POST-DISASTER CONSTRUCTION LABOR COST FLUCTUATIONS:

MEASUREMENT AND MODELING

by

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ABSTRACT

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The United States has been one of the top five countries most frequently hit by natural disasters. The post-disaster survival of cities and communities depend on their capabilities to reconstruct and repair damages to buildings and other infrastructure systems. The significant increase in the repair costs following large-scale natural disasters, also called "demand surge," slows down the repair process that impacts many lives touched by large-scale natural disasters. Previous studies showed that post-disaster construction labor cost escalation drives the total post-disaster construction cost escalation in the U.S. The ultimate goal of this research is to (1) measure post-disaster construction labor wage changes in different sub-sectors of the construction sector and compare the sub-sectors against each other to determine which construction sub-sectors are most vulnerable to disasters, (2) assess the role of pre-disaster construction market conditions in influencing post-disaster construction labor changes, and (3) create Spatial Panel Data Models (SPDM) to find the spatial interaction effects as well as time-specific effects in the existing cross-sectional demand surge models. The historical county-level data of five construction market indicators (establishment count, contribution level, average weekly wages, employment level, and building permits) prior to disasters along

with disaster magnitudes (property damages) were collected for more than 35 of the largest weather-related disasters (floods, storms, and tornadoes) in the United States. These disasters affected more than 600 counties from 2007 to 2014. It is expected that the results of this study will help cost engineers to prepare more accurate bids in the volatile post-disaster construction markets and help capital planners and post-disaster risk-mitigation agencies to identify the more vulnerable construction markets. It is also expected that the results of this study will help demand surge modelers to create more accurate models.

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To my precious family and my love, Niloofar

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LIST OF ABBREVIATIONS

AWW	Average Weekly Wages
BLS	Bureau of Labor Statistics
DHS	Department of Homeland Security
EM-DAT	Emergency Events Database
FEMA	Federal Emergency Management Agency
IQR	Inter-Quantile Range
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
SEM	Spatial Error Model
SPDM	Spatial Panel Data Model
UNDP	United Nations Development Program

CHAPTER 1: INTRODUCTION

In the past few decades, a dramatic increase in the number and severity of catastrophes has been observed (Kunreuther and Michel-Kerjan, 2009). Moreover, climate change can lead to natural disasters that are more frequent and more severe. (Fenner et al, 2017).

Socio-economic losses following natural disasters have risen dramatically (Munich-Re, 2007). The United States has been one of the top five countries in the world most frequently struck by natural disasters (Guha-Sapir et al., 2015). More than 90% of the natural disasters in the U.S. are weather-related (United Nations, 2017). The post-disaster survival of cities and communities depends on their capabilities to reconstruct and repair damages to the buildings following large-scale natural disasters. The significant post-disaster increase in repair costs slows down the repair process. The socio-economic phenomenon of increased construction costs following large-scale natural disasters, also called “demand surge,” cripples our capabilities to recover from disasters effectively.

Demand surge is broadly defined as a sudden increase in the costs of materials, services, and labor due to the increased demand following a catastrophe (Subcommittee on Ratemaking of the Casualty Committee, 2000). The increased costs to repair or rebuild after large-scale natural disasters is simply the percentage increase in construction costs due to the restricted supply of construction materials and labor following a natural disaster (Kuzak and Larsen, 2005). Demand surge for hurricane Katrina, for example, was assumed to lie in the range of 30% to 40%. Demand surge arises when the demand for products and services surpasses the regional capacity to efficiently supply them (Munich-

Re, 2007). The additional costs for these products and services are directly passed on to the consumers and their insurers. The amount of demand surge is important to building owners, insurers, reinsurers, and cost engineers because it gives a better understanding of how the construction industry operates in the aftermath of a natural disaster.

The construction sector plays an important role in the recovery phase of natural disasters (Lloyd-Jones, 2006; Jayaraj, 2006; Benson et al., 2007; Owen and Dumashie, 2007; Amaratunga and Haigh, 2008; UN/ISDR, 2009; Hallegatte, 2014). Moreover, most indirect economic losses in the aftermath of natural disasters are construction-related losses (Hallegatte, 2014). The construction sector is comprised of establishments that have primarily been engaged in the construction of buildings or engineering projects and includes new work, additions, alterations, or maintenance and repairs (Bureau of Labor Statistics, 2017).

Labor cost fluctuation following natural disasters is known to be a driving factor in demand surge measurement (Olsen and Porter, 2013). The ultimate goal of this research is to (1) measure post-disaster construction labor wage changes in different sub-sectors of the construction sector and compare the sub-sectors against each other to determine which construction sub-sectors are most vulnerable to disasters, (2) assess the role of pre-disaster construction market conditions in influencing post-disaster construction labor changes, and (3) create Spatial Panel Data Models (SPDM) to assess the spatial interaction effects as well as time-specific effects in the existing cross-sectional demand surge models.

CHAPTER 2: BACKGROUND

Demand surge studies can be classified into two major categories: Quantitative and qualitative.

2.1. Quantitative Studies

Quantitative studies for measuring and modeling demand surge can be classified into three categories:

2.1.1. Demand surge represented by economic loss models

These models analyze the economic consequences of natural disasters to create regional economic loss models that predict economic losses following natural disasters. Economic loss in these models is the difference between economic output following a natural disaster and economic output if there were no disasters. These models consider the economic sectors and the interactions between them to estimate economic losses following natural disasters. Input-output models and computable general equilibrium models are the most common types of these models. Each model has its own pros and cons (Olsen and Porter, 2011). The input-output models are believed to be an upper bound on economic loss, while the computable general equilibrium models represent a lower bound on economic loss (Okuyama ,2007). For example, Hallegatte et al. (2008) modeled the economic losses in the aftermath of 2004–2005 Hurricane Katrina. They proposed an adaptive regional input-output model that was used to simulate the economic loss in Louisiana after Katrina. They considered forward and backward propagations within the economic system and introduced adaptive behavior. Although these models help estimate total economic losses in the affected regions following natural disasters, they do not characterize fine-grained construction cost changes.

2.1.2. Demand surge represented by ground-up loss in properties

The second category focuses on demand surge as a ground-up loss at the individual-property level or portfolio level following a natural disaster in a region. Data, in this category, are collected from insurance companies to model ground-up losses in the affected properties. For example, after Hurricane Andrew in the Gulf and Atlantic coasts of the U.S, Olsen and Porter (2011) defined demand surge at the portfolio level using data from estimated replacement costs of properties, a damage factor, and environmental excitation (wind speeds). Florida International University (2009) defined a demand surge model as a function of total state-wide property losses in Florida. Insurers and reinsurers use these models to estimate how much reinsurance they need in the aftermath of a natural disaster. Although these models are highly valuable for insurance companies, they do not characterize fine-grained construction cost changes.

2.1.3. Demand surge represented by fine-grained cost changes

These models focus on labor and material components and define the demand surge as the consequence of a boost in the costs of a sector`s labors and materials. For example, Mueller and Osgood (2009) investigated the impact of droughts on Brazilian agricultural labor markets and found that severity of losses varies depending on agricultural income. Belasen and Polachek (2009), using the quarterly wage data in Florida, concluded that in the aftermath of hurricanes in Florida, labor markets experienced faster earnings growth in the affected counties compared to workers in unaffected counties. Mueller and Quisumbing (2010) found that non-agricultural labor markets were more severely affected by the 1998 “flood of the century” in Bangladesh compared to agricultural labor markets. Olsen and Porter (2013) focused on the construction sector and defined the demand surge as the cost increase over a 6-month period in local construction labor wages, material prices, and other specific costs following large-scale natural disasters. They considered nine hurricane seasons in the southeastern United States and concluded that the magnitude of the storm and the number of associated storms in a hurricane season could slightly affect the increase in residential construction labor wages. They also realized that construction material costs are not subject to recognizable fluctuations even after large-scale disasters. Döhrmann et al. (2013) defined demand surge as cumulative construction labor index changes in a two-year period following natural disasters using data from 2002 to 2009 in the U.S. They concluded that the total amount of repair work, alternative catastrophes in a region before and after the main disaster, and the amount of insurance claims per event—all may influence the amount of construction demand surge. Kirchberger (2017) studied the effects of earthquakes on local labor markets in Indonesia and found significant and long-lasting wage premia for individuals employed in sectors producing non-tradable construction goods. Cost estimators in addition to capital planners and insurers, can take advantage of these studies.

2.2. Qualitative Studies

Qualitative studies with a focus on construction demand surge discuss the increased construction costs and factors impacting the increased construction costs throughout a few case studies. For example, the United Nations Development Program (UNDP) noted that the characteristics of good governance participation (responsiveness, transparency, equity, etc.) are crucial for sustainable development and disaster risk mitigation (UNDP, 2004). Lloyd-Jones (2006) underlined that construction professions have key roles to play during all pre- and post-disaster phases. Coordination between construction professionals and other construction stakeholders is vital for post-disaster risk mitigation (Fard et al, 2016). Benson et al. (2007) mentioned that effective post-disaster reconstruction may require the affected society to have access to a range of capacities such as organizations, well-developed disaster plans, and coping mechanisms. It is also important to include local community participation (unskilled workers) in the reconstruction process (Jayaraj, 2006; Owen and Dumashie, 2007), since construction workforce shortage has shown to be problematic in the U.S. construction market (Razkenari et al., 2018; Habibi and Kermanshachi, 2018). Capacity development is also known to be an important factor in post-disaster cost increase deduction (Amaratunga and Haigh, 2008; UN/ISDR, 2009). Chang-Richards, et al. (2017) studied the 2010-2011 earthquakes in New Zealand and highlighted the existing capacity gaps due to the heightened demand during reconstruction. Their survey recognized that the limited technical capability available nationally, shortage of temporary accommodation to house additional workers, time needed for trainees to become skilled workers, lack of information about reconstruction workloads, and lack of operational capacity within construction organizations were critical constraints for providing adequate resources for disaster recovery projects after earthquakes. Although the recommendations of qualitative studies help policymakers to better plan for their risk-mitigation strategies in the aftermath of natural disasters, they do not help predict post-disaster construction cost changes.

2.3. Gaps in Knowledge

Although there have been several studies in the demand surge area, three major gaps have not been addressed:

Gap 1. Despite the important role of the construction labor markets in construction cost fluctuations in the aftermath of weather-related disasters, it is not yet known which construction sub-sectors are most vulnerable to natural disasters.

Gap 2. Despite the significant role of the construction market conditions in post-disaster labor cost fluctuations, the existing construction demand surge models do not consider the relationships between pre-disaster regional construction market conditions and post-disaster construction labor cost changes.

Gap 3. The current models are cross-sectional models. The three limitations of these cross-sectional models are: 1) these models do not consider the “spatial endogenous interaction effects” of post-disaster construction labor wage changes in the neighboring regions on the post-disaster construction labor wage changes in the region under study; 2) these models do not consider the spatial interaction effects among the error terms over the space; and 3) these models do not consider time-specific impacts of observed/unobserved variables in the models.

2.4. Research Objectives

The primary objectives of this research are to:

(1) Measure post-disaster construction labor wage changes in different sub-sectors of the construction sector and compare the sub-sectors against each other to determine which construction sub-sectors are most vulnerable to these disasters.

(2) Assess the role of pre-disaster construction market conditions in influencing post-disaster construction labor changes.

(3) Find the spatial interaction effects as well as time-specific effects in the existing cross-sectional models to assess and measure the spatio-temporal autocorrelations among the variables in the cross-sectional models, using spatial panel data models. Ignoring these effects in the models will result in creation of biased models, when spatial and temporal autocorrelations exist in cross-sectional models (Elhorst, 2017).

CHAPTER 3: POST-DISASTER LABOR WAGE FLUCTUATIONS: A COMPARATIVE EMPIRICAL ANALYSIS AMONG DIFFERENT SUB-SECTORS OF THE U.S. CONSTRUCTION SECTOR

The primary objectives of this chapter are to 1) highlight sub-sectors and industry groups of the construction sector that are most vulnerable to weather-related disasters (with highest labor wage escalation); and 2) analyze how immediate this labor wage escalation happens in different sub-sectors of the construction sector.

3.1. Methodology

The research methodology consists of three steps: (i) Integrating various data sources to enable measurement of the county-level labor wage changes following large-scale weather-related disasters; (ii) Measuring post-disaster labor wage changes (LWC) at the county-level; and (iii) Comparing amount and timing of post-disaster labor wage changes among all sub-sectors (and industry groups) of the construction sector. I collected quarterly average weekly wage (AWW) data for more than 600 counties affected by weather-related disasters in the U.S. from 2007 to 2014. These county-level data were collected from one quarter before the event of a disaster up to three quarters after the event of the disaster for different sub-sectors (and industry groups) of the construction sector. Figure 3.1 summarizes the methodology implemented in this study.

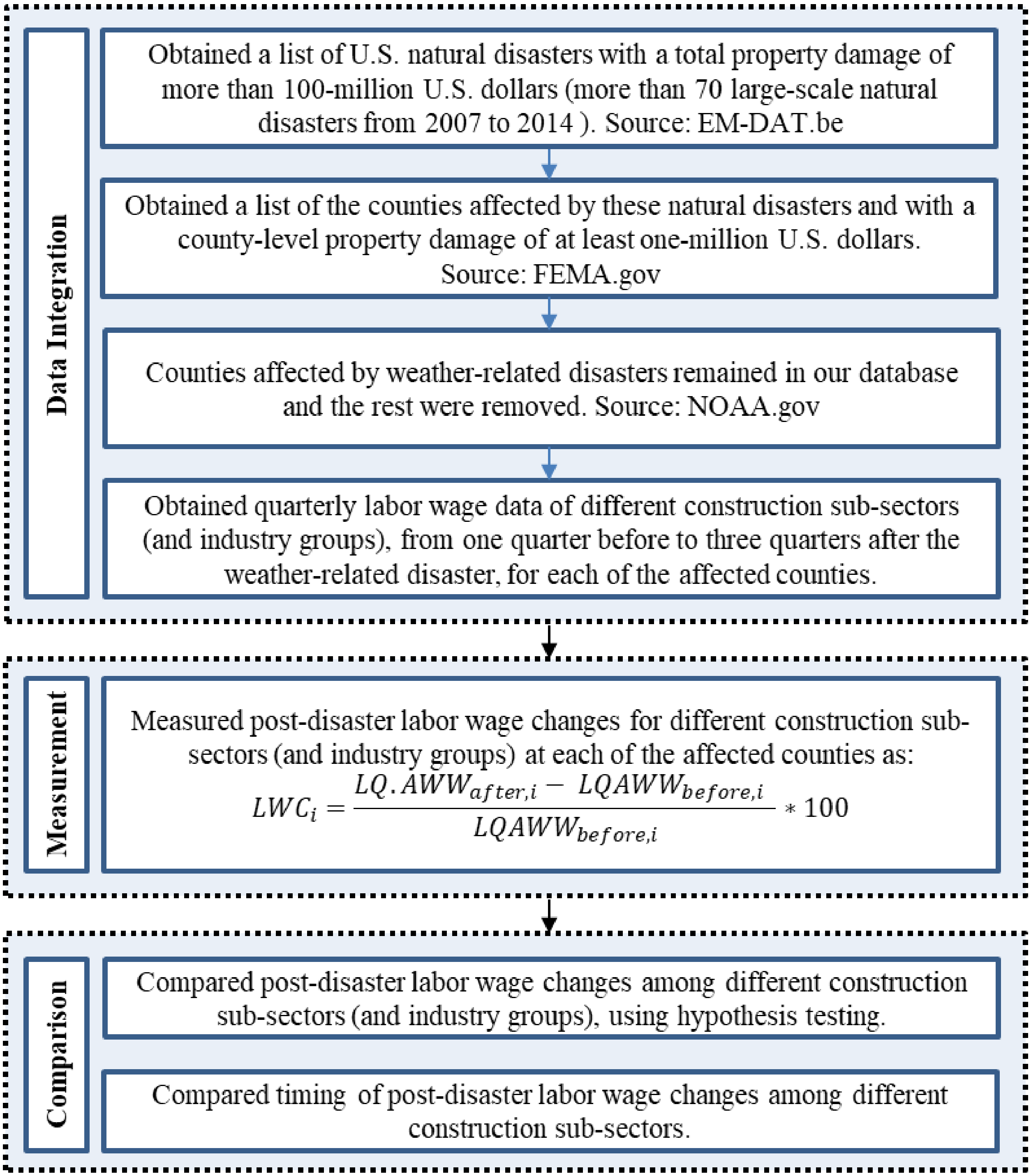


Fig. 3.1: Methodology

3.1.1. Data integration

The process of selecting the counties affected by weather-related disasters is as follows: 1) The U.S. natural disasters with total property damage of more than 100-million U.S. dollars, from 2007 to 2014, were obtained from Emergency Events Database (EM-DAT). EM-DAT is an international disaster database that collects information such as “total property damages” and “affected regions” after disasters all around the world. 2) I obtained a list of the counties affected by these large-scale natural disasters along with the county-level property damages from the Federal Emergency Management Agency (FEMA). FEMA is an agency of the U.S. Department of Homeland Security (DHS) that declares a list of affected counties in the affected states where the governor of the state declared a state of emergency and officially requested for national or international assistance. The counties with property damage of one-million dollars or more remained in my database, and the rest were removed, since changes in labor wages in the low damaged counties are less likely to be the consequence of the disaster in those counties. 3) Information on the types of natural disasters, at the county-level, were collected from the National Oceanic and Atmospheric Administration (NOAA) and the counties affected by weather-related disasters remained in my database. The weather-related disasters include high wind, tornado, thunderstorm wind, tropical storm, hurricane, ice storm, heavy rain, flash flood. These weather-related disasters encompass more than 90% of all types of natural disasters in the period from 2007 to 2014. My database comprises more than 600 damaged counties.

The Bureau of Labor Statistics of the U.S. Department of Labor measures labor market activities, working conditions, and price changes in the U.S. (BLS, 2017). BLS has provided crucial economic information to support both private and public decision-making (BLS, 2017). BLS provides categorized quarterly labor wage data for all sub-sectors and industry groups of the construction sector. Figure 3.2 illustrates all sub-sectors, industry groups, and industries of the construction sector.

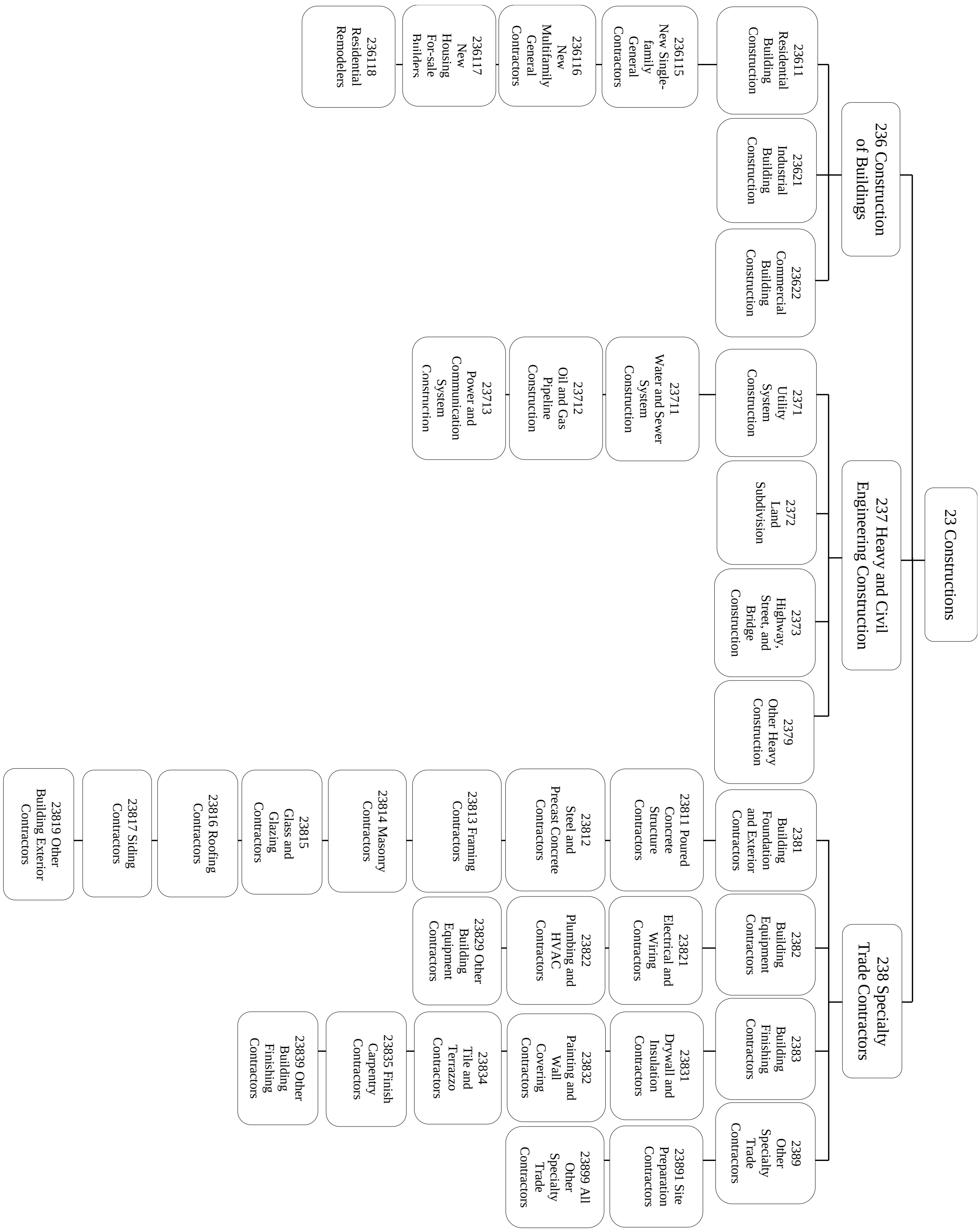


Fig. 3.2: Construction sectors, sub-sectors, and industry groups

The construction sector is comprised of establishments that have primarily been engaged in the construction of buildings or engineering projects and includes new work, additions, alterations, or maintenance and repairs. The North American Industry Classification System (NAICS) is the standard used by Federal statistical agencies in classifying these establishments. The construction sector consists of three sub-sectors: Construction of Buildings sub-sector: NAICS 236; Heavy and Civil Engineering Construction sub-sector: NAICS 237; and Specialty Trade Contractors sub-sector: NAICS 238 (BLS, 2017).

The Construction of Buildings sub-sector is comprised of establishments that have primarily been engaged in the construction of buildings. The on-site assembly of precut, panelized, and prefabricated buildings and construction of temporary buildings are included in this sub-sector. The Construction of Buildings sub-sector consists of three industry groups: Residential Building Construction: NAICS 23611; Industrial Building Construction: NAICS 23621; and Commercial Building Construction: NAICS 2362 (BLS, 2017).

The Heavy and Civil Engineering Construction sub-sector comprises of establishments whose primary activity is the construction of entire engineering projects such as highways and dams. This sub-sector consists of four industry groups: Utility System Construction (NAICS 2371), Land Subdivision (NAICS 2372), Highway, Street, and Bridge Construction (NAICS 2373), and Other Heavy and Civil Engineering Construction (NAICS 2379) (BLS, 2017).

The Specialty Trade Contractors sub-sector comprises establishments whose primary activity is performing specific activities such as pouring concrete, site preparation, plumbing, and painting, and are involved in building construction or other activities that are similar for all types of construction, but that are not responsible for the entire project. This sub-sector consists of four industry groups: Foundation, Structure, and Building Exterior Contractors (NAICS 2381), Building Equipment Contractors (NAICS 2382), Building Finishing Contractors (NAICS 2383), and Other Specialty Trade Contractors (NAICS 2389) (BLS, 2017).

3.1.2. Labor wage change measurement

BLS provides wage data in both raw and location quotient (LQ) format. LQs are ratios that allow a county`s distribution of employment by sector to be compared with the United States' distribution. LQ data make the comparisons between the counties easier (BLS, 2017) since they are seasonally and locally adjusted. LQ is forced to be one for the U.S. at any time and LQs for the counties are calculated in comparison with the U.S. A county with an industry LQ greater (smaller) than one has a local industry greater (smaller) than the U.S. average. This study uses the pre- and post-disaster quarterly LQ average weekly wage data to measure changes in construction labor wages.

The quarterly county-level LQ average weekly wage (LQ.AWW) data for all sub-sectors (and industry groups) of the construction sector in the period starting from one quarter before a weather-related disaster up to three quarters after the event, were obtained from BLS website for the affected counties (for which data were available). The main reason that we selected three quarters following the disasters was to exclude the impact of disasters in the following year(s) on the data under analysis. To measure LWC, the greatest value of LQ.AWW during the period starting from the quarter in which disaster occurred and the following three quarters was selected to be the $LQ.AWW_{after}$. This selection allows us to measure the greatest increase in labor wages in the almost one-year period following a disaster compared to one quarter before the disaster:

$$\boldsymbol{LWC_{i,j}} = \frac{\boldsymbol{LQ.AWW_{after,i,j} - LQ.AWW_{before,i,j}}}{\boldsymbol{LQ.AWW_{before,i,j}}} * \mathbf{100} \text{ (\%)}$$

where $LWC_{i,j}$ is the calculated maximum percentage increase (or decrease) in labor wages following a weather-related disaster for sub-sector (industry group) *j* in county *i*; $LQ.AWW_{after,i,j}$ is the maximum level of LQ.AWW for sub-sector (industry group) *j* in county *i* over four quarters after the weather- related disaster (including the quarter of disaster); and $LQ.AWW_{before,i,j}$ is the level of LQAWW in one quarter before the disaster for sub-sector (industry group) *j* in county *i*. LWCs for all sub-sectors (industry groups) of the construction sector were calculated for each of the damaged counties.

A positive value of LWC shows that, at least in one of the four quarters following a weather-related disaster (including the quarter of disaster) labor wage in the construction sub-sector (industry group) in the county increased, and a negative value of LWC shows that labor wage decreased following the disaster over the four quarters.

3.1.3. Comparative analysis of post-disaster labor wage changes

To measure the central tendency of labor wage changes (LWC) of a specific sub-sector (industry group), I measured mean, mode, and median values of labor wage changes among the affected counties for that sub-sector (industry group). I used Inter-Quartile Ranges (IQR) as a measure of statistical dispersion. Box plots are presented under “Results” section to illustrate both central tendency and dispersion of the measured labor wage changes for each sub-sector (industry group).

To compare the sub-sectors (industry groups) against each other, the mean values of LWC for different sub-sectors (and industry groups) were compared against each other, using an unpaired two-sample t-test, to assess whether the average changes in labor wages in a sub-sector (industry group) is significantly greater than one another. The null hypothesis of this test is that the mean value of LWC in a sub-sector (industry group) is not greater than the mean of another sub-sector (industry group). Rejection of null hypothesis shows that the mean value of LWC in a sub-sector (industry group) is significantly greater than one another. Before conducting the t-test, I compared the variances of two samples using F-test. The null hypothesis of F-test is that the two variances are equal. Rejection of null hypothesis shows that the two variances are not equal, and thus, “unpooled” variances should be measured to conduct the t-test. Otherwise, pooled variances should be used.

The distributions of the labor wage changes for each sub-sector (and industry group) are presented in the next section, and skewness and kurtosis of the distributions are discussed. Skewness is the third standardized moment of a dataset and is a measure of the asymmetry of a distribution (Joanes and Gill, 1998). Kurtosis is a measure of “tailedness” of a distribution and is the fourth standardized moment of a distribution. It is common to compare the kurtosis value of a distribution with that of a normal distribution. The kurtosis of a normal distribution is 3. Excess kurtosis is an adjusted version of Pearson`s kurtosis (Pearson, 1929) and is equal to kurtosis minus 3. Distributions with excess kurtosis greater than 0 are said to be leptokurtic, i.e. most of the mass of the data are in the central peak and the tails, and less mass is on the “shoulders”, compared to a normally distributed dataset (Joanes and Grill, 1998).

The quarter in which LWC was calculated (the quarter that faced a maximum increase in labor wages among the four quarters following the disaster) for each sub-sector in a county was monitored. The comparisons are provided in the next section.

Finally, the quarterly cumulative percent change of labor wages for each of the three sub-sectors in a county was calculated by comparing average county-level wages at each quarter with one quarter before. Then, the average of this value among the counties for each sub-sector was calculated. The results are presented in the last section of the "Results" section.

3.2. Results

Table 3.1 presents the summary statistics of LWC for the construction sector and its sub-sectors. The mean value of LWC for the construction sector is 9.3%; The mean values of LWC for the three sub-sectors of the construction sector (Construction of Buildings; Heavy and Civil Engineering Construction; and Specialty Trades Contractors) are 10.5%, 16.2%, and 8.8%, respectively. Table 3.2 presents the results of t-tests that were conducted to compare the mean values of LWC in different sub-sectors of the construction sector. The results show that the mean of LWC in Heavy and Civil Engineering Construction sub-sector is significantly greater than that of the Construction of Buildings sub-sector and the Specialty Trade Contractors sub-sector. Thus, the Heavy and Civil Engineering Construction sub-sector faces the highest average increase in labor wages following large-scale weather-related disasters. The value of Q_1 (25^{th} percentile) for the three sub-sectors are around zero which means that in almost 75% of the affected counties; labor wages increased (during at least one quarter) compared to one quarter before the disaster.

Table 3.1: Summary statistics of LWC for construction sector and its sub-sectors

Sector	Mean	Std. Dev.	Min	Q_1	Median	Q_3	Max
23 Construction (%)	9.3	15.3	-61.6	0.0	4.9	11.3	92.7
236 Construction of Buildings (%)	10.5	17.6	-47.3	0.0	5.9	16.6	101.1
237 Heavy and Civil Engineering Constructions (%)	16.2	24.6	-51.9	1.2	9.1	22.6	141.7
238 Specialty Trade Contractors (%)	8.8	14.2	-52.2	1.0	5.9	13.4	110.0

Table 3.2: Two-sample t-test results

Null hypothesis	F-statistics (equality of variances)	T-statistics (Mean comparison)
Mean of LWC in Heavy and Civil Engineering Construction is not greater than Construction of Buildings	1.95**	3.92**
Mean of LWC in Heavy and Civil Engineering Construction is not greater than Specialty Trade Contractors	2.97**	5.04**
Mean of LWC in Construction of Buildings is not greater than Construction of Buildings	1.53**	1.05

Notes: * and ** represent rejection of null hypothesis at the 5%, and 1% significance level, respectively.

Figure 3.3 shows the box plots of LWC for each of the construction sub-sectors. The difference between the 75th and 25th percentiles (Q_3 and Q_1), also referred to as the IQR, is a measure of statistical dispersion. The box plots for the three sub-sectors show that the Heavy and Civil Engineering sub-sector is also the most volatile sub-sector among the construction sub-sectors, since the IQR for this sub-sector is the greatest among them (21.4%) and the maximum expected value of LWC, measured as Q_3 + 1.5 IQR, is the highest at this sub-sector (54.7%). The lower value of mean and IQR for Specialty Trades Contractors makes this sub-sector the most resilient among the all. In fact, in 50% of cases, counties faced a maximum increase of somewhere between 1% to 13.4% among Specialty Trade Contractors. The maximum expected value of LWC for Specialty Trade Contractors is 32%; however, in some rare cases, laborer experienced a higher increase in their wages.

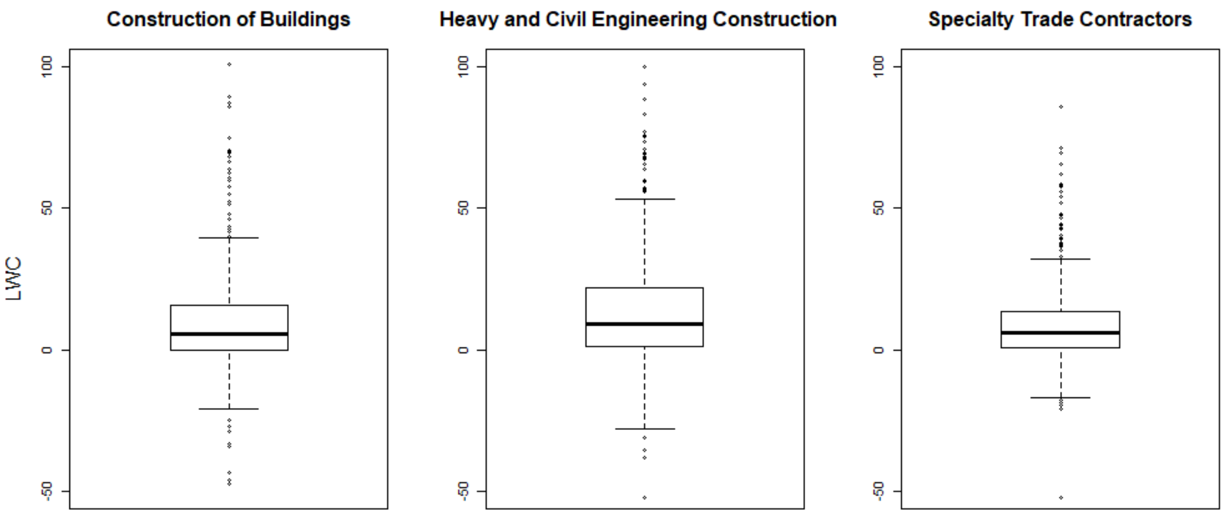


Fig. 3.3: Box plots of LWC for construction sub-sectors

3.2.1. Construction of buildings sub-sector

Table 3.3 presents the summary statistics of LWC for Construction of Buildings` industry groups and their industries. The mean values of LWC for the three industry groups of the Construction of Buildings sub-sector (Residential Building Constructions; Industrial Building Constructions; and Commercial Building Constructions) are 11.8%, 22.3%, and 13.5%, respectively. The results of Table 3.4 show that the mean of LWC in Industrial Building Construction is significantly greater than Commercial Building Construction and Residential Building Construction. Hence, Industrial Building Construction labor wages face the highest average increase among the Construction of Buildings` industry groups. The 25th percentile of the three industry groups remain around zero which means in almost 75% of the affected counties, at least one quarter exhibition increase in labor wages compared to before the disaster. The summary statistics of the industries (e.g. New Single Family General Contractors, etc.) are also presented in Table 3.3.

Table 3.3: Summary statistics of LWC for construction of buildings` industry groups

Sector	Mean	Std. Dev.	Min	Q_1	Median	Q_3	Max
236 Construction of Buildings (%)	10.5	17.6	-47.3	0.0	5.9	16.6	101.1
23611 Residential Building Constructions (%)	11.8	17.4	-46.3	2.2	8.2	18.3	132.0
236115 New Single-family General Contractors (%)	12.8	21.7	-33.8	1.1	8.8	18.7	144.7
236116 New Multifamily General Contractors (%)	15.4	33.7	-33.2	-6.0	6.3	26.7	124.4
236117 New Housing For-sale Builders (%)	12.5	26.5	-76.6	-5.8	6.3	21.7	75.3
236118 Residential Remodelers (%)	9.9	20.0	-39.7	-0.8	7.0	14.7	134.1
23621 Industrial Building Constructions (%)	22.3	33.1	-53.7	3.3	19.0	37.8	128.1
23622 Commercial Building Constructions (%)	13.5	23.4	-16.3	0.0	8.3	13.1	88.5

Table 3.4: Two-sample t-test results for construction of buildings` industry groups

Null hypothesis	F-statistics (equality of variances)	T-statistics (Mean comparison)
Mean of LWC in Industrial Building Construction is not greater than Commercial Building Construction	1.96*	1.89*
Mean of LWC in Industrial Building Construction is not greater than Residential Building Construction	3.64**	3.50**
Mean of LWC in Commercial Building Construction is not greater than Residential Building Construction	0.53**	0.45

Notes: * and ** represent rejection of null hypothesis at the 5%, and 1% significance level, respectively.

Figure 3.4 shows the box plots of LWC in the Construction of Buildings` industry groups. Industrial Building Construction industry group is also the most volatile industry group among the Construction of Buildings` industry groups, since the IQR and the maximum expected value of LWC are the greatest for this industry group (34.5% and 89.5%, respectively). The lower IQR for the Commercial Building industry group, makes this industry group the most resilient among them. In fact, in 50% of cases, counties faced a maximum increase of somewhere between 0% to 13.1% in labor wages in Commercial Building Construction. The maximum expected value of LWC (the upper end of the whiskers) for the three industry groups are 42%, 90%, and 33%, respectively.

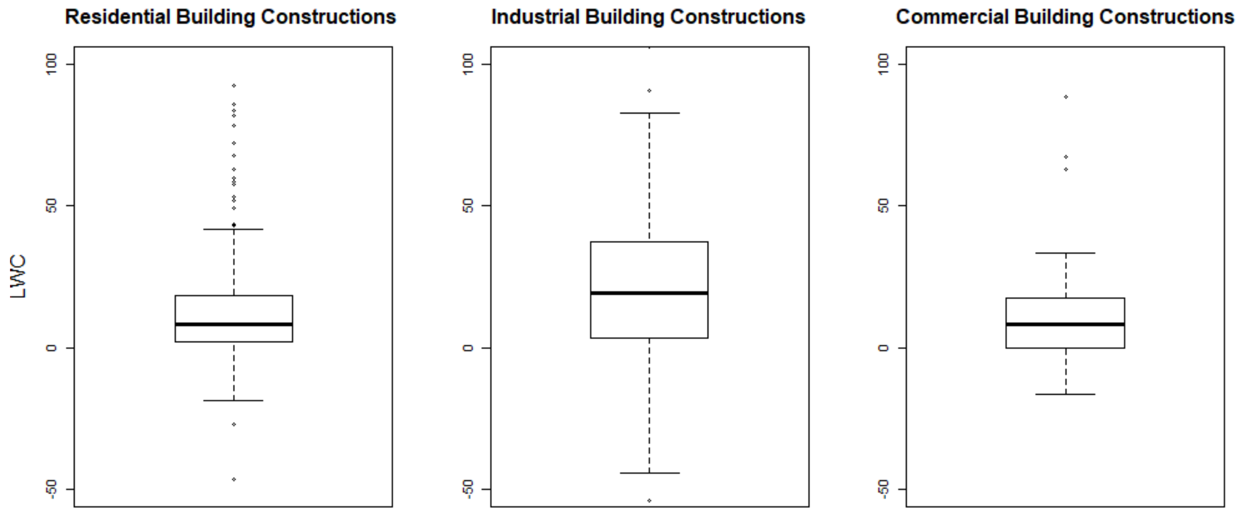


Fig. 3.4: Box plots of LWC for construction of buildings` industry groups

3.2.2. Heavy and civil engineering constructions sub-sector

Table 3.5 presents the summary statistics of LWC for Heavy and Civil Engineering Construction`s industry groups and their industries. The mean value of LWC for the four industry groups of the Heavy and Civil Engineering Construction sub-sector (Utility System Construction; Land Subdivision; Highway, Street, and Bridge Construction; and Other Heavy Construction) are 14.7%, 16.3%, 14.8%, and 15.7%, respectively. However, the results of Table 3.6 show that I cannot rank the industry groups. The 25th percentile of the four industry groups remain around zero which means almost 75% of the affected counties, experience an increase in labor wages compared to before the disaster.

Table 3.5: Summary statistics of LWC for heavy and civil engineering construction`s industry groups

Sector	**Mean**	**Std. Dev.**	**Min**	**Q_1**	**Median**	**Q_3**	**Max**
237 Heavy and Civil Engineering Constructions (%)	16.2	24.6	-51.9	1.2	9.1	22.6	141.7
2371 Utility System Construction (%)	14.8	24.7	-41.6	1.0	10.4	22.1	139.8
23711 Water and Sewer System Construction (%)	52.5	38.7	-63.5	2.7	14.6	45.8	704.2
23712 Oil and Gas Pipeline Construction (%)	12.2	24.6	-26.7	-1.6	8.6	24.2	108.2
23713 Power and Communication System Construction (%)	14.4	27.2	-65.0	-1.2	9.9	20.9	149.1
2372 Land Subdivision (%)	16.3	29.2	-44.9	0.0	12.3	29.7	130.9
2373 Highway, Street, and Bridge Construction (%)	14.8	22.8	-58.5	2.0	10.2	25.6	132.5
2379 Other Heavy Construction (%)	15.7	27.2	-51.9	1.2	12.6	23.1	144.4

Table 3.6: Two-sample t-test results for heavy and civil engineering construction`s industry groups

Null hypothesis	**F-statistics (equality of variances)**	**T-statistics (Mean comparison)**
Mean of LWC in Land Subdivision is not greater than Other Heavy Construction	1.15	0.20
Mean of LWC in Land Subdivision is not greater than Highway, Street, and Bridge Construction	1.65**	0.50
Mean of LWC in Land Subdivision is not greater than Utility System Construction	1.40*	0.51
Mean of LWC in Other Heavy Construction is not greater than Highway, Street, and Bridge Construction	1.42*	0.30
Mean of LWC in Other Heavy Construction is not greater than Utility System Construction	1.21	0.32
Mean of LWC in Highway, Street, and Bridge Construction Utility System Construction	0.84	0.01

Notes: * and ** represent rejection of null hypothesis at the 5%, and 1% significance level, respectively.

Figure 3.5 shows the box plots of LWC for Heavy and Civil Engineering Construction`s industry groups. The Land Subdivision is the most volatile among the Heavy and Civil Engineering Construction industry groups since the IQR and the maximum expected value of LWC for this industry group is the greatest compared to the other three industry groups (29.7% and 74.2%, respectively). The maximum expected values of LWC (the upper end of the whiskers) for the four industry groups (Utility System Construction; Land Subdivision; Highway, Street, and Bridge Construction; and Other Heavy Construction) are 54%, 74%, 61% and 56%, respectively, that are relatively high compared to the other construction industry groups.

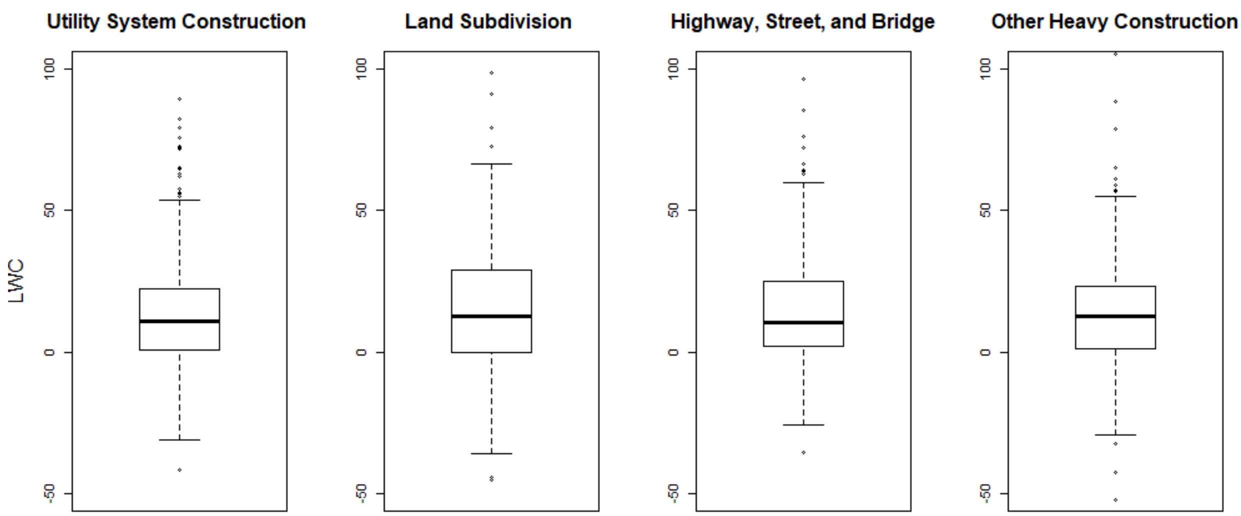


Fig. 3.5: Box plots of LWC for heavy and civil engineering construction`s industry groups

3.2.3. Specialty trade contractors' sub-sector

Table 3.7 presents the summary statistics of LWC for Specialty Trades Contractors` industry groups and their industries. The mean value of LWC for the four industry groups of the Specialty Trade Contractors sub-sector (Building Foundation and Exterior Contractors, Building Equipment Contractors, Building Finishing Contractors, and Other Specialty Trade Contractors) are 13.4%, 9.8%, 10.2%, and 13.1%, respectively. The results of Table 3.8 show that Building Foundation and Exterior Contractors and Other Specialty Trades Contractors are more vulnerable industry groups compared to Building Finishing Contractors and Building Equipment Contractors. The 25th percentile of the four industry groups are around zero which means almost 75% of the affected counties, experience an increase in labor wages compared to before the disaster.

Table 3.7: Summary statistics of LWC for specialty trade contractors` industry groups

Sector	Mean	Std. Dev.	Min	Q_1	Median	Q_3	Max
238 Specialty Trade Contractors (%)	8.8	14.3	-52.2	1.0	5.9	13.4	110.0
2381 Building Foundation and Exterior Contractors (%)	13.4	20.9	-28.5	2.0	8.7	20.0	143.0
23811 Poured Concrete Structure Contractors (%)	16.7	20.4	-35.3	2.1	10.6	24.2	122.1
23812 Steel and Precast Concrete Contractors (%)	14.6	25.5	-50.9	1.8	10.1	19.6	126.7
23813 Framing Contractors (%)	24.6	46.3	-82.5	-12.4	14.1	53.3	144.4
23814 Masonry Contractors (%)	18.5	28.9	-37.9	0.0	9.7	24.3	140.7
23815 Glass and Glazing Contractors (%)	14.4	26.8	-46.6	1.4	8.4	16.3	147.8
23816 Roofing Contractors (%)	14.0	24.5	-32.8	0.2	8.7	18.8	143.5
23817 Siding Contractors (%)	14.5	24.5	-41.0	0.0	9.9	22.5	116.5
23819 Other Building Exterior Contractors (%)	17.2	29.8	-27.1	0.0	11.3	25.6	130.6
2382 Building Equipment Contractors (%)	9.8	17.1	-32.9	0.0	6.1	14.3	103.1
23821 Electrical and Wiring Contractors (%)	10.3	16.3	-45.0	1.0	6.6	13.5	91.1
23822 Plumbing and HVAC Contractors (%)	8.2	15.8	-35.4	0.0	6.2	13.3	95.2
23829 Other Building Equipment Contractors (%)	11.6	22.6	-44.8	0.0	8.5	20.5	103.5
2383 Building Finishing Contractors (%)	10.2	21.0	-54.5	-0.2	6.9	17.8	136.6
23831 Drywall and Insulation Contractors (%)	8.3	21.7	-45.0	-2.1	6.3	15.3	141.6
23832 Painting and Wall Covering Contractors (%)	11.8	21.6	-55.4	-0.8	8.6	18.2	147.3
23833 Flooring Contractors (%)	9.5	18.6	-28.8	-2.0	6.3	18.4	96.0
23834 Tile and Terrazzo Contractors (%)	15.6	29.2	-65.3	-.04	10.6	23.7	143.0
23835 Finish Carpentry Contractors (%)	11.6	18.9	-44.2	-0.4	9.2	18.7	125.8
23839 Other Building Finishing Contractors (%)	14.6	27.9	-19.7	-1.4	8.1	21.8	145.0
2389 Other Specialty Trade Contractors (%)	13.1	21.3	-33.7	1.2	9.4	20.0	136.2
23891 Site Preparation Contractors (%)	10.2	21.2	-39.9	-0.7	7.7	17.6	144.3
23899 All Other Specialty Trade Contractors (%)	19.8	22.8	-50.0	2.1	10.5	24.1	146.0

Table 3.8: Two-sample t-test results for specialty trade contractors` industry groups

Null hypothesis	**F-statistics (equality of variances)**	**T-statistics (Mean comparison)**
Mean of LWC in Building Foundation and Exterior Contractors is not greater than Other Specialty Trade Contractors	0.96	0.23
Mean of LWC in Building Foundation and Exterior Contractors is not greater than Building Finishing Contractors	0.98	2.17*
Mean of LWC in Building Foundation and Exterior Contractors is not greater than Building Equipment Contractors	1.49**	2.82**
Mean of LWC in Other Specialty Trade Contractors is not greater than Building Finishing Contractors	1.02	2.38**
Mean of LWC in Other Specialty Trade Contractors is not greater than Building Equipment Contractors	1.55**	3.05**
Mean of LWC in Building Finishing Contractors is not greater than Building Equipment Contractors	1.51**	0.27

Notes: * and ** represent rejection of null hypothesis at the 5%, and 1% significance level, respectively.

Figure 3.6 shows the box plots of LWC for the Specialty Trade Contractors` industry groups. The IQR for the four industry groups are 18%; 14%; 18%, 19%, respectively. Thus, the Building Foundation and Exterior Contractors industry group and Other Specialty Trade Contractors industry group are the most volatile among the Specialty Trades Contractors industry groups, since the IQR and the maximum expected value of LWC for these two industry groups are the greatest among them.

According to Figure 3.6, although in some cases LWC increases by more than 100% for all four industry groups, the maximum expected values of the LWC for the four industry groups are 45%, 36%, 45% and 48%, respectively.

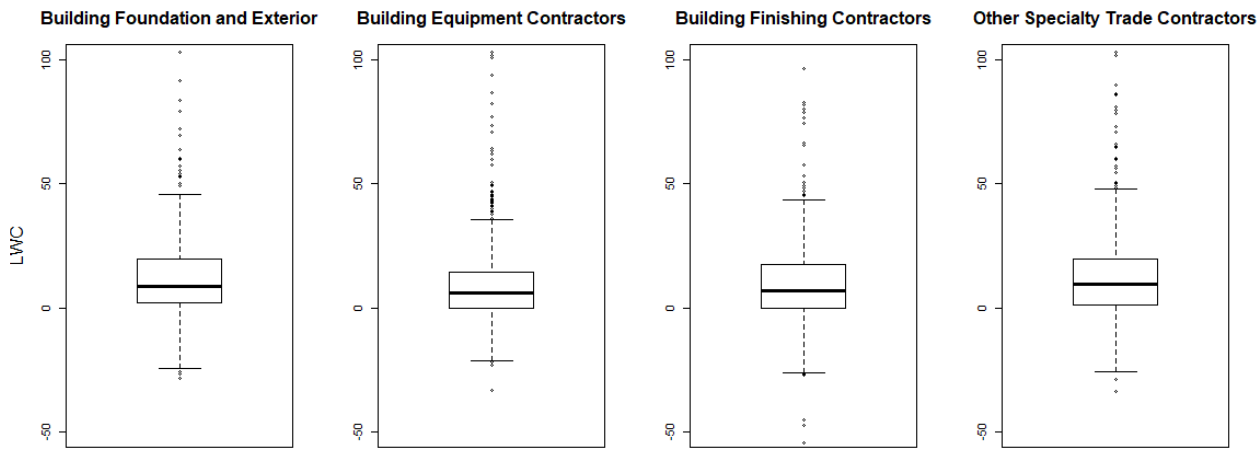


Fig. 3.6: Box plots of LWC for specialty trade contractors` industry groups

Since Building Exterior Construction is among the most exposed to the natural disaster, data of the average weekly wages for the 4 industry groups of the Building Exterior Construction (Framing Contractors, Masonry Contractors, Glass and Glazing Contractors, and Roofing Contractors), provided by BLS, were also collected and LWC was calculated for each county at each industry group for both Residential and Non-Residential laborer.

3.2.3.1. Framing contractors

Table 3.9 shows the summary statistics of LWC for the Residential Framing Contractors. The mean value of LWC for this sector is almost 12 percent. Thus, an average maximum of 12 percent increase in Residential Framing labor wages occurs in at least one of the 4 quarters following the weather-related disasters (including the quarter of the disaster); however, the median of 8 percent indicates that in 50 percent of the counties under study, the increase in wages were less than 8 percent (or wages decreased). Information on the first quartile (Q1) shows that in 75 percent of the counties, there were an "increase" in Residential Framing labor wages following disasters occurred and the third quartile (Q3) shows that in 25 percent of the counties, the wages increased were more than 19 percent. The difference between Q3 and Q1, also known as Inter Quartile Range (IQR), is a measure of statistical dispersion and shows the range in which the middle 50% data take place. The IQR for this sector is 19 percent.

Table 3.9: Summary statistics of LWC for the residential framing contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Framing Contractors (%)	12.1	22.3	-48.1	-0.3	8.0	19.4	80.1

Table 3.10 shows the summary statistics of LWC for the Non-Residential Framing Contractors. The mean value of LWC for this sector is 16 percent, which is almost 4 percent greater than Residential Building Framing Contractors. Thus, an average of 16 percent increase in Non-Residential Framing labor wages occurs in at least one of the 4 quarters following the weather-related disasters. The IQR for this sector is 25 percent. The greater IQR for the Non-Residential sector and the greater mean and median values, make the Non-Residential sector more vulnerable compared to the Residential sector.

Table 3.10: Summary statistics of LWC for the non-residential framing contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Framing Contractors (%)	16.4	23.1	-27.4	0.5	13.7	25.1	80.8

Figure 3.7 illustrates the proportional LWC by quarter for Framing Contractors. The first pie chart in Figure 1 shows that in 23 percent of cases, the maximum labor wage increases occurred in the quarter that the disaster happened. In 16 percent of cases, the maximum LWC occurred one quarter after the disaster. In 41 percent of cases, the maximum LWC was 2 quarters after the disaster, and in 20 percent of cases, the

maximum LWC was 3 quarters after the disaster. The second pie chart shows the same values for Non-Residential Framing Contractors. In both Residential and Non-Residential sectors, the maximum increase in labor wages, mostly, occurs 2 quarters after the weather-related disasters.

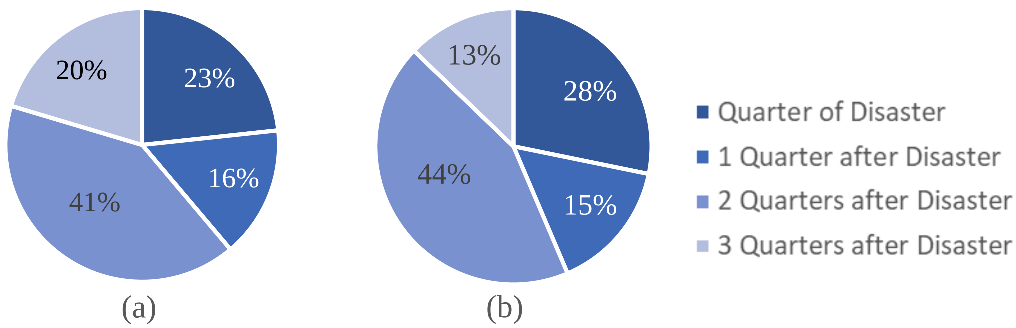


Fig. 3.7: Proportional LWC by quarter for framing contractors (a) residential, (b) non-residential

3.2.3.2. Masonry contractors

Table 3.11 shows the summary statistics of LWC for the Residential Masonry Contractors. The mean value of LWC for this sector is 15 percent which is 3 percent higher than Framing Contractors. Thus, a maximum average increase of 15 percent in Residential Masonry Contractors` wages occurs in at least one of the 4 quarters following the weather-related disasters (including the quarter of disaster); however, the median is 10 percent. Q1 equals 2 percent which means in 75 percent of the counties, an increase of greater than 2 percent in Residential Masonry Contractors` wages occurs and Q3 shows that in 25 percent of the counties, wages increased by more than 21 percent. IQR for this sector is 19 percent.

Table 3.11: Summary statistics of LWC for the residential masonry contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Masonry Contractors (%)	15.1	27.8	-46.5	1.8	9.7	20.8	188.9

Table 3.12 shows the summary statistics of LWC for the Non-Residential Masonry Contractors. The mean value of LWC for this sector is 18 percent which is almost 3 percent greater than Residential Building Masonry Contractors. Thus, an average maximum of 18 percent increase in Non-Residential Masonry Contractors` wages occurs in at least one of the 4 quarters following the weather-related disasters. The IQR for this sector is 28 percent which is greater than the other sectors. The high IQR for the Non-Residential Masonry sector makes this sector the most vulnerable among all Building Exterior Contractors.

Table 3.12: Summary statistics of LWC for the non-residential masonry contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Masonry Contractors (%)	18.3	31.0	-30.0	-0.7	13.1	26.8	160.4

Figure 3.8 shows the pie charts for the Residential and Non-residential Masonry Contractors. Both pie charts indicate that most wage increases occur in the second quarter after weather-related disasters; however, the shares appear almost equally spread over the 4 quarters for both Residential and Non-Residential Masonry Contractors.

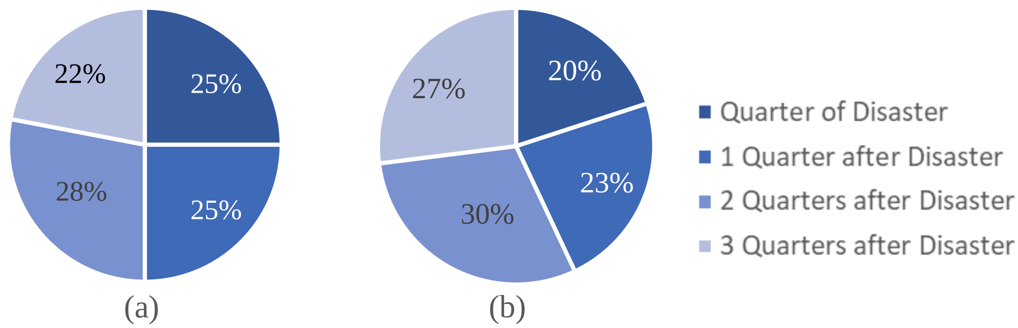


Fig. 3.8: Proportional LWC by quarter for masonry contractors (a) residential, (b) non-residential

3.2.3.3. Glass and glazing contractors

Table 3.13 presents the summary statistics of the LWC for the Residential Glass and Glazing Contractors. The mean value of the LWC for this sector is 13 percent. Thus, an average of 13 percent increase in Residential Glass and Glazing Contractors` wages occurs in at least one of the 4 quarters following the weather-related disasters (including the quarter of disaster). An increase of greater than 2 percent in Glass and Glazing Contractors` wages occurs in almost 75 percent of the counties. In 25 percent of the counties, an LWC greater than 19 percent happens. The IQR for this sector is 17 percent.

Table 3.13: Summary statistics of LWC for the residential glass and glazing contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Glass and Glazing Contractors (%)	12.9	21.0	-40.9	2.1	9.5	19.3	94.3

Table 3.14 shows the summary statistics of LWC for the Non-Residential Glass and Glazing Contractors. The mean value of LWC for this sector is 19 percent which is almost 6 percent greater than the Residential Building Glass and Glazing Contractors. So, an average maximum of 19 percent increase in Non-Residential Glass and Glazing Contractors` wages occurs in at least one of the 4 quarters following the weather-related disasters. Q1 shows that, 75 percent of the counties experience an increase of 4 percent

or more in Non-Residential Glass and Glazing labor wages. The greater IQR for the Non-Residential sector (21 percent) makes this sector more vulnerable compared to the Residential sector.

Table 3.14: Summary statistics of LWC for the non-residential glass and glazing contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Glass and Glazing Contractors (%)	18.8	35.4	-36.2	4.2	11.6	25.1	216.3

Figure 3.9 shows the pie charts for the Residential and Non-residential Glass and Glazing Contractors. Both pie charts indicate that most wage increases occurred in 2 quarters after weather-related disasters; however, the shares appear almost equally spread over the 4 quarters for the Non-Residential Glass and Glazing Contractors. In rare cases (16 percent of cases), Residential Glass and Glazing Contractors faced the highest increase in wages in the quarter of the disaster.

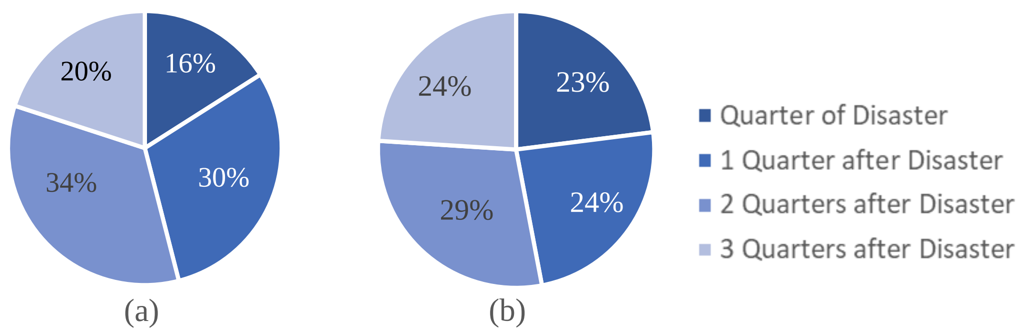


Fig. 3.9: Proportional LWC by quarter for glass and glazing contractors (a) residential, (b) non-residential

3.2.3.4. Roofing contractors

Table 3.15 presents the summary statistics of LWC for the Residential Roofing Contractors. The mean value of LWC for this sector is 14 percent. Thus, an average maximum of 14 percent increase in Residential Roofing Contractors` wages occurs in at least one of the 4 quarters following the weather-related disasters (including the quarter of disaster). Seventy five percent of counties experience at least one quarter (out of 4) in which Roofing Contractors` wages “increased” compared to 1 quarter before the disaster; however, 25 percent of the counties faced an increase of greater than 22 percent, in Residential Roofing Contractors` wages. The IQR for this sector is 22 percent.

Table 3.15: Summary statistics of LWC for the residential roofing contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Roofing Contractors (%)	14.0	25.5	-25.7	0.0	9.0	22.2	183.3

Table 3.16 shows the summary statistics of LWC for the Non-Residential Roofing Contractors. The mean value of LWC for this sector is 13 percent which appers almost equal to Residential Roofing Contractors. The IQR for this sector ranges from 2 to 18 percent. The IQR for this sector has a smaller value (16 percent) than Residential sector. This makes the Non-Residential sector more resilient, compared to the Residential sector. In addition, in almost 75 percent of the counties, an increase of greater than 2 percent in Non-Residential Roofing Contractors` wages occurs in the 4-quarter-period.

Table 3.16: Summary statistics of LWC for the non-residential roofing contractors

Sector	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Roofing Contractors (%)	13.2	27.9	-48.5	2.0	10.7	18.0	196.6

Figure 3.10 shows the pie charts for the Residential and Non-Residential Roofing Contractors. Both pie charts indicate that most wage increases occurred 2 quarters after the weather-related disasters.

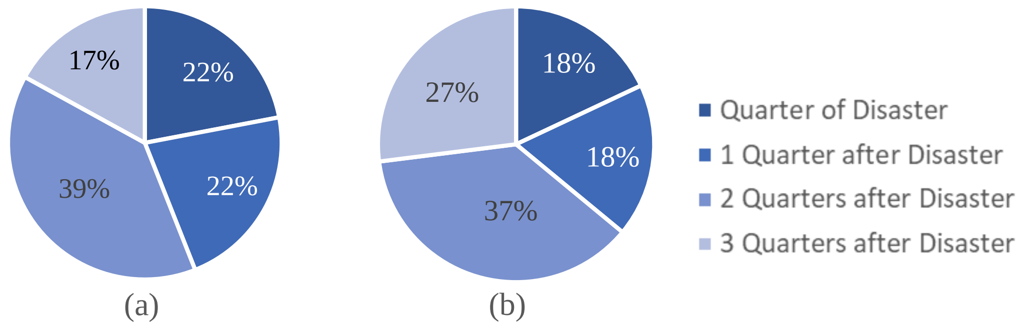


Fig. 3.10: Proportional LWC by quarter for roofing contractors: (a) residential, (b) non-residential

3.2.4. Distributions of labor wage changes

Figure 3.11 shows the distributions of LWC for different sub-sectors and industry groups of the construction sector. The red vertical line shows the mean of the dataset and the black vertical line shows the median. Table 3.17 presents the skewness and kurtosis of each distribution. Information from Figure 3.11 and Table 3.17 show that LWC for all sub-sectors and industry groups of the construction sector are highly right-skewed since the mean of the datasets are greater than their medians and skewness of the distributions are greater than 1 (except for Industrial Building Construction that is “moderately” right-skewed). Thus, most of the mass of the distributions are at the left side of the mean values, i.e. in most cases, LWC values are less than the calculated mean value of LWC for the sub-sectors (and industry groups). The high values of excess kurtosis, in Table 3.17, show that most counties experience a labor wage change of around the values in the central peak and the tails, and less experience the values on the “shoulders,” compared to a normally distributed dataset with an excess kurtosis of zero. Figure 3.11 shows that the right tails of the distributions are longer than the left tails. Thus, a county is more likely to face a "significant increase" in construction labor wages than a "significant decrease."

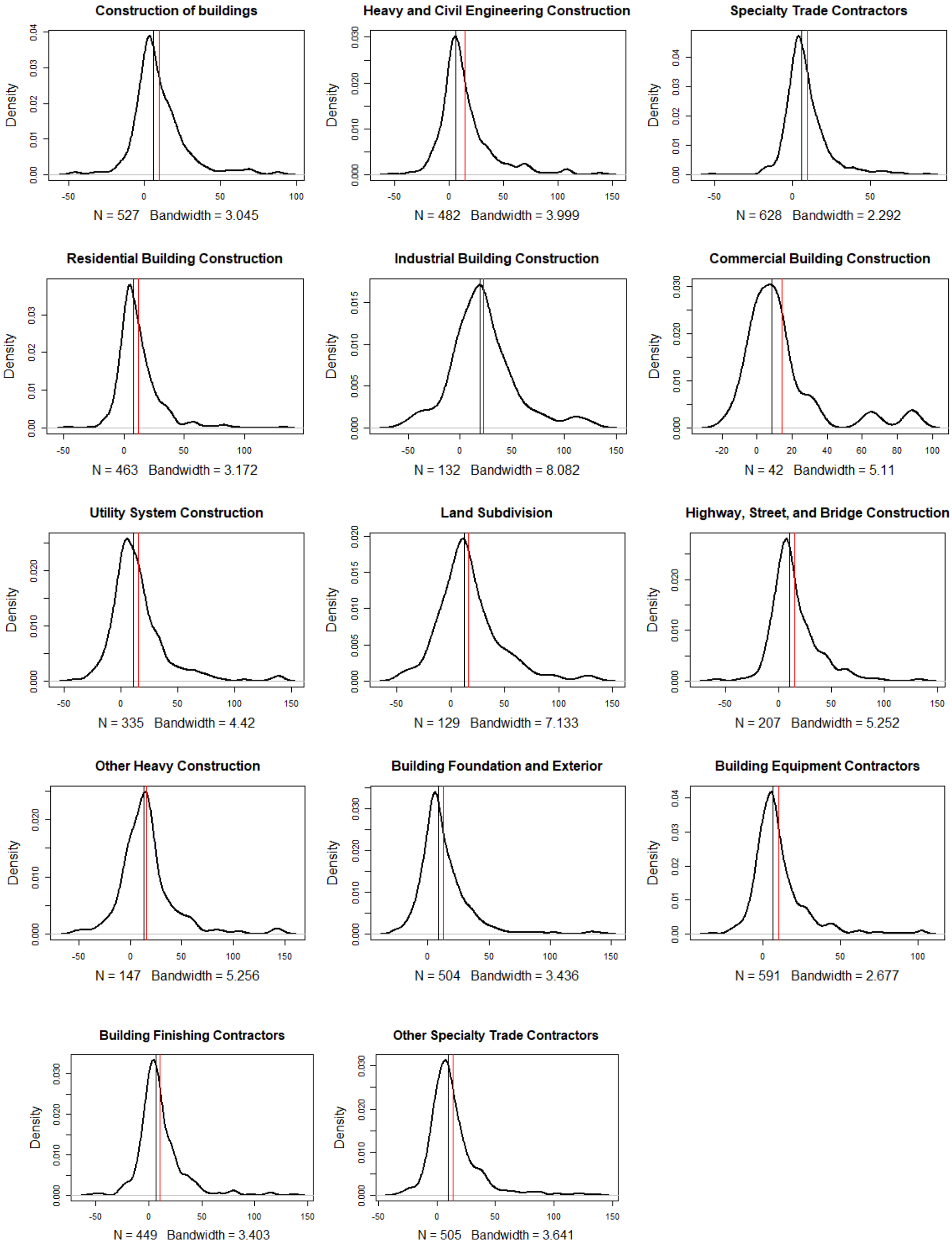


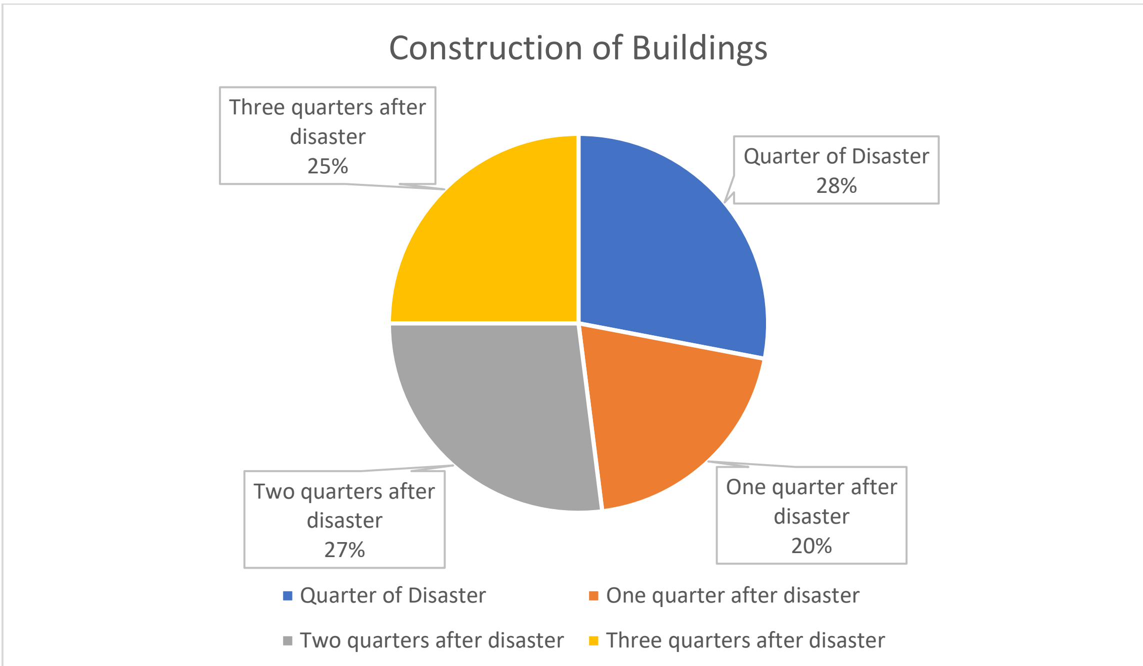
Fig. 3.11: Distribution of LWC for all construction sectors and sub-sectors

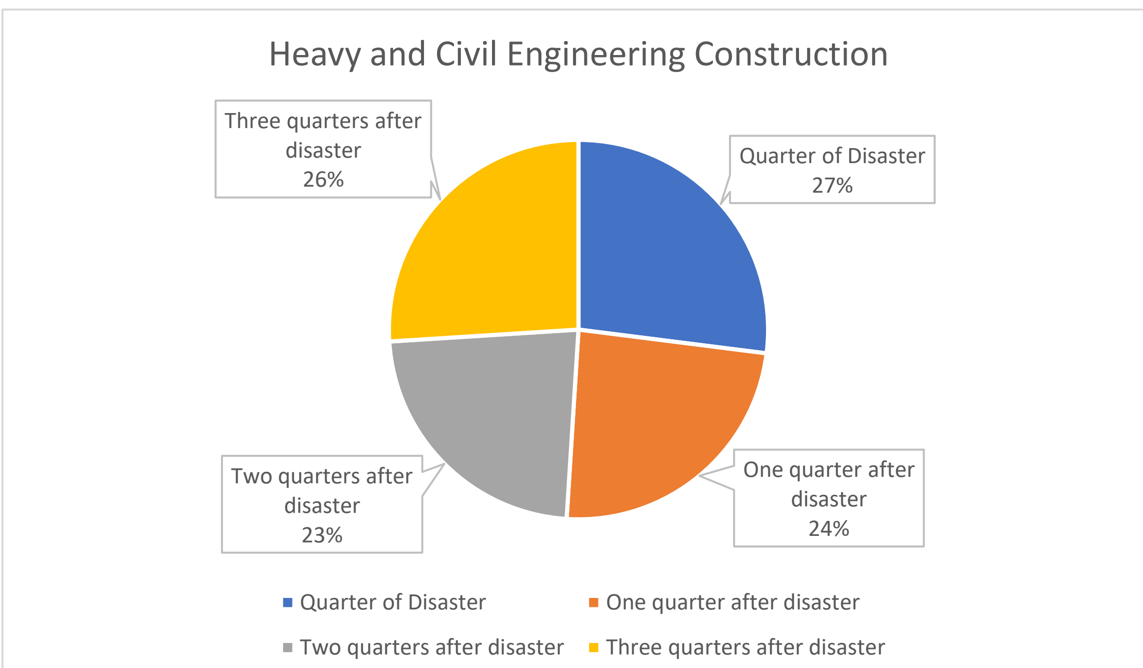
Table 3.17: Skewness and Kurtosis values of distributions of LWC for construction sub-sectors and industry groups

Sector	Skewness	Excess Kurtosis
236 Construction of Buildings (%)	1.37	4.98
23611 Residential Building Constructions (%)	1.88	8.19
23621 Industrial Building Constructions (%)	0.80	1.76
23622 Commercial Building Constructions (%)	1.92	3.83
237 Heavy and Civil Engineering Constructions (%)	1.71	4.82
2371 Utility System Construction (%)	1.99	7.02
2372 Land Subdivision (%)	1.06	2.61
2373 Highway, Street, and Bridge Construction (%)	1.14	4.58
2379 Other Heavy Construction (%)	1.58	6.27
238 Specialty trade contractors (%)	1.75	8.45
2381 Building Foundation and Exterior Contractors (%)	2.43	10.39
2382 Building Equipment Contractors (%)	2.18	7.99
2383 Building Finishing Contractors (%)	1.86	7.83
2389 Other Specialty Trade Contractors (%)	2.08	7.29

3.2.5. Quarter of maximum increase in labor wages

Figure 3.12 represents the quarters in which the maximum labor wages occurred by their percentage of occurrence. This Figure shows that in the Construction of Buildings sub-sector, in 28 percent of cases, the maximum percentage increase in labor wages (compared to one quarter before the disasters) occurred in the same quarter as the disaster. In 20 percent of cases, the maximum percentage increase occurred 1 quarter after the disasters; in 27 percent of cases, the maximum percentage increase was 2 quarters after the disaster; and in 25 percent of cases, the maximum percentage escalation was 3 quarters after the disasters. These percentages have almost the same spread for the other two sub-sectors. Thus, the maximum increase in labor wage could occur anytime over the one-year-period after the disasters or possibly after one year.





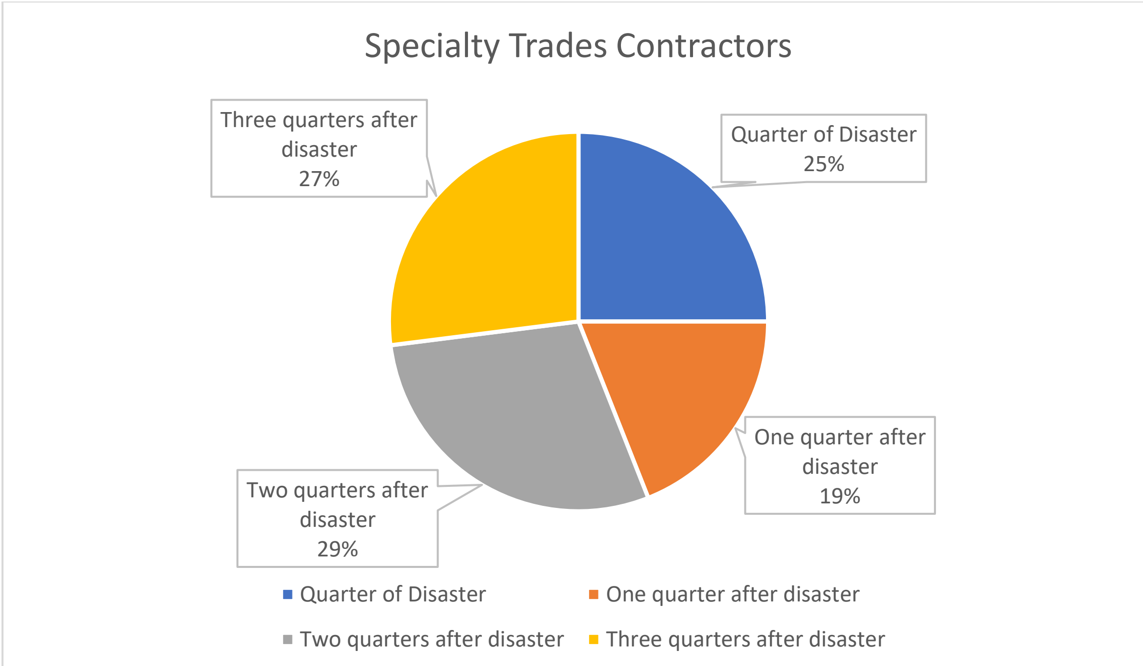


Fig. 3.12: Distribution of LWC for all construction sectors

3.2.6. Cumulative percent change in construction labor wages

Figure 3.13 shows the cumulative percent change of labor wages for the three sub-sectors of the construction sector. Labor wages in Construction of Buildings sub-sector, on average, decreased by 0.6% in the quarter of the disaster and gradually increased by 4.4% in the following three quarters. Specialty Trade Contractors` wages, on average, decreased by 0.8% in the quarter of the disaster and increased by 4.6% in the following three quarters. Heavy and Civil Engineering Construction`s labor wages did not exhibit this decrease after the disasters; wages increased immediately after disasters hit the counties and then rapidly increased by 8.6% in the three quarters after the disasters. One reason could be that Heavy and Civil Engineering projects are in high priority for repairs after disasters, while homeowners may need to wait until the claim adjusters assess the damage.

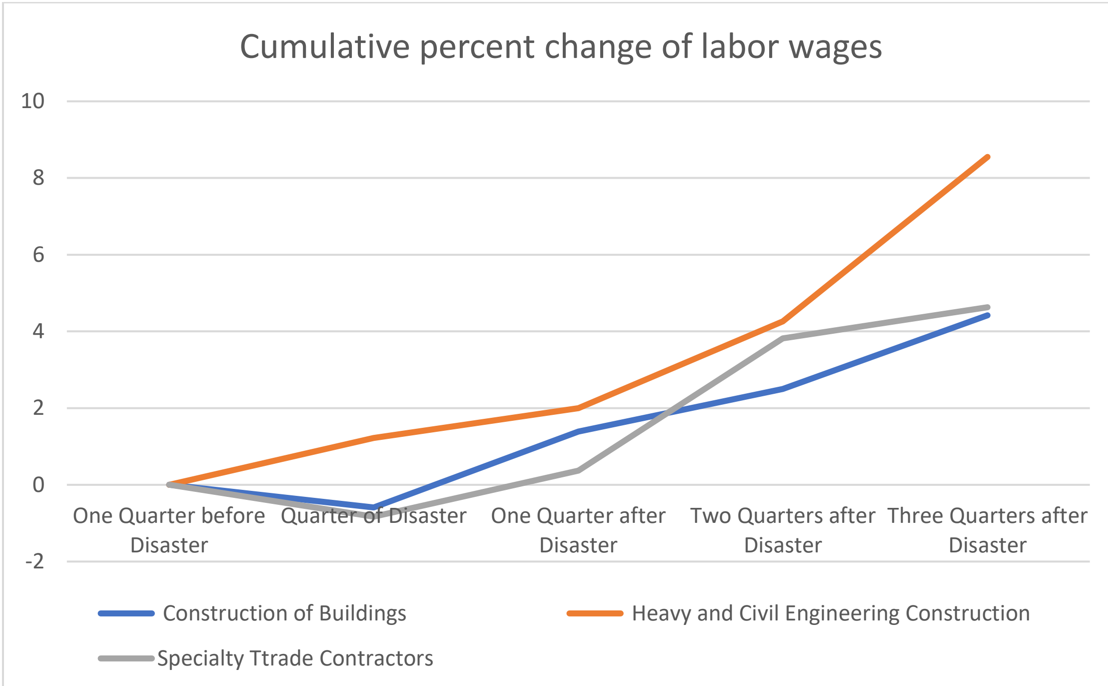


Fig. 3.13: Cumulative percent change of labor wages

3.3. Assumptions and Research Limitations

The labor wage data, used in this chapter, does not distinguish between different types of laborer (foreman, supervisor, manager, etc.). The results of this research are limited to the average labor wage data, published by BLS, for all sub-sectors (and industry groups) of the Construction industry. More rigorous research should go forward to compare different types of laborer, in an industry, against each other.

CHAPTER 4: ROLE OF PRE-DISASTER CONSTRUCTION MARKET CONDITIONS IN INFLUENCING POST-DISASTER DEMAND SURGE

The relationships between construction labor wage fluctuations and a disaster's magnitude and the number of associated disasters is well documented (Döhrmann et al., 2013; Olsen and Porter, 2013). Despite the significant role of the construction industry in post-disaster labor wage changes, the relationship between pre-disaster construction market conditions and labor wage changes has not been studied. This chapter investigates the relationship between the pre-disaster residential construction market conditions and the post-disaster residential labor wage changes based on weather-related disasters in the United States.

4.1. Methodology

The pre-disaster level of five residential construction market indicators (establishment count, construction contributions, average weekly wages, employment level, and building permits) are used as potential explanatory variables to quantify the impacts of pre-disaster residential construction market conditions on the percentage change in residential building labor wages, using regression analyses.

4.1.1. Data collection

I used two criteria to select these variables. First, these variables are used in the literature to represent construction market conditions and their impacts on construction wage changes (Ashuri et al., 2012) and labor wage fluctuations (Phillips, 1958; Friedman, 1968; Forder, 2014). The availability of the county-level data on construction market indicators was the second criterion.

Data on establishment count, construction contributions, average weekly wages, and employment level were collected from Bureau of Labor Statistics (BLS) and data on Building Permits were collected from the United States Census Bureau. BLS measures labor market activities, working conditions, and price changes in the U.S. economy and has provided crucial economic information to support both private and public decision-making since 1884 (BLS, 2017). BLS provides the county-level information on construction market indicators (establishment count, construction contributions, employment level, and labor wages).

4.1.1.1. Establishment count for residential building construction

An establishment is an economic unit that produces goods or provides services (BLS, 2017). The LQ establishment count data for residential building construction provides the opportunity to compare the number of establishments in a county against the other counties regardless of the size of the counties. I obtained the county-level LQ establishment count data associated with one quarter before the disaster event from the BLS website to analyze the impact of the number of establishments providing residential building construction services on the post-disaster LWC.

4.1.1.2. Construction contribution for residential building construction

Contributions are the monies deposited in trust funds to pay unemployment claims. Contributions are calculated on taxable wages and are reported quarterly to BLS (BLS, 2017). Construction contributions data associated with one quarter before the disaster were collected from BLS to analyze the impact of pre-disaster residential construction contributions on the post-disaster LWC.

4.1.1.3. Average weekly wages for residential building construction

The county-level quarterly average weekly wages data for the residential building construction industry are provided by BLS. Average weekly wages per employee is computed by dividing total wages by the number of employees (BLS, 2017). The pre-disaster level of average weekly wages for residential building construction were collected from BLS to analyze the impact of pre-disaster level of labor wages on the post-disaster LWC.

4.1.1.4. Employment level for residential building construction

BLS monthly employment data for each sub-division of an industry represent the number of covered workers who have worked during the pay period that includes the 12th day of each month (BLS, 2017). The average LQ employment level data for residential building construction labor within the last three months before a natural disaster provides the opportunity to compare the number of employees among the counties. A county with a higher level of LQ employment might experience a different LWC compared to a county with a lower level.

4.1.1.5. Building permits

The United States Census Bureau as a part of U.S. Department of Commerce provides monthly state-level data on the number of building permits. Building permits data were collected for the period of 2 years before the disasters for the affected counties to quantify the impact of changes in building permit issues on the amount of LWC. Table 4.1 represents the summary statistics for the full data set.

Table 4.1: Summary statistics

Cat.	Variable	Obs.	Mean	Std. Dev.	Min.	Q25	Q50	Q75	Max.
1	LWC	58	7.21	9.08	-9.59	1.53	5.13	13.67	27.37
	EC	58	1.05	0.39	0.44	0.77	0.98	1.25	2.09
	CC	58	1.11	0.87	0.11	0.61	0.84	1.31	5.41
	WW	58	0.99	0.21	0.53	0.87	0.97	1.14	1.46
	EL	58	1.02	0.59	0.29	0.58	0.81	1.32	2.77
	BP (% change)	58	-6.91	30.34	-45.3	-28.46	-11.29	4.87	57.56
	Damage (M)	58	162.8	153	30.7	56.6	100.3	227.5	750
2	LWC	56	11.69	11.21	-16.7	6.12	11.76	17.96	40.98
	EC	56	1.10	0.44	0.31	0.81	1.11	1.24	2.44
	CC	56	1.11	0.65	0.10	0.54	1.05	1.48	2.62
	WW	56	0.91	0.21	0.47	0.78	0.90	1.07	1.37
	EL	56	1.00	0.56	0.25	0.61	0.87	1.23	2.25
	BP (% change)	56	-10.43	23.59	-58.3	-29.37	-11.06	4.48	57.56
	Damage (M)	56	20.73	42.18	15	17.24	20	23.96	30
3	LWC	97	10.07	11.11	-18.5	3.61	7.14	15.96	41.86
	EC	97	1.25	0.53	0.43	0.89	1.19	1.47	3.55
	CC	97	1.02	0.78	0.01	0.56	0.85	1.26	4.14
	WW	97	0.96	0.25	0.40	0.79	0.94	1.10	1.93
	EL	97	1.07	0.77	0.19	0.59	0.82	1.27	5.22
	BP (% change)	97	-11.59	27.75	-51.2	-31.57	-11.06	2.08	67.99
	Damage (M)	97	9.9	2.6	5.1	6.9	10	11.2	14.1
4	LWC	114	9.97	15.13	-26.9	0.88	6.10	16.36	63.16
	EC	114	1.13	0.48	0.25	0.79	1.04	1.42	2.60
	CC	114	1.03	0.71	0.08	0.55	0.91	1.31	5.07
	WW	114	0.93	0.18	0.56	0.82	0.90	1.05	1.58

Cat.	Variable	Obs.	Mean	Std. Dev.	Min.	Q25	Q50	Q75	Max.
	EL	114	1.02	0.60	0.31	0.59	0.84	1.31	3.36
	BP (% change)	114	-4.30	37.25	-62.9	-34.46	-6.98	14.03	111.48
	Damage (M)	114	2.97	0.95	1.55	2.11	3	3.72	4.9
5	LWC	70	8.05	12.08	-15.7	-1.01	6.76	13.62	58.62
	EC	70	1.20	0.58	0.43	0.79	1.09	1.38	3.63
	CC	70	0.97	0.74	0.07	0.42	0.75	1.35	3.40
	WW	70	0.94	0.20	0.54	0.82	0.93	1.03	1.41
	EL	70	1.00	0.68	0.18	0.53	0.82	1.37	3.64
	BP (% change)	70	-10.09	25.78	-51.3	-30.69	-11.06	12.90	59.27
	Damage (M)	70	1.15	0.18	1	1	1.1	1.25	1.5

In this section, the null hypothesis is that no relationship exists between the pre-disaster level of the above five potentially explanatory variables and the level of changes in residential building labor wages in the aftermath of large-scale weather-related disasters. Rejection of null hypothesis means that these variables have impacts on the level of post-disaster residential building labor wage changes. Two types of regression models (constant variance and category dependent variance) were created to quantify the impacts of potential explanatory variables on labor wage changes following disasters.

4.1.2. Regression analysis

The regression method is widely used to estimate the magnitude and significance of the effects of independent variables on a dependent variable (Neale et al., 1994). Five potentially explanatory variables were defined as construction market indicators in the introductory paragraph of this methodology section. At this step, the methodology used to create multiple linear regression models are presented. These models were created to quantify the effects of the potential explanatory variables on the amount of labor wage changes (LWC). I first propose a multiple linear regression model regardless of the damages caused by catastrophes (Model 1). Later, the data will be categorized into five groups considering the property damage to the counties to quantify the relationship between LWC and potential explanatory variables for different levels of damage (from significant to minimal, Models 2 through 6).

To create a multiple linear regression model, I started with the full model including all possible interaction terms between the predictors. Then, the backward elimination method (Hocking, 1976) was utilized to identify the best reduced model. This method starts with the full model and at each step evaluates the elimination of the variable whose loss gives the most statistically insignificant deterioration of the fitted model and repeats this elimination until no further variable can be deleted from the model. This study uses the Akaike information criterion (Akaike, 1973) for its backward elimination method. This criterion compares model complexity (measured by the number of parameters) against the likelihood of observing the available data given the proposed model. Akaike information criterion (AIC) is defined as:

$$\text{AIC} = 2\text{K} - 2\ \text{Ln}\ (\hat{L})$$

where K is the number of model parameters and $\hat{L}$ is the maximum value of the likelihood function of the model. An ideal proposed model should have fewer parameters and a larger likelihood, and thus, a smaller AIC value. For each of the proposed Models 1 through 6, a reduced model with the lowest AIC value was selected to be the best model of its category. Since AIC is an estimator of the “relative” quality of statistical models, these AIC values will then be used to compare Models 1 through 6 against each other.

Burnham & Anderson (2004) showed that AIC has two theoretical advantages over Bayesian information criterion (BIC): 1) AIC is derived from principles of information while BIC is not. 2) The Bayesian-framework derivation of BIC has a prior of 1/R (R is the number of candidate models), that is "not sensible," since the prior should be a decreasing function of k. Stone (1977) and Fang (2011) argued that the cross-validation method is asymptotically equivalent to AIC for both ordinary linear regression and mixed-effects models. Boisbunon et al. (2014) showed that Mallows' Cp is equivalent to AIC for linear regression models. Therefore, for my application, AIC is superior or at least equivalent to other methods.

4.1.2.1. Regression model assuming a constant variance

The first model assumes that LWC reacts the same to the explanatory variables after all weather-related disasters. In other words, I assume no relationship between LWC and the amount of property damages because the plot of LWC vs. property damages does not signal any upward or downward trend (Figure 4.1).

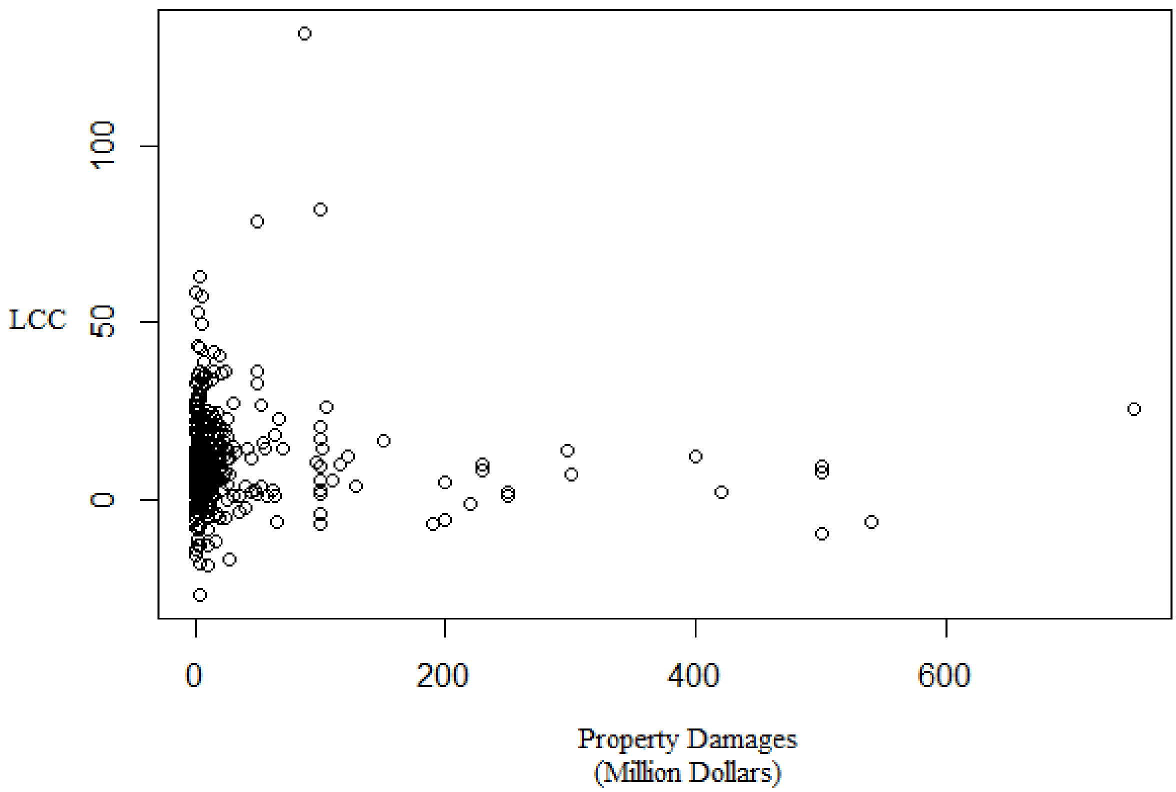


Fig. 4.1: Plot of labor wage change vs. property damages

In fact, even after large-scale disasters with high property damages, labor wages in some counties did not increase, and in some cases, they even decreased. On the other hand, after small disasters, some counties encountered significant increases in labor wages. Thus, the first model assumes a constant residual variance for all weather-related disasters:

$$LWC_i = \alpha_0 + \alpha_1 EC_i + \alpha_2 CC_i + \alpha_3 WW_i + \alpha_4 EL_i + \alpha_5 BP_i + \sum_{k=1}^{p} \beta_k * IT_k + \varepsilon_i$$

where LWC_i represents labor wage changes in county i; α_0, α_1, α_2, α_3, α_4, α_5, and β_k are the model parameters; *IT* represents the interaction terms (combination of variables); *p* is the number of all possible interaction terms; EC_i is the establishment count for residential building construction at one quarter before the catastrophe in county i; CC_i

is the construction contribution for residential building construction at one quarter before the catastrophe in county i; WW_i is the average weekly wages for residential building construction at one quarter before the catastrophe in county i; EL_i is the average employment level for residential building construction at three months before catastrophe in county i; BP_i is the state-wide percent change in the average number of building permits issued three months before the catastrophe compared to that of one year earlier; and ε_i is the error term.

All interaction terms are mean-centred to avoid high multicollinearity problems. Centering the data is a method of standardization that decreases multicollinearity and has the added benefit of not changing the interpretation of the coefficients. By subtracting data from their mean (mean-centring), each coefficient continues to estimate the change in the mean response for each unit change in the explanatory variable while all other explanatory variables are held constant.

4.1.2.2. Regression models assuming a category dependent variance

At this step, the data are categorized into five categories based on property damage in all the counties. The National Oceanic and Atmospheric Administration (NOAA) collects information on property damage from insurance companies and other qualified individuals. If data are not available, estimates are obtained from emergency managers, such as the U.S. Geological Survey, U.S. Army Corps of Engineers, power utility companies, and newspaper articles (NOAA, 2017). Property damage includes damages to buildings (destroyed houses, destroyed garages, destroyed porches, damaged awnings, destroyed poles, destroyed roofs, and electrical damage), as well as powerlines/poles, roads, bridges, and agriculture. Unfortunately, NOAA does not provide detailed information on the types of property damages incurred at the county-level; thus, in this study, I categorize the disasters based on the rough estimates on their total property damages provided by NOAA. Table 4.2 summarizes these categories and presents the number of observations collected for each category.

Table 4.2: Categories of damages to the counties

Category (j)	Description	No. of obs.
1	Disasters causing significant property damages to a county (greater than \$30M)	58
2	Disasters causing high property damages to a county (between \$15M and \$30M)	56
3	Disasters causing medium property damages to a county (between \$5M and \$15M)	97
4	Disasters causing low property damages to a county (between \$1.5M and \$5M)	114
5	Disasters causing very low property damages to a county (between \$1M and \$1.5M)	70

Regression models assuming a category-dependent variance allow the coefficients and the error terms to be different among the groups:

$$LWC_{i,j} = \alpha_{0,j} + \alpha_{1,j}EC_i + \alpha_{2,j}CC_i + \alpha_{3,j}WW_i + \alpha_{4,j}EL_i + \alpha_{5,j}BP_i + \sum_{k=1}^{p} \beta_{k,j} * IT_{k,j} + \varepsilon_{i,j}$$

where $LWC_{i,j}$ is the labor wage change in county *i* and category *j*; $\alpha_{0,j}$, $\alpha_{1,j}$, $\alpha_{2,j}$, $\alpha_{3,j}$, $\alpha_{4,j}$, $\alpha_{5,j}$, and $\beta_{k,j}$ are the model parameters and are independently distributed in category *j*; *IT* represents the interaction terms; *p* is the number of all possible interaction terms; and $\varepsilon_{i,j}$ is the error term in county *i* and category j.

4.2. Results

Table 4.3 presents Pearson correlation coefficients between each pair of explanatory variables. Considering the common threshold of 0.7, only EC and EL seem to be highly correlated, i.e., the higher number of establishments providing residential building services will typically lead to a higher employment level in residential building construction in a county and vice versa; however, some counties might have a lower number of establishments while each establishment hires more employees. Thus, I keep both variables in the initial full models.

Also, all the interaction terms between variables remain in the model, since they are conceptually reasonable. For example, a comparison could be made for a case in which the number of building permits have increased, the number of establishments providing construction services are high, and employment level is high, against a case in which the number of building permits have increased, but the levels of the other variables are low.

Table 4.3: Pearson correlation coefficients

	EC	**CC**	**WW**	**EL**	**BP**
EC	1	0.55	0.22	0.78	0.18
CC	0.55	1	0.27	0.68	0.11
WW	0.22	0.27	1	0.38	0.16
EL	0.78	0.68	0.38	1	0.17
BP	0.18	0.11	0.16	0.17	1

To continue with the constant variance model, explanatory variables are plotted vs. response variables (LWC). Figure 4.2 shows the scatter plot of the response variable (LWC) vs. each explanatory variable (EC, CC, WW, WL, BP). Some linear downward (or upward) trends between LWC and any of the explanatory variables exist. No curvature could be seen in these plots; thus, the assumption of linear regression would be reasonable. The assumptions of the linear regression method will be investigated next.

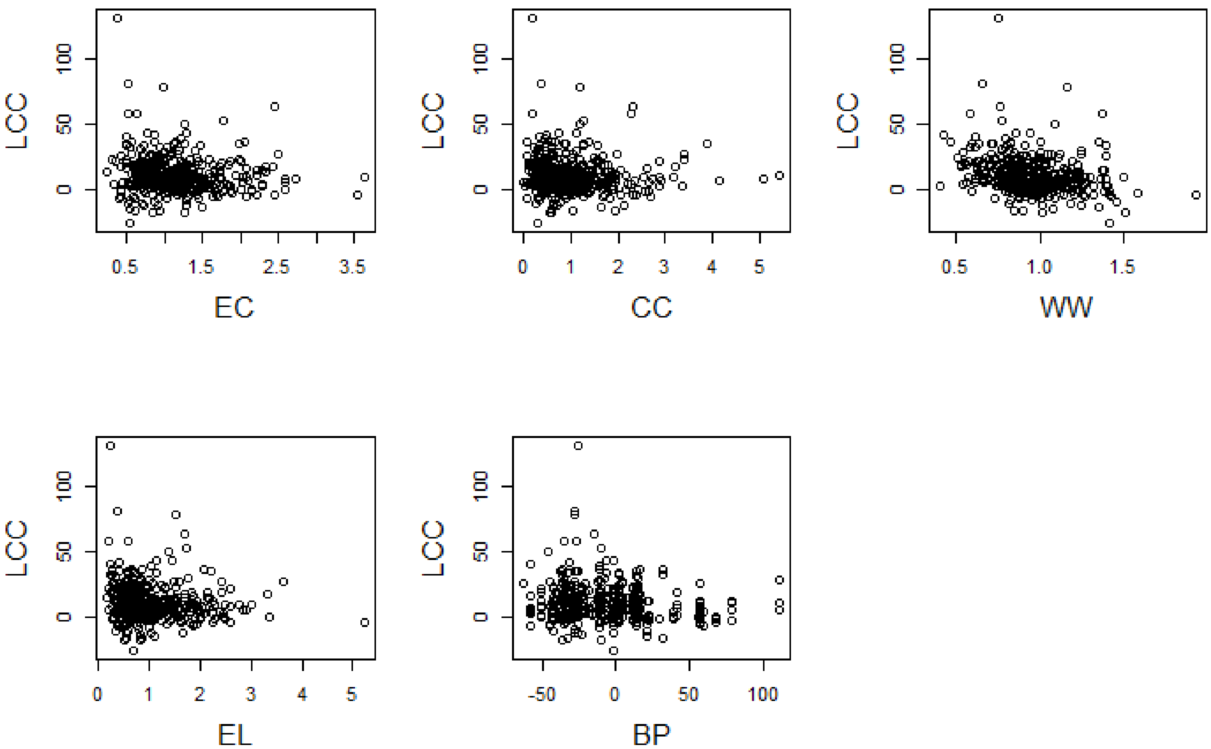


Fig. 4.2: Scatter plots of response variable vs. each explanatory variable

4.2.1. Regression model assuming a constant variance

The initial full model was set to be the model assuming constant variance. Using the backward elimination method, the model that minimized Akaike information criteria (AIC) among the reduced models is:

<u>Model 1:</u>

$$DS_i = Intercept_i + WW_i + EC_i{*}WW_i + CC_i{*}EL_i + CC_i{*}BP_i + WW_i{*}EL_i + EL_i{*}BP_i + EC_i{*}CC_i{*}WW_i + EC_i{*}CC_i{*}EL_i + EC_i{*}CC_i{*}BP_i + CC_i{*}WW_i{*}BP_i + EC_i{*}CC_i{*}WW_i{*}EL_i + EC_i{*}CC_i{*}WW_i{*}BP_i + CC_i{*}WW_i{*}EL_i{*}BP_i$$

Table 4.4 shows the parameter estimates and the variance inflation factors (VIFs) that are used to check multicollinearity. The adjusted R-squared for this model is 17%, which means 17% of the variability in the amount of LWC could be explained using these explanatory variables regardless of the magnitude of the disasters.

Table 4.4: Parameter estimates for model 1

	Estimate	t-value	Pr. (>|t|)	VIF
Intercept	19.9450	6.165	1.80E-09 ***	
WW	-11.5779	-3.458	0.00061 ***	1.59
EC*WW	-25.6301	-2.787	0.0056 ***	6.83
CC*EL	-2.7910	-1.668	0.09611 *	4.44
CC*BP	0.1400	2.661	0.00812 ***	2.73
WW*EL	21.9264	3.184	0.00157 ***	9.16
EL*BP	-0.1070	-2.052	0.04081 **	4.49
EC*CC*WW	-52.4096	-5.241	2.65E-07 ***	6.40
EC*CC*EL	3.2924	2.176	0.03014 **	4.96
EC*CC*BP	-0.1349	-2.236	0.02585 **	1.60
CC*WW*BP	0.3019	1.609	0.10845	1.73
EC*CC*WW*EL	30.2556	3.726	0.00022 ***	8.25
EC*CC*WW*BP	0.6771	1.582	0.11672	4.17
CC*WW*EL*BP	-0.63922	-1.762	0.07893 *	5.30

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Residual standard error: 11.27 on 391 degrees of freedom; Multiple R-squared: 0.20; Adjusted R-squared: 0.17; F-statistic: 7.178 on 13 and 381 DF; p-value: 1.465e-12; AIC: 1927.22.

4.2.2. Regression models assuming a category dependent variance

In this step, the data are categorized into five categories based on the amount of property damage, and each category is analyzed individually. The full models including all interaction terms were first created, and then the best reduced models were selected for each category using the backward elimination method.

4.2.2.1. Significant-impact disasters (more than $30 M damage to the county)

Significant impact disasters are weather-related disasters, which cause property damage of 30-million dollars or more in a county in the United States. The full category-dependent variance model is first assumed as the full model for this category (category 1) and then backward elimination method is utilized to select the reduced model:

Model 2:

$LWC_{i,1}$ = $Intercept_{i,1}$ + $EC_{i,1}$ + $WW_{i,1}$ + $EC_{i,1}$*$CC_{i,1}$ + $EC_{i,1}$*$BP_{i,1}$ + $CC_{i,1}$*$BP_{i,1}$ + $WW_{i,1}$*$EL_{i,1}$ + WW*$BP_{i,1}$ + $EL_{i,1}$*$BP_{i,1}$ + $EC_{i,1}$*$CC_{i,1}$*$WW_{i,1}$ + $EC_{i,1}$*$CC_{i,1}$*$EL_{i,1}$ + $EC_{i,1}$*$CC_{i,1}$*$BP_{i,1}$ + $EC_{i,1}$*$CC_{i,1}$*$WW_{i,1}$*$EL_{i,1}$ + $CC_{i,1}$*$WW_{i,1}$*$EL_{i,1}$*$BP_{i,1}$

Table 4.5 shows the parameter estimates for Model 2 and the calculated VIFs.

Table 4.5: Parameter estimates for model 2

	Estimate	t-value	Pr. (>|t|)	VIF
Intercept	3.1215	0.417	0.67847	
EC	-5.8687	-1.460	0.15141	3.44
WW	11.4742	1.666	0.10275	2.87
EC*CC	-13.044	-2.187	0.03409 **	5.75
EC*BP	-0.4018	-3.738	0.00053 ***	3.46
CC*BP	0.5908	5.401	2.5e-06 ***	8.06
WW*EL	54.3421	3.445	0.00126 ***	6.42
WW*BP	0.7984	3.167	0.00279 ***	3.98
EL*BP	-0.4225	-3.013	0.00428 ***	8.45
EC*CC*WW	-41.0716	-1.280	0.20740	12.05
EC*CC*EL	29.7063	2.827	0.00704 ***	17.06
EC*CC*BP	-0.2061	-1.410	0.16554	3.65
EC*CC*WW*EL	-73.4501	-2.382	0.02159 **	15.18
CC*WW*EL*BP	-1.6568	-2.794	0.00768 ***	6.27

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Residual standard error: 6.52 on 44 degrees of freedom; Multiple R-squared: 0.61; Adjusted R-squared: 0.50; F-statistic: 5.276 on 13 and 44 DF; p-value: 1.436e-05; AIC: 229.47.

4.2.2.2. High-impact disasters (between $15 M and $30 M damage to the county)

High impact disasters are the weather-related disasters which cause property damage between 15- and 30-million dollars in a county in the United States. The full category-dependent variance model is first assumed to be the full model (including all possible interaction terms) for this category (category 2). The backward elimination method is then utilized to create the best reduced model, which is:

Model 3:

$LWC_{i,2} = Intercept_{i,2} + EC_{i,2} + CC_{i,2} + EC_{i,2}*CC_{i,2} + EC_{i,2}*WW_{i,2} + CC_{i,2}*EL_{i,2} + WW_{i,2}*EL_{i,2} + EC_{i,2}*CC_{i,2}*EL_{i,2} + EC_{i,2}*CC_{i,2}*BP_{i,2} + CC_{i,2}*WW_{i,2}*EL_{i,2} + CC_{i,2}*WW_{i,2}*BP_{i,2} + WW_{i,2}*EL_{i,2}*BP_{i,2} + EC_{i,2}*CC_{i,2}*WW_{i,2}*BP_{i,2} + CC_{i,2}*WW_{i,2}*EL_{i,2}*BP_{i,2} + EC_{i,2}*CC_{i,2}*WW_{i,2}*EL_{i,2}*BP_{i,2}$

Table 4.6 shows the parameter estimates for Model 3 and the calculated VIFs.

Table 4.6: Parameter estimates for model 3

	Estimate	t-value	Pr. (>|t|)	VIF
Intercept	-3.7416	-0.776	0.44246	
EC	13.9633	3.141	0.002950 ***	5.06
CC	-3.6651	-1.690	0.09822 *	2.71
EC*CC	33.4539	4.025	0.00024 ***	11.12
EC*WW	-51.4505	-2.688	0.01033 **	6.54
CC*EL	-10.7548	-1.627	0.11131	8.53
WW*EL	66.3682	5.081	8.63e-06 ***	5.12
EC*CC*EL	-28.2761	-3.983	0.00027 ***	9.38
EC*CC*BP	0.7688	2.825	0.00727 ***	4.75
CC*WW*EL	-30.9288	-2.754	0.00873 ***	3.07
CC*WW*BP	1.4269	1.748	0.08793 *	11.28
WW*EL*BP	-2.7418	-3.492	0.00116 ***	9.18
EC*CC*WW*BP	9.1469	3.994	0.00026 ***	18.96
CC*WW*EL*BP	-2.7923	-1.782	0.08212 *	19.58
EC*CC*WW*EL*BP	4.9416	1.960	0.05683 *	15.24

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Residual standard error: 6.352 on 41 degrees of freedom; Multiple R-squared: 0.76, Adjusted R-squared: 0.68; F-statistic: 9.313 on 14 and 41 DF; p-value: 1.023e-08; AIC: 219.6.

4.2.2.3. Medium-impact disasters (between $5 M and $15 M damage to the county)

Medium impact disasters are weather-related disasters which cause property damage between 5- and 15-million dollars in a county in the United States. The full category-dependent variance model is first assumed as the full model for this category (Category 3). The backward elimination method was then utilized to create the best reduced model, which is:

Model 4:

$$LWC_{i,3} = Intercept_{i,3} + WW_{i,3} + BP_{i,3} + CC_{i,3}*BP_{i,3} + WW_{i,3}*EL_{i,3} + EC_{i,3}*CC_{i,3}*WW_{i,3} + EC_{i,3}*CC_{i,3}*EL_{i,3} + EC_{i,3}*CC_{i,3}*BP_{i,3} + CC_{i,3}*WW_{i,3}*EL_{i,3} + WW_{i,3}*EL_{i,3}*BP_{i,3} + EC_{i,3}*CC_{i,3}*WW_{i,3}*BP_{i,3} + EC_{i,3}*CC_{i,3}*WW_{i,3}*EL_{i,3}*BP_{i,3}$$

Table 4.7 shows the parameter estimates and the VIFs.

Table 4.7: Parameter estimates for model 4

	Estimate	**t-value**	**Pr. (>|t|)**	**VIF**
Intercept	36.9822	7.229	1.96e-10 ***	
WW	-28.5023	-5.461	4.62e-07 ***	2.05
BP	0.05929	1.412	0.16172	1.59
CC*BP	0.20527	2.758	0.0071***	2.29
WW*EL	9.3897	1.542	0.1267	8.44
EC*CC*WW	79.6195	2.838	0.0056 ***	19.38
EC*CC*EL	3.3472	1.971	0.05198 *	2.399
EC*CC*BP	-0.3648	-2.466	0.0156 **	4.634
CC*WW*EL	-42.6820	-2.545	0.0127 **	19.56
WW*EL*BP	-0.1985	-1.764	0.0813 *	15.81
EC*CC*WW*BP	-3.0249	-4.365	3.56e-05 ***	5.16
WC*CC*WW*EL*BP	1.6214	2.438	0.0168 **	15.27

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Residual standard error: 9.05 on 85 degrees of freedom; Multiple R-squared: 0.41; Adjusted R-squared: 0.34; F-statistic: 5.425 on 11 and 85 DF; p-value: 1.778e-06; AIC= 438.52.

4.2.2.4. Low-impact disasters (between $1.5 M and $5 M damage to a county)

Low-impact disasters are weather-related disasters, which cause property damage between 1.5- and 5-million dollars to a county. The full category-dependent variance model is first assumed as the full model for this category (category 4). The backward elimination method was then utilized to create the best reduced model, which is:

Model 5:

$LWC_{i,4} = WW_{i,4} + EL_{i,4} + EC_{i,4}*WW_{i,4} + EC_{i,4}*EL_{i,4} + CC_{i,4}*WW_{i,4} + EC_{i,4}*CC_{i,4}*WW_{i,4} + EC_{i,4}*CC_{i,4}*WW_{i,4}*BP_{i,4} + CC_{i,4}*WW_{i,4}*EL_{i,4}*BP_{i,4} + EC_{i,4}*CC_{i,4}*WW_{i,4}*EL_{i,4}*BP_{i,4}$

Table 4.8 shows the parameter estimates and the VIFs.

Table 4.8: Parameter estimates for model 5

	Estimate	t-value	Pr. (>|t|)	VIF
Intercept	16.1386	2.380	0.01913 **	
WW	-14.2348	-1.854	0.06655 *	1.38
EL	7.1704	2.519	0.01330 **	2.03
EC*WW	-25.7388	-1.643	0.10336	1.65
EC*EL	-11.3897	-2.236	0.02749 **	2.59
CC*WW	45.6697	3.222	0.00170 ***	3.32
EC*CC*WW	-94.4505	-4.382	2.81e-05 ***	9.90
EC*CC*WW*BP	2.7678	2.535	0.01272 **	7.40
CC*WW*EL*BP	-2.3043	-2.473	0.01503 **	7.50
EC*CC*WW*EL*BP	2.9723	2.812	0.0059 ***	14.56

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Residual standard error: 12.7 on 104 degrees of freedom; Multiple R-squared: 0.35, Adjusted R-squared: 0.30; F-statistic: 6.265 on 9 and 104 DF; p-value: 4.86e-07; AIC: 588.95.

4.2.2.5. Very low-impact disasters (less than $1.5M damage to a county)

Very low-impact disasters are weather-related disasters, which cause property damage of less than 1.5-million dollars in a county. The full category-dependent variance model is first assumed as the full model for this category (category 5). The backward elimination method is then used to create the best reduced, model which is:

<u>*Model 6:*</u>

$LWC_{i,5} = Intercept_{i,5} + CC_{i,5} + EC_{i,5} * CC_{i,5} + CC_{i,5} * WW_{i,5} + WW_{i,5} * EL_{i,5} + EC_{i,5} * CC_{i,5} * WW_{i,5} + EC_{i,5} * CC_{i,5} * EL_{i,5} + EC_{i,5} * CC_{i,5} * BP_{i,5} + CC_{i,5} * WW_{i,5} * BP_{i,5} + WW_{i,5} * EL_{i,5} * BP_{i,5} + EC_{i,5} * CC_{i,5} * WW_{i,5} * EL_{i,5}$

Table 4.9 shows the parameter estimates and the VIFs.

Table 4.9: Parameter estimates for model 6

	Estimate	t-value	Pr. (>|t|)	VIF
Intercept	-0.4684	-0.220	0.826864	
CC	5.9841	3.154	0.002534 ***	2.07
EC*CC	12.5289	3.143	0.002618 ***	3.97
CC*WW	-21.2590	-1.915	0.060335 *	3.31
WW*EL	24.1230	1.751	0.085066 *	3.66
EC*CC*WW	-117.0780	-7.002	2.69e-09 ***	4.15
EC*CC*EL	-13.2973	-4.106	0.000126 ***	12.77
EC*CC*BP	-0.4641	-4.225	8.40e-05 ***	1.28
CC*WW*BP	1.2740	1.969	0.053684 *	3.38
WW*EL*BP	-1.6600	-2.832	0.006326 ***	3.24
EC*CC*WW*EL	95.3601	4.744	1.37e-05 ***	17.99

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Residual standard error: 8.099 on 59 degrees of freedom; Multiple R-squared: 0.62; Adjusted R-squared: 0.55; F-statistic: 9.44 on 10 and 59 DF; p-value: 3.894e-09; AIC: 302.87.

4.2.3. Diagnosis of model assumptions

Four common model assumptions are discussed for all the regression models. The assumptions are linearity, homoscedasticity, multicollinearity, and normality.

4.2.3.1. Linearity

Linearity is known to be one of the most important assumptions while conducting regression analyses. Plotting the data of residuals vs. fitted values is still known to be the best way to detect the violation of linearity assumption (Stevens, 2009). Figure 4.3 shows the plots of residuals vs. fitted values for all Models 1 through 6. The residuals for all models are well scattered around the mean of zero and no curvilinearity is detected for any of them. We also considered the plots of the response variable vs. each independent variable for all Models 1 through 6 and did not find any evidence for the existence of curvilinearity. Thus, the assumption of linearity is satisfied for all Models and adding curve components to the models is not reasonable.

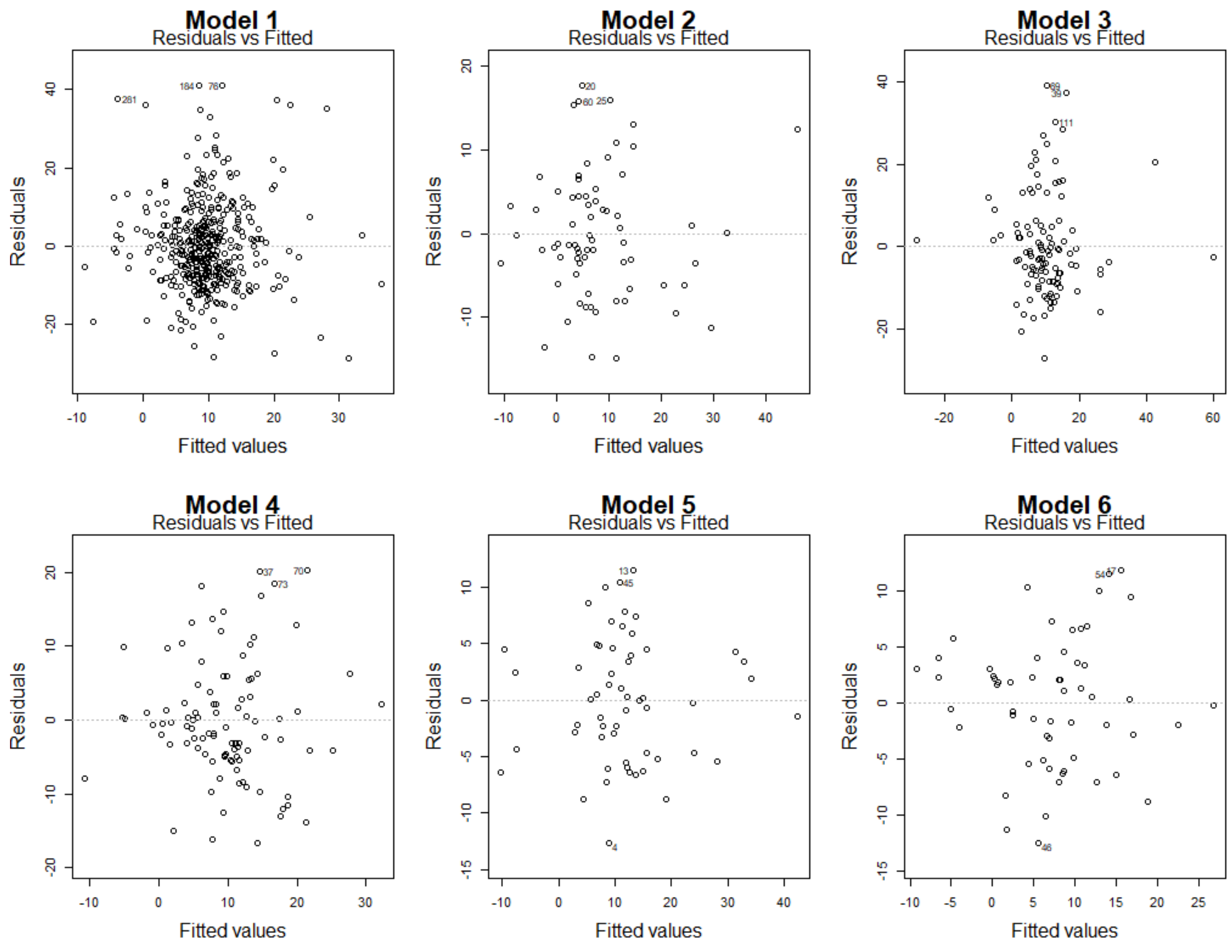


Fig. 4.3: Plots of residuals vs. fitted values

4.2.3.2. Homoscedasticity

Homoscedasticity assumption refers to equality of variance of errors across all levels of independent variables (Osborne and Waters, 2002), i.e., errors are spread consistently among the variables. Bartlett's test (Bartlett, 1937) and Levene`s test

(Levene and Howard, 1960) are used in this study to assess homoscedasticity. In both tests, the data of residuals of the fitted values for each model are divided into two equal groups (around the median), and the assumption of homoscedasticity is tested. The null hypothesis of these tests is that the variances of the two groups are equal. Rejection of the null hypothesis means that the residuals do not have constant variances that leads to heteroscedasticity. Table 4.10 and 4.11 show the results of Bartlett’s test and Levene`s test. All of the p-values are greater than 0.05 except for the Levene`s test for Model 1; thus, the assumption of homoscedasticity was satisfied for all models except for Model 1.

Table 4.10: Results of Bartlett`s test

	Bartlett`s test	
	Bartlett`s K-squared	**P-value**
Model1	6.81	0.01
Model 2	0.16	0.69
Model 3	0.01	0.91
Model 4	1.70	0.19
Model 5	0.36	0.55
Model 6	0.02	0.88

Table 4.11: Results of Levene`s test

	Levene`s test	
	Levene`s F-value	**P-value**
Model1	1.71	0.19
Model 2	0.70	0.405
Model 3	2e-04	0.98
Model 4	0.28	0.59
Model 5	0.30	0.58
Model 6	0.001	0.97

4.2.3.3. Multicollinearity

The multicollinearity assumption assumes that the independent variables are not highly correlated (Darlington, 1968; Keith, 2006). Multicollinearity occurs when the independent variables are correlated or when one independent variable is a near linear combination of other independent variables (Keith, 2006).

A VIF greater than 10 indicates a multicollinearity problem (O'Brien, 2007). Multicollinearity does not reduce the predictive power or reliability of the model as a whole, at least within the sample data set; it only affects calculations regarding individual predictors. The predictor variables depend on each other and cannot be individual predictors of the dependent variable. Some sources define serious multicollinearity to be problematic when the VIF is greater than 100, especially when interaction terms are being considered (Belsley, 1980). The VIF for each explanatory variable is calculated and shown in the tables of parameters estimates. Except for 15 explanatory variables that have VIFs greater than 10 (and less than 20), the rest of the explanatory variables have

VIFs of less than 10. To avoid high multicollinearity problems in Models 2 through 6 (Tables 5 through 9), interaction terms are mean-centred (by subtracting data from their mean). By mean-centring, each coefficient continues to estimate the change in the mean response for each unit change in the explanatory variable, while all other explanatory variables are held constant. Mean-centring reduces the “nonessential collinearity” and does not change the fit of regression models (Dalal and Zickar, 2012).

4.2.3.4. Normality

Regression analysis assumes that errors of the model are normally distributed (Osborne and Waters, 2002). The Anderson and Darling test (Anderson and Darling, 1954) and the Shapiro-Wilk test (Shapiro and Wilk, 1965) were utilized in this study to check the assumption of normality for the five models. The null hypothesis of these tests is that the residuals of the fitted model are normally distributed. A p-value of smaller than 0.05 results in rejection of the null hypothesis. Tables 4.12 and 4.13 summarize the results of these two tests. The null hypothesis was rejected for Model 1 but was not rejected for any of the five categorized models, which means the assumption of normality was not satisfied for Model 1 and is satisfied for the categorized models.

Table 4.12: Results of Shapiro-Wilk test

	Shapiro-Wilk test	
	W-Value	**P-value**
Model 1	0.95	5.8e-10
Model 2	0.97	0.75
Model 3	0.97	0.31
Model 4	0.97	0.07
Model 5	0.97	0.08
Model 6	0.97	0.22

Table 4.13: Results of Anderson Darling test

	Anderson Darling test	
	A-Value	**P-value**
Model 1	3.88	1.11e-09
Model 2	0.19	0.90
Model 3	0.42	0.31
Model 4	0.08	0.07
Model 5	0.77	0.06
Model 6	0.38	0.39

4.2.4. Comparison of results

Two types of models were created to forecast the amount of LWC after weather-related disasters. Model 1 assumes that LWC reacts the same to the explanatory variables for any magnitude of weather-related disasters. Models 2 through 6 categorize the data based on the magnitudes of disasters (property damage) and assume that LWC reacts differently to the explanatory variables based on the magnitudes of the weather-related disasters. The predictability of Model 1 is compared to that of Models 2 through 6 using their sum of squared residuals (SSR). The following equation shows how SSR is calculated:

$$SSR = \sum_{i=1}^{n} (\widehat{LWC_i} - LWC_i)^2$$

where $\widehat{LWC_i}$ is the predicted LWC for observation i, and LCC_i is the actual LWC for observation i. To compare the predictability of the models, SSR for Model 1 is compared against the sum of SSR for Models 2 through 6. Thus, both have the same sample sizes and become comparable. The results of Table 4.12 show that the SSR for the categorized models are 37% lower than the SSR for model 1. Thus, using these models would give more accurate estimations. Furthermore, Models 2 through 6 have higher adjusted R-squares that make them more reliable and useful. Also, all the model assumptions were satisfied for Models 2 through 6.

Table 4.14: Comparison between models

Measure	Model 1	Models 2 to 6
SSR	49314	31120

4.2.5. Discussion of results

The scatter plots of response variable vs. each explanatory variable (Figure 4.2) show linear relationships between any of the explanatory variables and the response variable, and the plots of residuals vs. fitted values (Figure 4.3) do not signal any patterns or curvatures. Thus, the assumption of linearity is satisfied for all Models 1 through 6, and there is no need for non-linear transformation. The results show that the pre-disaster levels of the residential construction market indicators signal the post-disaster levels of changes in residential labor wages.

To avoid high multicollinearity problems in Models 1 through 6, interaction terms are mean-centred (by subtracting data from their mean). By mean-centring, each coefficient continues to estimate the change in the mean response for each unit change in the explanatory variable while all other explanatory variables are held constant.

The results of this study show that Models 2 through 6 have higher predictability power compared to Model 1. Four criteria were considered in selecting the best set of predicting models:

1. The sum of squared residuals for Models 2 through 6 (category dependent models) is 31120 which is smaller than that of Model 1 (49314).
2. The adjusted R-squared values of Models 2 through 6 (0.5, 0.68, 0.34, 0.30, 0.55, respectively) are greater than that of Model 1 (0.17).
3. The AIC values of Models 2 through 6 (229, 219, 439, 589, 302.9, respectively) are less than the AIC value of Model 1 (1927).
4. Models 2 through 6 passed all the linear regression assumptions while Model 1 did not.
5. Thus, using Models 2 through 6 would give more accurate estimations in the event of a weather-related disaster. A comparison of AIC values and adjusted R-squared values of models 2 through 6 shows that model 3 with the highest adjusted R-squared (0.68) and the lowest AIC value (219) has the best performance among the category dependent models and model 5 with the lowest adjusted R-squared (0.34) and the highest AIC has the least

predictability power among the category dependent models. Hence, in case of a disaster with a property damage between 15-million and 30-million dollars to a county, Model 3 would be helpful, and for very low-impact disasters (with a property damage less than 1.5-million dollars to the county), Model 6 could be used to predict the maximum county-level percentage change in residential construction labor wages.

4.3. Assumptions and Research Limitations

This chapter focuses on the residential building construction data to model the post-disaster changes in labor wages in the residential building construction sector. Future research is needed to model construction labor wage changes in other construction sectors (heavy and civil engineering construction, and specialty trade contractors) or their smaller industry groups. Moreover, the labor wage data, used in this study, does not distinguish between different types of laborer (foreman, supervisor, manager, etc.) in the residential building construction sector.

This study used the pre-disaster construction economic data (establishment count, construction contributions, average weekly wages, employment level, and building permits) to assess their impact on the post-disaster labor wage changes. I included some other economic variables, such as GDP at the state level, in my models but they did not exhibit any relationship with labor wage changes nor did they improve the predictability power of the models. On the other hand, availability of the data at the county-level was one of my main constraints in obtaining data for other unobserved potential explanatory variables. Future research may include those unobserved variables to create new models with possibly higher accuracy.

CHAPTER 5: ASSESSING SPATIO-TEMPORAL AUTOCORRELATIONS IN EXISTING DEMAND SURGE MODELS USING SPATIAL PANEL DATA MODELS

Different predictive models have been created to study the underlying factors affecting post disaster construction labor cost escalations; however, all of these models are cross-sectional models and do not consider the spatial interaction effects and time-specific effects in the models. Failing to account for these effects, as in cross-sectional studies, increases the risk of obtaining biased estimation results. The objective of this chapter is to create spatial panel data models (SPDM) to find the spatial interaction effects as well as time-specific effects in the existing cross-sectional demand surge models.

5.1. Methodology

The county-level labor wage changes were measured as the seasonally adjusted percent change of labor wage following each disaster season. The pre-disaster levels of construction economic indicators were used as the explanatory variables. Spatial weight matrices were created to describe the spatial arrangement of the counties under study. Geary`s C test was conducted to test for the spatial autocorrelation among the values of post-disaster labor wage changes (dependent variable). Spatial panel data models were created, and the parameters were estimated through maximum likelihood implementation. Finally, to test for the assumption of random effects models (versus fixed effects models), the Hausman test was implemented.

5.1.1. Explanatory variables

For each of the disaster seasons, the county-level data of pre-disaster construction economic indicators were obtained from BLS. The pre-disaster construction economic data, used in the literature, are LQs of:

1) Employment level in construction that represents the number of covered workers who have worked during the pay period that includes the 12th day of each month (BLS, 2018)
2) Construction labor wage that is the average weekly wages per employee and is computed by dividing total wages by the number of employment (BLS, 2018).
3) Construction contributions, that are the monies deposited in trust funds in order to pay unemployment claims. Construction contributions are calculated on taxable wages and are reported quarterly to BLS (BLS, 2018).
4) Construction establishment counts that are the number of economic units that provide residential construction services (BLS, 2018).

5.1.2. Spatial weight matrix

Before starting spatial analysis, I need to create spatial weight matrices that describe the spatial arrangement of the counties under study. Let W denote an (N×N) spatial weight matrix and wij the (i,j)th element of W, where i and j = (1, . . ., N) and N represents the number of counties. It is assumed that W is a matrix of known constants, which all diagonal elements of the weight matrix are zero. I implemented three methods to measure the spatial distance of neighboring counties (off-diagonal w_{ij} elements):

1) First-order binary contiguity matrix that is only the counties which share border are considered neighbors;

2) K= q nearest neighbors where q neighboring counties are considered neighbors (usually q is an integer between 2 to 6);

3) Distance-based neighbors that creates an inverse distance matrix that decays the spatial weight of farther counties.

Since spatial panel data models are sensitive to the selection of weight matrix, I created all the three different types of weight matrices and compared their effects in the spatial panel data models.

5.1.3. Geary`s *C* test

To test for the spatial autocorrelation among the values of labor wage changes (dependent variable), I perform a preliminary test on spatial dependence of labor wage changes among the neighboring counties. Geary's C (Geary, 1954) is a measure of spatial autocorrelation to determine if the values of the dependent variable are correlated. Geary`s C is defined as:

$$C = \frac{(\boldsymbol{N-1}) \sum_i \sum_j w_{ij}(x_i - x_j)^{\mathbf{2}}}{\mathbf{2}\boldsymbol{W} \sum_i (x_i - \bar{\boldsymbol{x}})^{\mathbf{2}}}$$

where N is the number of spatial units indexed by i and j; x is the variable of interest; $\bar{x}$ is the mean of x; w_{ij} is a matrix of spatial weights with zeros on the diagonal; and W is the sum of all w_{ij}. A Geary`s C value of between 0 and 1 demonstrates a positive spatial autocorrelation, while a value of greater than 1 demonstrates a negative spatial autocorrelation.

5.1.4. Spatial panel data model

Spatial panel data models were created to capture spatial interactions across counties and over time. I started from a general spatial panel data model that includes a spatial lag of the dependent variable (LWC) and spatial autoregressive disturbances:

$$LWC = \lambda(I_T * W_N)LWC + \beta X + u$$

where LWC is an NT × 1 vector of observations on the dependent variable (N= number of spatial units, and T= number of disaster seasons), X is an NT × 4 matrix of observations on the four exogenous explanatory variables (employment level in construction, construction labor wages, construction contributions, and construction establishment counts), I_T is an identity matrix of dimension T, W_N is the N × N spatial weights matrix of known constants, and λ the corresponding spatial autoregressive parameter, and u is the disturbance vector that is (Baltagi et al. 2003):

$$u = (l_T * I_N)\mu + \rho(I_T * W_N)\varepsilon + \nu$$

where l_T is a T×1 vector of ones, I_N an N×N identity matrix, μ is a vector of time invariant individual specific effects that are not spatially autocorrelated, ρ is the spatial autoregressive parameter, ν is the vector of remainder error components, and $\nu \sim IID(0, {\sigma_\nu}^2)$ and $\varepsilon \sim IID(0, {\sigma_\varepsilon}^2)$. Two different models were created considering the existence of spatial lag of dependent variable (lag = True) and absence of spatial lag of dependent variable (lag = False).

A second specification for the vector of disturbances is described in Kapoor et al. (2007). They assumed that spatial correlation applies to both the individual effects and the remainder error components. This assumption implies a different spatial spillover mechanism governed by a different structure of the implied variance covariance matrix (Millo and Piras, 2012). I considered the implementation of both error term specifications in my analysis.

Considering the three types of spatial interaction effects in the full spatial panel data model, three types of reduced models could be created (Halleck and Elhorst, 2015): 1) the spatial autoregressive (SAR) model containing the endogenous interaction effects

$\lambda.LWC$; 2) the spatial error model (SEM) containing the error terms\` interaction effects u; 3) the spatial autoregressive combined (SAC) model containing both $\lambda.LWC$ and u. More models are proposed by researchers that include the spatial interaction effects of explanatory variables on the dependent variables of neighboring counties; however, due to the overfitting problems associated with these models (Halleck and Elhorst, 2015), they were not considered in this analysis.

5.1.5. Maximum likelihood implementation

The following likelihood function was maximized to estimate the model parameters $\beta, {\sigma_\varepsilon}^2, \Phi, \lambda$ and ρ (Anselin 1988):

$$L(\beta, {\sigma_\varepsilon}^2, \Phi, \lambda, \rho) = -\frac{NT}{2}2\pi - \frac{NT}{2}\ln {\sigma_\nu}^2 + T\ln|\mathrm{A}| - \frac{1}{2}\ln|T\Phi I_N + (B^{\mathrm{T}}B)^{-1}| + (T-1)\ln|B| - \frac{1}{2{\sigma_\nu}^2}u^{\mathrm{T}}\textstyle\sum^{-1}u$$

where $\Phi = {\sigma_\mu}^2/{\sigma_\varepsilon}^2$, $A = I_N - \lambda W_N$, $B = I_N - \rho W_N$, ${\sigma_\nu}^2 = (AY - X\beta)^{\mathrm{T}}\Sigma^{-1}(AY - X\beta)/NT$, $u = [I_T * (I_N - \rho W_N)^{-1}]\varepsilon$ and $\beta = (X^{\mathrm{T}}\Sigma^{-1}X)^{-1}X^{\mathrm{T}}\Sigma^{-1}AY$.

5.1.6. Spatial Hausman test

Overall, two types of spatial panel data models are proposed in the literature: random effects and fixed effects models. A random effects model assumes that the unobserved individual effects are not correlated with the other explanatory variables in the model (Millo and Piras, 2012). The Hausman test, proposed by Hausman (1978), compares random versus fixed effects estimators and tests whether the assumption of random effects model is supported by the data. Mutl and Pfaffermayr (2011) extended Hausman\`s procedure to a spatial framework.

5.2. Results

Texas is among the top three states in the U.S. with highest property damages from natural disasters. Over the past decade, ten major weather-related disasters hit Texas over four different disaster seasons (Table 5.1):

Table 5.1: Texas weather-related disasters from 2007 to 2015

No.	Property Damages	Disaster	Incident Period
1	$486M	Severe Storms and Tornadoes	April 21, 2007 – April 24, 2007
		Hurricane Dean	August 17, 2007 - September 05, 2007
		Tropical Storm Erin	August 14, 2007 – August 20, 2007
2	$15B	Hurricane Dolly	July 22, 2008 – August 01, 2008
		Hurricane Gustav	August 27, 2008 - September 07, 2008
		Hurricane Ike	September 07, 2008 - September 26, 2008
		Hurricane Ike	September 07, 2008 - October 02, 2008
3	$169M	Tropical Storm Alex	June 27, 2010 – August 14, 2010
		Hurricane Alex	June 30, 2010 – August 14, 2010
4	$947M	Severe Storms, Tornadoes, Straight-line Winds, and Flooding	May 04, 2015 – June 23, 2015

Figure 5.1 shows the state of Texas and its county boundaries. For each of the above disasters, I obtained the pre-disaster construction economic data of those Texas counties for which the data were published by Bureau of Labor Statistics (BLS) and created spatial panel data models to take into account both spatial and time specific effects in my models. Since spatial panel data models are sensitive to the selection of weight matrix, all the three different types of weight matrices were created, and their effects were compared in the spatial panel data models (Figure 5.2).

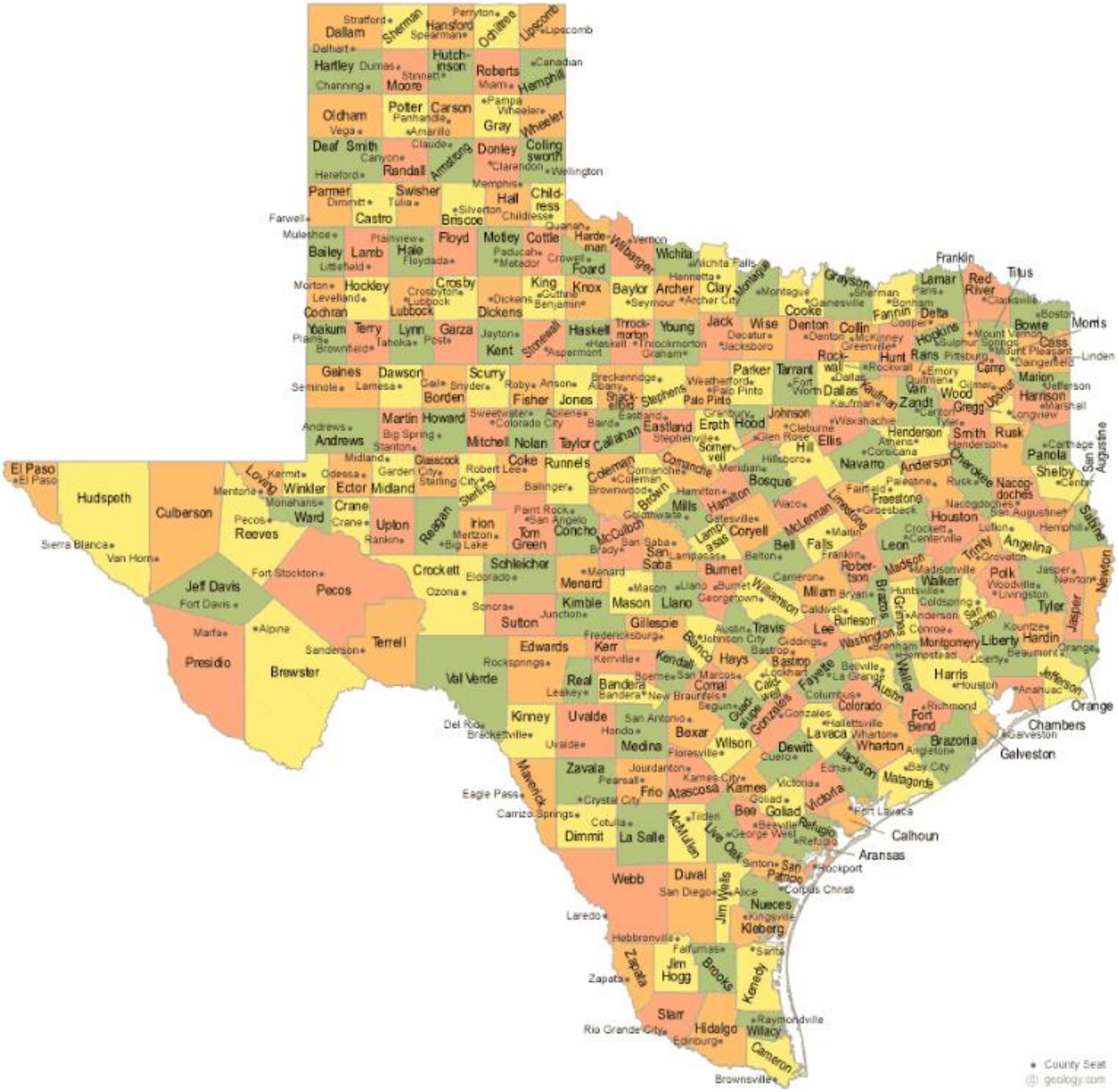


Fig. 5.1: Texas state

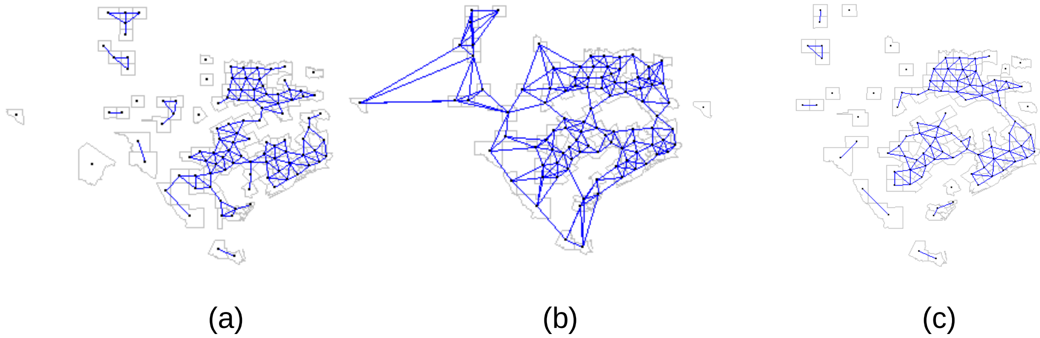


Fig. 5.2: a) Contiguity binary matrix; b) 4-nearest-neighbors' matrix; c) Distance-based matrix (100 km)

Figure 5.3 shows the percentage change in the amount of residential building construction labor wage, at the county-level, for each of the four disaster seasons in Texas, from 2007 to 2015. The labor wage changes in the neighboring counties have, to some extent, a similar behavior, which suggests the existence of spatial autocorrelations.

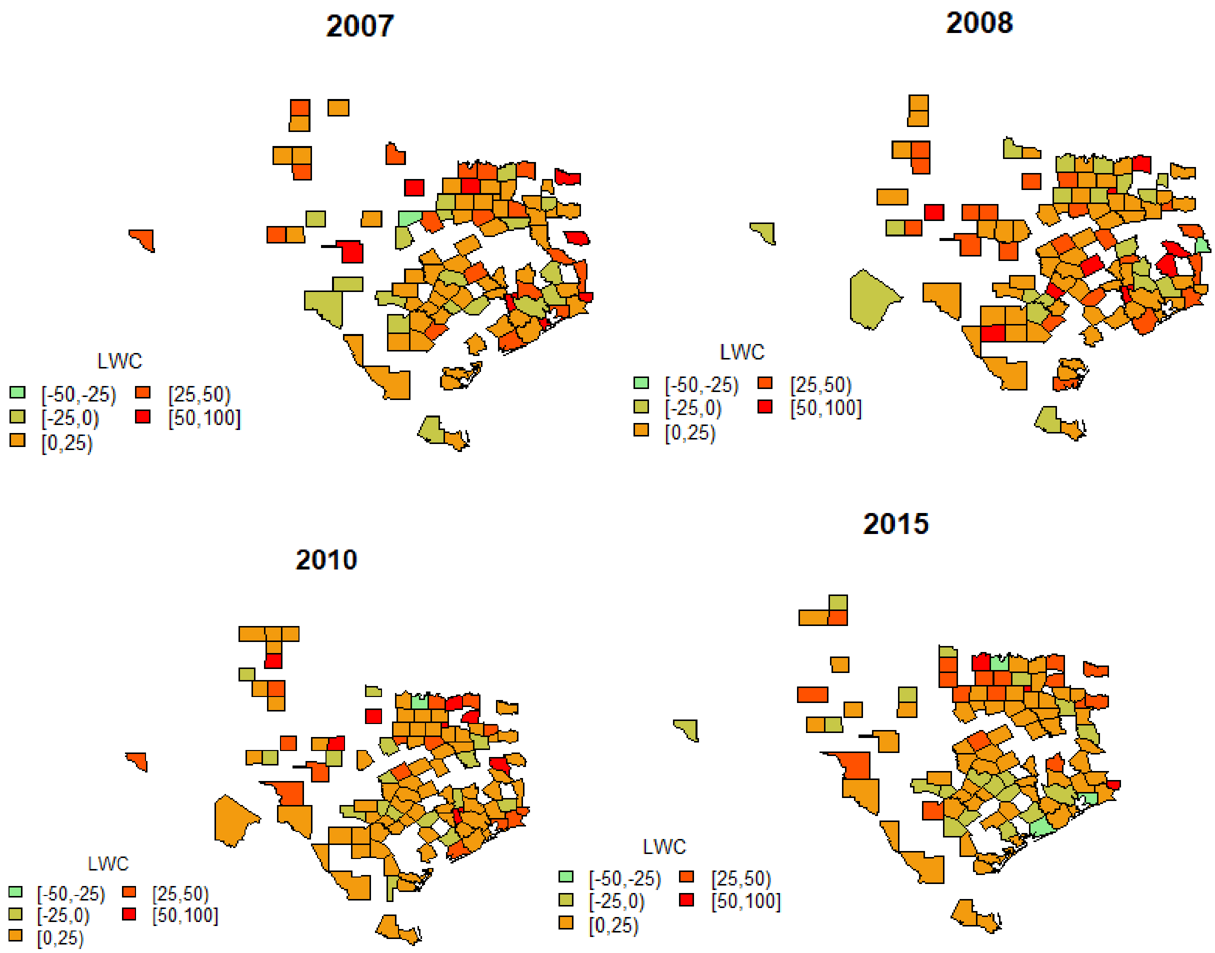


Fig. 5.3: Percentage change in labor wage following different disaster seasons in Texas

Table 5.2 represents the results of Geary`s C for each of the disaster seasons in Texas. The results show that for all four disaster seasons, Geary`s C is less than 1 that means there is a positive spatial autocorrelation among the values of the dependent variable exists. In other words, an increase (decrease) in the construction labor wage in a county will lead to an increase (decrease) in the construction labor wage in the neighboring counties.

Table 5.2: Geary`s C statistics

Year	Geary`s *C* Statistics	Expectation	Variance	P-value
2007	0.79	1.00	0.019	0.07
2008	0.81	1.00	0.013	0.01
2010	0.93	1.00	0.030	0.08
2015	0.73	1.00	0.020	0.03

I also regressed labor wage change on the four explanatory variables (employment level in construction, construction labor wages, construction contributions, and construction establishment counts) for each of the disaster seasons in Texas. Figure 5.4 shows the plots of residuals from OLS models. Neighboring counties shared some unexplained properties in their model residuals that suggests the existence of spatial autocorrelations.

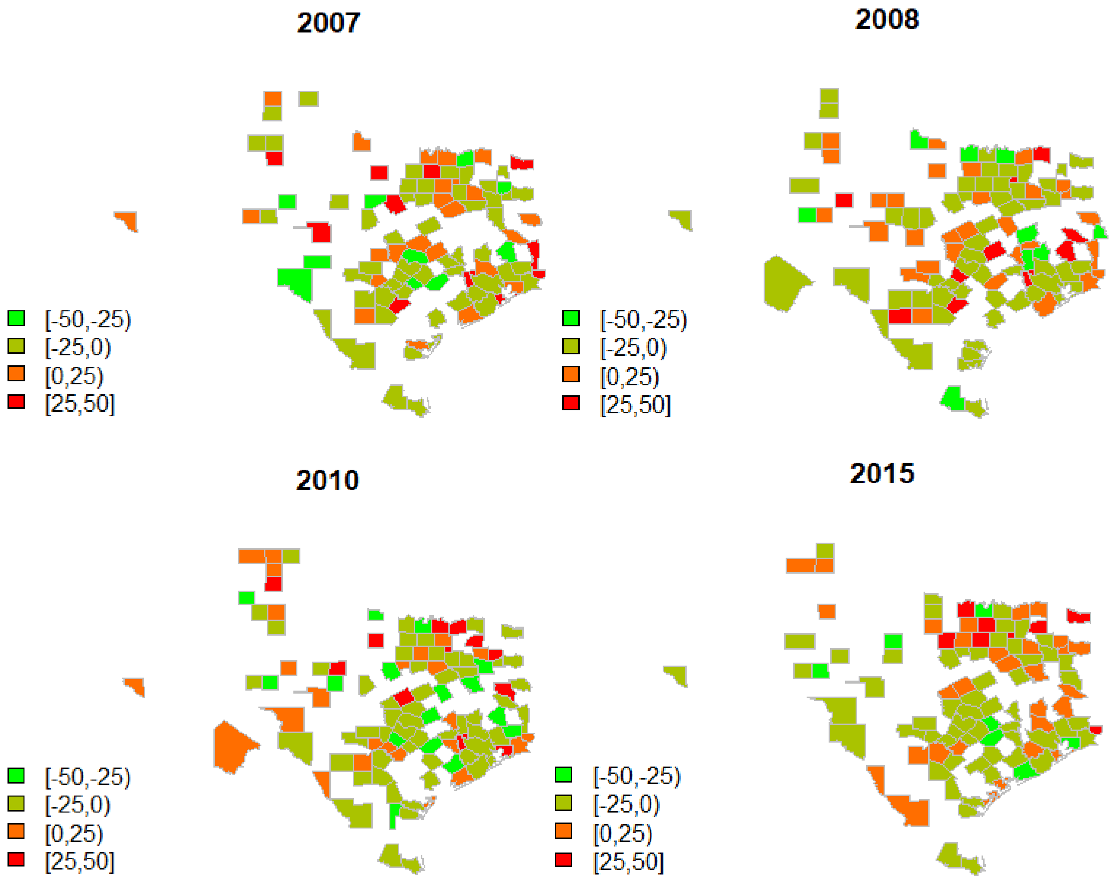


Fig. 5.4: Residuals from OLS model

Tables 5.3 to 5.5 show the parameter estimates of spatial panel data models assuming three different spatial weight matrices. When all spatial parameters are included in the model (using both Baltagi and Kapoor methods) and neighboring counties are considered as counties within 100 km distance from each other, all spatial parameters (Φ, ρ, λ) are significant in the model.

Table 5.3: SPDM parameter estimates: contiguity binary matrix

Weight Matrix	Contiguity binary					
Lag	False			True		
Error	Baltagi	Kapoor	None	Baltagi	Kapoor	None
Intercept	56.4[a]	56.5[a]	56.4[a]	56.5[a]	56.7a	56.2[a]
EC	-8.0[b]	-7.7[b]	-8.0[b]	-7.8[b]	-7.5[b]	-8.0[b]
CC	-1.1	-1.2	-1.1	-1.2	-1.2	-1.1
WW	-35.8[a]	-36.0[a]	-35.8[a]	-35.8[a]	-35.9[a]	-35.8[a]
EL	4.6	4.7	4.6	4.6	4.6	4.6
Φ	0.39[a]	0.38[a]	0.39[a]	0.38[a]	0.38[a]	0.39[a]
ρ	-	0.05	-	0.05	0.07	-
λ	-	-	-	-0.02	0.04	0.02

Note: a and b represent rejection of null hypothesis at the 1% and 10% significance level, respectively.

Table 5.4: SPDM parameter estimates: 4NN matrix

Weight Matrix	4NN matrix					
Lag	False			True		
Error	Baltagi	Kapoor	None	Baltagi	Kapoor	None
Intercept	55.9[a]	55.8[a]	56.4[a]	59.1[a]	60.1[a]	58.6[a]
EC	-8.4[b]	-8.4[b]	-8.0[b]	-8.6[b]	-8.4[b]	-8.6[b]
CC	-0.9	-0.9	-1.1	-0.9	-1.0	-0.9
WW	-35.1[a]	-34.9[a]	-35.8[a]	-36.0[a]	-36.4[a]	-35.8[a]
EL	4.4	4.4	4.6	4.4	4.4	4.4
Φ	0.39[a]	0.38[a]	0.38[a]	0.40[a]	0.40[a]	0.39[a]
ρ	-0.12	-0.09	-	0.04	0.16	-
λ	-	-	-	-0.15	-0.19	-0.12

Note: a and b represent rejection of null hypothesis at the 1% and 10% significance level, respectively.

Table 5.5: SPDM parameter estimates: distance-based matrix (100 km)

Weight Matrix	Distance based matrix (100 km)					
Lag	False			True		
Error	Baltagi	Kapoor	None	Baltagi	Kapoor	None
Intercept	56.3[a]	56.4[a]	56.4[a]	46.9[a]	62.5[a]	57.9[a]
EC	-8.4[b]	-8.4[b]	-8.0[b]	-7.4[b]	-6.6[b]	-8.4[b]
CC	-0.9	-1.0	-1.1	-0.8	-1.2	-1.0
WW	-35.5[a]	-35.5[a]	-35.8[a]	-32.8[a]	-34.4[a]	-35.8[a]
EL	4.6	4.6	4.6	4.9	3.8	4.5
Φ	0.40[a]	0.39[a]	0.39[a]	0.39[a]	0.43[a]	0.40[a]
ρ	-0.11	-0.08	-	-0.57[a]	0.12[a]	-
λ	-	-	-	0.39[a]	0.58[a]	-0.08

Note: a and b represent rejection of null hypothesis at the 1% and 10% significance level, respectively.

All of the above models assume that random effects exist in the models. Table 5.6 shows the results of Hausman test. Since the p-value of the test is less than 1% and the null hypothesis of existence of fixed effects is rejected, I accepted the alternative hypothesis.

Table 5.6: SPDM parameter estimates: contiguity + 100 km matrix

Lagrange Multiplier	p-value	Alternative hypothesis
4.75	2.033e-06	Random Effects

5.3. Model Selection and Diagnosis

To select the best model among those proposed in this chapter, three criteria were considered: 1) significance level of the entire model, 2) log-likelihood of the model, and 3) significance level of the model parameters. The results showed that, after creating the distance-based-neighbors weight matrix (where neighboring counties are assumed to be within 100 km distance from each other) and including both lag of dependent variable and spatial error terms (considering Baltagi`s assumption) in the model: 1) the model is significant (has p-value of less than 1%), 2) the model has the highest loglikelihood i.e. the highest prediction accuracy, and 3) all of the spatial model parameters (Φ, ρ, λ) are significant. Different weight matrices were created considering different distances; however, the best model results were obtained when the distance between the center of the counties were set to 100 km. This distance seems to be a reasonable commute distance for laborer to perform their work in the neighboring areas.

The Baltagi method in creation of vector of disturbances assumes that error terms are autocorrelated across the counties; and the vector of remainder error components are the errors that are not spatially autocorrelated. To test the existence of autocorrelations among the values of vector of remainder error components, a Geary`s *C* test was conducted on the data of this vector for each data panel (2007, 2008, 2010, and 2015). The results of Geary`s *C* test, summarized in table 5.7, show that the p-values for all data panels are greater than 10% and thus, the null hypothesis of existence of autocorrelations among the values of the vector of remainder error components would be rejected. In other words, the proposed spatial panel data model captured the autocorrelations in the vector of spatially autocorrelated error terms (ε), and no spatial autocorrelations exist in the vector of remainder error components (ν).

Table 5.7: Geary`s C statistics of the vector of remainder components

Year	Geary`s *C* Statistics	Expectation	P-value
2007	1.08	1.00	0.91
2008	1.01	1.00	0.60
2010	0.96	1.00	0.25
2015	0.98	1.00	0.36

5.4. Assumptions and Research Limitations

This chapter focuses on the labor wage data in the state of Texas. Future research is required to create more general models that include the labor wage data of the other states in the United States. Moreover, unobserved variables in this study (e.g. regional economic indicators, physical properties of the disasters, risk-mitigation or other disaster-related policies made before or after the disasters, etc.) could be added and tested in the spatial panel data models to possibly create more comprehensive and accurate models.

CHAPTER 6: DISCUSSION OF RESULTS

Chapter 4 proposes models 2 to 6 to be used as cross-sectional models for predicting the residential building construction labor wage changes in the events of weather-related disasters in the U.S. To create these models, I started from the full models and then used backward elimination method (using AIC) to get to the reduced models. One may still prefer to use the less complex models, although the adjusted R-squared decreases slightly. I removed insignificant variables in the models 2 to 5, one at each step, until all model parameters became significant. This resulted in creation of less complex models; however, the adjusted R-squared for models 2 to 5 changed from 0.50, 0.68, 0.34, and 0.30 to 0.43, 0.59, 0.31, and 0.27, respectively. Since all variables in model 6 are significant, this model remains unchanged. Tables 6.1 to 6.4 show the new parameters for these models.

Table 6.1: New parameter estimates for model 2

	Estimate	**t-value**	**Pr. (>|t|)**
Intercept	7.73	7.46	1.15e-09***
EC*BP	-0.34	-3.25	0.002***
CC*BP	0.49	5.60	9.21e-07***
WW*EL	39.39	3.13	0.002***
WW*BP	0.76	3.01	0.004***
EL*BP	-0.43	-3.66	0.0006***
EC*CC*WW*EL	-33.18	-1.93	0.05**
CC*WW*EL*BP	-1.63	-2.90	0.005***

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Multiple R-squared: 0.50; Adjusted R-squared: 0.43; F-statistic: 7.23 on 7 and 50 DF; p-value: 5.61e-06.

Table 6.2: New parameter estimates for model 3

	Estimate	t-value	Pr. (>|t|)
Intercept	-2.39	-0.54	0.59
EC	9.77	2.45	0.01***
EC*CC	17.22	4.03	0.0001***
WW*EL	39.63	5.28	2.99e-06***
EC*CC*EL	-27.48	-4.24	9.86e-05***
CC*WW*EL	-32.70	-3.25	0.002***
EC*CC*WW*BP	1.47	2.68	0.01***

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Multiple R-squared: 0.63, Adjusted R-squared: 0.59; F-statistic: 14.2 on 6 and 42 DF; p-value: 2.72e-09.

Table 6.3: New parameter estimates for model 4

	Estimate	t-value	Pr. (>|t|)
Intercept	38.55	7.63	2.4e-11***
WW	29.72	-5.74	1.23e-07***
CC*BP	0.09	1.79	0.077*
EC*CC*WW	86.27	3.32	0.001***
CC*WW*EL	37.24	-2.33	0.02**
EC*CC*WW*BP	-2.38	-4.10	9.06e-05***
WC*CC*WW*EL*BP	0.85	2.67	0.009***

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Multiple R-squared: 0.35; Adjusted R-squared: 0.31; F-statistic: 8.11 on 6 and 90 DF; p-value: 5.148e-07.

Table 6.4: New parameter estimates for model 5

	Estimate	t-value	Pr. (>|t|)
Intercept	4.49	1.65	0.1
EL	5.61	2.09	0.038**
EC*EL	-10.99	-2.18	0.03**
CC*WW	35.94	2.74	0.007***
EC*CC*WW	-111.65	-5.45	3.22e-07***
EC*CC*WW*BP	3.12	2.88	0.004***
CC*WW*EL*BP	-2.55	-2.72	0.007***
EC*CC*WW*EL*BP	3.50	3.38	0.001***

Note: *, **, and *** represent rejection of null hypothesis at the 10%, 5%, and 1% significance level, respectively. Multiple R-squared: 0.32, Adjusted R-squared: 0.27; F-statistic: 7.1 on 7 and 106 DF; p-value: 5.98e-07.

I created cross-sectional models to predict the post-disaster residential building construction labor wage changes in the events of weather-related disasters in the U.S. I also created spatial panel data models to predict this change for the state of Texas. Future research may use data of the other U.S. states or collect more comprehensive data and create national-level spatial panel data models. Figure 6.1 shows the framework that is needed to be followed in order to select the best cross-sectional/spatial panel data model, for any similar application.

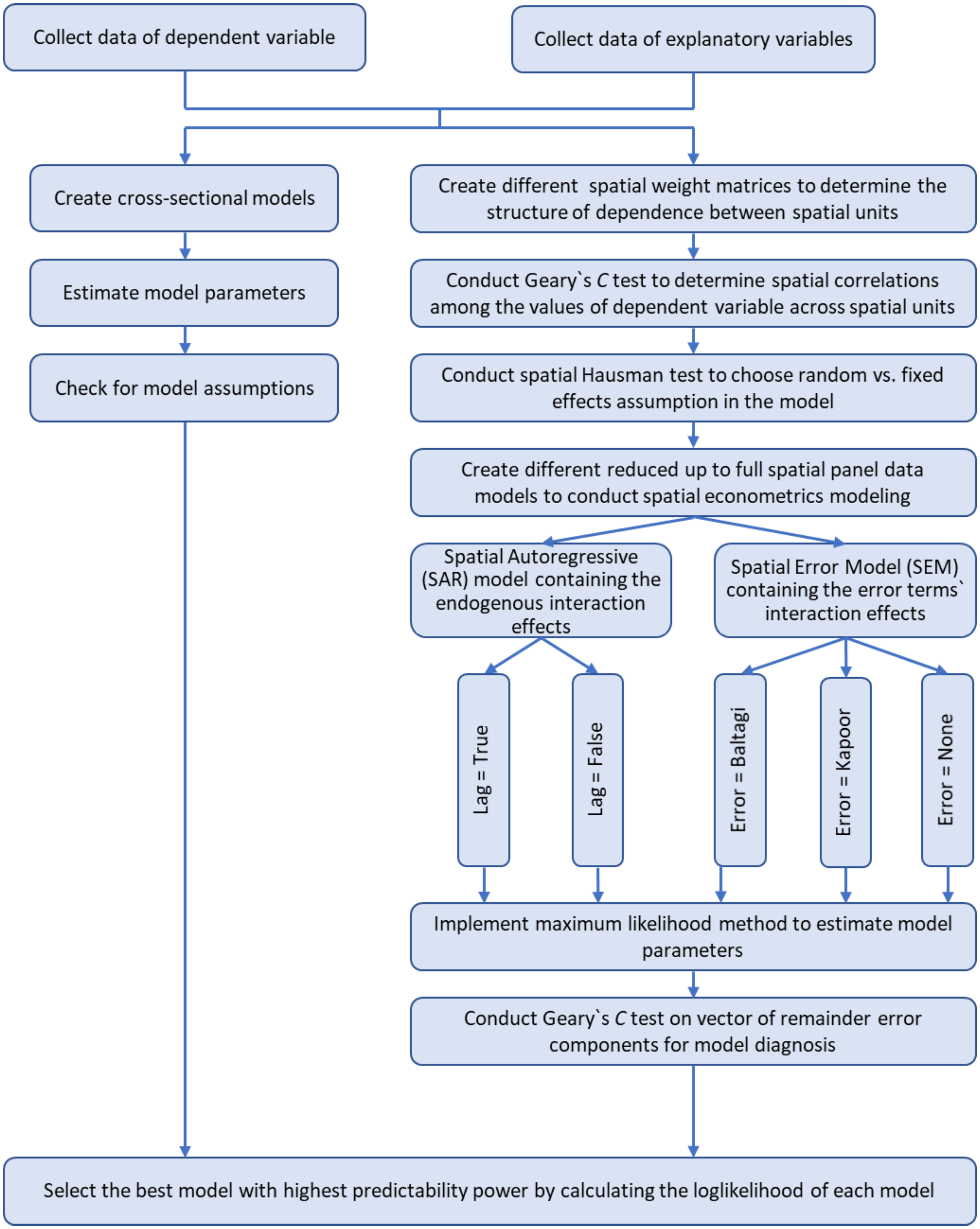


Fig. 6.1: Proposed framework to create demand surge models

CHAPTER 7: CONCLUSIONS

The results of this study showed that among the construction sub-sectors, Heavy and Civil Engineering Construction is the most vulnerable to weather-related disasters. Under the Construction of Buildings sub-sector, the Industrial Building Construction industry group is the most vulnerable; and under the Specialty Trade Contractors sub-sector, the Building Foundation and Exterior Contractors industry group and Other Specialty Trades Contractors industry group are the most vulnerable to weather-related disasters.

In almost 75% of the affected counties, an increase in the construction labor wages in the quarter of the disaster or one of the following three quarters occurs. A county is more likely to face a significant increase in the construction labor wages in the aftermath of weather-related disasters than a significant decrease. The skewness and kurtosis of the distributions of historical labor wage changes in different construction sub-sectors (industry groups) showed that in most cases labor wage changes are less than the calculated mean value; however, in rare cases, very high levels of increase in wages were observed.

On average, labor wages in the Construction of Buildings sub-sector and the Specialty Trade Contractors sub-sector decreased by 0.6% and 0.8%, respectively, in the quarter of the disaster and gradually increased by 4.4% and 4.6%, respectively, in the following three quarters. On the other hand, Heavy and Civil Engineering Construction`s labor wages did not experience this decrease right after the disasters; wages increased immediately after disasters hit the counties and then rapidly increased by 8.6% in the three quarters after the disasters.

LWC represents the highest percentage increase in labor wages over the four quarters following the weather-related disasters (including the quarter of disaster) and, in most cases, the counties did not face such an increase in the other three quarters following the disasters. The longer tails of the LWC in the right hand showed the possibility of significant increases (up to more than 100%) in labor wages in all sub-sectors (industry groups).

The relationship between pre-disaster construction market conditions and residential building labor cost changes following weather-related disasters was quantified. The multiple linear regression method was used to quantify the relationship between the pre-disaster level of residential construction market indicators and the maximum percentage change in the residential building labor wages following weather-related disasters. First, two types of regression models (constant variance and category dependent variance) were proposed. Then, using the SSR method, the best set of models were proposed. A lower SSR shows a tighter fit of the model to the actual values of the empirical data. The second type of models (category dependent variance) had lower SSR. Thus, a relationship between LCC and all five explanatory variables (establishment count, contribution level, average weekly wages, employment level, and building permits) based on the magnitude of the weather-related disasters (property damages to the counties) exists. In other words, changes in the residential building labor wages following weather-related disasters significantly depend on the level of property damages and the pre-disaster level of construction market indicators (and the interactions between the construction market indicators).

Predictive models were proposed to forecast construction labor cost changes following large-scale weather-related disasters in the United States, using pre-disaster construction economic indicators. Since the data of all predictor variables are known at the quarter in which the disaster occurs (data are publicly available by the Bureau of Labor Statistics and the U.S. Census Bureau), cost estimators and construction firms can use these models to estimate the expected percentage increase in the residential building labor wages in the event of a weather-related disaster to prepare more accurate bids. Capital planners and disaster-risk-mitigation stakeholders, on the other hand, could identify the more vulnerable counties before or at the event of a catastrophe to get involved in disaster risk mitigation strategies, such as improving labor market capacity gaps. Vulnerable counties are those with higher levels of labor wage changes.

The spatio-temporal autocorrelations among the variables in the existing cross-sectional demand surge models were also evaluated. The results showed that spatio-temporal autocorrelations exist among the values of dependent variable (labor wage change) as well as the values of error terms in the OLS models. Since spatial panel data models are sensitive to the selection of weight matrix, three different types of weight matrices (first-order binary contiguity matrix, 4-nearest-neighbors matrix, and distance-based-neighbors matrix) were created and their effects were compared in the spatial panel data models. After arranging the counties based on these weight matrices, two types of spatial panel data models were created. The first type (lag = false) assumed that no endogenous interaction effects exist in the model i.e. the values of dependent variable are not autocorrelated over space, and the second type (lag = true) assumed existence of spatial autocorrelations among the values of dependent variable. Then, for each type, three methods were used to construct the vector of disturbances: Baltagi method, Kapoor method, and no spatial autocorrelations among the error terms. The results showed that, after creating the distance-based-neighbors weight matrix (where neighboring counties are assumed to be within 100 km distance from each other) and including both lag of dependent variable and spatial error terms (considering Baltagi`s assumption) in the model: 1) the model is significant (has p-value of less than 1%), 2) the model has the highest loglikelihood i.e. the highest prediction accuracy, and 3) all of the spatial model parameters (Φ, ρ, λ) are significant. Different weight matrices were created considering different distances; however, the best model results were obtained when the distance between the center of the counties were set to 100 km. This distance seems to be a reasonable commute distance for laborer to perform their work in the neighboring areas.

I proposed a framework to be followed for creating demand surge models for other U.S. states or for other regions in the world. It is expected that this work will help demand surge modelers to create more accurate predictive models.

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