THE EFFECT OF NATURAL DISASTERS ON CONSTRUCTION LABOR WAGE FLUCTUATIONS: A SPATIAL DIFFERENCE-IN-DIFFERENCE ANALYSIS

by

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DISSERTATION

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Dedicated to

My parents, and my beloved husband, Sirwan, for their endless support, encouragement, patience, and unconditional love.

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AWW	Average Weekly Wages
BLS	Bureau of Labor Statistics
DHS	Department of Homeland Security
FEMA	Federal Emergency Management Agency
LQ	Location Quotient
LWC	Labor Wage Change
NAICS	North American Industry Classification System
NOAA	National Oceanic and Atmospheric Administration
SAC	Spatial Autoregressive Combined
SAR	Spatial Autoregressive
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SPDM	Spatial Panel Data Model
HUD	Housing and Urban Development
GLO	General Land Office
CDBG-DR	Community Development Block Grant-Disaster Recovery
MOD	Method of Distribution

ABSTRACT

THE EFFECT OF NATURAL DISASTERS ON CONSTRUCTION LABOR WAGE FLUCTUATIONS: A SPATIAL DIFFERENCE-IN-DIFFERENCE ANALYSIS

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The United States is one of the top five countries in the world prone to natural disasters. Natural disasters could have a significant impact on the construction industry. In a large-scale disaster, labor cost fluctuation is known to be an important driving factor in the construction cost increases. Labor cost fluctuation could increase the reconstruction cost by 20 to 50 percent after a large-scale disaster. In the literature, the effect of a disaster on the construction market condition has been calculated through two stages, measurement and quantification. Merging two stages, measurement and quantification, in one stage, provides an opportunity to decrease the amount of error in the quantification step due to measurement error. Merging two stages, measurement and quantification, in one stage using an appropriate regression model has not been studied in the literature for the construction market indices. This research has two main objectives. The first objective of this research is to estimate the spatio-temporal effect of natural

disasters on the fluctuation of the labor weekly wages in the residential construction sector, using the difference-in-difference technique. This technique is capable of eliminating the need for measurement in this analysis and can directly quantify the effect of natural disasters on the labor wage fluctuations. This technique has not been used in this context before.

The second objective in this research is to use a spatial multiple imputation method to tackle the missing data problem. This spatial imputation method has not been used in this context before. In this research, the required construction county-level data of 67 counties in Florida State has been collected from the Bureau of Labor Statistics (BLS) to create the county-level panel data models for Florida State from 2014 to 2018. Historical county-level data of those counties impacted by weather-related disasters (flood, tornado, and storm) from the Federal Emergency Management Agency (FEMA) from 2014 to 2018 were also collected to conduct the analysis.

Three commonly used construction market exogenous variables are used within spatial panel data models to explore natural disasters' effect on labor weekly wage fluctuations in the residential construction market. Also, a disaster dummy variable is used to capture these fluctuations in the county level dataset. To have less biased results and increase the efficiency of our spatial model, four strategies were used to tackle the missing data problem. Thus, in this research, multiple spatial panel data models (Spatial Autoregressive Model (SAR), Spatial Autocorrelation Model (SAC), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) models) have been developed to investigate the effect of natural disasters on labor wage fluctuations. Based on the Breusch–Pagan LM test and Hausman test results, the fixed-effect Spatial Durbin Model (SDM) using a multiple imputation method is identified to be a more appropriate model in this research. The total effect obtained from SDM using the multiple imputation methods indicates that labor weekly wage increases by 7.5 percent in counties affected by natural disasters compared to those that are not affected. This study helps risk managers, cost engineers, city policymakers, construction companies, property owners, and insurers to have a better understanding of post-disaster construction cost fluctuations aftermath of a natural disaster.

CHAPTER 1

INTRODUCTION

Due to dramatic climate change over the last decade, the most severe and catastrophic natural disasters have wreaked havoc globally (Fenner et al., 2017). In the United States, the number of billion-dollar weather-related disasters has more than doubled between the years of 2010 to 2019 compared to two decades ago (2000-2009) (NOAA, 2020). The United States is amongst the top five countries affected by these natural disasters the most (Guha-Sapir et al., 2012). In the United States, a staggering 119 billion-dollar weather-related disasters have been declared in the last decade alone (NOAA NCEI 2020). The cumulative estimated damage of these 119 weather-related disasters exceeded 800 billion dollars (NOAA, 2020). Since 1980, 250 weather-related events declared in the United States exceeded 1.75 trillion dollars in total damages (NOAA, 2020). Anecdotal evidence shows the significant effect of natural disasters on increasing construction costs (Olsen and porter, 2011b).

If the demand for products and services surpasses the regional capacity to supply them efficiently, post-disaster construction costs will increase (Munich-Re, 2007). In a massive disaster, labor wage fluctuation is one of the most critical factors in the increase of reconstruction costs (Olsen and Porter, 2013). Labor wage increases are due to the increase in demand for resources relative to the supply in the regional market after a natural disaster (Dohrmann et al., 2013). Labor cost fluctuations could increase the reconstruction cost by up to 50 percent after a large-scale disaster (Olsen and Porter, 2011a). For example, in some projects, up to 30 percent of labor prices increased after Hurricane Katrina (Grogan and Angelo, 2005). In the aftermath of a natural disaster, these construction cost increases do not appear all of the sudden. They accumulate gradually for the duration of the recovery period (Chang and Miles, 2004). Quantifying the construction cost increase due to a natural disaster allows for a more precise anticipation of disaster losses and improved planning to the reconstruction process (Brown, 2014; Finucane et al., 2014). One of the main concerns of affected cities and communities is how to recover from natural disaster fully (Brown, 2014). Measuring construction cost fluctuation due to natural disasters has been the subject in much econometric research.

In the previous research studies, the impact of natural disasters on the construction cost fluctuation is calculated through two main stages: measurement and quantification. For example, Ahmadi and Shahandashti characterized construction demand surge using spatial panel data models through two stages analysis (measurement and quantification), (Ahmadi and Shahandashti, 2020a).

The accuracy of the second stage depends on the correctness of the measurement stage. Simply put, using analytical models that can merge both measurement and quantification into one stage could greatly reduce the errors.

The objective of this research is to estimate the spatio-temporal effect of a natural disaster(s) on labor wage fluctuations at a county level by merging both measurement and quantification stages. This research aims to estimate the spatio-temporal effect of a natural disaster(s) on labor wage fluctuations using spatial paned data models combined with the difference-in-difference technique at a county level. Spatio-temporal analyses have many advantages over purely spatial or time-series analyses because they can simultaneously investigate possible patterns over time and space. These analyses emerge when data are collected both across time and space. An observation in a spatio-temporal dataset specifies spatial and temporal characteristics that exist at the time *t* and location *x*. Spatial panel data models can be used to do spatio-temporal analyses to investigate a particular phenomenon.

The spatial panel data models combined with a difference-in-difference technique was used to examine the effect of an exogenous shock (natural disaster) on a local construction residential labor wage fluctuation. Combining spatial panel models with the difference-in-difference technique reduces the error in the modeling step by eliminating the need for the measurement step. Hurricanes, tornadoes, and severe storms are viable options for this research. They can affect several counties at a time, and they can occur more than once in a specific period during the study. If an exogenous shock (natural disaster) affects the construction market in one specific county, it could affect the nearby county construction market. Thus, we can examine multiple exogenous shocks affecting more than one county at a time. In the spatial panel models, regions may be correlated with their neighbors in three different ways (Elhorst, 2014). First, the value of y in the region might impact (or be related to) the value of y in the neighboring region, which is called the spillover effect. Second, the value of x's in the region might affect (or be related to) the value of y in the neighboring region. Third, the residuals in the region might affect (or be related to) the residuals in the neighboring region, which is known as spatial heteroskedasticity (Elhorst, 2014). According to the three correlations between the neighboring region, different spatial models have been used such as Spatial Durbin Model (SDM), Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Autocorrelation Model (SAC). All of these spatial models are thoroughly discussed in Chapter 3.

The innovation of this research is to use counties that are not affected by natural disasters as a baseline to capture the labor wage fluctuations resulted from a natural disaster(s) in many affected counties. This research is defined in a given geographical region over a specific time period to implement this innovative method. In this study, the state of Florida is selected as the desired geographical region.

Although the exact path of a weather-related natural disaster is not clear, most hurricanes strike the Gulf Coast and Southeastern States (Cutter and Emrich, 2005). The state of Florida belongs to both regions. The natural disaster affects Florida State more than other states in that region (Cutter and Emrich, 2005). In this research, Florida has been selected to be investigated between 2014 to 2018. Over the last decade, the state of Florida has been struck by 13 hurricanes. Every year, hurricane season starts from early June through late November. In October 2018, Florida was hit by Hurricane Michael with winds in excess of 160 miles-per-hour. Hurricane Michael was the first category 5 to strike the U.S. since 1992 and was the fourth category 5 hurricane ever recorded (NOAA, 2020). In 2016, Florida was affected by Hurricane Matthew, boasting wind speeds of 165 mph, and Hurricane Hermine with wind speeds topping 81 mph (Armestrong, 2017).

It is expected that the results of this study will help disaster policymakers and risk-mitigation agencies make more effective funding policies and how funds will be allocated to eligible counties. It could also help the National Flood Insurance Program (NFIP) policyholders make more effective insurance policies, calculate affordable insurance premiums and insurance ratings, especially for low-income and middle-income households, specifically at the state-local level. Furthermore, it could help cost engineers prepare more accurate bids in the vulnerable post-disaster construction markets.

This research is organized as follows. The next chapters present the theoretical framework, investigating the parameters that are affecting construction loss and construction cost increase due to natural disaster occurrence. The author recognizes these parameters through quantitative and qualitative studies. Chapter 3 explains the methodology used for analyzing the effect of natural disasters on construction residential labor wage fluctuation. Moreover, the recommended difference-in-difference technique, combined with conventional spatial panel methods, is discussed in this chapter. Chapter 4 presents the standard handling of missing data methods. Significant findings and interpretations are presented in Chapter 5. In the penultimate chapter, validating the results of the spatial models is discussed. Lastly, the final results, the contributions of this research to the state of knowledge, and the state of practice are explicitly presented in Chapter 7.

CHAPTER 2

BACKGROUND

Methods of investigating construction cost fluctuations can be classified into two groups: Quantitative studies and Qualitative studies. Figure 2-1 illustrates the common qualitative and quantitative methods used to investigate cost fluctuations due to natural disasters.

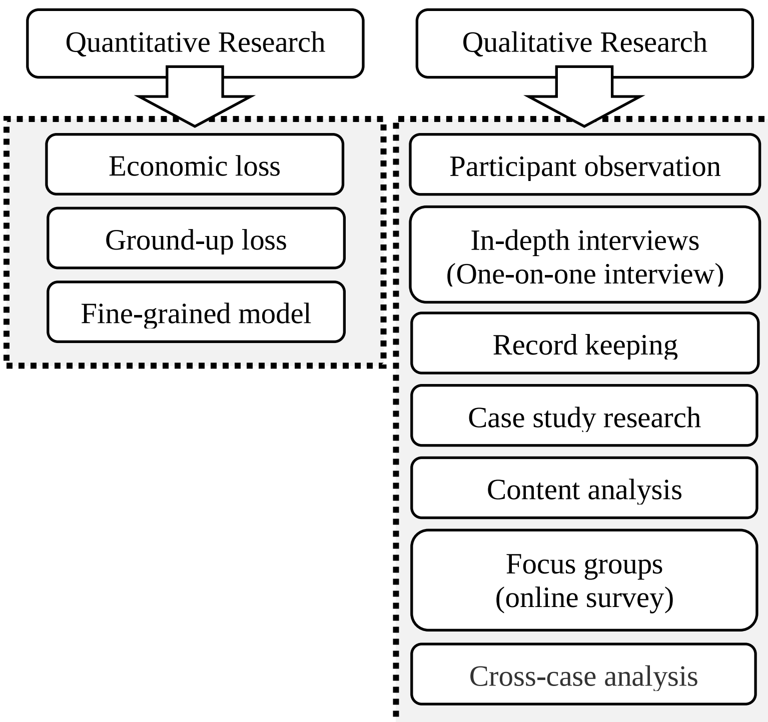

Figure 2-1 List of the quantitative and qualitative methods used to measure construction cost fluctuations, the aftermath of natural disasters

2.1 Quantitative Studies

2.1.1 Economic Loss Models

In this category, regional economic loss models were created to quantify the economic consequences of natural disasters. The difference between economic inputs after a natural disaster versus normal conditions is considered a total loss in these models (Olsen and Porter, 2011b). In quantitative disaster analysis, Input-output (I/O) models are known as the upper bound on economic loss, and they are used for short-horizon estimation (Galbusera and Giannopoulos, 2018). In contrast, Computable General Equilibrium (CGE) models are classified as lower bound on economic loss and used for long-horizon estimations (Galbusera and Giannopoulos, 2018). For example, Hallegatte (2008) used I/O models to estimate economic loss after Hurricane Katrina. Using the Regional Economic models could help capital planners estimate a total cost due to a natural disaster. Although these models are valuable in estimating total economic losses due to disasters, they do not consider fine-grained construction cost fluctuations.

2.1.2 Ground-up Loss Models

This category focuses on ground-up loss at an individual property level or portfolio level following a natural disaster. Ground-up loss is the total amount of money covered by insurance (Astoul et al., 2013). The deductibles paid by an insurance policy, and reinsurance recoverable is excluded from the ground-up loss

(Astoul et al., 2013). Data from insurance companies need to be collected to model the ground-up loss. Olsen and Porter (2011b) determined the increased cost at the portfolio level using data from estimated replacement cost for property, a damage factor, and environmental excitation after Hurricane Andrew. Although these models are very advantageous for insurance and reinsurance companies to estimate what to charge for insurance, they do not characterize fine-grained construction fluctuation following a natural disaster (Ahmadi and Shahandashti, 2018a).

2.1.3 Fine-grained Models

The third group focused on the labor and material line item fluctuations in a fine-grained analysis after a natural disaster. For example, Mueller and Quisumbing (2010) compared nonagricultural labor and agricultural labor fluctuations after floods in Bangladesh, and they realized that floods had more effect on the nonagricultural sectors. Dohrmann et al. (2013) reported Gross Domestic Products (GDP), number of establishments in the construction sector, amount of loss of a catastrophe, catastrophe occurrence in the same region, number of claims, and government price regulation have a significant effect on the reconstruction cost aftermath of a natural disaster. Ahmadi and shahandashti (2018a, 2018b, 2020a, 2020b) studied the role of pre-disaster construction market conditions in the post-disaster labor wage fluctuation using multiple cross-sectional models. They indicated that property damage and preconstruction market conditions have a significant effect on the labor wage fluctuation after a natural disaster.

Besides these three models, researchers have created a variety of models (e.g., univariate and multivariate time series models) to forecast construction cost variations under normal conditions (Kim, et al., 2020, Abediniangerabi, et al., 2018, Abediniangerabi, et al., 2017, Shahandashti and Ashuri, 2016, Shahandashti, 2014a, Shahandashti, 2014b, Shahandashti and Ashuri, 2013, Ashuri et al., 2012a, Ashuri et al., 2012b, Ashuri and Shahandashti, 2012). These models that are developed to represent construction cost variations under normal conditions are usually used to represent the baseline to determine demand surge (Khodahemmati and Shahandashti, 2020).

2.2 Qualitative Studies

Qualitative studies use a variety of methods to discover and gain an in-depth understanding of construction cost fluctuations after a natural disaster. They provide insights into factors that lead to cost increases in the construction sectors. These factors can be served as a platform for quantitative studies. These qualitative studies are mostly based on interviews, questionnaires, content analysis, and reviews of government and media documents.

In the communities that are vulnerable to natural disasters, the level of damage after a disaster is higher (Masozera et al., 2007). The inadequate supply of laborers and materials after a natural disaster leads to higher reconstruction costs (Chang-Richards et al., 2017). The negative impact of natural disasters on the construction market can be reduced by decreasing the risk and vulnerability of construction activities and communities to natural disasters (Masozera et al., 2007). Akintoye and MacLeod (1997) denoted the relationship of risk and construction uncertainty and its effect on the final cost of the construction projects. Previous qualitative studies have highlighted the factors that can be effective in the post-disaster construction cost increase. For example, Krüger et al. (2015) did the content analysis and denoted those cultural aspects that need to be considered in a Disaster Risk Reduction intervention. The dominant ideology and religion within a disaster-affected area are important for designing an intervention to reduce risk (Krüger et al., 2015).

Familiarity with socio-demographic factors of the disaster-affected area such as gender, class, ethnicity, caste, and age makes it easy to work with local people outside (Krüger et al., 2015) to control for the risk resulted from the natural disaster. Bendimerad (2003) underlined that poor land management, increased population concentrations in hazard areas, environmental mismanagement, lack of enforcement of regulation, social destitution, social injustice, unprepared populations, unprepared institutions, and inappropriate use of resources increase susceptibility and reduced resilience to a natural disaster. Bendimerad (2003) denoted that community/stakeholder participation, public policy actions, safer construction, urban development, and development of a culture of prevention are four important lines of action to mitigate disaster risk. Erratic apprenticeship schemes, the poor public image of the industry, and an emphasis on a high-tech knowledge economy by the government cause skills shortages in the New Zealand construction industry.

Chang-Richards et al. (2017) denoted five challenges faced by the construction industry in Christchurch, New Zealand, during its recovery from the 2010 and 2011 earthquakes. These five construction market challenges are known as limited technical capability, limited accommodation for additional workers, the time limitation for training skilled workers, limited information about reconstruction workloads, and a limited operational capacity within construction organizations (Chang-Richards et al., 2017). Bosher et al. (2007) studied the disaster risk management in the UK. Their survey and semi-structured interviews recognized the poorly integrated approaches in disaster risk management. They recommend that hazard awareness be integrated into the professional training of experts in the construction industry, and disaster risk management needs to be more considered in the construction decision making process. Chang et al. (2010) conducted the mixed-method research that was a combination of semi-structured interviews and desk reviews of government and media documents. They defined that the integration among four resourcing components of the reconstruction is essential after a disaster. These four components are legislation and policy, the construction industry, the construction market, and the transportation system.

2.3 Gaps in Knowledge

In the literature, the effect of a disaster on the construction market condition has been calculated through two stages, measurement and quantification. In the measurement step, the fluctuation due to the natural disaster is calculated. Then based on that measurement, the impact of a natural disaster on the construction market is quantified using an appropriate regression model. Because the measurement step is done separately, the possibility of having an error in this step will affect the quantification step’s accuracy. Merging two stages, measurement and quantification, into one stage will decrease the amount of error in the quantification step due to measurement error. Merging two stages, measurement and quantification, in one stage using an appropriate regression model has not been studied in the literature for the construction market indices.

2.4 Research Objectives

This research has two main objectives. The first objective of this research is to estimate the spatio-temporal effect of natural disasters on the fluctuation of the labor weekly wages in the residential construction sector, using the difference-in-difference technique that merges measurement and quantification stages in one stage. The second objective in this research is to use a spatial multiple imputation method to tackle the missing data problem. This spatial imputation method has not been used in this context before.

CHAPTER 3

RESEARCH METHODOLOGY

The research methodology consists of six steps: (1) Creating difference-in-difference models to measure the construction labor wage fluctuations resulted from natural disasters; (2) collecting all the required data from the Federal Emergency Management Agency (FEMA) and Bureau of Labor Statistics (BLS) to create the county-level panel data models for Florida state from 2014 to 2018; (3) defining a weight matrix for 67 counties in Florida; (4) conducting the spatial autocorrelation Moran's I test; (5) creating base models and spatial panel models using difference-in-difference models. Figure 3-1 illustrates the research methodology steps.

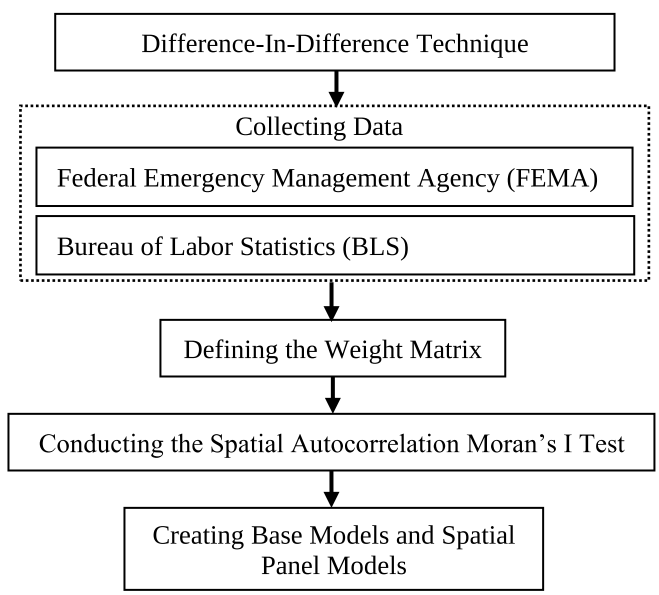

Figure 3-1 Research methodology steps

3.1 Difference-In-Difference (DID) Technique in Construction Labor Wage Fluctuation

The difference-in-difference (DID) technique is used to estimate the effect of a treatment by comparing the changes over time between the control group and the treatment group (see Figure 3-2). This technique can extract the effects of natural disasters from any construction market index. In other words, the difference-in-difference technique has been used to compare the outcome of groups exposed to natural disasters over specific areas at different times (Wing et al., 2018).

In our research, the control group and the treatment group are defined as below:

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

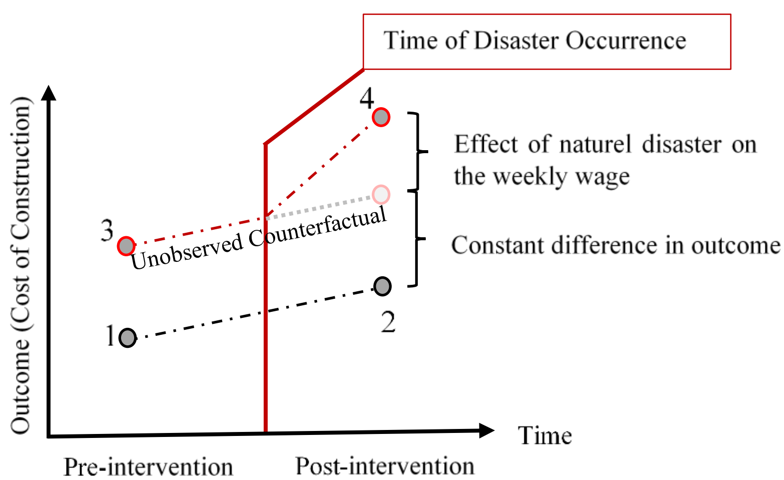

Figure 3-2 Concept of difference-in-differences model

This technique is capable of eliminating the need for measurement in this analysis. By combining the spatial panel models with the difference-in-difference technique the effect of natural disasters on the labor wage fluctuations can be directly quantified without the possibility of being affected by errors due to the measurement step.

This research used the difference-in-difference technique to investigate the effect of the disaster on the “Average labor weekly wages in the residential construction sector” in the county-level database in Florida from 2014 to 2018.

3.2 Data Collection and Data Processing

3.2.1 Residential Construction Market Indices Data

Following our research objective, three criteria were considered for selecting the model variables (construction market indices):

1. The variables should be accessible from publicly available data resources.
2. The variables should influence the residential construction market.
3. The variables should be in their simple form to meet the criteria of our spatial models.

While the first criterion (publicly available) means the data should be freely available through governmental or reliable nongovernmental resources, the second criterion satisfies the objective of this research, and it is backed up by the literature. To meet the third criteria, we were looking for the base form of each variable in the BLS database for the residential construction market. For example, although different forms of the “average weekly wage” variable were provided in the database, such as, “Over the year average weekly wage” or “Location quotient average weekly wage’, the “Average weekly wage” has been selected.

The Bureau of Labor Statistics of the U.S. Department of Labor (BLS) provides construction employment/unemployment information, market activities, and working conditions in the U.S. (BLS, 2020). The North American Industry Classification System (NAICS) is used by BLS to classify business establishments in order to collect, analyze, and publish statistical data (BLS, 2020). Figure 3-3 shows sub-sectors, industry groups, and industries of the construction sector. In this study, the effect of natural disasters on residential building construction labor wage fluctuations has been investigated.

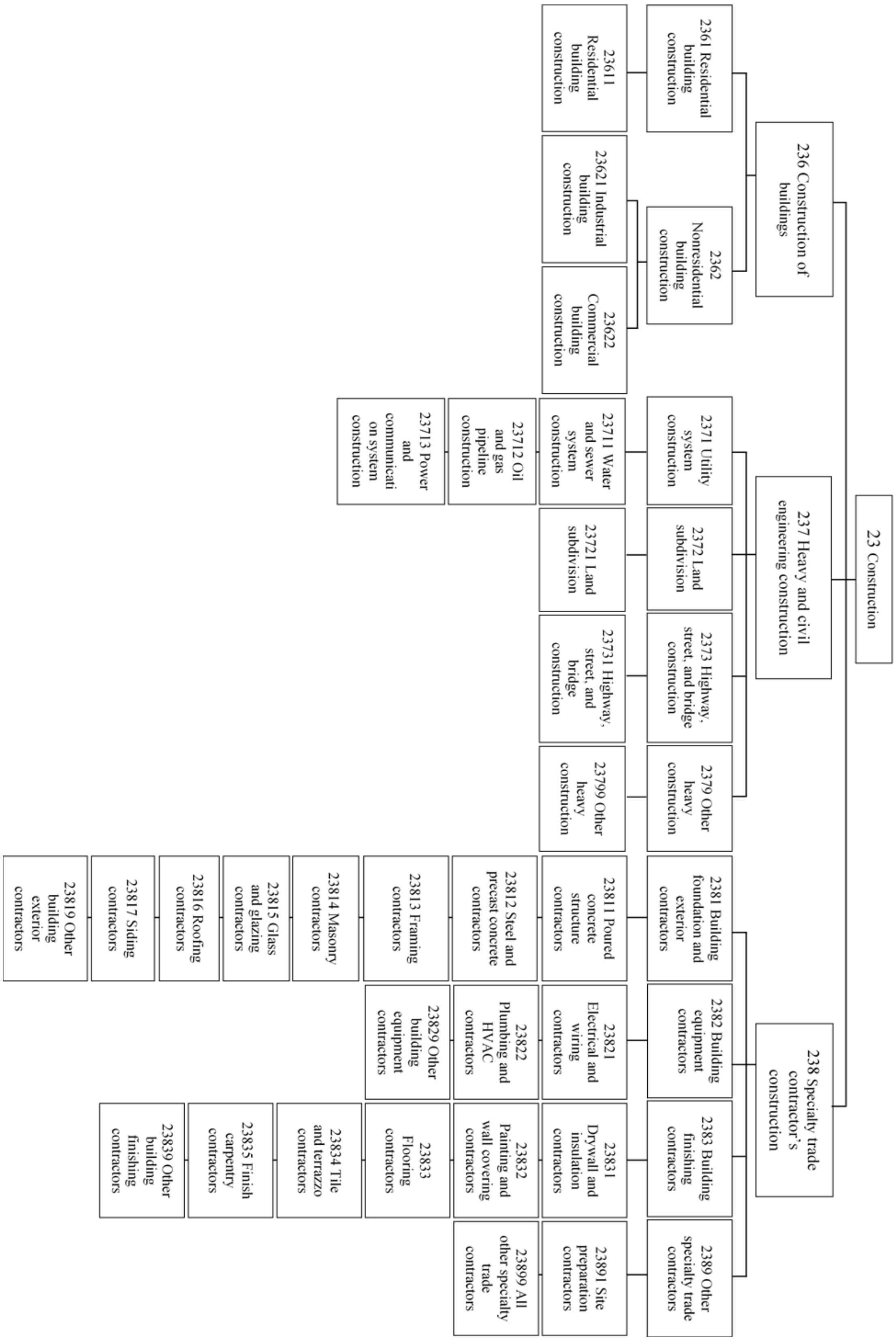

Figure 3-3 Construction sectors, sub-sectors, and industry groups

3.2.2 Disaster-related Data

Following our research objective, two criteria were considered for selecting the disaster-related variable (dummy for disaster):

1. The data should be accessible from publicly available data resources.

2. The disasters should have a level of damage greater than a hundred thousand dollars.

First, a list of all major disaster declarations in Florida was obtained from the Federal Emergency Management Agency (FEMA). Those disasters with the total damages of at least a hundred thousand dollars were selected (see Figure 3-4).

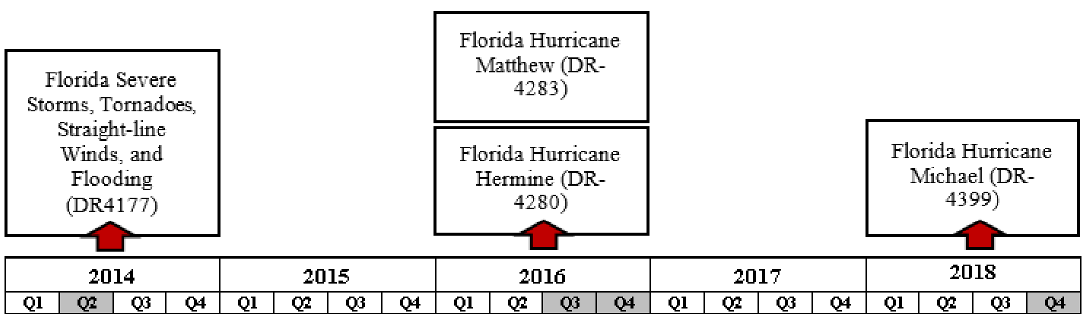

Figure 3-4 Major disaster declaration in Florida from 2014 to 2018 and quarter of the disaster occurrence

Second, all the counties affected by those selected disasters were specified. Figure 3-5 shows an example of a Disaster Declaration for Florida Hurricane Hermine in 2016 with affected counties.

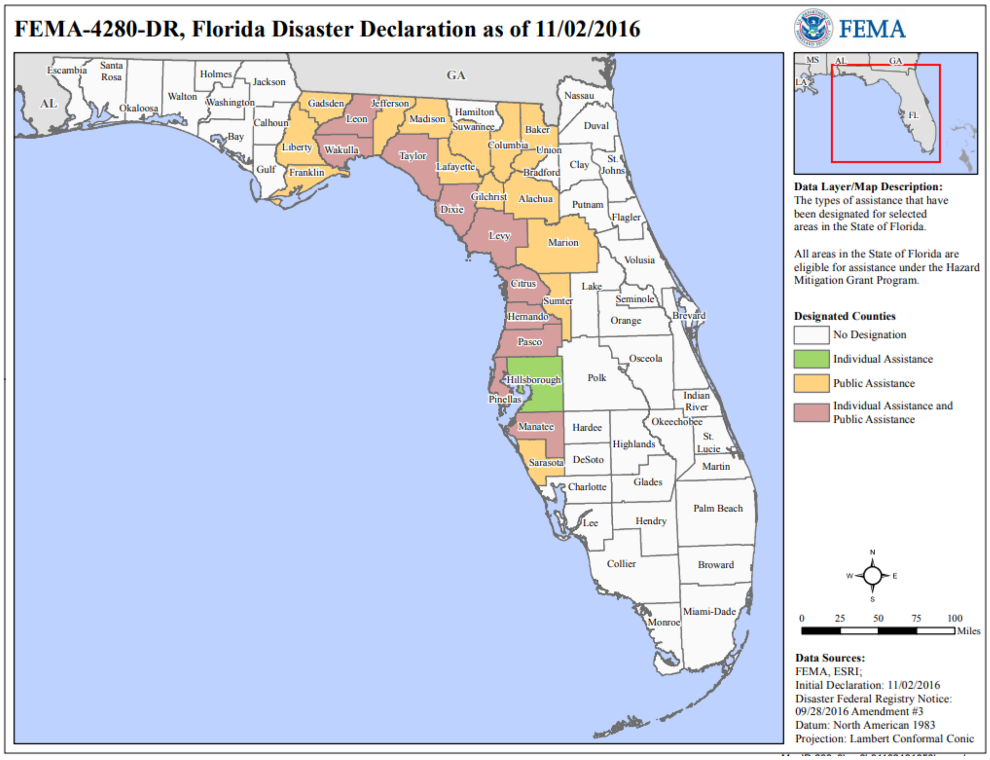

Figure 3-5 FEMA disaster declaration zone for Florida Hurricane Hermine in 2016

Finally, data collected from BLS and data obtained from FEMA were combined to form the research panel data set. Figure 3-6 summarizes the process of obtaining the data for the panel models. The panel data covers Florida with 67 counties over 5 years from 2014 to 2018.

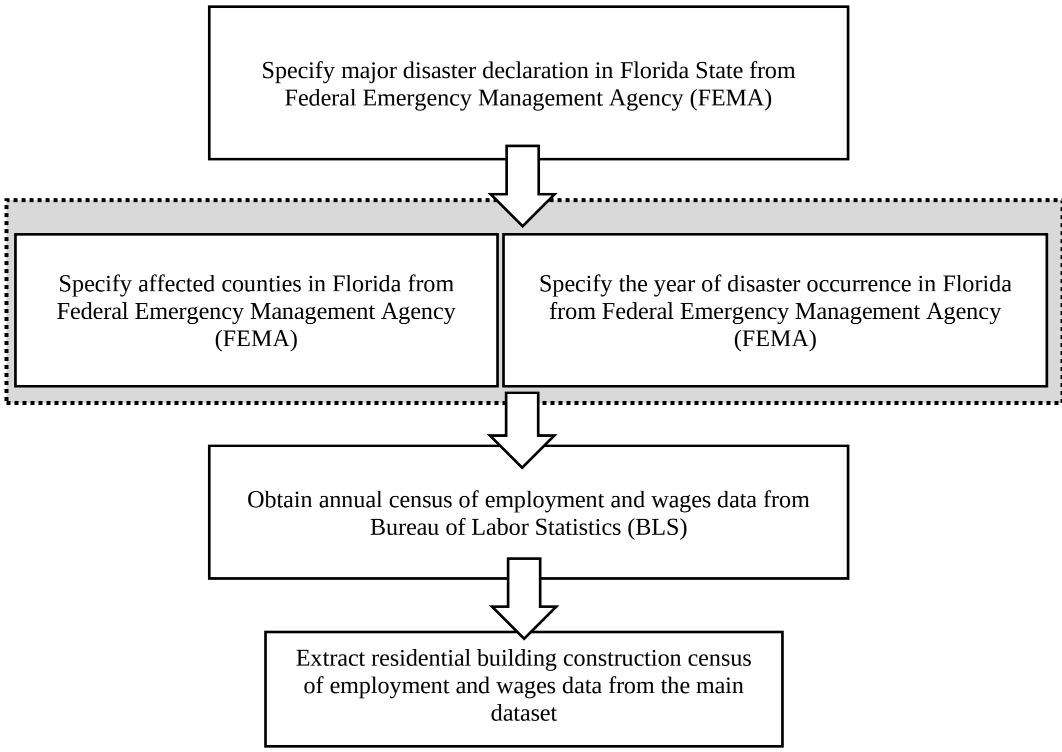

Figure 3-6 Process of data obtained for the panel data analysis from 2014 to 2018

3.3 Weight Matrix

For creating spatial econometrics models, every single observation in our dataset needs to be geocoded. In other words, the weight matrix defines the neighbors and describes which observations are spatially close and how much they influence each other. The spacial 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 standard convention, "self-influence" of county *i* on itself is excluded by assuming that w_{ii} = 0 for all i = 1,2, 3,…, n. So, the matrix of *W* has zero diagonal elements (Smith, 2014). In this research, spatial contiguity weight matrix was used with the following convention (see Eq. 3-1):

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

This matrix allows the condition that counties, even with a common border point, are still considered as neighbors.

In this research, First, U.S counties shapefile in GIS[1] was used to extract the Florida shapefile, which includes the counties of Florida and the geographical boundaries of each county. Then, the GeoDa[2] software was used to create the weight matrix from the Florida shapefile (see Figure 3-7). Then, the created weight matrix was row standardized by dividing each element by the total for that row. Row standardization is recommended because, in a weighted average formula, the weights need to sum up to one, so the values for each county based on the values of its neighbors can be predicted.

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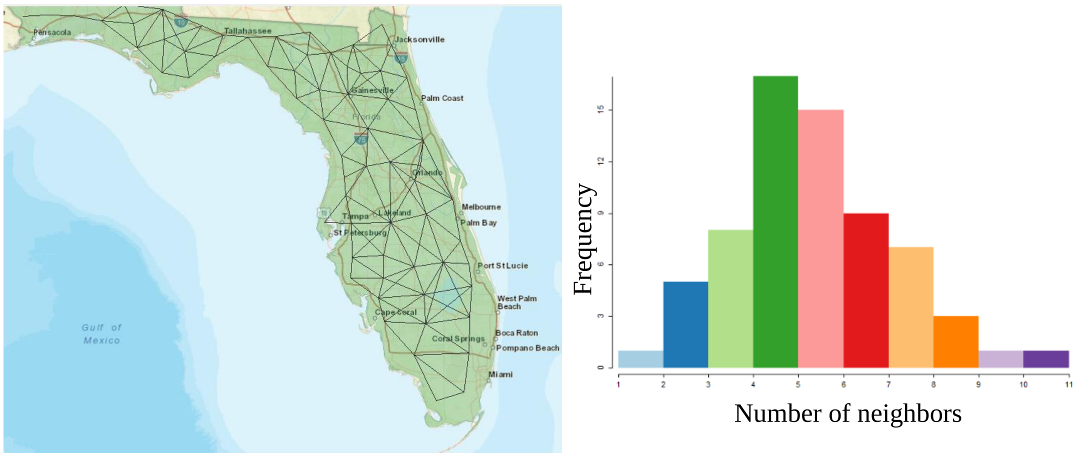
[1] Geographic Information Systems is a mapping technology that allows the user to create and interact with a variety of maps and data sources

[2] GeoDa is a free software program that acts as an introduction to spatial analysis



(a) (b)

Figure 3-7 (a) Counties in Florida contiguity binary matrix (Queen) from GeoDa; (b) Counties in Florida connectivity histogram from GeoDa

3.4 Spatial Autocorrelation Moran's I Test

Moran's I is a coefficient correlation that measures the spatial autocorrelation of the dependent variable in the dataset over the space (Tiefelsdorf, 2006). This coefficient shows how our dependent variable in a specific county is similar to the dependent variable in neighboring county(s). To rephrase it, it is expected that the close observations are more likely to be similar than those far apart. A weight is associated with each pair (y_i, y_j which), which quantifies this neighboring relationship. These weights are set to be 1 for close neighbors, and 0 otherwise. To obtain the Moran's I coefficient, the Moran's I test was conducted in

GIS to see whether our dependent variables are spatially correlated. Moran's I formula is (see Eq. 3-2):

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{Equation 3-2}$$

Where w_{ij} is the weight between observation *i* and *j*, and S_0 is the sum of all wij 's (see Eq. 3-3).

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \quad \text{Equation 3-3}$$

3.5 Panel Data Models

In this section, the econometrics methods that are used to examine the impact of a disaster on labor wage fluctuation are discussed. First, the following panel data model was used to estimate the construction labor wage fluctuation as a result of a natural disaster (see Eq. 3-4)

$$\text{we\_wag}_{it} = \beta_0 + \beta_1 est_{it} + \beta_2 emp_{it} + \beta_3 con_{it} + \beta_4 dis_{it} + \alpha_i + \alpha_t + u_{it} \quad \text{Equation 3-4}$$

Where we_wag_{it} is the average weekly labor wage in the residential construction market sector in county i and year t; esc_{it} is the average establishment count in the residential construction market sector in county *i* and year *t*; emp_{it} the is average employment level in the residential construction market sector in county *i* and year *t*; con_{it} is the level of contributions in the residential construction market sector in county *i* and year *t*; dis_{it} is the disaster dummy variable for the county i and year t; α_i represents the unobservable time-invariant county fixed-effects such as cultural factors; α_t is a vector of year dummy variables, that is controlled for an unobserved variable which is not different county to county but may vary over time, such as government policies; u_{it} is the time-varying idiosyncratic error and it represents the unobservable variable which is different from county to county and different over the time; β_4 is our coefficient of interest, which represents the effect of a natural disaster on weekly labor wage fluctuations. Smith & McCarty (2009) mention that after one year during hurricane season in Florida, about 35 percent of damage structures have been repaired. Anecdotal evidence shows that disasters will start affecting the construction market during the next year. Given that most of the natural disasters in Florida have occurred towards the end of the year, the disaster dummy is created so that it takes a value of one when the economic impact is currently due to the disaster that occurred one year earlier. For example, if disasters occurred in late 2016, the construction market will be affected in 2017, so the dummy variable gets one for 2017, and zero otherwise.

3.5.1 Base Models

Ordinary Least Squares (OLS) were used to estimate the Equation (2). 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. 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. 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.

Although the fixed-effect model can control for heterogeneity across the counties, it cannot take spatial dependency into account. In simpler terms, it cannot check if disaster occurrence in one county affects weekly wage fluctuation in its neighboring county(s). LeSage and Pace (2009) indicated that a change in a specific observation not only affects that observation (a direct impact) but also may potentially affect all other observations indirectly (an indirect impact). This phenomenon is called *interactive heterogeneity* or *multi-county interaction* (LeSage and Pace, 2009)

3.5.2 Spatial Panel Models with Difference-in-Difference Technique

To take interactive heterogeneity into account, the following spatial panel models were used. In the following panel models, a disaster dummy variable is added to capture the effect of natural disasters on labor wage fluctuation through the difference-in-difference technique (see Eq. 3-5, Eq. 3-6, Eq. 3-7, Eq. 3-8).

Spatial Durbin Model (SDM)

$$\text{we\_wag}_{it} = \beta_0 + \rho \text{W}_{ij}\text{we\_wag}_{jt} + \beta_1 est_{it} + \beta_2 emp_{it} + \beta_3 con_{it} + \beta_4 dis_{it} + \delta_1 \text{W}_{ij} est_{jt} + \delta_2 \text{W}_{ij} emp_{jt} + \delta_3 \text{W}_{ij} con_{jt} + \delta_4 \text{W}_{ij} dis_{jt} + \alpha_i + \alpha_t + u_{it}$$ Equation 3-5

i= 1,…, 67 and t= 2014, 2015, 2016, 2017, 2018

Spatial Autoregressive Model (SAR)

$$\text{we\_wag}_{it} = \beta_0 + \rho \text{W}_{ij}\text{we\_wag}_{jt} + \beta_1 est_{it} + \beta_2 emp_{it} + \beta_3 con_{it} + \beta_4 dis_{it} + \alpha_i + \alpha_t + u_{it}$$

Equation 3-6

i= 1,…, 67 and t= 2014, 2015, 2016, 2017, 2018

Spatial Error Model (SEM)

$$\text{we\_wag}_{it} = \beta_0 + \beta_1 est_{it} + \beta_2 emp_{it} + \beta_3 con_{it} + \beta_4 dis_{it} + \alpha_i + \alpha_t + u_{it}$$ Equation 3-7

$u_{it} = \psi \text{W}_{ji} \text{u}_{it} + \varepsilon_{it}$ i= 1,…, 67 and t= 2014, 2015, 2016, 2017, 2018

Spatial Autocorrelation Model (SAC)

$$\text{we\_wag}_{it} = \beta_0 + \rho \text{W}_{ij}\text{we\_wag}_{jt} + \beta_1 est_{it} + \beta_2 emp_{it} + \beta_3 con_{it} + \beta_4 dis_{it} + \alpha_i + \alpha_t + u_{it}$$

$u_{it} = \psi \text{W}_{ji} \text{u}_{it} + \varepsilon_{it}$ i= 1,…, 67 and t= 2014, 2015, 2016, 2017, 2018 Equation 3-8

Where we_wag_{it} is the average weekly labor wage in the residential construction market sector in county *i* and year *t*; esc_{it} is the average establishment count in the residential construction market sector in county *i* and year *t*; emp_{it} the is average employment level in the residential construction market sector in county *i* and year *t*; con_{it} is the level of contributions in the residential construction market sector in county *i* and year *t*; dis_{it} is the disaster dummy variable for the county *i* and year *t*; α_i represents the unobservable time-invariant county fixed-effects such as cultural factors; α_t is a vector of year dummy variables, that is controlled for an unobserved variable which is not different county to county but may vary over time, such as government policies; u_{it} is the time-varying idiosyncratic error; W is the 67×67 spatial weight matrix that represents the queen contiguity weight matrix of 67 counties in Florida state. In the Spatial Error Model (SEM) and Spatial Autocorrelation Model (SAC), $\mathrm{W}_{ji}\mathrm{u}_{it}$ is a spatial lag of the error terms (u). This term is expected to capture the neighborhood effects among the error term. Connected counties may be subjected to a similar policy or institutional environment, so similar outcomes are expected from them (Elhorst, 2014). In these models, Ψ is the spatial autocorrelation coefficient, which shows the spatial correlation of the error terms among neighboring observations.

The spatial autocorrelation model is a mix of the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM) (Anselin, 1988; LeSage and Pace, 2009).

In the SDM, SAR, and SAC models (see Eq. 3-5, 3-6, 3-8), the levels of the county weekly wage are expected to depend on the weekly wage in the neighboring counties. This dependency is taking into consideration by the spatial lag vector $\mathrm{W}_{ij}\mathrm{we\_wag}_{jt}$. The weekly wage in county i affects the weekly wage in county j, which in turn affects the weekly wage in county k, which then affects the amount of weekly wage in county i. Each $\mathrm{we\_wag}_{jt}$ depends on the weighted average of other observation i, the dependent variable over the neighboring counties. ρ is the spatial dependence parameter that measures the dependence of weekly wages in county i on the neighboring counties' weekly wages. There is no dependence if $\rho = 0$. The high level of positive ρ indicates that if the weekly wage is high in the neighborhood of a county, weekly wage in that county is high too.

In the SDM model (see Eq. 3-5), the establishment count, level of employment, level of contribution, and disaster occurrence (independent variables) of neighboring regions proxied by $\mathrm{W}_{ij}est_{jt}, \mathrm{W}_{ij}emp_{jt}, \mathrm{W}_{ij}con_{jt},$ and $\mathrm{W}_{ij}dis_{jt}$ respectively. This model helps to control for omitted variable bias by including the spatial lag of the independent and independent variables. Spatial Durbin Model includes both endogenous interaction/neighborhood effects ($\rho\mathrm{W}_{ij}\mathrm{we\_wag}_{jt}$) and exogenous interaction/neighborhood effects

$(\delta_1\mathrm{W}_{ij}est_{jt},\ \delta_2\mathrm{W}_{ij}emp_{jt},\ \delta_3\mathrm{W}_{ij}con_{jt},\ \delta_4\mathrm{W}_{ij}dis_{jt})$.

In the standard models, to interpret the effect of one explanatory variable on the dependent variable, the partial derivative of the dependent variable with respect to the desired explanatory variable must be taken. For example, the partial derivative of the dependent variable $\mathrm{we\_wag}_{it}$ with respect to the explanatory variable dis_{it} is expected to be β_4, while the interpretation of the spatial models would be different from the base models. This difference arises from considering the effect of the feedbacking loop among the neighboring counties (LeSage and

Pace, 2009). For example, in the county *i*, Spatial Durbin Model can capture feedback effects from weekly wage fluctuation in neighboring county *j* that arise from a weekly wage change originating in the county *i*. According to Elhorst (2014), to interpret the spatial panel model, partial derivative of the expected values of the dependent variable with respect to the explanatory variables ∂x_{nk} was taken (see Eq. 3-9).

$$\begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \frac{\partial E(y_1)}{\partial x_{2k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{nk}} \\ \frac{\partial E(y_2)}{\partial x_{1k}} & \frac{\partial E(y_2)}{\partial x_{2k}} & \cdots & \frac{\partial E(y_2)}{\partial x_{nk}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \frac{\partial E(y_N)}{\partial x_{2k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{nk}} \end{bmatrix} = ((I_N - \rho W)^{-1}) \begin{bmatrix} \beta_k & w_{12}\delta_k & \cdots & w_{1N}\delta_k \\ w_{21}\delta_k & \beta_k & \cdots & w_{2N}\delta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\delta_k & w_{N2}\delta_k & \cdots & \beta_k \end{bmatrix}$$

Equation 3-9

Taking partial derivative allows us to measure the direct, indirect, and total effects. The diagonal elements represent direct effects, while the off-diagonal elements represent the spillover effects.

In the SAR and SAC models, the direct and indirect spillover effects can be obtained as (see Eq. 3-10)

$$\begin{bmatrix} \frac{\partial E(y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & . & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ . & . & . \\ \frac{\partial E(y_{Nn})}{\partial x_{1k}} & . & \frac{\partial E(y_n)}{\partial x_{1k}} \end{bmatrix} = (I_N - \rho W)^{-1}\beta_k$$

Equation 3-10

In this model, the diagonal elements of the partial derivative matrix $(I_N - \rho W)^{-1}\beta_k$ indicate the direct impact and the off-diagonal elements of $(I_N - \rho W)^{-1}\beta_k$ indicate the indirect impact.

While, in the Spatial Durbin Model, the ratio between the indirect effects and the direct effect may be different for different explanatory variables (Eilers, 2016), in the SAR and SAC models, this ratio is the same for every explanatory variable, which resulted in a considerable limitation (Elhorst, 2014). Elhorst (2014) denoted that this limitation makes SAR and SAC models less appropriate in empirical research.

Since the focus of this research is to investigate the impact of natural disasters on the labor weekly wage, the direct effect, indirect effect, and total effect of a natural disaster on the labor weekly wage were measured. Direct effect, indirect effect, and total effect were defined as below:

The direct effect is the effect of the natural disaster occurrence in county *i* on the county *i*'s labor weekly wage fluctuation.

The indirect effect is the weekly wage fluctuation that stems from the disaster occurrence in the neighboring counties.

The total effect is the weekly wage fluctuation that stems from the disaster occurrence in all counties.

CHAPTER 4

HANDLING OF MISSING DATA

In this research, the data set suffers from missing values. Among 335 collected observations, 48 observations were missing from different counties over different years. In this chapter, different methods were discussed to handle missing data. One of the common problems in data analysis is handling the missing data. Missing data is defined as data value that is not available for a variable of interest in the dataset (Kang, H., 2013). If there are any missing observation(s), a common way to handle that is to delete the observation from the data set. However, rather than removing valuable data that can impact results, missing data can be imputed using other information from the dataset. Figure 4-1 shows, four methods were used to handle the missing data: Removing observations with missing values, mean imputation, imputation using average nearest neighbors, and imputation using multiple imputation methods. Each method has pros and cons, which will be discussed in Chapter 5.

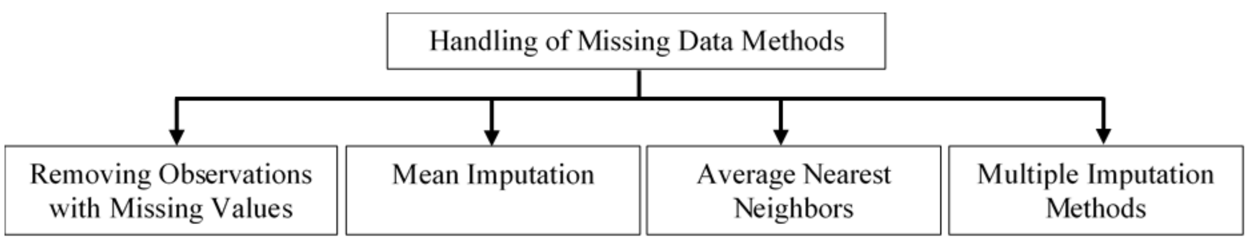


Figure 4-1 Handling of Missing Data Methods

This research began with obtaining data on the annual census of employment and wages from the Bureau of Labor Statistics (BLS). Data in 67 counties in Florida over the period of 2014 to 2018 was obtained from BLS.

4.1 Removing Counties with Missing Observations from Analysis

The first strategy to use incomplete datasets is to discard entire rows containing missing values. This strategy results in losing data, which may be valuable despite it being incomplete. In the panel data modeling, losing those counties with missing data may affect contiguity relationships, and the spatial panel results dramatically. In this method, the treatment group and the control group with no missing observations need to set up. For example, all the counties with missing data from the control group and treatment group were removed. Table 4-1 shows an example of removing the observations with a missing value(s) from the dataset. In this example, observations A, C, and E have missing value(s) that were removed from the dataset.

Table 4-1 (a) Specifying the observations with missing values; (b) Removing the observations with missing values from the dataset

County ID \ Year	2014	2015	2016	2017	2018
A	Missing	3	4	6	8
B	9	6	7	3	4
C	5	1	Missing	Missing	3
D	8	5	9	1	3
E	Missing	Missing	Missing	Missing	Missing
F	2	3	5	2	8

(a)

County ID \ Year	2014	2015	2016	2017	2018
B	9	6	7	3	4
D	8	5	9	1	3
F	2	3	5	2	8

(b)

4.2 Imputation Using Mean Value

In the dataset, two patterns for missing data were observed. In the first pattern, there were missing values in some years. Moreover, there was at least one non-missing value over the five years. In the second pattern, all the observations over five years were missing in some counties. In the first case, the mean of non-missing values in the specific county over the years was calculated. Then the missing values were imputed by the calculated means. In the second case, where all values were missing for all years, the mean of non-missing values in all counties over the specific year was calculated. Afterward, the missing values for that specific year were imputed by the calculated mean. To follow with a consistent structure, in this research, the first cases were addressed first. Then the second cases were addressed thereafter. To clarify the imputation stages in this method, an example is explained through Table 4-2, Table 4-3, and Table 4-4.

Table 4-2 illustrates the row mean calculation. In this step, the mean in each county over the non-missing year was calculated.

Table 4-2 Calculating the mean in each county over the non-missing year (row mean)

Year / County ID	2014	2015	2016	2017	2018	Row mean
A	Missing	3	4	6	8	5.25
B	9	6	7	3	4	5.8
C	5	1	Missing	Missing	3	3
D	8	5	9	1	3	5.2
E	Missing	Missing	Missing	Missing	Missing	
F	2	3	5	2	8	4
Column average						

Table 4-3 shows how the missing values in the counties with at least one non-missing value over a period of five years were imputed by calculated row means.

Table 4-3 Imputing the missing values in the counties with at least one non-missing value over a period of five years

County ID \ Year	2014	2015	2016	2017	2018	Row mean
A	5.25	3	4	6	8	5.25
B	9	6	7	3	4	5.8
C	5	1	3	3	3	3
D	8	5	9	1	3	5.2
E	Missing	Missing	Missing	Missing	Missing	
F	2	3	5	2	8	4
Column mean						

Table 4-4 shows how the mean in the specific year for all non-missing values (column mean) was calculated, and the missing values in the counties with five missing values over a period of five years were imputed by that calculated mean.

Table 4-4 Calculating the mean in the specific year for all non-missing values (column mean) and impute the missing values in the counties with five missing values over a period of five years

County ID \ Year	2014	2015	2016	2017	2018	Row mean
A	5.25	3	4	6	8	5.25
B	9	6	7	3	4	5.8
C	5	1	3	3	3	3
D	8	5	9	1	3	5.2
E	5.85	3.6	5.6	3	5.2	
F	2	3	5	2	8	4
Column mean	5.85	3.6	5.6	3	5.2	

4.3 Imputation Using Average Nearest Neighbors

Another imputation method proposed by this research was an Average Nearest Neighbors algorithm based on the cluster analysis. Based on the Moran's I test, the spatial autocorrelation of the dependent variable in the dataset over the space was observed. As a queen method was used to conduct the Moran's I test, the same method is used to determine the neighboring counties. County *i* and *j* are neighbors if county *i* is adjacent to zone *j*. Non-missing values of the adjacent neighbors were used to calculate missing values in a specific county with missing data. Figure 4-2 shows an example of missing data calculation. If county *i* (specified by the blue dot) has missing data, non-missing values of the adjacent neighbors (specified with the red dots) were used to impute the missing value in county *i*.

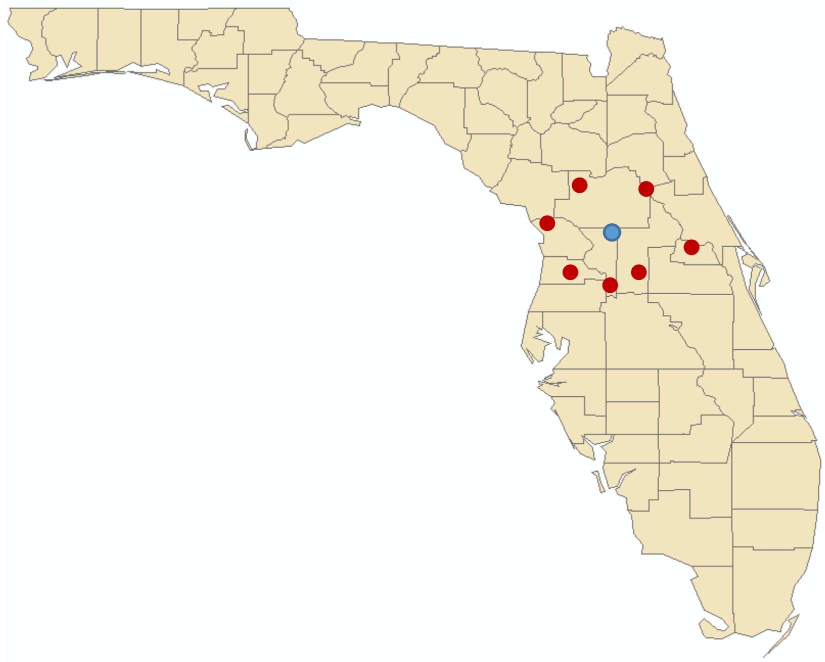


Figure 4-2 Florida county map, blue dot specifies county i, red dots specify the adjacent counties of the county i

4.4 Imputation Using Multiple Imputation Method

In the Multiple Imputation method, instead of filling in a single missing value, the distribution of the observed data is used to estimate multiple values that reflect the uncertainty around the true missing value. These values are then used in the analysis, such as the OLS model, and spatial models. The multiple imputation method has three main phases: Imputation Phase, Analysis Phase, and Pooling Phase. In the imputation phase, the missing values are filled with estimated values to create the complete data set. This process is repeated *m* times to create *m* completed datasets. In other words, *m* copies of the data set are created with different imputed values. The means and covariance of the non-missing data are used to estimate the missing values. Then, to predict the incomplete values from the complete values, regression equations are used and the regression parameters are updated after every iteration to generate different imputed values. After each iteration, one dataset is stored until all missing values are imputed in the dataset. In the analysis phase, those *m* completed datasets are used to analyze using statistical methods. In the pooling phase, the parameter estimates obtained from the analysis phase are combined to present the result.

In the pooling phase, all imputed datasets are used to obtain the final parameter estimates by taking the average over the parameter estimates from imputed datasets. Equation 4-1, Equation 4-2, and Equation 4-3 show how the standard errors are obtained by combining the within and between imputation variance.

$$Var_{within} = \frac{\sum_{i=1}^{M} SE^2 i}{M}$$ Equation 4-1

$$Var_{between} = \frac{\sum_{i=1}^{M} (\beta_i - \overline{\beta})^2 i}{M-1}$$ Equation 4-2

$$Var_{total} = Var_{within} + Var_{between} + \frac{Var_{between}}{M}$$ Equation 4-3

Where β is the parameter estimate, Var is variance, SE is standard error, M is the number of imputed datasets.

CHAPTER 5

RESULTS AND INTERPRETATIONS

First, the presence of spatial autocorrelation among our dependent variables is tested. Described in basic terms, this test measures how one dependent variable in the dataset is similar to others surrounding it. If the variables are spatially correlated with each other, it means that they are not independent, and the spatial relationship of the data in statistical models must be considered. In the second part of this chapter, the results of base models (non-spatial models) and spatial panel models are presented and discussed in two separate categories. The data used in this research had missing values. Having statistical models with the missing values can drastically impact the model's quality. The dataset used in this study is suffered due to missing 14% of its values. In this research, four different methods are used to handle missing values, including the mean imputation method, removing observations with a missing value(s) from the dataset, average nearest neighbors' method, and multiple imputation method. Among all four methods used in this study, the multiple imputation method is specifically designed for handling missing data in spatial panel data models. One of the main contributions in this study is the use of the multiple imputation method that is specifically designed for spatial panel datasets with missing values. The results obtained from these methods are compared in the final part of this chapter.

5.1 Moran's I Test Results

Moran's I test has been conducted to test for spatial autocorrelation among our dependent variable (construction labor weekly wage). Figure 6 illustrates one sample of GIS report for our dependent variable in 2017. Moran's I test is conducted for the years 2014 to 2018 separately, and the results showed the clustering pattern in all years (see Table 5-1).

Table 5-1 spatial autocorrelation Moran's I test on the dependent variable from 2014-2018

Dependent Variable	Moran's I Index	Z-score	P-value	Clustered/Dispersed/Random
Average weekly wage year 2014	0.376	4.839	0.000	Clustered
Average weekly wage year 2015	0.462	5.923	0.000	Clustered
Average weekly wage year 2016	0.403	5.232	0.000	Clustered
Average weekly wage year 2017	0.297	3.862	0.000	Clustered
Average weekly wage year 2018	0.430	5.485	0.000	Clustered

Florax and Nijkamp (2003) indicated that the interpretation of Moran's I is parallel to a correlation coefficient. A positive value shows a positive spatial autocorrelation. These positive values, from 2014 to 2018, show the occurrence of similar values of a variable being found over contiguous or adjacent spaces. For example, in 2017, the Moran's I statistic on the labor weekly wage, shows a positive value of 3.862 with a p-value of 0.000 (see Figure 5-1). As expected, this result indicates that the null hypothesis of no spatial dependence is rejected. Furthermore, the test statistic indicates that positive spatial autocorrelation exists. Spatial models should be adopted instead of the non-spatial OLS estimations to obtain unbiased and consistent estimators.

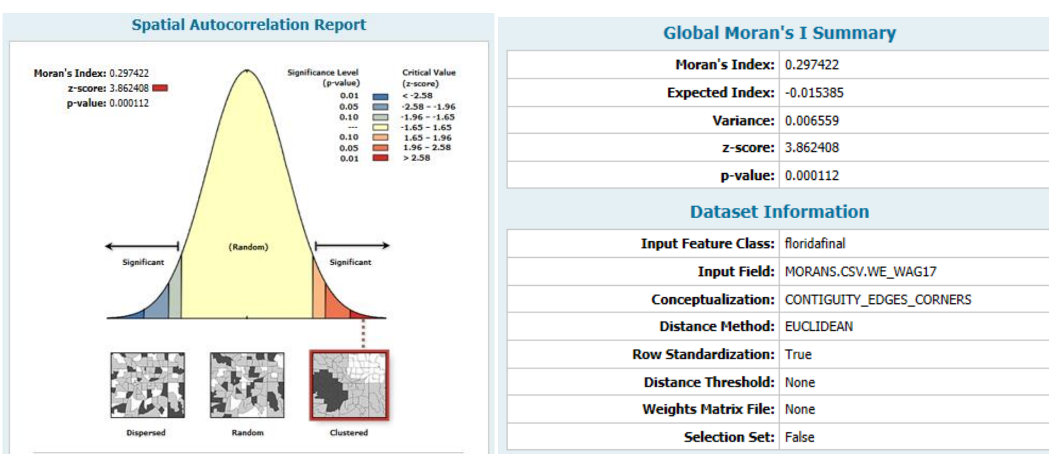


Figure 5-1 Sample of spatial autocorrelation report from GIS for dependent variable in 2017 across the state of Florida

5.2 Results of Panel Data Models

In this section, the results of panel data models are presented in two main categories. In the first category, the results of the base models are presented. In the second category, the results of spatial panel models are presented. Each category is divided into four subcategories. In each subcategory, the result of one of the methods for handling missing data is presented. Figure 5-2 shows the layout of the presentation of the results.

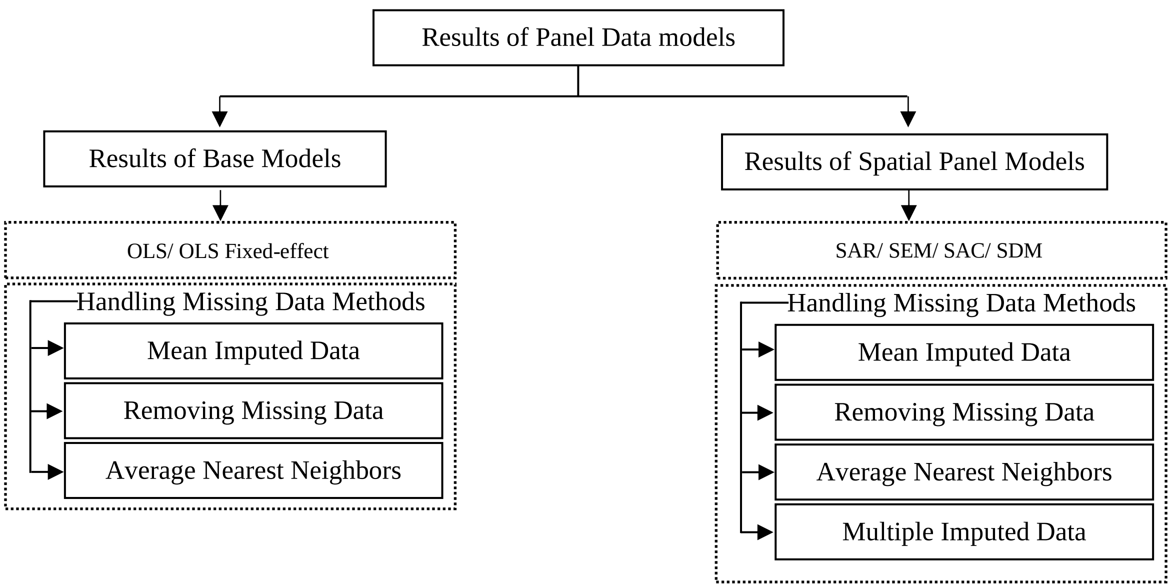


Figure 5-2 Layout of results

5.2.1 Results of Base Models

The results of the OLS model and the fixed-effect model are given in the first column and the second column of Table 6, Table 7, and Table 8, respectively. The missing data in the data set were handled using three common techniques, mean imputation, removing counties with missing data, and average nearest neighbors. While the result of the regression from imputed data is tabulated in Table 6, the result of regression from removing counties with missing data is shown in Table 7, and the result of regression from average nearest neighbors methods are tabulated in Table 8.

5.2.1.1 Results of Base Models from the Mean Imputed Data

While fixed-effects estimator accounts for the unobserved county heterogeneity (α_i), OLS estimator does not control for that (α_i). The results from the OLS model indicated that the average labor weekly wage in those counties that are affected by disaster is 10 percent higher than those counties next year which are not affected by the disaster (see Table 5-2). However, as the results from the Moran's I statistic and model diagnostic tests in Table 5-1 show, estimates using the OLS method suffer from a major problem. There is evidence of a positive spatial autocorrelation, that the OLS result simply ignores this spatial variation and produces biased estimates. Also, the LM test statistic suggests that the fixed-effect model is an appropriate alternative. Downward bias is found in the OLS estimates, suggesting an underestimation of the disaster impact on the labor weekly wage increase. The fixed-effect result shows that the average labor weekly wage in those counties that are affected by a disaster is 11 percent higher next year than those counties that are not affected by the disaster. Table 5-2 indicates that the results from both the OLS and fixed-effect models are significant at a 99 percent level of confidence.

Table 5-2 Estimated results from pooled OLS and fixed-effect model (mean imputed data)

Variables	OLS lnwe_wag	OLSfe lnwe_wag
Establishment Count	0.000 (0.000)	-0.001 (0.001)
Employment Level	0.000 (0.000)	0.000 (0.000)
Level of Contribution	0.000*** (0.000)	0.000 (0.000)
Disaster	0.106*** (0.036)	0.113*** (0.037)
Constant	6.157*** (0.050)	6.358*** (0.145)
Breusch and Pagan Lagrange multiplier test (P-value)	N/A	0.0000
Year Dummies	Yes	Yes
Observations	335	335
R-squared	--	0.251
Number of poly_id	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.1.2 Results of Base Models from Removing Missing Data

The results from the OLS model indicated that the average labor weekly wage in those counties that are affected by a disaster is 6.2 percent higher in the next year than those counties, which are not affected by the disaster (see Table 5-3). The fixed-effect result shows that the average labor weekly wage in those counties that are affected by disaster is 6.4 percent higher in the next year than those counties that are not affected by the disaster. Table 5-3 indicates that both results from OLS and fixed-effect models are significant at a 95 percent level of confidence.

Table 5-3 Estimated results from pooled OLS and fixed-effect model (removing missing data)

Variables	OLS lnwe_wag	OLSfe lnwe_wag
Establishment Count	0.000 (0.000)	-0.000 (0.001)
Employment Level	0.000 (0.000)	0.000 (0.000)
Level of Contribution	0.000 (0.000)	-0.000 (0.000)
Disaster	0.062** (0.026)	0.064** (0.026)
Constant	6.371*** (0.048)	6.562*** (0.139)
Breusch and Pagan Lagrange Multiplier Test (P-value)	N/A	0.0000
Year Dummies	Yes	Yes
Observations	230	230
R-squared	--	0.375
Number of poly_id	46	46

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.1.3 Results of Base Models from the Average Nearest Neighbors

The results from the OLS model indicated that the average labor weekly wage in those counties that are affected by disaster is 6.8 percent higher in the next year than those counties, which are not affected by the disaster (see Table 5-4). The fixed-effect result shows that the average labor weekly wage in those counties that are affected by disaster is 7 percent higher in the next year than those counties that are not affected by the disaster. Table 5-4 indicates that both results from OLS and fixed-effect models are significant at a 95 percent level of confidence.

Table 5-4 Estimated results from pooled OLS and fixed-effect model (average nearest neighbors)

Variables	OLS lnwe_wag	OLSfe lnwe_wag
Establishment Count	0.001 (0.000)	0.000 (0.001)
Employment Level	0.000 (0.000)	0.000 (0.000)
Level of Contribution	0.000 (0.000)	0.000 (0.000)
Disaster	0.068 (0.042)	0.070 (0.043)
Constant	6.233*** (0.044)	6.313*** (0.168)
Breusch and Pagan Lagrange Multiplier Test (P-value)	N/A	0.0000
Year Dummies	Yes	Yes
Observations	335	335
R-squared	--	0.150
Number of poly_id	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.2 Results of Spatial Models

As mentioned above, the fixed-effect model accounts for both individual and temporal heterogeneity but not for the interactive heterogeneity or the spatial dependence among neighboring counties. Thus, we estimated our model using spatial panel data models (SAR, SEM, SAC, and SDM). As we mentioned before, Spatial Durbin Model (SDM) is taking both endogenous and exogenous interactions (neighborhood effects) into account.

5.2.2.1 Results of Spatial Panel Models from the Mean Imputed Data

The results from the SDM model indicated that the coefficient on the natural disaster is statistically significant and positive. This result indicates that the disaster occurrence in county *i* is associated with an increase in the labor weekly wage of this county one year after the disaster occurrence. The disaster occurrence in neighboring counties is also negatively associated with the labor weekly wage in county *i*. However, this coefficient is not statistically significant, meaning that the labor weekly wage in a particular county is not affected by the disaster occurrence in the neighboring counties (see Table 5-5).

Table 5-5 Estimated results from spatial panel models imputed (mean imputed data)

Variables	SARfe	SEMfe	SACfe	SDMfe Main	SDMfe Wx
Establishment Count	-0.000 (0.000)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.003* (0.002)
Employment Level	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
Level of Contribution	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Disaster	0.096*** (0.026)	0.114*** (0.036)	0.063*** (0.021)	0.122** (0.056)	-0.003 (0.067)
W_{ij}lnwe_wag	0.257*** (.095)	N/A	0.592*** (0.147)	0.220*** (0.079)	N/A
Ψ	N/A	0.261*** (0.077)	-0.487** (0.198)	N/A	N/A
Hausman Test (chi2)	N/A	N/A	N/A	0.027	N/A
Observations	268	268	268	268	268
R-squared	0.247	0.313	0.179	0.010	0.010
Number of poly_id	67	67	67	67	67

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

As highlighted above, in order to accurately quantify the impact of the natural disaster on the wage fluctuation, we rely on the own partial derivatives and the cross partial derivatives.

The direct, indirect, and total impacts of the natural disaster on the labor weekly wage in all four different spatial panel models that we used are illustrated in Table 5-6. Aforementioned above, the direct impact is the average impact of the natural disaster occurrence in county *i* on the weekly wage fluctuation in that county. The indirect impact is the weekly wage fluctuation that stems from the disaster occurrence in the neighboring counties. The total impact is the sum of direct and indirect impacts. The weekly wage impacts of natural disasters go through connected counties and then return to the initial counties. By way of illustration, the natural disaster occurrence in county *i* are expected to impact the labor weekly wage in county *j*, which impacts the outcome in county *k*, which eventually impacts the labor weekly wage fluctuation in county *i*.

We also find that natural disaster occurrence is associated with an indirect or spillover effect. This spillover effect indicates that the disaster occurrence in one county negatively impacts the labor weekly wage in neighboring counties. It should be noted that the coefficient of the indirect impact of natural disasters on the weekly wage is not statistically significant.

Overall, the results from Table 5-6 suggest that the disaster occurrence in a particular county has a significant positive impact on the labor weekly wage in that county itself.

Table 5-6 Direct, Indirect, and Total Impacts from spatial panel data models (mean imputed data)

Variables	SAR fe				SAC fe				SDM fe				
	Main	Direct	Indirect	Total	Main	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.007)	-0.002 (0.008)	-0.001 (0.001)	-0.003* (0.002)	-0.001 (0.001)	-0.004* (0.002)	-0.005* (0.002)
Employment Level	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000* (0.000)	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.001* (0.000)	0.001* (0.000)
Level of Contribution	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Disaster	0.096*** (0.026)	0.099*** (0.027)	0.035* (0.021)	0.133*** (0.044)	0.063*** (0.021)	0.072*** (0.022)	0.108 (0.148)	0.181 (0.155)	0.122** (0.056)	-0.003 (0.067)	0.123** (0.053)	0.026 (0.069)	0.149*** (0.049)
Observations	268	268	268	268	268	268	268	268	268	268	268	268	268
Number of poly_id	67	67	67	67	67	67	67	67	67	67	67	67	67

Robust standard errors in parentheses

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

5.2.2.2 Results of Spatial Panel Models from the Removing of Missing Data

The results from the SDM model indicated that the coefficient on the natural disaster is positively associated with the labor weekly wage in county i, indicating that the disaster occurrence in county *i* is associated with an increase in the labor weekly wage of this county the year after the disaster occurrence. Table 5-7 indicates that the disaster occurrence in neighboring counties are also positively associated with the labor weekly wage in county *i*. However, both coefficients are not statistically significant, meaning that the labor weekly wage in a particular county is not affected by the disaster occurrence in the neighboring counties and the county *i*.

Table 5-7 Estimated results from spatial panel models imputed (removing missing data)

Variables	SARfe	SEMfe	SACfe	SDMfe Main	SDMfe Wx
Establishment Count	-0.001 (0.001)	-0.001 (0.001)	-0.001** (0.000)	-0.001* (0.001)	-0.001 (0.001)
Employment Level	0.000** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000* (0.000)
Level of Contribution	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Disaster	0.067** (0.027)	0.061*** (0.019)	0.042*** (0.013)	0.008 (0.057)	0.079 (0.062)
W_{ij}lnwe_wag	-0.130** (0.058)	N/A	0.345* (0.196)	-0.168* (0.089)	N/A
Ψ	N/A	-0.162* (0.091)	-0.504*** (0.181)	N/A	N/A
Hausman Test (chi2)	1.000	N/A	N/A	0.675	N/A
Observations	184	184	184	184	184
R-squared	0.193	0.212	0.266	0.251	0.251
Number of poly_id	46	46	46	46	46

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

As highlighted above, in order to accurately quantify the impact of the natural disaster on the wage fluctuation, we rely on the own partial derivatives and the cross partial derivatives. The direct, indirect, and total impacts of the natural disaster on the labor weekly wage in all four different spatial panel models that we used and are illustrated in Table 5-8.

Table 5-8 Direct, Indirect, and Total Impacts from spatial panel data models (removing missing data)

Variables	SAR fe				SAC fe				SDM fe				
	Main	Direct	Indirect	Total	Main	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)	-0.001 (0.000)	-0.001** (0.000)	-0.001* (0.001)	-0.001 (0.002)	-0.002 (0.002)	-0.001* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002* (0.001)
Employment Level	0.000** (0.000)	0.000* (0.000)	-0.000 (0.000)	0.000* (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000* (0.000)	0.000** (0.000)	0.000* (0.000)	0.000** (0.000)
Level of Contribution	-0.000* (0.000)	-0.000* (0.000)	0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Disaster	0.067** (0.027)	0.068* * (0.027)	-0.008* (0.004)	0.060** (0.024)	0.042*** (0.013)	0.045*** (0.015)	0.028 (0.042)	0.073 (0.051)	0.008 (0.057)	0.079 (0.062)	0.004 (0.060)	0.068 (0.063)	0.072*** (0.019)
Observations	184	184	184	184	184	184	184	184	184	184	184	184	184
Number of poly_id	46	46	46	46	46	46	46	46	46	46	46	46	46

Robust standard errors in parentheses

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

5.2.2.3 Results of Spatial Panel Models from the Average Nearest Neighbors

The results from the SDM model indicated that the coefficient on the natural disaster is positively associated with the labor weekly wage in county i, indicating that the disaster occurrence in county *i* is associated with an increase in the labor weekly wage of this county the year after the disaster occurrence. The disaster occurrence in neighboring counties are also positively associated with the labor weekly wage in county i. Table 5-9 indicates that both coefficients are not statistically significant, meaning that the labor weekly wage in a particular county is not affected by the disaster occurrence in the neighboring counties and the county i.

Table 5-9 Estimated Results from Spatial Panel Models Imputed (average nearest neighbors)

Variables	SARfe	SEMfe	SACfe	SDMfe	
				Main	Wx
Establishment Count	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.002 (0.002)
Employment Level	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Level of Contribution	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Disaster	0.061* (0.034)	0.065* (0.037)	0.075* (0.043)	0.074 (0.064)	0.003 (0.076)
W_{ij}lnwe_wag	0.096 (0.073)	N/A	-0.311 (0.343)	0.085 (0.087)	N/A
Ψ	N/A	0.099 (0.086)	0.364 (0.282)	N/A	N/A
Hausman Test (chi2)	N/A	N/A	N/A	0.000	N/A
Observations	268	268	268	268	268
R-squared	0.480	0.469	0.425	0.236	0.236
Number of poly_id	67	67	67	67	67

Robust standard errors in parentheses

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

As highlighted above, in order to accurately quantify the impact of the natural disaster on the wage fluctuation, we rely on the own partial derivatives and the cross partial derivatives. The direct, indirect, and total impacts of the natural disaster on the labor weekly wage in all four different spatial panel models that we used are illustrated in Table 5-10.

Table 5-10 Direct, Indirect, and Total Impacts from spatial panel data models (average nearest neighbors)

VARIABLES	SARfe				SACfe				SDMfe				
	Main	Direct	Indirect	Total	Main	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	0.001 (0.001)	0.001 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.000 (0.000)	0.001 (0.001)	0.000 (0.001)	-0.002 (0.002)	0.000 (0.001)	-0.002 (0.002)	-0.002 (0.002)
Employment Level	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Level of Contribution	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Disaster	0.061* (0.034)	0.062* (0.034)	0.006 (0.006)	0.068* (0.037)	0.075* (0.043)	0.079* (0.045)	-0.021 (0.026)	0.058* (0.034)	0.074 (0.064)	0.003 (0.076)	0.074 (0.062)	0.007 (0.078)	0.081* (0.048)
Observations	268	268	268	268	268	268	268	268	268	268	268	268	268
R-squared	0.480	0.480	0.480	0.480	0.425	0.425	0.425	0.425	0.236	0.236	0.236	0.236	0.236
Number of poly_id	67	67	67	67	67	67	67	67	67	67	67	67	67

Robust standard errors in parentheses

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

5.2.2.4 Results of Spatial Panel Models from the Multiple Imputed Data

Table 5-11 summarizes the results of three types of fixed-effect Spatial Durbin Models. In the *individual fixed-effect SDM,* the total effect of natural disasters on labor weekly wage is significant. In this model, the total effect of a natural disaster occurrence in the affected counties increases the labor weekly wage by 7.5 percent. This result is more consistent with the results obtained from Table 13 for SAC, SEM, and SAR models. In all four models, the total effect of natural disasters on labor weekly wage is significant, and the magnitude of the effect in all four models is similar.

Table 5-11 Direct, Indirect, and Total Impacts from spatial panel data models (multiple imputed data)

VARIABLES	SDMfe (time fixed-effect)					SDMfe (individual fixed-effect)					SDMfe (both time and individual fixed-effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	0.000*	-0.000	0.000*	-0.001	-0.002	0.001	0.000	0.001	0.000	0.002	0.001*	0.000	0.001*	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)	(0.002)
Employment Level	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Level of Contribution	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disaster	0.068	0.002	0.069	0.020	0.089	0.055	0.013	0.056	0.019	0.075*	0.057	0.004	0.057	0.004	0.061
	(0.123)	(0.149)	(0.114)	(0.165)	(0.108)	(0.101)	(0.115)	(0.098)	(0.118)	(0.046)	(0.100)	(0.121)	(0.099)	(0.124)	(0.062)
Observations	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335
Number of poly_id	67	67	67	67	67	67	67	67	67	67	67	67	67	67	67

Robust standard errors in parentheses

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

5.4 Summary of the Results

The results from the non-spatial empirical analysis from the first three imputation methods that have been used (*mean imputed data*, *removing missing data*, and *average nearest neighbors*) show that the OLS model can be biased and inconsistent since this estimator does not control for unobserved heterogeneity or omitted variable bias. The Breusch and Pagan (1980) test has been used to determine whether the unobserved time-invariant property fixed effects (α_i) exist. The corresponding P-value is 0.000 for this test, as illustrated in the sixth row in Table 6, Table 7, and Table 8. As expected, the test rejects the null hypothesis showing that unobserved time-invariant property fixed effects (α_i) exist. Which is to say, in our data sets, there are unobserved variables that change from county to county but are constant over time. These unobserved time-invariant country-specific characteristics (α_i) could be managerial and administrative differences, geological differences, local laws and regulations, and cultural parameters such as the types of business communication interaction at the local level. So, the fixed-effect OLS result is more appropriate in comparison with OLS results. In this research, the coefficient of interest is the coefficient of a natural disaster dummy variable. This coefficient indicates the effect of natural disasters on construction labor weekly wage fluctuation in the residential construction market. Other exogenous variables are added to the model based on the literature to control for other possible effective parameters.

Table 5-12 summarizes the estimated results from fixed-effect models obtained from handling missing data methods. The results from *removing the missing data* method and *average nearest neighbors* method are almost consistent, while the result obtained from the *mean imputed method* is higher. The fixed-effects OLS result from *average nearest neighbors* indicates that the average labor weekly wage in counties affected by the natural disasters is 7 percent higher than the counties that are not affected. While the fixed-effects OLS result from *removing missing data* indicates that the average labor weekly wage in counties affected by the natural disasters is 6.4 percent higher than the counties that are not affected. Table 5-12 shows that the estimated results from pooled OLS fixed-effect models obtained from *removing missing data* and *mean imputation method* are significant at a 95 percent level of confidence and 99 percent level of confidence, respectively.

Table 5-12 Estimated results from pooled OLS fixed-effect model (removing missing data)

Handling Missing Data Methods	**Disaster Dummy Variable Estimator (OLS Fixed-effect)**
Mean imputed data	0.113*** (0.037)
Removing missing data	0.064** (0.026)
Average nearest neighbors	0.070 (0.043)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The fixed-effects model accounts for heterogeneity across counties and temporal heterogeneity over time but not for the interactive heterogeneity or the spatial dependence among neighboring counties. Thus, we also estimated our parameters by using spatial panel data models. The results are obtained from the spatial SAR, SEM, SAC, and SDM models. The results from the Hausman test show fixed-effect SAR, fixed-effect SEM, and fixed-effect SAC models are not appropriate in comparison to random-effect models. Thus, fixed-effect models from SAR, SEM, SAC models need to be rejected. Table 5-13 summarizes the results from our preferred model, which is the Spatial Durbin Fixed-Effect Model obtained from the handling of missing data methods.

The Spatial Durbin Model allows for the construction labor weekly wage in a county to be dependent on the construction labor weekly wage of the neighboring counties, accounted for by the spatial lag vector $W_{ij}\ lnWW_{ij}$ (natural log of the labor average weekly wage) and the natural disaster occurrence in neighboring counties $W_{ij}\ dis_{ij}$.

The results from all imputation methods for the Spatial Durbin Model indicate the natural disasters have a significantly positive impact on the construction labor weekly wage. The fixed-effects SDM result from *mean imputed data* indicates that the average labor weekly wage in counties affected by the natural disasters is 12.2 percent higher than the counties that are not affected by natural disasters. The fixed-effects SDM result from *removing missing data* method indicates that the average labor weekly wage in counties affected by the natural disasters is 0.8 percent higher than the counties that are not affected by natural disasters. The next two fixed-effects SDM results from *average nearest neighbors* method and *multiple imputed data* indicate that the average labor weekly wage in counties affected by the natural disasters is 7.4 percent and 5.5 percent higher than the counties that are not affected by natural disasters, respectively. The results from the last two methods are more consistent with each other and with the other results obtained from other spatial models.

Based on the results presented in Table 5-13, just the coefficient on the natural disasters in the fixed-effect SDM from *mean imputed data* is statistically significant at 95 percent level of confidence, indicating that the occurrence of the natural disasters in county *i* is associated with an increase in the construction labor weekly wage of this county.

Table 5-12 Summary of the estimated results from the spatial panel data models from different handling missing data methods for the coefficient of interest in the Spatial Durbin Model

Panel Data Models	Main Disaster Coefficient	Effect Disaster Coefficient	
Spatial Durbin Model (SDM) Fixed-effect from ***Mean Imputed Data***	0.122** (0.056)	Direct effect	**0.123** (0.053)**
		Indirect effect	0.026 (0.069)
		Total effect	**0.149***** (0.049)
Spatial Durbin Model (SDM) Fixed-effect from **Removing Missing Data**	0.008 (0.057)	Direct effect	0.004 (0.060)
		Indirect effect	0.068 (0.063)
		Total effect	**0.072***** (0.019)
Spatial Durbin Model (SDM) Fixed-effect from **Average Nearest Neighbors**	0.074 (0.064)	Direct effect	0.074 (0.062)
		Indirect effect	0.007 (0.078)
		Total effect	**0.081*** (0.048)
Spatial Durbin Model (SDM) Fixed-effect From **Multiple Imputed Data**	0.055 (0.101)	Direct effect	0.056 (0.098)
		Indirect effect	0.019 (0.118)
		Total effect	**0.075*** (0.046)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In order to accurately quantify the impact of the natural disasters on the wage fluctuation, we rely on the own partial derivatives and the cross partial derivatives. The direct, indirect, and total impacts of the natural disasters on the labor weekly wage are illustrated in Table 5-13. As highlighted above, the direct impact is the average impact of the natural disaster occurrence in county *i* on the labor weekly wage in the county. The total impact is the average labor weekly wage fluctuation in county *i* resulted from natural disaster occurrence across all counties. The indirect impact is the construction labor weekly wage fluctuation that stems from the natural disaster occurrence in the neighboring counties. The total effects of the natural disasters on labor weekly wages obtained from all imputation methods are significant. The result in the *mean imputed data* and *removing missing data* methods are significant at a 99 percent level of confidence. In comparison, the results from the *average nearest neighbors* method and multiple imputation methods are significant at a 90 percent level of confidence. The magnitude of the results in *removing missing data* method, the *average nearest neighbors* method, and *multiple imputation method* are almost the same. In contrast, the magnitude of the result from *mean imputed data* is almost doubled. The *average nearest neighbors* method and *multiple imputation method* are compatible with the spatial nature of the data. Both are specifically designed to impute the spatial missing data. Especially the spatial *multiple imputation* method, which is used in this research, is one the main contribution of this study in the state of knowledge. Using spatial imputation methods resulted in preserving the spatial properties of the data. Thus, in this study, the interpretation focus should shift to the Spatial Durbin Model

Fixed-effect (SDM) from *multiple imputed data* and *average nearest neighbors* methods.

The total impact of natural disasters on labor weekly wage is 8.1 percent obtained from the *average nearest neighbor imputation* method. While the total impact of natural disasters on labor weekly wage is 7.5 percent obtained from the *multiple imputation* method. It is not clear which of these two (total results) best describes the data. Both models produce spillover effects that are almost consistent with each other, both in terms of magnitude and significance. The total effect obtained from multiple imputation method indicates that labor weekly wage increase by 7.5 percent in counties affected by a natural disaster compared to those that are not affected. This increased labor wage stems from natural disaster occurrences across all counties. Overall, the results suggest that the natural disaster occurrence in a particular county has a significant positive impact on the construction labor weekly wage not only in that county itself, but also in neighboring counties.

CHAPTER 6

VALIDATION

In this chapter, the performance of the spatial models used in this study was tested in two other states (Louisiana and Texas). In the first validation case of this chapter, the Spatial Durbin Models were used to examine the impact of a disaster on labor wage fluctuation in the State of Louisiana, and the results obtained from those models were discussed. In the second validation case of this chapter, the same models from the previous part were used to examine the impact of a disaster on labor wage fluctuation in the State of Texas, and the results obtained from those models were discussed.

6.1 First Validation Case (Louisiana State)

This part began with obtaining data on the annual census of employment and wages data from the Bureau of Labor Statistics (BLS). Data from 64 parishes in Louisiana were obtained from BLS over the time period from 2014 to 2018. Then, the year of disaster occurrence in Louisiana were obtained from the Federal Emergency Management Agency. Finally, the Spatial Durbin Models were used to examine the impact of a disaster on labor wage fluctuation. Table 6-1 summarized the results of three types of fixed-effect Spatial Durbin Models considering the time-lagged dependent variable. In *individual fixed-effect SDM* and *both time and individual fixed-effect SDM,* the total effect of natural disaster on labor weekly wage is significant. In the *individual fixed-effect SDM,* the total effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 7.7 percent. In *both time and individual fixed-effect SDM,* the total effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 11.9 percent. To compare the results obtained from the training model (in Florida State), the results obtained from the first testing model (Louisiana State) are similar in terms of significances and magnitude. Unlike the training model, in *both time and individual fixed effect SDM model,* considering the time-lagged dependent variable, the total effect of natural disaster on labor weekly wage is significant in the first testing case.

It should be denoted that the dataset size in both training and first testing case is similar, which can affect the similarity of the results in terms of significances and magnitude.

Table 6-1 Direct, Indirect, and Total Impacts from spatial panel data models with **Time-lagged Dependent Variable** (multiple imputed data, Louisiana State)

VARIABLES	SDM (time fixed effect)					SDM (individual fixed effect)					SDM (both time and individual fixed effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	-0.001	-0.000	-0.001	0.000	-0.001	0.000	0.003	0.000	0.003	0.003	0.000	0.001	0.000	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.005)
Employment Level	0.000	-0.001	0.000	-0.001	-0.001	0.001	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.003)
Level of Contribution	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disaster	0.068	0.021	0.068	0.030	0.099	0.080	-0.009	0.080	-0.003	**0.077****	0.084	0.031	0.084	0.035	**0.119***
	(0.068)	(0.100)	(0.066)	(0.103)	(0.083)	(0.061)	(0.066)	(0.059)	(0.065)	**(0.032)**	(0.060)	(0.088)	(0.058)	(0.086)	**(0.067)**
Observations	320	320	320	320	320	320	320	320	320	320	320	320	320	320	320
Number of poly_id	64	64	64	64	64	64	64	64	64	64	64	64	64	64	64

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

Table 6-2 summarizes the results of three types of fixed-effect Spatial Durbin Models considering space-time lagged dependent variables. In the *individual fixed-effect SDM*, the total effect of natural disasters on labor weekly wage is significant. In this model, the total effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 7.9 percent. The SDM considering *both time and individual fixed effect* did not converge in this stage.

To compare to the results obtained from the training model (Florida State), the total effect of natural disasters on labor weekly wage in the first testing case is significant in the individual fixed-effect SDM considering space-time lagged dependent variable.

Table 6-2 Direct, Indirect, and Total Impacts from spatial panel data models includes **Space-time Lagged Dependent Variable** (multiple imputed data, Louisiana State)

VARIABLES	SDM (time fixed effect)					SDM (individual fixed effect)					SDM (both time and individual fixed effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	-0.002	-0.002	-0.002	-0.002	-0.004	0.000	0.002	0.000	0.002	0.002	The model did not converge				
	(0.001)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)					
Employment Level	0.002	0.004	0.002	0.004	0.005	0.000	0.000	0.001	0.000	0.001					
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.003)					
Level of Contribution	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Disaster	0.108	-0.085	0.108	-0.080	0.028	0.081	-0.010	0.080	-0.002	**0.079****					
	(0.079)	(0.115)	(0.087)	(0.116)	(0.090)	(0.061)	(0.066)	(0.059)	(0.065)	**(0.033)**					
Observations	320	320	320	320	320	320	320	320	320	320					
Number of poly_id	64	64	64	64	64	64	64	64	64	64					

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

Table 6-3 summarizes the results of three types of fixed-effect Spatial Durbin Models considering both time-lagged and space-time lagged dependent variables. In the *individual fixed-effect SDM,* the total effect of natural disasters on labor weekly wage is significant. In this model, the total effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 8.1 percent. Both SDM considering time fixed effect and both time and individual fixed effect did not converge in this stage.

The results obtained from Table 6-3, have similarities with the results of the training model. The total effect of natural disasters on labor weekly wage in the first testing case is significant in the individual fixed-effect SDM considering both time-lagged and space-time lagged dependent variable.

Table 6-3 Direct, Indirect, and Total Impacts from spatial panel data models includes **Both Time-lagged and Space-time Lagged Dependent Variable** (multiple imputed data, Louisiana State)

VARIABLES	SDM (time fixed effect)					SDM (individual fixed effect)					SDM (both time and individual fixed effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Establishment Count	The Model Did Not Converge					0.000	0.002	0.000	0.002	0.002	The Model Did Not Converge				
						(0.003)	(0.005)	(0.003)	(0.005)	(0.006)					
Employment Level						0.001	0.000	0.001	0.000	0.001					
						(0.001)	(0.003)	(0.001)	(0.003)	(0.003)					
Level of Contribution						0.000	0.000	0.000	0.000	0.000					
						(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
Disaster						0.081	-0.007	0.084	-0.004	**0.081****					
						(0.061)	(0.066)	(0.060)	(0.065)	**(0.033)**					
Observations						335	335	335	335	335					
Number of poly_id						67	67	67	67	67					

Robust standard errors in parentheses

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

6.1.1 Results from The First Validation Case (Louisiana State)

Table 6-4 summarizes the total effects of three types of fixed-effect Spatial Durbin Models considering time-lagged, space-time lagged, and both time-lagged and space-time lagged dependent variables. Table 6-4 showed that in both time-lagged dependent variable individual fixed-effect SDM and Space-time lagged dependent variable individual fixed-effect SDM, the total effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 7.7 percent and 7.9 percent, respectively. Also, the results from both time-lagged and space-time lagged dependent variable individual fixed-effect SDM showed that the total effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 8.1 percent. All three results were almost consistent with the results obtained in the State of Florida. The results indicated that the impact of weather-related natural disasters on labor wage fluctuation in the residential market was almost the same in both Florida and Louisiana.

Table 6-4 Summary of the total effects from multiple imputed data Spatial Durbin Model in Louisiana State

Spatial Durbin Models (SDM)	**Type of Fixed-effect**	**Effect Disaster Coefficient**	
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Time-lagged Dependent Variable**	Time fixed effect	Total effect	0.099 (0.083)
	Individual fixed effect	Total effect	**0.077** (0.032)**
	Both time and individual fixed effect	Total effect	**0.119* (0.067)**
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Space-time Lagged Dependent Variable**	Time fixed effect	Total effect	0.028 (0.090)
	Individual fixed effect	Total effect	**0.079** (0.033)**
	Both time and individual fixed effect	Total effect	N/A
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Both Time-lagged and Space-time Lagged Dependent Variable**	Time fixed effect	Total effect	N/A
	Individual fixed effect	Total effect	**0.081** (0.033)**
	Both time and individual fixed effect	Total effect	N/A

6.2 Second Validation Case (Texas State)

This section began with obtaining data on the annual census of employment and wages data from the Bureau of Labor Statistics (BLS). Data from 254 counties in Texas were obtained from BLS over the time period from 2014 to 2018. Then, the year of disaster occurrence in Texas State had been obtained from the Federal Emergency Management Agency. Finally, the Spatial Durbin Models were used to examine the impact of a disaster on labor wage fluctuation. Table 6-5 summarizes the results of three types of fixed-effect Spatial Durbin Models considering the time-lagged dependent variable.

In all three types of fixed-effect (*time fixed-effect SDM*, *individual fixed-effect SDM*, and *both time and individual fixed-effect SDM)*, the main effect and direct effect of the natural disaster on labor weekly wage are significant. In the time fixed effect SDM, the main effect of natural disaster occurrence in the affected counties increases the labor weekly wage by 7.2 percent. In the *Individual fixed-effect SDM*, the main effect and direct effect of natural disaster occurrence in the affected counties increases the labor weekly wage by 7.3 percent and 7.4 percent, respectively. In *both time and individual fixed-effect SDM*, the main effect and direct effect of natural disaster occurrence in the affected counties increases the labor weekly wage by 7.4 percent.

Table 6-5 Direct, Indirect, and Total Impacts from spatial panel data models with **Time-lagged Dependent Variable** (multiple imputed data, Texas State)

VARIABLES	SDM (time fixed effect)					SDM (individual fixed effect)					SDM (both time and individual fixed effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Lnwe_wag	**0.504*** **	N/A	N/A	N/A	N/A	-0.004	N/A	N/A	N/A	N/A	-0.004	N/A	N/A	N/A	N/A
	0.046					0.047					0.047				
Establishment Count	**0.003*** **	0.000	**0.003*** **	0.000	**0.003***	**0.004*** **	0.001	**0.004*** **	0.001	**0.005*** *	**0.004*** **	0.000	**0.004*** **	0.000	**0.004*** *
	(0.001)	(0.001)	**(0.001)**	(0.002)	**(0.002)**	**(0.001)**	(0.002)	**(0.001)**	(0.002)	**(0.002)**	**(0.001)**	(0.002)	**(0.001)**	(0.002)	**(0.002)**
Employment Level	**0.000*** **	-0.001	**0.000*** **	-0.001	-0.001	**-0.001*** **	0.000	**-0.001*** **	0.000	**-0.001***	**-0.001*** **	0.000	**-0.001*** **	0.000	**-0.001***
	(0.001)	(0.002)	**(0.001)**	(0.002)	(0.002)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**	**(0.000)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**
Level of Contribution	**0.000***	0.000	**0.000***	0.000	0.000	**0.000***	0.000	**0.000***	0.000	0.000	**0.000***	0.000	**0.000***	0.000	0.000
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)
Disaster	**0.072*** *	-0.028	**0.072*** *	-0.023	0.050	**0.073***	-0.036	**0.074***	-0.033	0.040	**0.074***	-0.023	**0.074***	-0.021	0.054
	(0.037)	(0.047)	**(0.037)**	(0.048)	(0.039)	**(0.039)**	(0.048)	**(0.039)**	(0.048)	(0.038)	**(0.039)**	(0.052)	**(0.038)**	(0.052)	(0.040)
Observations	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016
Number of poly_id	254	254	254	254	254	254	254	254	254	254	254	254	254	254	254

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

Table 6-6 summarizes the results of three types of fixed-effect Spatial Durbin Models considering the space-time lagged dependent variable. In all three types of fixed-effect (*time fixed-effect SDM*, *individual fixed-effect SDM*, and *both time and individual fixed-effect SDM)*, the main effect and direct effect of natural disaster on labor weekly wage is significant. In the time fixed effect SDM, the main effect and direct effect of natural disaster occurrence in the affected counties increase the labor weekly wage by 7.7 percent. In the *Individual fixed-effect SDM*, the main effect and direct effect of natural disaster occurrence in the affected counties increase the labor weekly wage by 7.3 percent. In *both time and individual fixed-effect SDM*, the main effect and direct effect of natural disaster occurrence in the affected counties increase the labor weekly wage by 7.4 percent.

Table 6-6 Direct, Indirect, and Total Impacts from spatial panel data models includes **Space-time Lagged Dependent Variable** (multiple imputed data, Texas State)

VARIABLES	SDM (time fixed effect)					SDM (individual fixed effect)					SDM (both time and individual fixed effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
WLnwe_wag	0.123	N/A	N/A	N/A	N/A	-0.011	N/A	N/A	N/A	N/A	-0.013	N/A	N/A	N/A	N/A
	0.103					0.114					0.117				
Establishment Count	**0.004*** **	-0.001	**0.004*** **	-0.001	**0.003***	**0.004*** **	0.001	**0.004*** **	0.001	**0.005** **	**0.004*** **	0.000	**0.004*** **	0.000	**0.004** **
	(0.001)	(0.001)	**(0.001)**	(0.002)	**(0.002)**	**(0.001)**	(0.002)	**(0.001)**	(0.002)	**(0.002)**	**(0.001)**	(0.002)	**(0.001)**	(0.002)	**(0.002)**
Employment Level	**-0.001*** **	-0.000	**-0.001*** **	0.000	0.000	**-0.001*** **	0.000	**-0.001*** **	0.000	**-0.001***	**-0.001*** **	0.000	**-0.001*** **	0.000	**-0.001***
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**	**(0.000)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**
Level of	**0.000** **	0.000	**0.000** **	0.000	0.000	**0.000***	0.000	**0.000***	0.000	0.000	**0.000***	0.000	**0.000***	0.000	0.000
Contribution	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)
Disaster	**0.077** **	-0.046	**0.077** **	-0.040	0.037	**0.073***	-0.036	**0.073***	-0.033	0.041	**0.074***	-0.023	**0.074***	-0.020	0.054
	(0.036)	(0.048)	**(0.036)**	(0.049)	(0.039)	**(0.039)**	(0.049)	**(0.039)**	(0.049)	(0.038)	**(0.039)**	(0.052)	**(0.039)**	(0.052)	(0.040)
Observations	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016
Number of poly_id	254	254	254	254	254	254	254	254	254	254	254	254	254	254	254

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

Table 6-7 summarizes the results of three types of fixed-effect Spatial Durbin Models considering both time-lagged dependent variable and space-time lagged dependent variable. In all three types of fixed-effect (*time fixed-effect SDM, individual fixed-effect SDM,* and *both time and individual fixed-effect SDM),* the main effect and direct effect of natural disaster on labor weekly wage are significant. In the time fixed effect SDM, the main effect and direct effect of natural disaster occurrence in the affected counties increase the labor weekly wage by 7.3 percent and 7.4 percent, respectively. In the *individual fixed-effect SDM,* the main effect and direct effect of natural disaster occurrence in the affected counties increases the labor weekly wage by 7.3 percent and 7.5 percent, respectively. In *both time and individual fixed-effect SDM,* the main effect and direct effect of natural disaster occurrence in the affected counties increase the labor weekly wage by 7.4 percent and 7.6 percent, respectively.

Table 6-7 Direct, Indirect, and Total Impacts from spatial panel data models include **Both Time-lagged and Space-time Lagged Dependent Variable** (multiple imputed data, Texas State)

VARIABLES	SDM (time fixed effect)					SDM (individual fixed effect)					SDM (both time and individual fixed effect)				
	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total	Main	Wx	Direct	Indirect	Total
Lnwe_wag	**0.504*** **	N/A	N/A	N/A	N/A	-0.004	N/A	N/A	N/A	N/A	-0.005	N/A	N/A	N/A	N/A
	0.046					0.046					0.047				
WLnwe_wag	0.117	N/A	N/A	N/A	N/A	-0.012	N/A	N/A	N/A	N/A	-0.014	N/A	N/A	N/A	N/A
	0.112					0.108					0.111				
Establishment Count	**0.003*** **	-0.001	**0.003*** **	0.000	0.003	**0.004*** **	0.001	**0.004*** **	0.001	**0.005** **	**0.004*** **	0.000	**0.004*** **	0.000	**0.004** **
	(0.001)	(0.002)	**(0.001)**	(0.002)	(0.002)	**(0.001)**	(0.002)	**(0.001)**	(0.002)	**(0.002)**	**(0.001)**	(0.002)	**(0.001)**	(0.002)	**(0.002)**
Employment Level	**0.000*** **	0.000	**0.000*** **	0.000	0.000	**-0.001*** **	0.000	**-0.001*** **	0.000	**-0.001* **	**-0.001*** **	0.000	**-0.001*** **	0.000	**-0.001* **
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**	**(0.000)**	(0.000)	**(0.000)**	(0.000)	**(0.000)**
Level of Contribution	**0.000* **	0.000	**0.000* **	0.000	0.000	**0.000* **	0.000	**0.000* **	0.000	0.000	**0.000* **	0.000	**0.000* **	0.000	0.000
	(0.000)	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)	**(0.000)**	(0.000)	**(0.000)**	(0.000)	(0.000)
Disaster	**0.073* **	-0.028	**0.074** **	-0.026	0.049	**0.073* **	-0.036	**0.075* **	-0.035	0.039	**0.074* **	-0.023	**0.076* **	-0.023	0.052
	(0.037)	(0.048)	**(0.037)**	(0.049)	(0.040)	**(0.039)**	(0.048)	**(0.039)**	(0.048)	(0.037)	**(0.039)**	(0.052)	**(0.039)**	(0.051)	(0.040)
Observations	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016	1016
Number of poly_id	254	254	254	254	254	254	254	254	254	254	254	254	254	254	254

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

6.2.1 Results from The Second Validation Case (Texas State)

Table 6-8 summarizes the total effects of three types of fixed-effect Spatial Durbin Models considering time-lagged, space-time lagged, and both time-lagged and space-time lagged dependent variables. Although the results showed that none of the total effect disaster coefficients is significant, the main effect of disaster coefficients in all cases is significant with a magnitude consistent with both Florida and Louisiana's results. For example, in both time-lagged dependent variable individual fixed-effect SDM and space-time lagged dependent variable individual fixed-effect SDM, the main effect of natural disaster occurrence in the affected parishes increases the labor weekly wage by 7.3 percent.

Table 6-8 Summary of the Total effects from multiple imputed data Spatial Durbin Models in Texas State

Spatial Durbin Models (SDM)	Type of Fixed-effect	Effect Disaster Coefficient	
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Time-lagged Dependent Variable**	Time fixed effect	Total effect	0.050 (0.039)
	Individual fixed effect	Total effect	0.040 (0.038)
	Both time and individual fixed effect	Total effect	0.054 (0.040)
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Space-time Lagged Dependent Variable**	Time fixed effect	Total effect	0.037 (0.039)
	Individual fixed effect	Total effect	0.041 (0.038)
	Both time and individual fixed effect	Total effect	0.054 (0.040)
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Both Time-lagged and Space-time Lagged Dependent Variable**	Time fixed effect	Total effect	0.049 (0.040)
	Individual fixed effect	Total effect	0.039 (0.037)
	Both time and individual fixed effect	Total effect	0.052 (0.040)

Table 6-9 Summary of the Main effects from multiple imputed data Spatial Durbin Models in Texas State

Spatial Durbin Models (SDM)	Type of Fixed-effect	Effect Disaster Coefficient	
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Time-lagged Dependent Variable**	Time fixed effect	Main effect	0.072** (0.037)
	Individual fixed effect	Main effect	0.073* (0.039)
	Both time and individual fixed effect	Main effect	0.074* (0.039)
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Space-time Lagged Dependent Variable**	Time fixed effect	Main effect	0.077** (0.036)
	Individual fixed effect	Main effect	0.073* (0.039)
	Both time and individual fixed effect	Main effect	0.074* (0.039)
Spatial Durbin Model (SDM) Fixed-effect from Multiple Imputed Data **Both Time-lagged and Space-time Lagged Dependent Variable**	Time fixed effect	Main effect	0.073* (0.037)
	Individual fixed effect	Main effect	0.073* (0.039)
	Both time and individual fixed effect	Main effect	0.074* (0.039)

CHAPTER 7

CONCLUSION

The regional economic impact is common feature of natural hazards. Estimating the economic impact of natural hazards in the construction market, is one of the main concerns of many groups involved in the recovery and reconstruction process. The main purpose of this study is to help the groups involved in the reconstruction process to have a better understanding of the construction economic impact of natural hazards.

In this research, all of the data were obtained from the Bureau of Labor Statistics (BLS) and the Federal Emergency Management Agency (FEMA). The collected dataset suffered from missing values. Four strategies (mean imputation method, removing observations with a missing value(s) from the dataset, average nearest neighbors method, and multiple imputation method) were used to tackle the missing data problem and eliminate biased results and increase the efficiency of our spatial model. Moreover, the results of Maran's I test confirmed the need for using the spatial panel model rather than non-spatial models. Thus, in this research, multiple spatial panel data models (SAR, SAC, SEM, and SDM models) have been developed to investigate the effect of natural disasters on labor wage fluctuations. Based on the Breusch–Pagan LM test and Hausman test results, the fixed-effect Spatial Durbin Model (SDM) using a multiple imputation method is identified as a more appropriate model in this research. The total effect from SDM indicated that the coefficient on the natural disaster is statistically significant and positive, indicating that the natural disaster occurrence in a particular county has a significantly positive impact on the construction labor weekly wage not only in that county itself but also in neighboring counties. The total effect obtained from SDM using the multiple imputation method indicates that labor weekly wage increases by 7.5 percent in counties affected by natural disaster compared to those that are not affected.

7.1 Contribution to The State of Knowledge

This research has three main contributions to the state of knowledge. The first contribution of this study is to investigate the effect of the natural disaster on the construction cost fluctuation using a fixed-effect Spatial Durbin model combined with difference-in-difference technique at the spatial level. This technique is capable of eliminating the need for measurement in this analysis and can directly quantify the effect of natural disasters on the labor wage fluctuations.

Using the difference-in-difference technique combined with fixed-effect Spatial Durbin model in this research provides an opportunity to have a better interpretation of the impact of natural disasters on construction labor wage fluctuations. Also, using logarithmic transformation within dependent variables in our dataset, allows us to have better-predicted outcomes from the spatial regression models. In this research, for the first time, by taking the logarithmic transformation of the dependent variable (labor weekly wage) the direct impact of natural disasters on construction labor wage fluctuation is calculated. This amount is estimated to be approximately 7.5 percent higher in counties that are affected by natural disasters compared with those counties that are not affected in the gulf coast region.

It is expected that this methodology provides interest groups with more appropriate spatial panel models that can result in more accurate and consistent results. When dealing with spatial data, it is crucial to consider the spatial nature of the dataset in the measurement phase. This study takes the spatial nature of the dataset in both measurement and quantification phase. The second main contribution to the state of knowledge in this research is to use a spatial multiple imputation method to tackle the missing data problem. This spatial imputation method has not been used in this context before. In other words, using this method maintains the spatial relationship among the counties in the study. In this research, for the first time, even counties with missing values were included in the analysis.

In this study, for the first time, the results of different handling missing data methods were compared with each other to find a more appropriate method with consistent results. The proposed handling missing data method is Spatial Multiple Imputation Method, which can be used to tackle missing data problem that exists in the construction sector. Tackling missing data problem using Spatial Multiple Imputation Method is the third main contribution of this study.

7.2 Contribution to The State of Practice

Devastating natural disasters can have a severe effect on the construction market condition and the reconstruction process. Risk managers, cost engineers, city policymakers, construction companies, property owners, and insurers must be aware of this volatility in the construction market condition in the aftermath of a natural disaster. Volatility in the construction market can lead to negative effects on financial performance. By measuring unexpected costs resulted from this volatility, financial performance can be improved by conscious planning and effective insurance decisions. Quantifying the construction costs fluctuations due to natural disasters could be helpful in two main categories (see Figure 7-1).

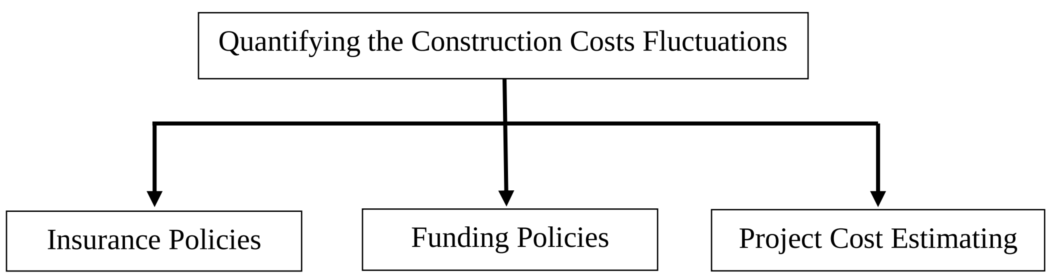


Figure 7-1 Two main categories affected by construction cost fluctuations.

Insurance policies:

Quantifying the construction cost fluctuations due to natural disasters could help to make more effective insurance policies, calculate affordable insurance premiums and insurance ratings, especially for low-income and middle-income households to recover from natural disasters.

Funding Policies:

After a natural disaster, many organizations and programs such as Housing and Urban Development (HUD), the U.S. Army Corps of Engineers, Community Development Block Grant (CDBG) Program, and HOME Disaster Recovery Program allocate disaster recovery grants to rebuild the affected regions. Each organization and program has its own method to allocate the grant to the eligible regions. For example, the General Land Office (GLO) is the responsible entity for determining the Method of Distribution (MOD) of funds in accordance with requirements provided by HUD. This method is used to specify the grant size limits and how funds will be allocated to the eligible counties.

Quantifying the construction cost fluctuations due to natural disasters could be helpful in making more effective formula allocations in funding distribution based on the needs of each state and each county due to the damages caused by natural disasters. Moreover, it could help establish funding policies and how funds will be allocated to eligible counties. For example, the region with a greater demand surge due to a natural disaster can receive a greater share of resource allocation to compensate for the lack of resources caused by natural disasters.

Project Cost Estimating

Cost engineers must be aware of the costs involved in any project in order to calculate the accurate project cost and offer a realistic bid. Labor cost is one of the main elements of a comprehensive project cost estimating. Familiarity with potential labor cost fluctuation due to natural disasters is one of the components of the feasibility study to make sure that the project goals will be achieved on time and under budget. This research can help cost engineers to quantify labor cost fluctuations due to natural disasters. Quantifying labor cost fluctuation provides accurate information to the cost engineers and project developers to reduce the possibility of project failure due to financial disruptions and unexpected costs.

7.3 Future Works

Many different improvements, tests, and models are left for the future. Below are some ideas that can be considered in the future.

1. There are limited imputation methods specifically designed for the spatial panel dataset with missing values. In this research, among all four imputation methods that we used, the Multiple Imputation Method is designed for tackling missing values in a spatial dataset. Because imputation methods can have a significant effect on the

results, it could be interesting to use other spatial imputation methods in the future and compare the results with the findings of this study.

2. In this research, the effect of weather-related natural disasters on the construction labor wage fluctuation was studied. Because the nature of different natural disaster damages are different, it could be useful to study the effect of other natural disasters such as earthquakes and wildfires on the labor wage fluctuation in the future.
3. Other states or countries can be the subject of this study in the future. Also, more datasets could be used to refine the models and improve the results.

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