

# The Long-run Effects of Natural Disaster Exposure: Evidence from the Great Galveston Hurricane

Jacob Van Leeuwen\*

This version: August 4, 2025

## Abstract

I use a natural experiment to examine the long-term and intergenerational effects of exposure to natural disasters, exploring how where we live can have long-lasting impacts. I examine outcomes of individuals impacted by the Galveston Hurricane of 1900, the deadliest and one of the most costly natural disasters in US history. Using historic newspaper records, I identify towns that sustained significant physical damage or were completely destroyed by the storm. Leveraging linked US Census records and IPUMS Full Count Census Data from 1880-1940, I find that individuals living in affected towns in southeast Texas in 1900 were more likely to migrate, had worse labor market outcomes, poorer literacy, and shorter lifespans compared to similar individuals in nearby unaffected towns. These negative effects persisted into the next generation, pointing to both persistent long-run and intergenerational effects of natural disaster exposure, which may be driven by individuals' migration behavior.

*JEL classifications: J61, J62, N31, N32, R23, Q54*

*Keywords: Intergenerational mobility, migration, natural disaster exposure*

---

The author thanks Andrew Barr, Jonathan Meer, Joanna Lahey, Joe Price, Zach Ward, and participants at the Texas A&M PLIO Workshop for their feedback. Additional thanks goes to Kasey Buckles, Joe Price, and the BYU Record Linking Lab for generously making longitudinally linked US Census data available through the Census Tree Project. Van Leeuwen declares no conflicts of interest.

\*Department of Economics, Brigham Young University, jacobrvl@tamu.edu

# 1 Introduction

Recent evidence suggests that climate change will increase the number displaced individuals worldwide this century, and many of these individuals will be displaced due to increasingly severe natural disasters (Berlemann & Steinhardt, 2017; Clement et al., 2021). It is increasingly essential to understand the long-term and intergenerational impacts of natural disasters on both socioeconomic and health outcomes. However, due to data limitations, existing evidence focuses on narrowly defined populations (Deryugina & Molitor, 2018; Karbownik & Wray, 2019), and is unable to estimate effects for descendants of those impacted by natural disasters, focusing instead on disparate impacts between children and adults (Nakamura, Sigurdsson, & Steinsson, 2022). In addition, understanding how location determines long run and intergenerational persistence in health and socioeconomic status is of increasing importance in the literature (Bullard & Van Leeuwen, 2025; Deryugina & Molitor, 2018; Green, 2025).

I use a unique natural experiment combined with longitudinally linked US Census data to estimate both long-run and intergenerational effects of natural disaster exposures among individuals who were impacted by the disaster and their descendants. The Galveston Hurricane of 1900 was one of the costliest natural disasters in US history, and remains the deadliest. The hurricane occurred less than six months after census enumeration in 1900, giving me the precise location of where individuals were living at the time of the storm. Additionally, I use the linked US Census data to estimate intergeneration impacts of the storm on descendants of impacted individuals

To examine both long-run and intergenerational effects of natural disasters on socioeconomic outcomes, I use a novel linked dataset (Buckles, Haws, Price, & Wilbert, 2023; Price, Buckles, Van Leeuwen, & Riley, 2021). Specifically, the linked data allow me to measure migration, employment, occupation, and literacy, a proxy for educational investment. This dataset includes linked US Census data from 1900 to 1940 for individuals living in counties in Southeast Texas nearest the hurricane path, which allows me to measure long-run

outcomes. In addition, these data are linked to a large genealogical database, allowing me to estimate lifespan, a key outcome not yet measured in the literature. Because these data follow both individuals and households overtime, I link parents to children and estimate the intergenerational effects of natural disaster exposure.

I employ a differences-in-differences design to estimate the long-run impacts of the hurricane. I identify individuals who were impacted by the Galveston Hurricane of 1900 using contemporary news records from Texas that reported towns in Southeast Texas that sustained significant damage. I also identify individuals who were living in nearby towns that did not sustain significant damage, who provide a good counterfactual to the individuals severely impacted by the storm. This differences-in-differences specification allows me to examine the long-run effects of the storm on migration, occupational quality, and literacy.

To estimate intergenerational effects, I use a refined linear comparison between impacted individuals and their control counterparts. Because of data limitations, I am unable to measure my intergenerational outcomes, employment and lifespan, prior to the hurricane, which prevents me from using a differences-in-differences design. Employment status was first recorded in the 1910 Census, after the hurricane occurred. Additionally, because lifespan is a very long-run outcome, all death dates used to calculate lifespan are well after the hurricane occurred. Since the path of the hurricane was exogenous to factors that influence socioeconomic and health outcomes, the individuals not impacted by the hurricane provide a reasonable comparison group, allowing me to estimate the intergenerational effects of the hurricane on lifespan and employment.

I find that individuals who survived the storm and were living in severely damaged towns were 7 p.p. more likely to migrate than similar individuals living in nearby towns in southeast Texas. Impacted individuals also lived nearly two years shorter, were 4 p.p. less likely to be in the labor force and 5.6 p.p. less likely to be employed 10 years later, and 2.5 p.p. less likely to be employed 30 years later. Impacted individuals were also 4 p.p. less likely to be literate.

I find intergenerational persistence in these effects, as children of impacted individuals lived more than two years shorter if their parent was an adult at the time of the storm. Children also were less likely to be in the labor force (4.2 p.p.) and employed (4.6 p.p.) in 1930, 3 decades after the catastrophic natural disaster. These results add to limited evidence of the impacts of major natural disasters on migration, longevity, education, and labor market performance. The rest of the paper is organized as follows. In Section 2, I discuss the relevant literature. In Section 3, I discuss the data used in the analysis. Section 4 describes the empirical strategy and Section 5 describes the results. Section 6 concludes.

## 2 Related Literature

The primary area of literature that this research adds is the literature on intergenerational effects and transmission. This literature includes descriptive work that describes intergenerational mobility over time in the United States ([Aaronson & Mazumder, 2008](#)), and describes the role neighborhoods play in intergenerational mobility ([Chetty & Hendren, 2018](#)). Recent advances in this literature have examined intergenerational effects of exposure to safety net programs as children ([Barr & Gibbs, 2022](#); [East, Miller, Page, & Wherry, 2023](#)), and intergenerational transmission of health ([Colmer & Voorheis, 2020](#); [Fletcher & Jajtner, 2021](#); [Halliday, Mazumder, & Wong, 2020](#)), and human capital ([Card, Domnisoru, & Taylor, 2022](#); [Lindahl, Palme, Massih, & Sjögren, 2015](#)).

The most similar papers in the this literature to this research examine intergenerational effects of disasters in Latin America ([Caruso, 2017](#)) and examine how place affects outcomes using Japanese internment camps during World War II ([Shoag & Carollo, 2016](#)). My research will add to this literature by examining a broader array of socioeconomic outcomes, including literacy, employment, and occupational quality. I will also be able to measure lifespan, a key outcome that they are unable to measure.

This paper also adds to the economic literature on natural disasters, much of which is

focused on recent disasters including Hurricane Katrina. This research has examined how the hurricane affected educational outcomes for students (Sacerdote, 2012), labor market outcomes (Deryugina & Molitor, 2018), and lifespan among Medicare enrollees (Deryugina & Molitor, 2018). In this literature, the paper most similar to this research examines labor market outcomes of WWI veterans who were exposed to hurricanes (Karbownik & Wray, 2019). They use as-good-as random timing of birth relative to hurricane exposure and compare labor market outcomes for individuals who experienced hurricanes as infants and in utero. I expand on this analysis in two important ways. First, I look at the effect of natural disasters for individuals across all ages, and a more representative sample including women and non-white people of color. Second, I look at a broader array of outcomes including lifespan, migration, literacy, and examine intergenerational effects.

The final area of literature to which this paper adds is the broader literature on migration and place (Boustan, Kahn, & Rhode, 2012; Deryugina & Molitor, 2018; Hornbeck, 2020). The most similar paper in this literature is a study that estimates earnings and education effects of individuals who were impacted by a volcanic eruption in Iceland in 1973 (Nakamura et al., 2022). They find large positive effects on earnings and education among individuals who moved as children, and small negative effects among adults. I expand on their work by examining the intergenerational effects on descendants of impacted individuals and measure the long-term impact of natural disasters on mortality.

### 3 Data

To estimate long-run and intergenerational effects of natural disasters on socioeconomic outcomes, I use a panel of US Census data from 1880 to 1940 (Buckles et al., 2023; Price et al., 2021). These data follow individuals and households over time, which I use to link parents to children and estimate intergenerational effects. These data allow me to measure migration, employment, occupation, literacy, and lifespan, the latter of which is a key outcome not yet

measured in the literature. I use a sample of this linked data for individuals in Southeast Texas who were impacted by the Galveston Hurricane of 1900.

Data that follow individuals across long periods of time are needed to estimate long-run effects. However, US Census records are cross-sectional and creating a panel requires individuals to be linked across time. To link individuals across censuses, a combination of rule-based and machine learning methods are used, as described in [Price et al. \(2021\)](#). Rule-based methods link individuals across censuses that satisfy a set of requirements, such as being born in the same year, having the same name, and living in the same state. Machine learning methods use a set of already linked Census records from a genealogical website to train a machine learning model to link individuals across censuses. Together, these methods allow for the creation of a large panel of data that facilitate estimating long-run effects.

These linked census data facilitate estimating intergenerational effects by linking parents to children. A key feature of the linked census data is that I can follow individuals within their households over time. This allows me to identify individuals in the households in earlier censuses where they are children as well as the households in later censuses where they are adults. Because of this, I am able to identify those who were children at the time of the hurricane in 1900 but have formed their own households as adults in 1920. I then identify two populations: the children in these households in 1920 to create a sample of second-generation individuals, and children of individuals who were adults at the time of the hurricane but were born after 1900. I combine these populations to create a second-generation sample and estimate intergenerational effects.

A useful feature of the linked census data is its richness, allowing me to examine effects for a broad array of outcomes. Because census data includes individuals' location, the linked data allows me to observe whether individuals migrate between censuses. The linked census data also allows me to measure literacy, a reasonable proxy for educational investment. In addition, the linked data allows me to measure labor market outcomes including employment and occupation. The occupation measure in the data is reports based on median earnings

in the 1950 Census created by the Census Bureau, which I have log-linearized. In addition to the outcomes in the census, the linked data are also matched to a large genealogical database to obtain death information for estimating lifespan, an outcome rarely measured in the literature.

To examine the effects of the Galveston Hurricane of 1900, I use a subsample of the linked census data that includes individuals living in Southeast Texas. Specifically, I include individuals living in 11 counties in Southeast Texas in 1900 that are nearest to the path of the hurricane. These counties include Galveston, Harris (Houston), and surrounding counties that make up the Greater Houston metropolitan area today. I include these counties because they contain the individuals who were the most significantly impacted by the hurricane. Additionally, these counties contain unaffected individuals that I expect to be the most similar to those impacted by the hurricane.

## 4 Empirical Design

I use historical records from contemporary local newspapers to identify individuals impacted by the storm. Following the hurricane, several contemporary newspapers published lists of cities and towns severely affected by the hurricane. An example of this published by *The Houston Post* is given in Figure 1. Using the linked census data, I identify individuals living in these affected (treated) towns and compare them with individuals living in nearby towns that were not severely affected (untreated).

### 4.1 Estimating Long-run Effects

In order to estimate the effect of the storm on migration, occupational quality, and literacy, I use a differences-in-differences approach. I define migration as living in a different county than where an individual was living in the previous census (i.e. an individual living in a different county in 1910 than 1900 would be coded as having migrated in the 1910 Census).

I then estimate the following differences-in-differences equation:

$$Y_{it} = \alpha + \theta Hurricane_i * Post_t + \gamma Hurricane_i + \delta Post_t + \varepsilon_{it} \quad (1)$$

In this Equation 1,  $Y_{it}$  is one of several outcomes including migration, occupational quality and literacy,  $Hurricane_i$  indicates whether an individual was impacted by the hurricane, and  $Post_t$  is an indicator for being after the storm in 1900. In order for this equation identify the causal impact of the natural disaster exposure ( $\theta$ ), the control group must provide a reasonable counterfactual of how outcomes in the treatment group would have evolved in the absence of the hurricane. I provide evidence of this in Section 4.4.

## 4.2 Estimating Intergenerational Effects

Because of data limitations, I am unable to estimate some outcomes of interest prior to the hurricane, including lifespan and employment. This prevents me from using a differences-in-differences framework to estimate the effect of the hurricanes on these outcomes. Since lifespan is a very long run outcome, I cannot estimate it prior to the hurricane and cannot use a differences-in-differences framework. The earliest labor market outcomes are recorded is the 1910 Census, preventing me from using differences-in-differences. To estimate the long-run effects of these outcomes, I estimate the following reduced form equation:

$$Y_i = \alpha + \theta Hurricane_i + \mathbf{X}_i \gamma + \varepsilon_i \quad (2)$$

Here,  $Y_i$  is one of several long-run outcomes including lifespan and employment in the 1910, 1930, and 1940 Censuses,  $Hurricane_i$  indicates whether an individual was impacted by the hurricane,  $\mathbf{X}_i$  is a vector of demographic controls including race, gender, age, and marital status, and  $\varepsilon_i$  is a random error term. For this equation to identify the causal effect of the impact of the negative shock ( $\theta$ ), whether or not an individual was impacted by the hurricane must be as-good-as random, and I provide evidence that this is likely to be the

case in Section 4.4.

### 4.3 Defining Treatment

I use historical records from contemporary local newspapers to identify individuals impacted by the storm. Following the hurricane, several newspapers reported the extend of the damage, including *The Houston Post*, *El Paso Herald*, and *Victoria Advocate*. An example of one of these reports is found in Figure 1. I define a town as being severely damaged by the storm if it is recorded in at least two news sources as having sustained significant damage.

Using the linked census data, I identify individuals living in these affected (treated) towns and compare them with individuals who were living in nearby towns that were not severely affected (untreated). I am able to approximate the locations of towns in the 1900 Census using county subdivisions. I map 1900 county subdivisions to county subdivisions in 2000 to plot the approximate spatial distribution of treatment and control towns. The impacted area is a largely contiguous area that includes several towns along the southwestern edge of the Greater Houston metropolitan area. This spatial distribution provides a reasonable estimate of the path of the storm. If the path of the hurricane was as-good-as random, we would expect that individuals living in the treated cities to be similar to the individuals living in control cities. I provide two pieces of evidence to show similarity between treatment and control groups.

### 4.4 Identifying Assumptions

First, for Equation 1 to have a causal interpretation, the control group should approximate how outcomes would have evolved for impacted individuals if the hurricane didn't occur, i.e. the parallel trends assumption holds. Because of data limitations, I can only measure outcomes prior to the hurricane in 1880 and 1900<sup>1</sup>. To determine if treatment and control individuals were trending similarly, I see if there is a significant difference in how treatment

---

<sup>1</sup>The 1890 Census was destroyed while being stored, and no microdata survived

and control were trending prior to the hurricane. I test this in Figures 3 and 4.

Figure 3 plots event studies for each of the three long-run treatments that I use Equation 1 to estimate: migration, literacy, and occupational quality. Figure 3 shows that, relative to differences in 1900, there are no significant differences between treatment and control in 1880 for any of the three outcomes. Figure 4 plots similar event studies, disaggregated by adult status at the time of the hurricane<sup>2</sup>. Similar to Figure 2, there are no significant differences for any treatment for both children and adults. Together, these support the parallel trends assumption and my treatment and control groups are similar.

Second, for Equation 2 to have a causal interpretation, whether an individual was living in a town impacted by the hurricane needs to be as-good-as-random. This implies that individuals' observable and unobservable characteristics that could affect socioeconomic and health outcomes are not influenced by the path of the hurricane. To test this, I examine if there are observable differences between individuals in each group in Table 1.

The first two columns of Table 1 suggest that individuals living in treated and control towns are similar across demographic characteristics including age, race, and marital status. Column 3 reports the difference between treatment and control groups, as well as a t-test of the difference. I find no statistically significant differences between treatment and control for all baseline characteristics with the exception of age. However, flexibly controlling for birth year has no effect on the direction, magnitude, or statistical significance of my findings. Together, these pieces of evidence suggests that the estimates of the impact of natural disaster exposure on longevity, literacy, and labor market outcomes are causal.

---

<sup>2</sup>This follows [Nakamura et al. \(2022\)](#), which compares results for adults and children.

## 5 Results

### 5.1 Long-run impacts

I present long-run results examining the effects of hurricane exposure on migration, literacy, and occupational outcomes in Tables 2, 3, and 4. Across all specifications, I find consistent evidence that natural disaster exposure generates substantial and persistent effects on human capital and mobility decisions.

Table 2 presents the effects on cross-county migration. Column 4 shows my preferred specification, which includes the full set of demographic controls, birth year fixed effects, and town population controls. I find that hurricane exposure increases the probability of cross-county migration by 6.9 percentage points (standard error = 2.3 percentage points), representing a 38 percent increase relative to the control group mean of 18 percent. This effect is remarkably stable across specifications, with point estimates ranging from 6.9 to 7.0 percentage points and all estimates statistically significant at the 1 percent level.

Migration effects vary by age at exposure. Panel B shows that adults (those over 21 in 1900) experienced an 8.4 percentage point increase in migration probability, while Panel C indicates that children (those under 21) experienced a somewhat smaller but still substantial 6.3 percentage point increase. Both effects remain highly significant across all specifications, suggesting that hurricane exposure caused widespread population displacement across age groups.

Table 3 examines effects on literacy, a key measure of human capital acquisition. My preferred estimates in column 4 indicate that hurricane exposure reduced literacy rates by 4.4 percentage points (standard error = 1.1 percentage points). Given that literacy rates increased by 37.7 percentage points for the control group in the years after the hurricane, this represents a meaningful disruption to human capital development.

The literacy effects also exhibit important age-related heterogeneity. Adults experienced a 2.6 percentage point reduction in literacy (Panel B), while children experienced a 3.1

percentage point decrease (Panel C). The effect on children is concerning, suggesting that the hurricane’s disruption to schooling and family resources had lasting consequences.

Table 4 presents results for occupational income scores, measured as log-linearized median earnings of adults working in that occupation in 1950. For the full sample (Panel A), I find no statistically significant effect on occupational quality. However, this aggregate result masks important age-related heterogeneity that reveals the complex nature of disaster effects.

Children who experienced the hurricane (Panel C) actually experienced an 8.7 percentage point increase in occupational income scores (standard error = 3.3 percentage points), significant at the 1 percent level. In contrast, adults (Panel B) show no significant effects. This pattern suggests that while the hurricane disrupted immediate educational attainment, younger people may have developed greater resilience or benefited from different long-term migration and occupational choices.

## 5.2 Intergenerational impacts

I find that the hurricane’s impact on lifespan reveals stark intergenerational patterns. First-generation survivors experienced substantial reductions in longevity, living 1.7 years shorter on average than their unaffected counterparts (Table 5, Panel A). This mortality penalty was particularly severe for those who were children at the time of exposure, who lost nearly 2.8 years of life expectancy, a finding that underscores the vulnerability of youth to major environmental shocks.

The intergenerational transmission of these mortality effects is striking. Although I did not find a significant reduction in lifespan for the general second generation (Panel D), children whose parents were adults during the hurricane experienced a devastating 2.7-year reduction in life expectancy (Panel E). This represents one of the largest documented intergenerational mortality effects of a natural disaster, suggesting that the trauma and economic disruption experienced by adult survivors persisted across generations.

The effects of the hurricane on labor market outcomes demonstrate both medium and

long-term impacts on affected individuals. First-generation survivors were 4.3 percentage points less likely to participate in the labor force and 5.4 percentage points less likely to be employed a decade after the disaster (Table 6, Panel A, columns 1 and 4). These employment penalties persisted even thirty years later, where survivors remained 2.6 percentage points less likely to be employed. This demonstrates the disaster’s economic effects were not merely temporary adjustments but represented permanent reductions in employability.

The intergenerational labor market effects I document are similarly persistent. Second-generation individuals were 4.2 percentage points less likely to participate in the labor force in 1930, three decades after the original disaster (Panel B, column 2). This suggests that parental exposure to the hurricane created lasting disadvantages that affected their children’s labor market prospects.

### 5.3 Discussion

This research demonstrates that hurricane exposure creates profound and lasting effects on human development and economic outcomes that persist across generations. The study finds that natural disasters significantly increase migration and reduce literacy rates. Interestingly, migration rates were slightly higher among people who experienced the hurricane as adults, while the effects of the hurricane on human capital development were more extreme among survivors who were children at the time of the storm. While there was no overall impact on occupational quality, there was stark divergence between young and old, as child survivors saw improved occupational quality while adult survivors did not. Further research is needed to understand the mechanisms behind this divergence in occupational quality

My findings also point to the lasting health and longevity effects of natural disasters, which are particularly acute for people who were impacted by the hurricane as children. This supports earlier findings that young children are more likely to have lasting impacts from natural disasters ([Caruso, 2017](#)). My research reveals that the effects of natural disasters extend beyond survivors, as children of adult survivors also saw significantly shorter lifespans.

The negative labor market impacts of natural disaster exposure also persist across generations, as survivors and their children were significantly less likely to be employed 30 years after the storm. One potential mechanism that could be driving this is the decreased literacy among storm survivors, which may make them less employable ([Araki, 2020](#); [de Baldini Rocha & Ponczek, 2011](#)). This decreased human capital development could be transmitted to children, making them less employable as well. Most importantly, my research reveals that the impacts of natural disaster exposure are long lasting and that the economic disruption survivors experience persists into the next generation.

## 6 Conclusion

I use a unique natural experiment to examine the long-run and intergenerational impacts of natural disaster exposure. Using the Galveston Hurricane of 1900, a major hurricane that remains the deadliest natural disaster and one of the costliest hurricanes<sup>3</sup> in United States history.

Using the fact that the hurricane made landfall only a few months after the enumeration of the 1900 census in conjunction with contemporary news reports of extensive storm damage, I identify individuals living in towns that were severely impacted by the hurricane in southeast Texas in 1900. Then, using a panel of longitudinally-linked US Census data that follows individuals and households from 1880 to 1940, I estimate the long-run and intergenerational effects of natural disaster exposure.

I find that exposure to natural disasters has consequences that last far longer than the immediate disruption of the disaster. Survivors of the hurricane were nearly 7 percentage points more likely to migrate to a different county following the storm, and were 4 percentage points less likely to be literate.

Importantly, exposure to natural disasters has impacts on health and labor market outcomes that persist among descendants of survivors. The storm survivors lived 1.7 years

---

<sup>3</sup>See [Weinkle et al. \(2018\)](#) for a discussion on the economic cost of hurricanes.

shorter on average than their control counterparts, an effect that was even greater for survivors who experienced the storm as children (2.8 years). The negative effects persisted among children of adult survivors, who lived 2.7 years shorter than their counterparts. Survivors of the storm were less likely to be employed three decades after the hurricane, and their children were also less likely to be employed and in the labor force. My findings indicate that environmental shocks disrupt individuals' economic well-being, and that these persist into the next generation.

These findings demonstrate the growing importance of understanding the persistent effects of major economic and environmental events, including natural disasters. Further research is required to better understand the channels through which these impacts persist, as well as the channels through which they are transmitted intergenerationally.

## References

- Aaronson, D., & Mazumder, B. (2008). Intergenerational economic mobility in the united states, 1940 to 2000. Journal of Human Resources, 43(1), 139–172.
- Araki, S. (2020). Educational expansion, skills diffusion, and the economic value of credentials and skills. American Sociological Review, 85(1), 128–175.
- Barr, A., & Gibbs, C. R. (2022). Breaking the cycle? intergenerational effects of an antipoverty program in early childhood. Journal of Political Economy, 130(12), 3253–3285.
- Berleermann, M., & Steinhardt, M. F. (2017). Climate change, natural disasters, and migration—a survey of the empirical evidence. CESifo Economic Studies, 63(4), 353–385.
- Boustan, L. P., Kahn, M. E., & Rhode, P. W. (2012). Moving to higher ground: Migration response to natural disasters in the early twentieth century. American Economic Review, 102(3), 238–244.
- Buckles, K., Haws, A., Price, J., & Wilbert, H. E. (2023). Breakthroughs in historical record linking using genealogy data: The census tree project (Tech. Rep.). National Bureau of Economic Research.
- Bullard, M., & Van Leeuwen, J. (2025). The economic effects of place: Evidence from child migration during the orphan train movement. Available at SSRN 5237871.
- Card, D., Domnisoru, C., & Taylor, L. (2022). The intergenerational transmission of human capital: Evidence from the golden age of upward mobility. Journal of Labor Economics, 40(S1), S39–S95.
- Caruso, G. D. (2017). The legacy of natural disasters: The intergenerational impact of 100 years of disasters in latin america. Journal of Development Economics, 127, 209–233.
- Chetty, R., & Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. The quarterly journal of economics, 133(3), 1107–1162.
- Clement, V., Rigaud, K. K., De Sherbinin, A., Jones, B., Adamo, S., Schewe, J., ... Shaba-

- hat, E. (2021). Groundswell part 2: Acting on internal climate migration.
- Colmer, J., & Voorheis, J. (2020). The grandkids aren't alright: the intergenerational effects of prenatal pollution exposure.
- de Baldini Rocha, M. S., & Ponczek, V. (2011). The effects of adult literacy on earnings and employment. Economics of Education Review, 30(4), 755–764.
- Deryugina, T., & Molitor, D. (2018). Does when you die depend on where you live? evidence from hurricane katrina (Tech. Rep.). National Bureau of Economic Research Cambridge, MA, USA:.
- East, C. N., Miller, S., Page, M., & Wherry, L. R. (2023). Multigenerational impacts of childhood access to the safety net: Early life exposure to medicaid and the next generation's health. American Economic Review, 113(1), 98–135.
- Fletcher, J., & Jajtner, K. M. (2021). Intergenerational health mobility: Magnitudes and importance of schools and place. Health economics, 30(7), 1648–1667.
- Green, A. (2025). Networks and geographic mobility: Evidence from world war ii navy ships (Tech. Rep.). Working Paper.
- Halliday, T. J., Mazumder, B., & Wong, A. (2020). The intergenerational transmission of health in the united states: A latent variables analysis. Health economics, 29(3), 367–381.
- Hornbeck, R. (2020). Dust bowl migrants: identifying an archetype (Tech. Rep.). National Bureau of Economic Research.
- Karbownik, K., & Wray, A. (2019). Long-run consequences of exposure to natural disasters. Journal of Labor Economics, 37(3), 949–1007.
- Lindahl, M., Palme, M., Massih, S. S., & Sjögren, A. (2015). Long-term intergenerational persistence of human capital: an empirical analysis of four generations. Journal of Human Resources, 50(1), 1–33.
- Nakamura, E., Sigurdsson, J., & Steinsson, J. (2022). The gift of moving: Intergenerational consequences of a mobility shock. The Review of Economic Studies, 89(3), 1557–1592.

- Price, J., Buckles, K., Van Leeuwen, J., & Riley, I. (2021). Combining family history and machine learning to link historical records: The census tree data set. Explorations in Economic History, 80, 101391.
- Sacerdote, B. (2012). When the saints come marching in: Effects of katrina evacuees on schools, student performance and crime. American Economic Journal: Applied, 4(1), 109–135.
- Shoag, D., & Carollo, N. (2016). The causal effect of place: Evidence from japanese-american internment.
- Weinkle, J., Landsea, C., Collins, D., Musulin, R., Crompton, R. P., Klotzbach, P. J., & Pielke Jr, R. (2018). Normalized hurricane damage in the continental united states 1900–2017. Nature sustainability, 1(12), 808–813.

## Tables and Figures

Figure 1: Estimated damages as reported by *The Houston Post* September 10, 1900

ESTIMATED LOSSES.		
Below is an estimate, based on reports believed to be accurate, of the number of lives lost and damage done by the hurricane:		
	Lives.	Property.
Galveston .....	5000	\$10,000,000
Houston .....	2	250,000
Alvin .....	9	50,000
Hitchcock .....	2	25,000
Richmond .....	3	75,000
Fort Bend county.....	19	100,000
Wharton .....	..	30,000
Wharton county.....	3	10,000
Colorado county.....	..	50,000
Angleton .....	3	75,000
Velasco .....	..	20,000
Other points Brazoria county .....	4	40,000
Sabine .....	..	10,000
Patton .....	..	5,000
Rollover .....	..	2,000
Bellville .....	1	5,000
Hempstead .....	1	25,000
Brookshire .....	2	15,000
Waller .....	3	100,000
Arcole .....	2	25,000
Sartartia .....	..	50,000
Dickinson .....	7	30,000
Texas City.....	5	150,000
Columbia .....	8	5,000
Sandy Point.....	8	5,000
Near Brazoria (convicts)	15	1,000
Damage to railroad outside of Galveston .....		\$50,000
of Galveston .....		\$50,000
Damage to telegraph and telephone poles outside of Galveston .....		75,000
Damage to cotton crop, estimated average crop of the counties affected, 50,000 bales at \$50 per bale .....		3,000,000
The damage to live stock can not be computed, but the reports from all over the storm district say that they have been killed in great numbers.		

Figure 2: Spatial distribution of treatment and control groups

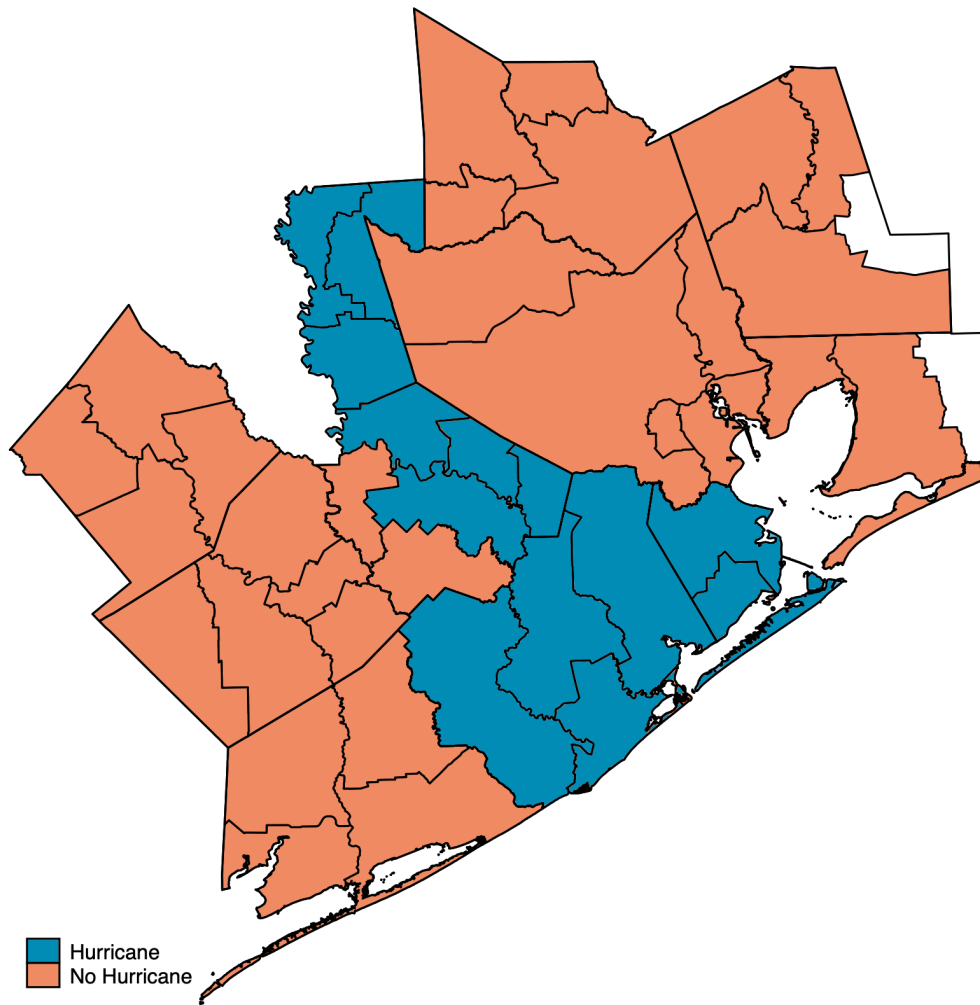
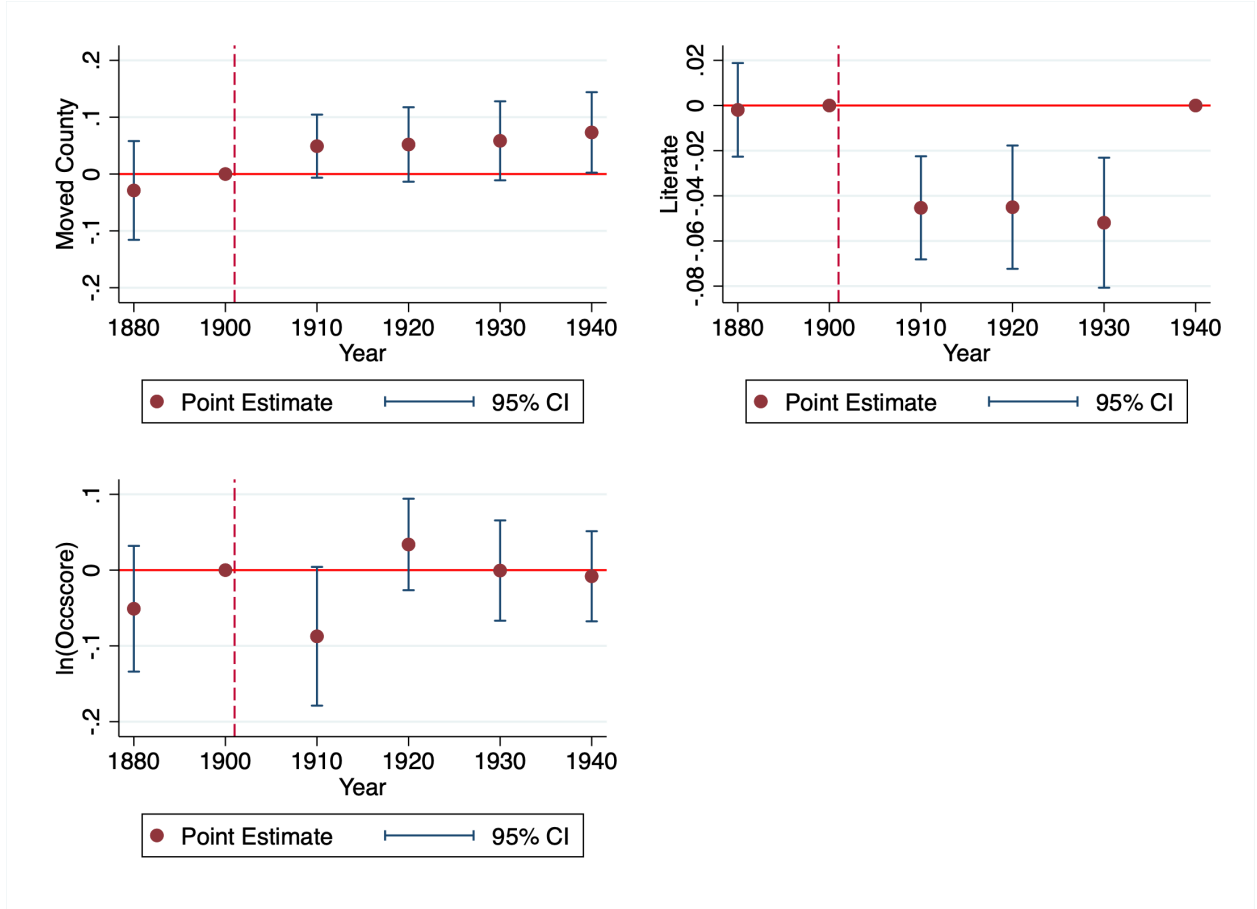
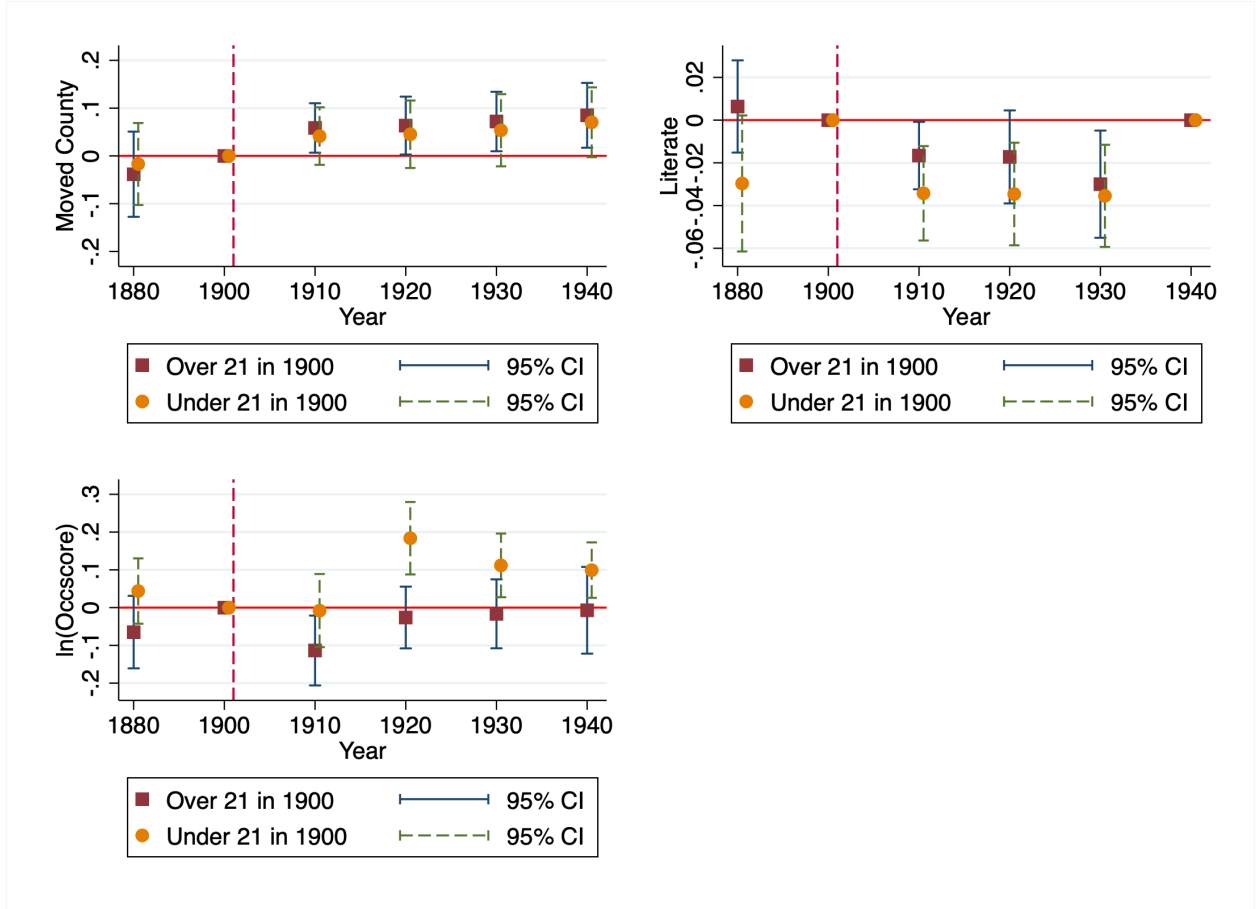


Figure 3: Event studies, full sample



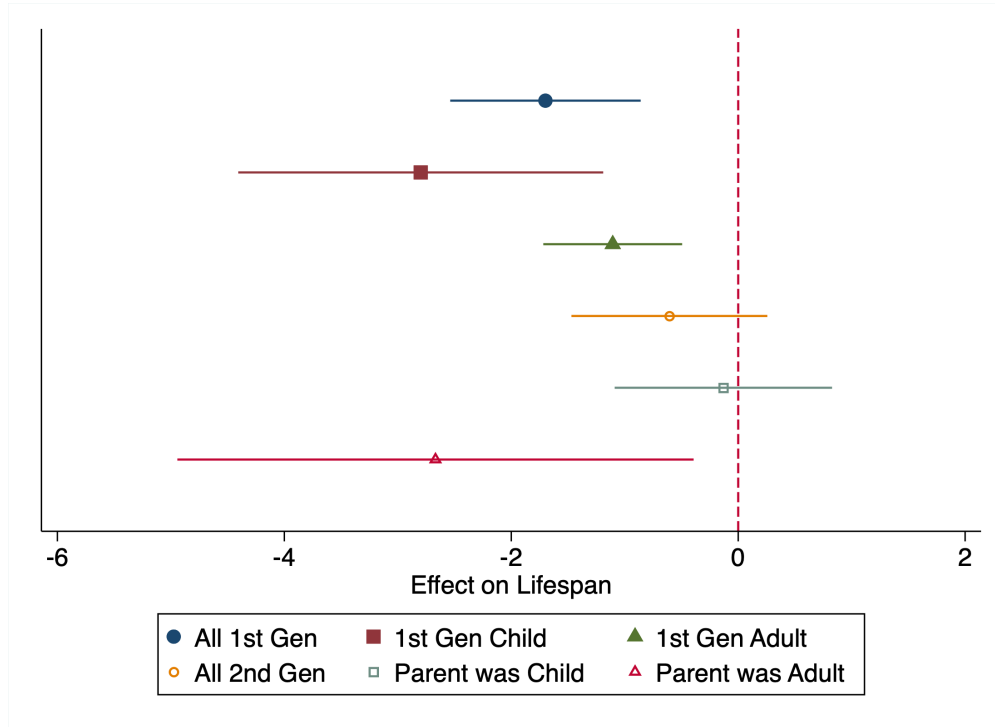
Each panel reports the estimates from a two-way fixed effects (TWFE) equation similar to equation 1. The outcomes measured are migration (defined as moving to a different county), literacy, and occupational quality (defined as the natural log of the occupational income score). Each coefficient reported is for the full pooled sample.

Figure 4: Event studies, by age in 1900



Each panel reports the estimates from a two-way fixed effects (TWFE) equation similar to equation 1. The outcomes measured are migration (defined as moving to a different county), literacy, and occupational quality (defined as the natural log of the occupational income score). The coefficients reported for each outcome have been disaggregated by adult status, defined as being 21 or older in 1900, the legal age of adulthood in Texas in 1900.

Figure 5: Estimates of the effect of natural disaster exposure on lifespan



The figure reports estimates and confidence intervals for the effect of the 1900 Galveston Hurricane on lifespan, measured as the difference between death year and birth year. Controls in each regression include gender, race, marital status, birth year fixed effects, literacy, occupational income score, and town population in the 1900 Census. Standard errors clustered at the 1900 town level.

Table 1: Summary Statistics, individual-level

	Hurricane	No Hurricane	Difference
<b>Moved County</b>	<b>.243</b> [.429]	<b>.18</b> [.384]	<b>0.063***</b> (0.016)
<b>Lifespan</b>	<b>70.854</b> [16.5]	<b>72.005</b> [16.159]	<b>-1.151**</b> (0.503)
Female	.476 [.499]	.469 [.499]	0.006 (0.005)
White	.804 [.397]	.737 [.44]	0.067 (0.043)
Black	.195 [.396]	.258 [.438]	-0.064 (0.043)
Married	.394 [.489]	.387 [.487]	0.007 (0.006)
Age	23.151 [16.973]	21.971 [16.847]	1.180*** (0.363)

Columns 1 and 2 report average values for the treatment (Hurricane) and control (No Hurricane) groups for several demographic characteristics, respectively. Outcomes including migration and lifespan are reported in bold. Baseline demographic characteristics include gender, race, marital status, and age. Column 3 reports the difference in means in columns 1 and 2 and reports the significance level of the t-test of the differences. Standard deviations in brackets, and standard errors in parentheses \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 2: Effect of Galveston Hurricane on cross-county migration

VARIABLES	(1) No Controls	(2) Add Demographics	(3) Add Birth Year FE	(4) Add Town Population
<b>A. Full Sample</b>				
Post*Hurricane	0.069*** (0.023)	0.070*** (0.023)	0.069*** (0.023)	0.069*** (0.023)
Hurricane	-0.015 (0.021)	-0.021 (0.020)	-0.019 (0.020)	-0.027 (0.022)
Post	0.190*** (0.020)	0.187*** (0.020)	0.183*** (0.020)	0.184*** (0.020)
Observations	308,286	308,286	308,286	308,286
R-squared	0.046	0.052	0.054	0.058
<b>B. Over 21 in 1900</b>				
Post*Hurricane	0.083*** (0.020)	0.084*** (0.020)	0.084*** (0.020)	0.084*** (0.020)
Hurricane	-0.019 (0.022)	-0.024 (0.021)	-0.023 (0.021)	-0.030 (0.022)
Post	0.139*** (0.018)	0.138*** (0.018)	0.131*** (0.018)	0.131*** (0.018)
Observations	139,179	139,179	139,179	139,179
R-squared	0.030	0.036	0.040	0.042
<b>C. Under 21 in 1900</b>				
Post*Hurricane	0.062** (0.025)	0.063** (0.025)	0.063** (0.025)	0.063** (0.024)
Hurricane	-0.013 (0.020)	-0.019 (0.019)	-0.018 (0.019)	-0.027 (0.021)
Post	0.229*** (0.021)	0.226*** (0.020)	0.227*** (0.020)	0.227*** (0.020)
Observations	169,107	169,107	169,107	169,107
R-squared	0.060	0.066	0.066	0.071

The outcome in each regression is an indicator for having moved to a different county than county of residence in 1900. Hurricane indicates that an individual lived in a town severely damaged by the storm. Post is an indicator for being after the hurricane in 1900. Panel A reports estimates for the full sample. Panel B reports estimates for the sample age 21 or older in 1900 at the time of the hurricane. Panel C reports estimates for the sample age 21 or younger in 1900. Column 1 reports estimates from a regression with no controls. Column 2 includes controls for gender, race, and marital status. Column 3 adds birth year fixed effects. Column 4 adds town population in the 1900 Census. Standard errors clustered at the town level in parentheses  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table 3: Effect of Galveston Hurricane on literacy

VARIABLES	(1) No Controls	(2) Add Demographics	(3) Add Birth Year FE	(4) Add Town Population
<b>A. Full Sample</b>				
Post*Hurricane	-0.045*** (0.012)	-0.045*** (0.011)	-0.044*** (0.011)	-0.044*** (0.011)
Hurricane	0.067*** (0.020)	0.053*** (0.014)	0.048*** (0.013)	0.053*** (0.010)
Post	0.368*** (0.010)	0.373*** (0.009)	0.377*** (0.009)	0.377*** (0.009)
Observations	250,509	250,509	250,509	250,509
R-squared	0.191	0.265	0.321	0.323
<b>B. Over 21 in 1900</b>				
Post*Hurricane	-0.026*** (0.008)	-0.026*** (0.007)	-0.026*** (0.007)	-0.026*** (0.007)
Hurricane	0.062*** (0.020)	0.046*** (0.012)	0.046*** (0.011)	0.052*** (0.009)
Post	0.162*** (0.005)	0.160*** (0.005)	0.160*** (0.005)	0.159*** (0.005)
Observations	124,685	124,685	124,685	124,685
R-squared	0.048	0.184	0.193	0.195
<b>C. Under 21 in 1900</b>				
Post*Hurricane	-0.035*** (0.010)	-0.033*** (0.010)	-0.031*** (0.010)	-0.031*** (0.010)
Hurricane	0.046*** (0.014)	0.038*** (0.012)	0.034*** (0.010)	0.037*** (0.009)
Post	0.619*** (0.008)	0.614*** (0.007)	0.613*** (0.007)	0.613*** (0.007)
Observations	125,824	125,824	125,824	125,824
R-squared	0.451	0.466	0.553	0.553

The outcome in each regression is a binary indicator for whether an individual is able to read and write. Hurricane indicates that an individual lived in a town severely damaged by the storm. Post is an indicator for being after the hurricane in 1900. Panel A reports estimates for the full sample. Panel B reports estimates for the sample age 21 or older in 1900 at the time of the hurricane. Panel C reports estimates for the sample age 21 or younger in 1900. Column 1 reports estimates from a regression with no controls. Column 2 includes controls for gender, race, and marital status. Column 3 adds birth year fixed effects. Column 4 adds town population in the 1900 Census. Standard errors clustered at the town level in parentheses \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 4: Effect of Galveston Hurricane on occupational income score

VARIABLES	(1) No Controls	(2) Add Demographics	(3) Add Birth Year FE	(4) Add Town Population
<b>A. Full Sample</b>				
Post*Hurricane	-0.022 (0.025)	-0.018 (0.024)	-0.013 (0.024)	-0.014 (0.024)
Hurricane	0.041** (0.021)	0.058** (0.026)	0.041* (0.023)	0.051*** (0.020)
Post	0.795*** (0.017)	0.806*** (0.017)	0.835*** (0.016)	0.835*** (0.016)
Observations	280,623	280,623	280,623	280,623
R-squared	0.060	0.385	0.403	0.403
<b>B. Over 21 in 1900</b>				
Post*Hurricane	-0.050 (0.031)	-0.038 (0.030)	-0.039 (0.030)	-0.039 (0.031)
Hurricane	0.037 (0.023)	0.060** (0.030)	0.059** (0.030)	0.074*** (0.025)
Post	0.225*** (0.016)	0.290*** (0.015)	0.298*** (0.016)	0.298*** (0.016)
Observations	134,843	134,843	134,843	134,843
R-squared	0.005	0.468	0.471	0.472
<b>C. Under 21 in 1900</b>				
Post*Hurricane	0.083** (0.034)	0.081** (0.032)	0.087*** (0.033)	0.087*** (0.033)
Hurricane	-0.025 (0.022)	-0.017 (0.023)	-0.027 (0.023)	-0.021 (0.024)
Post	1.466*** (0.023)	1.420*** (0.022)	1.423*** (0.023)	1.423*** (0.023)
Observations	145,780	145,780	145,780	145,780
R-squared	0.191	0.402	0.423	0.424

The outcome in each regression is the occupation income score (occscore) provided by IPUMS, which has been log-linearized so coefficients can be interpreted as the percentage change in occupational income score. Hurricane indicates that an individual lived in a town severely damaged by the storm. Post is an indicator for being after the hurricane in 1900. Panel A reports estimates for the full sample. Panel B reports estimates for the sample age 21 or older in 1900 at the time of the hurricane. Panel C reports estimates for the sample age 21 or younger in 1900. Column 1 reports estimates from a regression with no controls. Column 2 includes controls for gender, race, and marital status. Column 3 adds birth year fixed effects. Column 4 adds town population in the 1900 Census. Standard errors clustered at the town level in parentheses  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$ .

Table 5: Effect of Galveston Hurricane on lifespan

VARIABLES	(1) No Controls	(2) Add Demographics	(3) Add Birth Year FE	(4) Add Town Population
<b>A. First Generation, Full Sample</b>				
Hurricane	-1.151** (0.503)	-1.397*** (0.521)	-1.501*** (0.476)	-1.699*** (0.423)
Observations	44,014	30,700	30,700	30,700
R-squared	0.001	0.027	0.060	0.062
<b>B. First Generation, Over 21 in 1900</b>				
Hurricane	-0.962** (0.417)	-0.831** (0.394)	-0.943*** (0.334)	-1.106*** (0.308)
Observations	20,706	20,674	20,674	20,674
R-squared	0.001	0.015	0.067	0.068
<b>C. First Generation, Under 21 in 1900</b>				
Hurricane	-1.569** (0.641)	-2.628*** (0.878)	-2.592*** (0.868)	-2.798*** (0.811)
Observations	23,308	10,026	10,026	10,026
R-squared	0.001	0.032	0.035	0.037
<b>D. Second Generation, Full Sample</b>				
Hurricane	-0.330 (0.456)	-0.578 (0.429)	-0.560 (0.431)	-0.607 (0.435)
Observations	15,793	12,340	12,340	12,340
R-squared	0.000	0.053	0.056	0.057
<b>E. Second Generation, Parent Over 21 in 1900</b>				
Hurricane	-2.023* (1.127)	-2.463** (1.157)	-2.480** (1.159)	-2.668** (1.146)
Observations	2,463	1,842	1,842	1,842
R-squared	0.002	0.064	0.078	0.079
<b>F. Second Generation, Parent Under 21 in 1900</b>				
Hurricane	0.038 (0.494)	-0.155 (0.479)	-0.102 (0.474)	-0.131 (0.483)
Observations	13,330	10,498	10,498	10,498
R-squared	0.000	0.052	0.056	0.056

The outcome in each regression is lifespan, measured as the difference between death year and birth year. Hurricane indicates that an individual lived in a town severely damaged by the storm. Panel A reports estimates for the full sample. Panel B reports estimates for the sample age 21 or older in 1900 at the time of the hurricane. Panel C reports estimates for the sample age 21 or younger in 1900. Column 1 reports estimates from a regression with no controls. Column 2 includes controls for gender, race, marital status, literacy, and occupation income score. Column 3 adds birth year fixed effects. Column 4 adds town population in the 1900 Census. Standard errors clustered at the town level in parentheses \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Table 6: Effect of Galveston Hurricane on labor market outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Labor Force 1910	Labor Force 1930	Labor Force 1940	Employed 1910	Employed 1930	Employed 1940
<b>A. First Generation</b>						
Hurricane	-0.043*** (0.012)	-0.005 (0.006)	-0.004 (0.008)	-0.054*** (0.013)	-0.026*** (0.008)	-0.010 (0.008)
Observations	48,723	25,321	18,869	48,723	25,321	18,869
R-squared	0.463	0.588	0.465	0.414	0.510	0.423
<b>B. Second Generation</b>						
Hurricane		-0.042*** (0.009)	0.009 (0.008)		-0.046*** (0.011)	-0.004 (0.008)
Observations		14,869	9,789		14,869	9,789
R-squared		0.706	0.376		0.631	0.318

The outcome in each regression is lifespan, measured as the difference between death year and birth year. Hurricane indicates that an individual lived in a town severely damaged by the storm. Panel A reports estimates for the first generation. Panel B reports estimates for the second generation. Panel C reports estimates for the sample age 21 or younger in 1900. Columns 1-3 report estimates for the effect of the hurricane on labor force participation in 1910, 1930, and 1940, respectively. Columns 4-6 report estimates for the effect of the hurricane on employment in 1910, 1930, and 1940, respectively. Employment status is unavailable in 1920, and 1920 estimates are therefore excluded. Standard errors clustered at the town level in parentheses  $*p < 0.1$ ,  $**p < 0.05$ ,  $***p < 0.01$ .