Understanding the Labor Outcomes of Hurricane Sandy

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Abstract

Instances of forced climate migration such as Hurricane Katrina can lead to devastating economic outcomes for those involved. Though current economic literature has extensively covered the impact of Hurricane Katrina, there is still little research that has been done on Hurricane Sandy. These results show that there is very little impact from Hurricane Sandy on labor outcomes in the New York City area.

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2 Introduction

In late October of 2012, Hurricane Sandy, which to this day stands as one of the deadliest hurricanes to make landfall on the continental United States, began its path of destruction in the United States when it first hit Brigantine, New Jersey. For the next few days, hurricane-force winds struck the northeastern region of the United States, resulting in over $19 billion in losses and death tolls of at least 53 people in New York City. Almost a decade later, New York City is well on its way to recovery. However, there is still a gaping hole in terms of research around the labor outcomes of those affected by this event. Though the effects of past climate catastrophes such as Hurricane Katrina, especially on the labor market, are well-studied, there is very little research done on Hurricane Sandy. Past research on Hurricane Katrina, such as that done by Groen and Polivka (2008), found that evacuation status played a major role in determining labor market outcomes; those who were forced to evacuate experienced much worse outcomes compared to those who didn't. Zissimopoulos & Karoly (2010) also found adverse effects of evacuation, but they also found that, for the most part, there wasn't sustained depressions of employment in the states that were studied. Interestingly enough, Deryugina et al. (2018) found that there was actually higher post-Katrina labor income in those affected by the storm, which is the opposite of the previous findings. With these studies in mind, I wanted to see exactly what the labor outcomes of Hurricane Sandy were. One would imagine that these forms of forced climate migration/evacuation would not lead to optimal outcomes. With climate change becoming an increasingly large problem, it is imperative to study the different effects it has on the people involved in order to ensure that recovery is equitable and doesn't further systemic exclusion, such as gentrification. I hypothesize that those who were forced to evacuate due to Hurricane Sandy in New York would face worse labor outcomes than those who weren't.

To investigate this question, I used American Community Survey (ACS) data to obtain statistics on labor outcomes for various census tracts that were affected by Hurricane Sandy. I limited my research area to the New York City area since there were distinct evacuation orders that could be then used to delineate treatment and control groups.

My analysis of the data showed that, though there seemed to be a visual difference in the data, there wasn't a statistically significant difference between the those who were forced to evacuate and those who didn't for two out of the three data sets that I used. To further bolster my findings, I utilized a variety of different controls along with different data sets in order to verify the results. I also utilized a fourth regression that was very similar to the third data set, save for the addition of a few interaction terms. This fourth regression was meant to show how the impact of Hurricane Sandy varied in the years after the event.

The following sections will proceed as follows. Section III summarizes current literature on the effect of certain climate catastrophes on labor outcomes. Section IV describes the data that I am using from the ACS for my analysis. The granularity of my data that is used is the US Census tract, which is smaller than a County. Section V outlines the specific empirical strategy that is used to determine the causal effect of Hurricane Sandy on differences in labor outcome. Section VI contains the results of the analysis along with discussions of the numbers that were produced. Section VII details future directions that I hope to take in order to extend this current research. Finally, Section VIII concludes the paper, which is then followed by Tables and Figures at the end.

3 Literature Review

Research on the impact of Hurricane Katrina suggests that there was a negative impact on those who were forced to evacuate. In the paper titled "The Effect of Hurricane Katrina on the Labor Market Outcomes of Evacuees," Groen & Polivka (2008) use CPS data collected after Hurricane Katrina to investigate the effects. It was found that Hurricane Katrina had a substantial impact on the labor market outcomes of evacuees over the 13-month period following the tragedy. Evacuees were defined as anyone who had to evacuate in any of the months that surveys were conducted, along with the specification that they lived in Louisiana, Mississippi, or Alabama in a county designated by the Federal Emergency Management Agency (FEMA) as eligible for both public and individual disaster assistance as a result of Hurricane Katrina. Using a difference-in-difference method, Groein & Polivka (2008) measured the causal effect of Hurricane Katrina and determined that it led to substantially worse outcomes for those who were forced to evacuate. Of those who were forced to evacuate, the paper estimates that around 73 percent of the evacuees ended up returning to their original households. Notably, the unemployment rate for non-returnees was far worse than those who returned. Non-returnees had an unemployment rate of 30.6 percent compared to 6.0 percent for returnees. However, the estimates suggested that the effects of Hurricane Katrina diminished over time as adjustments were made. Rather than making a parallel trends assumption and finding a control group, the researchers looked at comparable evacuees in Katrina-affected areas and compared them to all residents of the affected area prior to Katrina. The various labor outcome variables that were looked at included labor force participation rate, employment-population ratio, and unemployment rate. Controls that were used included age, race, ethnicity, gender, educational attainment, marital status, number of children, indicators for living in an MSA, having ever served on active duty in the US armed forces, and being born outside the United States. Ultimately, this paper corroborates the intuitive sense that forced climate migration would lead to worse labor outcomes. Not only is there a physical uprooting of those involved, but the mental toil that the event brings on the victims could have lasting effects.

However, another similar study looking at the impact of Hurricane Katrina actually noted the opposite effect. In the paper titled "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns," Deryugina et al. (2018) notes that the income of those affected by the storm was actually greater than those who were in the control group when investigating it through the lens of individual tax returns. This was attributed to the rise in nominal wages rather than a rise in real wages, the widespread change on the New Orleans labor market, and the uprooting of people from a market with limited economic opportunities, such as the New Orleans labor market. To investigate this question, the paper focused on looking for comparative cities similar to New Orleans and regressing based on panel data including adjusted gross income, home ownership status, wage income, along with other control variables. What's interesting from this paper is that it seems to indicate that Hurricane Katrina had a positive effect on evacuees. Though contradictory to the previous paper, these findings are in line with another recent paper titled "The Gift of Moving: Intergenerational Consequences of a Mobility Shock" by Nakamura et al. (2020) which found that an Icelandic volcanic eruption had a positive effect on labor outcomes for those who were affected. The volcanic eruption in 1973 provided a natural experiment for Nakamura et al. (2020) to determine the causal effect of this forced climate migration. It was found that those who were forced to evacuate experienced an 83 percent increase in annual earnings over people's working life, and this effect peaked during prime age. Those who moved on average received 3.5 more years of schooling, and their children got 5.7 more years of schooling, suggesting the notion that this forced mobility allowed for better educational opportunities. These two papers have particularly important policy impacts, as it would imply that significant action would not need to be taken to ameliorate the situations of the victims of forced climate migration. In particular, the research done by Nakamura et al. (2020) was a big motivating factor in understanding the impact of Hurricane Sandy since it elucidates the importance of how forced moving could lead to people leaving environments that weren't conducive for success.

In addition, there has been research that has investigated how Hurricane Katrina evacuees impact the labor markets of other neighboring cities. In a paper titled "Measuring the Labor Market Impacts of Hurricane Katrina Migration: Evidence from Houston, Texas," McIntosh (2008) found that the wages and employment among native Houstonians were statistically significantly, yet modestly, adversely impacted by Hurricane Katrina evacuees into the Houston metro area labor market. This research by McIntosh employs CPS data to perform a difference-in-difference regression analysis, where the comparison is between before and after outcomes of the Houston natives. The model controlled for sex, age, education, marital status, and race. The analysis showed that Hurricane Katrina migration is associated with a 1.8 percent decline in wages and 0.5 percentage point decline in the probability of being employed among native Houstonians, both of which were statistically significant at the 5 percent level. While McIntosh (2008) seems to suggest a negative impact of the influx of Hurricane Katrina evacuees on the labor market of neighboring cities, there has also been contrary evidence. In the paper titled "The Impact of the Mariel Boatlift of the Miami Labor Market," Card (1990) finds that the influx of Cuban laborers from the Mariel boatlift increased the labor force in the Miami metropolitan area while having virtually no effect on the wages or unemployment rates of less-skilled workers. Though Card (1990) does not look at a forced climate migration event, the natural experiment provided by the Mariel boatlift can still help us understand the impact of new workers to an existing market. While this paper will focus on areas that were specifically hit by Hurricane Sandy, understanding the impact of evacuees on neighboring cities again has important policy impacts. The government would not only have to be concerned with the recovery of the specific area impacted by the climate catastrophe, but also with the well-being of neighboring areas.

A final study on the impact of Hurricane Katrina used a time trend analysis rather than a difference-in-difference analysis, and the results were that evacuation had a negative impact on the labor outcomes of those involved. In the paper titled "Employment an Self-Employment in the Wake of Hurricane Katrina," Zissimopoulos & Karoly (2010) used CPS data to conduct a time trend analysis on various states most impacted by the storm, such as Alabama, Florida, Louisiana, and Mississippi. The study looked at various sources of labor data to measure the impact, such as labor force participation rate, employment rate, unemployment rate, and self-employment rate. The controls used were similar to past literature, such as controlling for age, sex, marital status, education, and race. The time-trends found that there was a relatively short-term negative outcome in all the states studied, followed by eventual recovery. Only Mississippi showed continued lower rates of unemployment a year after the storm. The importance of this research is that it serves to further corroborate the notion that forced climate migration leads to negative impacts on labor outcomes by using a different statistical approach. The addition of a time trend analysis helps bolster the findings of the difference-in-difference approach from Groen & Polivka (2008).

My research will build on this wealth of past literature that seeks to understand the impact of climate migration on labor outcomes. Hurricane Katrina is one of these events that has been thoroughly studied and, curiously enough, the results change dramatically based on the data source that is used. By taking a look at Hurricane Sandy, another example of forced climate migration, I will be able to further our understanding of this topic.

4 Data

The data source that I will be using comes from the American Community Survey (ACS), particularly looking at the 5-year estimates. Though all my data comes from the ACS, I will be using four separate data sets containing different number of years after Hurricane Sandy. The first will be looking at 2011 and 2013, so only one year of post-treatment data. The second will be looking at 2011, 2013, and 2014, while the third data set will include 2011, 2013, 2014, and 2015. The rationale for including increasing numbers of years was to see if there were effects on the labor outcome that weren't necessarily seen in the immediate year following Hurricane Sandy. As mentioned before, I will also have a fourth data set that includes 2011, 2013, 2014, and 2015, but with three interaction terms for each post-Hurricane Sandy year rather than one general interaction term like the rest. These interaction terms should theoretically capture the how the impact of Hurricane Sandy varies.

The granularity of the data is based off of census tracts in the affected area and the exact data points are aggregates of the census tracts. The census tracts were picked based off the tracts outlined in the evacuation map shown in Figure 2. In addition, the ACS data is cross-sectional across the different census tracts. The specific tracts were picked by using the New York City evacuation map to determine which tracts would fall under each zone. The census tracts are around 100 to 150 for each group, but being that this is aggregate data from thousands of individuals, the relatively low number is not a concern. The mandatory evacuation orders only applied to those who were in Zone A in

New York, which included some, but not all, coastal areas. Since there were other coastal areas that did not fall under the mandatory evacuation orders, I designated the coastal areas in Zone A as the treatment group, while those that weren't as the control group. The assumption is that the coastal areas should have had similar characteristics prior to Hurricane Sandy, and the only difference is Hurricane Sandy, which would have hit Zone A harder.

The main variable I will be using to evaluate labor outcomes will be employment rate. My control variables include sex, age, race, and citizenship status. ACS data breaks this up into multiple delineations, but the control variables broadly fall in those aforementioned categories.

5 Empirical Strategy

To investigate this problem, I will be using a difference-in-difference approach. I will be performing four separate difference-in-difference regressions that follow a similar regression structure but employ different data sets as mentioned above. The regression equation that is used for the first difference-in-difference analysis is listed below:

$$employ_{it} = \beta_1 + \beta_2 Sandy_i + \beta_3 2013_t + \beta_4 (Sandy * 2013)_{it} + \beta_5 X_{it} + \epsilon_{it}$$

$employ_{it}$: Employment rate of entity i in period t

$Sandy_i$: Dummy that equals one for observations in areas affected by Hurricane Sandy

2013_t: Dummy that equals one for observations in 2013

$(Sandy * 2013)_{it}$: Interaction term that indicates the effect of Hurricane Sandy

X_{it}: Control variables that include sex, age, race, and citizenship status

ϵ_{it}: Error term

The second difference-in-difference equation is listed below:

$$employ_{it} = \beta_1 + \beta_2 Sandy_i + \beta_3 2014_t + \beta_4 (Sandy * 2014)_{it} + \beta_5 X_{it} + \epsilon_{it}$$

$employ_{it}$: Employment rate of entity i in period t

$Sandy_i$: Dummy that equals one for observations in areas affected by Hurricane Sandy

2014_t: Dummy that equals one for observations in 2013 and 2014

$(Sandy * 2014)_{it}$: Interaction term that indicates the effect of Hurricane Sandy

X_{it}: Control variables that include sex, age, race, and citizenship status

ϵ_{it}: Error term

The third difference-in-difference equation is listed below:

$$employ_{it} = \beta_1 + \beta_2 Sandy_i + \beta_3 2015_t + \beta_4 (Sandy * 2015)_{it} + \beta_5 X_{it} + \epsilon_{it}$$

$employ_{it}$: Employment rate of entity i in period t

$Sandy_i$: Dummy that equals one for observations in areas affected by Hurricane Sandy

2015_t: Dummy that equals one for observations in 2013, 2014, and 2015

$(Sandy * 2015)_{it}$: Interaction term that indicates the effect of Hurricane Sandy

X_{it}: Control variables that include sex, age, race, and citizenship status

ϵ_{it}: Error term

In addition to the first three models, I also used another model that could potentially look at the heterogeneity in the effect over time. To do this, I used dummy variables for all the years in the data set while having multiple interaction terms (3 in this case) based on treatment and post-Sandy years (2013-2015).

The difference-in-difference equation is listed below:

$$employ_{it} = \beta_1 + \beta_2 Sandy_i + \beta_3 2011_t + \beta_4 2013_t + \beta_5 2014_t + \beta_6 2015_t + \beta_7 (Sandy * 2013)_{it} +$$
$$\beta_8 (Sandy * 2014)_{it} + \beta_9 (Sandy * 2015)_{it} + +\beta_1 0 X_{it} + \epsilon_{it}$$

$employ_{it}$: Employment rate of entity i in period t

$Sandy_i$: Dummy that equals one for observations in areas affected by Hurricane Sandy

2011_t: Dummy that equals one for observations in 2011

2013_t: Dummy that equals one for observations in 2013

2014_t: Dummy that equals one for observations in 2014

2015_t: Dummy that equals one for observations in 2015

$(Sandy * 2013)_{it}$: Interaction term that indicates the effect of Hurricane Sandy in 2013

$(Sandy * 2014)_{it}$: Interaction term that indicates the effect of Hurricane Sandy in 2014

$(Sandy * 2015)_{it}$: Interaction term that indicates the effect of Hurricane Sandy in 2015

X_{it}: Control variables that include sex, age, race, and citizenship status

ϵ_{it}: Error term

In the first three difference-in-difference approaches, the variable of interest that will provide the causal effect of Hurricane Sandy will be β_4. Specifically, β_4 measures the change in mean employment rate in evacuated tracts minus the change in mean employment rate in non-evacuated tracts due to Hurricane Sandy. For example, taking the first regression as an example, we get the result below:

$(E[Y_{it} \mid Sandy_i = 1, 2013_t = 1] - E[Y_{it} \mid Sandy_i = 1, 2013_t = 0]) -$
$(E[Y_{it} \mid Sandy_i = 0, 2013_t = 1] - E[Y_{it} \mid Sandy_i = 0, 2013_t = 0])$

This equation would then equal:
$((\beta_1 + \beta_2 + \beta_3 + \beta_4) - (\beta_1 + \beta_2)) - ((\beta_1 + \beta_3) - (\beta_1))$ which results in β_4

The fourth regression equation allows us to understand how the population is impacted over the years, and from the results seen in Table 7, we can see that the trends change over the years. Aggregating all the post-years allows us to capture this dynamic.

The crux of a difference-in-difference strategy relies on the parallel-trends assumption to hold true, which states that the two groups behaved in a similar fashion prior to the event. Figure 1 shows the proof for parallel trends for employment rates between the two groups. From the visual, it would seem to suggest that the two groups behaved very similarly if not completely the same prior to Hurricane Sandy. This would lend us to believe that any difference in labor outcomes afterwards can be attributed to Hurricane Sandy.

6 Results and Discussion

In my parallel trends graph, I included data from 2013 to initially inspect if there was any notable difference in outcomes. Looking at Figure 1, it would seem that those who evacuated had higher employment rates. This would mean that Hurricane Sandy had a *positive* impact on labor outcomes, which would go against my initial hypothesis. However, when looking at the actual employment rates, we see that there is a very small difference, with it being around half a percent difference. Of the three regressions that I took, there was only one which resulted in a statistically significant coefficient for the interaction term. For the rest of this section, I will be going through the different regressions and explaining the results.

In my first regression, the interaction term has a coefficient of $3.8*10^{-9}$ and a t-statistic of 1.16. This means that there is no statistical significance at any standard level. What's interesting to note is that the coefficient of the interaction term, which again represents the impact that Hurricane Sandy has on employment rates, is positive. When looking at Table 1, we can rule out any interference from variation in the distribution of the age groups. We can see that there is a roughly normal distribution in ages with no groups having a dominant share of the total. Most importantly it seems that the distribution is highest around the working age group, which is important when examining the question of labor market outcomes. This could also provide an explanation for the relatively high employment rate, since there weren't as many people who were on the verge of leaving the labor force anyways.

In my second regression, the interaction term has a coefficient of $5.8 * 10^{-9}$ and a t statistic of 2.05. A t-statistic of 2.05 means that this result is statistically significant at the 95 percent level. In addition, the coefficient indicates that Hurricane Sandy again has a *positive* impact on labor outcomes. However, the economic magnitude that this coefficient presents is incredibly small. If we were to multiply the coefficient by the average labor force in this dataset, there wouldn't even be a difference in employment since the coefficient is so small. With that in mind, though the sign of the coefficient would indicate that there is a positive relationship between Hurricane Sandy and labor outcomes, the absolute magnitude of this would go against that notion. Once we include data from the second year after Hurricane Sandy, we get a statistically significant result. This could indicate that the effects of Hurricane Sandy are not immediate and would take a longer period of time to appear. This would go against the findings of some of the other research that was discussed earlier in this paper, such as the work done by Zissimopoulos & Karoly (2010), who saw that there were immediate negative effects from Hurricane Katrina, but was short-term. When looking at Table 3, we also see that the distribution of the population in terms of the control variables are also very similar to that of the first regression. This gives us confidence that the difference in results was not from a differing population or skewed data sources.

In my third regression, the interaction term has a coefficient of $4.27 * 10^{-9}$ and a t-statistic of 1.6. Similarly to the first regression, this t statistic would not be considered statistically significant at any standard level. This could be explained by the fact that, although there were delayed impacts of Hurricane Sandy on labor outcomes that could be seen when including data from 2014, the effects are diminished or negligible three years after the event. As a result, including data from 2015 would then dilute any effects that were noticed in the second regression. One of the problems with increasing sample size when it comes to t statistics is that tiny differences are magnified and can be seen as significant. This can be seen by looking at the equation for the t-statistic below.

$$t = \frac{\overline{x} - \mu}{s_D / \sqrt{n}}$$

In my fourth regression, we can see that the sign changes over time in the interaction term. It changes from -.00152 to .00401 to .00182. The coefficients are all greater in magnitude than my interaction terms in my previous regressions. Crucially, these coefficients are still not statistically significant, as the greatest t-statistic out of the three is an absolute value of .52. As a result, though we can see a difference over time, we should be wary of it. This is also important considering how our previous regression was also run with a very similar data set with the exception being the additional interaction terms. The lower statistical power would most likely be due to additional explanatory variables. However, looking at the change in signs of our coefficients, we can observe the dynamics of labor outcomes in a population that has recently been affected by a natural disaster. We can see that immediately after Hurricane Sandy, the employment rate goes down, followed by two years of increasing employment rate. This intuitively makes sense considering how we would expect the population to initially suffer and take time to recover. Afterwards, and in line with previous literature, it seems this forced climate migration increases employment opportunities in some cases .

We can see that by increasing n, we get a greater t-statistic. This could've been the issue that resulted in a statistically significant t-statistic in the second regression that I ran. However, the aforementioned effect that 2015 had on the data set could've diminished even this small difference, making it so that the third regression no longer has a statistically significant coefficient. Going off this notion, the muted effects of Hurricane Sandy on the 2015 employment rates would have had to been less impactful than the positive effect that increasing the sample size has on the t-statistic.

Looking at Figure 3, we can potentially understand the reasons why there wasn't as big of a difference in employment rates due to Hurricane Sandy when compared to other storms, such as the well-studied Hurricane Katrina. We can see that the number of housing units that was affected in Hurricane Katrina quadrupled that of Hurricane Sandy. The ability to return to areas that were devastated by the storms is a big indicator of economic success in the future as seen in the work done by Groen & Polivka (2008). This is further corroborated by the fact that 600,000 families were homeless a month after Hurricane Katrina while there was 30,000 residents of New York and New Jersey displaced two months later. Though 30,000 people displaced in one of the most populous cities in the world is not negligible, the scale is far smaller than that of Hurricane Katrina. The damage from Hurricane Sandy still resulted in nearly 20 billion dollars of insurance compensation, but again this is only a fraction of the damage from Hurricane Katrina.

My results from my difference-in-difference regressions would indicate that Hurricane Sandy had very little impact on labor outcomes, which is contrary to my hypothesis. There was a statistically significant positive impact of Hurricane Sandy when including data from two years after the storm, but even then the economic magnitude was incredibly small. This difference in results when compared to Hurricane Katrina could be due to the smaller impact that Hurricane Sandy had on the areas it hit. The fourth data set revealed an initial negative impact of Hurricane Sandy followed by years of increases in employment rate, which synthesizes some of the observations from Hurricane Katrina in which some observed positive impacts while others observed negative impacts from the natural disaster. However, this again was not statistically significant, so little conclusions can be made.

7 Future Directions

My research has established the groundwork for analyzing the impact of Hurricane Sandy. However, there is still a lot to be done in regards to this problem. One of the main issues is how I chose to create the two groups. The evacuation order may have affected similar commuting zones. As a result, even if evacuation orders differed, the outcome might've been the same for the individuals since they're all in such close proximity. A future extension of this research would then be to look at different groups for the control and treatment group. This could be in the form of coastal regions in New York City and Boston, for example, that had similar starting economic situations. We could select for census tracts that had similar median income, housing price, etc. in order to truly separate the groups geographically. We could also look at closer regions, such as New Jersey, in order to try and get similar starting situations for our two groups; however, we would have to be careful so as to ensure that New Jersey was not also affected by Hurricane Sandy.

In addition to finding better groups, I would also want to use a data set that was more complete and potentially more granular. The ACS data that I used did not have data for all the census tracts when going back to 2008 or 2009 when establishing parallel trends. As a result, it reduces the strength of my analysis. In previous literature, I have seen researchers use tax returns from individuals to conduct a difference-in-difference analysis. Getting access to this type of data would be incredibly hard for me, but this would be something that I would be interested in doing in order to get a better picture on the effects of Hurricane Sandy. In general, I would want to be able to use some sort of panel data in order to track the outcomes of the same individuals. The data that I used were all aggregates and didn't specify the individuals, thus leading to a lot of confounding variables such as inflow and outflow of people.

Finally, I can also look at different explanatory variables. My research focused on using the employment rate as the explanatory variable. However, there may be better explanatory variables that measure the economic health of a region. This could be through median household income or even home prices. Future work in this field could look at including a panel of explanatory variables to find one that has more statistical power.

8 Conclusion

There is a currently a wealth of economic literature that seeks to understand the impact of forced migration on labor outcomes. The results are mixed, as some researchers such as Nakamura et al. (2020) would indicate that forced climate migration leads to improved economic outcomes for those impact along with their offspring, while other researchers, such as Groen & Polivka (2008), would indicate the complete opposite. Issues of forced climate migration will only be exacerbated in the future with increasing effects of global warming and climate change. As a result, it is imperative to understand these effects in order to implement equitable policies for recovery. This could be in the form of aiding those directly impacted by the storm, but also in the form of ensuring neighboring cities are not overwhelmed by the influx of workers. While my research did not find an economically significant impact of Hurricane Sandy, this does not mean that these catastrophes do not have devastating effects. Further research needs to be conducted in order to understand the outcomes.

9 Tables and Figures

Table 1: Summary Statistics of First Regression

	(1)					
	Count	Mean	SD	Min	Max	Median
labor_force	502	3461.705	2667.684	13	21886	2780.5
employment_rate	502	.9071493	.0659667	.3731343	1	.9207781
unemployment_rate	502	.0928507	.0659667	0	.6268657	.0792219
prop_male	502	.4780299	.0506015	.278	.831	.476
prop_female	502	.5220817	.050593	.169	.722	.524
under_5	502	.057498	.0310542	0	.273	.056
_to_9	502	.0547072	.0274002	0	.193	.052
_to_14	502	.0567251	.0376098	0	.514	.053
_to_17	502	.0339681	.0196483	0	.114	.0325
_to_24	502	.0900159	.0457666	0	.375	.084
_to_34	502	.1520876	.0774155	0	.542	.136
_to_44	502	.1373546	.0456367	0	.391	.1355
_to_54	502	.145249	.0474369	.023	.486	.139
_to_64	502	.1202211	.0417414	0	.252	.12
_to_74	502	.0765797	.0405743	0	.242	.0735
_to_84	502	.0523048	.0378272	0	.346	.0465
_and_over	502	.0238227	.0256694	0	.201	.018
white	502	.6206833	.271069	0	1	.663
african_american	502	.1472112	.2221861	0	.95	.03
american_indian	502	.0033526	.0106121	0	.18	0
asian	502	.1283825	.1475669	0	.863	.069
pacific_islander	502	.0008048	.008645	0	.146	0
other_race	502	.0783964	.1148268	0	1	.033
two_or_more_races	502	.0213267	.0238648	0	.188	.015
native_born	502	.6614582	.1669257	.132	1	.684
foreign_born	502	.3386494	.1669621	0	.868	.316
naturalized_citizen	502	.2132231	.1302913	0	.647	.186
non_citizen	502	.1254641	.0791194	0	.459	.118
post_sandy	502	.5	.5004988	0	1	.5
treatment	502	.3864542	.4874224	0	1	0
interaction	502	.1932271	.3952234	0	1	0
N	502					

Table 2: Regression Results of First Regression

	(1)
	employment_rate
interaction	3.80e-09
	(1.16)
post_sandy	-5.88e-10
	(-0.28)
treatment	-4.63e-09
	(-1.92)
_cons	1.000***
	(261780.79)
N	502

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Summary Statistics of Second Regression

	(1)					
	Count	Mean	SD	Min	Max	Median
labor_force	753	3502.274	2695.74	13	21886	2875
employment_rate	753	.9062488	.0664789	.3449782	1	.92
unemployment_rate	753	.0937512	.0664789	0	.6550218	.08
prop_male	753	.4793293	.0508338	.278	.853	.477
prop_female	753	.5207822	.0508193	.148	.722	.523
under_5	753	.0580279	.030729	0	.273	.056
_to_9	753	.0549562	.0265836	0	.193	.053
_to_14	753	.056162	.0364386	0	.514	.053
_to_17	753	.0334502	.0192634	0	.114	.032
_to_24	753	.0887397	.0450516	0	.375	.083
_to_34	753	.153571	.0772829	0	.542	.136
_to_44	753	.1366335	.0442523	0	.391	.135
_to_54	753	.1446321	.0455979	.023	.486	.14
_to_64	753	.122332	.0435652	0	.5	.124
_to_74	753	.0770677	.0396474	0	.242	.074
_to_84	753	.051158	.037651	0	.349	.045
_and_over	753	.023826	.0250694	0	.201	.018
white	753	.6173161	.2705983	0	1	.661
african_american	753	.1462776	.2224583	0	.97	.031
american_indian	753	.0033732	.0098912	0	.18	0
asian	753	.1296282	.146396	0	.863	.069
pacific_islander	753	.0006003	.0070983	0	.146	0
other_race	753	.0800969	.1145584	0	1	.035
two_or_more_races	753	.0226361	.0239214	0	.188	.017
native_born	753	.6590319	.1678707	.132	1	.684
foreign_born	753	.3410744	.1678932	0	.868	.316
naturalized_citizen	753	.2153825	.1306807	0	.647	.189
non_citizen	753	.1257158	.0788521	0	.464	.118
post_sandy	753	.6666667	.4717179	0	1	1
treatment	753	.3851262	.4869486	0	1	0
interaction	753	.2563081	.4368841	0	1	0
N	753					

Table 4: Regression Results of Second Regression

	(1)
	employment_rate
interaction	5.83e-09*
	(2.05)
post_sandy	-5.75e-10
	(-0.32)
treatment	-4.77e-09*
	(-2.00)
_cons	1.000***
	(314265.56)
N	753

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Summary Statistics of Third Regression

	(1)					
	Count	Mean	SD	Min	Max	Median
labor_force	1004	3532.594	2707.925	13	21886	2893
employment_rate	1004	.9074845	.0647966	.3449782	1	.9205573
unemployment_rate	1004	.0925155	.0647966	0	.6550218	.0794427
prop_male	1004	.4796444	.0518176	.103	.856	.479
prop_female	1004	.5204562	.0517997	.145	.897	.521
under_5	1004	.0586853	.0305385	0	.273	.057
_to_9	1004	.0549203	.0258616	0	.193	.0535
_to_14	1004	.0554422	.0339658	0	.514	.053
_to_17	1004	.0330588	.0189961	0	.127	.032
_to_24	1004	.0876046	.0443635	0	.375	.0825
_to_34	1004	.1552301	.0776234	0	.564	.137
_to_44	1004	.1361992	.0434271	0	.391	.134
_to_54	1004	.1435229	.0437236	0	.486	.139
_to_64	1004	.1235697	.0446465	0	.5	.125
_to_74	1004	.0777151	.039171	0	.242	.075
_to_84	1004	.0507082	.0373385	0	.349	.045
_and_over	1004	.0239064	.0247091	0	.201	.018
white	1004	.6139363	.2703552	0	1	.6575
african_american	1004	.1463118	.2226077	0	.97	.031
american_indian	1004	.0034094	.0097626	0	.18	0
asian	1004	.1308725	.1458282	0	.863	.069
pacific_islander	1004	.0005	.0061863	0	.146	0
other_race	1004	.0816733	.1144825	0	1	.039
two_or_more_races	1004	.0233058	.0237582	0	.188	.017
native_born	1004	.6579392	.168644	.132	1	.6835
foreign_born	1004	.3421564	.1686584	0	.868	.3165
naturalized_citizen	1004	.2167789	.1308424	0	.663	.192
non_citizen	1004	.1254163	.0787191	0	.464	.1175
post_sandy	1004	.75	.4332285	0	1	1
treatment	1004	.3844622	.4867103	0	1	0
interaction	1004	.2878486	.4529858	0	1	0
N	1004					

Table 6: Regression Results of Third Regression

	(1)
	employment_rate
interaction	4.27e-09
	(1.60)
post_sandy	-4.00e-10
	(-0.24)
treatment	-4.50e-09
	(-1.91)
_cons	1.000***
	(354557.54)
N	1004

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

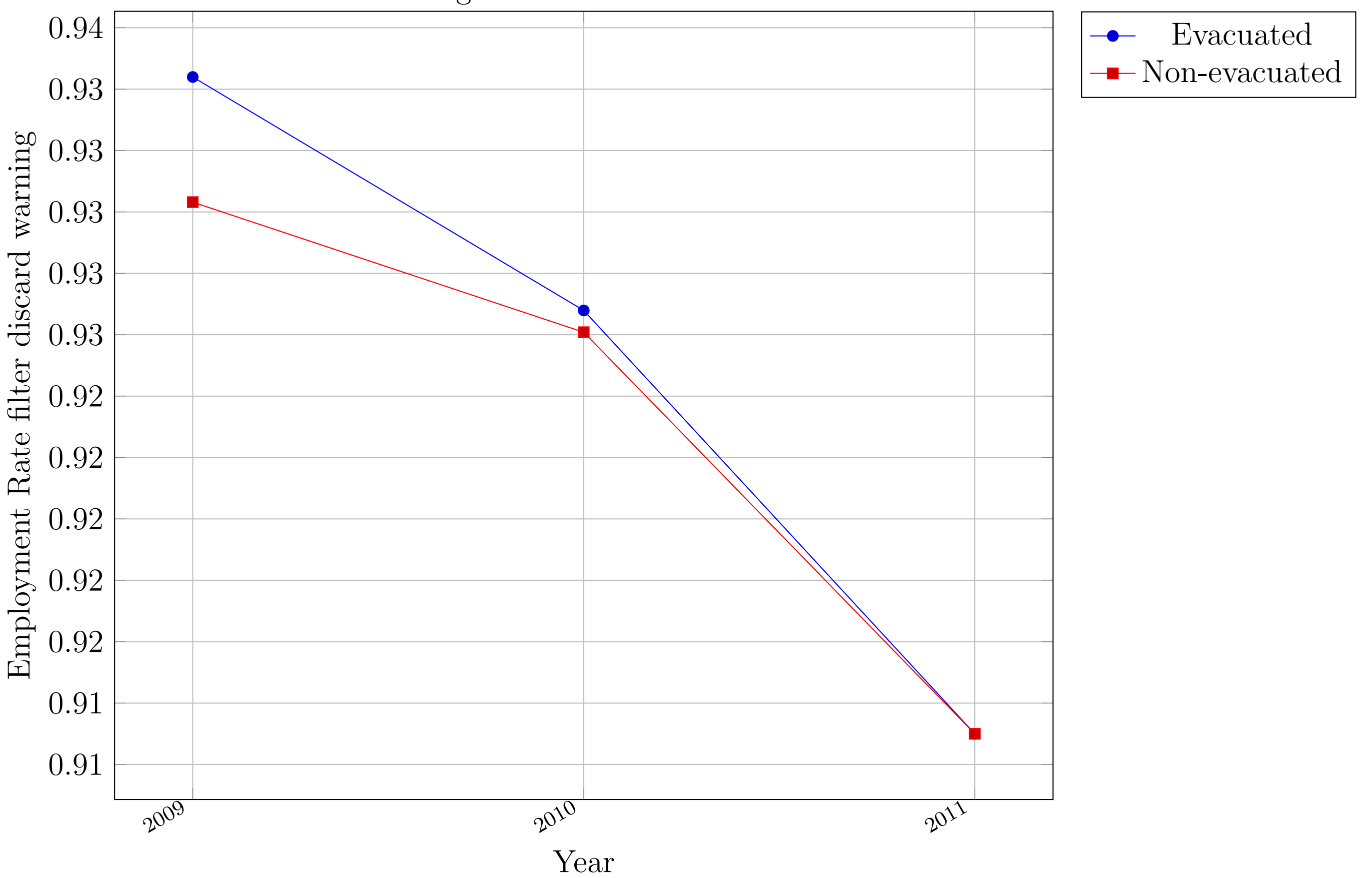
Table 7: Regression Results of Fourth Regression

	(1)
	employment_rate
interaction_2013	-0.00152
	(-0.20)
interaction_2014	0.00401
	(0.52)
interaction_2015	0.00182
	(0.24)
treatment	-0.0109
	(-1.42)
_cons	5.812
	(0.63)
N	1004

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Parallel Trends



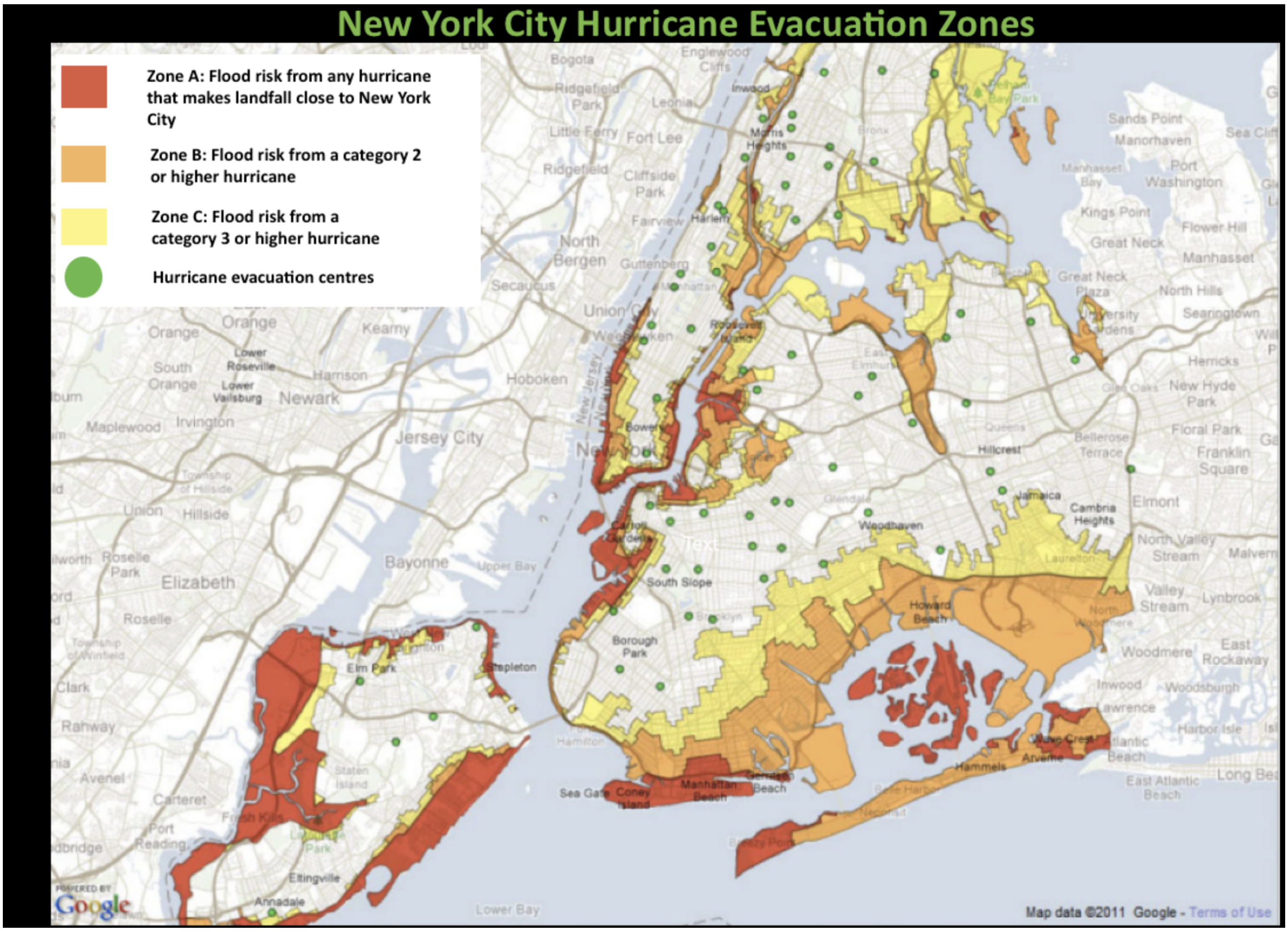


Figure 2: New York City Evacuation Map (Bloch 2011)

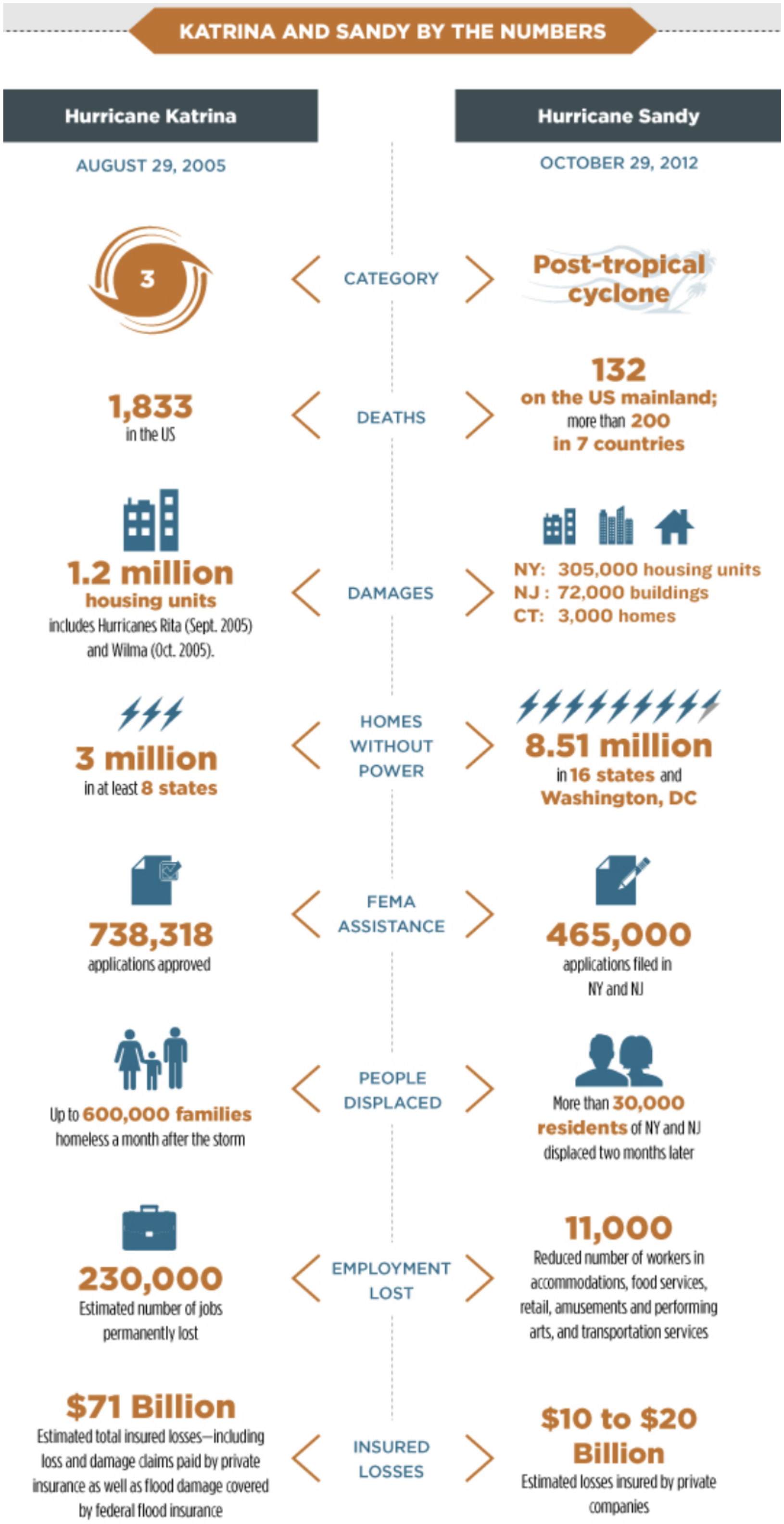


Figure 3: Hurricane Katrina vs. Hurricane Sandy Impact (Levenson 2014)

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