & Pace, 2014).

3.1.4.2. Dynamic Spatial Durbin Models

The dynamic Spatial Durbin models (SDM) were used to examine the spatiotemporal effects of a disaster on construction wages considering the multi-county spatial interactions. The dynamic SDM includes both the temporal and spatial lags of the dependent variable and independent covariates to account for the spatiotemporal interactive heterogeneities among counties (Belotti et al., 2017; LeSage & Pace, 2014). The SDM is a more extensive model than SAR (spatial autoregressive model) and SEM (spatial error model) as it embeds both SAR and SEM (Bu et al., 2022; Elhorst, 2014). While the SAR and SEM suffer from estimating the accurate spillover effects, the SDM has been popularly adopted in applied research to quantify the direct, indirect spillover, and total effects of independent variables on the dependent variable, accounting for both endogenous and exogenous interaction effects (Elhorst, 2014; LeSage & Pace, 2014). Eq. 3-3 represents Texas construction wages estimated by dynamic SDM containing the temporally and spatially lagged dependent variables (i.e., construction wages). The dynamic SDM model was used to examine the direct, indirect, and total effects of a disaster on construction wages in the short-run and long-run.

Dynamic Spatial Durbin Model (SDM)

$$lnWAGE_{it} = \beta_0 + \tau WAGE_{it-1} + \varphi W_{ij}WAGE_{jt-1} + \rho W_{ij}WAGE_{jt} + \beta_1 DIS_{it} + \beta_2 EMP_{it} + \beta_3 EST_{it} + \delta_1 W_{ij}DIS_{jt} + \delta_2 W_{ij}EMP_{jt} + \delta_3 W_{ij}EST_{jt} + \alpha_i + \alpha_t + \varepsilon_{it} \quad \text{Eq. 3-3}$$

i= 1,…, 254 and t= 2015, 2016, 2017, 2018, 2019

where $WAGE_{it}$ is average weekly wages in the construction industry in county *i* and time t; W_{ij} is the 254×254 spatial weight matrix representing the queen contiguity weight matrix of 254 counties in Texas; $WAGE_{it-1}$ is temporally lagged construction wages; $W_{ij}WAGE_{jt-1}$ is temporally and spatially lagged construction wages; $W_{ij}WAGE_{jt}$ is spatially lagged construction wages; DIS_{it} is a dummy variable that is equal to one if county *i* at time *t* experienced Hurricane declared as a major disaster by FEMA, and zero otherwise; EMP_{it} is the number of employees in the construction industry in county *i* and time *t*; EST_{it} is the number of establishments in the construction industry in county *i* and time *t*; ρ is a spatial dependence parameter; α_i is the unobservable time-invariant county fixed-effects; α_t is the unobservable county-invariant time fixed-effects; ε_{it} is the time-varying idiosyncratic error; $\rho W_{ij}WAGE_{jt}$ is endogenous interaction effects; and $\delta_1 W_{ij}DIS_{jt,}\delta_2 W_{ij}EMP_{jt}, \delta_3 W_{ij}EST_{jt}$ are exogeneous interaction effects.

Disaster often has a lagged effect on the post-disaster construction industry (Capelle-Blancard & Laguna, 2010; Hallegatte et al., 2011; Higuchi et al., 2012; Kajitani & Tatano, 2018; Naqvi & Rehm, 2014). The lagged effect of a disaster on the county-level construction wages one quarter after the disaster was estimated using Eq. 3-4.

Dynamic Spatial Durbin Model (SDM) with a temporally lagged independent variable

$$lnWAGE_{it} = \beta_0 + \tau WAGE_{it-1} + \varphi W_{ij}WAGE_{jt-1} + \rho W_{ij}WAGE_{jt} + \beta_1 DIS_{it-1} + \beta_2 DIS_{it} + \beta_3 EMP_{it} + \beta_4 EST_{it} + \delta_1 W_{ij} l.DIS_{jt} + \delta_2 W_{ij} DIS_{jt} + \delta_3 W_{ij} EMP_{jt} + \delta_4 W_{ij} EST_{jt} + \alpha_i + \alpha_t + \varepsilon_{it}$$

i = 1,…, 254 and t = 2015, 2016, 2017, 2018, 2019 Eq. 3-4

where $WAGE_{it}$ is average weekly wages in the construction industry in county *i* and time t; W_{ij} is the 254×254 spatial weight matrix representing the queen contiguity weight matrix of 254 counties in Texas; $WAGE_{it-1}$ is temporally lagged construction wages; $W_{ij}WAGE_{jt-1}$ is temporally and spatially lagged construction wages; $W_{ij}WAGE_{jt}$ is spatially lagged construction wages; DIS_{it-1} is a temporally lagged disaster dummy variable that is equal to one if county *i* at time *t-1* experienced a Hurricane declared as a major disaster by FEMA, and zero otherwise; DIS_{it} is a dummy variable that is equal to one if county *i* at time *t* experienced Hurricane declared as a major disaster by FEMA, and zero otherwise; EMP_{it} is the number of employees in the construction industry in county *i* and time *t*; EST_{it} is the number of establishments in the construction industry in county *i* and time *t*; ρ is a spatial dependence parameter; α_i is the unobservable time-invariant county fixed-effects; α_t is the unobservable county-invariant time fixed-effects; ε_{it} is the time-varying idiosyncratic error; $\rho \mathrm{W}_{ij}\mathrm{WAGE}_{jt}$ is endogenous interaction effects; and $\delta_1 W_{ij} l.DIS_{jt}, \delta_2 W_{ij} DIS_{jt}, \delta_3 W_{ij} EMP_{jt}, \delta_4 W_{ij} EST_{jt}$ are exogeneous interaction effects.

The direct, indirect, and total marginal effects of an independent variable (e.g., disaster) on the dependent variable (e.g., construction wages) can be estimated by taking the partial derivative of the expected value of the dependent variable with respect to the independent variable in the dynamic SDM. Eq. 3-5 shows the partial derivatives of the expected values of construction wages in 254 counties in Texas with respect to the disaster variable for measuring the direct, indirect, and total marginal effects of a disaster on post-disaster construction wages.

$$\begin{bmatrix} \frac{\partial E(lnWAGE_1)}{\partial DIS_1} & \frac{\partial E(lnWAGE_1)}{\partial DIS_2} & \cdots & \frac{\partial E(lnWAGE_i)}{\partial DIS_i} \\ \frac{\partial E(lnWAGE_2)}{\partial DIS_1} & \frac{\partial E(lnWAGE_2)}{\partial DIS_2} & \cdots & \frac{\partial E(lnWAGE_i)}{\partial DIS_i} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial E(lnWAGE_i)}{\partial DIS_1} & \frac{\partial E(lnWAGE_i)}{\partial DIS_2} & \cdots & \frac{\partial E(lnWAGE_i)}{\partial DIS_i} \end{bmatrix} = ((I_i - \rho W)^{-1}) \begin{bmatrix} \beta_1 & w_{12}\delta_1 & \cdots & w_{1i}\delta_1 \\ w_{21}\delta_1 & \beta_1 & \cdots & w_{2i}\delta_1 \\ \vdots & \vdots & \ddots & \vdots \\ w_{i1}\delta_1 & w_{i2}\delta_1 & \cdots & \beta_1 \end{bmatrix}$$

i= 1, …, 254 Eq. 3-5

The direct effect is the effect of a disaster occurrence in county *i* on the construction wages of county *i*. The indirect effect is the effect of a disaster that occurred in the neighboring county *j* on the construction wages of county *i*. The total effect is the effect of a disaster occurrence in all counties on the construction wages of county *i*. The direct effects are estimated by diagonal elements, while the indirect spillover effects are estimated by off-diagonal elements in Eq. 3-5 (Belotti et al., 2017; Elhorst, 2014; LeSage & Pace, 2014). Table 3-2 summarizes the estimation of the direct and indirect effects of a disaster on construction wages in the short-run and long-run using dynamic SDM.

Table 3-2**.** Direct and indirect effects of a disaster on construction wages in the short-run and long-run estimated by dynamic SDM

Dynamic SDM	Direct effect	Indirect effect
Short-run	$\{((I_i - \rho W)^{-1} \times (\beta_1 I_i + \delta_1 W)\}^{\bar{d}}$	$\{((I_i - \rho W)^{-1} \times (\beta_1 I_i + \delta_1 W)\}^{\overline{rsum}}$
Long-run	$\{((1-\tau)I_i - (\rho + \varphi)W)^{-1} \times (\beta_1 I_i + \delta_1 W)\}^{\bar{d}}$	$\{((1-\tau)I_i - (\rho + \varphi)W)^{-1} \times (\beta_1 I_i + \delta_1 W)\}^{\overline{rsum}}$

Note: I_i is the identity matrix for county i; W is the 254×254 spatial weight matrix representing the queen contiguity weight matrix of 254 counties in Texas; β_1 is a parameter of the disaster variable (DIS_i); δ_1 is the parameter of the exogenous interaction effect of a disaster ($W_{ij}DIS_{jt}$); ρ is a spatial dependence parameter of the spatially lagged construction wages ($W_{ij}WAGE_{jt}$); τ is the parameter of the temporally lagged construction wages($WAGE_{it-1}$); φ is the parameter of the spatially and temporally lagged construction wages($W_{ij}WAGE_{jt-1}$); superscript $\bar{d}$ is the operator that calculates the mean diagonal element of a matrix; and superscript $\overline{rsum}$ is the operator that calculates the mean row sum of the nondiagonal elements.

3.2. **RESULTS**

3.2.1. Results of the Base Models

Table 3-3 presents the results of OLS regression models. The missing data in the dataset were handled using spatial multiple imputation and missing data deletion methods.

Table 3-3. The results from the OLS models combined with missing data handling methods

State	**Texas**		**Louisiana**		**Florida**	
Missing Data Handling	Imputed	Deleted	Imputed	Deleted	Imputed	Deleted
Variables	lnWAGE	lnWAGE	lnWAGE	lnWAGE	lnWAGE	lnWAGE
Disaster	-0.0180 (0.0174)	-0.0251 (0.0184)	-0.0368* (0.0212)	-0.0465** (0.0222)	0.00436 (0.00912)	0.00402 (0.00905)
Employment	0.0216*** (0.00277)	0.145*** (0.00941)	0.0220*** (0.00781)	0.0893*** (0.0165)	0.0921*** (0.0137)	0.156*** (0.0201)
Establishment Count	0.0103 (0.00908)	-0.101*** (0.0230)	0.0757** (0.0385)	-0.00730 (0.0489)	-0.0169 (0.0336)	-0.0577 (0.0353)

Constant	6.513*** (0.0405)	6.077*** (0.0885)	6.237*** (0.170)	6.088*** (0.197)	5.792*** (0.191)	5.482*** (0.202)
Year_Q Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,080	4,168	1,280	1,163	1,340	1,317
R-squared	0.329	0.347	0.238	0.243	0.624	0.634
Number of counties	254	227	64	63	67	67

Note: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

The disaster effect on the construction wages in the quarter when the disaster occurred (hereafter, the disaster quarter) is not statistically significant in Texas and Florida. The disaster decreased the construction wages in the disaster-affected counties by 3.68 percent compared to the non-disaster-affected counties based on the imputed Louisiana dataset and by 4.65 percent based on the deleted Louisiana dataset.

The positive relationship between employment and wages in the construction industry was found to be statistically significant in all three datasets of Gulf Coast states. This positive relationship between employment and construction wages is consistent with the findings in the previous studies (Barth & Dale-Olsen, 2011; Blanchflower & Oswald, 1995; Green et al., 2021).

3.2.2. Results of the Spatial Durbin Models

Table 3-4 represents the results of the Spatial Durbin Models (SDM).

Table 3-4. The results of the Spatial Durbin fixed effects models combined with missing data handling methods

State	Texas		Louisiana		Florida	
Missing Data Handling	Imputed	Deleted	Imputed	Deleted	Imputed	Deleted
Variables	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage
Disaster	-0.0259** (0.0121)	-0.0203 (0.0138)	-0.0402*** (0.0143)	-0.0152 (0.0155)	0.00211 (0.00667)	0.00688 (0.00616)
Employment	0.0210*** (0.00327)	0.115*** (0.0222)	0.0245 (0.0156)	0.0745 (0.0460)	0.100 (0.0680)	0.125 (0.172)
Establishment Count	0.0130 (0.00946)	-0.104** (0.0422)	0.0830 (0.0882)	0.0566 (0.135)	0.0325 (0.0762)	0.0167 (0.139)
$\mathbf{W_{ij}\ln WAGE}$ (Spatially Lagged Wage)	0.375*** (0.0362)	0.346*** (0.0371)	0.306*** (0.0652)	0.302*** (0.0773)	0.295*** (0.0829)	0.294*** (0.0933)
$\boldsymbol{\rho}$ (Spatial	0.368*** (0.0197)	0.305*** (0.0253)	0.272*** (0.0320)	0.262*** (0.0431)	0.490*** (0.0408)	0.483*** (0.0432)

dependencies)						
$\boldsymbol{\sigma_\varepsilon^2}$ (Variance of the error)	0.0104*** (0.000860)	0.0105*** (0.000915)	0.0126*** (0.00171)	0.011*** (0.00183)	0.004*** (0.000849)	0.004*** (0.000870)
Year_Q Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,826	3,591	1,216	1,007	1,273	1,197
R-squared	0.650	0.398	0.213	0.157	0.589	0.620
Number of counties	254	189	64	53	67	63

Note: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

The effect of a disaster on construction wages in the disaster quarter was estimated to be negative at the 5% significance level based on the imputed panel datasets of Texas and Louisiana. The construction wages in the Texas counties struck by a disaster (i.e., disaster-affected counties) were estimated 2.59 percent lower than the wages in the non-disaster-affected counties in Texas. Similarly, the construction wages in the disaster-affected counties in Louisiana were measured as 4.02 percent lower than the wages in the non-disaster-affected counties in Louisiana. However, this negative effect of a disaster on construction wages was not reported in Florida counties.

The endogenous spatial interaction effect of construction wages (i.e., $\rho \mathrm{W}_{ij}\mathrm{lnWAGE}$) was found to be positive in all three Gulf Coast states. It indicates that the construction wages in county *i* are positively associated with the wages in the neighboring county *j*. The positive coefficient on $\mathrm{W}_{ij}\mathrm{lnWAGE}$ (Spatially Lagged Wage) indicates that the construction wages in county i are positively influenced by the construction wages in the neighboring county *j*. The positive coefficient on ρ (Spatial dependencies) shows a higher spatial dependency of construction wages between county *i* and neighboring county *j*. This positive spatial interaction effect of construction wages aligns with the findings in the previous studies (Buettner, 1999; Fingleton & Szumilo, 2019).

The disaster effects on construction wages can be more accurately scrutinized and quantified by the partial derivatives of the expected values of the dependent variable (i.e., construction wages) with respect to the independent variables (Eq. 3-5). The direct, indirect, and total effects of a disaster on the construction wage were investigated using fixed-effects dynamic SDMs in Table 3-5.

Table 3-5. Direct, Indirect, and Total Effects from Spatial Durbin Models (Imputed Datasets)

VARIABLES			DISASTER	EMPLOYMENT	ESTABLISHMENT COUNT
TX	**Main**		-0.0259** (0.0121)	0.0210*** (0.00327)	0.0130 (0.00946)
	Wx		0.00196 (0.0205)	-0.00341 (0.00797)	-0.0133 (0.0232)
	SR	**Direct**	-0.0268** (0.0110)	0.0217*** (0.00320)	0.0122 (0.00938)
		Indirect	-0.00955 (0.0267)	0.00650 (0.0120)	-0.0144 (0.0334)
		Total	-0.0364 (0.0241)	0.0282** (0.0131)	-0.00220 (0.0367)
	LR	**Direct**	-0.0452*** (0.0173)	0.0364*** (0.00557)	0.0191 (0.0163)
		Indirect	-0.0449 (0.0610)	0.0332 (0.0295)	-0.0248 (0.0825)
		Total	-0.0901 (0.0600)	0.0697** (0.0323)	-0.00568 (0.0912)
LA	**Main**		-0.0402*** (0.0143)	0.0245 (0.0156)	0.0830 (0.0882)
	Wx		0.0725*** (0.0233)	0.0333** (0.0163)	0.251** (0.101)
	SR	**Direct**	-0.0369*** (0.0132)	0.0287* (0.0153)	0.103 (0.0867)

		Indirect	0.0823*** (0.0282)	0.0538** (0.0238)	0.361*** (0.133)
		Total	0.0454* (0.0259)	0.0824** (0.0331)	0.464*** (0.168)
	LR	**Direct**	-0.0506*** (0.0189)	0.0439* (0.0226)	0.164 (0.127)
		Indirect	0.130*** (0.0471)	0.0993** (0.0434)	0.640*** (0.231)
		Total	0.0792* (0.0457)	0.143** (0.0583)	0.804*** (0.292)
FL	**Main**		0.00211 (0.00667)	0.100 (0.0680)	0.0325 (0.0762)
	Wx		0.0130 (0.00919)	-0.0740* (0.0390)	0.0594 (0.0749)
	SR	**Direct**	0.00405 (0.00607)	0.0992 (0.0695)	0.0415 (0.0741)
		Indirect	0.0261* (0.0142)	-0.0443 (0.0770)	0.145 (0.131)
		Total	0.0302** (0.0143)	0.0549 (0.128)	0.186 (0.168)
	LR	**Direct**	0.00871 (0.00885)	0.144 (0.109)	0.0784 (0.119)
		Indirect	0.0666* (0.0388)	-0.0251 (0.230)	0.406 (0.397)
		Total	0.0753* (0.0407)	0.119 (0.320)	0.484 (0.478)

Notes: Robust standard errors in the parentheses;
SR denotes ‘Short-run’ effects and LR denotes ‘Long-run’ effects.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The Main equation contains the β vector and the Wx reports the δ vector in Eq. 3-3 (Belotti et al., 2017). The main disaster effect on construction wages in the Texas panel dataset was estimated to be -2.59 percent. In other words, the construction wages in disaster-affected counties in Texas are 2.59 percent lower than the wages in non-disaster-affected counties in Texas. This negative effect of a disaster on construction wages can be attributed to the short-run direct effect of -2.68 percent and the long-run direct effect of -4.52 percent. The disaster that occurred in county *i* in Texas decreased the county's construction wages by 2.68 percent in the short-run, by 4.52 percent in the long-run, and by 2.59 percent in total accounting for all the direct and indirect effects in the short-run and long-run.

The construction wages in disaster-affected counties in Louisiana are 4.02 percent lower than the wages in non-disaster-affected counties. The main disaster effect of – 4.02 percent in Louisiana can be attributed to the short-run direct effect of -3.69 percent, the short-run indirect effect of 8.23 percent, the long-run direct effect of -5.06 percent, and the long-run indirect effect of 13 percent. The direct effect of a disaster on construction wages in the disaster-affected Louisiana counties was estimated to be negative. This negative direct effect of a disaster which was consistently reported both in Texas and Louisiana is probably because the local market system is damaged immediately after a disaster (Capelle-Blancard & Laguna, 2010; Hallegatte et al., 2011; Higuchi et al., 2012; Kajitani & Tatano, 2018; Naqvi & Rehm, 2014). However, the indirect effect of a disaster on construction wages in Louisiana counties was found to be statistically significantly positive. The positive indirect effect of a disaster indicates that the construction wages in a county increase when a disaster strikes its neighboring county. This result seems plausible because the post-disaster surge in construction labor demand can be met by the supply of construction labor from the adjacent counties, inflating the construction wages in the county neighboring the disaster-affected county (Sadri et al., 2018).

The main effect of a disaster on construction wages was not found statistically significant in the Florida counties. However, the positive indirect spillover effects and total effects of a disaster on construction wages were reported in the Florida counties both in the short-run and long-run.

3.2.3. Results of the Spatial Durbin Models with Lagged Disaster Variables

The Spatial Durbin Models (SDM) with lagged disaster variables were developed to examine the lagged spatiotemporal effect of a disaster on construction wages considering the spatial interactions and dependence among counties.

Table 3-6 represents the results of the SDMs with the first-lagged disaster variable.

Table 3-6. Direct, Indirect, and Total Effects from Spatial Durbin Models with First Lagged Disaster Variable (Imputed Datasets)

<table>
<tr><th colspan="3">VARIABLES</th><th>FIRST-LAGGED DISASTER</th><th>DISASTER</th><th>EMPLOYMENT</th><th>ESTABLISHMENT COUNT</th></tr>
<tr><td rowspan="3">TX</td><td colspan="2">Main</td><td>0.0441***
(0.0106)</td><td>-0.0226*
(0.0121)</td><td>0.0210***
(0.00360)</td><td>0.0152
(0.00984)</td></tr>
<tr><td rowspan="2">SR</td><td>Direct</td><td>0.0450***
(0.0106)</td><td>-0.0220**
(0.0110)</td><td>0.0213***
(0.00347)</td><td>0.0150
(0.0103)</td></tr>
<tr><td>Indirect</td><td>0.0255***
(0.00630)</td><td>-0.0123
(0.0281)</td><td>0.00683
(0.0120)</td><td>-0.00644
(0.0359)</td></tr>
</table>

<table>
<tr><td rowspan="4"></td><td></td><td>Total</td><td>0.0706***
(0.0167)</td><td>-0.0344
(0.0265)</td><td>0.0282**
(0.0128)</td><td>0.00856
(0.0407)</td></tr>
<tr><td rowspan="3">LR</td><td>Direct</td><td>0.0742***
(0.0174)</td><td>-0.0363**
(0.0170)</td><td>0.0348***
(0.00572)</td><td>0.0236
(0.0176)</td></tr>
<tr><td>Indirect</td><td>0.0928***
(0.0246)</td><td>-0.0451
(0.0623)</td><td>0.0317
(0.0282)</td><td>-0.00397
(0.0855)</td></tr>
<tr><td>Total</td><td>0.167***
(0.0409)</td><td>-0.0813
(0.0629)</td><td>0.0665**
(0.0306)</td><td>0.0196
(0.0962)</td></tr>
<tr><td rowspan="7">LA</td><td colspan="2">Main</td><td>0.0469**
(0.0203)</td><td>-0.0338**
(0.0137)</td><td>0.0288*
(0.0169)</td><td>0.0707
(0.0925)</td></tr>
<tr><td rowspan="3">SR</td><td>Direct</td><td>0.0396**
(0.0189)</td><td>-0.0286**
(0.0128)</td><td>0.0305*
(0.0168)</td><td>0.0865
(0.0931)</td></tr>
<tr><td>Indirect</td><td>-0.160***
(0.0448)</td><td>0.0917***
(0.0267)</td><td>0.0376*
(0.0213)</td><td>0.343***
(0.131)</td></tr>
<tr><td>Total</td><td>-0.121***
(0.0409)</td><td>0.0631**
(0.0253)</td><td>0.0682**
(0.0320)</td><td>0.429**
(0.177)</td></tr>
<tr><td rowspan="3">LR</td><td>Direct</td><td>0.0500**
(0.0253)</td><td>-0.0366**
(0.0172)</td><td>0.0422*
(0.0230)</td><td>0.125
(0.127)</td></tr>
<tr><td>Indirect</td><td>-0.231***
(0.0652)</td><td>0.132***
(0.0392)</td><td>0.0604*
(0.0330)</td><td>0.520***
(0.197)</td></tr>
<tr><td>Total</td><td>-0.181***
(0.0617)</td><td>0.0952**
(0.0385)</td><td>0.103**
(0.0483)</td><td>0.645**
(0.264)</td></tr>
<tr><td rowspan="7">FL</td><td colspan="2">Main</td><td>0.0179***
(0.00516)</td><td>0.00589
(0.00690)</td><td>0.114*
(0.0684)</td><td>0.0272
(0.0859)</td></tr>
<tr><td rowspan="3">SR</td><td>Direct</td><td>0.0190***
(0.00528)</td><td>0.00877
(0.00646)</td><td>0.112
(0.0724)</td><td>0.0394
(0.0867)</td></tr>
<tr><td>Indirect</td><td>0.0155***
(0.00470)</td><td>0.0273*
(0.0152)</td><td>-0.0569
(0.0658)</td><td>0.190
(0.133)</td></tr>
<tr><td>Total</td><td>0.0345***
(0.00963)</td><td>0.0361**
(0.0165)</td><td>0.0548
(0.120)</td><td>0.230
(0.179)</td></tr>
<tr><td rowspan="3">LR</td><td>Direct</td><td>0.0289***
(0.00798)</td><td>0.0150
(0.00935)</td><td>0.157
(0.108)</td><td>0.0734
(0.130)</td></tr>
<tr><td>Indirect</td><td>0.0470***
(0.0172)</td><td>0.0649*
(0.0362)</td><td>-0.0436
(0.172)</td><td>0.443
(0.335)</td></tr>
<tr><td>Total</td><td>0.0758***
(0.0239)</td><td>0.0799**
(0.0395)</td><td>0.113
(0.262)</td><td>0.517
(0.422)</td></tr>
</table>

Notes: Standard errors in parentheses;
SR denotes ‘Short-run’ effects and LR denotes ‘Long-run’ effects.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

While the disaster variable has a negative or nonsignificant effect on construction wages in three Gulf Coast states, the first-lagged disaster variable shows a statistically significant positive effect on wages consistently. The disaster decreased the construction wages in the disaster quarter by 2.26 percent but increased the wages by 4.41 percent one quarter after the disaster in Texas. This lagged effect of a disaster on construction wages can be attributable to 4.5 percent of short-run direct effects, 2.55 percent of short-run indirect effects, 7.42 percent of long-run direct effects, and 9.28 percent of long-run indirect effects in Texas. In other words, the construction wage inflation one quarter after a disaster in Texas was influenced by both the direct effect in a disaster-affected county and the indirect spillover effect in the neighboring counties in the short-run and long-run.

The lagged effect of a disaster on construction wages was reported consistently in the other two states, Louisiana, and Florida. A disaster decreased the construction wages in the disaster quarter by 3.38 percent but increased the wages by 4.69 percent one quarter after the disaster in Louisiana. In Florida, a disaster did not have a significant effect on the wages in the disaster quarter but increased the construction wages by 1.79 percent one quarter after the disaster. The direct and indirect spillover effects of a disaster were also found to influence the construction wage inflation one quarter after the disaster in Louisiana and Florida.

Table 3-7 represents the results of the SDMs with the second-lagged disaster variable. The spatiotemporal analysis using the SDMs with the second-lagged disaster variable provides mixed results for estimating the disaster effect on construction wages two quarters after the disaster.

Table 3-7. Direct, Indirect, and Total Effects from Spatial Durbin Models with Second Lagged Disaster Variable (Imputed Datasets)

VARIABLES			SECOND-LAGGED DISASTER	DISASTER	EMPLOYMENT	ESTABLISHMENT COUNT
TX	Main		-0.0275** (0.0116)	-0.0265** (0.0123)	0.0198*** (0.00346)	0.0168* (0.00954)
	SR	Direct	-0.0344*** (0.0110)	-0.0264** (0.0111)	0.0206*** (0.00348)	0.0162* (0.00986)
		Indirect	-0.115*** (0.0275)	-0.0170 (0.0279)	0.0149 (0.0129)	-0.0131 (0.0403)
		Total	-0.149*** (0.0287)	-0.0435* (0.0259)	0.0355** (0.0143)	0.00310 (0.0445)
	LR	Direct	-0.0648*** (0.0177)	-0.0442** (0.0172)	0.0346*** (0.00598)	0.0253 (0.0173)
		Indirect	-0.305*** (0.0712)	-0.0632 (0.0646)	0.0527* (0.0313)	-0.0182 (0.100)
		Total	-0.369*** (0.0763)	-0.107* (0.0646)	0.0873** (0.0347)	0.00708 (0.111)
LA	Main		-0.0132 (0.0160)	-0.0414*** (0.0143)	0.0357* (0.0194)	0.0777 (0.101)
	SR	Direct	-0.0114 (0.0147)	-0.0364*** (0.0132)	0.0386** (0.0197)	0.103 (0.103)
		Indirect	0.0519 (0.0458)	0.0778*** (0.0282)	0.0494** (0.0233)	0.557*** (0.208)
		Total	0.0406 (0.0430)	0.0414 (0.0264)	0.0880** (0.0369)	0.557*** (0.208)
	LR	Direct	-0.0141 (0.0201)	-0.0484*** (0.0182)	0.0557** (0.0279)	0.160 (0.146)
		Indirect	0.0812 (0.0733)	0.116*** (0.0447)	0.0886** (0.0408)	0.751*** (0.258)

		Total	0.0671	0.0681	0.144**	0.911***
			(0.0715)	(0.0440)	(0.0612)	(0.343)
FL	**Main**		-0.0211***	0.00256	0.141**	-0.00481
			(0.00541)	(0.00660)	(0.0682)	(0.0868)
	SR	**Direct**	-0.0230***	0.00477	0.140*	-0.000681
			(0.00560)	(0.00624)	(0.0733)	(0.0883)
		Indirect	-0.0209***	0.0174	-0.0568	0.0967
			(0.00539)	(0.0166)	(0.0747)	(0.148)
		Total	-0.0440***	0.0222	0.0828	0.0960
			(0.0105)	(0.0177)	(0.138)	(0.201)
	LR	**Direct**	-0.0350***	0.00845	0.196*	0.00847
			(0.00835)	(0.00909)	(0.110)	(0.134)
		Indirect	-0.0655***	0.0438	-0.0141	0.228
			(0.0215)	(0.0409)	(0.218)	(0.386)
		Total	-0.100***	0.0522	0.182	0.237
			(0.0278)	(0.0444)	(0.318)	(0.484)

Notes: Standard errors in parentheses;
SR denotes 'Short-run' effects and LR denotes 'Long-run' effects.
*** p<0.01, ** p<0.05, * p<0.1

The disaster variable has a negative or nonsignificant effect on the construction wages in the disaster quarter in the Gulf Coast states. The second-lagged disaster variable shows a negative or nonsignificant effect on wages. In Texas, a disaster decreased the construction wages in the disaster quarter by 2.65 percent and decreased the wages by 2.75 percent two quarters after the disaster. In Louisiana, a disaster decreased the construction wages in the disaster quarter by 4.14 percent but did not have a statistically significant effect on the wages two quarters after the disaster. In Florida, a disaster did not have a statistically significant effect on the construction wages in the disaster quarter but decreased the wages by 2.11 percent two quarters after the disaster.

Table 3-8 represents the results of the SDMs with the third-lagged disaster variable. The SDMs with the third-lagged disaster variable were implemented for the spatiotemporal analysis to examine the disaster effect on construction wages three quarters after the disaster. The disaster variable has a negative or nonsignificant effect on the construction wages in the disaster quarter in the three Gulf Coast states. The third-lagged disaster variable shows a nonsignificant effect on wages in all three states. It can be implied that a disaster occurrence does not have a statistically significant impact on the construction wages three quarters after the disaster in Texas, Louisiana, and Florida.

Table 3-8. Direct, Indirect, and Total Effects from Spatial Durbin Models with Third Lagged Disaster Variable (Imputed Datasets)

VARIABLES			THIRD-LAGGED DISASTER	DISASTER	EMPLOYMENT	ESTABLISHMENT COUNT
TX	Main		0.00622 (0.00884)	-0.0212* (0.0118)	0.0196*** (0.00383)	0.0146 (0.00958)
	SR	Direct	0.00457 (0.00823)	-0.0200* (0.0107)	0.0205*** (0.00383)	0.0127 (0.00985)
		Indirect	-0.0253 (0.0210)	0.00301 (0.0254)	0.0177 (0.0125)	-0.0376 (0.0385)
		Total	-0.0207 (0.0206)	-0.0170 (0.0229)	0.0382*** (0.0142)	-0.0249 (0.0427)
	LR	Direct	0.00564 (0.0124)	-0.0306* (0.0158)	0.0325*** (0.00611)	0.0175 (0.0160)
		Indirect	-0.0483 (0.0413)	-0.00433 (0.0488)	0.0459* (0.0253)	-0.0690 (0.0796)
		Total	-0.0426 (0.0426)	-0.0349 (0.0471)	0.0784*** (0.0287)	-0.0515 (0.0886)
LA	Main		0.00514 (0.0186)	-0.0406*** (0.0144)	0.0350* (0.0185)	0.0926 (0.104)
	SR	Direct	0.00501 (0.0172)	-0.0370*** (0.0135)	0.0364** (0.0184)	0.111 (0.105)
		Indirect	0.0151 (0.0359)	0.0684*** (0.0258)	0.0337* (0.0191)	0.458*** (0.139)
		Total	0.0201	0.0314	0.0701**	0.569***

			(0.0304)	(0.0229)	(0.0306)	(0.177)
	LR	**Direct**	0.00692 (0.0226)	-0.0481*** (0.0178)	0.0490** (0.0246)	0.156 (0.140)
	LR	**Indirect**	0.0219 (0.0501)	0.0933*** (0.0360)	0.0516* (0.0281)	0.660*** (0.199)
	LR	**Total**	0.0288 (0.0438)	0.0452 (0.0330)	0.101** (0.0442)	0.816*** (0.256)
FL	**Main**		-0.00646 (0.00729)	0.00541 (0.00688)	0.159** (0.0732)	-0.0319 (0.0897)
FL	**SR**	**Direct**	-0.00851 (0.00652)	0.00879 (0.00640)	0.161** (0.0767)	-0.0361 (0.0867)
FL	**SR**	**Indirect**	-0.0226** (0.0105)	0.0342*** (0.0132)	-0.0124 (0.0720)	-0.0290 (0.124)
FL	**SR**	**Total**	-0.0311*** (0.00844)	0.0430*** (0.0137)	0.149 (0.141)	-0.0651 (0.180)
FL	**LR**	**Direct**	-0.0122 (0.00826)	0.0131 (0.00831)	0.210** (0.103)	-0.0484 (0.116)
FL	**LR**	**Indirect**	-0.0402** (0.0161)	0.0601** (0.0239)	0.0385 (0.143)	-0.0588 (0.222)
FL	**LR**	**Total**	-0.0524*** (0.0144)	0.0732*** (0.0256)	0.249 (0.238)	-0.107 (0.306)

Notes: Standard errors in parentheses;
SR denotes 'Short-run' effects and LR denotes 'Long-run' effects.
*** p<0.01, ** p<0.05, * p<0.1

3.3. **DISCUSSIONS OF RESULTS**

The current research investigated the spatiotemporal effects of a disaster on construction wages in three Gulf Coast states to understand the quantitative dynamics of demand surge in the post-disaster construction labor market. The spatiotemporal effect of a disaster on construction wages changed over time after the disaster. The disaster had a negative or nonsignificant effect on the construction wages in the disaster quarter when the disaster struck communities. However, the disaster increased construction wages one quarter after the disaster in all three Gulf Coast states. The disaster effect on the wages two quarters after the disaster was found to be negative or nonsignificant, varying across states. The disaster did not have a statistically significant effect on wages three quarters after the disaster. This lagged effect of a disaster on construction wages aligns with the findings in the previous studies. Kajitani and Tatano (2018) reported that price increases occurred four months after the disaster, the 2011 Great East Japan Earthquake. Hallegatte et al. (2011) found that the production capacity of the overall economic system was damaged immediately after a disaster and the number of construction jobs started to increase three months after the disaster.

Table 3-9 summarizes the disaster effects on construction wages over time after the disaster in Texas, Louisiana, and Florida. The construction wages one quarter after a disaster in the disaster-affected counties are higher than the wages in the non-disaster-affected counties by 4.41 percent, 4.69 percent, and 1.79 percent in Texas, Louisiana, and Florida, respectively.

Table 3-9. The disaster effects on construction wages over time

Disaster effect	***Wages in the disaster quarter***	***Wages 1Q after***	***Wages 2Q after***	***Wages 3Q after***
Texas	-2.59%**	4.41%***	-2.75%**	0.62%
Louisiana	-4.02%***	4.69%**	-1.32%	0.51%
Florida	0.21%	1.79%***	-2.11%***	-0.65%

*** p<0.01, ** p<0.05, * p<0.1

Figure 3-3 illustrates a consistent pattern of spatiotemporal dynamic effects of a disaster on construction wages in Texas, Louisiana, and Florida. The disaster increases construction wages one quarter after the disaster in all three states. The disaster effect on wages became nonsignificant three quarters after the disaster, implying that the post-disaster construction wages were not statistically significantly affected anymore by the disaster (Lima & Barbosa, 2019).

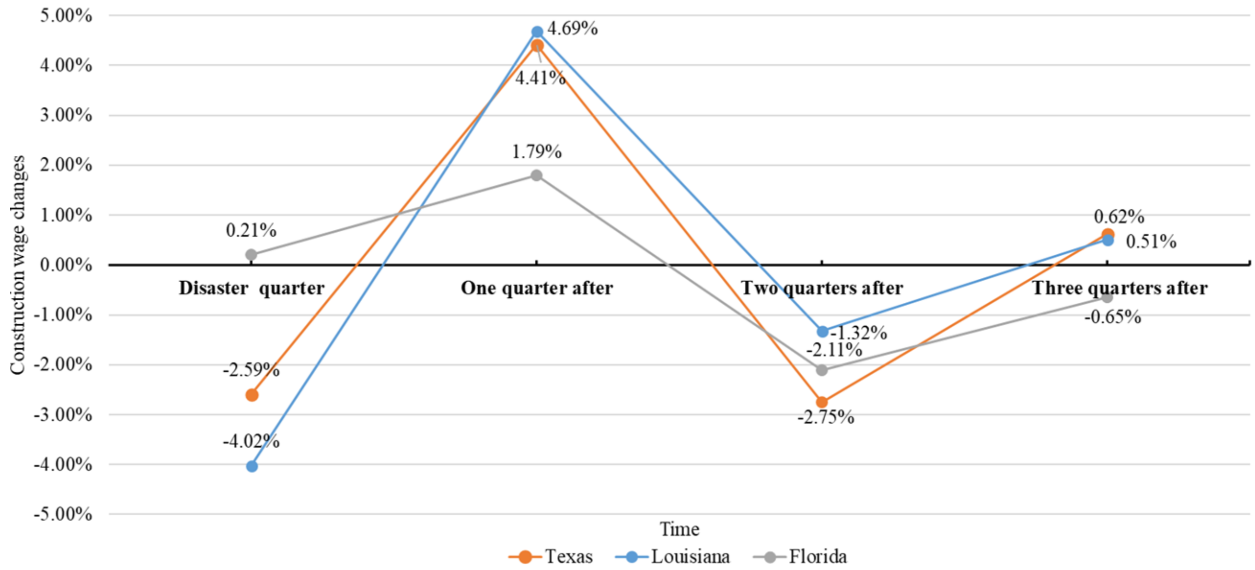


Figure 3-3. The spatiotemporal dynamic effects of a disaster on construction wages

The spatiotemporal analysis using dynamic SDMs exploits the spatial dependencies among counties and further estimates the short-run direct, short-run indirect, long-run direct, and long-run indirect effects of a disaster on construction wages (Table 3-5). The positive effect of a disaster on construction wages in Texas (i.e., 4.41 percent increase in wages) can be attributable to the direct and indirect spillover effects in the short-run and long-run. The construction wage inflation one quarter after the disaster in the disaster-affected counties in Florida was also influenced by the positive direct and indirect spillover effects in the short-run and long-run. The disaster increased the construction wages not only in the disaster-affected counties but also in the neighboring counties of the disaster-affected counties one quarter after the disaster. The positive direct and indirect spillover effects of a disaster on wages align with the previous findings in disaster studies (Fu & Gregory, 2019; Tran & Wilson, 2022; Zeenat Fouzia et al., 2020). The demand surge for reconstruction resources inflates the prices of reconstruction resources not only in the disaster-affected counties but also in the neighboring counties of the disaster-affected counties (Ahmadi & Shahandashti, 2020).

The disaster in Louisiana yielded 4.69 percent higher construction wages in the disaster-affected counties than in the non-disaster-affected counties one quarter after the disaster. While the direct effect of a disaster in Louisiana increased the construction wages one quarter after the disaster, the indirect spillover effect of a disaster decreased the wages both in the short-run and long-run. It indicates that the disaster in county *i* in Louisiana directly increased the construction wages in county *i* but the disaster in county *j* which is adjacent to county *i* decreased the construction wages in county *i* one quarter after the disaster. This negative indirect spillover effect of a disaster has been discussed in previous studies (Belasen & Polachek, 2009; Hornbeck & Keniston, 2017; Kellenberg & Mobarak, 2011; Tran & Wilson, 2022; Zeenat Fouzia et al., 2020). Neighboring counties of the disaster-affected counties suffered from the influx of workers and experienced a decrease in earnings of 4.51 percent compared with directly affected counties (Belasen & Polachek, 2009). Tran and Wilson (2022) found that the longer-run local impact of a disaster on income per capita in the area directly hit by a disaster is positive, while the longer-run impact for the broader region appears to be negative. Also, the spatial and temporal transmission of the disaster effects varies across counties and types of disasters (Zeenat Fouzia et al., 2020).

CHAPTER 4 EVALUATING THE IMPACTS OF ANTI-PRICE GOUGING LAW ON POST-DISASTER RECOVERY

Disaster policies are closely related to the post-disaster recovery process. Disaster policies can have a positive or negative impact on the recovery process. Despite the significance of understanding the impacts of disaster policies in the recovery process, the impacts of disaster policies have not been fully understood with empirical evidence. This chapter proposes to evaluate the impacts of anti-price gouging law on post-disaster recovery using panel data models with DID approach.

4.1. **THE IMPACT OF ANTI-PRICE GOUGING LAW ON HOUSING RECOVERY SPEED**

In the wake of a disaster, the price of essential goods and services including reconstruction materials and labor sharply increases. This price inflation generally evokes emotional and reactive outrage from people. Stores and companies that increase their prices during a time of emergency are often blamed as "price gougers" who enrich themselves at the expense of needy people with opportunistic pricing. Price gouging refers to when sellers and supply companies take advantage of spikes in demand by charging exorbitant prices for necessities. Thirty-seven states out of fifty in the U.S. have legislation that regulates price gouging regarded as an unfair or deceptive trade practice during a time of disaster or emergency.

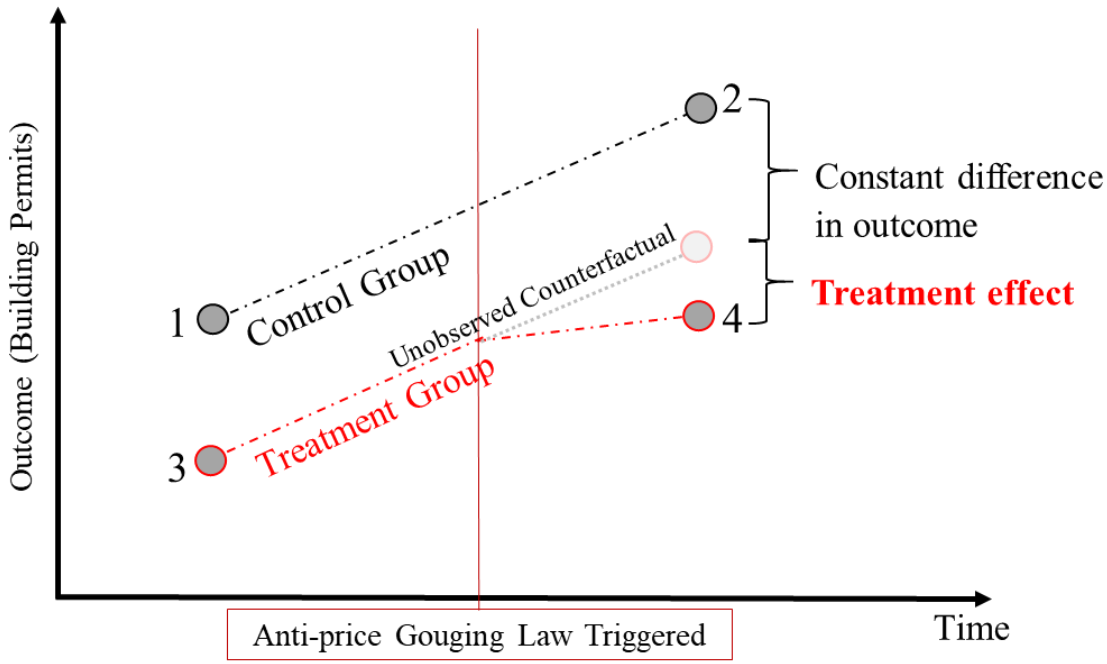
Consumers, academics, and practitioners have mixed opinions about the effectiveness and fairness of this anti-price gouging law. Existing studies have discussed the effect of anti-price gouging laws on post-disaster recovery. However, most focus on the effect of general price control qualitatively and theoretically. The study of this section aims to empirically examine the effect of the anti-price gouging law on the speed of reconstruction in Virginia and Maryland in the aftermath of Hurricane Sandy. Difference-in-differences (DID) approach was implemented to estimate the effect of the anti-price gouging law on post-disaster reconstruction speed. The DID estimators were employed to compare the changes in the number of building permits in Virginia counties under the state-level anti-price gouging law relative to the number in Maryland counties not under the anti-price gouging law, controlling for time-invariant county-specific heterogeneities.

4.1.1. Methodology

4.1.1.1. Difference-in-differences (DID) Approach

The difference-in-differences (DID) approach investigates whether an intervention influences an outcome over time by comparing observed differences in a case sample that receives the intervention with observed differences in a control sample that does not (Fredriksson & Oliveira, 2019). In other words, the DID approach analyzes whether a hypothesized treatment causes a difference in an outcome over a difference in time (Heckert & Mennis, 2012). This DID approach enables a one-step analysis by isolating and controlling for any difference that is not attributable to the treatment based on the assumption that the control and treatment groups differ similarly systematically over the two periods (Athey & Imbens, 2006; Card & Krueger, 1993; Kiel & McClain, 1995). The DID approach can directly measure the effect of a policy intervention by estimating the effects both before and after the intervention at the same site in one stage instead of quantifying and modeling the differences between sites in two stages (Davis et al., 2023; Kim & Shahandashti, 2022a). Therefore, the DID approach allows us to reduce errors or bias in examining the effect of an intervention by decreasing the complexity of the model specification (Mohan et al., 2020; Vella & Verbeek, 1999).

Figure 4-1 represents the difference-in-differences (DID) framework to estimate the effect of the anti-price gouging (APG) law on the number of building permits.



A control group and a treatment group are defined as:

1. The control group (MD counties) before the disaster
2. The control group (MD counties) after the disaster
3. The treatment group (VA counties) before the disaster
4. The treatment group (VA counties) after the disaster

Figure 4-1. Difference-in-differences framework for estimating the effect of the anti-price gouging law on building permits

The DID approach quantifies the effect of the intervention by comparing the changes in the outcomes from one time moment (before the disaster) to another time moment (after the disaster) between the treatment and control groups. The treatment effect represented in Figure 1 is estimated by the difference between the observed number of building permits and the unobserved counterfactual trend in the treatment group. The unobserved counterfactual trend indicates the number of building permits in the treatment group in the absence of the APG law triggered.

4.1.1.2. Data Collection

Building permit data are frequently utilized to estimate the speed of post-disaster reconstruction as local statistics on new privately-owned residential construction (Arneson et al., 2020; Stevenson et al., 2010). Building permits are issued monthly to authorize the new construction of privately-owned housing, counting over 98 percent of all privately-owned residential building constructions (US Census Bureau, 2012). The current study collected the number of total housing units newly constructed and authorized by building permits one year before and after Hurricane Sandy struck Virginia and Maryland counties on October 26, 2012. Table 4-1 summarizes the data collection used in this study. The determinants of building permits were included in the analysis to control for confounding effects. Population, housing units, median household income, and the percentages of White, Black, and Hispanic populations were considered to monitor the changes in building permits (Lévêque, 2020; Stevenson et al., 2010). The poverty rates were also discussed as a predictor of building permit issuances (Kim & Shahandashti, 2022a; Kitchens & Wallace, 2022; Lusugga Kironde, 2006; Peacock et al., 2022).

Table 4-1. Data Collection

Data	***Frequency***	***Level***	***Period***	***Source***
Dependent variable				
Building Permits	Monthly	County-level	Nov 2011 – Oct 2013	Census Bureau
Independent variable				
Anti-Price Gouging Law	-	County-level	Nov 2011 – Oct 2013	State Legislature
Disaster Occurrence	Daily	County-level	Nov 1, 2011 – Oct 31, 2013	FEMA
Control variables				
Population	Yearly	County-level	2011 - 2013	Census Bureau
Poverty Rates	Yearly	County-level	2011 - 2013	Census Bureau

Housing Units	Yearly	County-level	2011 - 2013	Census Bureau
Median Income	Yearly	County-level	2011 - 2013	Census Bureau
%White Population	Yearly	County-level	2011 - 2013	Census Bureau
%Black Population	Yearly	County-level	2011 - 2013	Census Bureau
%Hispanic Population	Yearly	County-level	2011 - 2013	Census Bureau

Table 4-2 shows the sample design of this research and descriptive statistics of the building permit variable. Seventy-six counties in Virginia and fourteen counties in Maryland were selected as disaster-affected counties since those counties received federal assistance from FEMA in the Hurricane Sandy aftermath. The building permit data in those counties were collected from November 2011 (one year before Hurricane Sandy) to October 2013 (one year after Hurricane Sandy). The number of total building permit issuances was acquired from U.S. Census Bureau to enumerate newly constructed housing units.

Table 4-2. Sample Design and Descriptive Statistics

Descriptive statistics	***All***	***VA***	***MD***
Number of counties in the sample data	90	76	14
Number of the pre-disaster sample data	1,080	912	168
Number of the post-disaster sample data	1,080	912	168
Mean (Units):			
Pre-disaster building permit counts	32.9	25.38	73.70
Post-disaster building permit counts	41.04	30.69	97.26

4.1.1.3. Non-Parametric DID Approach

DID methods can be implemented using two different approaches: non-parametric and parametric approaches (Callaway & Sant'Anna, 2021; Wooldridge, 2007). The non-parametric approach estimates the treatment effect as the difference in the changes in the outcome (i.e., monthly building permits) from the pre-disaster level to the post-disaster level between the control and treatment groups. The non-parametric approach is expressed in Eq. 4-1.

$$\tau = (BP_{AT} - BP_{AC}) - (BP_{BT} - BP_{BC}) \qquad \text{Eq. 4-1}$$

where τ is the treatment effect; BP_{AT} is the observed monthly building permits in the treatment group (i.e., disaster-affected counties in Virginia) after the disaster; BP_{AC} is the observed monthly building permits in the control group (i.e., disaster-affected counties in Maryland) after the disaster; BP_{BT} is the observed monthly building permits in the treatment group before the disaster; and BP_{BC} is the observed monthly building permits in the control group before the disaster.

4.1.1.4. Parametric DID Approach

The parametric DID approach assumes a linear regression model with a response variable (i.e., building permits) and explanatory variables including dummy variables that indicate the treatment status (Kaneko et al., 2019). Pooled OLS regression, fixed-effects model, and random-effects model were employed as a parametric DID approach to examine the effect of an APG law on post-disaster reconstruction speed in this study.

The pooled OLS regression with a DID specification is represented by Eq. 4-2.

$$BP_{it} = \beta_0 + \beta_1 APG_i + \beta_2 DIS_{it} + \beta_3 APG_i DIS_{it} + \beta_4 log(POP)_{it} + \beta_5 POV_{it} + \beta_6 BLK_{it} + \beta_7 HISP_{it} + \varepsilon_{it} \quad \text{Eq. 4-2}$$

where BP_{it} is the number of building permits in a county i at time t; APG_i is a dummy variable set to 1 if a county i is located in Virginia with anti-price gouging law and 0 if a county i is located in Maryland without anti-price gouging law; DIS_{it} is a dummy variable set to 1 if time t is post-disaster for a county i and 0 if time t is pre-disaster for a county i; APG_iDIS_{it} (i.e., the interaction term defined as APG_i times DIS_{it}) is a dummy variable set to 1 if a county i is in Virginia state and time t is post-disaster and 0 otherwise; $log(POP)_{it}$ is a logarithmic form of the population in county i at time t; POV_{it} is poverty rates in county i at time t; BLK_{it} is the percentage of the Black population in county i at time t; $HISP_{it}$ is the percentage of the Hispanic population in county i at time t; ε_{it} is an error term; and β terms are the coefficients to be estimated by the model.

A significant coefficient of APG_iDIS_{it} (β_3) as known as a DID estimator indicates that the effect of a disaster on the number of building permits is moderated by whether a county i is located in Virginia with the anti-price gouging law or in Maryland without the anti-price gouging law.

Although new housing construction authorized by building permits depends on several factors including geographical locations, policies, land use, regulations, and urban characteristics (Caldera & Johansson, 2013; Saiz, 2010), the abovementioned pooled OLS regression is too simple to control for the effects of other omitted variables that can systematically affect the number of building permits. Therefore, the panel data models were used to control for the unobserved individual county-specific effects on the number of building permits. Eq. 4-3 expresses the panel data model to examine the effect of APG legislation on the number of building permits accounting for the county-specific fixed effects (α_i). The panel data model to examine the effect of APG legislation on the number of building permits accounting for the county-specific fixed effects (α_i) is represented by Eq. 4-3. Time-varying heterogenous county-level control variables were selected based on the literature review and the results of multicollinearity test.

$$BP_{it} = \delta_0 + \beta_1 APG_i + \beta_2 DIS_{it} + \beta_3 APG_i DIS_{it} + \beta_4 log(POP)_{it} + \beta_5 POV_{it} + \beta_6 BLK_{it} + \beta_7 HISP_{it} + \alpha_i + \varepsilon_{it} \qquad \text{Eq. 4-3}$$

where BP_{it} is the number of building permits in a county i at time t; APG_i is a dummy variable set to 1 if a county i is located in Virginia with the anti-price gouging law and 0 if a county i is located in Maryland without the anti-price gouging law; DIS_{it} is a dummy variable set to 1 if time t is post-disaster for a county i and 0 if time t is pre-disaster for a county i; $APG_i DIS_{it}$ is a dummy variable set to 1 if a county i is in Virginia state and time t is post-disaster and 0 otherwise; $log(POP)_{it}$ is a logarithmic form of the population in county i at time t; POV_{it} is poverty rates in county i at time t; BLK_{it} is the percentage of the Black population in county i at time t; $HISP_{it}$ is the percentage of the Hispanic population in county i at time t; ε_{it} is an error term; α_i is individual effects to account for time-invariant county-specific heterogeneities; and β terms are the coefficients to be estimated by the model.

Two panel data models including fixed-effects (FE) and random-effects (RE) models were utilized in this current study. The data were preprocessed to make a balanced sample panel data before establishing FE and RE models. FE and RE models have different assumptions on the omitted individual effects (α_i) which are expressed in Eq. 4-4.

$$\alpha_i = w_i\delta + z_i\lambda \qquad \text{Eq. 4-4}$$

where w_i represents all the unobserved county-level effects correlated with explanatory variables, z_i represents all the unobserved county-level effects uncorrelated with explanatory variables, and δ and λ are unknown parameters.

The RE model assumes the exogeneity of the unobserved county-level effects indicating that the unobserved individual effects are not correlated with explanatory variables. The assumption of the RE model is that the covariance of the unobserved individual effects and the explanatory variable is zero (i.e., cov(α_i, X_{it}) = 0). On the other hand, the FE model assumes the endogeneity of the county-level effects indicating that the unobserved county-level effects (α_i) are correlated with explanatory variables (i.e., cov(α_i, X_{it}) $\neq$ 0).

4.1.1.5. Model Selection using Breusch-Pagan and Hausman tests

Figure 4-2 illustrates the framework of the DID parametric model selection process.

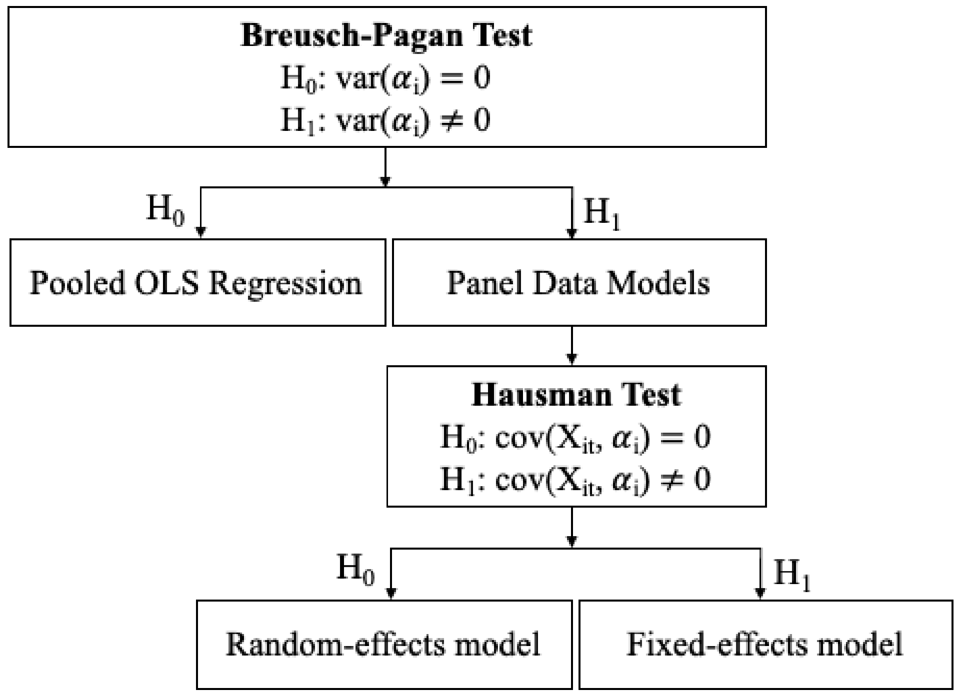


Figure 4-2. Framework for DID parametric model selection

Two specification tests (Breusch-Pagan and Hausman tests) were used to identify the appropriate method for the data. These tests help us to assess whether the unobserved time-invariant county-specific effects (α_i) exist and are correlated with the independent variables. To determine whether the unobserved time-invariant county-specific effects (α_i) exist, the Lagrange multiplier test proposed by Breusch and Pagan (1980) was used. The null hypothesis in this test is that there are no unobserved time-invariant county-specific effects (i.e., var(α_i) is zero). A failure to reject the null hypothesis would support using the OLS regression. Otherwise, the Hausman (1978) test needs to be conducted to choose between fixed effects and random effects models. The null hypothesis in this Hausman test is that the independent variables and the unobserved time-invariant county-specific effects (α_i) are not correlated. The fixed effects model is chosen instead of the random effects model if the null hypothesis is rejected. When the unobserved time-invariant county-specific effects (α_i) are correlated with the independent variables, the fixed effects model is preferred as it will yield unbiased and consistent estimates. On the other hand, the random effects model is preferred if the null hypothesis is not rejected. In this case, the random effects will produce both consistent and efficient estimates. Regardless, the random effects estimator allows us to control for the within-county correlation in the error term, and thus yields more efficient estimates (Bell et al., 2019). It also yields consistent estimates if the independent variables are not correlated with the unobserved heterogeneity. However, the results from the random effects estimator suffer from omitted variable bias if the independent variables are correlated with the time-invariant unobservable factors.

4.1.2. Results

Both non-parametric and parametric approaches of DID were employed to examine the effect of the anti-price gouging law that regulates the reconstruction market price on monthly building permits in Virginia and Maryland after Hurricane Sandy.

4.1.2.1. Results of Non-parametric DID Analysis

Table 4-3 shows the non-parametric DID analysis results on the anti-price gouging law's effect on post-disaster monthly building permit issuances that can represent the reconstruction speed. Virginia counties issued 25.38 building permits monthly on average, while Maryland counties issued 73.69 permits before Hurricane Sandy. After Hurricane Sandy struck both Virginia and Maryland, the average number of building permits in Virginia counties increased by 5.3 units monthly, while the number in Maryland counties increased by 23.56 units monthly in the aftermath. The treatment effect (τ) of the anti-price gouging law triggered during Hurricane Sandy was calculated as -18.26 units using Eq. 4-1 and -17.88 units when controlling for the confounding effects. The results of non-parametric DID analysis show that the anti-price gouging law decreased the building permit issuances by 17.88 units monthly during the post-disaster situation. The anti-price gouging law that governs the reconstruction market can negatively affect the speed of post-disaster recovery in Virginia relative to Maryland. This finding is consistent with many economists' expectations that price control under the anti-price gouging law can impede the speed of post-disaster reconstruction (Culpepper & Block, 2008; Giberson, 2011; Shannon, 1989; Wilson, 2014; Zwolinski, 2008).

Table 4-3. Results of the Non-Parametric DID Analysis

Monthly Building Permits	***All***	***Before Sandy***	***After Sandy***	***DID***	***DID with controls***
VA (Treatment)	28.04	25.38	30.68	5.3 (3.01)	5.25*** (1.89)
MD (Control)	85.48	73.69	97.26	23.56** (11.01)	21.9** (8.65)
Change in monthly BP (τ)	-57.44	-48.31	-66.58	-18.26** (8.47)	-17.88** (8.94)

Note: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.1.2.2. Results of Parametric DID Analysis

Table 4-4 summarizes the results of parametric DID analyses using fixed effects and random effects models. The treatment effect was measured to be negative by the parameter of APG_iDIS_{it}. The effect of the anti-price gouging law was estimated as 18 units decrease monthly in the number of building permits in post-disaster situations according to the results of both the fixed effects and random effects models. This indicates that the monthly building permits decreased by 18 units in Virginia counties where the anti-price gouging law was triggered in the wake of Hurricane Sandy compared to Maryland counties without the anti-price gouging law in the post-disaster recovery process.

The disaster shows a statistically significant positive effect on the number of monthly building permits regardless of the existence of the anti-price gouging law. The disaster occurrence increases the number of monthly building permits by approximately 15 units. This result seems plausible because housing reconstruction and repair projects are largely and quickly undertaken in the aftermath of a disaster (Dikmen & Elias-Ozkan, 2016). The number of monthly building permits increases as the population increase. This positive relationship between monthly building permits and the population is consistent with the findings in the previous studies (Carlucci et al., 2018; McDonald & McMillen, 2000; McGibany, 1991).

Table 4-4. Results of the Parametric DID analyses

Data	***Monthly Building Permits (Units)***	
Variables	**FE (Fixed effects)**	**RE (Random effects)**
APG_i	-	2.505
		(13.45)
DIS_{it}	15.36^{b}	15.65^{b}
	(6.416)	(6.384)
APG_iDIS_{it}	-18.04^{a}	-18.05^{a}
	(5.76)	(5.73)

$log(POP)_{it}$	442.8[b]	28.60[a]
	(172.7)	(3.945)
POV_{it}	0.777	-0.924
	(1.334)	(0.739)
BLK_{it}	622.0	3.619
	(770.8)	(29.36)
$HISP_{it}$	-327.7	123.2[c]
	(973.0)	(73.69)
Intercept	-	-283.5[a]
		(48.9)
Time dummy	Yes	Yes
Observations	2,160	2,160

Note: Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.1.2.3. Results of the Breusch-Pagan Tests

The null hypothesis of no individual effects was rejected according to the results of the Breusch-Pagan tests. In other words, statistically significant individual heterogeneity exists among the county-level monthly building permit data. Table 4-5 summarizes the results of the Breusch-Pagan test to choose between the pooled OLS regression and the fixed effects model. The null hypothesis of no individual fixed effects was rejected at the 1% significance level. Therefore, the fixed effects model is more appropriate to control for the county-specific effects than the pooled OLS regression.

Table 4-5. Results of the Breusch-Pagan Test (Pooled OLS vs. Fixed Effects)

Monthly Building Permits	***F-statistic***	***degree of freedom 1***	***degree of freedom 2***	***p-value***
F-test for individual effects	15.248	88	2042	0.00

Table 4-6 shows the results of the Breusch-Pagan test to choose between the pooled OLS regression and the random effects model. The null hypothesis of no individual random effects was rejected at the 1% significance level. Therefore, the random effects model is more appropriate to control for the county-specific effects than the pooled OLS regression. Both results of the Breusch-Pagan tests in Tables 4-5 and 4-6 indicate that county-level heterogeneity exists, and thus the results from pooled OLS will be biased and inconsistent.

Table 4-6. Results of the Breusch-Pagan Test (Pooled OLS vs. Random Effects)

Monthly Building Permits	***chi-square statistic***	***degree of freedom***	***p-value***
Lagrange Multiplier test for balanced panels	3346.1	1	0.00

4.1.2.4. Results of the Hausman Test

The Hausman test failed to reject the null hypothesis that the independent variables and fixed effects (α_i) are not correlated. Given the test results reported in Table 4-7, the null hypothesis of the Hausman test was not rejected at the 5% significance level, indicating that the random effects model is likely more appropriate than the fixed effects model for the data.

Table 4-7. Results of the Hausman Test

Hausman Test	***chi-square statistic***	***p-value***
fixed effects vs. random effects	9.969	0.126

4.1.3. Discussions of Results

The anti-price gouging law triggered by the declaration of a state of emergency or disaster enforces civil or criminal penalties for price gouging violations that happened during a disaster. The effect of the anti-price gouging law on post-disaster reconstruction speed was estimated using panel data models (fixed effects and random effects) with a DID specification. The reconstruction speed was quantified by the number of monthly building permits that authorize the new construction of housing units. The number of monthly building permits was compared between Virginia counties with the anti-price gouging law enforcement and Maryland counties without the anti-price gouging law enforcement to examine the effect of the anti-price gouging law in the aftermath of Hurricane Sandy using the DID approach. The DID estimators present evidence that the number of building permits that authorize new housing construction decreases by 18 units monthly in Virginia counties where the anti-price gouging law was triggered relative to Maryland counties without anti-price gouging law in the aftermath of Hurricane Sandy. The change in the number of monthly building permits in both Virginia and Maryland counties after Hurricane Sandy is a 15 increase in new housing units. Hurricane Sandy increased the monthly number of new housing units authorized by monthly building permits by 15 units in both Virginia and Maryland. This result is consistent with the findings of existing disaster studies that reconstruction activities largely increase following a disaster (Celentano et al., 2019; Dikmen & Elias-Ozkan, 2016).

The results of the Breusch-Pagan tests show unobserved time-invariant county-specific effects (α_i) exist in the monthly building permit data. Therefore, panel data models, including fixed effects and random effects models, are recommended to include and control for those county-specific effects (α_i). Then, the Hausman test was conducted to choose between fixed effects and random effects models. Since the null hypothesis of the Hausman test was not rejected at the 5% significance level, the random effects model was preferred as it produces both consistent and efficient estimates. The random effects estimator enables us to control for the within-county correlation in the error term and thus yields more efficient estimates. The random effects estimator also yields consistent estimates if the independent variables are not correlated with the unobserved heterogeneity.

The random effects estimator can be helpful when the entities are randomly assigned to the treatment and control groups. In this case, the correlation between the independent variables and the unobserved time-invariant variables is likely insignificant, validating the use of random effects. This is likely relevant to disaster treatment in the current study. Tofighi et al. (2016) reported that the occurrence of a disaster followed an inherently random process. Note also that the fixed effects model eliminates the cross-section variation in the explanatory variables, and only uses the within-county variation over time, thus relying on enough within-county variation in the variables. The results from both fixed effects and random effects estimators are consistent. There is a significantly negative effect of the anti-price gouging law on monthly building permits regardless of the methods used.

Some caveats are made for policymakers, decision-makers, and disaster recovery practitioners. First, empirical evidence was found suggesting that the free market be allowed to accelerate reconstruction speed via the invisible hand without price control. It can be implied that people's emotional denunciation and legal accusations against the post-disaster price escalation, often referred to as "price gouging," did not help to expedite the reconstruction process in the aftermath of a disaster but rather decelerated the speed of reconstruction. Second, because of the nonnegligible individual county-specific heterogeneity in the housing reconstruction process, it is recommended to implement panel data models to include and control for these county-specific effects on the post-disaster reconstruction process. Last but not least, the unobservable county-specific heterogeneity is neither related to the enforcement of anti-price gouging law nor the occurrence of Hurricane Sandy according to the results of the Hausman test. This seems plausible because the anti-price gouging law is a state-level price control that does not rely on county-specific factors but affects all the counties in the state equally. The occurrence of a disaster is considered to follow an inherently random process (Tofighi et al., 2016) and is unrelated to county-specific heterogeneity.

4.2. **THE IMPACTS OF ANTI-PRICE GOUGING LAW ON RECONSTRUCTION COSTS**

The anti-price gouging law is enforced to control reconstruction labor and material costs in the aftermath of disasters. There is a controversy over the effectiveness of anti-price gouging laws. However, few studies have carefully examined the effect of anti-price gouging laws on post-disaster reconstruction costs. Particularly, no empirical evidence is found about the impact of anti-price gouging law on post-disaster reconstruction wages. The objective of this study is to empirically examine the effect of the anti-price gouging law on post-disaster reconstruction wages at the U.S. national level following major disasters declared by the Federal Emergency Management Agency (FEMA). Difference-in-differences (DID) approach was implemented to estimate the effect of the anti-price gouging law on post-disaster reconstruction wages. The DID estimators were employed to compare the changes in reconstruction wages in the U.S. counties under the state-level anti-price gouging law relative to the wages in the U.S. counties not under the anti-price gouging law, controlling for time-invariant county-specific heterogeneities.

4.2.1. Methodology

4.2.1.1. Data Collection

Labor costs can account for around 50 percent of the total reconstruction costs in the aftermath of disasters because construction is a highly labor-intensive industry (Barbosa et al., 2017). Post-disaster labor costs are subject to a post-disaster demand surge, inflating by approximately 10 percent (Ahmadi Esfahani & Shahandashti, 2020; Farooghi et al., 2021; Kim et al., 2022d). Therefore, construction wages are often used to estimate post-disaster reconstruction cost fluctuations (Ahmadi & Shahandashti, 2020, 2018; Farooghi et al., 2021; Kim et al., 2022d). Construction wages are published quarterly at the U.S. county-level by the U.S. Bureau of Labor Statistics. This study collected quarterly construction wages of 3,579 counties in 50 U.S. states and the District of Columbia for 10 years from 2013 to 2022. Table 4-8 summarizes the data collection used in this study. Major disasters declared by FEMA were collected for 10 years from 2013 to 2022. The number of employment and establishment counts in the U.S. construction industry were included to monitor the changes in construction wages and control for confounding effects (Barth & Dale-Olsen, 2011; Blanchflower & Oswald, 1995; Green et al., 2021).

Table 4-8. Data Collection

Data	***Frequency***	***Level***	***Period***	***Source***
Dependent variable				
Construction Wages	Quarterly	County-level	Q1 2013 – Q4 2022	Bureau of Labor Statistics
Independent variable				
Anti-Price Gouging Law	-	County-level	2013 – Oct 2022	State Legislature
Disaster Occurrence	Daily	County-level	Jan 1, 2013 – Dec 31, 2022	FEMA
Control variables				
Employment	Quarterly	County-level	Q1 2013 – Q4 2022	Bureau of Labor Statistics
Establishment Count	Quarterly	County-level	Q1 2013 – Q4 2022	Bureau of Labor Statistics

Table 4-9 shows the sample design of this research and descriptive statistics of the average weekly wages in the U.S. construction industry. Over three thousand counties in fifty-one U.S. states were covered in this study. Average weekly wages representing construction wages decreased in the quarter when a disaster occurred. This statistic aligns with the finding in previous studies that reconstruction wages would not increase until a quarter after a disaster occurred when reconstruction demand increased.

Table 4-9. Sample Design and Descriptive Statistics

Descriptive statistics	***All***	***Counties with APGL***	***Counties without APGL***
Number of states (including the District of Columbia) in the sample data	51	35	16

Number of counties in the sample data	3,579	2,943	636
Number of the pre-disaster sample data	128,144	106,296	21,848
Number of the post-disaster sample data	10,691	8,879	1,812
Mean (Dollars):			
Average weekly construction wages in the quarter that a disaster did not occur	847.59	857.91	797.35
Average weekly construction wages in the quarter that a disaster occurred	810.43	822.76	750.02

4.2.1.2. Panel Data Model with Difference-in-Differences Technique

A panel data model was employed as a parametric DID approach to evaluate the impact of an APG law on post-disaster county-level reconstruction wages in the U.S. as represented by Eq. 4-5.

$$lnWAGE_{it} = \beta_0 + \beta_1 APG_{it} DIS_{it} + \beta_2 APG_{it} + \beta_3 DIS_{it} + \beta_4 logEMP_{it} + \beta_4 logEST_{it} + \alpha_i + \alpha_t + \varepsilon_{it}$$

Eq. 4-5

where $WAGE_{it}$ is average weekly wages in the construction industry in county *i* and time t; APG_{it} is a dummy variable that is equal to one if county *i* at time *t* had an anti-price gouging state-level statute, and zero otherwise; DIS_{it} is a dummy variable that is equal to one if county *i* at time *t* experienced a major disaster declared by FEMA, and zero otherwise; EMP_{it} is the number of employees in the construction industry in county *i* and time *t*; EST_{it} is the number of establishments in the construction industry in county i and time *t*; α_i is the unobservable time-invariant county fixed-effects; α_t is the unobservable county-invariant time fixed-effects; ε_{it} is the time-varying idiosyncratic error; β_1 is the coefficient of interest to estimate the effect of a disaster on the county-level construction wages

4.2.2. Results

Table 4-10 shows the results of panel data models including pooled OLS, fixed effects, and random effects models described by Eq. 4-5. The treatment effect was measured to be negative by the parameter of $APG_{it}DIS_{it}$ according to the results of all the panel data models (i.e., pooled OLS, fixed effects, and random effects models). The anti-price gouging law triggered by FEMA's major disaster declaration has decreased county-level average weekly construction wages by 2.5 percent according to the result of the fixed effects model. This indicates that the average weekly wages decreased by 2.5 percent in the U.S. counties where the anti-price gouging law was triggered in the wake of major disasters compared to the U.S. counties without the anti-price gouging law in the post-disaster recovery process.

The disaster shows a statistically significant positive effect on the average weekly construction wags regardless of the existence of the anti-price gouging law. The disaster occurrence increases average weekly wages in the construction industry by 2.5 percent. This result seems plausible because of the increasing reconstruction demand in the aftermath of a disaster (Dikmen & Elias-Ozkan, 2016). The positive relationship between employment and wages in the construction industry was found to be statistically significant. This positive relationship between employment and construction wages is consistent with the findings in the previous studies (Barth and Dale-Olsen 2011; Blanchflower and Oswald 1995; Green et al. 2021). Establishment counts in the U.S. construction industry show a statistically significant negative relationship with average weekly construction wages. The findings in the previous studies explain that the increase in the number of establishments representing the market supply can reduce wages (Barth & Dale-Olsen, 2011; Benmelech et al., 2022).

Table 4-10. Results of the Panel Data Model Estimation

Data	***ln(Average Weekly Construction Wages)***		
Variables	**Pooled OLS**	**FE (Fixed effects)**	**RE (Random effects)**
$APG_{it}*DIS_{it}$	-0.0734***	-0.025**	-0.023**
	(0.019)	(0.011)	(0.011)
APG_{it}	-0.136***	-0.001	-0.07***
	(0.005)	(0.018)	(0.015)
DIS_{it}	0.0487***	0.024**	0.022**
	(0.018)	(0.010)	(0.010)
EMP_{it}	0.982***	0.989***	0.987***
	(0.001)	(0.001)	(0.001)
EST_{it}	-0.842***	-0.243***	-0.644***
	(0.001)	(0.010)	(0.005)
Constant	3.294***	-	2.291***
	(0.013)		(0.028)
Year_Quarter Dummies	Yes	Yes	Yes
Observations	138,835	138,835	138,835
R-squared	0.88	0.89	0.88
Number of Counties	3,579	3,579	3,579

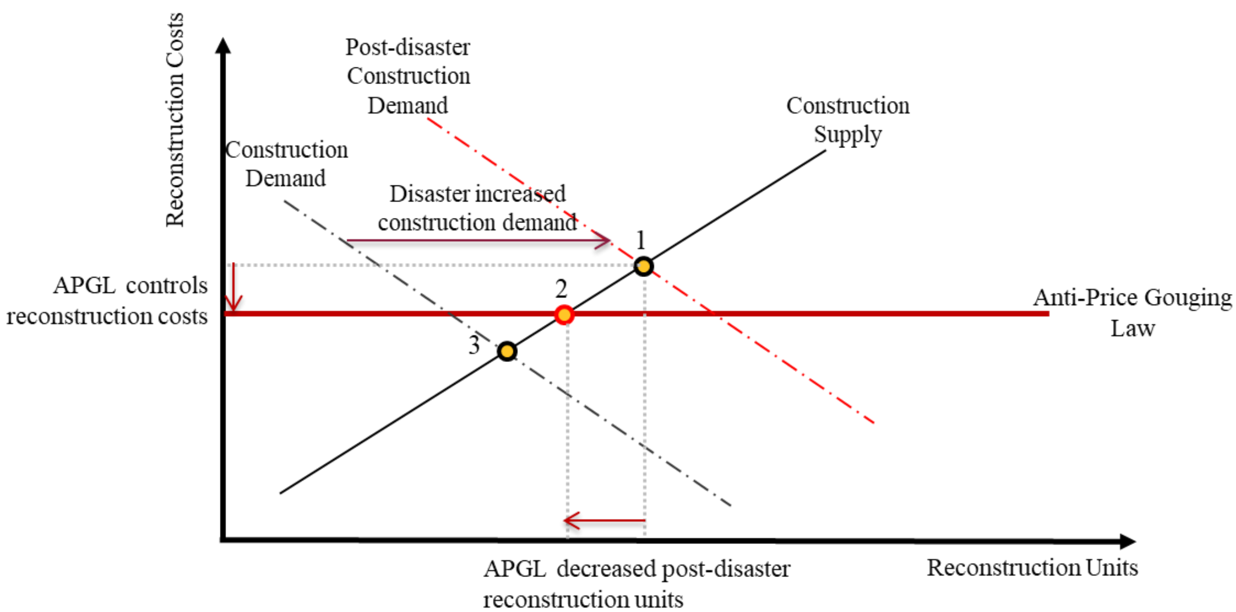
Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.2.3. Discussions of Results

The impact of the anti-price gouging law (APGL) in the post-disaster reconstruction market is illustrated in Figure 4-3. The anti-price gouging law places a price ceiling on reconstruction costs to regulate sudden cost inflation in the aftermath of disasters. Construction market equilibrium before a disaster occurs is represented by Point 3. Disaster increases construction demand, moving the downward construction demand curve to the right. Therefore, post-disaster construction market equilibrium is determined at Point 1 when there is no anti-price gouging law enforcement. In the aftermath of disasters, the U.S. counties without anti-price gouging law at Point 3 are expected to experience an increase in reconstruction costs and housing reconstruction units compared to the pre-disaster construction market equilibrium (Point 1).

However, the anti-price gouging law controls reconstruction costs by setting the maximum reconstruction cost as described by the red line in Figure 4-3. Therefore, the U.S. counties under anti-price gouging law enforcement have a post-disaster market equilibrium at Point 2. The U.S.

counties where the anti-price gouging law was triggered following a disaster experience less reconstruction cost and fewer reconstruction units than the U.S. counties without the anti-price gouging law enforcement. Shortly, anti-price gouging law enforcement can mitigate reconstruction cost inflation but also decrease reconstruction speed by regulating the free market prices in the post-disaster reconstruction market.



1. Post-disaster construction market equilibrium for the control group (i.e., counties without anti-price gouging law)
2. Post-disaster construction market equilibrium for the treatment group (i.e., counties under anti-price gouging law)
3. Pre-disaster construction market equilibrium

Figure 4-3. Economic Theoretical Explanation for the Empirical Evidence of the Anti-Price Gouging Law (APGL) Effects on the Reconstruction Process

CHAPTER 5 ASSESSING THE IMPACT OF FMCSA SAFETY REGULATION WAIVERS ON POST-DISASTER FUEL PRICE

Emergency declarations by the President, Governors of States, or the Federal Motor Carrier Safety Administration (FMCSA) trigger the temporary suspension of certain Federal safety regulations. Drivers that provide "direct assistance" to an "emergency" declared by FMCSA or a governor are exempt from applicable safety regulations such as federal Hours of Service (HOS) on their route to the emergency. Despite the significant volume of qualitative discussions on these safety regulation waivers, the effect of the waivers on the post-disaster recovery process has not been investigated quantitatively using empirical data. The objective of this research is to examine whether these waivers have any impact on the price of fuel which is an essential item for post-disaster recovery.

5.1. METHODOLOGY

5.1.1. Data Collection

The FMCSA safety regulations waivers are expected to have a positive effect on price stabilization for essential items such as fuel in the wake of disasters or emergencies (Azanza, 2017; Kingston, 2022; B. Lee, 2019; Walters et al., 2020). Table 5-1 summarizes the data collection to estimate the effect of the FMCSA safety regulation waiver on fuel prices in Southern Texas and

Louisiana in the aftermath of Hurricane Harvey. The determinants of fuel prices were included in the analysis to control for confounding effects.

Table 5-1. Data Collection

Group	***Variable***	***Definition***	***Frequency***	***Source & Unit of measure***
Policy	*WAV*	FMCSA safety regulation waiver	-	FMCSA
Disaster	*DIS*	Hurricane Harvey disaster dummy variable	-	FEMA
Natural fuel price	*FUEL*	Regional natural gas spot price indices in south Texas and Louisiana	Daily	EIA (Dollar/MMbtu)
Other energy prices	*WTI* *COAL*	Global crude oil price NYMEX coal futures	Daily Daily	EIA ($/Barrel) EIA ($/short ton)
Supply and demand	*USPROD*	U.S. Field Production of Crude Oil	Monthly	EIA (Thousand Barrels/Day)
	TXPROD	The volume of crude oil production in TX	Monthly	EIA (Thousand Barrels)
	LAPROD	The volume of crude oil production in LA	Monthly	EIA (Thousand Barrels)
	CON	The volume of natural gas consumption in the US	Weekly	EIA (Thousand Barrels/Day)
	STR	The volume of commercial gas storage on the Gulf Coast (PADD3)	Weekly	EIA (Thousand Barrels)
Weather	*HDD* *CDD*	Heating degree days Cooling degree days	Daily Daily	NOAA NOAA
Financial factors	*VIX*	CBOE (Chicago Board Options Exchange) volatility index	Daily	Federal Reserve Bank of St.Louis
	TWX	Trade-weighted U.S. dollar index	Weekly	Federal Reserve Bank of St.Louis

The data were collected one month before and after Hurricane Harvey struck Texas (TX) and Louisiana (LA). Table 5-2 shows the time windows for ‘Before Hurricane Harvey’ period and ‘Hurricane Harvey Incident’ period that includes ‘Regulation Waived’ and ‘Regulation Affected’ periods. One month of time windows before and after disasters have been used to identify and measure disaster-related economic losses and construction cost changes (Hallegatte & Vogt-Schilb, 2019; Khodahemmati & Shahandashti, 2020; Olsen & Porter, 2011). A longer window will likely lead to spurious relationships due to various unobservable factors.

Table 5-2. Time Windows

Region	***Before Hurricane Harvey***	***Hurricane Harvey Incident Period***	***Regulation Waived***	***Regulation Affected***
TX	July 23-Aug 22	Aug 23 - Sep 15	Aug 25 - Sep 15	Aug 23 - Aug 24, Sep 16 - Oct 24
LA	July 23-Aug 27	Aug 27 - Sep 10	Aug 25 - Sep 10	Sep 11 - Oct 24

The ‘Hurricane Harvey Incident Period’ in Table 4-5 was acquired from Federal Emergency Management Agency (FEMA) database. The ‘Before Hurricane Harvey’ period started one month before the ‘Hurricane incident period’ and lasted up to one day before the ‘Hurricane incident period.’ The ‘After Hurricane Harvey’ period started on the first day of the ‘Hurricane incident period’ and lasted up to one month after the ‘Hurricane Incident period’ ended, including the ‘Regulation waived’ and ‘Regulation affected’ periods. The ‘Regulation waived’ period was acquired from the FMCSA database.

Figure 5-1 illustrates regional fuel price changes in south Texas and Louisiana before and after Hurricane Harvey. The red-dotted box indicates the FMCSA safety regulation waiver period after Hurricane Harvey struck Texas and Louisiana.

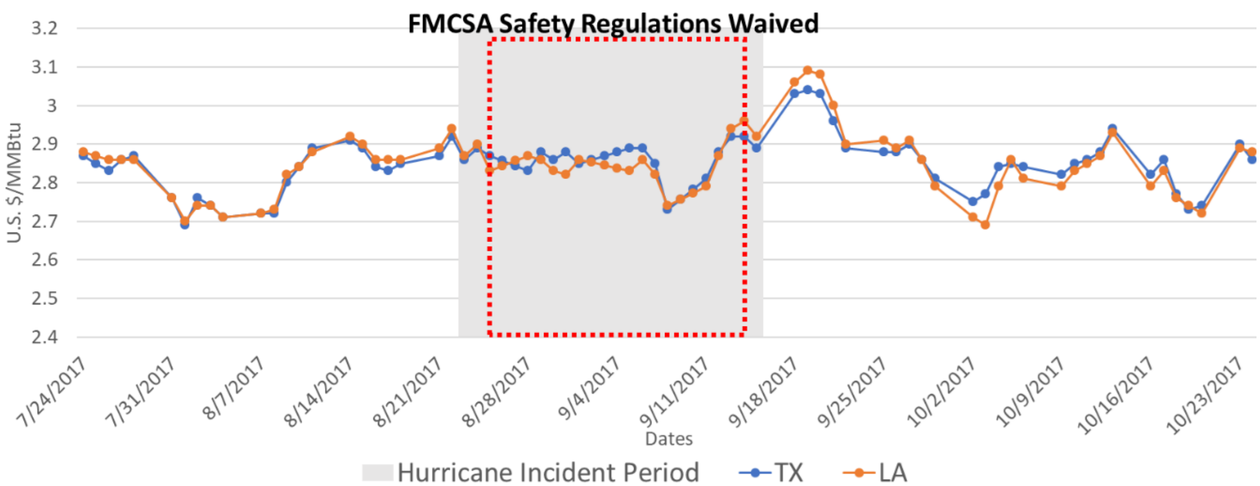


Figure 5-1. Regional Fuel Price Changes in South Texas and Louisiana

Table 5-3 shows the summary statistics of the variables for South Texas and Louisiana datasets. The daily data includes *WAV*, *DIS*, *FUEL*, *WTI*, *COAL*, *HDD*, *CDD*, and *VIX*. Natural gas production data, which includes variables *USPROD*, *TXPROD*, and *LAPROD*, is published monthly, while the gas consumption *(CON)*, storage *(STR*), and trade-weighted U.S. dollar *(TWX)* index data are published weekly.

Table 5-3. Sample Design and Descriptive Statistics

Variables	***TX (85 days of Time Window)***				***LA (80 days of Time Window)***			
	Avg	**Min**	**Max**	**Sum**	**Avg**	**Min**	**Max**	**Sum**
WAV (days)	0.26	0	1	22	0.21	0	1	17
DIS (days)	0.64	0	1	54	0.56	0	1	45
FUEL ($/MMbtu)	2.86	2.69	3.04	243.24	2.88	2.7	3.14	230.66
WTI ($/Barrel)	49.08	45.96	52.14	4,171.99	48.95	45.96	52.14	3,916.23
COAL ($/ton)	34.59	33.3	35.82	2,940.85	34.53	33.3	35.8	2,762.51
USPROD (Thousand Barrels/Day)	9,416.5	9,245	9,659	37,666	9,416.5	9,245	9,659	37,666
TXPROD (Thousand Barrels)	108,573.5	104,229	116,369	434,294	108,573.5	104,229	116,369	434,294
LAPROD (Thousand Barrels)	4,219.25	4,054	4,386	16,877	4,219.25	4,054	4,386	16,877
CON (Thousand Barrels/Day)	20,464	19,123	21,946	1,739,483	20,548	19,123	21,946	1,643,868
STR (Thousand Barrels)	237,489	223,185	249,429	3,097,505	238,383	223,185	249,429	3,097,505
HDD (days)	0	0	0	0	0	0	0	0
CDD (days)	16.43	4	24	1,397	15.01	6	20	1,201
VIX	10.79	9.19	16.04	917.73	10.85	9.19	16.04	868.47
TWX	118.79	117.12	120.11	10,097.5	118.74	117.12	120.11	9,499.5

5.1.2. Panel Data Model with Difference-in-Differences Technique

Eq. 5-1 describes the panel data model to estimate the effect of the FMCSA safety regulation waiver on the fuel price in the aftermath of Hurricane Harvey in Texas and Louisiana.

$$lnFUEL_t = \beta_1 WAV_t + \beta_2 DIS_t + \beta_3 lnWTI_t + \beta_4 log(CDD_t + 1) + \beta_5 lnCON_t + \beta_6 lnSTR_t + \beta_7 lnVIX_t + \beta_8 lnTWX_t + Time + \varepsilon_t \qquad \text{Eq. 5-1}$$

where $lnFUEL_t$ is the natural logarithm of the average regional fuel price at Texas or Louisiana at time t (t = 85 days); WAV_t is a temporary FMCSA regulation waiver variable that is equal to one when Texas or Louisiana at time t are exempt from the FMCSA safety regulations; DIS_t is a dummy variable that is equal to one if Texas or Louisiana at time t experienced Hurricane Harvey; $lnWTI_t$ is the natural logarithm of global crude oil price; $logCDD_t$ is the logarithm of cooling degree days; $lnCON_t$ is the natural logarithm of the volume of natural gas consumption in the US; $lnSTR_t$ is the natural logarithm of the volume of commercial gas storage on the Gulf Coast; $lnVIX_t$ is the natural logarithm of the CBOE (Chicago Board Options Exchange) Volatility Index; $lnTWX_t$ is the natural logarithm of the trade-weighted U.S. dollar index; *Time* denotes a vector of monthly dummies, and ε_t is the disturbance term.

The main coefficient of interest is β_1, which shows whether the average fuel price is different during the FMCSA safety regulation waiver period than during the pre-regulation period, ceteris paribus.

5.2. **RESULTS**

Multicollinearity between predictor variables was checked because multicollinearity can threaten the results obtained by estimating Eq. 5-1. The variance inflation factors (VIFs) As shown in Table 5-4, the VIFs are less than 10 for all independent variables, indicating that there is no multicollinearity problem.

Table 5-4. Variance inflation factors (VIFs) for Texas and Louisiana datasets

Variables	***Texas***	***Louisiana***
FMCSA safety regulation waiver	4.28	2.69
Disaster	8.36	7.47
Global crude oil price	3.45	2.92
The volume of natural gas consumption in the US	4.16	4.40
The volume of commercial gas storage on the Gulf Coast	5.81	4.43
Cooling degree days	2.86	2.48
CBOE volatility index	2.51	2.77
Trade-weighted U.S. $ index	8.93	9.16

Table 5-5 shows the results of estimating equation (1) using the OLS method. The first column shows the results for Texas and the second one for Louisiana. These results show that the temporary FMCSA safety regulation waiver decreased the regional fuel prices in south Texas and Louisiana by 2.65% and 3.47%, respectively. In other words, south Texas's daily fuel price during the period when the FMCSA safety regulations were waived (hereafter, 'Regulation waived' period) was approximately 2.65% lower than the price during the period when the FMCSA safety regulations were affected (hereafter, 'Regulation affected' period) in Texas, ceteris paribus. Similarly, south Louisiana's daily fuel price was 3.47% lower during the 'Regulation waived' period than the price during the 'Regulation affected' period in Louisiana. This is consistent with theoretical predictions that less regulation can benefit market price stabilization (Kellogg, 2018; Litman, 2021). The finding indicates that the policymakers partially achieved the FMCSA safety regulation waiver's goal of rapidly responding to emergencies and addressing post-disaster price spikes. The results also show that the disaster increased regional fuel prices by 3.74% in south Louisiana, but it is statistically significant at a 0.10 significance level. These findings are consistent with previous studies about substantial fuel price spikes following disasters (Beatty et al., 2021; Wen et al., 2021).

Table 5-5. Results of the OLS Method Estimation

Variables	***Texas***	***Louisiana***
FMCSA safety regulation waiver	-0.0265**	-0.0347***
	(0.0104)	(0.0131)
Disaster	0.0177	0.0374*
	(0.0141)	(0.0198)
Global crude oil price	-0.157	-0.226
	(0.167)	(0.197)
The volume of natural gas consumption in the US	0.0626	0.213
	(0.141)	(0.177)
The volume of commercial gas storage on the Gulf Coast	-0.602***	-0.632***
	(0.213)	(0.227)
Cooling degree days	0.0237**	0.0334*
	(0.0113)	(0.0183)
CBOE volatility index	0.0416	0.0497*
	(0.0257)	(0.0297)
Trade-weighted U.S. $ index	-3.007***	-2.410**
	(0.922)	(1.116)
Intercept	21.56***	17.76***
	(5.576)	(6.580)
Month dummies	Yes	Yes
Observations	85	80
R-squared	0.589	0.614

Notes: Robust standard errors are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The global crude oil price index shows a negative but statistically insignificant relationship with the regional fuel price. This result seems inconsistent with the previous findings about the positive correlations between global crude oil prices and regional gasoline prices (Ferreira et al., 2022; Ji et al., 2014). However, those positive correlations are based on the long-run cointegrating relationships between global crude oil prices and regional gasoline prices (Apergis & Vouzavalis, 2018). The spot prices for generic gasoline often showed asymmetric responses to crude oil price changes, reflecting inventory adjustment effects (Borenstein et al., 1997; Bumpass et al., 2015; T.

Wang et al., 2019; Zhang & Ji, 2018). This explanation is consistent with the negative impact of the gas storage volume on regional fuel prices shown in Table 5-5.

One percent increase in volume (in a thousand barrels) of commercial gas storage in the Gulf Coast decreased the daily regional fuel prices in south Texas and Louisiana by 0.602% and 0.632%, respectively. On the other hand, the volume of natural gas consumption was positively related to regional fuel prices. One percent increase in natural gas consumption volume increased the daily regional fuel prices in south Texas and Louisiana by 0.0626% and 0.213%, respectively. This result is consistent with the economic theory that an increase in demand causes an increase in fuel prices (Jadidzadeh & Serletis, 2017).

However, this positive relationship between consumption and fuel prices is statistically insignificant. This is perhaps because no evidence was found in the short-run dynamic relationships but the evidence was found in the long-run cointegrating relationship between natural gas demand and prices in the U.S. natural gas market (Burns & Houghton, 2019). Short-run gas price responses to demand are likely to be smaller than long-run gas price responses because of less flexibility of gas prices in the short run (Burns, 2021; Burns & Houghton, 2019).

Also, the national-level natural gas consumption in the U.S. may have small effects on regional retail fuel prices (Bergeaud & Raimbault, 2020; Xiang & Lawley, 2019). Regional fuel prices are often explained by different socioeconomic regional features such as regional household gas consumption, territorial inequalities, geographical characteristics, and consumer preferences (Bergeaud & Raimbault, 2020). Xiang and Lawley (2019) reported that the regional gas demand changes did not result in large regional gas price changes in Canada but they found that the regional residential gas prices were integrated with the wholesale market prices from producing areas, gas pipeline transportation costs, and local distribution and storage charges.

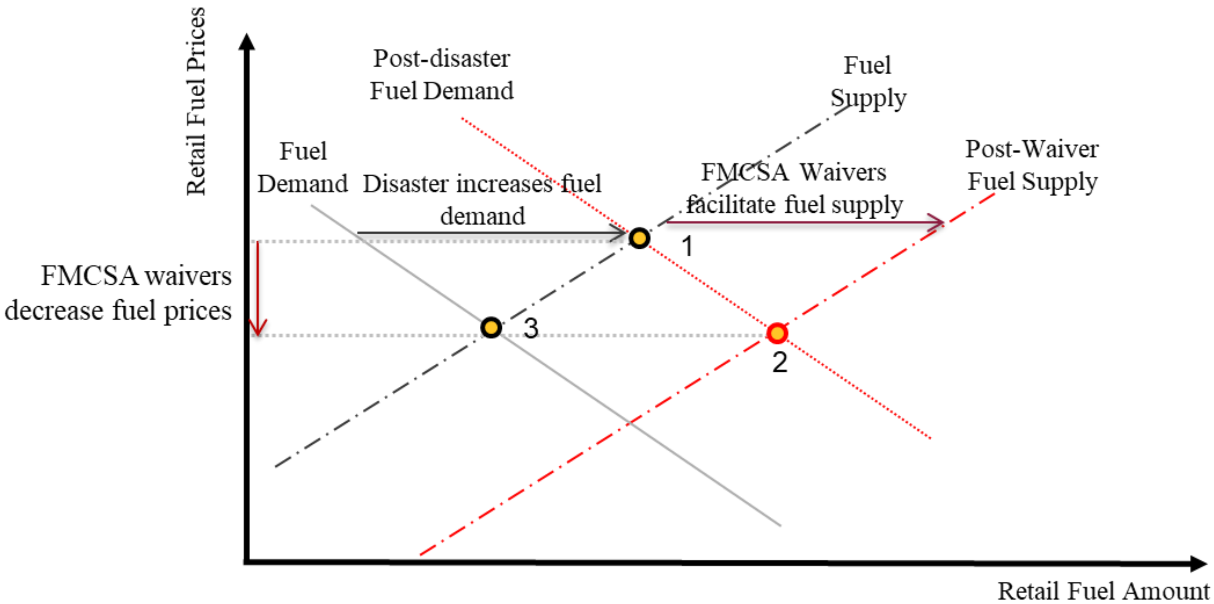
As one of the weather-related explanatory variables, cooling degree days significantly positively impacted the regional fuel prices in south Texas and Louisiana by 0.0237% and 0.0334%, respectively. Cooling degree days can increase energy use and put upward pressure on the gas price (Hulshof et al., 2016). The trade-weighted U.S. dollar index decreased the regional fuel prices by 3.007% and 2.41% in south Texas and Louisiana, respectively. The trade-weighted dollar index measures the value of the U.S. dollar relative to a basket of other foreign currencies (Board of Governors of the Federal Reserve System (US), 2022). Since the trade-weighted U.S. dollar index increase indicates the increasing purchasing power of the U.S. dollar, the regional fuel price decreased with the trade-weighted U.S. dollar index increase. This negative correlation between the fuel price and the U.S. dollar index found in this study is consistent with the findings in previous studies (Liao et al., 2018; F. Wen et al., 2018).

5.3. **DISCUSSIONS OF RESULTS**

Disasters often disrupt supply chains, logistics, and freight transportation systems (Elluru et al., 2019; Reddy et al., 2016). Disaster agencies must preemptively respond to disasters and mitigate disaster-related supply chain disruptions for communities' post-disaster safety, recovery, and resilience (Dixit et al., 2020; Kim & Shahandashti, 2022b). A reliable and affordable fuel supply is essential for people's immediate survival and basic functioning and rapid building infrastructure recovery in post-disaster situations (Kim & Shahandashti, 2022c; National Academies of Sciences, 2020; Palin et al., 2018; Yang et al., 2022). The FMCSA issued safety regulation waivers for motor carriers and drivers that provided fuel supplies to Texas and Louisiana following Hurricane Harvey. Therefore, the drivers became exempt from applicable safety regulations, such as the eleven-hour limitations of service hours on their route to Texas and Louisiana. Furthermore, state governors of Texas and Louisiana lifted oversize or overweight freight truckload restrictions for providing disaster relief efforts in response to Hurricane Harvey (Proclamation, 2017).

The current study found that the post-disaster FMCSA safety regulation waivers can help stabilize fuel prices, which is essential for post-disaster recovery. After Hurricane Harvey, the temporary FMCSA safety regulation waivers significantly impacted regional fuel price stabilization, decreasing fuel prices by 2.65% and 3.47% in south Texas and Louisiana, respectively. This impact is perhaps because drivers who became exempt from safety regulations, including hours of service limitations and oversize/overweight restrictions, could expedite their fuel transport to the disaster-affected south Texas and Louisiana areas and subsequently facilitate the fuel flow across the regional supply chain. This finding aligns with the results of previous studies that less regulation can increase the efficiency of supply chain systems with the efficient allocation of resources, faster responses to market forces, and supply chain reliability (Knudsen, 2016; Muckstadt et al., 2001; Zhu et al., 2017).

The impact of FMCSA safety regulation waivers on fuel supply facilitation can be explained in Figure 5-2. Pre-disaster retail fuel market equilibrium is represented by Point 3. Disaster increases fuel demand, moving the downward fuel demand curve toward the right. Therefore, post-disaster retail fuel market equilibrium was determined at Point 1 before FMCSA waives safety regulations. The counties at Point 1 experience higher retail fuel prices than pre-disaster prices. However, when FMCSA waives safety regulations, the waivers facilitate and increase fuel supply by temporarily lifting the hours of service and oversize/overweight restrictions. These FMCSA waivers move the upward fuel supply curve toward the left side, decreasing the retail fuel prices at Point 2.



1. Post-disaster retail fuel market equilibrium for counties before FMCSA waives safety regulations
2. Post-disaster retail fuel market equilibrium for counties after FMCSA waives safety regulations
3. Pre-disaster retail fuel market equilibrium

Figure 5-2. Economic Theoretical Explanation for the Empirical Evidence of FMCSA Regulation Waivers on Fuel Price Stabilization

The results for the relationships between fuel price and its key determinants in the current study are consistent with the findings in previous studies. The volume of commercial gas storage on the Gulf Coast has a negative relationship with the daily fuel prices in south Texas and Louisiana. According to the storage theory in the energy commodity markets, spot energy prices are inversely related to energy inventory levels (Ederington et al., 2019). Cooling degree days are positively related to regional fuel prices, reflecting the increasing demand for energy use. The increase in the trade-weighted U.S. dollar index decreased the regional fuel prices in south Texas and Louisiana, showing the rising purchasing power of the U.S. dollar relative to foreign currencies. The findings are expected to assist policymakers and decision-makers in understanding the FMCSA safety regulation waiver’s impact on post-disaster fuel prices and the short-run relationships between regional daily fuel prices and its key determinants for enhancing their disaster recovery plans, strategies, and policies.

CHAPTER 6 ASSESSING THE IMPACT OF EPA FUEL WAIVERS ON POST-DISASTER AIR QUALITY

The U.S. Environmental Protection Agency (EPA) implements environmental policies and regulations for protecting human health and the environment (Anastas & Zimmerman, 2021). The EPA has a wide range of responsibilities, including monitoring air and water quality, regulating hazardous waste disposal, and setting emission standards for industries (Shareefdeen & Elkamel, 2022). Some of the most significant EPA environmental policies and regulations include the Clean Water Act, the Clean Air Act, and the Resource Conservation and Recovery Act (Hofmann, 2021). These policies and regulations have had a significant impact on reducing pollution and protecting public health and the environment (Thomson et al., 2020).

The EPA has the authority to issue emergency waivers to ensure that necessary actions such as first responses and fuel supply can be taken in disaster situations (Gerrard, 2006). One such waiver is waving the fuel standard of Ultra Low Sulfur Diesel (ULSD) in emergency response vehicles and equipment in disaster-affected areas (Rodgers & Rodgers, 2020). The waiver allows the use of regular diesel fuel if ULSD is not available, to ensure that emergency responders can quickly and efficiently respond to the disaster (EPA, 2023).

After Hurricane Sandy hit the East Coast in 2012, the EPA waived certain Clean Air Act requirements to address fuel supply disruptions for power generators, emergency vehicles, and other equipment critical to responding to the disaster. The waivers allowed the use of USLD in emergency response vehicles and equipment in the State of New Jersey, the five boroughs of New York City, Nassau, Suffolk, Rockland, and Westchester counties in New York, and the

Commonwealth of Pennsylvania. These waivers helped to ensure that essential services and recovery efforts could continue to operate in disaster-affected areas (EPA, 2023).

The effects of disaster policies have been of interest in the literature. The safety regulation waiver issued by the Federal Motor Safety Carrier Administration helped to stabilize the retail gasoline prices after Hurricane Harvey in Texas and Louisiana (Kim et al., 2023). The EPA environmental regulation waivers after Hurricane Katrina posed significant threats to human health and welfare by generating widespread spills and leaks of oil and toxic gases and chemicals in the disaster recovery process (Stevens, 2022). Furthermore, there was no evidence found that EPA waivers expedited disaster relief and reconstruction efforts (Stevens, 2022). The emergency waivers of the air and water pollution environmental rules after Hurricane Harvey caused over 100 toxic pollution releases on land, in water, and in air in Houston and the Texas Gulf Coast area, harming public health (Flatt, 2020). Although environmental regulation waivers can be necessary for quickly starting the disaster recovery process, those waivers are often issued in an overly broad range with little to no procedural requirements, causing significant risks to public health and ecosystem resilience (Drake, 2020).

Despite the qualitative discussions on disaster-related policies for recovery, the effect of EPA fuel waivers has not been fully investigated quantitatively using empirical evidence. The current research aims to examine the effect of the EPA waiver for the sale, distribution, and use of USLD on the sulfur dioxide concentration in the regional air after Hurricane Sandy struck northeastern states. The findings of this research can assist disaster mitigation agencies and policymakers in understanding the effect of EPA fuel waivers and enhancing their environmental policies and strategies in disaster situations.

6.1. **METHODOLOGY**

6.1.1. Data Explanation

Table 6-1 describes the data to estimate the impact of environmental fuel regulation waivers from the EPA on the air quality after Hurricane Sandy. Since EPA waived the fuel regulation under the Clean Air Act that restricts the sulfur content of motor vehicle diesel fuel, the impact of this waiver on sulfur dioxide emission is investigated. The other determinants of sulfur dioxide emission are included in the analysis to control for confounding effects. Table 1 summarizes data used to investigate the effect of the EPA fuel waiver on the post-disaster regional air quality in northeastern states.

Table 6-1. Data Collection

Group	***Variable***	***Definition***	***Frequency***	***Source & Unit of measure***
Policy	*WAV*	EPA Fuel Waiver Dummy Variable	-	EPA
Disaster	*DIS*	Hurricane Sandy Disaster Dummy Variable	-	FEMA
Pollutants	SO_2	Sulfur Dioxide Concentration in Air	Daily	EPA (ppb)
	CO	Carbon Oxide Concentration in Air	Daily	EPA (ppm)
	NO_2	Nitrogen Dioxide Concentration in Air	Daily	EPA (ppb)
	O_3	Ozone Concentration in Air	Daily	EPA (ppm)
	PM_2	Fine Particulate Matter Concentration in Air	Daily	EPA ($\mu g/m^3$)

The difference-in-differences technique for this study was designed as described in Table 6-2. Both the treatment and control group states received a disaster declaration and federal assistance from FEMA after Hurricane Sandy. The treatment group consists of New York City and Nassau, Suffolk, Rockland, and Westchester counties in New York, all the New Jersey counties, and all the Pennsylvania counties which received the EPA waiver of fuel regulation that restricts sulfur emission. The other hurricane-affected states where the EPA fuel regulation was not waived in the aftermath of Hurricane Sandy are included in the control group.

Table 6-2. Difference-in-differences Technique

DID	***Before Fuel Waiver***	***After Fuel Waiver***
Treatment Group	NY (New York City, Nassau, Suffolk, Rockland, and Westchester), NJ, PA	NY (New York City, Nassau, Suffolk, Rockland, and Westchester), NJ, PA
Control Group	NH, WV, VA. MA, MD, RI, DE, CT, OH, DC	NH, WV, VA, MA, MD, RI, DE, CT, OH, DC

The data in Table 6-1 were collected from October to December 2012 with a one-month time window (Table 6-3) before and after Hurricane Sandy. Researchers have utilized the one-month time window before and after disasters to examine the economic losses and construction cost variations (Hallegatte & Vogt-Schilb, 2019; Khodahemmati & Shahandashti, 2020; Olsen & Porter, 2011). A longer time window can result in spurious relationships between variables due to various unobservable factors.

Table 6-3. Time Windows

Region	***Before Hurricane Sandy***	***After Hurricane Sandy***	***Regulation waived***
CT	Oct 1 – Oct 26, 2012	Oct 27 - Nov 8, 2012	N/A
DC	Oct 1 – Oct 25, 2012	Oct 26 - Oct 31, 2012	N/A
DE	Oct 1 – Oct 26, 2012	Oct 27 - Nov 8, 2012	N/A
MA	Oct 1 – Oct 26, 2012	Oct 27 - Nov 8, 2012	N/A
MD	Oct 1 – Oct 25, 2012	Oct 26 - Nov 4, 2012	N/A
NH	Oct 1 – Oct 25, 2012	Oct 26 - Nov 8, 2012	N/A
NJ	Oct 1 – Oct 25, 2012	Oct 26 - Nov 8, 2012	Oct 31 – Dec 7
NY	Oct 1 – Oct 26, 2012	Oct 27 - Nov 8, 2012	Oct 31 – Dec 7
PA	Oct 1 – Oct 25, 2012	Oct 26 - Nov 8, 2012	Nov 2 – Nov 20
RI	Oct 1 – Oct 25, 2012	Oct 26 - Oct 31, 2012	N/A
VA	Oct 1 – Oct 25, 2012	Oct 26 - Nov 8, 2012	N/A
WV	Oct 1 – Oct 28, 2012	Oct 29 - Nov 8, 2012	N/A

Table 6-4 presents the summary statistics of the variables. The negative values of air pollutants are allowed due to the value adjustments between monitoring instruments (EPA, 2016).

Table 6-4. Summary Statistics

Variables	**Mean**	**Standard Deviation**	**Min**	**Max**
WAV (days)	0.41	0.49	0	1
DIS (days)	0.14	0.34	0	1
SO_2 (ppb)	5.19	9.43	-1.7	350
CO (ppm)	0.56	0.64	0	9.2
NO_2 (ppb)	23.61	12.73	0	96
O_3 (ppm)	0.027	0.011	0	0.11
PM_2 (μg/m^3)	9.9	6.54	-1	75

6.1.2. Panel Data Model with Difference-in-Differences Technique

Eq. 6-1 was estimated using fixed-effects (FE) and random-effects (RE) estimators to examine the effect of the EPA fuel waiver on air quality.

$$SO_{2it}=\beta_1 WAV_{it}+\beta_2 DIS_{it}+\beta_3 CO_{it}+\beta_4 NO_{2it}+\beta_5 O_{3it}+\beta_6 PM_{2it}+a_i+a_t+u_{it} \qquad \text{Eq. 6-1}$$

where SO_{2it} is the sulfur dioxide concentration (ppb) in monitor site i at time t; WAV_t is an EPA fuel waiver dummy variable that is equal to one when emergency vehicles in the site i at time t are waived for the use of ULSD; DIS_t is a disaster dummy variable that is equal to one if Hurricane Sandy was declared in site i at time t; CO_{it} is the carbon oxide concentration (ppm) in monitor site i at time t; NO_{2it} is the nitrogen dioxide concentration (ppb) in monitor site i at time t; O_{3it} is the ozone concentration (ppm) in monitor site i at time t; PM_{2it} is the fine particulate matter concentration (µg/m^3) in monitor site i at time t; a_i is an individual-specific effect; a_t is a daily time-specific effect; and u_{it} is an idiosyncratic error term. β_1 is the main coefficient of interest, which proxies the effect of EPA fuel waiver on sulfur dioxide concentration. β_1 is the main coefficient of interest for both Eq 6-1 investigating the effect of EPA fuel waiver on sulfur dioxide concentration in the regional air.

The Hausman test was used to identify the appropriate panel data model for investigating the effect of EPA fuel waivers on SO_2 concentration. The Hausman test was conducted to select between FE and RE models. The null hypothesis of the Hausman test is that the independent variables and the individual-specific effects (a_i) are not correlated. If the null hypothesis is rejected, the FE model is preferred to the RE model. If the null hypothesis is not rejected, the RE model is recommended rather than the FE model. The RE estimator can control for within-county correlation in the error term and thus yields more efficient estimates.

6.2. **RESULTS**

Before estimating the model, I tested whether multicollinearity is a threat to the results. The Variance Inflation Factor (VIF) is less than 10 for all independent variables, as shown in Table 6-5, suggesting the absence of multicollinearity.

Table 6-5. Variance Inflation Factors (VIFs) for Independent Variables

Variables	**VIFs**
WAV_{it}	1.07
DIS_{it}	1.11
CO_{it}	1.41
NO_{2it}	1.59
O_{3it}	1.05
PM_{2it}	1.72

The results of panel data models for investigating the effect of EPA fuel waiver on sulfur dioxide concentration are presented in Table 6-6. According to the results of the FE panel data models, the EPA fuel waiver increased the sulfur dioxide concentration by 1.34 ppb without controlling for the confounding effects of other air pollutants and 0.57 ppb with controlling for those confounding effects. The RE panel data model also shows the increasing effect of the EPA fuel waiver on the sulfur dioxide concentration by 0.55 ppb in the regional air. The result shows that the EPA waiver allowing the use of high-sulfur diesel fuel increased the sulfur dioxide concentration, contributing to air pollution in hurricane-affected regions. Sulfur dioxide (SO_2) is a major industrial pollutant (Wang & Crutzen, 1995) and can decrease during a disaster incident period when human and industrial activities decrease (Filonchyk et al., 2020; Li et al., 2021a). The National Oceanic and Atmospheric Administration (NOAA) reported a negative relationship between air quality in the U.S. and Atlantic hurricanes (Murakami, 2022). The impact of hurricanes on air quality was found to vary across regions in previous studies (Hu et al., 2019; Lieberman-Cribbin et al., 2021; Pozo et al., 2020; Subramanian et al., 2018). Other air pollutants, including nitrogen dioxide (NO_2), show a statistically significant positive relationship with the sulfur dioxide (SO_2) concentration in the air. This positive relationship is consistent with the association between air pollutants concentration, which was found in previous studies (Iqbal et al., 2021).

Table 6-6. Results of the Panel Data Models for Air Quality

Data	SO_2 Concentration in Air		
Variables	**FE**	**FE**	**RE**
WAV_{it}	**1.34*** (0.15)**	**0.57** (0.24)**	**0.55** (0.24)**
DIS_{it}	- 2.76*** (0.22)	- 0.21 (0.35)	- 0.19 (0.35)
CO_{it}	-	0.24 (0.22)	0.38* (0.22)
NO_{2it}	-	0.13*** (0.01)	0.12*** (0.01)
O_{3it}	-	10.24 (11.86)	14.86 (11.77)
PM_{2it}	-	0.14*** (0.02)	0.14*** (0.02)
Intercept	4.29*** (0.93)	- 2.82* (1.55)	- 3.11* (1.64)
Time dummy	Yes	Yes	Yes

Notes: The number in parentheses indicates robust standard errors.
*** p<0.01; ** p<0.05; * p<0.1

The Hausman test rejected the null hypothesis that the independent variables and fixed effects (a_i) are not correlated at the 5% significance level, as reported in Table 6-7. The Hausman test results indicate that the FE model is more appropriate to control for the individual-specific fixed effects (a_i) than the RE model for estimating the effect of EPA ULSD waivers on SO_2 concentration.

Table 6-7. Results of the Hausman Test

Hausman Test	*Chi-Square Statistic*	*p-value*
FE vs. RE	14.69 (7)	0.04

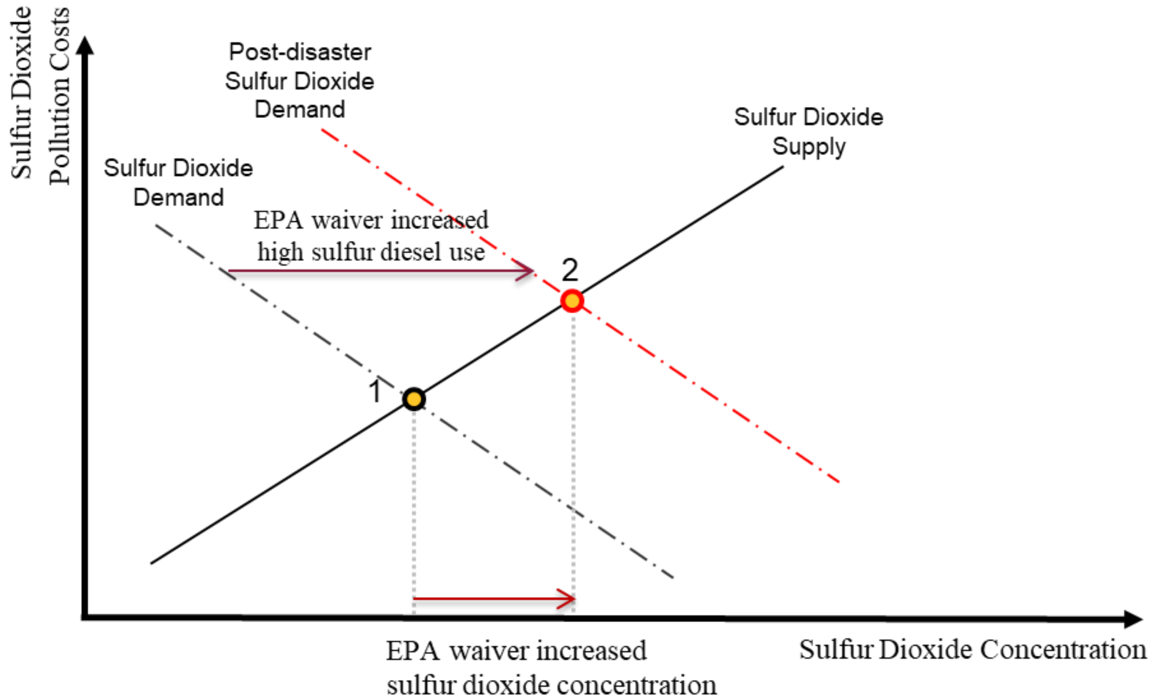
Notes: The number in parentheses represents a degree of freedom.

6.3. **DISCUSSIONS OF RESULTS**

When disasters strike, concerns have been raised about whether environmental regulations may slow down or obstruct response efforts (McCarthy & Copeland, 2005). To address these concerns, state, local, and federal government officials can request for a waiver to the EPA to waive or modify any requirement under its jurisdiction in response to damages related to disasters. In the case of Hurricane Sandy, the EPA, in consultation with the Department of Energy (DOE), issued a series of fuel waivers in late October and early November of 2012 to assist adequate and responsive disaster recovery efforts in the affected areas.

The empirical results show that the EPA waiver for the use of USLD increased SO_2 concentration in the regional air by 0.57 ppb daily in the northeastern states affected by Hurricane Sandy. This is perhaps due to the increasing use and distribution of high-sulfur (such as greater than 500 ppm) diesel fuel allowed by the EPA fuel waiver.

The increasing impact of the EPA fuel waiver on sulfur-dioxide concentrations is described in Figure 6-1. The post-disaster sulfur dioxide concentration is determined at Point 1. However, the EPA fuel waiver whose objective is to facilitate disaster recovery efforts allows high sulfur diesel use, increasing sulfur dioxide demand to the right. Therefore, the post-disaster sulfur dioxide concentration equilibrium is established at Point 2, increasing sulfur dioxide concentration in the post-disaster regional air.



1. Post-disaster sulfur dioxide concentration equilibrium for counties before EPA waives ULSD fuel use regulation
2. Post-disaster sulfur dioxide concentration equilibrium for counties after EPA waives ULSD fuel use regulation

Figure 6-1. Economic Theoretical Explanation for the Empirical Evidence of EPA Environmental Regulation Waivers on SO_2 Concentration

Daily SO_2 concentration in northeastern states positively correlates with the concentration of major air pollutants, including CO, NO_2, O_3, and PM_2. This finding aligns with the previous studies that investigated high positive correlations between air pollutants concentration (Li et al., 2021b; Wang et al., 2019).

According to the results of the Hausman test, unobserved time-invariant individual-specific effects (a_i) were found to be correlated with the independent variables. Therefore, the FE panel data model was used to include and control for the individual-specific effects (a_i). The FE estimator enables us to control for various unobservable factors that are correlated with the observed covariates in the model and thus leads to unbiased and consistent estimates. Although the EPA fuel waivers showed an adverse impact on the regional air quality, increasing SO_2 concentration, this result does not necessarily imply that the EPA fuel waivers should not be provided. It is important to understand and further investigate the impact of the EPA fuel waivers on disaster response efforts and the consequences of no EPA fuel waiver issuance during the disaster.

CHAPTER 7 POLICY IMPLICATIONS FOR EFFECTIVE DISASTER MANAGEMENT AND RECOVERY

This doctoral study discovered the spatiotemporal impacts of disasters on the construction market and the effects of policies on the disaster management and recovery process. The practical and technical policy implications of this study are highlighted in this chapter.

7.1. DEMAND SURGE

The demand surge as a socioeconomic phenomenon has been found in the construction industry after disasters. This study first investigated the spatiotemporal dynamics of demand surge in the construction market. The impact of a disaster on construction labor costs was not found in the quarter when a disaster occurred but was found to be statistically significant one quarter after a disaster occurred. This finding implies that the faster supply of reconstruction resources including material and labor to disaster-affected counties, for example, in less than a quarter after a disaster occurred can reduce the amount of demand surge which can exacerbate socioeconomic losses one quarter after a disaster occurred. This finding also highlights the significance of supply chain security and management not only for disaster recovery but also for disaster loss mitigation.

The indirect impact of a disaster on a neighboring county's construction market was examined to be statistically significant in all three Gulf Coast States (i.e., TX, LA, FL) but in different directions. The spillover effect of a disaster on neighboring county's construction wages was found positive in Texas and Florida while it was found negative in Louisiana. This finding is probably due to heterogenous construction market structures. One possible explanation for this finding can be different migration responses to disasters among states (Raker, 2020). People in Louisiana showed a tendency to quickly displace and migrate to other neighboring counties or other states in a year after hurricanes (Marandi & Main, 2021). The influx of people and laborers from disaster-affected counties to non-disaster-affected neighboring counties can decrease construction wages in the non-disaster-affected neighboring counties in Louisiana (Peri et al., 2020). On the other hand, people in Texas and Florida were more likely to return and rebuild their houses in the aftermath of disasters (Cantwell Fraase, 2020; Palinkas, 2020). This tendency to rebuild and reconstruct houses will increase construction demand not only in disaster-affected counties but also in non-disaster-affected counties as a spatial spillover effect (Lee, 2020). The findings of this study are limited to the spillover effects of a disaster on wages in construction industry. It is noteworthy to mention that the spillover effects of a disaster on wages can vary across industries, regions, and types of disasters (Davis et al., 2023).

Disaster responses to recover, secure, and facilitate the supply chain for reconstruction resources in less than a quarter after a disaster occurred are crucial for minimizing the socioeconomic losses that can be exacerbated by a demand surge. Policymakers and disaster mitigation agencies can subsidize and incentivize the suppliers to expedite the supply of critical resources for reconstruction and recovery. For example, subsidizing or investing in workforce training and development programs can help increase the pool of skilled construction laborers, enabling a more robust response to post-disaster reconstruction demands. These programs can focus on skills specific to disaster recovery, such as debris removal, structural repairs, and resilient construction practices.

Also, incentives such as tax credits or grants can be provided to private entities that contribute to post-disaster recovery efforts, including affordable housing initiatives and infrastructure projects. These incentives can help offset increased construction labor costs and encourage private sector engagement in the recovery process.

In this line of suggestion, fostering public-private partnerships can enhance the efficiency and effectiveness of post-disaster reconstruction. Collaboration between government entities, non-profit organizations, and private sector industry stakeholders can leverage reconstruction resources, expertise, and funding to address labor cost inflation and optimize the resource allocation for disaster recovery efforts.

This study also found that a spatial spillover effect of a disaster in the construction labor market depends on the regional market structure and human responses. Further investigation of the regional market structure can assist policymakers and practitioners in better understanding, quantifying, and predicting the spatial spillover effects of a disaster.

7.2. **ANTI-PRICE GOUGING LAW**

The current study first investigated the effect of anti-price gouging law triggered by emergencies or disaster declarations on reconstruction prices and speed in the disaster recovery process. To protect consumers from exploitative pricing practices in the wake of disasters, thirty-seven states have implemented anti-price gouging laws. These laws aim to regulate and limit the prices that businesses can charge for goods and services in the aftermath of natural disasters. While the intent behind anti-price gouging laws is laudable, their effectiveness and effects on the reconstruction market warrant careful consideration. The findings of this study provide the policy implications associated with these laws.

Anti-price gouging laws are intended to shield consumers from exorbitant pricing during times of emergency. By capping prices or setting limits on permissible price increases, these laws aim to ensure that essential goods and services remain affordable and accessible to affected communities. According to the results of this study, anti-price gouging law successfully decreased construction wages following disasters in the United States, presenting its effectiveness to control market prices in the construction industry.

Although the anti-price gouging laws can address concerns about exploitative practices, these laws do not necessarily ensure a smooth recovery process. One potential consequence of anti-price gouging laws is the risk of supply shortages. When businesses are unable to charge higher prices to reflect increased costs, they may be discouraged from entering the reconstruction market or may choose to allocate their limited supplies to other regions with more favorable pricing conditions. This can exacerbate the scarcity of essential goods and services in disaster-affected areas, hindering the recovery process.

Also, anti-price gouging laws can diminish the financial incentives for suppliers to participate in the reconstruction market. If suppliers cannot recoup their costs or make a reasonable profit due to price controls, they may be less motivated to invest resources or provide their services in disaster-stricken regions. This can lead to a decrease in the overall availability of reconstruction goods and services.

Price controls imposed by anti-price gouging laws can create distortions in the market. By interfering with the natural price signals of supply and demand, these laws can disrupt the efficient allocation of resources. This study found a decreasing impact of Virginia's anti-price gouging law on housing reconstruction speed, using a case study of Virginia's and Maryland's counties hit by Hurricane Sandy. Anti-price gouging laws may result in misallocation, inefficiencies, and unintended consequences such as black markets or the emergence of unregulated alternative markets with higher prices.

The current study on anti-price gouging law does not conclude that anti-price gouging law should be abolished. It is recommended to balance consumer protection and market dynamics in the disaster recovery process. Policymakers need to recognize the effectiveness and effects of anti-price gouging law in the post-disaster reconstruction process and strike a delicate balance between protecting consumers and ensuring the smooth functioning of the reconstruction market. Recognizing the unique circumstances following a natural disaster, policymakers may consider incorporating flexibility and exceptions within anti-price gouging laws. For example, allowing temporary price increases to accommodate increased costs or providing exemptions for certain goods and services that are not essential for immediate survival can help maintain market equilibrium without unintended consequences that hinder the recovery process while still protecting vulnerable consumers.

7.3. **FEDERAL MOTOR CARRIER SAFETY REGULATION WAIVER**

Natural hazards can disrupt transportation systems and hinder the delivery of essential goods and services to affected areas. To facilitate a swift recovery, governments may implement waivers or exemptions to certain Federal Motor Carrier Safety Administration (FMCSA)'s regulations to address logistical challenges and expedite the transportation of critical supplies. While these waivers aim to enhance the efficiency and effectiveness of the recovery process, their effectiveness and effects on safety and regulatory compliance require careful consideration.

The current study presented empirical evidence that waiving certain motor carrier-related safety regulations can enable a more rapid response to the logistical challenges posed by Hurricane Harvey in Louisiana and Texas. The temporary waivers of hours of service and freight size/weight regulations facilitated the transportation of fuel to affected areas, stabilizing the retail fuel prices in south Louisiana and Texas. This study explores the policy implications associated with FMCSA's safety regulation waivers in the disaster recovery process.

The FMCSA's safety regulation waivers can provide flexibility in resource allocation during the disaster recovery process to help overcome supply chain disruptions and ensure the efficient delivery of critical supplies, such as fuel, food, water, medical equipment, and building materials. It is suggested for FMCSA and government agencies that can issue the regulation waivers to collaborate and coordinate with other disaster mitigation and management agencies, industry stakeholders, and transportation providers. By streamlining regulatory processes and creating a more cooperative environment, these waivers facilitate effective communication and cooperation, resulting in a more coordinated and efficient response to the transportation and logistics challenges following a disaster.

While the FMCSA's safety regulation waivers play a significant role in facilitating the disaster recovery process by addressing logistical challenges and expediting the transportation of critical supplies, policymakers must carefully consider the effectiveness, safety implications, and regulatory compliance aspects of these waivers. The relaxation of certain regulations through waivers raises legitimate safety concerns. Regulations such as hours of service restrictions are designed to prevent driver fatigue and maintain road safety. Waiving these regulations could potentially increase the risk of accidents if drivers are not adequately rested. Ensuring that safety remains a priority while implementing the FMCSA's regulation waivers is crucial during times of emergency.

Also, the FMCSA's safety regulation waivers may lead to a temporary relaxation of regulatory compliance standards. While this flexibility is necessary in the immediate aftermath of a natural disaster, there is a risk of non-compliance becoming a precedent or being extended beyond the recovery period. Monitoring and oversight mechanisms should be in place to ensure that regulatory compliance is reinstated once the emergency situation subsides.

Last but not least, the FMCSA's safety regulation waivers should be implemented in a manner that ensures fairness and equity among transportation providers. Small operators and independent drivers might face challenges in keeping up with the changes and requirements associated with waivers. Policymakers should strive to provide clear guidance and support to all stakeholders, ensuring that the benefits of waivers are accessible to all who participate in the recovery process.

Policymakers must strike a balance between safety considerations and the need for an efficient recovery process for maximizing the benefits of the waivers while safeguarding public safety and regulatory compliance. Temporary waivers should be carefully evaluated to ensure that safety risks are mitigated, such as by implementing alternative safety measures. Regular assessment and monitoring should be conducted to adjust the waivers based on evolving circumstances. Guidelines for the safety regulation waivers should be clear and transparent, outlining the scope, duration, and conditions of the exemptions. Accountability mechanisms should be established to ensure that waivers are implemented responsibly, with appropriate oversight and reporting requirements to maintain transparency and minimize the potential for abuse. Collaboration among government agencies, industry stakeholders, and transportation providers is crucial for the effective implementation and monitoring of the regulation waivers. Engaging these stakeholders in the decision-making process and considering their input can help identify potential challenges, foster innovation, and ensure that waivers align with the specific needs of the recovery process.

7.4. ENVIRONMENTAL REGULATION WAIVER

In the aftermath of natural disasters, the U.S. Environmental Protection Agency (EPA) may issue regulatory waivers or exemptions to certain environmental regulations to expedite the recovery and reconstruction process. These environmental regulation waivers aim to address the challenges posed by the immediate need for cleanup, debris removal, and restoration of critical infrastructure. For example, EPA often issues waivers to temporarily allow the use of Ultra-Low Sulfur Diesel (ULSD) fuel that does not meet the standard specifications during times of emergency. These waivers are designed to address fuel supply disruptions, facilitate emergency response, and streamline recovery efforts. However, the implications of such waivers on air quality, public health, and long-term environmental sustainability must be carefully considered.

The current study showed that the EPA waivers for the ULSD fuel use increased the daily SO_2 concentration, harming the regional air quality in northeastern states struck by Hurricane Sandy. However, this result does not necessarily imply that the EPA ULSD diesel fuel waivers should not be provided because the waivers can play a role in ensuring fuel supply stability and expediting emergency response efforts in the aftermath of natural disasters.

Post-disaster fuel waivers by EPA can help ensure a stable fuel supply for critical emergency response and recovery operations. By temporarily allowing the use of non-compliant fuel, these waivers address supply disruptions that may occur due to damage to refineries, transportation infrastructure, or distribution systems. This enables the uninterrupted provision of fuel for essential vehicles and equipment involved in the recovery process. For example, the fuel waivers help mobilize and deploy emergency vehicles, generators, and equipment, facilitating timely assistance and recovery efforts to affected communities. This can potentially save lives, protect property, and mitigate the immediate impacts of the disaster. The fuel waivers provide flexibility in fuel options during an emergency, helping ensure the continuation of essential services and support the resumption of critical infrastructure operations.

However, as this research found the adverse impact of the waivers on the air quality, the EPA fuel waivers can result in increased emissions of pollutants such as sulfur dioxides (SO_2). These emissions can contribute to poor air quality, especially near recovery operations in disaster-affected communities. Such air pollution can have adverse health effects, particularly for vulnerable populations, including those with respiratory conditions and children. It is essential to assess and manage these environmental impacts during the waiver period.

While the fuel waivers address immediate fuel supply challenges, they may have long-term consequences for environmental sustainability. The ULSD fuel requirements were implemented to reduce air pollution, improve public health, and minimize environmental harm. Waiving these requirements should be a temporary measure, and efforts should be made to restore compliance with the standards as soon as feasible to ensure long-term environmental benefits.

Therefore, a time-bound and targeted approach, implementation of mitigation strategies, and effective public awareness are suggested as key policy considerations to balance the immediate needs of disaster recovery with long-term environmental protection.

The ULSD diesel fuel waivers should be time-bound and targeted specifically to address fuel supply disruptions in the immediate aftermath of a natural disaster. Clear timelines and criteria for reestablishing compliance with ULSD fuel standards should be established to minimize the duration of the waivers and expedite the return to normal compliance levels.

Also, environmental policies should be in place to mitigate the environmental impacts of ULSD diesel fuel waivers. This may include additional measures such as emission controls on non-compliant vehicles or equipment, enhanced monitoring of air quality, and public health advisories to minimize exposure to increased pollutants. These strategies should be implemented concurrently with the waivers to ensure that environmental harm is minimized.

Furthermore, it is essential to engage and inform the public about the temporary nature of ULSD diesel fuel waivers and the associated environmental implications and consequences. Public awareness campaigns can help educate communities about the need for these waivers, the importance of compliance with other environmental regulations, and the commitment to restoring environmental sustainability once the emergency situation subsides.

CHAPTER 8 CONCLUSIONS

The disaster recovery process is highly associated with not only the construction industry but also disaster policies. This study investigated the spatiotemporal dynamic effects of a disaster on county-level construction wages in the short-run and long-run in three Gulf Coast states (Texas, Louisiana, and Florida) using dynamic SDMs with the DID specification. The results showed that a disaster had a negative or nonsignificant effect on construction wages in the quarter when the disaster occurred. However, one quarter after the disaster, the disaster increased the construction wages in the disaster-affected counties compared with the non-disaster-affected counties. This lagged positive effect of a disaster on construction wages was attributable to the direct and indirect spillover effects. The direct effect of a disaster on construction wages one quarter after the disaster was consistently estimated to be positive in all three Gulf Coast states. However, the indirect spillover effect of a disaster that occurred in the neighboring county on the construction wages varied across the states. The findings of this research are expected to clarify the endogenous and exogenous interaction effects between communities and enhance the understanding of the dynamic process of demand surge in the construction labor market.

The research on various disaster policies was proposed to assess the impact of disaster policies on the disaster recovery process using the panel data models with the DID specification. Disaster policies considered in this study are the anti-price gouging law, the FMCSA safety regulation waiver, and the EPA fuel waiver.

The impacts of the anti-price gouging law on reconstruction speed and reconstruction costs were investigated using the empirical datasets. Thirty-seven U.S. states and the District of Columbia have anti-price gouging laws or regulations to control the increased price in the aftermath of a disaster. The anti-price gouging laws enforce civil or criminal penalties for price gouging violations. First, I found empirical evidence that the anti-price gouging law triggered in the wake of a disaster decreased the number of new housing constructions authorized by monthly building permits using panel data models with a DID technique. All the DID estimators yield a consistent result that the presence of the anti-price gouging law decreased the number of new housing constructions by 18 units in Virginia counties relative to Maryland counties that were not subject to the anti-price gouging law during Hurricane Sandy. Furthermore, the anti-price gouging law showed a decreasing impact on reconstruction wages in the aftermath of disasters by regulating reconstruction market prices. It is implied that the anti-price gouging law can mitigate reconstruction cost inflation but also slow down reconstruction speed by controlling the market prices in the aftermath of disasters.

The FMCSA safety regulation waiver was examined if the waiver has a significant effect on fuel price stabilization after Hurricane Harvey struck Texas and Louisiana. The results show that the post-disaster FMCSA safety regulation waiver had a statistically significant adverse impact on the daily fuel prices, assisting in stabilizing the daily fuel prices in South Texas and Louisiana in the aftermath of Hurricane Harvey. The FMCSA safety regulation waivers can facilitate and increase post-disaster fuel supply, mitigating the daily fuel price inflation by 2.65% and 3.47% in South Texas and Louisiana, respectively.

Lastly, this research investigated the impacts of the EPA waivers for ULSD fuel use on the regional air quality in northeastern states after Hurricane Sandy. The results show that the post-disaster EPA waiver for the ULSD fuel use had an increasing impact on the daily SO_2 concentration in the hurricane-affected areas. The FE panel data model controlling for the unobserved individual-specific effects (a_i) shows that the EPA fuel waiver increased the daily SO_2 concentration by 9.85 ppm.

This research can contribute to the state of knowledge by connecting three critical disciplines: Post-disaster Construction, Economics, and Policy Analysis. The primary contribution of this research to the body of knowledge is the development of econometric measurement methods to estimate disaster impacts and evaluate policy effects in the post-disaster reconstruction management and recovery process. This study is the first attempt to investigate the spatiotemporal impacts of disaster on construction wages and examine the short-run and long-run dynamic process of post-disaster construction demand surge. The dynamic fixed-effect Spatial Durbin models with temporally lagged disaster variables and difference-in-difference technique were used to incorporate the spatial and temporal dependencies between county-level construction wages and enable us to understand the lagged effects of disasters on construction wage inflation. Furthermore, this research addressed the fundamental limitations of existing demand surge models by solving missing data problems with spatial multiple imputation methods.

This research evaluated and quantified the impacts of disaster-related policies on the post-disaster reconstruction process, for the first time, presenting empirical evidence. The panel data models with DID techniques were implemented to compare the changes in the post-disaster reconstruction variables between the treatment group affected by the policy and the control group not affected by the policy. The research quantitatively investigated the impacts of various policies including anti-price gouging law, FMCSA safety regulation waivers, and EPA fuel waivers which have been qualitatively discussed over controversy in previous studies and practice. The proposed approach and discovery of this research will aid disaster mitigation and recovery agencies in better understanding a post-disaster reconstruction process, developing a greater construction capacity, setting effective reconstruction goals, initiating risk mitigation and resourcing strategies, and enforcing effective regulations and policies.

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