Do Rural Areas Experience the Same Benefit as Urban Areas from Disasters?

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Abstract

This study makes a unique contribution to the economic and regional science literature on the impacts of disasters by focusing on an understudied area of fiscal impacts of disasters in rural areas. Specifically, it focuses on the differences in sales tax collections in Appalachian and non-Appalachian Ohio counties following a series of Derecho wind storms in the summer of 2012. We find Appalachian counties experience a decrease in sales tax collections of $254,845 per county post storm compared to their non-Appalachian counterparts in the state. In total, the Appalachian region lost nearly $5.1 million in sales tax collections. We argue that the limited economic base of rural economies not only makes them less resilient to natural disasters, but also prevents them from experiencing the post-disaster economic and fiscal benefits that often occur in urban areas.

1 Introduction

The purpose of this paper is to examine the fiscal impact of natural disasters on rural counties. It contends that the fiscal impact of disasters is substantially different in rural counties compared to their more urbanized counterparts in a state. This theory is tested using the case of straight-line wind storms with winds from 60 to 80 miles per hour, called Derecho storms, that occurred in Ohio in the summer of 2012 (Weather Forecast Office, 2012). This historic Derecho wind weather system resulted in the third costliest natural disaster in Ohio in nearly 40 years (Williams, 2013). The disaster led to over $400 million in insurance losses and a presidential disaster declaration in 39 of Ohio's 88 counties. Both Appalachian and non-Appalachian counties were impacted by the storm.

Some studies of the disasters have found that there is an immediate net positive economic effect (Ewing et al., 2005, 2009) or fiscal effect (Harper and Hawkins, 2006), while others have found longer-term economic improvements (Ewing and Kruse, 2001; Skidmore and Toya, 2002) or employment growth stability (Ewing et al., 2004) post disaster. Other studies have found some sectors benefit but the net economic loss is negative (Guimaraes et al., 1993; Ewing et al., 2003). Yet, a gap in the economic literature exists examining this variation across urban and rural contexts for the same disaster. Most of these studies have focused on relatively urban counties with dense populations and diverse economic bases. We question whether the findings of a positive economic or fiscal impact are generalizable to rural counties with less dense populations and less diverse economies. In general, the fiscal impact of disasters (i.e., tax collections) is largely understudied in the economic and regional science literature.

Our rationale for reexamining the findings on the fiscal impact of a disaster is two-fold. First, different types of people in a community tend to feel the effects of a disaster and be more susceptible to the damage caused by a disaster more acutely than others (Cutter et al., 2008). Given this idea, we argue that when individual economic behavior is aggregated to the county level, some counties will feel the effects of a disaster more acutely than others. And, second, some communities tend to be resilient or "bounce back" after a disaster more keenly than others. This is in large part due to the wide degree of variability from one community to another community in how they prioritize disaster planning and balance it with economic growth (Berke, 1996), the quality of their disaster plans (Berke and French, 1994; Burby and May, 1997; Berke et al., 2012), and the robustness of their economic, political, and social institutions (Boettke et al., 2007). Because of the variability in priorities and quality, we question the ease that rural counties can bounce back after disaster, particularly in fiscal terms. The differences in how rural counties bounce back after disaster and return to regular daily life, as indicated by fiscal impact, is different when compared to more urban counties in the same state experiencing the same disaster.

The central theory of this study is that the 32 Appalachian counties in Ohio are more rural and more impoverished than their non-Appalachian counterparts. As such, they are more vulnerable to the effects of a disaster. Ohio's Development Services Agency (2017) reported 15 of the state's 16 counties with the highest poverty rates in Ohio were Appalachian. Our rationale is that more vulnerable groups tend to feel the effects of disaster more acutely and tend to need more sheltering and recovery services than other individuals in their communities (Bolin and Kurtz, 2007). We focus on sales tax collections post disaster in Appalachian vs. non-Appalachian Ohio counties. We contend that Appalachian counties, which have a more limited economic retail base, will not experience the same post disaster fiscal benefit from retail sales. We test that by examining pre– and post-disaster sales tax collections in Appalachian and non-Appalachian counties impacted by the Derecho storms.

2 Literature Review

Major disasters, like the Midwest Floods, Hurricane Andrew, or the Northridge Earthquake, can cause more harm to the economy than just property damage in a community by disrupting business activity and generating economic losses (Webb et al., 2000). However, the economic losses caused by a natural disaster are reduced by the relative resilience of a community. The concepts of disaster vulnerability and resilience are interrelated. Vulnerability generally refers to how much natural hazard risk there is in a given physical location, within a social group, and based on the extent to which individuals in that group are advantaged or disadvantaged (National Research Council, 2006).

Disaster resilience is defined as a community's ability to bounce back from the impact of a disaster (Rose, 2004). The economic impact of a disaster is defined as the economic consequences of a disaster and is usually measured in dollars (Chang and Rose, 2012). Disaster resilience has two key components: inherent resilience that refers to the resources and capacity that communities have in non-disaster times; and adaptive resilience in which resources and opportunities are mobilized after a disaster (Rose, 2004). This study is focused on the economic consequences of a disaster for vulnerable rural communities.

The economic impact of disasters is generally divided into two types of studies. The first examines the economic impact on businesses affected by a disaster. The key findings about the economic effects of disasters on businesses are that while they do recover, that recovery varies by type of business (Webb et al., 2000; National Research Council, 2006; Chang and Rose, 2012). Small businesses and locally based businesses that rely on customers that have been affected by a disaster tend to have the greatest negative economic impact (Dahlhamer and Tierney, 1998; Webb et al., 2000; Chang, 2010). We anticipate that this will be true for rural communities that typically do not have diverse economic bases. Simply put, in rural communities with fewer businesses and thin markets, the owners, employees, and customers are all likely to feel the effects of a disaster, thereby reducing sales tax collections after a storm.

In addition, businesses that tend to be on the decline before a disaster tend to continue that trend after a disaster (Chang, 2010; National Research Council, 2006). This particular category of impacts is central to this study because it is directly related to sales tax collections. If businesses in rural Appalachian counties were generally on the decline, we would expect that sales tax collections to also be on the same declining trend after a disaster.

The second type studies the economic impact of disasters on communities. There is far less consensus on what the effect of a disaster is on a community's economy. Early research in the field asserted that there was no noticeable economic impact of a disaster on a community, and that the economic trends occurring would continue at relatively the same rate after a disaster (Rossi et al., 1981; Friesema, 1979). In contrast, in developing countries the economic impact of a disaster was an opportunity for economic development, creating a boon for investment and economic benefits (Dacy and Kunreuther, 1969).

Economic and regional science studies of disasters have also found mixed results. Ewing, Kruse, and Thompson have studied a variety of disasters and the effects of those disasters on local economies. Their studies include findings that Corpus Christi, Texas saw a labor market improvement post hurricane (Ewing et al., 2005), Oklahoma City's Metropolitan Statistical Area saw increased employment growth with some negative impact to some sectors post tornado (Ewing et al., 2009), Nashville, Tennessee's labor market saw more stable aggregate employment growth with some variation (both positive and negative) across sectors (Ewing et al., 2003), and that Fort Worth, Texas saw a decline in employment growth post tornado (Ewing et al., 2003).

Skidmore and Toya (2002) conducted a study of cross-country impacts of disasters on long-run growth and found disasters associated with increased rates of human capital accumulation, total factor productivity, and economic growth. Other studies have noted the challenges of model fit in determining the economic impacts of disasters on income inequality (Shaughnessy et al., 2010).

Some studies have found that testing of the economic development hypothesis has revealed that disasters are not necessarily an engine for economic growth. In the near-term after a major disaster, like the 1995 earthquake in Kobe, Japan, communities experience an economic boost from reconstruction efforts after a disaster for a few years following the event but the lasting effect dissipated over time (Chang, 2010). At best, the consensus in the literature is that disasters can concentrate economic benefits in one sector of the economy or one level of economic activity, but it occurs at the cost of another sector or level of economic activity (National Research Council, 2006).

The local fiscal impact of disasters is understudied in the economic and regional science literature. Chang (1983) found the influx of recovery funds to Mobile, Alabama in the aftermath of Hurricane Frederic led to a \$2.5 million increase in municipal revenue over the next year. Harper and Hawkins (2006) studied the local sales tax base following a series of hurricanes in Florida in 2004. They found some evidence of a "fiscal blessing" in the form of increased taxable sales from the rebuilding effort. The magnitude of this effect was mitigated depending on the impact to major retailers and level of evacuation. Unlike these two studies, we are skeptical that reconstruction and rebuilding efforts after a disaster would be sufficient to create a fiscal boon for local governments in Appalachian counties after a disaster due to the lower population density and retail economic base in a rural area.

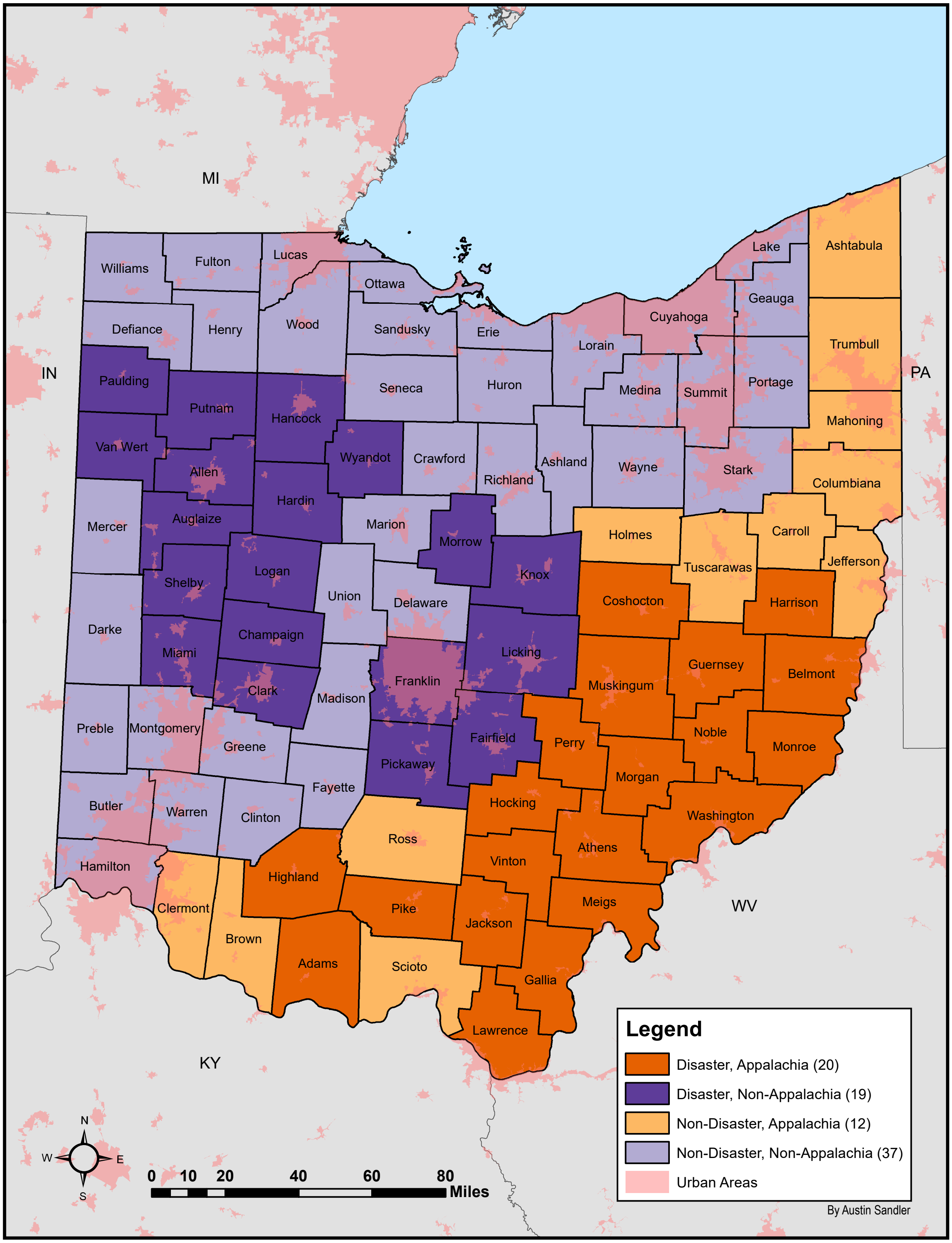
3 Data, Methods and Model Approach

We show this disaster discrepancy effect by looking at the sales tax collections for each county in the state over a 15-year time span. The Derecho disaster serves as an ideal scenario to explore this difference in collections pre- and post-disaster. Figure 1 shows that of the 88 counties in Ohio, 32 are Appalachian counties and 56 are non-Appalachian; with 39 disaster designated counties and 49 non-disaster designated counties. Of the 32 Appalachian counties, 20 are disaster designated counties and 12 non-disaster designated counties. And of the 56 non-Appalachian counties, 19 are disaster designated counties and 37 non-disaster designated counties.

We defer to the Appalachian Regional Commission definition for designating the 32 counties that are considered part of the Appalachian region. These include Adams, Ashtabula, Athens, Belmont, Brown, Carroll, Clermont, Columbiana, Coshocton, Gallia, Guernsey, Harrison, Highland, Hocking, Holmes, Jackson, Jefferson, Lawrence, Mahoning, Meigs, Monroe, Morgan, Muskingum, Noble, Perry, Pike, Ross, Scioto, Trumbull, Tuscarawas, Vinton, and Washington counties (ARC, 2017).

The U.S. Department of Homeland Security's Federal Emergency Management Agency (FEMA), desig-

Figure 1: Map of Ohio Highlighting Derecho and Appalachian Counties



nated federal disaster assistance to Ohio on August 20, 2012, declaring 37 counties as disaster areas from severe storms and straight-line winds during the period of June 29 to July 2, 2012. These include Adams, Allen, Athens, Auglaize, Belmont, Champaign, Clark, Coshocton, Fairfield, Franklin, Gallia, Guernsey, Hancock, Hardin, Harrison, Highland, Hocking, Jackson, Knox, Lawrence, Licking, Logan, Meigs, Miami, Monroe, Morgan, Morrow, Muskingum, Noble, Paulding, Perry, Pickaway, Pike, Putnam, Shelby, Van Wert, and Washington counties. On September 21, 2012, Vinton and Wyandot counties were added to the disaster declaration. Public Assistance Grants have totaled $16,609,403.85 for both emergency and permanent work (FEMA, 2012).

We assembled monthly permissive sales tax and use tax collections by county from January 2000 to December 2015 (see Table 1). The Ohio Department of Taxation administers permissive sales tax and use taxes for all 88 counties. County taxes are enacted at the local level, but are collected by the state along with a state sales tax. Taxes are either filed monthly or semi-annually, with most of the revenue coming from monthly sales filers of the previous month. Each monthly tax figure represents the tax returns collected in a county during the indicated month; the state will then distribute the funds back to the county after one month. This means that most sales in June are reflected in July collections, which are distributed back to counties in September. The Ohio Department of Taxation also has records on the state sales tax rate and each county's sales tax rate changes through time. We adjust prices using the Consumer Price Index (CPI), All Urban Consumers, Annual Average, Period 1982-84=100, to put dollar values in term of year 2000 prices.

Table 1: Summary Statistics of Permissive Sales Tax and Use Tax[a]

Sales Tax and Use Tax Categories	Observations	Mean	Std. Dev.	Min	Max
All	16,896	1,084,028	2,065,648	0	20,224,535
Pre Storm	13,200	1,037,894	1,961,717	0	19,177,785
Post Storm	3,696	1,248,793	2,393,426	52,008	20,224,535
NonDerecho	9,408	1,421,366	2,335,757	0	19,177,785
Derecho	7,488	660,193	1,565,594	0	20,224,535
NonAppalachian	10,752	1,415,444	2,507,011	0	20,224,535
Appalachian	6,144	504,049	454,775	0	2,767,453
Pre Storm & NonDerecho	7,350	1,377,300	2,284,307	0	19,117,785
Pre Storm & Derecho	5,850	611,460	1,342,146	0	16,174,684
Post Storm & NonDerecho	2,058	1,578,744	2,505,181	151,298	18,904,286
Post Storm & Derecho	1,638	834,241	2,176,066	52,008	20,224,535
Pre Storm & NonAppalachian	8,400	1,354,174	2,378,719	0	19,177,785
Pre Storm & Appalachain	4,800	484,402	447,087	0	2,567,319
Post Storm & NonAppalachian	2,352	1,634,266	2,909,592	91,937	20,224,535
Post Storm & Appalachian	1,344	574,217	474,808	52,008	2,767,453
NonDerecho & NonAppalachian	7,104	1,622,405	2,639,737	0	19,177,785
NonDerecho & Appalachian	2,304	801,494	533,186	0	2,767,543
Derecho & NonAppalachian	3,648	1,012,415	2,170,364	17,478	20,224,535
Derecho & Appalachian	3,840	325,582	2,746,763	0	2,089,920
Post Storm & Derecho & Appalachian	840	384,734	292,657	52,008	2,089,920
Pre Storm & Derecho & Appalachian	3,000	309,020	267,136	0	1,412,696
Post Storm & NonDerecho & Appalachian	504	890,021	546,971	151,298	2,767,453
Pre Storm & NonDerecho & Appalachian	1,800	776,707	526,775	0	2,567,319
Post Storm & Derecho & NonAppalachian	798	1,307,405	3,032,940	91,937	20,224,535
Pre Storm & Derecho & NonAppalachian	2,850	929,818	1,850,773	17,478	16,174,684
Post Storm & NonDerecho & NonAppalachian	1,554	1,802,113	2,830,532	193,743	18,904,286
Pre Storm & NonDerecho & NonAppalachian	5,550	1,572,087	2,581,819	0	19,177,785

[a]Statistics are rounded to nearest whole number for simplicity. Dollar values across time are normalized to base year 2000 dollar values.

As Wooldridge (2010) notes, "Much of the recent literature in policy analysis using natural experiments can be cast as regression with pooled cross sections with appropriately chosen interactions (pp. 147)." Following Wooldridge's suggestions, the simplest scenario involves two time periods (e.g., year 1 and 2) or more generally two clustered time frames (e.g., all months of 2000-2008 and all months of 2008-2015). There are also two groups, a control group and a treatment group. In the natural experiment literature, people often find themselves in the treatment group by accident (Wooldridge, 2010).

The natural experiment approach captures possible differences between the treatment and control groups prior to the policy change, and aggregate factors that would cause changes even in the absence of a policy change. Let $\overline{Revenue}_{D,1}$ denote the average of *Revenue* for the Derecho treatment group (D) in year 1, and let $\overline{Revenue}_{D,2}$ be the average of *Revenue* for the Derecho treatment group (D) in year 2. Let $\overline{Revenue}_{ND,1}$ denote the average of *Revenue* for the non-Derecho control group (ND) in year 1, and let $\overline{Revenue}_{ND,2}$ be the average of *Revenue* for the non-Derecho control group (ND) in year 2. The estimate can be expressed as:

$$(\overline{Revenue}_{D,2} - \overline{Revenue}_{D,1}) - (\overline{Revenue}_{ND,2} - \overline{Revenue}_{ND,1}). \tag{1}$$

The estimator has been labeled the difference-in-differences estimator in the recent program evaluation and policy analysis literature, although it has a long history in analysis of variance. By comparing the time changes in the means for the treatment and control groups, both group-specific and time-specific effects are controlled for.

In some cases, a more convincing analysis of a policy change is available by further refining the definition of treatment and control groups. The potential problem with difference-in-differences analysis is that other factors unrelated to the policy might produce different effects within groups. A more robust analysis can be obtained by using a control group across the treatment and control groups. We add the Appalachian (A) and non-Appalachian (NA) cross-policy grouping. The estimate can be expressed as:

$$\begin{aligned}&[(\overline{Revenue}_{A,D,2} - \overline{Revenue}_{A,D,1}) - (\overline{Revenue}_{A,ND,2} - \overline{Revenue}_{A,ND,1})]\\ &-[(\overline{Revenue}_{NA,D,2} - \overline{Revenue}_{NA,D,1}) - (\overline{Revenue}_{NA,ND,2} - \overline{Revenue}_{NA,ND,1})].\end{aligned} \tag{2}$$

Each of the square brackets contain a stand-alone (sub-regional) difference-in-differences estimate. This structure is called the difference-in-difference-in-differences estimate. Each of the effects can be interpreted as:

$$\begin{aligned}&[DerechoAppalachian - NonDerechoAppalachian]\\ &-[DerechoNonAppalachian - NonDerechoNonAppalachian].\end{aligned} \tag{3}$$

Specifically, our inputs are given by:

$$\begin{aligned}&[(384,734 - 309,020) - (890,021 - 776,707)]\\ &-[(1,307,405 - 929,818) - (1,802,113 - 1,572,087)],\end{aligned} \tag{4}$$

average loss for Appalachian counties in tax returns of \$185,161. Expressed in 2015 dollars as a loss of \$254,845. The loss is not trivial. It accounts for over half of the average monthly revenue for these Appalachian counties. Taken together, this means a total loss of \$3,703,220 for the region in 2000 dollars. Expressed in 2015 dollars, this loss amounts to \$5,096,900.

The difference-in-difference-in-differences framework measures the average sales tax decline (effect) in disaster declared Appalachian counties after netting out the change in the average effect in non-disaster declared Appalachian counties and the change in average effect in disaster declared non-Appalachian counties. Each curved bracket of the formula controls for time effects: the average difference of tax returns across time. Each square bracket of the formula controls for cross-sectional disaster effects: the average difference tax returns across the involved areas. The entire formula then controls for regional effects in and out of Appalachia (and cross-sectional and time).

We use the population analogue of the triple-difference approach. Our goal is to diagnose the idiosyncratic impact of the 2012 Derecho storm event in Appalachian Ohio. The 15-year panel dataset of Ohio county sales tax collections does not constitute a random sample. Instead the observations are the entire universe (population) of such data or else they are a nonrandom sample of Midwest/Greatlakes/Appalachian/East North Central counties from the first 15 years of the 21st century. Indeed, arguments from sampling theory are not relevant to our measurements (McCloskey and Ziliak, 1996). We do not use significance testing.

We do use the intuitive policy analysis framework of difference-in-difference-in-differences. Framing the problem this way we are able to directly measure the disproportional tax burden in Appalachian counties after a disaster. And consistent with previous disaster and differenced policy analysis, we observe an increase in sales tax collection after a disaster in non-Appalachian counties (Harper and Hawkins, 2006). The increase is, however, a gross measure and irrespective of income and substitution effects. Using the difference-in-difference-in-differences approach we account for mean response changes over time that are unrelated to the disaster effect. Appalachia counties do not show the same economic and financial recovery patterns as non-Appalachian counties. We suspect that this is largely due to the more rural setting with fewer retail and post-disaster recovery businesses like general contracting, roofing, building etc.

On adjusting for different tax rates across counties and time a historical perspective is utilized, not a hypothetical scenario. We have observations, data, and the entire population which we use to show the difference. To evoke hypotheses of ifs and suppositions is superfluous. We observe a loss of $185,161 (in 2000 dollars) from the population (i.e., the entire universe of possible observations). One could perform a simple regression and get the same result (but with inappropriate confidence intervals and a t-statistic tacked on). Some methodologists may even then be tempted to add in other covariates to make the model more "robust" (i.e., unnecessarily complicated). This again is a mistake, abusing the population, and adds further, more significant, sources of error such as efficiency, consistency, misclassification, endogeneity, heterogeneity, heteroskedasticity, multicollinearity, idiosyncratic error, specification error, and functional form (Bertrand et al., 2004; Ziliak and McCloskey, 2004).

4 Conclusion

While limited to the Derecho disaster that occurred in Ohio in 2012, our findings demonstrate two important lessons for other rural areas. First, we find Appalachian Ohio Counties experience an average loss of $185,161 in 2000 dollars ($254,845 in 2015 dollars) per county in sales tax collections as a result of the Derecho storm. This particular finding contradicts previous work that found disasters to be an economic boon (Chang, 1983; Harper and Hawkins, 2006). Our finding suggests that rural areas, and more specifically rural Appalachian counties, experience the economic and fiscal impact of a disaster in a fundamentally different way because of their sparse population density and lack of a diverse economy. This finding of an economic loss after a disaster warrants future investigation as Appalachian communities and the types of disasters they experience tend not to get significant attention compared to other communities that experience disasters.

Second, not only do rural counties fail to experience the post-disaster fiscal boon experienced in prior (albeit limited) studies of fiscal benefits of disasters in urban areas, they actually experience a net fiscal loss. Moreover, the net fiscal loss is one that will persist for years following the disaster. Fundamentally this finding means that for rural Appalachian communities in this study that were already at an economic disadvantage before the Derecho disaster, they suffer further disadvantage as a result of the storm. They do not bounce back to normal levels of economic activity after the disaster. Simply put, there is a new, lower level of normal sales tax collections after a disaster in the counties in our study. The implication of the lack of fiscal benefits to rural areas suggests additional policy interventions may be required to ensure the gap between urban and rural communities are not further exacerbated as the result of disasters.

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