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The Effects of Devastating Tornados on Employment and Income

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Abstract

Tornados can be some of the most devastating natural disasters. Understanding the effects of said devastation is important for planning for extreme weather. Using a difference-in-differences regression method, this paper highlights the impacts of the most devastating tornados across the United States on employment, income, and wages for the effected area and the surrounding communities. The results imply some growth in employment and wages one year following the extreme tornado event, while income has little to no change. It could be that certain labor sectors experience growth in the job market, while others see no change or a decline. Overall, the results show that when a damaging tornado strikes, the affected community will experience miniscule growth in employment and wages. [1]

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Introduction

Comfortably living in a home with no risk of disaster is somewhat obsolete in the 21st century. Natural disasters have recently set records of intensity and extremes all over the world (NOAA, National Centers for Environmental Information (NCEI) 2020). With natural disasters increasing in frequency and intensity in the past decade alone, environmental refugees are becoming more prevalent. Today there are more migrants that flee due to environmental disasters or climate related reasons than refugees of war or conflict (Heimann 2019). With thousands displaced in the blink of an eye, there are bound to be impacts on those communities as well as the surrounding areas where these refugees flee.

Tornado disasters are extremely common in the United States and can be detrimental to infrastructure. A tornado is a violently rotating column of air that contacts the Earth and rips through anything in its path. The smaller tornados produce 110 mph windspeeds; the largest pushing 300 mph and spreading over two miles in diameter. Roughly 1,200 tornados strike the United States per year, however since data only dates back to 1950, we do not know if the average number of tornados per year follows a certain trend.[2] Tornados are also extremely dangerous, with flying debris and strong windspeeds threatening life and property. Many homes have basement areas to shelter from such events, however the home structure above land could be completely torn apart.

There are multiple tornados yearly in the United States. Figure 1 shows the average number of tornados for each state from 1991-2015.

[2] Tornado information and data from National Oceanic and Atmospheric Association (NOAA). Tornado Alley compromised of the middle most states in the U.S. from Minnesota to Texas experiences the highest averages of tornados each year.

Figure 1

Average Annual Number of Tornados for the Continental U.S. from 1991-2015

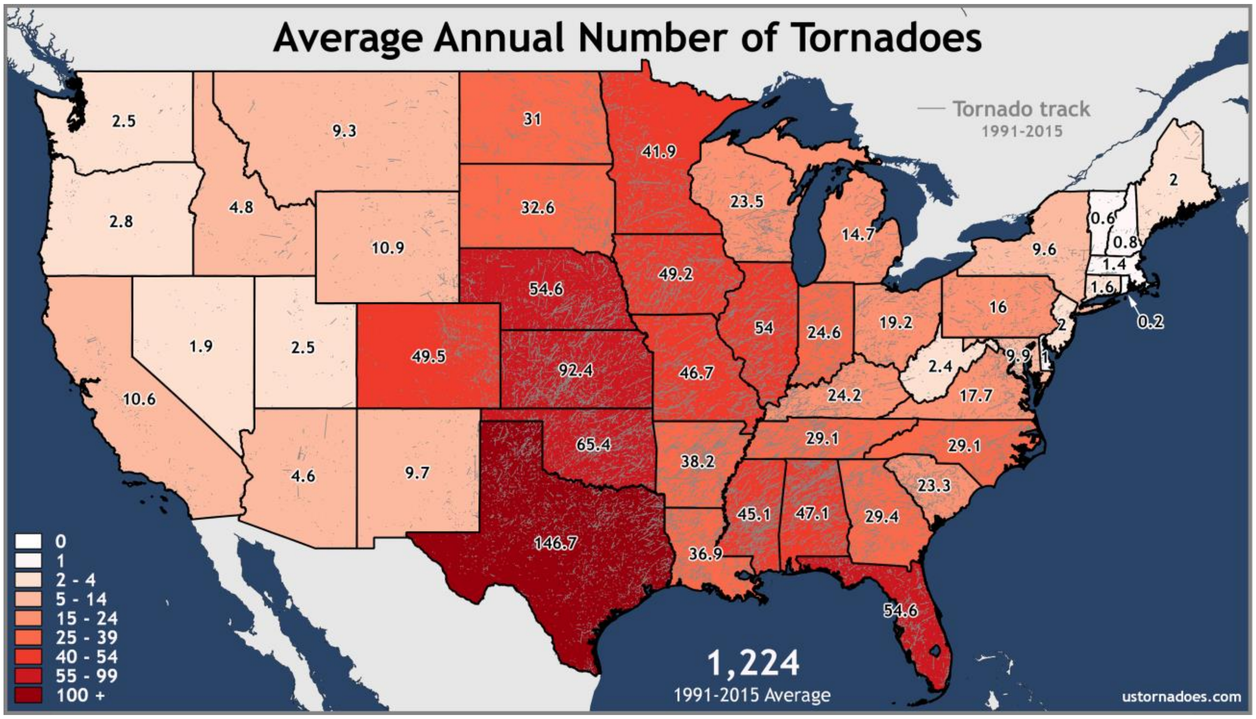

Image from ustornados.com

In 1925 the Tri-State Area experienced such a large tornado that killed 695 people and destroyed many towns. This tornado is known as one of the deadliest of all time and set records for duration and distance. The winds hit around 300 mph (480 km) classifying it as an EF5 tornado in the Enhanced Fujita Scale.[3] Overall, this tornado traveled 219 miles and lasted around 3 hours. Thousands of people were left stranded from this storm and fires, looting, and theft increased after the tornado hit, only making the hardship worse (Brittanica, Tri-State Tornado). Thinking about how devastating tornados can be, how these communities rebuild is important

[3] Prior to 2007, tornados were categorized in the *Fujita Scale*, which did not consider precise windspeeds. The National weather service began using the *Enhanced Fujita Scale* to provide an indicator of damages and a wind speed rating. (NOAA)

and what economically is affected from this damage needs to be determined for adequate planning. Figure 2 is a graphic that visualizes the weight of tornados ranked by the Enhanced Fujita Scale.

Figure 2

Category (EF Scale) of all Tornados from 1950-2019

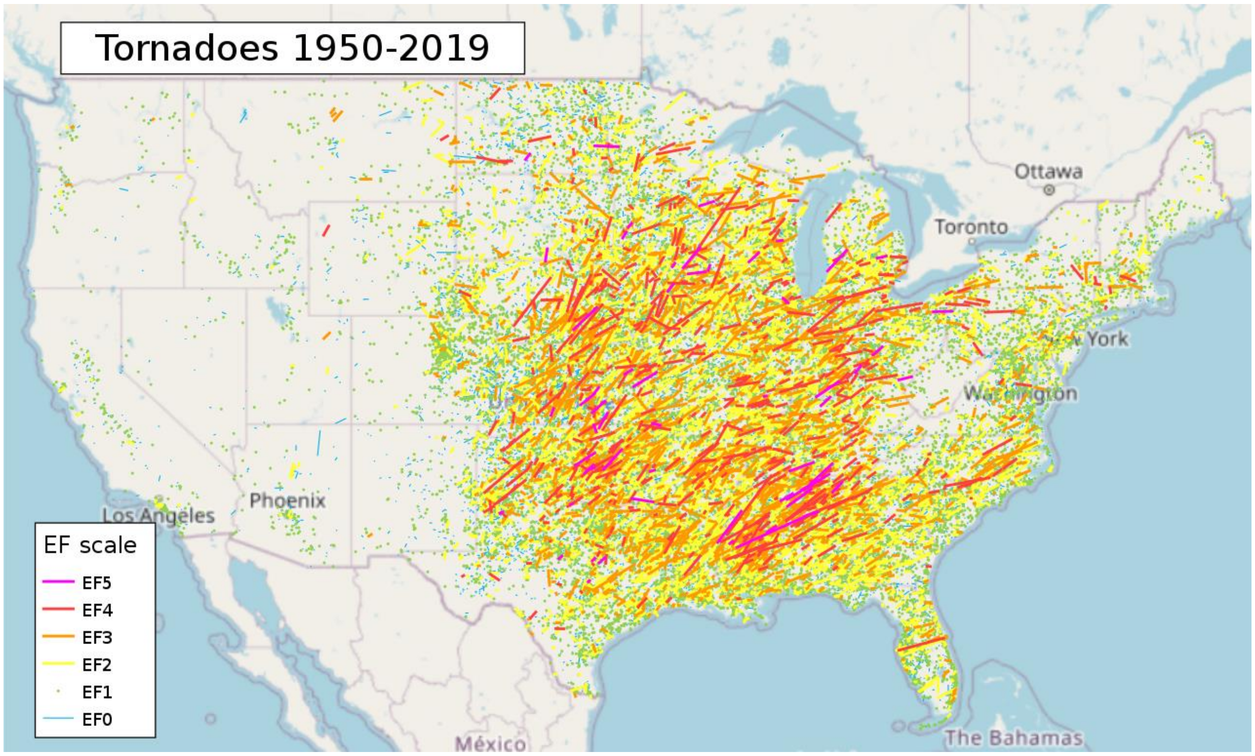

Image from Google Images/Wikipedia

As Figure 2 shows, most tornados fall into the EF2-EF5 category, meaning they produce strong winds and large impacts. Tornados are completely randomized, and localized events that can happen anywhere. Narrowing in on tornados versus other natural disasters provides a benefit to this research. Where flooding and natural disasters can affect multiple areas and the effects can linger, as well as flooding areas typically have more mitigation efforts in play due to the knowledge of being located in a flood-prone area, tornados can happen in any location and there is not much preparation one can partake to mitigate the devastation risk.

The interest of this paper is to focus on how natural disasters, specifically tornados, can affect the job market and incomes of the affected area and of surrounding areas where the environmental refugees are forced to flee. Looking at the most devastating tornados in the recorded history of the United States, this paper will show how these major events affected the economy of the county that experienced the tornado compared to their neighboring counties.

Background

Literature on natural disasters is extensive. There are multiple kinds of natural disaster events such as hurricanes, floods, ice storms, earthquakes, and tsunamis. There is a plethora of studies done on the economic impacts of these disasters. How these disasters effect migration, employment, incomes, and wages is widely discussed in the economic world as well as the environmental science industry. Understanding the full capacity of impacts that tornados in particular can have on the affected area as well as the surrounding areas requires a comprehensive literature review on the impacts of natural disasters.

To look at the impact of natural disasters on in/out migration and accompanying impacts on surrounding counties it is important to understand how migration models are designed, what type of data is commonly used, and the underlying assumptions and theories developed regarding the topic.

Migration rates differ by income and education level with the higher income and educated households able to flee when disasters strike. Saldana-Zorrilla and Sandberg (2009) look at the impact of climate-related disasters across Mexico using a spatial model that examines the difference in migration relative to incomes for specific areas. Their results find regions frequently affected by natural disasters with high increases in poverty have higher migration rates. They also find high levels of migration occur in regions with high education levels in marginalized regions, confirming human capital drain (Saldana-Zorrilla, Sandberg, 2009). Drabo and Mbaye's (2014) analysis of panel data from developing countries showed that those with higher education levels are the most likely to migrate after a natural disaster.

Ruiz and Vargas-Silva (2013) study the economics of forced migration and the impacts on host communities. Their paper highlights major issues with previous forced migration literature and examines possible solutions to these challenges. When estimating the impact of displacement on the host communities it is difficult to establish a counterfactual, increases in forced migrant populations are not always exogenous, and data collection is a problem. They show that using the difference-in-differences method can be useful for dealing with the counterfactual issue. Their results suggest consequences for those forced to migrate, with those who can capitalize off the new market with the influx of population; their incomes are shown to increase, whereas those who are not as well off or not entrepreneurs tend to suffer more.

Berlemann and Steinhardt (2017) study climate change, natural disasters, and migration using the available empirical evidence. They discuss many models that were previously used to measure the impact of natural disasters on migration flows highlighting the data limitations that arise when dealing with this topic. Distinguishing between internal and international migration is key in this study to have access to the correct data. Bilateral migration flows have become a major database for migration studies starting in the 2000's and seem to be the most commonly used in this type of research at the macro level.

Almost all micro studies focus on a country or region and use census or survey data, which can differ in each case and lead to reporting and reinterpretation bias. Yet micro panel data sets can be used to identify internal migrants by comparing the residence of an individual over time (Berlemann, Steinhardt, 2017). This overview highlights many different sources for environmental disasters and climate variations, pointing out the most commonly used as the Emergency Events Database (EM-DAT), which contains data on over 22,000 major disasters in the world from 1900 to the present day (Berlemann, Steinhardt, 2017).[4]

Hornbeck (2012) uses an empirical analysis that focuses on the speed and magnitude of relative agricultural adjustments in eroded counties form the 1930's dust bowl. Hornbeck (2012) looks at the difference in short-run and long-run agricultural costs, and the geographic reallocation of labor and capital. The balanced panel data used is constructed from information on 779 Plains counties from 1910 to 1997. The framework for the empirical analysis is estimating the average changes for more eroded counties compared to the average changes for less-eroded counties in the same state. The identifying assumption for this case is the common trend assumption; that all counties with different erosion levels would change the same in the absence of the Dust bowl.

The results of the Hornbeck (2012) analysis imply agricultural land values declining in high-erosion and medium-erosion counties relative to changes in low-erosion counties. Land values declined more in high-erosion counties than the others, and these declines were substantial and persistent. "From 1930 to 1940, land values fell by 30 percent in high-erosion

[4] The Emergency Events Database, *EM-DAT*, contains extreme weather event data for most regions around the globe. This historically accurate database has been used in many natural disaster and climate change studies, however, only contains regional or by country data.

counties and 17 percent in medium-erosion counties" (Hornbeck, 2012). These estimates indicate an economic loss of $2.4 billion.

Boustan, Kahn, and Rhode (2012) use migration data from the 1920's and 1930's to study how the population responded to disaster shocks during a time of minimal public investment using a conditional logit model of migration. They find that young men tend to move away from areas hit by tornados but toward areas that experience flooding. This increase of migration toward flooded areas and away from tornado struck areas seems related to public financial support for disaster mitigation in flood-prone areas. This influx of young entrepreneurial men is due to the increase in demand for goods and services they may be able to provide.

Ewing, Kruse, and Thompson (2004) look at the employment effects of the 1988 Nashville tornado. They use a variation of Enders (2004) intervention time series econometric model to find how differing industries employment was affected. Their research finds that while there is minimal effect on the growth rate of total employment, there were substantial employment disruptions in some sectors such as the services industry while others expanded. Employment losses and gains roughly counteracted one another.

Ewing, Kruse, and Thompson (2004) did another study on employment growth after a tornado in Fort Worth, Texas. In this paper they find the regional labor market experiences a decline in the employment growth rate after the tornado, and mining is the only industry to see a significant increase. Most industries, however, saw little to no change in employment growth from before to after the tornado. If indeed there is no change to employment after a tornado, it could be that wages or income absorb the lost employment demand rather than lost jobs. That is why this paper will look at the effects of a tornado on employment, wages, and incomes of the affected counties and their neighbors.

Data

The data used for this paper was constructed out of three existing databases. Using a dataset from the National Oceanic and Atmospheric Association (NOAA) containing extensive information on tornado activity from 1950-2019, another set including Federal Information Processing Standard (FIPS) county codes and their neighboring counties FIPS codes, and lastly, data compiled by the U.S. Bureau of Economic Analysis that includes county-level information on employment, income, and wages from 1969-2019.[5] I assign this data to each treatment and control by year, using the county FIPS code.

The NOAA tornado data included values for property damage, crop damage, injuries and fatalities, location, and year of the event. The location for the tornado was measured using the state code as one variable and the county code as another. To obtain the FIPS code the state and county codes had to be merged and created as a new variable. This was done by multiplying the state code by 1000 and adding that value to the county code. Another stumble with the tornado data is the measurement of property damages. From 1950-1996 property damages were measured by a range of dollars represented with a number from 1-9, where 1 represents <$50, 8 is $50-$500 million, and 9 is over $500 million. From 1996 to 2019 this same variable is measured in real millions of dollars. To account for this difference, the percentiles of tornado damages before 1996 and after 1996 were measured separately. Tornados were included if they were in the top 7% of damaging tornados. Since the economic information for each county

[5] The U.S. Bureau of Economic Analysis provided information on each county in the United States, containing over 160,000 observations. This dataset included values for each county’s employment, wage, and income per capita.

ranged in years from 1969-2019 the tornado data beginning in 1950 was dropped to observations from 1970-2019.

The employment, income, and wage per county data were merged by county and year, allowing for the observation (tornado) to align with each affected county, the neighbor counties, the year the tornado took place, and the corresponding employment, income, and wage values. From there new variables were generated that took the values from the next one, two, and three years after the tornado event, and one year before.

Method

The model used in this analysis is the Difference-in-Differences regression, controlling for county and time effects, and grouping the control as neighbor counties to the treatment tornado counties should give an estimation of the causal impact of tornados on the economy of those areas. The underlying economic theory here is that when a significant tornado hits a specific area, the devastation to infrastructure causes a large movement of people to neighbor counties as environmental refugees, which then impacts the employment opportunities, wage rates, and income levels of the population in that neighboring county.

The estimation method was set up as follows. Let Y_{t+T}^{T} be the observed economic outcome in a county hit by a tornado in year *t.* The superscript *T* stands for treatment or tornado. We will measure the outcomes from *t-1,* the year before the tornado hits, to *t+T, T* years after the tornado hits. The proportional change in economic outcome from before to *T* years after the tornado is $\left(\frac{Y_{t+T}^{T}}{Y_{t-1}^{T}}\right)$. The related measure of economic change for a control county, defined as a county adjacent to the tornado county, is $\left(\frac{Y_{t+T}^{C}}{Y_{t-1}^{C}}\right)$. The difference between these measures is the difference-in differences estimator, interpretable as the growth in the neighbor county relative to the tornado county, $\left(\frac{Y_{t+T}^{C}}{Y_{t-1}^{C}}\right) - \left(\frac{Y_{t+T}^{T}}{Y_{t-1}^{T}}\right)$.

We analyze the differences in two ways. The most straightforward is to derive the average value of the difference-in-differences, which is just a regression of the measure on a constant term,

$$\left(\frac{Y_{t+T}^{C}}{Y_{t-1}^{C}}\right) - \left(\frac{Y_{t+T}^{T}}{Y_{t-1}^{T}}\right) = \beta + \varepsilon_{t+T}^{T}; T = 1,2,3$$

The constant term, β, is the average effect of the tornado on the neighboring county compared to the economic changes occurring at the same time in the tornado county. If the tornado disrupts economic activity in the treatment county and/or if neighboring counties absorb displaced residents or are contracted to help rebuild the tornado county, we would expect that $\beta > 0.$ On the other hand, if the tornado attracts resources to be used in rebuilding, employment or income could rise in the tornado county compared to its neighbors. In that case, $\beta < 0.$ I vary T from one to three years after the tornado year to examine if initial effects dissipate over time. I cluster the standard errors by tornado county to control for correlated errors across adjacent counties.

This equation gives nine outputs, including the year effects of employment, income, and wages. From here, these new differences outputs are regressed with no added controls since time and location are controlled in the equation.

The effect of the tornado may depend on the magnitude of the damage. Although I look at only the 7% most damaging tornados over the sample period, it may be that only the most damaging tornados have an effect. Define a dummy variable D_t^T to be one when the tornado was one of the 1% most destructive tornados. If it is only the very most destructive tornados that affect economic outcomes, in the regression,

$$\left(\frac{Y_{t+T}^{C}}{Y_{t-1}^{C}}\right) - \left(\frac{Y_{t+T}^{T}}{Y_{t-1}^{T}}\right) = \beta_{2-7} + \beta_1 D_t^T + \varepsilon_{t+T}^{T}; T = 1,2,3$$

Regressing the differenced outputs controlling for the weight of the tornado's destruction could show a difference in impacts, which would reveal whether the effect of a large tornado on employment or income is greater than from a less devastating tornado. The coefficient β_{2-7} will be the effect of tornados with damage in the 2nd through 7th percentile, and β_1 will be the added effect of the 1% most devastating tornados. Negative coefficients will imply faster growth in the tornado counties while positive coefficients imply a decline in growth.

The Difference-in-Differences estimation should not be affected by endogenous sorting into the treatment group. I assume that tornados are random events that are not anticipated by residents in treatment or control counties. That way, the coefficients will reflect the impacts of unanticipated disasters on household choices.

Results

Below are the regression outputs revealing the impact that tornados have on employment, income, and wages. Total employment and wages had the most significant impacts one year after the tornado year. Income does not seem to be affected from the devastation of tornados. The DID method used here takes the control minus the treatment, so the results need to be interpreted in this way. The results are given in Table 1.

To account for county proximity and tornados that may have affected multiple counites, the regressions were done with clustering by each FIPS county. With clustering, the first regressions on the differenced variables did not include controls, besides the time and location effects controlled for in the differencing equation. These outputs represent the causal impact of tornados on the local economy’s wages, employment, and incomes. Employment and wages after the first year seem to have a significant impact and a coefficient of -0.0019019 and -0.0023834, respectively.

Table 1

Difference-in-Differences Regression Estimates of Tornado Effects on Employment, Wage Employment, and Income

	Year 1	**Year 1**	**Year 2**	**Year 2**	**Year 3**	**Year 3**
Equation	**1**	**2**	**1**	**2**	**1**	**2**
Employment						
Cons	-0.0019 (-2.53)**	-0.0017 (-2.36)**	-0.0167 (-0.51)	-0.0208 (-0.61)	0.0083 (0.19)	0.0043 (0.10)
Intensity		-0.0030 (-0.76)		0.1189 (1.19)		0.1132 (1.01)
N	15,353	15,353	15,351	15,351	15,351	15,351
R^2	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000
Wage Employment	**Year 1**	**Year 1**	**Year 2**	**Year 2**	**Year 3**	**Year 3**
Equation	**1**	**2**	**1**	**2**	**1**	**2**
Cons	-0.0023 (-2.52)**	-0.0022 (-2.30)**	-0.0292 (-0.58)	-0.0368 (-0.71)	0.0067 (0.11)	-0.0007 (-0.01)
Intensity		-0.0052 (-1.04)		0.2196 (1.17)		0.2163 (1.08)
N	15,353	15,353	15,351	15,351	15,351	15,351
R^2	0.0000	0.0002	0.0000	0.0001	0.0000	0.0001
Income	**Year 1**	**Year 1**	**Year 2**	**Year 2**	**Year 3**	**Year 3**
Equation	**1**	**2**	**1**	**2**	**1**	**2**
Cons	0.0005 (0.55)	0.0006 (0.71)	0.0007 (0.61)	0.0007 (0.62)	0.0013 (1.15)	0.0014 (1.24)
Intensity		-0.0046 (-1.32)		-0.0008 (-0.21)		-0.0041 (-0.86)
N	15,353	15,353	15,351	15,351	15,351	15,351
R^2	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001

Notes: These results are for the period of 1970-2019. The two stars (**) show statistical significance at the 95% level. Equation 1 refers to the regression without the tornado dummy variable, equation 2 includes the tornado dummy control.

Next, the regression on the differenced variables included a control for the weight of the tornado. Adding a dummy variable for the top 1% of damages caused from a tornado and controlling for this dummy produced very similar results. Again, employment and wages were affected one year after the tornado with negative coefficients. Meaning the most damaging tornados recorded in the United States caused some growth to employment and wages in those counties.

It is clear that tornados have some impact on the labor market causing employment and wage growth one year after the tornado. For the next subsequent years, the coefficients become smaller, showing the growth levels out to pre-tornado levels. This temporary increase could be due to volatility in the labor market, and certain sectors are growing in demand compared to others. An area for future research would be to look at the impacts by sector like Ewing, Kruse, and Thompson (2004) papers, to measure how each industry is affected separately. [6]

These coefficients show that employment and wages one year after a tornado devastation actually increase in growth, although the effects are small. This signifies that a tornado that causes significant damages can cause growth in the local job market for that county compared to its neighbors. This could be due to the rebuilding that is required after a large tornado, causing certain industries to expand employment. Another reason could be that some people choose to leave the area completely (i.e., another state) causing job supply to decrease in that area, which would increase demand and wages for employment.

[6] As mentioned in the literature review, Ewing, Kruse, and Thompson have multiple research papers on the effects of tornados on employment looking at county level. These studies include the Nashville tornado, the Fort Worth, TX tornado, and (not mentioned) an Oklahoma tornado. Their results align with this study.

Looking at the negative coefficient from the regression, it is clear there is some growth in employment after a tornado, but this growth could be due to growth in the treatment county or a decline in growth in the neighbor county. To distinguish between which is the cause, new variables are created as a measure of change for each dependent variable. The model decomposes the two parts of the difference in differences into their first difference component.

$$\left(\frac{Y_{t+T}^{C}}{Y_{t-1}^{C}}\right) = \gamma_C + \epsilon_{t+T}^{C}; T = 1,2,3$$

$$\left(\frac{Y_{t+T}^{T}}{Y_{t-1}^{T}}\right) = \gamma_T + \epsilon_{t+T}^{T}; T = 1,2,3$$

The coefficients γ_C and γ_T represent 1 plus the proportional growth in the dependent variable for the control and treatment groups, respectively. Values greater than one imply increasing values while those less than one imply shrinking values.

The results of these first difference regressions for each dependent variable are given in Table 2.

Interestingly, both the control and treatment counties experience some growth in employment, however the treatment counties are experiencing more growth in employment compared to their neighbors. This faster growth in the tornado counties compared to the control counties accounts for the negative coefficient in the differenced regression. For example, the control counties adjacent to the county hit by the tornado grew 2.9 percent in the following year, but the county hit by the tornado grew slightly faster at 3.1%. Growth accelerates dramatically in year 2 and again in year 3, but the advantage of employment growth in the tornado county does not disappear until the third year. Results for wage employment growth are nearly identical to those of overall employment.

Table 2 First Difference Regressions Showing Changes in Employment, Wage Employment and Income in Treatment and Control Counties

	Year 1		**Year 2**		**Year 3**	
Measure of Change	Control	Treatment	Control	Treatment	Control	Treatment
Employment						
Cons	1.0295 (0.000)	1.0314 (0.000)	1.1166 (0.000)	1.1332 (0.000)	1.2473 (0.000)	1.2388 (0.000)
N	15,355	15,363	15,353	15,363	15,353	15,363
R^2	0.000	0.000	0.000	0.000	0.000	0.000
Income	**Year 1**		**Year 2**		**Year 3**	
Cons	1.1203 (0.000)	1.1199 (0.000)	1.1003 (0.000)	1.0995 (0.000)	1.0456 (0.000)	1.0456 (0.000)
N	15,355	15,363	15,353	15,363	15,353	15,353
R^2	0.000	0.000	0.000	0.000	0.000	0.000
Wage Employment	**Year 1**		**Year 2**		**Year 3**	
Cons	1.029 (0.000)	1.0318 (0.000)	1.1626 (0.000)	1.1917 (0.000)	1.3538 (0.000)	1.3468 (0.000)
N	15,355	15,363	15,353	15,363	15,353	15,363
R^2	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Treatment counties were hit by a tornado and control counties were adjacent to a county hit by a tornado. Each measure of change is calculated taking the value of the dependent variable one year, two years, and three years after the tornado divided by the value one year before. Employment shows both the control and treatment groups increasing over the time period, and treatment is increasing at a faster rate.

With income, both treatment and control counties get a surge in income of about 12 percent after the first year, but the income falls thereafter. By year 3 after the tornado, the growth in income is just 4.6% above its pre-tornadic level in both treatment and control counties.

Conclusion

Natural disasters today are more prevalent than ever, with increasing intensity and duration, and climate change inciting fear across the globe. To adequately prepare for devastating weather events, we need to understand the economic impacts they can cause. This paper highlights the economic effects that tornados can have on employment, income, and wages for not only the effected county, but its neighbor counties as well. This research shows that employment and wages are slightly affected by a damaging tornado by actually causing growth for one year after and leveling out to pre-tornado levels by three years after. Incomes do not seem to be affected at all by these extreme weather events. This growth could be attributed to rebuilding efforts, showing more growth in certain job markets compared to others. City planning officials need to look at these affects to prepare for fluctuations in the labor market directly following a tornado.

Areas for future research include separating the data out by labor sector to identify which industries are growing/decreasing following a tornado. Incorporating FEMA and Red Cross donations could also be useful to see if these payments have any effect on the local labor market. Another area of interest could be narrowing the scope of counties to rural areas compared with major cities, as the effects of a tornado may be different.

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