# Impacts of Natural Hazards on County-level Per Capita Income in the United States

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### Introduction

Between 1960 and 2011, approximately 782 thousands natural hazards occurred in the U.S, causing a total $670.8 billion (in 2011 dollars value) economic damage, more than 30 thousand deaths and 227 thousand injuries (HVRI 2012). While we have all observed the economic disruptions caused by large natural disasters like the 2005 Hurricane Katrina and the recent severe winter storm on the eastern states, to date, there is still no clear answer on the impact of natural disasters on regional economy in general. Comparing to the voluminous social and scientific researches trying to improve the accuracy of disaster prediction, economic researches on the impact of natural disasters are very limited. Among the limited economic researches, almost all of them focus on the impact at the national level. This paper fills the gap by estimating the regional level impact of large natural disasters, using a difference-in-difference (DID) approach. To the best of our knowledge, this is also the first study that considers all types of natural disasters in the U.S. over the span of 40 years from 1969-2012.

The theoretical predictions on the impacts of natural disasters are mixed. Treating natural disasters as exogenous shocks that reduce physical capital, traditional neoclassical growth theory predicts that natural disasters do not affect long-run economic growth. However, natural disasters may lead to faster short-run economic growth because the consequent decrease in capital generates a temporal deviation from the balanced growth path. In contrast, the predictions of endogenous growth models are more diverse depending on the model assumptions. Models based on Schumpeter's creative destruction process assume that the destruction of physical capital can accelerate the adoption of new technology through the need to replace the damaged capital (Caballero and Hammour, 1994). Endogenous growth models that assume constant return to scale predict that natural disasters have no impact on long term economic growth. Those with increasing return to scale, however, predict that natural disasters decrease the long term economic growth. While recent empirical studies on the disasters' impact on national economy seem to converge to the consensus that disasters lower short-run economic growth, the findings are still inclusive, as reviewed in Cavallo and Noy (2011). On the one hand, Albala-Betrand (1993) and Skidmore and Toya (2002) find that natural disasters increase short-run economic growth. On the other hand, Raddatz (2007) Noy (2009) and Hochrainer (2009) reach the opposite conclusion. Loayza et al. (2009) reconciles the conflicting findings by suggesting that small disasters may have a positive impact due to the Schumpeter's creative destruction process but larger disasters always negatively affect the economic growth.

These theoretical and empirical predictions are based on economic analysis at national level at which factors of production typically do not have free mobility. At regional level, however, households and firms are much more mobile in their location choices. For this reason, the severity of natural disasters, either in terms of property damage or fatalities or injuries, might all be endogenous to households' and firms' location decisions that are typically unobservable to the researchers. With the advance of science and technology, particularly in developed countries like the U.S., households and firms are in general aware of their exposure to natural hazards when they make the location decisions. Consequently, households and firms are expected to pay higher premiums for life and home insurance when they choose a location with higher exposure to natural hazards. This also implies that the pre-disaster spatial distribution of population and economic activities across regions might have already embodied people's perception of spatial variations in the exposure to natural hazards. Because of this selection bias, a direct comparison between disaster affected and unaffected regions cannot reveal the true economic impact of natural disasters as seen in the analyses at the national level. For this reason, we adopt the quasi-experiment DID method to investigate the impact of larger natural disasters on regional economy in the U.S.

For each county and each occurrence of major natural disaster, a fixed effect is introduced to control for the county specific un-observables. The inclusion of the fixed effects helps to delineate the impacts of large natural disasters from all unobserved time-invariant determinants of county level per capita income. For instance, the exposure to flooding hazard also implies the proximity to water bodies like lakes, rivers or oceans. This proximity to water bodies can generate natural amenity services that are valued by many households, which can also affect household sorting and the consequent income distribution. However, the quality of the amenity services is usually unobserved or difficult to measure. The inclusion of fixed effect helps to identify the impact of natural disasters from these time-invariant community characteristics.

The data used for in this paper is the county level data for the U.S. from 1969 through 2012. To address the potential serial correlation problem discussed, we follow the recommendation proposed by Bertrand et al. (2004) to remove the time series dimension by aggregating the data into two periods: pre- and post-intervention, because this method is found to work well even for small samples.

Regarding the investigation of impact of natural disasters on regional income at a sub-national level for U.S.[1], the pioneering work of Strobl (2011) is the first and the only one in the existing literature. Using a standard conditional convergence growth equation, Strobl (2011)

[1] A few articles have looked at local impacts of natural disasters other than income. Evans, et al. (2010) investigates the impact on fertility rates in the U.S. Atlantic and Gulf of Mexico regions. Rodriguez-Oreggia et al. (2012) find that natural disasters adversely affect municipal-level human development and poverty indices. Belasen and Polacheck (2009) find that hurricanes reduce employment in Florida. Noy and Vu (2010) find that natural disasters decreases the provincial output in Vietnam.

examines the impact of 21 hurricanes with at least Saffir-Simpson (SS) category 3 on per capita income growth for 409 U.S. coastal counties in the North Atlantic Basin region during 1970-2005. The research finds that in the year when a county is hit by an average hurricane, the annual growth rate falls by 0.45 percentage point. However, hurricanes have no significant long-term effect.

The choice of DID method, the use of the SHELDUS dataset that covers different types of natural hazards for all U.S. counties and the explicit treatment on the potential serial correlation problem distinguish this paper from the pioneering work of Strobl (2011). We find that as the direct damage from natural disaster increases, the impact of county per capita income tends to last longer. More interestingly, we find that in the short-run income levels in metropolitan counties are more responsive to the damages of natural disasters and those for non-metropolitan counties are more resilient to small to medium damages from natural disasters. In the longer run, however, metropolitan counties are more resilient to damages in natural disasters than the non-metropolitan counties

## Data

### *Data sources*

The data on natural hazards and their human and economic losses are obtained from the Spatial Hazard Events and Losses Database for the United States (SHELDUS™ Version 10.0) [2]maintained by the Hazards & Vulnerability Research Institute (HVRI) at the University of South Carolina. SHELDUS is a county level dataset for the U.S. on 18 different natural hazard event types from January 1960 to December 2012. The main data source of this dataset is the "Storm Data and Unusual Weather Phenomena" by the National Climatic Data Center (NCDC).

[2] Data are available through http://webra.cas.sc.edu/hvriapps/sheldus_web/sheldus_login.aspx

From 1969 to 1989 and 1995 on, every event listed in NCDC's storm data set that had exact damage figures assigned was entered into the database. Each record from 1990 through 1995 refers to a hazard event affecting a county and generating total losses higher than $50,000 of either property or crop damage (HVRI 2014).

There are 18 hazard categories in SHELDUS dataset based on the NCDC hazard classification, including Avalanche, Coastal, Drought, Earthquake, Flooding, Fog, Hail, Heat, Hurricane/Tropical Storm, Landslide, Lightning, Severe Storm/Thunder Storm, Tornado, Tsunami/Seiche, Volcano, Wildfire, Wind, and Winter Weather. For each event, five measurements are recorded in the dataset: (1) the hazard begin date; (2) the hazard end date; (3) the number of people injured; (4) the number of people killed; (5) the amount of property damage; and (6) the amount of crop damage. Figure 1 shows the histograms of logged total damage losses including property losses and crop losses. We could see there are large variations of total damage losses due to occurrences of natural disasters across time and space, indicating the importance to consider different treatment events (cutoffs).

Figure 2 shows the spatial distribution of disaster damages in 2005. Even in a specific year, the economic losses due to natural disasters are distributed heterogeneously with some counties lose less than $1 million and others, such as counties in the southern and western costs, losses could reach $10 million or more. It is reasonable to assume an instant impact of small natural disaster in some counties with high capacity to recover as has been done in the previous literature, however, for large disasters, the impact could last for more than one year. Therefore, the magnitude and duration of the natural disaster impact on local economy could be different between counties with small and large losses, which also justify the necessity of using different treatment events (cutoffs) in this study.

Per capita income and population data collected from the U.S. Bureau of Economic Analysis (BEA) are available from 1969 to 2012. Per capita income is defined as the average income received by all persons from all sources and constitutes the sum of net earnings by place of residence, rental income of persons, personal dividend income, personal interest income, and personal current transfer receipts. Nominal values of per capita income were converted to real terms using the U.S. consumer price index. Figure 3 shows the time trend of averaged real per capita income and population from 1979 to 2012[3]. Both real per capita income and population have an increasing trend, suggesting there is a potential problem of time correlation in our data if we precede using traditional method, which also indicates the superiority of the DID approach we use in this paper. In addition, Figure 3 shows the importance of controlling population in the econometric model as it changes with time.

***Selection of the control group***

The quality of a DID estimation hinges on the quality of the control group selection, which in the essence depends on the degree at which the selected control group can help to control the other factors that may simultaneously affect the outcome of the treatment group. The introduction of the fixed effects in the econometric model helps to control the unobserved time-invariant county specific characteristics. However, the unobserved time-varying factors cannot be well controlled with the inclusion of only the population, which is the only variable that exists at county-level annually. So we resort to the Tobler's first law of geography: "Everything is related to everything else, but near things are more related than distant things" (Tobler 1970). For each county in the treatment group, we construct a control group county based on geographical adjacency, that is, a candidate control-group county needs to share some common

[3] Since we assume there was 10 years of no disaster occurrence pre each treatment, the earlier period we use for estimation is from 1979.

border with the corresponding county in the treatment group. Because rural and urban counties are generally regarded as quite different, we include an additional requirement, that is, a candidate control-group county should have the same rural-urban classification as the corresponding county in the treatment group. For example, if a rural county is included in the treatment group, its control group counties should also be rural. As a result, the neighboring urban counties are excluded. If the treatment group county is urban, its neighboring rural counties cannot be included in the corresponding control group. Finally, a candidate control-group county should suffer property damage larger than the cutoff level for the treatment group. That is, a candidate control-group county cannot be a member of the treatment group in the current year.

Based on the concern that the impact of a natural disaster may last for more than one year, we require that to be included in the treatment group, the treatment event should not occur in the county in the ten years before the current treatment event. The same requirement applies to the control-group counties. This ensures that the pre-event per capita income of the treatment and control groups are not contaminated by previous treatment events[4] . Based on the same rationale, when we are interested in the impact of the treatment event after five years, we require that no other treatment event occurs in the treatment and control group in the five years after the current treatment event. This ensures that the per capita income of the treatment and control groups are not contaminated by similar treatment events happened later. This also implies, the sample sizes decrease when we try to capture the longer run treatment effects.

For a county that receives a treatment event, if it has multiple candidate control-group counties, the average income of those candidates is taken as the income for the control group county. If a county receiving a treatment event does not have any candidate control-group

[4] Implicitly, we assume the impact of natural disaster does not last for more than ten years.

counties, the county is excluded from the treatment group. This can occur for several reasons. First, all the neighboring counties fall into a different urban-rural category. Second, all the neighboring counties receives a treatment event in the current period. Third, all the neighboring counties receives a treatment event in the 10 years before the current period, or immediately after the current period.

The above data creation process can be illustrated using the example in Figure 4. Suppose the treatment event is defined as a damage with average property loss exceeding $1 million and the impact duraction is nine years, that is, whether the impact on income lasts for nine years after the treatmetn event. Suppose that according to the SHELDUS dataset, County A has a treatment event occuring in the year 2000. In order to be included in the treatment group, no treatment event should have occurred in County A between 1990 and 2009. Assume that this is true. We can then proceed to construct its counterfactural county in the control group. We start with the neighboring counties for County A. Because we require that a candidate control-group county should share some common border with County A, County B8 in the top-right corner of Figure 1 is excluded. Because County A is a rural non-metropolitan county, County B1 and B2 at the lower left corner are excluded because they are metropolitan counties. County B3 is excluded because treatment event occurred in the county in the year 2000. County B4 is excluded because a treatment event occurred within the ten years prior to the treatment year (2000). County B5 is excluded because a treatment event occurred within the 2005, that is, a treatment event occurred five years after the treatment year which is less than the imapct duration of nine years in this case. Consequently, only Counties B6, B7 and B9 are left. We then contruct one conterfactural county in the control group using the average income and population of these three counties. And County A is included in the treatment group. In cases that we cannot contruct a counterfactual county for County A, for example when all the neighboring counties of County A have a treatment event in 2000,  then County A is not included in the treatment group.

This way of constructin g the treatment and control group can lead to an underestimate of the impact of natural disasters. First, in cases that we cannot contruct a counterfactual county, County A is not included in the treatment group. Take hurricanes as an example, while the counties closer to the centers or the “eye” of the hurricane tend to suffer a larger damage, they are typically excluded from the treament group because it is likely that all of their neighboring counties are affected by the hurricane.  As shown in Figure 2, while the 2005 Hurricane Katrina affects a wide spread area, only the counties at the outskirts of the affected area are included in the treatment group. This implies that we have probably dropped the observations that suffers the biggest damage in the case of hurricanes. Second, because the SHELDUS dataset averages the total property damage over all the affected counties,  the data on the property damage overestimates the damage on counties that are marginally affected by the disaster. Take the case of Hurricane Katrina as an example, this implies that counties at the outskirts of the affected area may show up in the treatment group even if they are only marginally affected. Finally, the treatment event is defined as the maximum property damage exceeding the cutoff level. For counties that suffered multiple disasters in a year, even if the sum of the property damage eceeds the cutoff level, they are excluded from the treatment group if no single disaster generates enough damage. In all these cases, we either drop observations that are likely to show a significant treatment effect or including observations that are unlikley to show a significnat treatment effect. In either way, it tends to underestimate the treatment effect and lead to a statistically insignificant outcome.

***Variable statistics***

One strong assumption of using the DID method to estimate causal effect is that in absence of treatment, difference between the "treatment" and "control" group is constant over time. Suppose counties have a treatment event with damage larger than $10 million and the impact duration is one year, graphs in Figure 5 show examples of the comparison of the treatment and control group with back dash lines indicating the year having natural disasters. From Figure 5(a), we see treatment and control group have similar trend in pre-treatment period. We future spilt our total sample into metro counties (Figure 5(b)) and non-metro counties (Figure 5 (c)) using rural-urban continuum codes from USDA Economic Research Service (ERS)[5], we find the difference between treatment and control group is insignificant, suggesting that the control group selected using the approached above is appropriate and also valid.

We have drawn similar patterns of treatment and control group for different treatment years and treatment events as shown in the appendix, and found that there is no significant difference between treatment and control group and this result are the consistent for most treatment years and treatment events that we discussed in the paper[6].

After we selected the control group, we then construct the sample to run the econometric model which will be discussed in the following session. Table 1 presents the statistics of variables used in the people for three treatment events with the cutoff damage level equals to1 million, 4 million and 10 million, respectively and impact duration from one year to nine years. To determinate the damage cutoff level, we first consider natural disasters with large damage based on information from Figure 1, and then select the damage level with 13% (cutoff=$1million), 6%  (cutoff=$4 million)and 3%(cutoff=$10 million) of total observations.

[5] We treat counties as metro if its rural-urban continuum code are less than or equal to 3 and non-metro otherwise.
[6] In some treatment years, there is no enough sample size to construct the graph, for example, we only have on observation in the 1986 treatment year, which makes the comparison between treatment and control group nonsense. Thus, we only present graph with enough sample size in the appendix.

**Econometric Models**

We apply the difference-in-differences (DID) method to examine the research question using observations constructed and tested above to examine the research question. Let $y_{it}$ be the county level real per capita income for county $i$ in period $t$. Thus the regression-based estimator to estimate the causal effect is written as:

$$y_{it} = \alpha + \beta_1 T + \beta_2 DID_{it} + \beta_3 pop_{it} + c_i + u_{it}, t = 1, 2 \quad (1)$$

Where $T = 1$ is the dummy variable for the post-disaster period, that is if $t = 2$ and $T = 0$ otherwise; $y_{it=1}$ is the county real per capita income of the year preceding the occurrence of natural disasters and $y_{it=2}$ represents the county-level real per capita income of the year after the occurrence of natural disasters. $DID_{it}$ is a dummy variable that takes the value one only for the treatment group in the post-treatment period $t$; $pop_{it}$ is the total population for county $i$ in period $t$ to control population movements among counties or states; $c_i$ is an individual county effect, and $u_{it}$ are the idiosyncratic errors. The coefficient $\beta_2$ is the treatment effect that we are interested.

To investigate the short- and long-run impacts on county per capita income, we define the impact duration of the disasters to be one year, two years up to nine years. The regression model (1) is run for each case. To control for the unobserved time-unvarying county characteristics, we introduce a fixed effect for each observation in the treatment and control group. For example, if a county is included in the treatment group twice because it is stricken by a disaster in 1980 and later in 2005, then one fixed effect is used for the 1980 county and one is used for the 2005 county, because this helps to control for the possible changes in the county between 1980 and 2005 that we do not have data on. To investigate how the severity of damage affects the shortand long-run impacts on county income, we explore various levels of disaster damage. Here, we present three treatment events with cutoff damage level equal $1 million, $4 million, and $10 million respectively, because the results from these three cases are representative for various cutoff levels we have tried.

To compare with previous literature, we also run equation (1) using the per capita income growth rate as the dependent variable. Suppose $y_{it=1}$ is the county-level per capita income growth rate of the year preceding the occurrence of natural disasters, which is written as,

$$y_{it=1} = (inc_{i,year-1} - inc_{i,year-2}) \times 100 \Big/ inc_{i,year-2}$$

where $year$ indicates the year when natural disasters occurrence, so we calculate the income growth rate by taking the difference per capita income in two years preceding the occurrence of natural disasters and dividing the income in the pre-second year. To calculate the income growth rate for the impact duration, for instance, post 6-year impact duration, we compute the income growth rate using income in post 7-year minus income in post 6-year and dividing the income in post 6-year. Thus, we only have impact duration of disasters on income growth rate to be one to eight years.

**Results and discussion**

The estimated treatment effect $\beta_2$ in equation (1) for each treatment event and each impact duration is summarized in Table 2. The rows specifies the impact duration, which changes consecutively from one year to nine years. The columns specify the treatment events with cutoff damage values equal to $1 million, $4 million and $10 million respectively. For each specification, we first report the estimated treatment effect when fixed effect is introduced for each observation in the treatment and control group. These results are listed under the column named “FE”, an abbreviation for fixed effect model. We then estimate equation (1) excluding the fixed effects and these results are reported under the column “Non-FE” in Table 2. The total observation (N) of the panel dataset is reported as well.

The first regularity shown in the estimation results in Table 2 is that as the cutoff damage level increases, the impact of disaster damage lasts longer. In the first case with the cutoff damage value equal $1 million, the impact on county income is statistically significant only for the two years immediately after the natural disaster. As the cutoff damage increases to $4 million, the impact of natural disaster lasts longer as shown in the fact that the treatment effect becomes statistically insignificant except for the cases when the impact duration equal two- and five-year. When the cutoff damage increases further to $10 million, the treatment effect becomes statistically significant for all cases of impact duration.

While the incidence of various treatment events in this paper have significantly reduced the per capita income of counties hit by the natural disasters, they have no significant impact on the growth rate of the per capita income in either short- or long-run. This is shown in Table 3.. These results are different from Strobl (2011), which finds that a county’s annual economic growth rate falls on average by 0.45 percentage points. This difference could be due to the different scope of analysis and methodology used. Strobl (2011) investigates only the impact of hurricanes, while we investigate multiple hazards. While Strobl (2011)’s study area covers coastal counties in the North Atlantic Basin region, we cover all the U.S. Counties. Finally, it could be due to the different methodology employed in the analysis.

In order to investigate whether impacts of natural disasters affect the metropolitan and non-metropolitan counties differently, we split our dataset into two subsets. In one subset, the counties in the treatment group are all metropolitan counties. By the way, we construct the control group, the counterfactual counties in the control group are all based on metropolitan data. So the comparison between the treatment and control group for this subsample is reasonable. The other subset is the non-metropolitan counties. We then conduct the same analyses on each of the two subsets. The results for the metropolitan counties are reported in Table 4 and those for non-metropolitan counties are reported in Table 5.

As shown in Table 4, impacts of natural disasters are only significant in the short-run: the per capita income level between the treatment and control group are statistically different only up to four years, regardless of the cutoff damage level specified. In contrast, impact of natural disasters tend to last longer in non-metropolitan counties (see Table 5). When the cutoff damage equals $1 million, the income per capita for the treatment group is statistically no different from that of the control group. This seems to suggest that the nonmetropolitan counties are quite robust to small disasters. As the cutoff value increases to $4 million, while there is still no significant short-run difference, the per capita income in the treatment group is significantly lower than the neighboring counties. in longer run. If the cutoff increases further to $10 million, both short- and long-run effects become statistically significant. The different responses of the metro and non-metropolitan counties are interesting. In metropolitan counties, the density of population and development are usually higher their non-metropolitan counterparts. When stricken by a natural disaster with same total damage, we would expect that metropolitan counties are more resilient in both the short- and long-run, because the relative damage, the ratio between the property damage and the property stock in the county, is usually smaller in metropolitan counties. Our results on the long-run impacts are consistent with this explanation. However, our results on the short-run effects suggest the opposite, which is an interesting phenomenon worth future exploration. One speculative explanation could be that property damage in non-metropolitan counties could be accompanied by crop damages, which could be more effectively recovered with subsidies and government payments. In fact, subsidies and government payments comprise a large percent of total farm income in most agricultural counties in the U.S. Nevertheless, as the damage from natural disaster increase, it becomes less likely to get the damage fully covered through government payments. None of the regression on the income growth rate is statistically significant for each of the subsample.

**Conclusion and Discussion**

In this paper, we conduct a quasi-experiment analysis on the impact of natural disasters on county-level income using the SHELDUS dataset that covers 18 types of natural hazards occurred between 1969 and 2012. To the best of our knowledge, this is the only paper that discusses how natural disasters affect regional income in the U.S. after the pioneering work of Strobl (2011). This paper contributes to the literature by the use of quasi-experiment method with explicit treatment of potential serial correlation in the data, as compared to Stobl (2011).

We find that as the direct damage from natural disaster increases, the impact of county per capita income tends to last longer. More interestingly, we find that in the short-run income levels in metropolitan counties are more responsive to the damages of natural disasters and those for non-metropolitan counties are more resilient to small to medium damages from natural disasters. In the longer run, however, metropolitan counties are more resilient to damages in natural disasters than the non-metropolitan counties.

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**Table 1 Variables statistics across cutoffs and post-treatment periods**

| | Cutoff=$1 million | | Cutoff=$4 million | | Cutoff=$10 million | |
|---|---|---|---|---|---|---|
| Impact duration | real per capita income | population | real per capita income | population | real per capita income | population |
| (year) | Mean | Mean | Mean | Mean | Mean | Mean |
| 1 | 18821.59 | 164068.1 | 17534.5 | 149025.1 | 18011.83 | 144211.4 |
| | (57006.42) | (2928987) | (38864.55) | (2279282) | (42101.31) | (385795) |
| | [3883.737, 1435494] | [276, 1.19E+08] | [3883.737, 899348.4] | [673, 1.19E+08] | [3230.435, 871819.3] | [1223, 8033598] |
| 2 | 19515.58 | 179208.7 | 17952.77 | 154390.6 | 18778.82 | 144980.2 |
| | (73307.61) | (3248270) | (41864.84) | (2443569) | (45648.93) | (403811.6) |
| | [4417.979, 2610885 | [718, 1.19E+08] | [3883.737, 974102.7] | [647, 1.19E+08] | [3230.435, 896817.6] | [1205, 8337467] |
| 3 | 19936.76 | 152640.2 | 17961.44 | 153657.6 | 19212.8 | 133985.3 |
| | (78437.94) | (2817770) | (41882.97) | (2662916) | (48980.29) | (392636.1) |
| | [4349.737, 2727107] | [760, 1.22E+08] | [3883.737, 1056828] | [665, 1.22E+08] | [3230.435, 944938.8] | [1209, 8748444] |
| 4 | 19477.67 | 105963.6 | 17462.36 | 95301.92 | 18856.44 | 131520 |
| | (78364.9) | (1458932) | (36343.95) | (656573.2) | (49610.7) | (402663.4) |
| | [4296.588, 2921766] | [749, 5.69E+07] | [3883.737, 826833.2] | [642, 2.76E+07] | [3230.435, 995782.1] | [1196, 9075963] |
| 5 | 20167.16 | 90498.25 | 17078.64 | 80732.47 | 19070.5 | 130720.6 |
| | (87236.06) | (1352578) | (33109.78) | (261851.2) | (47694.29) | (421796.8) |
| | [4192.257, 3091663] | [747, 5.95E+07] | [5205.534, 876855.7] | [656, 6766890] | [5170.799, 1038333] | [1237, 9297969] |
| 6 | 21840.8 | 64766.21 | 16676.24 | 79292.11 | 17761.1 | 116738.1 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (97025.67) | (510917.1) | (30995.21) | (277588.7) | (38362.1) | (318912.9) |
| | [4162.729, 3220889] | [744, 2.04E+07] | [5203.839, 915386.5] | [627, 7150456] | [5170.799, 981408.9] | [1233, 9122370] |
| 7 | 22280.07 | 65883.74 | 16832.22 | 75125.89 | 17165.2 | 113315.6 |
| | (101760.8) | (550568.2) | (31649.94) | (293284.2) | (34987.59) | (322774.3) |
| | [4061.023, 3222194] | [732, 2.08E+07 | [5170.525, 979157.1] | [665, 7630520] | [5170.525, 992629.3] | [1262, 9081054] |
| 8 | 23763.2 | 65570.09 | 17489.56 | 73022.57 | 17606.93 | 114554.7 |
| | (109627.4) | (583014.7) | (34041.22) | (307914.5) | (36799.75) | (335494.8) |
| | [4063.648, 3355002] | [732, 2.12E+07] | [5089.78, 1003637] | [660, 7790216] | [5089.78, 1031370] | [1219, 9248284] |
| 9 | 25603.12 | 69895.77 | 17824.08 | 72059.76 | 17729.02 | 112249.1 |
| | (121948.8) | (645269.3) | (34849.32) | (324315.7) | (37196.19) | (346737.9) |
| | [4037.401, 3520459] | [744, 2.19E+07] | [4965.556, 1014862] | [662, 7803648] | [4965.556, 1058093] | [1262, 9732528] |

Note: standard deviations are in parentheses, and minimum and maximum values are in square brackets

**Table 2 Estimation results of treatment effect on per capita income from the total sample**

| Impact duration | Cutoff=$1 million | | | Cutoff=$4 million | | | Cutoff=$10 million | | |
|---|---|---|---|---|---|---|---|---|---|
| (year) | FE | Non-FE | N | FE | Non-FE | N | FE | Non-FE | N |
| 1 | -416.6* | -405.5* | 6728 | -318.0* | -309.9* | 5540 | -543.0** | -486.6** | 4036 |
| | (220.1) | (220.1) | | (181.6) | (183.4) | | (226.0) | (219.1) | |
| 2 | -915.9* | -918.4* | 5560 | -469.4 | -482.0 | 4928 | -871.4*** | -767.5** | 3580 |
| | (485.4) | (485.1) | | (292.2) | (300.0) | | (328.0) | (332.7) | |
| 3 | -1140.9 | -1154.8 | 4688 | -1008.7** | -986.5** | 4308 | -1489.4*** | -1435.4*** | 3128 |
| | (721.8) | (721.2) | | (431.7) | (430.9) | | (464.1) | (480.4) | |
| 4 | -1121.9 | -1085.8 | 4112 | -981.9** | -990.7** | 3916 | -1423.5** | -1465.3** | 2876 |
| | (940.7) | (940.4) | | (427.2) | (435.1) | | (567.0) | (593.2) | |
| 5 | -1850.2 | -1815.6 | 3536 | -492.3 | -385.7 | 3428 | -1702.1*** | -1733.0*** | 2608 |
| | (1387.3) | (1387.1) | | (347.4) | (401.0) | | (624.5) | (658.1) | |
| 6 | -2644.6 | -2680.2 | 3020 | -911.6** | -765.6* | 3940 | -2231.0*** | -2142.1*** | 2312 |
| | (1866.0) | (1878.4) | | (387.7) | (462.4) | | (700.0) | (732.3) | |
| 7 | -2745.8 | -2780.9 | 2672 | -969.1** | -787.8 | 2708 | -1917.6*** | -1836.2*** | 2152 |
| | (2100.3) | (2115.6) | | (463.5) | (564.8) | | (595.7) | (626.7) | |
| 8 | -3438.1 | -3515.4 | 2404 | -1306.2** | -1027.9 | 2432 | -1937.7*** | -1852.1*** | 1936 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (2569.7) | (2587.6) | | (570.6) | (694.2) | | (651.3) | (699.3) | |
| 9 | -4051.3 | -4160.9 | 2052 | -1365.6** | -978.6 | 2256 | -1903.0*** | -1864.8*** | 1840 |
| | (3396.0) | (3417.9) | | (639.0) | (789.2) | | (635.3) | (691.8) | |

Note: Standard errors in parentheses; * p<0.1, ** p<0.05, and *** p<0.01; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.

**Table 3 Estimation results of treatment effect on per capita income growth rate from all counties**

| Impact duration (year) | Cutoff=$1 million | | | Cutoff=$4 million | | | Cutoff=$10 million | | |
|---|---|---|---|---|---|---|---|---|---|
| | FE | Non-FE | N | FE | Non-FE | N | FE | Non-FE | N |
| 1 | 0.637 | 0.640 | 5478 | 0.0612 | 0.0573 | 4866 | 0.136 | 0.153 | 3534 |
| | (0.631) | (0.630) | | (0.305) | (0.305) | | (0.289) | (0.289) | |
| 2 | 0.393 | 0.383 | 4624 | -0.0336 | -0.0278 | 4254 | -0.0762 | -0.0657 | 3086 |
| | (0.723) | (0.723) | | (0.338) | (0.338) | | (0.278) | (0.278) | |
| 3 | 0.296 | 0.282 | 4061 | -0.486 | -0.487 | 3866 | 0.144 | 0.128 | 2835 |
| | (0.830) | (0.828) | | (0.362) | (0.362) | | (0.337) | (0.337) | |
| 4 | 1.156 | 1.174 | 3487 | -0.126 | -0.140 | 3383 | -0.187 | -0.195 | 2570 |
| | (1.149) | (1.149) | | (0.387) | (0.387) | | (0.390) | (0.390) | |
| 5 | 1.474 | 1.452 | 2975 | -0.211 | -0.219 | 2998 | -0.250 | -0.243 | 2277 |
| | (1.340) | (1.340) | | (0.432) | (0.432) | | (0.326) | (0.326) | |
| 6 | 1.806 | 1.787 | 2637 | 0.0893 | 0.0838 | 2670 | 0.142 | 0.145 | 2117 |
| | (1.580) | (1.580) | | (0.507) | (0.507) | | (0.457) | (0.457) | |
| 7 | 1.729 | 1.762 | 2372 | -0.141 | -0.150 | 2394 | 0.434 | 0.443 | 1901 |
| | (1.743) | (1.743) | | (0.503) | (0.503) | | (0.471) | (0.471) | |
| 8 | 1.912 | 1.903 | 2027 | -0.00580 | -0.0108 | 2220 | -0.299 | -0.264 | 1805 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (2.067) | (2.067) | | (0.558) | (0.558) | (0.440) | (0.440) |

Note: all results are statistically insignificant at the 10% confident level; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.

**Table 4 Estimation results of treatment effect on per capita income from the metro counties**

| Impact duration (year) | Cutoff=$1 million | | | Cutoff=$4 million | | | Cutoff=$10 million | | |
|---|---|---|---|---|---|---|---|---|---|
| | FE | Non-FE | N | FE | Non-FE | N | FE | Non-FE | N |
| 1 | -1529.4** | -1404.7** | 1092 | -404.7 | -383.7 | 1604 | -430.7* | -376.2 | 1600 |
| | (684.4) | (680.8) | | (301.9) | (302.2) | | (256.9) | (250.4) | |
| 2 | -2558.7* | -2379.9 | 872 | -610.9 | -539.0 | 1348 | -738.0* | -634.6 | 1356 |
| | (1522.0) | (1543.4) | | (518.1) | (520.0) | | (437.9) | (427.9) | |
| 3 | -4555.4* | -4231.4 | 692 | -1683.4** | -1484.2* | 1084 | -1300.7* | -1163.8 | 1148 |
| | (2643.9) | (2671.4) | | (809.8) | (810.1) | | (752.2) | (730.8) | |
| 4 | -4107.0 | -3506.6 | 580 | -2482.0** | -2202.3* | 940 | -1853.7* | -1670.5 | 1048 |
| | (2726.3) | (2677.0) | | (1166.8) | (1165.5) | | (1118.5) | (1102.7) | |
| 5 | -6032.9 | -5667.0 | 428 | -285.4 | -221.6 | 780 | -1390.6 | -1181.9 | 900 |
| | (4691.4) | (4553.4) | | (290.5) | (262.9) | | (968.4) | (967.0) | |
| 6 | -9246.8 | -8334.6 | 352 | -398.9 | -296.3 | 680 | -1908.1* | -1580.9 | 784 |
| | (7125.4) | (6686.7) | | (410.3) | (365.1) | | (1148.0) | (1128.4) | |
| 7 | -13794.2 | -13228.7 | 244 | -630.7 | -469.9 | 556 | -1614.5 | -1547.6 | 708 |
| | (10565.4) | (10225.0) | | (591.3) | (526.1) | | (1041.2) | (1030.5) | |
| 8 | -19788.6 | -19303.6 | 184 | -1112.2 | -878.9 | 444 | -1971.9 | -1884.5 | 644 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (14801.2) | (14481.6) | | (842.3) | (741.6) | | (1297.6) | (1286.5) | |
| 9 | -26845.2 | -26193.7 | 144 | -1200.2 | -926.1 | 376 | -2244.1 | -2143.5 | 588 |
| | (20466.5) | (19986.4) | | (982.3) | (879.7) | | (1536.3) | (1529.0) | |

Note: Standard errors in parentheses; * p<0.1, ** p<0.05, and *** p<0.01; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.

**Table 5 Estimation results of treatment effect on per capita income from the non-metro counties**

| Impact duration (year) | Cutoff=$1 million | | | Cutoff=$4 million | | | Cutoff=$10 million | | |
|---|---|---|---|---|---|---|---|---|---|
| | FE | Non-FE | N | FE | Non-FE | N | FE | Non-FE | N |
| 1 | -222.5 | -208.9 | 5636 | -292.9 | -278.5 | 3936 | -495.2* | -478.9 | 2436 |
| | (225.9) | (225.9) | | (223.0) | (226.5) | | (292.5) | (291.9) | |
| 2 | -637.9 | -640.8 | 4688 | -433.8 | -456.5 | 3580 | -618.6 | -655.0 | 2224 |
| | (496.3) | (495.8) | | (346.8) | (363.0) | | (405.3) | (420.4) | |
| 3 | -594.5 | -611.8 | 3996 | -833.0* | -821.0 | 3224 | -1226.2** | -1343.4** | 1980 |
| | (703.0) | (702.4) | | (503.0) | (505.3) | | (561.5) | (586.1) | |
| 4 | -725.2 | -680.3 | 3532 | -576.8 | -591.3 | 2976 | -986.2 | -1158.7* | 1828 |
| | (999.5) | (999.0) | | (413.1) | (433.8) | | (620.1) | (653.0) | |
| 5 | -1293.1 | -1251.2 | 3108 | -528.4 | -193.9 | 2648 | -1687.0** | -1834.2** | 1708 |
| | (1439.3) | (1438.9) | | (439.2) | (522.0) | | (803.8) | (833.4) | |
| 6 | -1844.1 | -1859.2 | 2668 | -1031.7** | -605.8 | 2360 | -2046.2** | -2163.5** | 1528 |
| | (1903.1) | (1920.3) | | (485.4) | (590.7) | | (850.2) | (883.2) | |
| 7 | -1647.0 | -1668.4 | 2428 | -1039.6* | -584.5 | 2152 | -1616.9** | -1720.9** | 1444 |
| | (2053.4) | (2074.0) | | (567.2) | (699.2) | | (642.4) | (690.1) | |
| 8 | -2075.9 | -2148.4 | 2220 | -1341.5** | -791.7 | 1988 | -1384.0** | -1522.3** | 1292 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (2494.2) | (2516.8) | | (677.0) | (831.8) | | (620.3) | (697.0) | |
| 9 | -2300.5 | -2405.2 | 1908 | -1395.8* | -708.6 | 1880 | -1149.5** | -1324.5** | 1252 |
| | (3299.4) | (3326.4) | | (742.2) | (928.6) | | (472.5) | (553.5) | |

Note: Standard errors in parentheses; * p<0.1, ** p<0.05, and *** p<0.01; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.

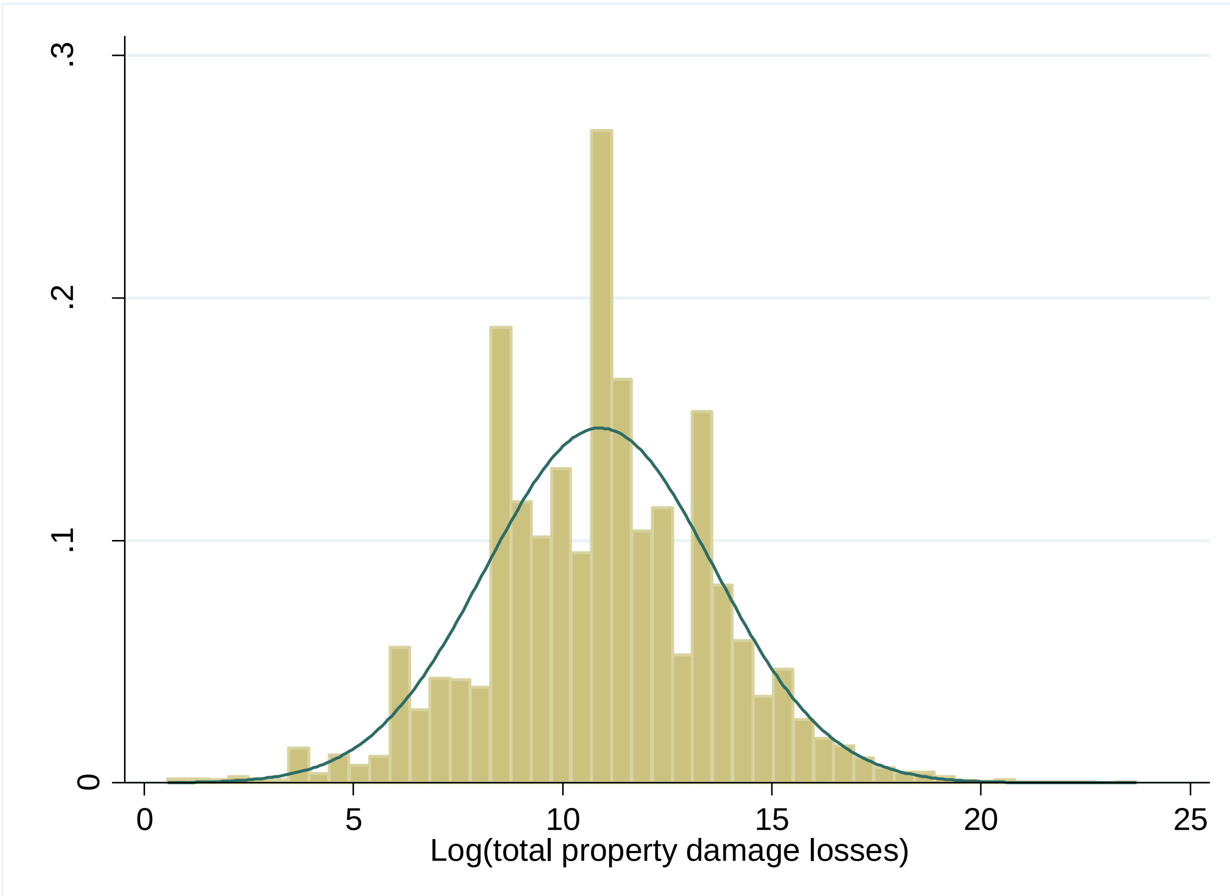



**Figure 1 Histograms of logged total damage losses**

Spatial Distribution of Disaster Damage 2005

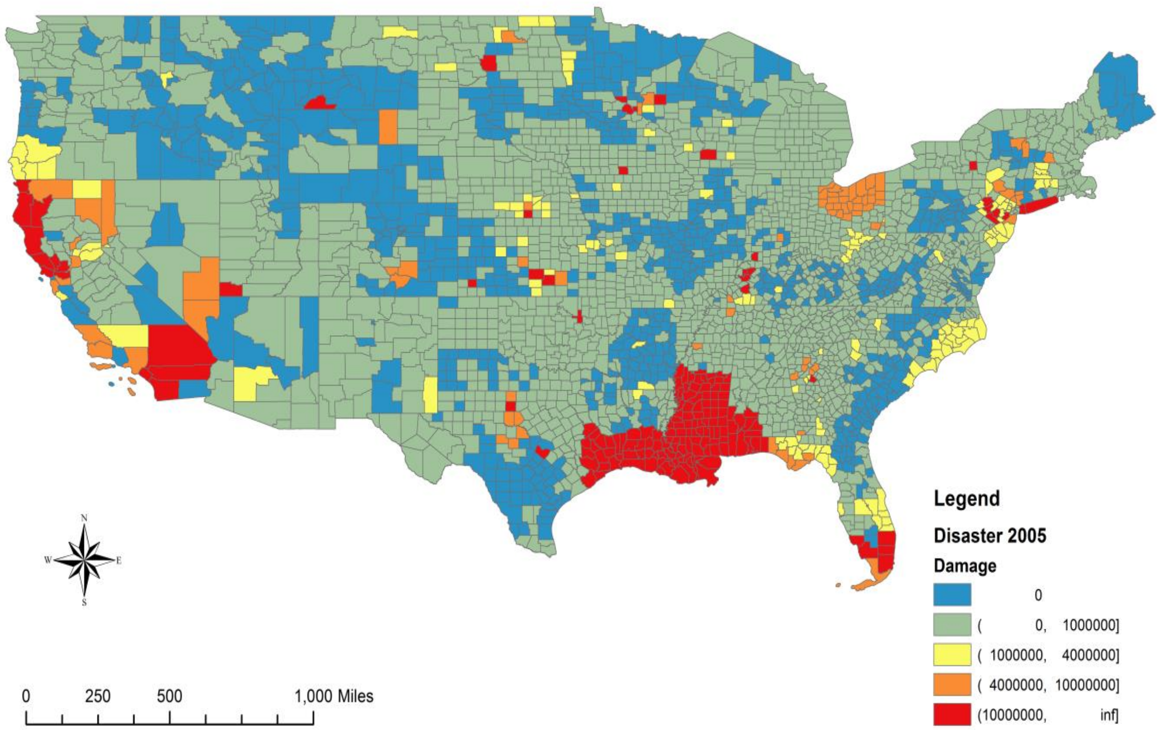



**Figure 2 Spatial distribution of disaster damage in 2005**

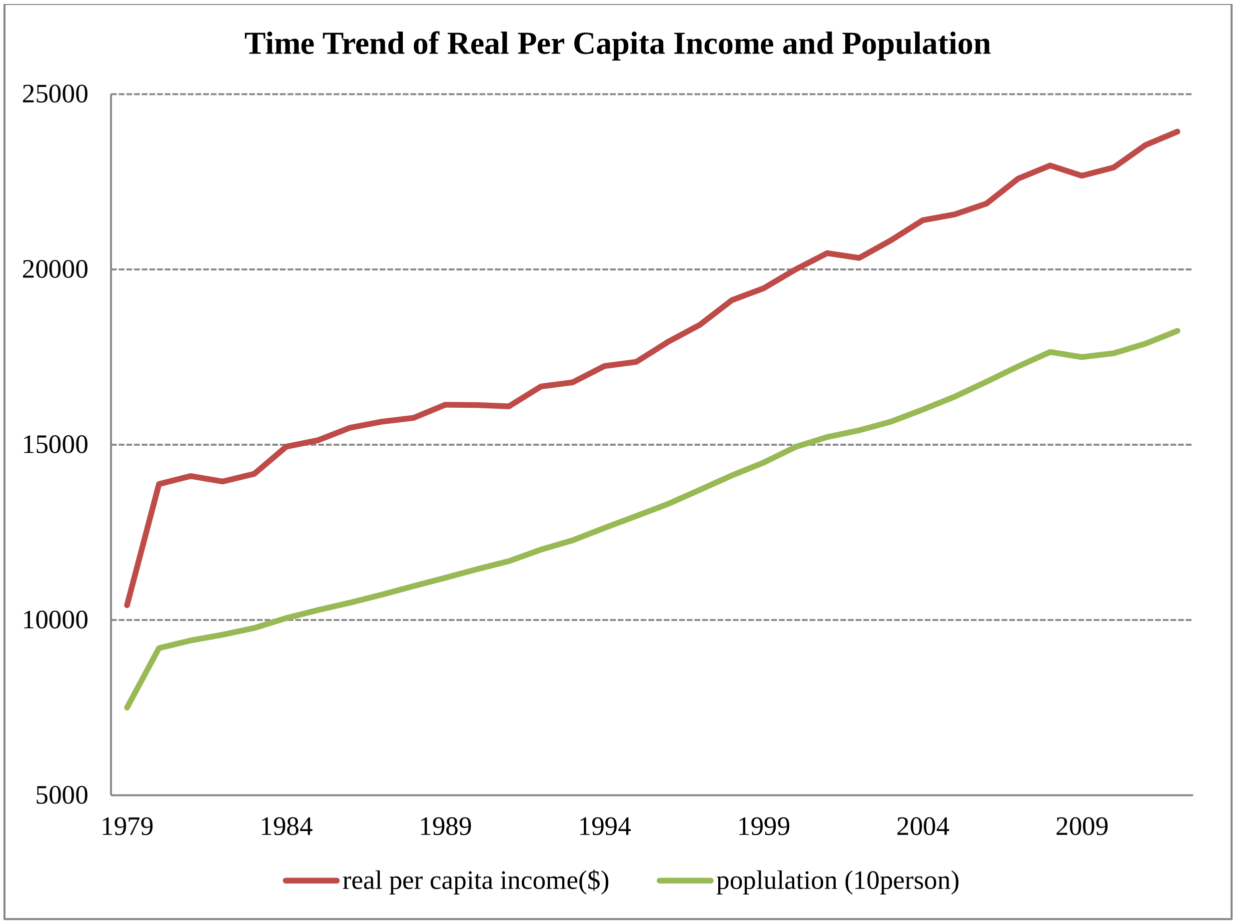
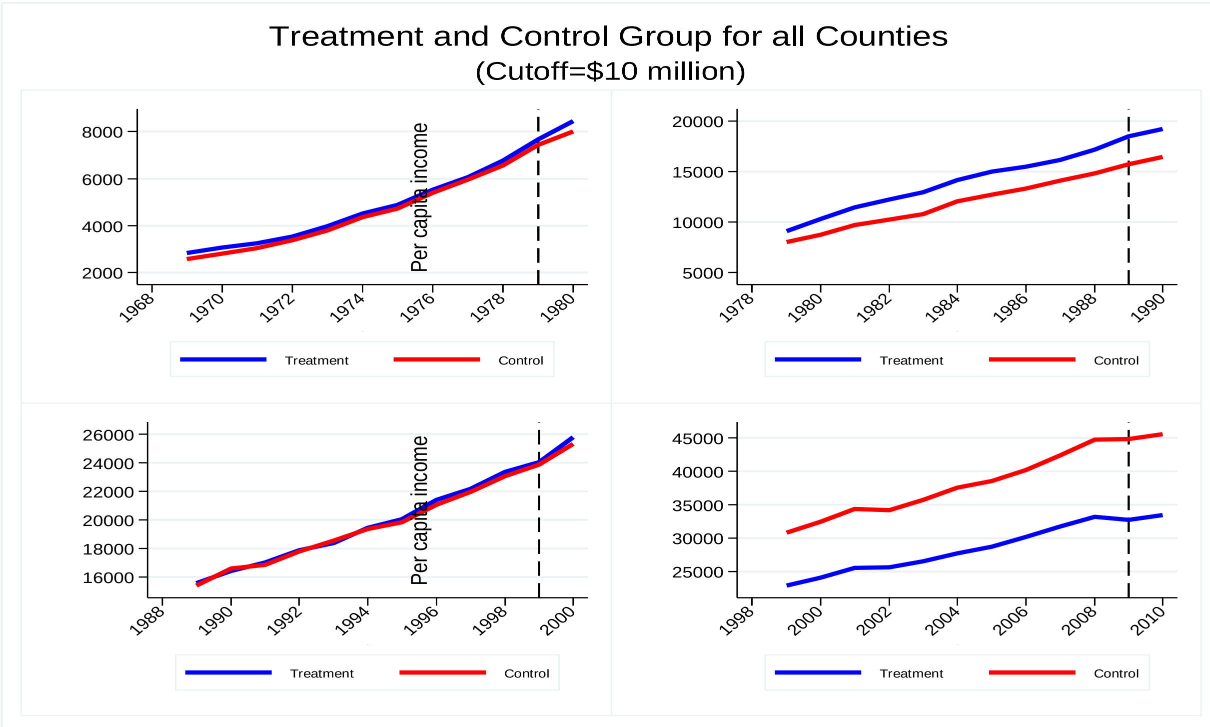


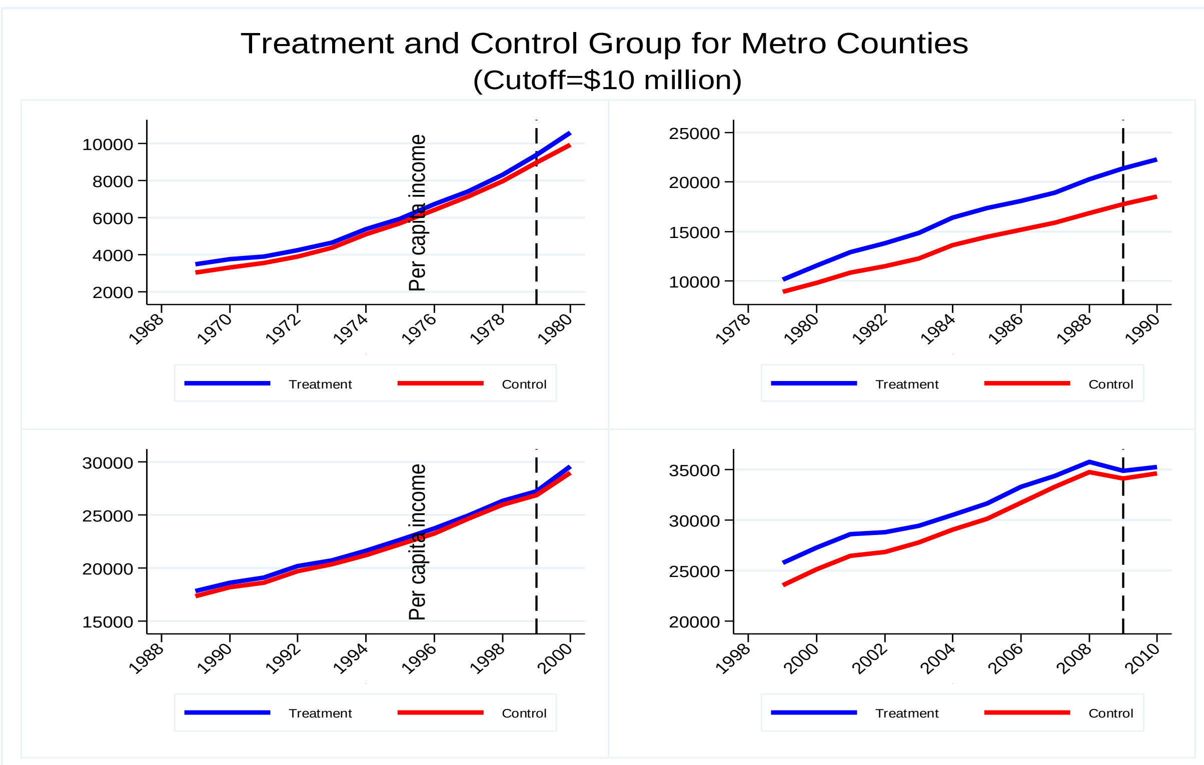

**Figure 3 Time trend of real per capita income and population**

<table>
<tr><td rowspan="2">County B6:<br>Rural</td><td rowspan="2">County B7:<br>Rural</td><td>County B8:<br>Rural</td></tr>
<tr><td>County B9:<br>Rural</td></tr>
<tr><td>County B4:<br>Rural<br>Treatment event in 1990</td><td>County A:<br>Rural<br>Treatment event:<br>damage >=$1 million<br>Treatment year: 2000<br>Impact duration: 9 years</td><td>County B5:<br>Rural<br>Treatment event in 2005</td></tr>
<tr><td>County B1:<br>Urban</td><td>County B2:<br>Urban</td><td>County B3:<br>Rural<br>Treatment event in 2000</td></tr>
</table>

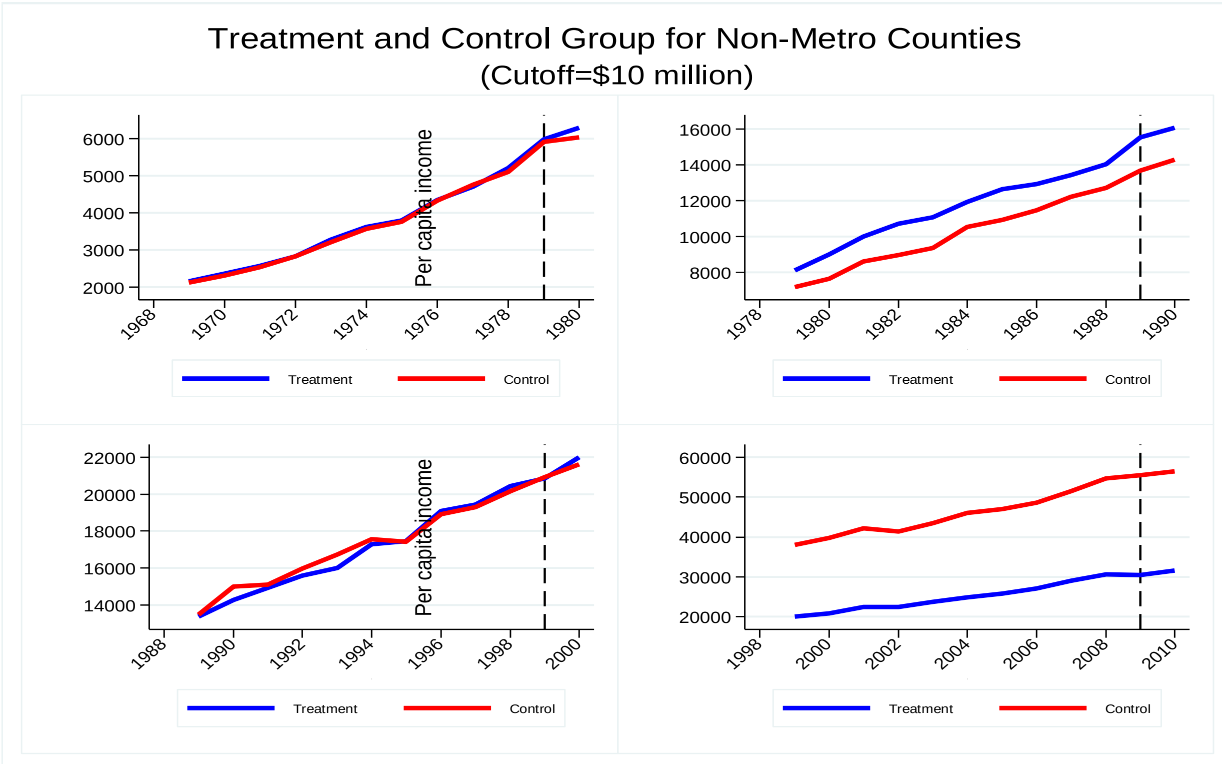
**Figure 4 Construction of the control group**




(a) All counties




(b) Metro counties




(c) Non-metro counties

**Figure 5 Comparison between treatment and control group for damage level=$10 million**

## Appendix

**Table A1. Estimated coefficients of per capita income level**

**(cutoff=$10 million and impact duration=1 year)**

| | All Counties | | Metro Counties | | Non-Metro Counties | |
|---|---|---|---|---|---|---|
| | FE | Non-FE | FE | Non-FE | FE | Non-FE |
| post | 1632.7*** | 1731.4*** | 1661.5*** | 1737.5*** | 1749.8*** | 1804.4*** |
| | (143.9) | (150.8) | (239.2) | (250.5) | (185.7) | (208.2) |
| DID | -543.0** | -486.6** | -430.7* | -376.2 | -495.2* | -478.9 |
| | (226.0) | (219.1) | (256.9) | (250.4) | (292.5) | (291.9) |
| pop | 0.0820** | 0.0474*** | 0.0192** | 0.00306* | 0.117* | 0.0840*** |
| | (0.0338) | (0.0163) | (0.00884) | (0.00157) | (0.0607) | (0.0152) |
| treatment | | -6142.2*** | | -4189.3* | | -4100.4** |
| | | (1862.3) | | (2262.6) | | (1831.9) |
| constant | 5503.6 | 13499.5*** | 12227.0*** | 18764.8*** | 10473.3*** | 14369.0*** |
| | (4833.7) | (1938.5) | (2453.5) | (2584.4) | (3392.7) | (1476.8) |
| N | 4036 | 4036 | 1600 | 1600 | 2436 | 2436 |

Note: Standard errors in parentheses; * p<0.1, ** p<0.05, and *** p<0.01; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.

**Table A2. Estimated coefficients of per capita income growth rate**

**(cutoff=$10 million and impact duration=1 year)**

| | All Counties | | Metro Counties | | Non-Metro Counties | |
|---|---|---|---|---|---|---|
| | FE | Non-FE | FE | Non-FE | FE | Non-FE |
| post | -1.083*** | -1.044*** | -0.608*** | -0.582*** | -1.358*** | -1.336*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.216) | (0.214) | (0.226) | (0.225) | (0.319) | (0.317) |
| DID | 0.136 | 0.153 | 0.317 | 0.339 | 0.0486 | 0.0443 |
| | (0.289) | (0.289) | (0.313) | (0.313) | (0.425) | (0.425) |
| pop | 8.21E-06*** | 2.66E-07* | 3.98E-06 | 4.76E-07 | 7.15E-06*** | 5.20E-07*** |
| | (2.21E-06) | (1.39E-07) | (3.71E-06) | (3.25E-07) | (1.64E-06) | (1.01E-07) |
| treatment | | -0.156 | | -0.346 | | -0.102 |
| | | (0.235) | | (0.285) | | (0.337) |
| constant | 4.015*** | 5.311*** | 3.538*** | 4.707*** | 5.114*** | 5.599*** |
| | (0.303) | (0.176) | (1.057) | (0.213) | (0.107) | (0.252) |
| N | 3534 | 3534 | 1350 | 1350 | 2184 | 2184 |

Note: Standard errors in parentheses; * $p<0.1$, ** $p<0.05$, and *** $p<0.01$; “FE” indicates results by including fixed effects and “Non-FE” indicates results excluding the fixed effects; N is the total observation number.

**Table A3. Estimation results of treatment effect on per capita income growth rate from metro counties**

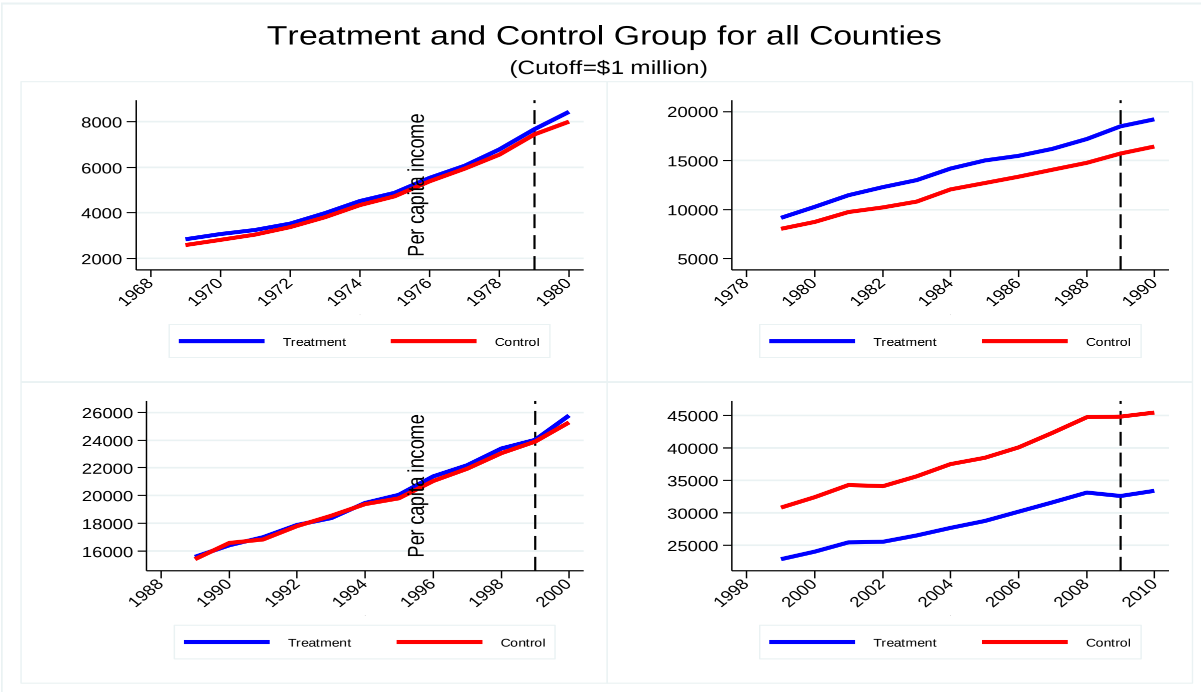
| Impact duration | Cutoff=$1 million | | | Cutoff=$4 million | | | Cutoff=$10 million | | |
|---|---|---|---|---|---|---|---|---|---|
| (year) | FE | Non-FE | N | | FE | Non-FE | N | | FE |
| 1 | 0.538 | 0.441 | 864 | 0.276 | 0.272 | 1340 | 0.317 | 0.339 | 1350 |
| | (0.393) | (0.396) | | (0.300) | (0.300) | | (0.313) | (0.313) | |
| 2 | -0.228 | -0.320 | 688 | 0.0392 | -0.0642 | 1076 | 0.354 | 0.294 | 1144 |
| | (0.423) | (0.426) | | (0.332) | (0.338) | | (0.333) | (0.334) | |
| 3 | -0.407 | -0.408 | 576 | 0.0246 | -0.0114 | 932 | 0.278 | 0.249 | 1044 |
| | (0.479) | (0.479) | | (0.357) | (0.355) | | (0.357) | (0.359) | |
| 4 | -0.306 | -0.352 | 424 | -0.0345 | -0.0835 | 774 | -0.0711 | -0.109 | 898 |
| | (0.553) | (0.549) | | (0.396) | (0.393) | | (0.346) | (0.348) | |
| 5 | -0.0396 | -0.254 | 350 | -0.00266 | 0.0194 | 674 | 0.220 | 0.173 | 782 |
| | (0.509) | (0.511) | | (0.419) | (0.415) | | (0.386) | (0.385) | |
| 6 | 0.273 | 0.0984 | 242 | 0.371 | 0.398 | 552 | 0.190 | 0.157 | 706 |
| | (0.653) | (0.667) | | (0.483) | (0.481) | | (0.430) | (0.426) | |
| 7 | -0.0873 | -0.135 | 182 | 0.0834 | 0.0889 | 440 | 0.502 | 0.484 | 642 |
| | (0.801) | (0.799) | | (0.604) | (0.591) | | (0.492) | (0.489) | |
| 8 | 0.532 | 0.563 | 144 | 0.295 | 0.308 | 372 | 0.194 | 0.193 | 586 |
| | (0.677) | (0.675) | | (0.643) | (0.631) | | (0.526) | (0.524) | |

Note: all results are statistically insignificant at the 10% confident level; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.

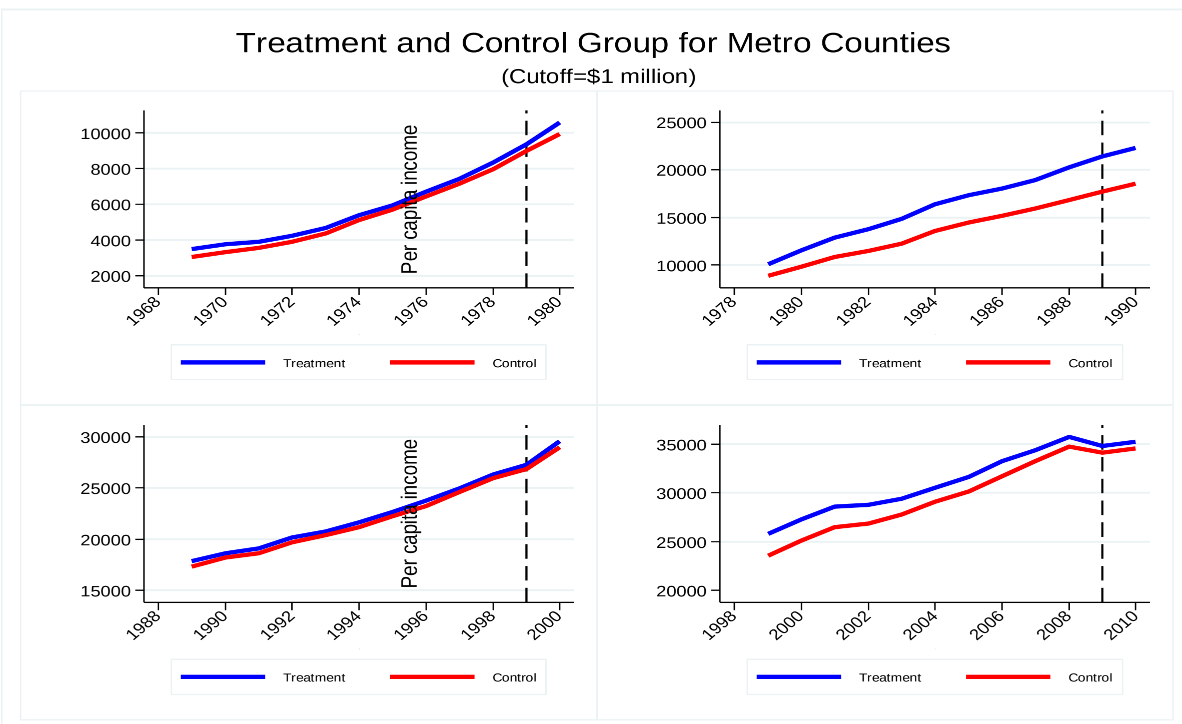
**Table A4. Estimation results of treatment effect on per capita income growth rate from non-metro counties**

| Impact duration | Cutoff=$1 million | | | Cutoff=$4 million | | | Cutoff=$10 million | | |
|---|---|---|---|---|---|---|---|---|---|
| (year) | FE | Non-FE | N | | FE | Non-FE | N | | FE |
| 1 | 0.675 | 0.678 | 4614 | -0.0127 | -0.0184 | 3526 | 0.0486 | 0.0443 | 2184 |
| | (0.746) | (0.744) | | (0.405) | (0.405) | | (0.425) | (0.425) | |
| 2 | 0.521 | 0.509 | 3936 | -0.0209 | -0.0123 | 3178 | -0.279 | -0.279 | 1942 |
| | (0.847) | (0.846) | | (0.437) | (0.437) | | (0.395) | (0.396) | |
| 3 | 0.414 | 0.397 | 3485 | -0.631 | -0.633 | 2934 | 0.103 | 0.0669 | 1791 |
| | (0.965) | (0.962) | | (0.463) | (0.463) | | (0.491) | (0.491) | |
| 4 | 1.365 | 1.385 | 3063 | -0.136 | -0.155 | 2609 | -0.242 | -0.256 | 1672 |
| | (1.307) | (1.306) | | (0.489) | (0.489) | | (0.570) | (0.569) | |
| 5 | 1.705 | 1.679 | 2625 | -0.279 | -0.288 | 2324 | -0.478 | -0.468 | 1495 |
| | (1.519) | (1.519) | | (0.545) | (0.545) | | (0.455) | (0.455) | |
| 6 | 1.980 | 1.959 | 2395 | 0.0122 | 0.00663 | 2118 | 0.165 | 0.153 | 1411 |
| | (1.739) | (1.739) | | (0.626) | (0.626) | | (0.651) | (0.650) | |
| 7 | 1.885 | 1.920 | 2190 | -0.192 | -0.202 | 1954 | 0.405 | 0.414 | 1259 |
| | (1.887) | (1.887) | | (0.602) | (0.602) | | (0.669) | (0.667) | |
| 8 | 2.017 | 2.007 | 1883 | -0.0692 | -0.0751 | 1848 | -0.536 | -0.491 | 1219 |
| | (2.226) | (2.226) | | (0.658) | (0.658) | | (0.602) | (0.602) | |

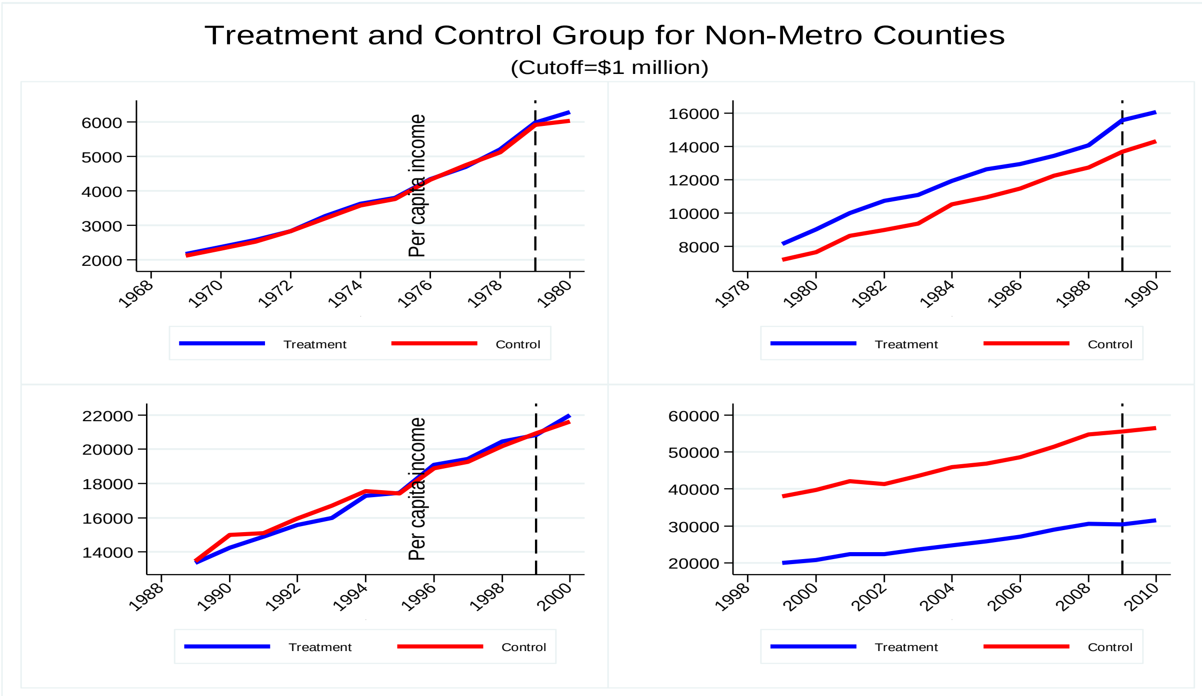
Note: all results are statistically insignificant at the 10% confident level; "FE" indicates results by including fixed effects and "Non-FE" indicates results excluding the fixed effects; N is the total observation number.




(a) All counties

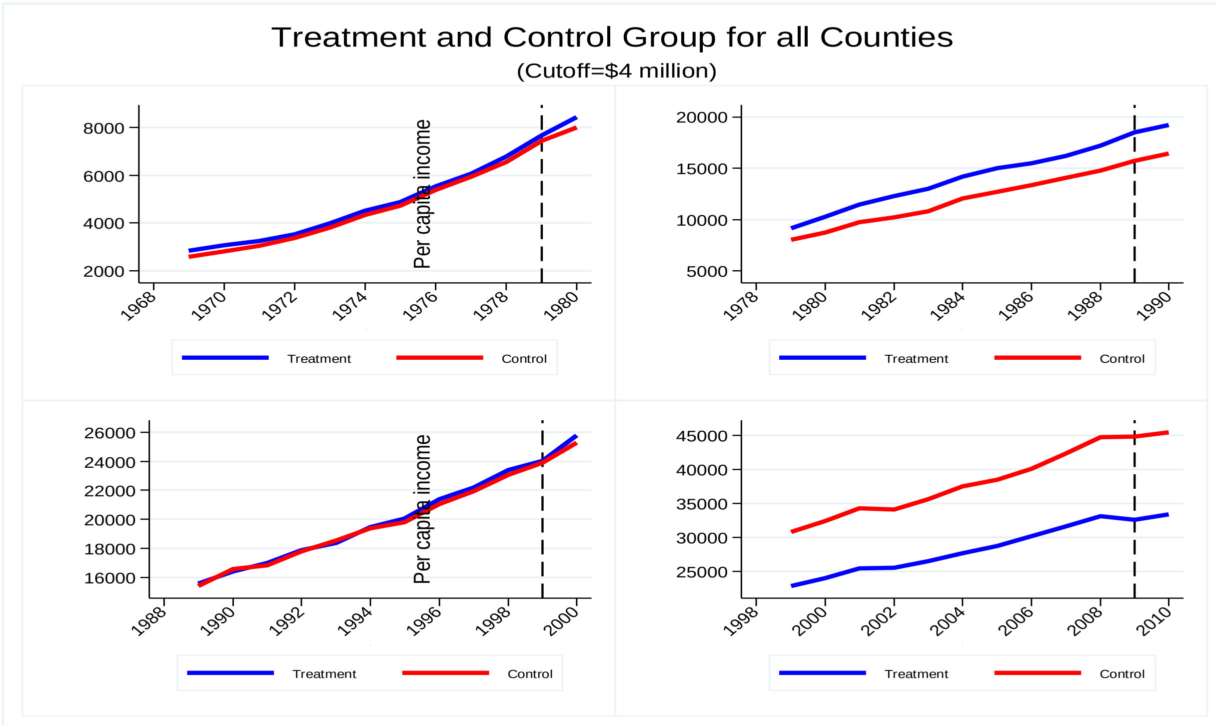


(b) Metro counties

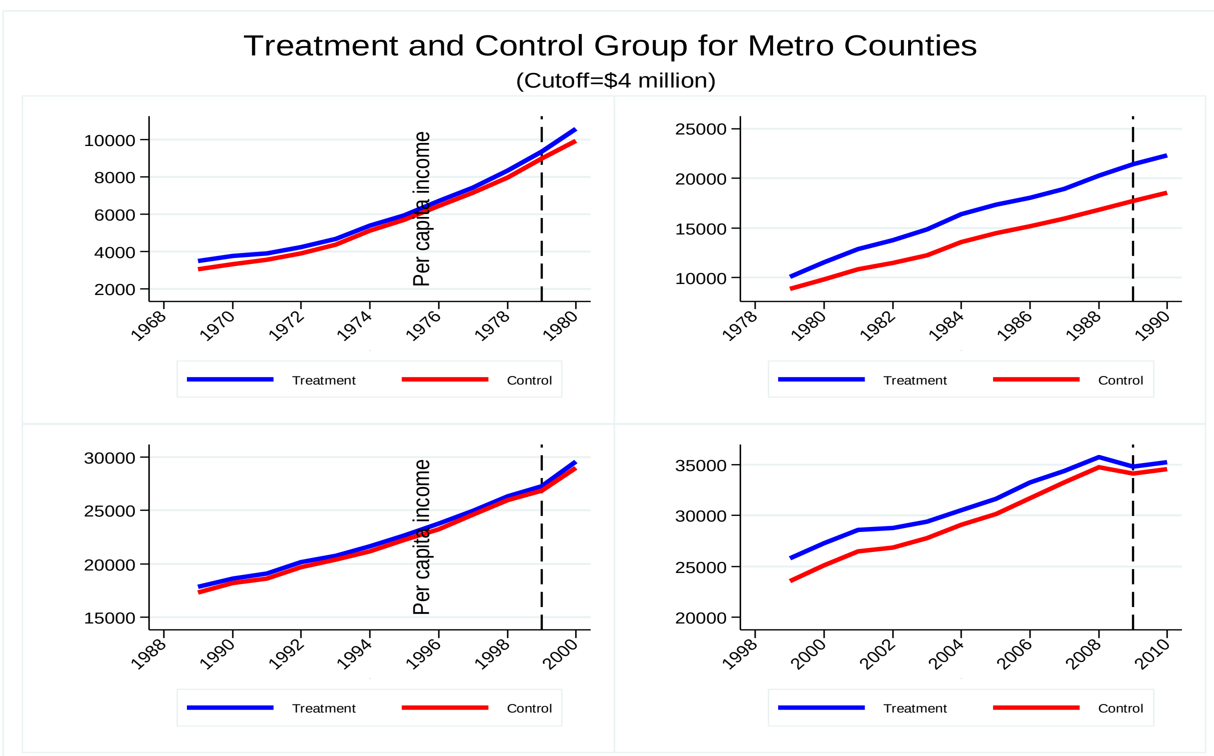



(c) Non-metro counties

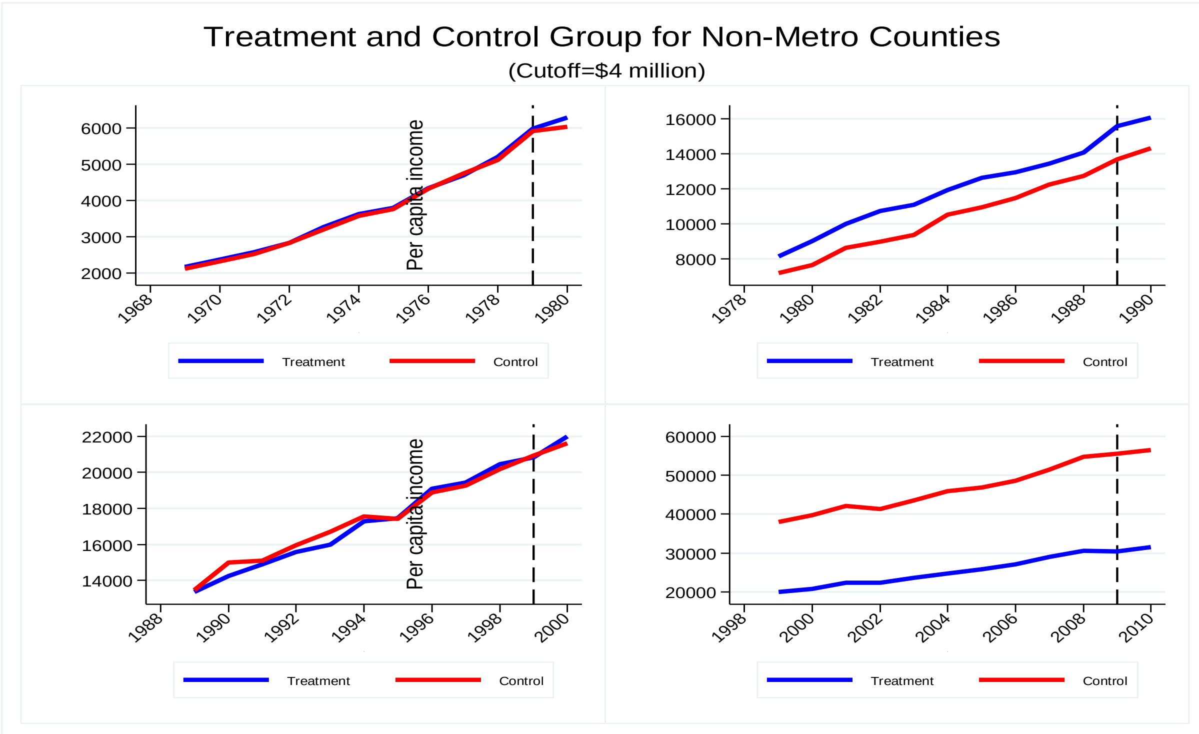
**Figure A1. Comparison between treatment and control group for damage level=$1 million**




(a) All counties




(b) Metro counties




(c) Non-metro counties

**Figure A2. Comparison between treatment and control group for damage level=$4 million**