8-2022

Moderate, Overlooked Weather Events and Local Labor Markets

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MODERATE, OVERLOOKED WEATHER EVENTS AND LOCAL LABOR MARKETS

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Masters of Arts
Economics

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by
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August 2022

Accepted by:
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ABSTRACT

A substantial amount of research exists on the economic effects of natural disasters and extreme weather, as well as comparatively minor variations in daily weather conditions such as precipitation, temperature, and wind. I construct a sample of over a million storms that range from intense daily weather conditions to extreme weather. I analyze written descriptions of the damages caused by many of these storms to identify 93,743 weather events within the sample that appear to be underemphasized in the existing economic literature. These storms cause more damage and disruptions to commerce than 63.5% of storms in the sample, yet do not inflict enough damage to meet the minimum criteria to be included in databases that track extreme weather. During the twenty-first century, these “moderate” storms occur an average of once a year in 2075 counties in the U.S. Accounting for more intense weather, the average storm is associated with a decrease of .054% in county total payroll and a decline of .047% in county total employment compared to the previous quarter. These storms are expected to decrease total payroll by $186,125.60 and total employment by 16.22 people each quarter in the average county. Total payroll or total employment in most sectors within a county are sensitive to these storms. Most types of moderate storms have a negative effect on total payroll growth, with high temperatures, cyclones, droughts, precipitation, and floods all being associated with the largest decreases in county total payroll. The effects of moderate storms on labor markets appear to primarily be confined to the quarters in which these storms occur.

ACKNOWLEDGMENTS

This paper would not have been possible without input and guidance from Dr. Robert Fleck. I am also very appreciative to Dr. Yichen Christy Zhou and Dr. Molly Espey for their insight and advice. A big thanks as well to experts at the Census Bureau and National Oceanic Atmospheric Administration who provided in-depth answers to my emails. Any mistakes or errors are solely my own.

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1. INTRODUCTION

It is increasingly common for economic studies to model weather as shocks that occur within a geographic location (Botzen, Deschenes, and Sanders 2019). Because the economy is affected by different weather conditions that can be correlated, such as temperature, wind, precipitation, and humidity, empirical estimates of a weather shock may be biased if they only measure one dimension of weather (Dell, Jones, and Olken 2014). Especially in recent years, there are some examples of economic studies that incorporate different types of weather that are correlated with economic outcomes and the variable of interest (S. M. Hsiang 2010; Strobl 2011; Wilson 2017; Boustan et al. 2020; Wilson and Roth Tran 2020). However, bias could still be introduced through only analyzing certain types of weather, such as natural disasters or changes in everyday weather conditions, or by using weather datasets that exclude relevant information. I minimize these potential sources of bias by constructing a large sample of over a million storms. The sample contains written descriptions of the damages many of these storms caused. I identify 45 keywords within these descriptions that allows me to pinpoint storms that are more disruptive or damaging than even most intense commonplace weather, while still being less destructive than extreme weather and natural disasters. Accounting for more intense weather, I estimate how county labor markets are affected by these storms, which I will often refer to as "moderate" or "intermediate" storms.

I focus on moderate storms because there is a lack of rigorous research on these storms, yet the existing research suggests they are intense enough to influence the economy. The most likely reason, in my mind, that these storms are underemphasized is that they are difficult to measure with the most common weather datasets. Many economic studies focus on the damages caused by the most intense storms. For instance, the Centre for Research on the Epidemiology of Disasters' Emergency Events Database (EM-DAT) is a popular database that tracks fatalities, injuries, the number of people who were made homeless, the costs of reconstruction, and insured damages from storms that killed ten or more people, were declared an emergency, or affected 100 or more people (Gall, Borden, and Cutter 2009). Storms that are this intense occur rarely, so these databases exclude many storms. There is strong evidence that excluded storms are still intense enough to affect the economy. According to a literature review by Dell, Jones, and Olken (2014), the economy in rich countries is sensitive to extreme daily weather. Many of the studies that Dell and her coauthors reference estimate the economic effects of weather by using large datasets of measurements from weather stations on daily weather conditions, including maximum and minimum temperatures, inches of precipitation, humidity, and wind speeds. Measurements from weather stations often do not account for the damages caused by weather, or when damages are modeled based upon measurements from weather stations, exclude other types of weather (S. Hsiang and Jina 2014).

It is possible to capture a more complete picture of the weather by using the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database. This database contains information on weather events that range from the commonplace all the way up to natural disasters like Hurricane Katrina. Each storm in the database has quantitative information on the amount of crop damage, property damage, injuries, and deaths it caused. Additionally, if a storm caused damages, disrupted commerce, or was otherwise "significant," it is supposed to contain a written description called an "Event Narrative." An Event Narrative describes the damages caused by a storm and the storm's physical characteristics. For example, an Event Narrative may say four inches of rain led to a flash flood that damaged someone's basement.

There are notable differences between many of the Event Narratives and the quantitative information on the damages storms caused. Many of the storms supposedly did not cause deaths, injuries, fatalities, or property damage, yet their Event Narratives describe minor damages or disruptions to commerce that presumably harmed the economy, for example a traffic jam. This is partially driven by missing data, with around 10 percent of the storms before 2007 missing property or crop damage. However, after reading many of the Event Narratives, I believe these storms are genuinely less intense than those storms that NOAA reports caused numerical damages. As such, I define moderate storms as storms that have Event Narratives that describe damages or disruptions to commerce, and that NOAA reports caused zero property damage, crop damage, injuries, and fatalities. A total of 93,743 intermediate storms occurred between the third quarter of 2000 to the third quarter of 2020 in counties in the U.S. without missing labor market data. Additionally, 226,235 storms that caused crop damage, property damage, injuries, or deaths are included in the sample to ensure the estimated effects of moderate storms are not biased.

Based on my assumptions, moderate storms are between the 63.5 and the 75.33 percentiles for the intensity of storms in the NOAA Storm Events Database. These estimates should only be viewed as a rough approximation for how the intensity of moderate storms compares to storms that are studied in other economic studies. A more detailed review of the methodologies that are used in existing studies to define intensity, the shortcomings of different weather datasets (Gall, Borden, and Cutter 2009), and the types of weather that are measured in these studies would be required to get a precise estimate. For example, about 40% of moderate storms are types of weather that are typically represented as significant shocks in the existing literature: floods (32%), tornadoes and funnel clouds (10%), wildfires or smoke from wildfires (2%), or cyclones (1%). Most of the existing research on these types of weather focuses on macroeconomic shocks (Klomp and Valckx 2014; Lazzaroni and Bergeijk 2014) or large natural disasters (Groen, Kutzbach, and Polivka 2020). A smaller group of studies examines these storms at the county-level (Strobl 2011; Wilson 2017; Wilson and Roth; Boustan et al. 2020; Tran 2020), but many of the storms in these studies took lives or caused significant damage. Conversely, common examples of these types of moderate storms, include floods that make roads inaccessible, tornadoes that pass overhead or briefly touch down, and wind and precipitation that cause minor power outages.

Previous studies provide more information on intermediate storms related to cold, heat, precipitation, and wind, but the average effect is difficult to discern. In perhaps the most detailed study of extreme daily weather, Wilson (2017) shows that different types of extreme daily weather have very different outcomes. The most negative and widespread damages came from extreme temperatures and snow. If moderate storms are similar to extreme heat, then there are a number of channels through which they may affect the labor market and the wider economy (Heal and Park 2016). High temperatures appear to be linked to decreased economic activity across various industries (S. M. Hsiang 2010; Graff Zivin and Neidell 2014; Wilson 2017; Colacito, Hoffmann, and Phan 2019), reduced county income (Deryugina and Hsiang 2014), lower labor productivity (Zhang et al. 2018), more crime (Ranson 2012), worse education outcomes (Park et al. 2020), irrational decision making (Almås et al. 2019), and declines in employment (Wilson 2017). Damages from extreme heat may even be severe enough to hinder economic growth in the United States (Deryugina and Hsiang 2014; Wilson 2017; Colacito, Hoffmann, and Phan 2019).

Most of the studies on heat focus on the effects within the local economy. Additionally, the research on intense storms like natural disasters indirectly suggests that the effects of low-intensity storms are confined to the local economy. Studies on natural disasters show that as the intensity of a storm increases; buildings suffer increased physical damages (Burrus et al. 2002; Nordhaus 2006); counties receive more transfers from the social safety net, disaster aid, and private insurance (Deryugina 2016); and county migration increases (Tse 2011; Strobl 2011; Boustan et al. 2020). It is also likely that increasing intensity is correlated with increased attention from policymakers and the media and with large effects on regional labor markets (Wilson and Roth Tran 2020). Consequently, as the intensity of storms decreases, these channels should have a weaker relationship with a local economy. Given this research, it is likely that intermediate storms mostly affect the local economy.

I measure the effects of moderate storms within local economies by examining how they affect earnings and employment within counties between the third quarter of 2000 to the third quarter of 2020. Research suggests that people who work outside (Graff Zivin and Neidell 2014), rely on customers physically going to their places of business (Colacito, Hoffmann, and Phan 2019), or are employed in capital-intensive industries (Zhang et al. 2018) are more likely to be negatively impacted by storms. People may also shift their consumption habits and employment due to these storms (Wilson 2017). All of these factors make it difficult to determine if changes in earnings and employment reflect changes in the supply of or demand for labor. The only exceptions are if earnings and employment both decrease or increase, because this would signal that the supply and demand for labor are simultaneously decreasing or increasing. If either of these occur, then I believe an intermediate storm has led to a decrease or increase in economic activity. The effects of moderate storms are measured by using information on quarterly, county total payroll and total employment from the Census Bureau's Quarterly Workforce Indicators. Total payroll is a combination of all wages paid to every worker. This means that wages and employment only both increase or decrease if percentage changes in total payroll and total employment move in the same direction, and the change in total payroll is greater than the change in total employment.

Intermediate storms are associated with statistically significant decreases of .054% in total payroll and .047% in total employment compared to the previous quarter in the county. These results suggest that the immediate impact of a moderate storm is a decrease in county economic activity. These effects are not experienced evenly among different NAICS sectors within counties. I find that the effects of intermediate storms on the Information, Other Services (except Public Administration), and the Real Estate and Rental and Leasing sectors are no different than the effect of moderate storms on counties. Economic activity is higher in the Arts, Entertainment, and Recreation and Healthcare and Social Assistance sectors, while the Agriculture, Forestry, Fishing and Hunting sector may experience a decrease in economic activity. The effects of intermediate storms also vary by the type of storm. From the largest negative estimate to the smallest, the following storms have a negative and statistically significant effect on total payroll growth: heat event (-0.6%), hurricanes (which also includes cyclones), drought, precipitation, and flood (-0.1%). Meanwhile, wildfires have a positive impact on total payroll, which is consistent with research on larger wildfires (Paveglio et al. 2016).

Subsamples of moderate storms are then used to verify that the text analysis techniques that are used truly select for intermediate storms. Moderate storms are identified as storms that they have an Event Narrative that contains at least one of 45 keywords. These keywords are chosen because they are present in many Event Narratives that describe damages or disruptions to commerce. For example, *power* is a keyword, and it is related to power outages. Furthermore, *road* and *car* are also both keywords that are often related to disruptions to transportation. I verify the validity of this approach by grouping similar keywords and identifying subsamples of intermediate storms that contain these keywords. The effects of these groups of keywords on the labor market are estimated to ensure keywords are actually correlated with different economic outcomes. Different groups of keywords clearly select for storms that have different effects upon the labor market.

One key difference is that moderate storms that have Event Narratives that mention words related to transport or transportation infrastructure have a larger negative effect on the labor market than the rest of the sample. Based on these findings, the effect of these intermediate storms is estimated upon total payroll growth for counties and the sectors within counties. The findings suggest that county labor markets and sectors within counties are mostly affected by intermediate storms during the quarters in which they occur.

The average county in the sample experiences a moderate storm slightly more than once a year. The average county reflects an aggregate of 2091 different counties across 40 different states. Counties that are very poor or have a small population are excluded. Counties are also excluded due to a lack of labor data, but counties are not excluded based upon weather data. There are significant differences between the number of intermediate storms counties experience, with sixteen counties never experiencing a moderate storm and many counties experiencing more intermediate storms than the average county.

This paper makes a methodological contribution to the study of weather by using text as data. Recent applications of text analysis in environment economics include Jha, Liu, and Manela (2021) and Baylis (2020) that respectively pair natural disaster and temperature data with a sentiment analysis of text data. Moreno and Caminero (2020) construct an index of words to measure how well twelve Spanish financial institutions are following climate disclosure rules. However, my paper is the first to use text data to classify storms by the damage they cause. Furthermore, the analysis of moderate storms whose Event Narratives mention words related to transport or transportation infrastructure indicates that different types of text may be able to substitute for quantitative information when it is unavailable. There are very few studies that take this approach (Gentzkow, Kelly, and Taddy 2019). One exception to this is Stephens-Davidowitz (2014), who uses Google Search results on a racial epithet in different areas to estimate how racial animus influenced votes for President Obama.

This paper also provides empirical results that contribute to research on several important topics. The first is comprehensively examining how low-intensity storms affect the labor market. To the best of my knowledge, this is the first study that provides estimates that allow comparable comparisons between low-intensity floods, tornadoes, wildfires, and hurricanes and heat, precipitation, and wind. Given the research showing that heat impacts economic growth (Colacito, Hoffmann, and Phan 2019) and the fact that heat events in this paper have the largest effect on total payroll growth, these findings may indicate that storms need to have a certain intensity before affecting economic growth. This paper also complements findings from recent studies that show storms have wide-ranges effects across a number of different sectors in U.S. counties (Wilson 2017; Colacito, Hoffmann, and Phan 2019; Boustan et al. 2020). Interestingly, the estimates in this paper show that earnings and employment in different sectors respond differently to moderate storms.

The next section provides empirical evidence from a sample of storms from the NOAA Storm Events Database that many existing studies are overlooking potentially significant moderate storms. After discussing these findings, this section explains how intermediate storms in this sample are classified, and also provides information on relevant labor market and weather data. This is followed by Empirical and Results sections. The Results section delves into county labor market outcomes; how county estimates may vary by sector, storm type, and time; and the validity of the assumptions made in this paper. I conclude by summarizing the results in this paper and discussing several possible avenues for future research.

2. METHOD

2.1 Weather and the Economy

My presumption is that storms must have a certain intensity before having an appreciable effect upon the economy. I use the documentation for the NOAA Storm Events Database ("Database") to identify storms that plausibly are intense enough to have a measurable effect. Many storms in the Database are denoted as "significant," meaning they have "sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce," are rare enough to be noteworthy like snow in Florida, or are otherwise meteorologically significant, such as record temperatures, and linked to another significant event ("Storm Events Database" n.d.). When someone enters a "significant" storm into the Database, that person is supposed to write and include an "Event Narrative" that describes the damages caused by a storm and its characteristics (United States 2018). Additionally, the Database contains measurements on hundreds of thousands of storms that caused damages (injuries, fatalities, crop damage, and property damage). I compile a sample of 669,566 storms from 2000 to 2020 with an Event Narrative or that cause injuries, fatalities, crop damage, or property damage, because I believe these storms plausibly impact the economy. After removing storms that were mislabeled due to human error and storms that did not make landfall, this sample represents 65% of the total observations during that time in the Database. The intensity of these storms ranges from catastrophes like Hurricane Katrina to common events like rain storms and noteworthy wind, and the sample contains 47 different types of storms.

There are a number of storms in this sample that are likely intense enough to affect the economy but are not included in existing studies of natural disasters and extreme weather. While it is not feasible to evaluate the methodology used in every extreme weather or natural disaster study, one approach is to count every storm that causes a fatality as a natural disaster

(Boustan et al. 2020). My sample shows that these storms are costly and relatively rare. Fatal storms cause 45% of the property damage caused by storms in the sample, yet only represent 1% of the sample. The Database also allows storms to be grouped by weather systems. Weather systems that are responsible for at least one death account for 66% of total property damage while only representing 4% of the weather systems in the sample.

This sample also provides interesting information on the ways in which weather station measurements may neglect important information. Measurements of the physical characteristics of some types of storms are available in the NOAA Storm Events Database (United States 2018). There appear to be substantial differences in the damages caused by weather with the same physical characteristics. For example, the table below illustrates the differences in property damage caused by 27,223 hail events that were each estimated to be composed of hail one inch in diameter, which is the median diameter in the sample.

Table 1: Hail with a One Inch Diameter

Dollar Amount	Number of Observations	Total Property Damage
$0	14,551	$0
(0 - $100]	8,338	$7,001
($100 - $1,000]	832	$692,900
($1,000 - $10,000]	2,902	$14,160,150
$10,000+	600	$1,069,834,000

2.2 Classifying Storms

If a storm's Event Narrative does not describe damages or disruptions to business, my presumption is that its effect on the economy is similar to the effect of less intense weather that is already examined in studies on daily weather conditions. I make the distinction between different Event Narratives by identifying a series of keywords that are more common in Event Narratives that describe economic damages and uncommon in reports that do not contain information on economic damages. For example, *line* is mostly used to describe downed power lines and more rarely as part of a road name. Event Narratives do not seem to reference roads unless a moderate storm has occurred, so *line* simultaneously approximates specific damage caused by a loss of power and a more amorphous concept of economic damages. Furthermore, once *line* is known, then it is likely *road* and *power* are also useful. I ultimately identify 45 keywords, many of which are synonyms. For example, *road*, *highway*, and *street* are all keywords. As part of the estimates in Section 4, these words are shown below in Table 13.

To illustrate this point, Event Narratives for a handful of storms that did not cause damages are shown below for storms classified as "high winds." Using the text analysis methodology, the first two storms would not be included in the sample, but the last six would be since they include words such as *airport*, *car*, *line*, *roof*, and *power*.

1) National Weather Service Office in Reno recorded sustained winds of 45 mph with gusts to 52 mph.
2) A very strong cold front moved across western South Dakota during the morning and afternoon. Wind gusts of 61 mph were recorded behind the front in the northern foothills of the Black Hills.
3) A line of showers ahead of a strong cold front produced a wind gust to 58 mph at Lunken Municipal Airport.
4) Reported at Choteau City Airport (along border between zones 48 (Southern Rocky Mountain Front) and 49 (Eastern Teton county)).
5) A non thunderstorm wind gust of 45 mph was recorded at the New Orleans Armstrong International Airport.
6) Numerous trees and power lines down around Ewen and Trout Creek.
7) Roofs were blown off 3 mobile homes.
8) A tree fell on a car in Carmel.

My observation is that many of the Event Narratives for storms that cause property damage, crop damage, fatalities, or injuries appear to be more intense than storms that have Event Narratives, but NOAA reports did not cause damages. I use this observation to define any storm that caused damages as an intense storm. While this excludes some storms that are clearly intermediate storms, it also makes it easy to ensure that moderate storms are truly less intense than natural disasters and extreme weather. Allowing moderate storms to cause numerical damages would necessitate making difficult comparisons between property damage, crop damage, injuries, and fatalities. For instance, out of the 14,551 hail events in the example up above that did not cause property damage, 296 of them caused $64,784,700 worth of crop damage.

2.3 Labor Market Data

Earnings and employment are measured with county total payroll and county total employment data from the third quarter of 2000 to the third quarter of 2020 from the Census Bureau's Quarterly Workforce Indicators (QWI) database for 20 different NAICS sectors. QWI is part of the Longitudinal Employer-Household Dynamics (LEHD), which gathers information based upon the unemployment system so it can track workers across businesses. This methodology enables QWI to provide more specific information about worker demographics along race, education, and gender and firm characteristics like size and age. It also means the dataset tracks workers during the entire quarter. Therefore, total payroll is wages multiplied by earnings for everyone employed during a quarter, including end of quarter employees, full-quarter employees, accessions and total payroll of those transitioning across all 20 different sectors.

Counties with missing data are excluded from the sample. A few counties are excluded because they had missing data during a particular time or sector, but the more common source of missing data is suppression. QWI implements noise infusion and occasionally suppression to protect privacy if the population is too small to maintain anonymity (Abowd et al. 2012). Earnings are rarely suppressed, while information on total employment is much more likely to be suppressed (Abowd et al. 2009). A sample without suppressed data is identified by limiting the sample to counties with over 2000 employees and more than $12.5 million in total payroll during every quarter. Counties with less than $12.5 million likely have missing data, because $12.5 million is less than 50% of the quarterly GDP of Wheeler County Georgia, the poorest county in GDP per-capita in 2020. Additionally, a handful of counties are excluded that have average earnings greater than $38,950.69 per employee in one or more quarters. This number allows for the inclusion of Alameda County in California, which is wealthy, while excluding several unreliable outliers. After all the exclusions, the sample consists of 2091 counties across 40 different states in the continental United States.

2.4 Description of Dataset

After sorting the observations with the keywords, the sample contains 93,743 moderate storms. Additionally, each storm with property damage, crop damage, fatalities, or injuries are also included in the sample so that they can be used to account for more intense weather down below in Section 3. In total, the sample contains 319,978 events that took 8,385 lives, injured 39,042 people, cost $176,062,160,951 in property damage and damaged $29,070,679,394 worth of crops. These damages do not reflect truly catastrophic outliers like Hurricane Katrina. The effects of catastrophic storms are removed from the sample by only including counties that experienced quarters where less than $3 billion in property damage, $500 million in crop damage, 50 deaths, or 300 injuries occurred. Tables 4 and 5 respectively depict descriptive statistics for yearly damages and damages in the average county.

Based on my assumptions, moderate storms are between the 63.5 and the 75.33 percentiles for the intensity of storms in the original dataset from NOAA of 1,032,370 storms. There are 254,682 storms that are more intense than intermediate storms because they reportedly caused property damage, crop damage, injuries, or fatalities. Additionally, 655,711 storms did not cause numeric damages and either don't have an Event Narratives or have Event Narratives that do not contain any keywords. That leaves 121,917 moderate storms in the original data. In counties without missing labor market data, there are 93,743 moderate storms and 226,235 storms that reportedly caused property damage, crop damage, injuries, or fatalities. A summary of the storms in the original dataset and the sample that is used in this paper is provided in the table below.

***Table 2**: Summary of Sample*

Description of Data	Number of Observations
Total Number of Storms	1,032,370
Storms that Caused Numerical Damages	254,682
Less Intense than Moderate Storms (No Event Narrative)	362,804
Less Intense than Moderate Storms (Has Event Narrative)	292,967
Moderate Storms in Original Dataset	121,917
Storms that Caused Numerical Damages in Counties with Labor Market Data	226,235
Moderate Storms in Counties with Labor Market Data	93,743

2.5 Additional Weather Data

Monthly average temperature, the monthly average of maximum daily and minimum daily temperature, and total precipitation are gathered for each county from the NOAA Monthly U.S. Climate Divisional Database (NClimDiv), which provides monthly, county level estimates that NOAA has removed measurement errors from.

3. EMPIRICAL APPROACH

I determine how a moderate storm affects a county compared to a counterfactual where the county did not experience an intermediate storm, by adding the number of moderate storms that occur in county i and time t and estimating an auto-regressive distributed lag model. This is accomplished by estimating Equation 1:

$$L_{i,t} = \beta_1 * mod_{i,t} + \beta_2 * cat_{i,t} + \beta_3 * mod_{i,t-j} + \beta_4 * cat_{i,t-j} + \beta_5 * l_{i,t-q} + \tau + \chi + \epsilon$$

where $L_{i,t}$ is a set that contains the percentage change in county total payroll ($\log(totalpay_{i,t}) - \log(totalpay_{i,t-1})$) and county total employment ($\log(totalemp_{i,t}) - \log(totalemp_{i,t-1})$) between the quarter in which an intermediate storm (t) may occur and the preceding quarter ($t-1$). Modeling total payroll and total payroll by the percentage change allows each county to vary independently, which is useful given the substantial differences in the number of workers and earnings between different counties (S. M. Hsiang 2010). The variable l represents the $\log(totalpayroll)$ or $\log(totalemployment)$ and q represents the preceding 1st, 2nd, and 4th quarters and it ensures Equation 1 is an auto-regressive distributed lag model. The fourth lag should account for the seasonality of total payroll, which is sensitive to weather (Boldin and Wright 2015).

The term β_1 represents the coefficient on the main explanatory variable, the marginal effect of a county i experiencing a moderate storm in time t compared to the same county not experiencing a storm. For β_1 to represent what happens to a county in lieu of experiencing an intermediate storm, moderate storms must plausibly be random shocks (Dell, Jones, and Olken 2014; Botzen, Deschenes, and Sanders 2019). I follow the general framework for modeling weather as random shocks laid out in in Deschênes and Greenstone (2007). Time fixed effects for each quarter (τ) are included in Equation 1 to account for shocks, and, presuming that county conditions are time-invariant, fixed effects for each county (χ) are used to account for differences between counties, including wealth, geography, institutions, and other factors like zoning rules. As recommended in Dell, Jones, and Olken (2014), controls for confounding storms (cat) are utilized. Additionally, the effects of previous storms on the labor market, such as a rebuilding process that increases wages and employment (Wilson and Roth Tran 2020), are quantified through lags for *mod* and *cat* back to j = 11 quarters.

I determine that variations in local weather patterns are unlikely to be an omitted variable (the empirical test is discussed in the results section), so I only include controls for weather within the dataset. I define *cat* by calculating total quarterly property and crop damage, injuries, and fatalities and assigning these values to categorical variables. Boustan and her coauthors (Boustan et al. 2020) define a severe county-level storm as one that takes more than 25 lives. I extended this framework by graphing the distribution of fatalities and then visually identifying the amount of property damage, crop damage, and injuries that approximated the same distribution as observed for fatalities. Using this methodology, any quarter where 25 or more people die from a natural disaster, 100+ people are injured, property damage equals or exceeds $500 million in property, or crop damage is $100,000,000 or more is defined as a "Severe" quarter. Less intense "Absent," "Disruptive" and "Costly" quarters are identified in a similar manner. Quarters are defined by the most intense type of damage that occurs. For example, a quarter where $10,000,000 in property damage, $5,000 in crop damage, and one injury and one fatality occurred is a Costly quarter, because $10,000,000 in property damage is defined as a Costly quarter. The criteria are shown in the table below. For reference, while an Absent quarter is defined as zero, the minimum property and crop damages caused by any storm in the sample is actually $10.

***Table 3**: Criteria for Categorical Variables*

Categorical Variable	Property Damage	Crop Damage	Injuries	Fatalities
Absent	0	0	0	0
Disruptive	(0, $1,000,000]	(0, $500,000]	(0 - 20]	(0 - 5]
Costly	($1,000,000, $200,000,000)	($500,000, $100,000,000)	(20 - 100)	(5 - 25)
Severe	[$500,000,000, $3,000,000,000)	[$100,000,000, $500,000,000)	[100 - 300)	[25 - 50)

4. RESULTS

First, I investigate how moderate storms affect the growth of county total payroll and total employment relative to the previous quarter. Then I estimate the marginal effects of moderate storms on sectors within counties and how different types of storms affect county total payroll. I find evidence that the immediate impact of an intermediate storm is a decrease in economic activity, which is driven by declines in either total employment growth or total payroll growth in most sectors. I also find evidence that the keywords that are used to define moderate storms are associated with different effects on the labor market. Once this is established, I use a subsample of moderate storms that have Event Narratives that mention words related to transport or transportation infrastructure to determine if intense moderate storms affect total payroll growth. The results show that intermediate storms probably only affect counties and sectors within counties in the quarter during which the storms occur.

4.1 Main Findings

The fifth columns of Tables 6 and 7 depict my main result from Equation 1: the immediate effect of intermediate storms on county total payroll and total employment relative to a county's previous quarterly total payroll or total employment. In the average county, a moderate storm is associated with total payroll growth decreasing by .054% and total employment growth decreasing by .047%. The first columns of Tables 6 and 7 depict intermediate storms on $L_{i,t}$ with fixed effects for time and location and the second, third, and fourth columns in these tables each representing the inclusion of $l_{i,t-q}$, $mod_{i,t-j}$, or $cat_{i,t}$ and $cat_{i,t-j}$ respectively. The estimates in each column are consistently negative, statistically significant, and the decrease in total payroll exceeds the decrease in total employment. Additionally, there is a noticeable but small difference between the first and the fourth columns that demonstrates that not accounting for more intense storms with the variables $cat_{i,t}$ and $cat_{i,t-j}$ leads to a small upward bias in the estimates for moderate storms.

Table 8 restates the estimates from Equation 1 and details the probability of the average county experiencing one or more moderate storms and the expected value of a storm in a quarter. There is a 28% chance of a county experiencing one or more intermediate storms in a quarter and the expected value is .56. The standard deviation for the expected value is almost twice as big as the estimate of expected value. This spread demonstrates that there are substantial differences in exposure to moderate storms between different counties in the sample. At the extremes, sixteen counties never experience an intermediate storm and Charleston, SC has the highest chance of being hit by one of these storms, with a 70% chance each quarter of experiencing a moderate storm.

The frequency and statistical significance of these estimates indicates that moderate storms occur regularly in counties in the U.S. Since the decrease in total employment is almost as large as the decrease in total payroll, which is the total wages paid to all workers, it is likely that employment decreases more than earnings.

4.2 Sector

The effect of a moderate storm on the average county may be a combination of decreases in employment or payroll in some sectors and increases in other sectors. Due to differences in the economic composition of different counties, the average effect of moderate storms on sector total payroll and total employment could be misleading. Therefore, I investigate changes in sector labor market outcomes by modifying Equation 1. First, county total payroll and county total employment are decomposed into county-sector total payroll and total employment for twenty different NAICS sectors. Then payroll and employment for each sector in county i and time t are divided by total payroll or employment in county i and time t.

Lastly, the dependent variable and l (either lagged total payroll or total employment) in Equation 1 are changed to no longer be log(x). For reference, this equation is shown below for county-sector total employment:

$$\frac{totalemp_{nai,i,t}}{totalemp_{i,t}} - \frac{totalemp_{nai,i,t-1}}{totalemp_{i,t-1}}$$

$$= \beta_1 * mod_{i,t} + \beta_2 * cat_{i,t} + \beta_3 * mod_{i,t-j} + \beta_4 * cat_{i,t-j} + \beta_5 * \frac{totalemp_{nai,i,t-q}}{totalemp_{i,t-q}} + \tau + \chi + \epsilon$$

Under this formulation, the estimates for each sector now represent the average effect of an additional storm relative to economic performance in the county and the size of the sector in the county. Therefore, an increase or decrease in earnings and employment signifies an increase or decrease in economic activity relative to the county in which a storm occurs. The estimates for intermediate storms on county-sector total payroll and total employment are shown in Tables 9 and 10 respectively. These results support the idea that moderate storms mostly have heterogeneous effects on sectors within counties, but there are some exceptions. It is improbable that the Information, Other Services (except Public Administration), and the Real Estate and Rental and Leasing sectors are affected by intermediate storms, because they have small and unreliable estimates in these tables.

For the other sectors, the effect of moderate storms on earnings and employment are different than the average effect of a storm on the entire county. My expectation was that several sectors would see a decrease in earnings and wages because counties experience a decrease in total employment growth and total payroll growth. With the possible exception of the Agriculture, Forestry, Fishing and Hunting sector, where a moderate storm is associated with a statistically significant ($p < .05$) decrease in total employment (-.000025) and a slightly smaller and statistically significant decrease in total payroll (-.000023), this does not seem to occur. Alternatively, statistically significant estimates for several sectors indicate that they experience an increase in economic activity. Specifically, the Arts, Entertainment, and Recreation and Healthcare and Social Assistance sectors both experience an increase in earnings and employment that suggest overall economic activity has increased in these sectors.

The estimates show that in most sectors either earnings or employment are sensitive to intermediate storms. The magnitude of moderate storms on total payroll is smaller than -.00002 in the following sectors: Mining, Quarrying, and Oil and Gas Extraction (-.000047); Management of Companies and Enterprises; Transportation and Warehousing; Construction (not statistically significant); Finance and Insurance; and Agriculture, Forestry, Fishing, and Hunting (-.000023). The sectors where moderate storms are associated with the largest increases in total payroll are Healthcare and Social Assistance (.000090); Manufacturing; Retail Trade; Utilities; Professional, Scientific, and Technical Services; and Arts, Entertainment, and Recreation (.000024). Regarding total employment, Educational Services (.000058); Manufacturing; Healthcare and Social Assistance; and Public Administration (0.000039) experience the largest increase in employment after experiencing an intermediate storm. Meanwhile, the largest negative effects of moderate storms on total employment are in the Accommodation and Food Services and Agriculture, Forestry, Fishing, and Hunting sectors.

4.3 Storm Type

One explanation for the diverse effects of intermediate storms on sectors is that the averaged effects of moderate storms may be different than the effects of different types of intermediate storms, such as hurricanes, heat, wind, and precipitation. Due to the computational intensity of these calculations, I limit my analysis to the effects of storms on county total payroll. I further simplify the analysis by grouping the different types of storms in the original dataset into thirteen categories that are shown in Table 11. These categories are used to estimate Equation 2:

$$\log(totalpay_{i,t}) - \log(totalpay_{i,t-1}) = \beta_1 * mod_{s,i,t} + \beta_2 * mod_{oth,i,t} + \beta_3 * cat_{i,t} + \beta_4 * mod_{s,i,t-j} + \beta_5 * mod_{oth,i,t-j} + \beta_6 * cat_{i,t-j} + \beta_7 * \log(totalpay_{i,t-q}) + \tau + \chi + \epsilon$$

where $mod_{i,t}$ is disaggregated into the number of storms in one of the thirteen categories for county i in time t ($mod_{s,i,t}$) and the total number of storms in the other twelve categories ($mod_{oth,i,t}$). Each of the thirteen different types of storms are regressed on county total payroll as modeled in Equation 2.

These estimates are detailed in Table 12. The marginal effects of heat, droughts, floods, hurricanes, wildfires and smoke, and precipitation are particularly noteworthy due to these estimates being statistically significant around or below the 10% confidence level, and for the magnitude being substantially larger than the estimates in Equation 1. Out of the storms in these six categories, only wildfires and smoke have a positive impact on total payroll growth, with each additional storm causing a .47% uptick in total payroll compared to the previous quarter. From the largest negative effects to the smallest, the marginal effect of the following types of storms is a decrease in county total payroll growth: heat (-0.66%), hurricane, drought, precipitation, and flood (-0.11%). The fifth column of Table 12 shows the number of storms from the sample that impact counties. Out of the six categories of statistically significant storms, floods are the most common storms at 29,583.

Heat is the least common storm with only 233 heat events. Heat events are far more common in the original NOAA dataset, so I investigated this further. Heat events can be classified in the original data from NOAA as “heat” or “excessive heat.” The events in my sample are mostly storms that are classified by NOAA as excessive heat. Excessive heat is defined as a combination of high heat and humidity that exceeds local and regional thresholds (United States 2018). Most of the temperatures mentioned in the Event Narratives are 100 or more degrees Fahrenheit. This means the average storm in this paper has a smaller negative effect on the labor market than excessive heat.

I manually reviewed some of the different types of intermediate storms that do not have a statistically significant effect on total payroll: waves, colloid (fog), dust and landslides, wind, and cold. Many of the Event Narratives for the reviewed storms that are in the dust and landslides and cold categories describe snow and landslides that block roads. My expectation is that these events would negatively affect total payroll. If $mod_{i,t}$ is re-estimated to only include moderate storms that include mentions of words related to transport and transportation infrastructure in their Event Narratives, then cold storms become statistically significant.

4.4 Transport Moderate Storms and Total Payroll Growth

These results are shown in section D. Transport-Related Moderate Storms of the Data Appendix. The Data Appendix contains the results from a number of regressions that are used to investigate how different words in Event Narratives are correlated with labor market outcomes. These regressions show that intermediate storms that have Event Narratives that include keywords related to transport or transportation infrastructure ($modtrans_{i,t}$) reliably have larger negative effects on the labor market than the rest of storms in the sample. Moderate storms that have Event Narratives that mention words related to power also sometimes have a larger negative effect on the labor market than the average intermediate storm. On the other hand, some groups of keywords are associated with moderate storms having smaller and statistically weaker relationships with labor market outcomes. This suggests these storms either cause damages and disruptions that have a weaker effect on the labor market, or some of the damages they cause increase earnings or employment. For easy reference, the categories of keywords are shown in Table 13.

It is possible that moderate storms with different keywords will have heterogenous effects on total payroll growth. I focus on transport-related moderate storms because more intense moderate storms should have a higher chance of affecting total payroll growth. Based on my analysis of previous estimates of the lagged effects of moderate storms ($mod_{i,t-j}$), I believe total payroll growth could be affected up to three years after an intermediate storm has occurred. Consequently, I estimate the effect of moderate storms related to transport out to twelve quarters after an intermediate storm has occurred. Growth is estimated with a modified version of equation 1:

$$\log(totalpay_{i,t+f}) - \log(totalpay_{i,t}) = \beta_1 * modtran_{i,t} + \beta_2 * modtran_{i,t+f} + \beta_3 * cat_{i,t+f} + \beta_4 * cat_{i,t} + \beta_5 * modtran_{i,t-j} + \beta_6 * cat_{i,t-j} + \beta_7 * \log(p_{i,t-i}) + \tau + \chi + \epsilon$$

where f represents the next one through twelve quarters. In addition, the variable for moderate storms in Equation 1 ($mod_{i,t}$) is now replaced with transport-related moderate storms ($modtrans_{i,t}$). By including $modtran_{t+f}$ and cat_{t+f}, the effect of transport-related intermediate storms on the percentage change in future total payroll is isolated. The estimated effects of a moderate storm for each future quarter are shown in Table 14. These findings provide weak evidence for intermediate storms influencing total payroll growth. Some of these estimates are not statistically significant, and the statistically significant results appear to occur in an arbitrary manner that is inconsistent with moderate storms affecting payroll growth.

It is possible that total payroll growth for different sectors within counties may be negatively affected by an intermediate storm. The effect of a moderate storm on the difference between total payroll three years after an intermediate storm has occurred (f = 12) and current total payroll is estimated for each sector in a county with the following equation:

$$\frac{totalpay_{nai,i,t+12}}{totalemp_{i,t+12}} - \frac{totalpay_{nai,i,t}}{totalemp_{i,t}} = \beta_1 * modtran_{i,t} + \beta_2 * modtran_{i,t+f} + \beta_3 * cat_{i,t+f} + \beta_4 * cat_{i,t} + \beta_5 * modtran_{i,t-j} + \beta_6 * cat_{i,t-j} + \tau + \chi + \epsilon.$$

An important note, the term $\log(p_{t-i})$, which is included in the previous equation, is not present in this equation due to collinearity issues. The estimates for different sectors are show in Table 15. None of these results are statistically significant, and while only reflecting a snapshot in time, do not suggest that these storms affect total payroll growth in any sector within a county.

4.5 Alternative Specifications

A number of modeling decisions were made to estimate these results. This section explores the ramifications and the impact of those decisions.

A. Seasonality

It is well known that there are seasonal effects in labor markets (Boldin and Wright 2015) and that weather varies by the season. To examine if seasonality is influencing the results in this paper, the results in the first columns of Tables 6 and 7 are recalculated. The average county total payroll, county total employment, and moderate storms per quarter for each year between 2000 to 2020 are calculated for each county. The marginal effect of an additional intermediate storm is now a -0.0986% change in total payroll and a -0.1030% change in total employment. These results suggest that a detailed investigation of seasonality would produce additional interesting findings.

B. Apportioning Moderate Storms

Approximately 10% of moderate storms in the original data from the NOAA Storm Events Database are measured in a manner that means they could have occurred in multiple counties. For many storms, especially the storms that have Event Narratives that describe more damages, I was able to determine which counties were affected by parsing storms' Event Narratives for the names of counties or the names of cities in those counties. Many of these intermediate storms appear to cause noticeable disruptions in multiple communities, so they are modeled throughout the paper as occurring once in each county they affect. Another option for modeling these storms, which is used for property damage, crop damage, fatalities, and injuries, is to apportion the effect of moderate storms by the number of counties they occurred in. This alternative modeling choice is examined by re-estimating Equation 1. Under this new specification, the marginal effect of an intermediate storm on the county labor market is a decrease of 0.1813% in total payroll growth and a 0.1244% decrease in total employment. Although these estimates probably overestimate the effects of the average moderate storm, which affects one county, if these estimates are accurate, they only further support the economic importance of intermediate storms.

C. Quantitative Moderate Storms

I posit that moderate storms that are identified through text analysis are less intense than the storms that the NOAA Storm Events Database says caused injuries, deaths, property damage, or crop damage, which are measured through the term cat. To evaluate this assumption, I use information on property and crop damages to identify storms that have a similar impact on the economy as intermediate storms. It is important to note that property and crop damages are likely under-reported in the NOAA Storm Events Database (Gall, Borden, and Cutter 2009), so these estimates do not necessarily represent the effects of a storm that actually caused a certain amount of damages. To differentiate these storms from the moderate storms that are identified with text analysis, storms that caused a small amount of property or crop damage will be referred to as "quantitative" moderate or intermediate storms.

The impact of a quantitative moderate storm on the labor market is identified by adding a term to Equation 1 for the number of storms in quarter t and county i that caused \$1000 or less in crop or property damage ($mod1000_{i,t}$). The first to eleventh lags of quantitative moderate storms are included in this equation, just like how eleven previous quarters of intermediate storms ($mod_{i,t-j}$) are present in Equation 1. The estimates for $mod1000$ on county total payroll and total employment growth are shown in Table 16 and they are -.037% and -.0042% respectively. Meanwhile, the estimates for moderate storm that were identified through text analysis in Table 16 are a .054% decrease in total payroll and a .047% decrease in total employment. Because the estimated effects of $mod1000_{i,t}$ on county total payroll and employment are smaller than the effect of intermediate storms, I re-estimate quantitative moderate storms by replacing $mod1000_{i,t}$ with storms that caused $2000 or less in crop or property damage ($mod2000_{i,t}$). The estimates for this regression are shown in Table 17. One of these quantitative intermediate storms decreases county total payroll by .053% and total employment by .039%. A moderate storm identified through text analysis is associated with -.055% and -.047% change in county total payroll and total employment respectively. The chance of the average county experiencing $mod2000_{i,t}$ is 14%, which is significantly smaller than the chance of experiencing an intermediate storm (mod). For the probability of a county experiencing one or more quantitative moderate storms to be similar to the probability of a county experiencing at least one intermediate storm, quantitative moderate storms have to be defined as storms that do not cause injuries, deaths, and caused less than $10,000 in property or crop damage ($mod10000_{i,t}$). There is a 30% of a county experiencing one of these quantitative intermediate storms.

It is possible that the way damages are calculated skews the above comparisons between quantitative moderate storms and moderate storms. There are cases where the way the NOAA Storm Events Database defines the location of a storm means that some intermediate storms could have occurred in multiple counties. In these instances, the number of counties a moderate storm may have occurred is used to divide property and crop damages (along with injuries and fatalities). If instead crop and property damage are not divided, $mod1000_{i,t}$ is associated with a decrease in total payroll growth of .038% and a decrease in total employment growth of .0041%. For $mod2000_{i,t}$, this changes the estimates for the average county to a .048% decrease in total payroll growth and .036% decline in total employment growth. The similarity between the estimated effects of moderate storms and quantitative moderate storms indicates that it is generally reasonable to assume that intermediate storms are less intense than storms that reportedly caused quantitative damages.

D. Weather and Sample Selection

One lingering question is why there are so few heat events in the sample, yet they are common in the original NOAA data? I examine if the results in this paper are influenced by excluded heat events by modifying Equation 2 to include the original moderate storms that were identified through text analysis and the quantitative intermediate storms from the section above ($mod2000_{i,t}$). The magnitudes of some estimates change slightly, but the results are not particularly noteworthy. These results are not shown since they are insignificant.

E. Continuous Rather than Categorical Controls

Storms that caused quantitative damages are grouped into categorical variables (cat) in Equation 1. This decision was made because there are substantial variations in property and crop damage, fatalities, and injuries that led me to conclude that it is important to account for all four of these measurements of storm damages. For example, the drought events in the sample caused $1,920,785,950 in property damage and took zero lives, while heat events caused 2265 deaths but only cost $31,454,200 in property damage. Different types of damages are included in the model by defining cat as categorical variables that represent the total crop damage, property damage, fatalities, and injuries that occurred during a quarter in a county. Another approach would have been estimating cat by counting the number of storms that individually meet the criteria that define cat. This choice is examined by replacing $cat_{i,t}$ and

$cat_{i,t-j}$ in Equation 1 with the number of storms in quarter t and county i that meet the parameters in Table 3, which establish the Disruptive, Costly, and Severe categorical variables. For instance, if a storm caused $450,000 in crop damage, it would now be classified as a Disruptive storm. Table 18 shows the estimates for the modified equation. The marginal effects of a moderate storm on county total payroll and county total employment are -0.052% and -0.045% respectively. While the estimates are similar for both approaches, the categorical variables that are used throughout the paper are significantly faster for a computer to calculate.

F. Controlling for Daily Weather

The results in this paper may be biased by excluding variations in local weather patterns that are correlated with economic activity and intermediate storms. This is assessed by including monthly average maximum temperature, average minimum temperature, average temperature, and total precipitation from the NClimDiv dataset for each county in the sample into Equation 1. These variables are correlated with earnings and employment, but their inclusion into Equation 1 does not improve the overall predictive power of the model. Additionally, they often produce collinearity issues. These results suggest monthly weather is correlated with climate, but it is not an omitted variable that is biasing the estimates of moderate storms.

5. CONCLUSION AND DISCUSSION

Out of the 2091 counties that are examined in this paper, 2075 counties have experienced at least one moderate storm during the twenty-first century. The ubiquity of intermediate storms suggests that estimates of the economic impacts of weather are influenced by these storms. This is a minor issue if moderate storms are the only type of weather that have not been incorporated into existing studies. The average county is exposed to an intermediate storm once a year and it experiences a small percentage decrease in quarterly employment and a smaller decrease in quarterly earnings. Furthermore, the estimated effects of moderate storms are only slightly upwardly biased when excluding more intense weather ($cat_{i,t}$ and $cat_{i,t-j}$). However, intermediate storms are narrowly defined. This may be a more significant issue if existing studies exclude weather beyond moderate storms.

The economic effects of moderate storms are small and relatively common, so my preferred method to quantify the effects of these storms is expected value. The mean of average quarterly total payroll for the counties in the sample is $615,494,721, and the mean of average quarterly county total employment is 61,661.82 employees. The expected value of a moderate storm each quarter in the average county, which is reported in Table 8, is .56. This means moderate storms are expected to decrease total payroll by $186,125.60 and total employment by 16.22 people each quarter in the average county. That works out to an expected decrease of $389,188,629 in total payroll and 33,916 fewer employed people each quarter across the 2091 U.S. counties in the sample. Since the excluded counties tend to be economically unproductive, this estimate is a fairly accurate representation of the effect of intermediate storms on the labor market in the U.S.

The economic consequences associated with an intermediate storm vary based upon a number of factors. During the quarter in which a storm occurs there are declines in either earnings or employment across most sectors, and the Agriculture, Forestry, Fishing, and Hunting sector experiences a decrease in earnings and employment that potentially indicates a decrease in economic activity. With the exception of wildfires and smoke, earnings are negatively affected by different types of moderate storms. In the long-term, there is little evidence that intermediate storms affect labor market outcomes across a county or the sectors within a county. The best explanation for the effects of moderate storms is that they cause damages and disruptions that are intense enough to lead to a small decrease in earnings or employment in most sectors. These decreases seem to cumulatively lead to a decrease in county economic activity. However, intermediate storms are probably not intense enough to hinder economic growth.

Hypothetically, as climate change continues to increase the frequency and intensity of some types of weather (IPCC 2021), economic growth could one day be affected by moderate storms or similar weather events. The likelihood of this occurring is hard to determine. Economists have studied climate change and heat, but there is less research on other types of intermediate storms that climate change will exacerbate. In particular, I believe flash floods merit further study because they occur frequently, and their Event Narratives often describe disruptions to commerce that may not be well-quantified in existing studies.

The methodology used in this paper suggests several avenues for future research. To the best of my knowledge, this is the first paper that uses text analysis techniques to study weather, but the growing availability of text data and text analysis methods (Gentzkow, Kelly, and Taddy 2019) means this could be a valuable source of information. It is likely that text analysis could be used to more thoroughly understand the damages caused by weather. Text also appears to be a useful source of information to measure weather that is not well-represented by other sources of weather data. Additionally, since the estimated effects of moderate storms are similar whether categorical or continuous variables are utilized, categorical variables may be a dependable and computationally efficient methodology to use in future studies.

Weather is complicated and economists will probably never have a unified source of information that perfectly describes the attributes of weather and its full effect on the economy. Nonetheless, the advent of big data is making it possible to learn more about the weather by studying more weather events and applying new techniques. This paper furthers this research by systematically analyzing intermediate storms and introducing the use of text analysis to the economic study of weather.

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TABLES

Table 4: Yearly Summary Statistics

Year	Number of Moderate Storms	Total Payroll	Total Employees	Property Damage	Total Crop Damage	Deaths	Injuries
2000	919	$1,898B	65M	$1.6B	$0.97B	134	696
2001	2,250	$3,803B	126M	$3.1B	$1.03B	276	1,798
2002	2,505	$3,806B	123M	$2.9B	$0.73B	357	2,007
2003	2,794	$3,885B	121M	$7.8B	$0.73B	309	2,334
2004	3,328	$4,095B	123M	$14.3B	$0.97B	244	1,326
2005	3,103	$4,292B	126M	$12.2B	$1.19B	275	1,170
2006	3,157	$4,553B	128M	$6.0B	$1.36B	516	2,310
2007	4,409	$4,783B	129M	$6.2B	$2.66B	525	2,455
2008	5,306	$4,852B	126M	$13.5B	$2.78B	574	2,911
2009	4,697	$4,599B	118M	$3.9B	$0.46B	370	2,004
2010	5,058	$4,677B	117M	$5.6B	$1.58B	460	2,051
2011	5,908	$4,858B	119M	$9.7B	$1.06B	632	3,812
2012	4,539	$5,086B	121M	$7.4B	$4.31B	520	2,053
2013	4,966	$5,224B	124M	$7.1B	$2.21B	393	2,725
2014	4,929	$5,486B	127M	$4.8B	$1.70B	369	2,028
2015	5,856	$5,785B	130M	$3.6B	$0.12B	429	1,378
2016	5,249	$5,967B	133M	$17.6B	$0.20B	439	1,148
2017	5,644	$6,253B	135M	$21.1B	$1.46B	390	1,051
2018	6,442	$6,562B	137M	$10.8B	$2.53B	472	1,207
2019	7,424	$6,866B	139M	$3.2B	$0.69B	375	1,359
2020	5,260	$5,025B	98M	$13.7B	$0.32B	326	1,220

Table 5: Per-Worker Statistics for the Average County

Statistics for Average County	Per-capita
Payroll	$7,713
Property Damage	$45
Crop Damage	$17
Injury	0.000009
Fatalities	0.000002

A. Tables for Results

Table 6: Moderate Storm and Total Payroll

	Baseline Sample	Controlling for Autoregression	Controlling for Past Moderate Storms	Controlling for Confounding Weather	Main Specification
Moderate Storm	-0.00105 ***	-0.00070 ***	-0.00076 ***	-0.00104 ***	-0.00054 ***
	(0.00013)	(0.00010)	(0.00014)	(0.00014)	(0.00011)
1st lag Moderate Storms			0.00007		-0.00022
			(0.00014)		(0.00011)
Disruptive Categorical Variable				-0.00085 *	-0.00043
				(0.00043)	(0.00033)
Costly Categorical Variable				-0.00128	-0.00065
				(0.00091)	(0.00071)
Severe Categorical Variable				-0.00837	-0.00284
				(0.00525)	(0.00408)
1st lag Disruptive				-0.00083	-0.00073 *
				(0.00043)	(0.00033)
1st lag Costly				0.00140	0.00080
				(0.00091)	(0.00071)
1st lag Severe				0.01400 **	0.01304 **
				(0.00542)	(0.00422)
Time and location fixed effects	Yes	Yes	Yes	Yes	Yes
Autocorrelated lagged model	No	Yes	No	No	Yes
N	164240	158081	143710	143710	143710
R2	0.00039	0.38033	0.00140	0.00110	0.39595

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 7: Moderate Storm and Total Employment

	Baseline Sample	Controlling for Autoregression	Controlling for Past Moderate Storms	Controlling for Confounding Weather	Main Specification
Moderate Storm	-0.00090 ***	-0.00062 ***	-0.00068 ***	-0.00083 ***	-0.00047 ***
	(0.00009)	(0.00007)	(0.00009)	(0.00009)	(0.00007)
1st lag Moderate Storms			0.00002		-0.00002
			(0.00009)		(0.00008)
Disruptive Categorical Variable				-0.00190 ***	-0.00109 ***
				(0.00028)	(0.00022)
Costly Categorical Variable				-0.00093	-0.00056
				(0.00059)	(0.00047)
Severe Categorical Variable				-0.00906 **	-0.00186
				(0.00341)	(0.00272)
1st lag Disruptive				-0.00152 ***	-0.00082 ***
				(0.00028)	(0.00022)
1st lag Costly				0.00060	0.00069
				(0.00059)	(0.00047)
1st lag Severe				0.01363 ***	0.01319 ***
				(0.00352)	(0.00281)
Time and location fixed effects	Yes	Yes	Yes	Yes	Yes
Autocorrelated lagged model	No	Yes	No	No	Yes
N	164240	158081	143710	143710	143710
R2	0.00065	0.35143	0.00205	0.00465	0.36775

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 8: Moderate Storm Probability

Moderate Storm Statistics	Estimate	Std. Deviation
Marginal Effect on Total Payroll	-0.00054	
Marginal Effect on Total Employment	-0.00047	
Chance of Experiencing One or More	27.6%	0.15190
Expected Value	0.56372	1.39028

Table 9: Moderate Storm and Sector Total Payroll

Sector	Marginal Effect of Moderate Storm	Std. Error	P.Value
Agriculture, Forestry, Fishing and Hunting	-0.000023	0.000013	0.074682
Mining, Quarrying, and Oil and Gas Extraction	-0.000047	0.000019	0.016257
Utilities	0.000026	0.000013	0.041670
Construction	-0.000025	0.000028	0.371376
Manufacturing	0.000053	0.000036	0.147224
Wholesale Trade	-0.000011	0.000018	0.559770
Retail Trade	0.000028	0.000014	0.053065
Transportation and Warehousing	-0.000032	0.000012	0.009650
Information	-0.000000	0.000010	0.963207
Finance and Insurance	-0.000025	0.000016	0.110515
Real Estate and Rental and Leasing	0.000001	0.000005	0.769174
Professional, Scientific, and Technical Services	0.000024	0.000017	0.146479
Management of Companies and Enterprises	-0.000031	0.000013	0.016013
Administrative and Support and Waste Management and Remediation Services	-0.000001	0.000015	0.946132
Educational Services	0.000028	0.000028	0.317539
Health Care and Social Assistance	0.000090	0.000024	0.000135
Arts, Entertainment, and Recreation	0.000024	0.000010	0.015355
Accommodation and Food Services	-0.000010	0.000013	0.435554
Other Services (except Public Administration)	0.000006	0.000008	0.393089
Public Administration	0.000018	0.000016	0.279597

Table 10: Moderate Storm and Total Employment

Sector	Marginal Effect	Std. Error	P.Value
Agriculture, Forestry, Fishing and Hunting	-0.000025	0.000014	0.068168
Mining, Quarrying, and Oil and Gas Extraction	-0.000007	0.000008	0.391482
Utilities	0.000004	0.000005	0.462272
Construction	-0.000009	0.000017	0.588691
Manufacturing	0.000055	0.000019	0.004513
Wholesale Trade	0.000003	0.000008	0.740947
Retail Trade	0.000007	0.000013	0.566854
Transportation and Warehousing	-0.000004	0.000008	0.612881
Information	0.000001	0.000005	0.782834
Finance and Insurance	-0.000007	0.000008	0.332209
Real Estate and Rental and Leasing	-0.000001	0.000003	0.876794
Professional, Scientific, and Technical Services	-0.000001	0.000009	0.948580
Management of Companies and Enterprises	-0.000007	0.000005	0.187918
Administrative and Support and Waste Management and Remediation Services	-0.000018	0.000016	0.261426
Educational Services	0.000058	0.000021	0.004837
Health Care and Social Assistance	0.000050	0.000015	0.001144
Arts, Entertainment, and Recreation	0.000020	0.000011	0.058618
Accommodation and Food Services	-0.000050	0.000016	0.001780
Other Services (except Public Administration)	0.000005	0.000007	0.523909
Public Administration	0.000039	0.000011	0.000389

Table 11: Aggregated Storm Categories

Aggregated Category	Original Storms in Storm Events Database											
Wind	Strong Wind	Thunderstorm Wind	High Wind									
Flood	Flash Flood	Lakeshore Flood	Flood	Coastal Flood								
Precipitation	Hail	Heavy Rain										
Cold	Heavy Snow	Winter Storm	Ice Storm	Winter Weather	Lake-Effect Snow	Blizzard	Sleet	Avalanche	Frost/ Freeze	Cold /Wind Chill	Extreme Cold/ Wind Chill	Freezing Fog
Dust and Landslides	Landslide	Dust Devil	Debris Flow	OTHER	Dust Storm							
Wildfire and Smoke	Wildfire	Dense Smoke										
Wave	Storm Surge /Tide	Tsunami	Rip Current	Sneaker wave	Seiche	Astronomical Low Tide	High Surf					
Lightning	Lightning											
Tornado	Tornado	Funnel Cloud	Waterspout									
Heat	Heat	Excessive Heat										
Hurricane	Tropical Storm	Hurricane	Tropical Depression	Hurricane (Typhoon)								
Colloid	Dense Fog											
Drought	Drought											

Table 12: Different Types of Moderate Storms and Total Payroll

Type of Moderate Storm	Marginal Effect	Std. Error	P.Value	Number of Storms
Flood	-0.0011162	0.0002314	0.0000014	29,583
Heat	-0.0065887	0.0034191	0.0539760	233
Wind	-0.0002354	0.0001869	0.2078487	40,627
Cold	-0.0003066	0.0003480	0.3783023	16,607
Dust and Landslides	0.0009972	0.0011194	0.3729979	799
Precipitation	-0.0014724	0.0003721	0.0000760	15,159
Colloid	-0.0001825	0.0017687	0.9178236	580
Lightning	0.0018194	0.0033764	0.5899836	366
Drought	-0.0020261	0.0012601	0.1078642	1,390
Wildfire and Smoke	0.0047197	0.0009557	0.0000008	1,608
Tornado	-0.0006258	0.0005290	0.2368288	8,733
Wave	0.0033012	0.0032910	0.3158114	268
Hurricane	-0.0046229	0.0015953	0.0037575	922

Table 13: Groups of Keywords

Transport	Implied Harm	Building	Harm	Power
street	nickel	resort	damag	outag
road	penni	farm	injur	power
crossroad	dollar	market	kill	wire
expressway	slide	church	injuri	line
dock	employe	subdivis		
boat	cancel	driveway		
gas	intern	roof		
airport	evacu			
highway	close			
vehicl				
roadway				
interst				
car				
wheel				
bridg				
transport				
freeport				
turnpik				
automobil				
parkway				
overpass				

Table 14: Transport-related Moderate Storm and Total Payroll Growth

Future Quarter (f)	Marginal Effect	Std. Error	Statistic	P.Value
1	0.000025	0.000214	0.116944	0.906905
2	0.001047	0.000212	4.933008	0.000001
3	0.000809	0.000243	3.328428	0.000874
4	0.000340	0.000225	1.509521	0.131168
5	0.000111	0.000304	0.363438	0.716278
6	0.000699	0.000305	2.292409	0.021884
7	0.000568	0.000333	1.706974	0.087830
8	-0.000293	0.000319	-0.919053	0.358070
9	-0.000251	0.000380	-0.660792	0.508747
10	0.000747	0.000389	1.922544	0.054540
11	0.000325	0.000422	0.770536	0.440984
12	0.000108	0.000391	0.275774	0.782722

Table 15: Transport-related Moderate Storm and 3-Year Sector Total Payroll Growth

Sector	Marginal Effect	Std. Error	P.Value
Agriculture, Forestry, Fishing and Hunting	-0.000003	0.000038	0.936346
Mining, Quarrying, and Oil and Gas Extraction	0.000083	0.000084	0.323983
Utilities	0.000003	0.000041	0.935480
Construction	0.000063	0.000104	0.545784
Manufacturing	-0.000115	0.000122	0.343802
Wholesale Trade	-0.000065	0.000064	0.314179
Retail Trade	-0.000020	0.000051	0.695240
Transportation and Warehousing	0.000005	0.000054	0.925657
Information	-0.000027	0.000037	0.461522
Finance and Insurance	0.000003	0.000048	0.943084
Real Estate and Rental and Leasing	-0.000004	0.000021	0.854488
Professional, Scientific, and Technical Services	0.000004	0.000063	0.944068
Management of Companies and Enterprises	-0.000001	0.000046	0.990846
Administrative and Support and Waste Management and Remediation Services	-0.000005	0.000062	0.941017
Educational Services	-0.000072	0.000078	0.356005
Health Care and Social Assistance	0.000101	0.000080	0.206407
Arts, Entertainment, and Recreation	-0.000029	0.000035	0.403960
Accommodation and Food Services	0.000037	0.000038	0.338329
Other Services (except Public Administration)	0.000008	0.000029	0.791591
Public Administration	0.000025	0.000059	0.664859

B. Tables Alternative Specifications

Table 16: Quantitative Moderate Storms $0 - $1000 in Damages

	Total Payroll	Total Employment
Quantitative Moderate Storms	-0.00037 *	-0.00042 ***
	(0.00019)	(0.00012)
Moderate Storms (Identified with Text)	-0.00054 ***	-0.00047 ***
	(0.00011)	(0.00007)
N	143710	143710
R2	0.39620	0.36817

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 17: Quantitative Moderate Storms $0 - $2000 in Damages

	Total Payroll	Total Employment
Quantitative Moderate Storms	-0.00053 **	-0.00039 ***
	(0.00017)	(0.00012)
Moderate Storms (Identified with Text)	-0.00055 ***	-0.00047 ***
	(0.00011)	(0.00007)
N	143710	143710
R2	0.39622	0.36812

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 18: Moderate Storms with Continuous Controls and Total Payroll/ Total Employment

	Total Payroll	Total Employment
Moderate Storm	-0.00052 ***	-0.00045 ***
	(0.00011)	(0.00007)
Disruptive Storm	-0.00022 ***	-0.00028 ***
	(0.00007)	(0.00004)
Costly Storm	-0.00011	0.00037
	(0.00049)	(0.00033)
Severe Storm	-0.00156	0.00003
	(0.00417)	(0.00278)
N	143710	143710
R2	0.39635	0.36770

*** p < 0.001; ** p < 0.01; * p < 0.05.

DATA APPENDIX

A. Text Results

Table 19: Groups of Moderate Storms and Total Payroll

	(1)	(2)	(3)	(4)	(5)
Transport	-0.0008 ***				
	(0.0002)				
Power		-0.0007 **			
		(0.0003)			
Building			-0.0002		
			(0.0005)		
Implied Harm				0.0007	
				(0.0007)	
Harm					-0.0004
					(0.0003)
Disruptive Categorical Variable	-0.0004	-0.0005	-0.0005	-0.0005	-0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Costly Categorical Variable	-0.0006	-0.0009	-0.0009	-0.0009	-0.0009
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Severe Categorical Variable	-0.0029	-0.0034	-0.0033	-0.0034	-0.0033
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
N	143710	143710	143710	143710	143710
R2	0.3959	0.3958	0.3955	0.3956	0.3956

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 20: Groups of Moderate Storms and Total Employment

	(1)	(2)	(3)	(4)	(5)
Transport	-0.0006 ***				
	(0.0001)				
Power		-0.0005 **			
		(0.0002)			
Building			-0.0000		
			(0.0003)		
Implied Harm				0.0003	
				(0.0005)	
Harm					-0.0005 **
					(0.0002)
Disruptive Categorical Variable	-0.0011 ***	-0.0012 ***	-0.0012 ***	-0.0012 ***	-0.0012 ***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Costly Categorical Variable	-0.0005	-0.0008	-0.0008	-0.0007	-0.0007
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Severe Categorical Variable	-0.0020	-0.0023	-0.0023	-0.0022	-0.0021
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
N	143710	143710	143710	143710	143710
R2	0.3675	0.3674	0.3672	0.3672	0.3674

*** p < 0.001; ** p < 0.01; * p < 0.05.

B. Text Lags

Table 21: Lags of Power-related Moderate Storms and Total Payroll

Previous Quarter	Marginal Effect	Std. Error	P.Value
0	-0.000724	0.000258	0.005058
1	-0.000309	0.000280	0.269871
2	0.000603	0.000290	0.037609
3	0.000203	0.000290	0.484395
4	-0.000729	0.000291	0.012293
5	-0.000190	0.000304	0.531815
6	0.000953	0.000310	0.002115
7	0.000762	0.000311	0.014200
8	-0.000834	0.000310	0.007092
9	-0.000154	0.000315	0.625006
10	0.000576	0.000319	0.070571
11	0.000828	0.000318	0.009109

Table 22: Lags of Building-related Moderate Storms and Total Payroll

Previous Quarter	Marginal Effect	Std. Error	P.Value
0	-0.000160	0.000495	0.747243
1	-0.000286	0.000504	0.569740
2	0.001282	0.000513	0.012403
3	-0.000461	0.000513	0.368577
4	-0.000559	0.000514	0.276326
5	-0.000281	0.000516	0.585975
6	0.000431	0.000525	0.411127
7	-0.000094	0.000531	0.860206
8	0.000606	0.000535	0.257652
9	-0.000021	0.000543	0.969299
10	0.000387	0.000549	0.480505
11	-0.000194	0.000553	0.725365

Table 23: Lags of Transport-related Moderate Storms and Total Payroll

Previous Quarter	Marginal Effect	Std. Error	P.Value
0	-0.000789	0.000172	0.000004
1	-0.000139	0.000173	0.421382
2	0.000797	0.000175	0.000005
3	-0.000126	0.000175	0.472128
4	-0.000168	0.000175	0.337065
5	-0.000140	0.000176	0.426175
6	0.000183	0.000179	0.308665
7	-0.000270	0.000185	0.145101
8	-0.000654	0.000186	0.000431
9	-0.000297	0.000189	0.117515
10	0.000570	0.000192	0.003002
11	-0.000063	0.000192	0.744060

Table 24: Lags of Severe Categorical Variable for Groups of Moderate Storms and Total Payroll

Previous Quarter	Transport	Power	Building
1	-0.002947	-0.003380	-0.003325
2	0.012721	0.012798	0.012917
3	0.010584	0.011286	0.011281
4	0.004183	0.003873	0.003811
5	0.005532	0.005108	0.005033
6	0.011377	0.011628	0.011771
7	0.014850	0.015456	0.015504
8	0.009076	0.008831	0.008935
9	0.006995	0.006497	0.006627
10	0.006229	0.006156	0.006044
11	0.009467	0.010043	0.009663
12	-0.006502	-0.006538	-0.006506

C. Keywords Reliability

Table 25: Groups of Moderate Storms and Quantitative Moderate Storms (mod2000) and Total Payroll

Group of Moderate Storms	Marginal Effect	Std. Error	Statistic	P.Value
Transport	-0.000569	0.000119	-4.786374	0.000002
Power	-0.000531	0.000172	-3.081528	0.002060
Building	0.000179	0.000364	0.490857	0.623528
Harm	-0.000064	0.000151	-0.424135	0.671468
Implied Harm	-0.000866	0.000214	-4.052313	0.000051

D. Transport-related Moderate Storms

Table 26: Different Types of Transport-related Moderate Storms and Total Payroll

Type of Moderate Storm	Marginal Effect	Std. Error	P.Value
Flood	-0.0010450	0.0001911	0.0000000
Heat	-0.0048823	0.0039232	0.2133304
Wind	0.0000601	0.0003484	0.8629737
Cold	-0.0005866	0.0002792	0.0356245
Dust and Landslides	0.0007393	0.0012725	0.5612157
Precipitation	-0.0018955	0.0006119	0.0019513
Colloid (fog)	-0.0007152	0.0013272	0.5899581
Lightning	-0.0037040	0.0102215	0.7170699
Drought	-0.0026181	0.0046688	0.5749512
Wildfire and Smoke	0.0071574	0.0021288	0.0007734
Tornado	-0.0016792	0.0010416	0.1069231
Wave	0.0005055	0.0018314	0.7825488
Hurricane	-0.0041695	0.0015748	0.0081055

Table 27: Transport-related Moderate Storms and Total Payroll

Sector	Marginal Effect	Std. Error	P.Value
Agriculture, Forestry, Fishing and Hunting	-0.000027	0.000020	0.170081
Mining, Quarrying, and Oil and Gas Extraction	-0.000085	0.000030	0.005284
Utilities	0.000014	0.000020	0.489949
Construction	-0.000101	0.000043	0.019164
Manufacturing	0.000078	0.000057	0.168648
Wholesale Trade	-0.000024	0.000028	0.398828
Retail Trade	0.000043	0.000022	0.056394
Transportation and Warehousing	-0.000040	0.000019	0.038616
Information	0.000005	0.000015	0.724603
Finance and Insurance	-0.000019	0.000024	0.422713
Real Estate and Rental and Leasing	0.000019	0.000008	0.012059
Professional, Scientific, and Technical Services	0.000025	0.000026	0.334717
Management of Companies and Enterprises	-0.000036	0.000020	0.079091
Administrative and Support and Waste Management and Remediation Services	-0.000005	0.000023	0.814457
Educational Services	0.000081	0.000043	0.058597
Health Care and Social Assistance	0.000133	0.000037	0.000307
Arts, Entertainment, and Recreation	0.000026	0.000015	0.093088
Accommodation and Food Services	-0.000026	0.000020	0.187131
Other Services (except Public Administration)	0.000017	0.000012	0.144617
Public Administration	0.000022	0.000026	0.391707

Table 28: Transport-related Moderate Storms and Total Employment

Sector	Marginal Effect	Std. Error	P.Value
Agriculture, Forestry, Fishing and Hunting	-0.000035	0.000021	0.099545
Mining, Quarrying, and Oil and Gas Extraction	-0.000012	0.000013	0.356404
Utilities	0.000010	0.000008	0.250455
Construction	-0.000038	0.000027	0.149680
Manufacturing	0.000072	0.000030	0.016940
Wholesale Trade	0.000006	0.000012	0.596833
Retail Trade	0.000028	0.000020	0.161258
Transportation and Warehousing	0.000002	0.000013	0.862661
Information	0.000008	0.000008	0.312965
Finance and Insurance	0.000004	0.000012	0.753472
Real Estate and Rental and Leasing	0.000007	0.000005	0.191868
Professional, Scientific, and Technical Services	0.000005	0.000014	0.730972
Management of Companies and Enterprises	-0.000007	0.000008	0.345017
Administrative and Support and Waste Management and Remediation Services	-0.000021	0.000025	0.388875
Educational Services	0.000122	0.000032	0.000149
Health Care and Social Assistance	0.000076	0.000024	0.001535
Arts, Entertainment, and Recreation	0.000022	0.000017	0.181669
Accommodation and Food Services	-0.000084	0.000025	0.000678
Other Services (except Public Administration)	0.000012	0.000012	0.290198
Public Administration	0.000037	0.000017	0.033832