CLIMATE ADAPTATION
RESEARCH SYMPOSIUM

MEASURING & REDUCING SOCIETAL IMPACTS

After the Storm: Impacts of Climate-Related Disasters

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Have a question for presenters? Click the ? icon.

Emily Gallagher
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UCLA Luskin Center for Innovation

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Human Capital Investment After the Storm

Human Capital Investment After the Storm

Stephen Billings (U. Colorado Boulder)
Emily Gallagher (U. Colorado Boulder)
Lowell Ricketts (St. Louis Fed)

Motivation

- **This paper**: explores the use of student debt in the aftermath of a natural disaster
- Natural disasters have increased in frequency and severity (NOAA, 2020)
- Growing literature linking climate change to investment decisions:
    - housing (e.g., Baldauf et al., 2020); small businesses (e.g., Collier et al., 2021); financial assets (e.g., Kong et al., 2021)
- Relevant in the U.S., about 2/3 of college students graduated with student debt
- **Prior work suggests that wealth shocks (esp. housing) could lead to a rise in student debt** (e.g., Amromin, Eberly and Mondragon, 2017)
- **Implication:** Will climate change worsen the “student debt crisis”?
- Surprisingly, student debt has not been examined before in the context of a natural disaster
    - 2005 Katrina: Gallagher and Hartley (2017), McIntosh (2008), and Deryugina et al. (2018)

Predicted effect is ambiguous

Channels that would $\uparrow$ use of student loans:

- **Liquidity effects:** $\downarrow$ house values $\Rightarrow$ harder to extract equity to pay for college $\Rightarrow$ $\uparrow$ **use of student loans**
  - Up to 22% of households extracted equity to pay for college over 1999–2013 (Amromin, Eberly and Mondragon, 2017)
    - For every \$1 of home equity lost during Great Recession, households $\uparrow$ student loan debt by 20–80 cents
  - Bhutta and Keys (2016) show the extraction rate increases dramatically when mortgage rates are low
  - Harvey: 30-year mortgage rates were just 3.8% vs. Federal Stafford loans had rates of 4.45% for undergrads and 6.0% for grads

Predicted effect is ambiguous:

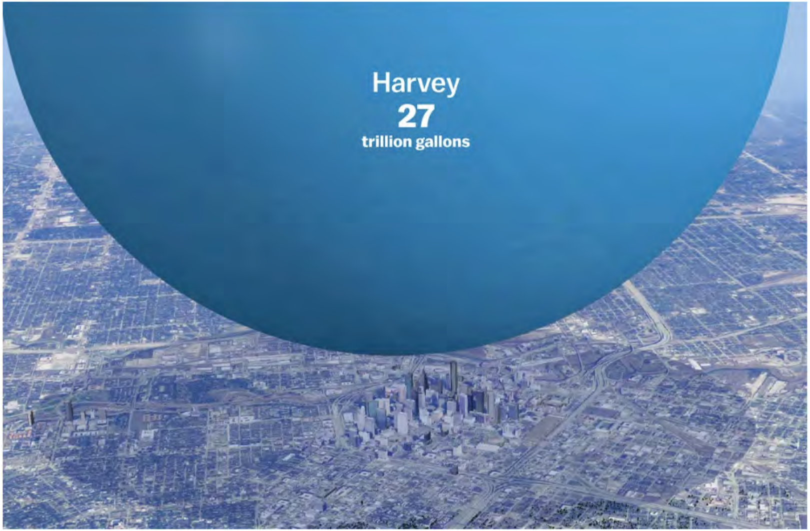
Channels that would $\downarrow$ use of student loans:

- **Wealth effects:** $\downarrow$ house values $\Rightarrow$ $\downarrow$ general consumption (Mian et al., 2013) + $\downarrow$ investment (e.g., pursuit of innovative projects, Bernstein et al., 2017) $\Rightarrow$ $\downarrow$ **use of student loans**
- **Debt overhang** (Myers, 1977)**:** $\downarrow$ house values $\Rightarrow$ $\uparrow$ leverage ratio $\Rightarrow$ enrollment in only very high NPV majors $\Rightarrow$ $\downarrow$ **use of student loans**
  - Substantial support in the context of student debt (Di Maggio, Kalda and Yao, 2019)
    - possibly due to limitations on bankruptcy discharge (Donaldson, Piacentino and Thakor, 2019) and, in Texas, mortgages are recourse
- **Opportunity costs:** attending school is less attractive if it means forgoing elevated wages (Charles, Hurst and Notowidigdo, 2018) $\Rightarrow$ $\downarrow$ **use of student loans**

Predicted effect of disasters on use of student loans is ambiguous!

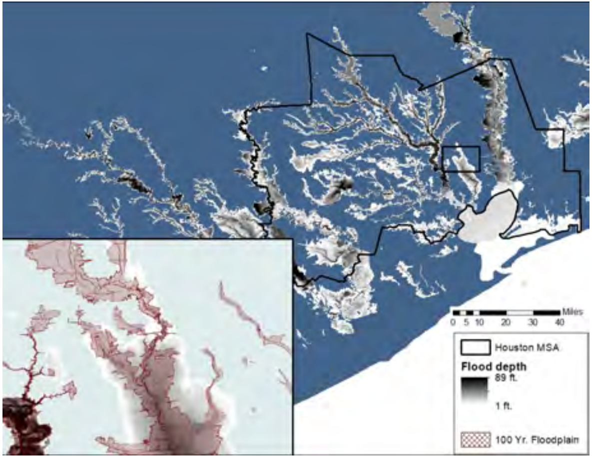
Background

Hurricane Harvey (Aug-Sep 2017) stalled over Houston.



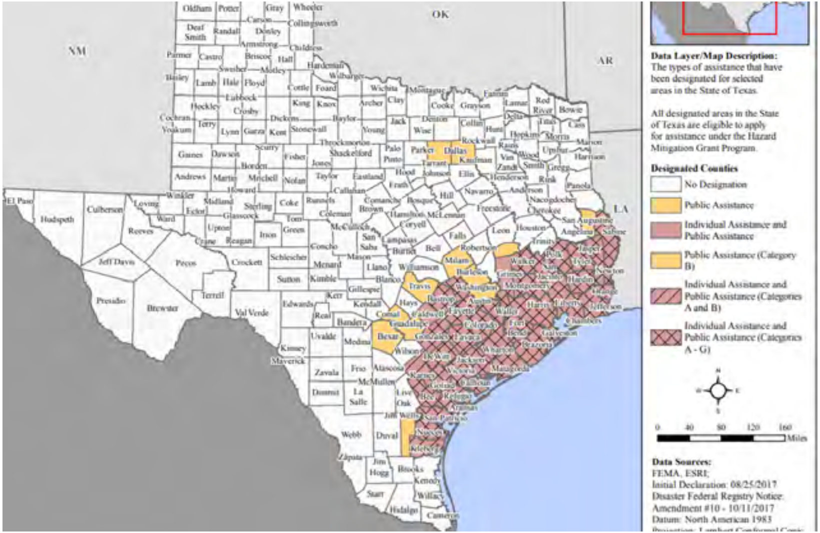
Source: vox.com

Flooding under Harvey relative to 100 year floodplain



Go to reg

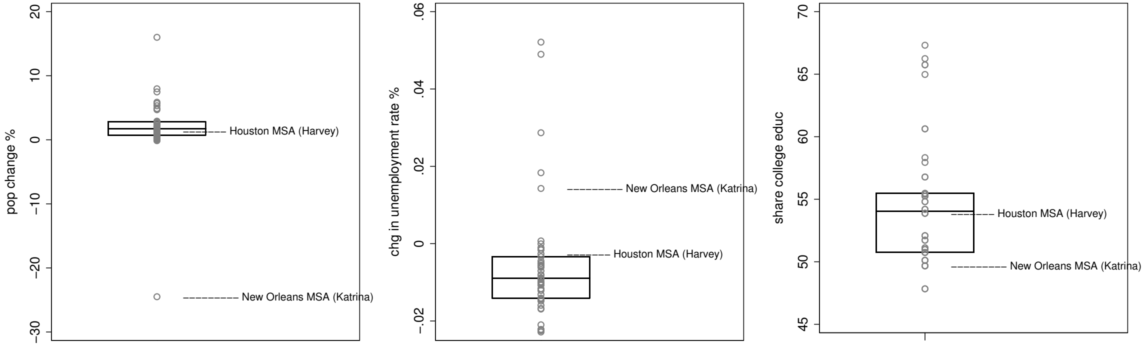
40 Texas counties were severely flooded



Source: USGS/FEMA

Is Houston/Harvey generalizable?

Large urban areas (>1 million people) that have experienced a hurricane between 2000 and 2017



- Harvey exists near or within the interquartile range along most measures (e.g., the population change, unemployment rate change, share with a college degree, median income, etc...)

Main results: Individual use of student debt

Data and empirical method

Data: NYFED/Equifax Consumer Credit Panel

- ~125,000 individuals with credit files and permanent addresses in Houston as of Q2 2017
  - of which ~7,000 were college-age adults (<26)
- Merged at the Census block-level with FEMA flood maps

Method**:** Treatment intensity diff-in-diff:

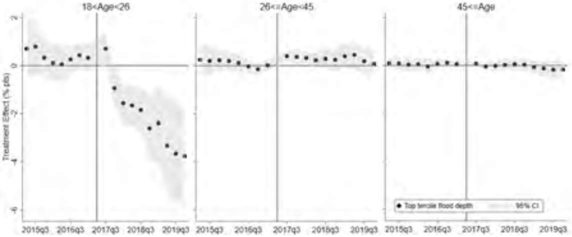
$$y_{it} = \beta \left(T_b^k \times P_t \right) + \alpha_i + D_t + \kappa A_{it}^2 + (X_b \times D_t)\,\eta + X_b\phi + \varepsilon_{it}$$

- T_b = *WAvg. Flood Depth* across the developed portion of Census block b
  - assigned according to block where that individual had a permanent address as of Q2 2017
  - split into terciles, k
- **β= post-hurricane change in blocks with top-tercile flooding relative to the post-hurricane change in blocks that did not flood**

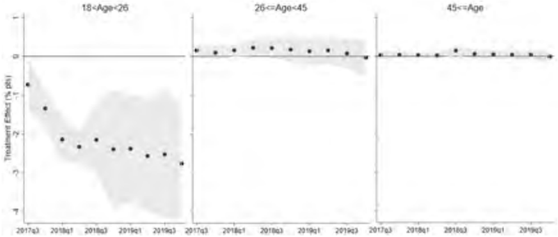
Go to Treatment Go to Supply

Effect of flooding on extensive margin of student debt

DiD model, probability of having student debt



Discrete-time hazard model, probability of <u>first opening</u> student debt



Go to InFlp

Heterogeneity: extensive margin treatment effect on college-aged

Dependent variable: $\mathbb{1}(\textit{Student debt} > 0)$

	Difference-in-difference model			Discrete-time hazard model ($Y_{Q22017} = 0$)		
$T_b^1 \times P_t$	-0.64	-0.62	-0.41	-1.02*	-1.01*	-1.47**
	(-0.94)	(-0.92)	(-0.36)	(-2.01)	(-2.01)	(-2.32)
$T_b^2 \times P_t$	-1.59**	-1.56**	-1.53*	-1.40***	-1.45***	-2.82***
	(-2.62)	(-2.65)	(-1.88)	(-4.06)	(-4.24)	(-4.90)
$T_b^3 \times P_t$	-2.45***	-1.75	-2.48	-2.13***	-0.92*	-1.54**
	(-3.01)	(-1.51)	(-1.61)	(-6.24)	(-2.00)	(-2.59)
$T_b^3 \times P_t \times LowIncome_b$		-1.69	-2.61		-2.90***	-4.49***
		(-1.22)	(-1.23)		(-4.78)	(-5.70)
Sample	*All*	*All*	*High Own*	*All*	*All*	*High Own*
N	128,269	128,269	63,726	41,987	41,987	20,053
Y-mean	43.08	43.08	45.03	3.89	3.89	4.31

- Effects are monotonically increasing in flood depth
- Significantly more negative treatment hazard in heavily flooded, lower-income blocks
  - Effect is 1.5x larger in high owner-occupied areas

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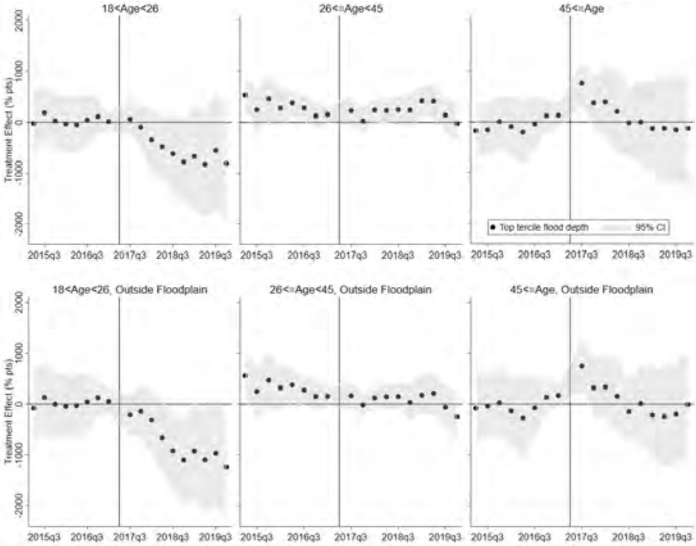
Effect of flooding on intensive margin of student debt



Exploring the mechanism:
Shifts in human capital investments

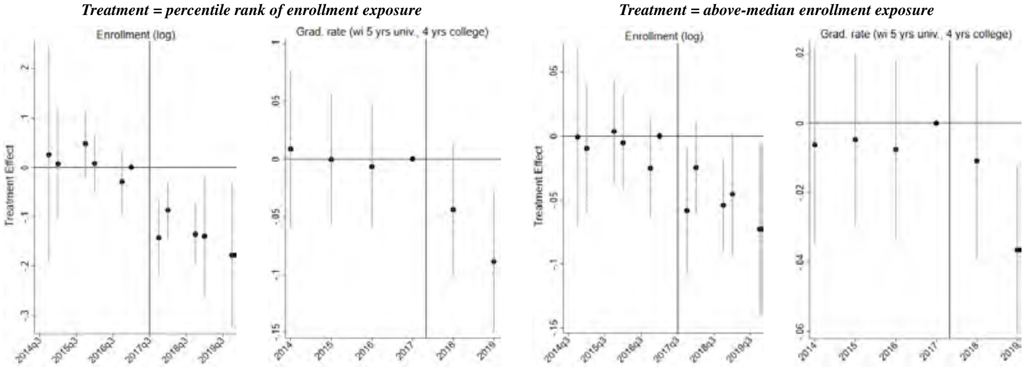
Data & method

- ***Data***: Texas Higher Education Coordinating Board (THECB) data on 110 public universities and colleges, Spring 2014 - Fall 2019
- ***Treatment*** **(T_s)**: A school's pre-Harvey enrollment share from the 40 counties that were most damaged by Harvey (continuous percentile rank)
  - ~Half of schools with above-median enrollment exposure – e.g., UT Austin and Midland College – are not, themselves, located in the 40 disaster-affected counties
- **Outcomes**: *Enrollment, Graduation rates, and Time-to-degree:*

$$y_{s,t} = \beta\,(T_s \times P_t) + \alpha_s + D_t + \lambda(UNIV_s \times D_t) + \phi(REGION_s \times D_t) + \varepsilon_{s,t} \quad (1)$$

  - **β = the post-hurricane effect of being the school with a larger, relative to a smaller, share of students from disaster counties**
- **Heterogeneity:** in enrollment effects across majors within schools

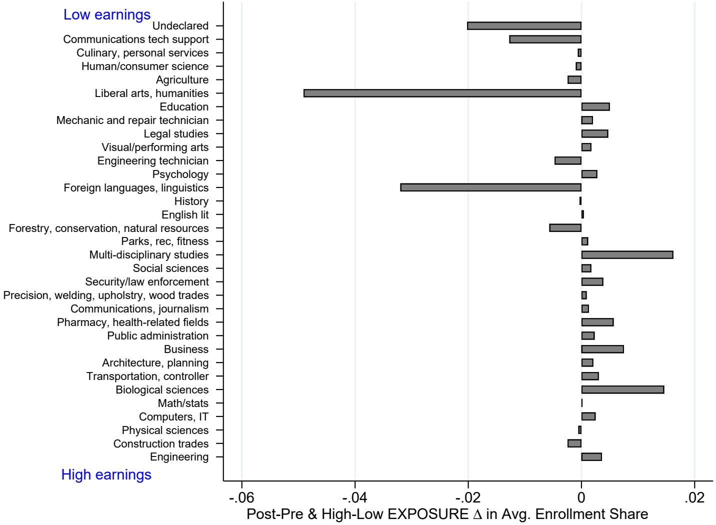
Effect of disaster exposure on school-time outcomes



- *Enrollment* ↓ 13.3% at the most exposed school relative to the least exposed school, or ↓ 3.6% splitting schools at the median
  - Compare to COVID Fall 2020: public colleges and universities recorded enrollment of -4% – driven by first-time students (-13%)
- ↓ *Graduation rate* suggests some drop outs Reg Table

Change in average share of total enrollment by major group

Post-pre period & high-low treatment Δ in average enrollment share by major group



e.g., Liberal arts becomes a 5 p.p. smaller share of enrollment, on average, at more treated schools relative to less treated schools

Conclusions

- **Natural disaster** $\Rightarrow \downarrow$ **use of student debt** (particularly for lower-income and when unexpected)
  - Explained, in part, by $\downarrow$ **in quantity of higher ed. attained**
- **Climate change is unlikely to directly exacerbate the student loan crisis in the U.S.**
- **But, the net long-term social welfare consequences are unresolved:**
  - Less aggregate higher education investment $\Longrightarrow$ exacerbate inequality, "brain drain"
  - More enrollment in high-earnings majors $\Longrightarrow$ boost aggregate productivity
- **Current policy tools are not mitigating the effect of disasters on schooling decisions**
  - Proliferation of emergency student relief programs during COVID-19 highlights the failure of standard financial aid to adapt to wealth and income shocks


THE END

Money is fungible. Why not pay tuition with aid?

Federal disaster aid cannot easily be applied to tuition

- Payouts often represent only a fraction of the damage (e.g., the average FEMA grant \$7,300 vs. \$72,162 in damage from 1 foot of flooding)
- Disaster loans are 10x larger, on average, but lower-income applicants ineligible
- Payouts are earmarked for specific purposes and FEMA can audit receipts

Financial aid programs fail to adapt to a student's *current* financial situation

- FAFSA: Student's expected family contribution is based on information from the 2nd proceeding tax year
- Dept. of Ed instructed students to ask for help from their school's financial aid office
- Anecdotal evidence is that school funds for student relief amounted to < \$1k per student with need

Were people able to self-select into flooding?

OLS regressions of our treatment measure on block characteristics

Dependent variable: *Weighted average flood depth (ft)*					
Credit	X	X	X		X
Block median household economics		X	X		X
Block socio-demographic shares			X		X
Floodplain share of developed block				X	X
Other geospatial				X	X
Cubics of geospatial				X	X
R-squared	**0.002**	**0.005**	**0.006**	**0.067**	**0.070**

- Individual credit and block-socioeconomics explain 0.6% of the variation in flooding across Houston census blocks
- Only 7% can be explained by floodplain share and pre-determined geo-spacial characteristics (including cubics of elevation and distance to streams)
  - Gallagher & Harley (2017) estimate this same figure to be around 40% for Hurricane Katrina

Go Back

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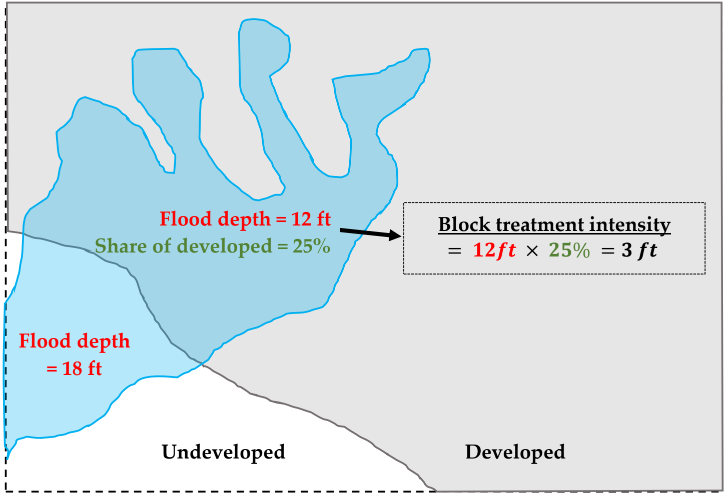
Treatment intensity for hypothetical census block



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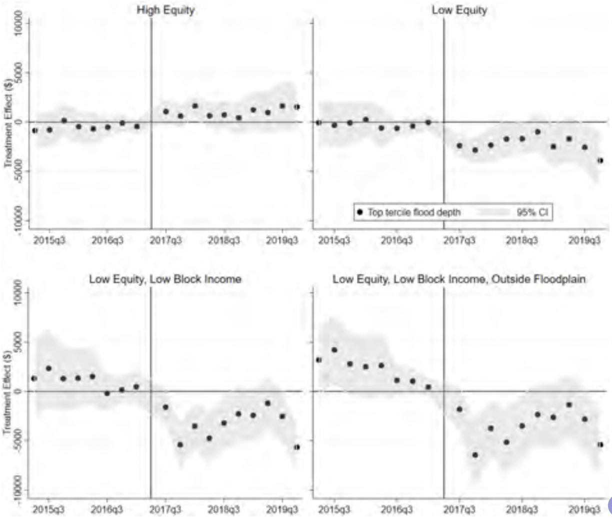
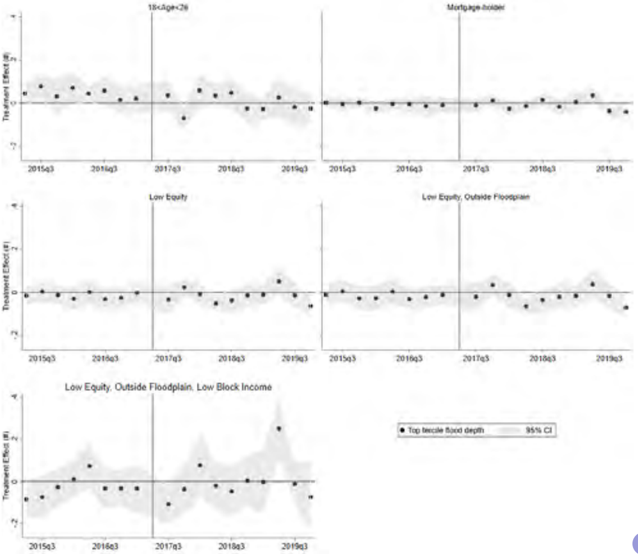
Homeowners of all ages: effect of flooding on student debt balances



Delinquency

- Homeowners with less in housing wealth and fewer outside resources grow their student debt balances less after flooding

Effect of flooding on *# of New Accounts per Inquiry*



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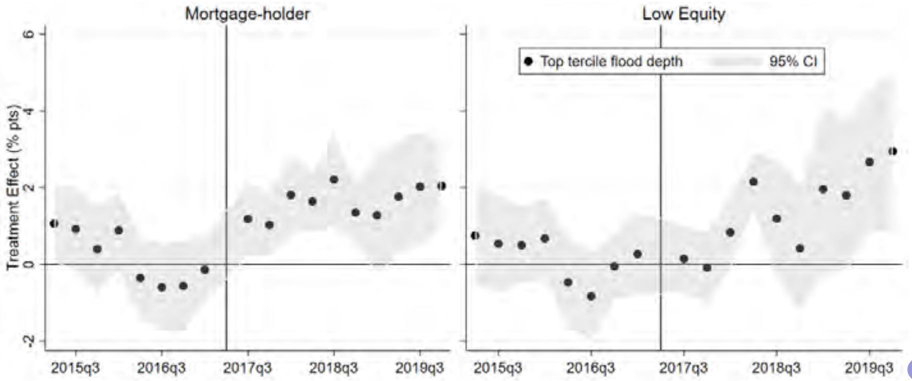
Effect of flooding on severe delinquency (student debt)



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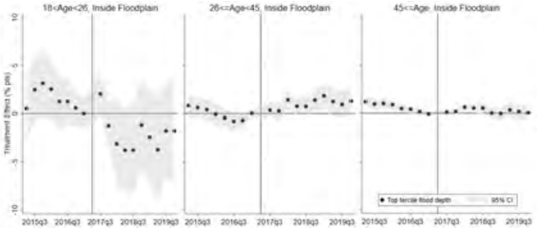
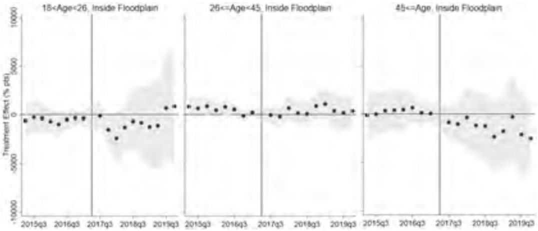
Effect of flooding on student debt inside floodplain

Extensive margin probability of having student debt (percentage points)



Intensive margin student loan balance (dollars)



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Effect of disaster exposure on school *Enrollment* and *4-year Graduation*

Treatment = the percentile rank of enrollment share from disaster counties (1=100th percentile)

	Enrollment$_{s,t}$ (log)			*Graduation rate$_{s,t}$ (within 4 years)*		
$T_s \times P_t$	-0.133***	-0.083**	-0.105**	-0.071***	-0.057**	-0.042**
	(-3.49)	(-2.10)	(-2.24)	(-4.32)	(-2.43)	(-2.07)
$T_s \times P_t \times Univ_s$			-0.077*			-0.103**
			(-1.76)			(-2.04)
Sample	*All*	*ex. Disaster*	*All*	*All*	*ex. Disaster*	*All*
N	1195	876	1195	627	456	627
Adj. R^2	0.98	0.99	0.98	0.81	0.87	0.81
Y-mean	9.01	8.98	9.01	0.28	0.28	0.28

- 13%pt ↓ in *Enrollment* for the school with the largest, relative to the smallest, student share from disaster counties
- Enrollment effects remain significant, though smaller in magnitude (8.3% vs. 13.3%), when we exclude the 27% of schools located in disaster-affected counties
- More negative treatment effect (marginally significant) on enrollment within universities
- Graduation rates follow a similar pattern

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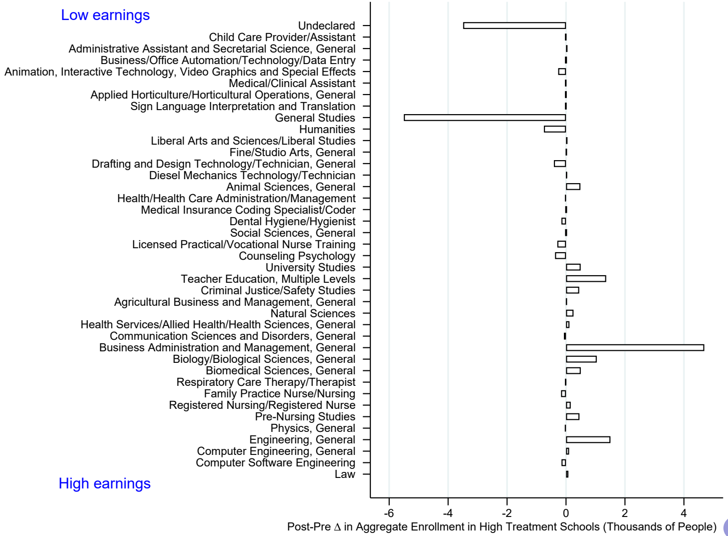
Post-minus-pre change in aggregate enrollment at high treatment schools



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Effect of disaster on school-major-time *Enrollment*, by expected earnings

$$ENROLL_{s,m,t} = \beta\left(T_s \times P_t\right) + \delta_{s,m} + \delta_{m,t} + \lambda(UNIV_s \times D_t) + \phi(REGION_s \times D_t) + \varepsilon_{s,m,t}$$

	$Enrollment_{s,m,t}(\#)$		
$T_s \times P_t$	18.265**		
	(2.51)		
$T_s \times P_t \times LoEarnY1_m$	-3.832		
	(-0.74)		
$T_s \times P_t \times LoEarnY5_m$	-16.861***		
	(-3.80)		
$T_s \times P_t \times LoEarnY10_m$	-35.064***	-64.274***	4.960
	(-6.51)	(-4.56)	(0.50)
$T_s \times P_t \times HiEarnY10_m$		21.904**	5.023
		(2.12)	(0.42)
$T_s \times P_t \times Undec_m$		70.482	-498.421**
		(0.46)	(-2.19)
Sample	*All*	*College*	*Univ.*
N	76206	46724	28219

- Low 10-year post-graduate salaries are most predictive of disenrollment
- Low (high) 10-year earnings majors lose (gain) 64 (22) students, on average, at the most treated college relative to the least treated college
- Fewer university students in undeclared major status at more disaster-enrollment exposed schools

Go Back

Effect of disaster on school-major-time *Enrollment*, by expected earnings

$$ENROLL_{s,m,t} = \beta\left(T_s \times P_t\right) + \delta_{s,m} + \delta_{m,t} + \lambda\left(UNIV_s \times D_t\right) + \phi\left(REGION_s \times D_t\right) + \varepsilon_{s,m,t}$$

	$Enrollment_{s,m,t}(\#)$		
$T_s \times P_t$	18.265**		
	(2.51)		
$T_s \times P_t \times LoEarnY1_m$	-3.832		
	(-0.74)		
$T_s \times P_t \times LoEarnY5_m$	-16.861***		
	(-3.80)		
$T_s \times P_t \times LoEarnY10_m$	-35.064***	-64.274***	4.960
	(-6.51)	(-4.56)	(0.50)
$T_s \times P_t \times HiEarnY10_m$		21.904**	5.023
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Go Back

Effect of disaster on school-time *Enrollment*, by UG status

Treatment = 1 when a school's enrollment share from disaster counties is above the median

	$Enrollment_{s,t}$							
	All		*First-time undergrad*		*Other undergrad*		*First-time transfer*	
	(log)	*(#)*	*(log)*	*(#)*	*(log)*	*(#)*	*(log)*	*(#)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)
$T_s \times P_t$	-0.068***	-533.195*	-0.237***	-306.616***	-0.050	-21.454	0.053	89.082
	(-3.41)	(-1.77)	(-5.13)	(-3.97)	(-1.61)	(-0.12)	(1.09)	(1.51)
N	200	200	200	200	200	200	200	200
Adj. R^2	0.99	1.00	0.99	0.99	0.99	0.99	0.98	0.98
Y-mean	9.45	18527.67	7.33	2468.13	8.88	10679.34	6.98	1543.58

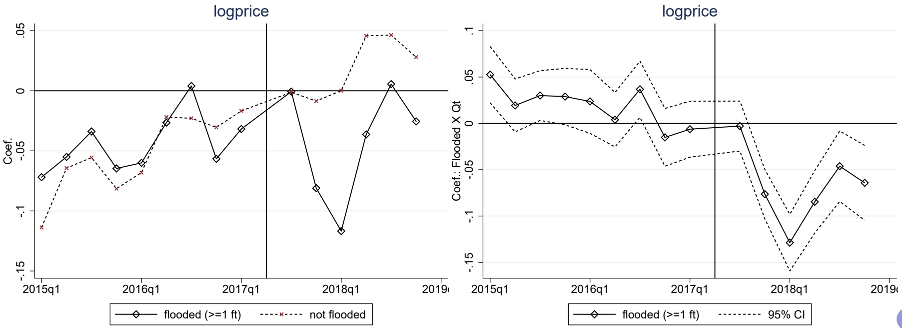
- Most (57%) of the drop in total enrollment numbers at more treated public universities is attributable to first-time undergraduates.
    - Since first-time undergrads are most likely to be undeclared, it is hard to separate a reduction in "education consumption" from there being a larger treatment effect of flooding on starting (rather than continuing) education.

Go Back

Mechanisms: Wealth and liquidity effects

Effect of flooding on house prices: $Log(P_{pt}) = \sum_{t=2015Q1}^{2018Q4} \beta_t \left(Flood_p * D_t\right) + D_t + FlP_p + X_{pt} + \varepsilon_{pt}$

Transaction prices on flooded versus not flooded properties (relative to Q2 2017)



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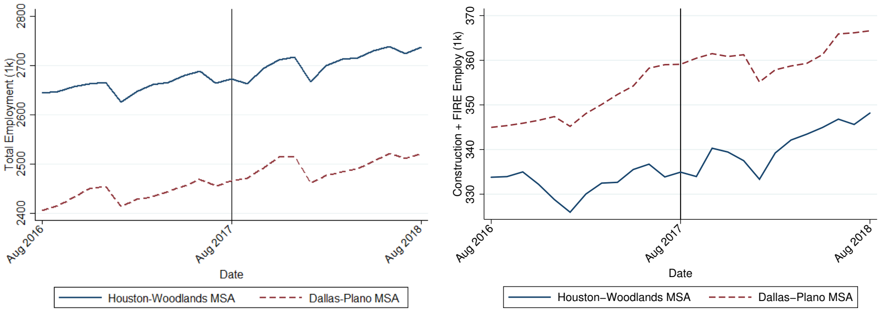
Mechanisms: Labor market opportunity cost



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Are You Experienced? Learning and Adaptation to Hurricanes in the United States

Are you Experienced? Learning and Adaptation to Hurricanes in the United States

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This paper is released to inform interested parties of research and to encourage discussion. The views expressed are those of the authors and not necessarily those of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. The statistical summaries reported in this paper have been cleared by the Census Bureau's Disclosure Review Board, release authorization numbers CBDRB-FY2021-CES010-023 and CBDRB-FY21-CES014-045.

The Importance of Information in Decision-Making

- Economists argue that without perfect information individuals are unable to optimize and markets will be less efficient (Stigler, 1961; Hirshleifer, 1971; Grossman and Stiglitz, 1976)
- The assumption that people access, trust, process, and respond to information rationally is deeply flawed.
- Do people learn from experience?
- **Today:** How does experience affect the translation of environmental shocks into economic damages?

Identifying the Effects of Experience

- Measuring the effects of experience is hard (Heckman, 1978; 1981; 1991)
- Most evidence of "learning from experience" comes from experimental settings (Dellavigna, 2009).
- The problem:
  - People know their type in terms of the ability to self protect and risk aversion.
  - If those with an edge at dealing with shocks are more likely to be exposed again "experience effects" might be spurious.
  - What we call differential responses due to experience might just be differential responses due to different types of people.
- Exposure to hurricane provides an opportunity to identify the empirical relevance of learning by experience:
  - being exposed once does not increase your likelihood of being exposed again.
  - exposure is relatively infrequent

This Project

- We combine spatially continuous data on individual-level hurricane exposure with tax and demographic data $\Rightarrow$ new facts about the role of experience in adapting to hurricanes in the United States.

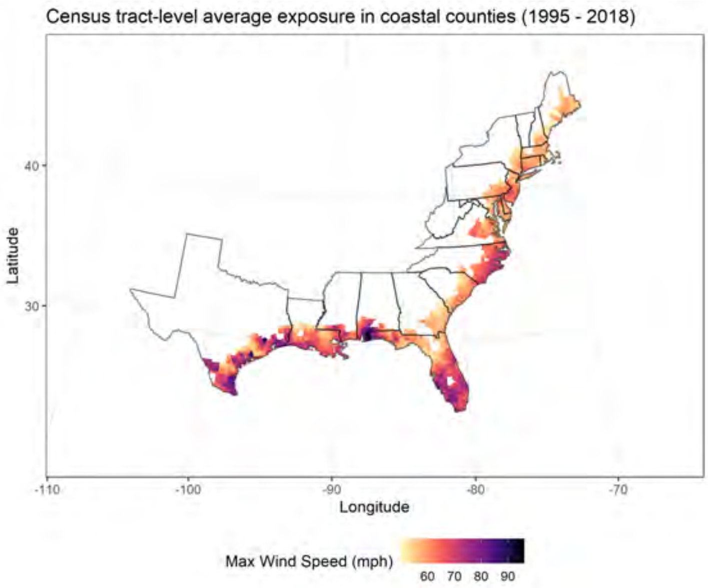
- Today:
  - Part 1: Stylized Facts about Equilibrium Hurricane Risk and Experience
  - Part 2: What are the Effects of Hurricane Exposure on Total Income, Earnings, and Transfers?
  - Part 3: How does Experience Affect the Earnings Response?

Administrative Data

- Primary sample is the 2000 Long Form (1-in-6 sample of all U.S. Households) + ACS (2001-2018)
- We link this to administrative tax return data with residence-level geo-identifiers.
- Combined we have panel data information on earnings, transfers, migration, race, education, sex, etc.
- **Sample restrictions:** Individuals aged 25-64 that have ever lived in
  - coastal counties
  - of the 21 “hurricane states”

Hurricane Data

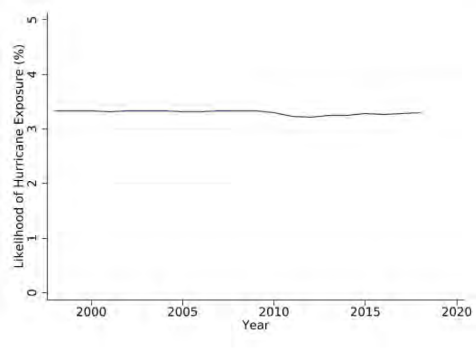
- We construct census tract-year level measures of maximum sustained wind speed.
  - 6-hourly storm track data from IBTrACS + structural wind field model (Willoughby et al., 2006)
- Avoids relying on endogenous measures of exposure, e.g., damages.
- An individual is exposed to a hurricane in a given year if they are living in a census tract that experiences maximum sustained wind speeds > 50mph.
- Experience is defined as the number of individual-level hurricane exposures.


Census tract-level average exposure in coastal counties (1995 - 2018)
Latitude
40
30
Longitude
-110
-100
-90
-80
-70
Max Wind Speed (mph)
60
70
80
90

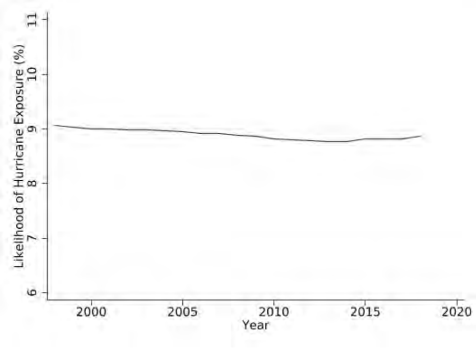
Stylized Facts

- We proxy for equilibrium hurricane risk using a location's average exposure between 1980 and 2019.
- Questions of interest:
  - How has exposure to equilibrium hurricane risk evolved over time?
  - Who is exposed to greater risk?
- For each individual, we calculate total experience as the maximum number of hurricane exposures
  - Who is exposed to more hurricanes?

Stylized Facts: Exposure to Hurricane Risk Over Time



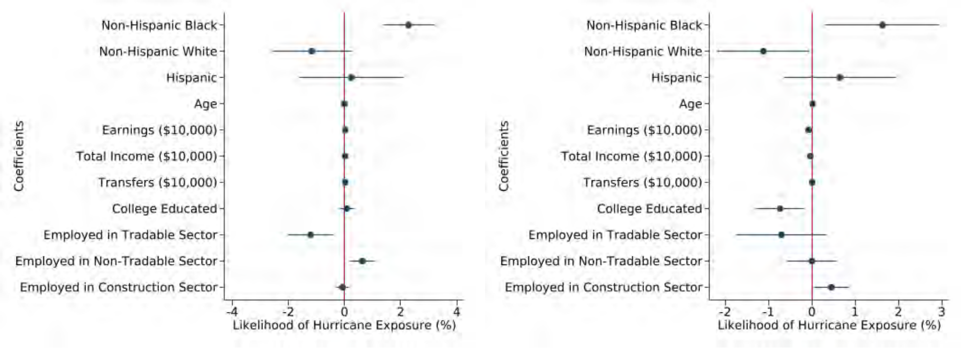
(a) The entire USA



(b) Coastal counties in hurricane states

- There has been no systematic movement towards or away from riskier areas.

Stylized Facts: Demographic Exposure to Hurricane Risk

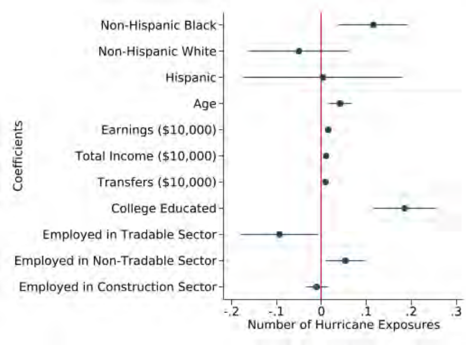


(a) The entire USA

(b) Coastal counties in hurricane states

- Black individuals and less educated individuals are exposed to greater risk.

Stylized Facts: Demographic Variation in Hurricane Experience



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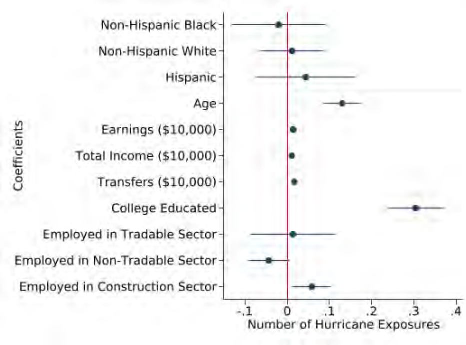


(b) Coastal counties in hurricane states

- Older individuals and more educated individuals have experienced more hurricanes.

Estimating the Dynamic Causal Effect of Shocks

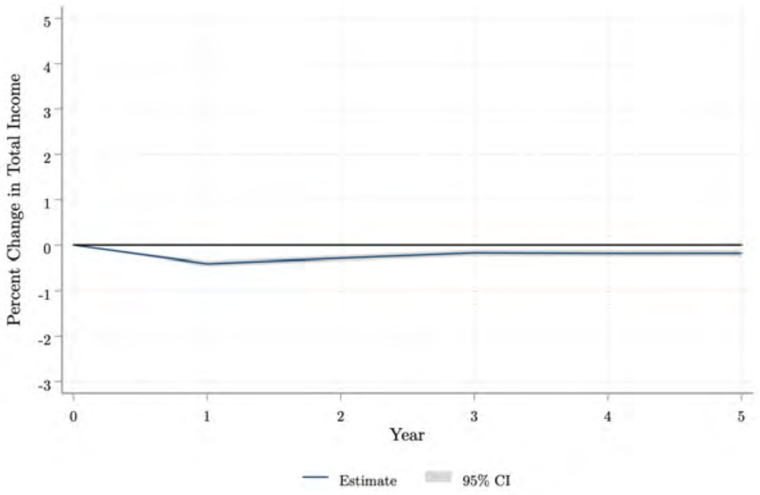
- Following Rambuchan and Shephard (2020) and Bojinov et al. (2021) we implement a panel-data local projection impulse response estimator (Jordà, 2005),

$$Y_{i,s,t+h} = \beta_h Windspeed_{i,t} + \alpha_i + \delta_{s,t} + \epsilon_{i,s,t}$$

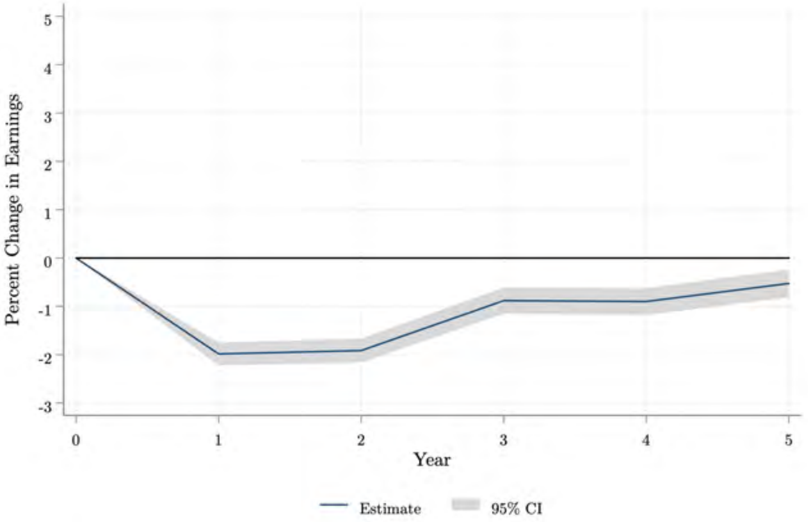
- Key assumption: conditional independence, i.e., $\mathbb{E}(\epsilon_{i,s,t}|\alpha_i, \delta_{s,t}) = 0$.

- If one is willing to buy this assumption β_h identifies the average causal effect of exposure to hurricane-force winds at horizon h

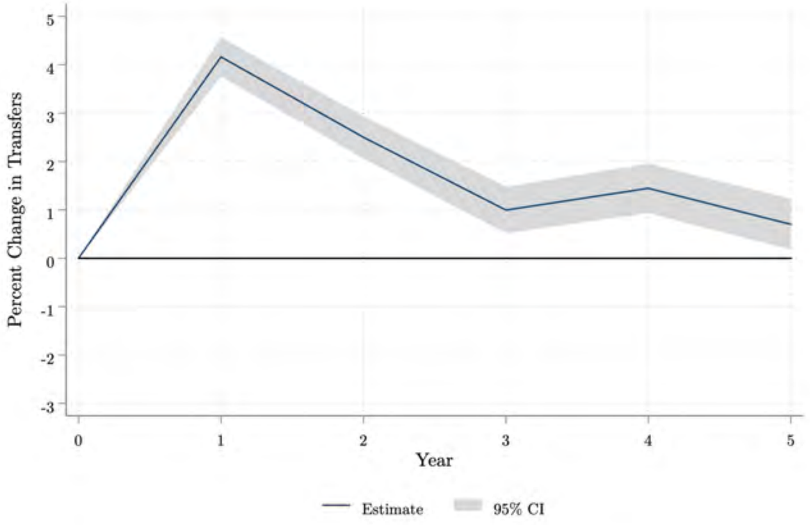
The Dynamic Causal Effect of Exposure to 70mph on Total Income



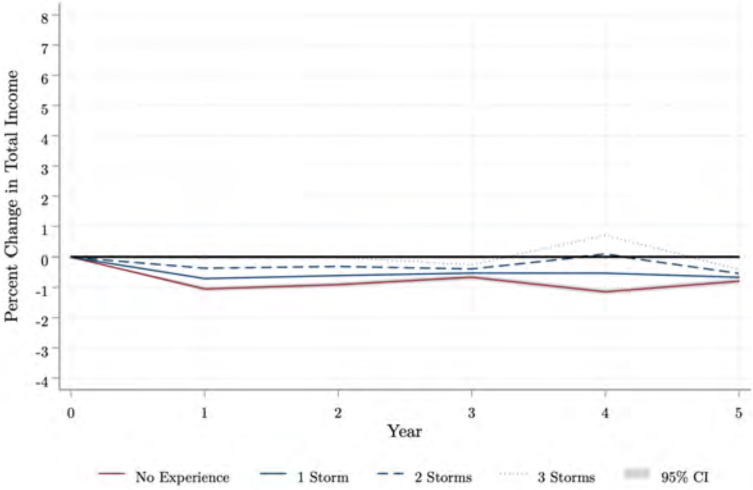
The Dynamic Causal Effect of Exposure to 70mph on Earnings



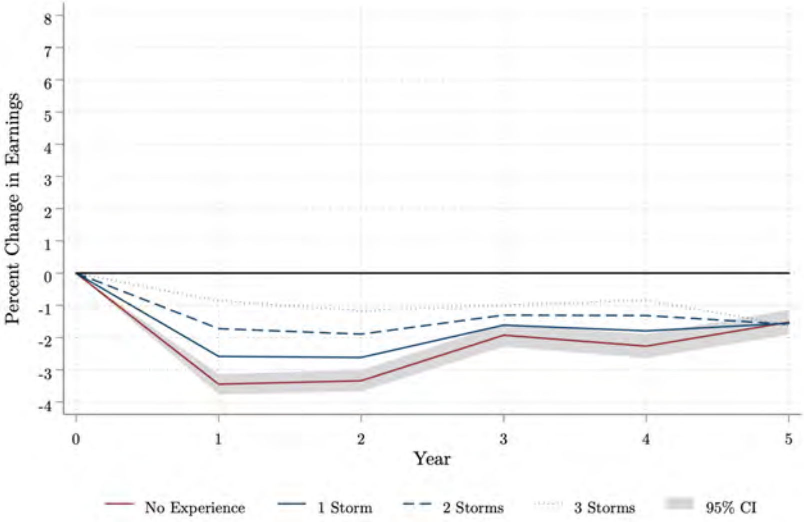
The Dynamic Causal Effect of Exposure to 70mph on Transfers



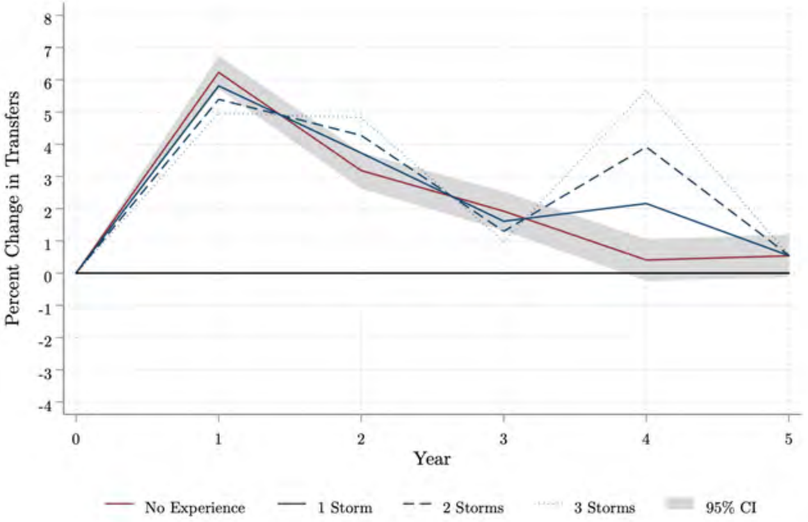
The Dynamic Causal Effect of Exposure to 70mph on Total Income, by Experience



The Dynamic Causal Effect of Exposure to 70mph on Earnings, by Experience



The Dynamic Causal Effect of Exposure to 70mph on Transfers, by Experience



Implications for Adaptation

- Traditionally, adaptation has been thought of as an equilibrium outcome of private/public decision-making:
  - Some people/places are better protected against climate risk than others.
  - Make private defensive investments until $MPB = MPC$.
  - Make public defensive investments until $MSB = MSC$.
- Our results suggest that individuals may be under-investing in private self-protection $\mathbb{E}[MPB] < MPB$, and that experience reduces this gap.
  - Implications for public investments?
- Defensive investments may be experience goods.

Thank You!

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The Short-Run Dynamic Employment Effects of Natural Disasters: New Insights

CLIMATE ADAPTATION
RESEARCH SYMPOSIUM
MEASURING & REDUCING SOCIETAL IMPACTS

UCLA Luskin Center for Innovation

The Short-Run Dynamic Employment Effects of Natural Disasters: New Insights

Alessandro Barattieri Patrice Borda Alberto Brugnoli
Martino Pelli Jeanne Tschopp

Climate Adaptation Research Symposium
UCLA Luskin Center for Innovation
September 7th, 2021

Motivation

- Let's start with 2 facts:
  - **In 2020**, for only the second time in history, the World Meteorological Organization **run out of letters to name Atlantic tropical storms**, and started pulling names from the Greek alphabet (NOAA, 2020).
  - **Reported losses** from natural disasters are projected to increase **from $195 billion a year to $234 billion a year by 2040** (Reuters, 2020).
- Studying the **economic effects of natural disasters** has become **a central research question in several fields** of economics (including labour and macro).
- **Scarcity of evidence using high frequency, detailed industry data**, especially in developing countries, due to data limitation.

Contribution

- We study the **employment effects of natural disasters** using an ideal laboratory. We exploit a unique feature of **Puerto Rico**: **frequent exposure to natural disasters** combined with the availability of **high-frequency detailed employment data**.

- This is the **first paper estimating the short-run, dynamic, disaggregated employment effects of natural disasters**. We use panel local projections with monthly data for 93 3-digits NAICS industries and 78 counties over the period 1995M1-2017m11.

- **Exogenous measure** of the intensity of disasters based on **satellite data on wind speed** during hurricanes and storms.

Preview of the Results

1. Disaster shocks cause on average a **temporary decrease in employment and wages** by up to 1%. The effects peak at 6 months, and disappear within 2 years.

2. **Heterogeneous responses across industries**. Three groups:

    1. Strengthened (i.e. Construction of Buildings, Special Contractors, Furniture Stores).
    2. Weakened (i.e. Accommodation, Retail, Printing Activities).
    3. Neutral (most of Manufacturing).

3. **Input-Output linkages** likely mechanism explaining some of the results.

Related Literature

- **Effects of natural disasters** on:
  - *Employment*: Belasen Polacheck (2008), McIntosh (2008), Groen Polivska (2008), Kirchberger (2017), Groen, Kutzback, Polivka (2020),
  - *Growth*: Strobl (2008), Bertinelli and Strobl (2013), Cavallo et al (2013), Hsiang and Jina (2014), Felbermayr and Groesch (2014)
  - *Firms*: Elliott et al (2019) Seetheram (2018) Vu and Noy (2013),
  - *Exports*: Pelli and Tschopp (2017),
  - *Government Spending*: Deryugina (2016),
  - *Education*: Sacerdote (2012).

- **Local projections**: Auerbach and Gorodnichenko (2013), Jorda and Taylor (2016), Leduc and Wilson (2013), and Ottonello and Winberry (2018), Barattieri and Cacciatore (2020).

- **Puerto Rico**: Lugo (2019), Watsins et al. (2020), Peri et al. (2020).

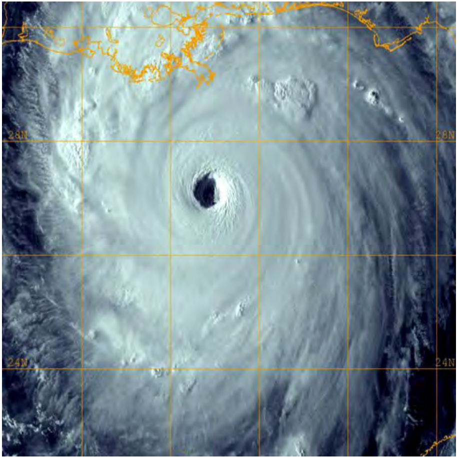
Outline

1. Measurement of disaster shocks
2. Empirical Strategy
3. Results
4. Conclusions

Measuring Disaster Shocks

The Eye of the Tiger

⇒ The position and wind speed of the **eye of a storm** can be used to obtain wind speed in all the areas around it.



Wind speed

- Storms' best tracks data, provided by NOAA, contain (every 6 hours):
  - Latitude and longitude of the eye.
  - Wind (in knots – nautical mile per hour).
- We linearly interpolate each storm's path and **create a landmark (eye's position) at every kilometre along the track**.
- For each landmark, we compute its distance to each county's population weighted centroid.
- We then use the HURRICON model (Boose, 2004) to **compute the windspeed at each county** c for each landmark h: w_{ch}.
- For each storm H, we retain the **maximum windspeed to which a county** c **was exposed**:

$$w_{cH} = \max_{h \in H} \{w_{ch}\}$$

Exposure to Storms

- Following previous literature, our **county-level storm exposure** measure for month (or quarter) t is:

$$S_{ct} = \sum_{H} x_{cHt} \quad \text{where} \quad x_{cHt} = \frac{(w_{cHt} - 33)^3}{(w^{max} - 33)^3} \quad \text{if} \quad w_{cHt} > 33$$

- x_{cHt}: max windspeed affecting county c during storm H at time t relative to the sample max.
  - We use the 33 knots threshold (defining a tropical storm).

- **The cube of windspeed expresses the force exerted on built structures** (Emanuel, 2005).

Examples: Georges and Jeanne

1998m9 (George)

1998m9 (George)

2004m9 (Jeanne)

2004m9 (Jeanne)

Examples: Irene and Maria

2011m8 (Irene)

2011m8 (Irene)

2017m9 (Maria)

2017m9 (Maria)

Empirical Strategy

Main Results: Panel Local Projection

- We use the Local Projection (Jorda, 2005). k-step ahead panel predictive regressions:

$$\Delta X_{ic,t+k} = \alpha^k + \gamma^k S_{ct} + \delta_t + \nu_i + \eta_c \ + \epsilon_{ic,t+k}, \tag{1}$$

- $\Delta X_{ic,t+k} \equiv \log X_{ic,t+k} - \log X_{ic,t-1}$.
- Our object of interest: γ^k is the average response of X at horizon k to a disaster shock at time t.
- X: Employment (monthly) or Average Weekly Wage (quarterly)
- S_{ct}: exposure to storms (max wind speed).
- Monthly data: 1995M1:2017M11.Quarterly data: 1995Q1-2017Q3. 93 NAICS3 industries. 78 municipalities (GEO).
- δ_t, ν_i, η_c are time, NAICS3 and GEO fixed effects.

Individual Industries: Local Projections

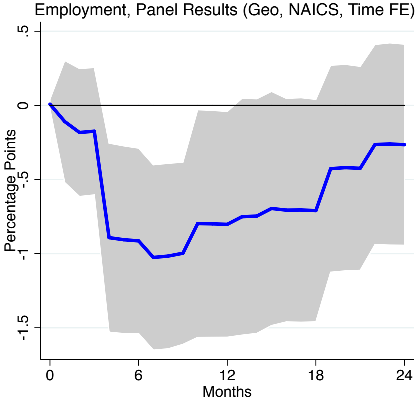
- The analog of (1) becomes:

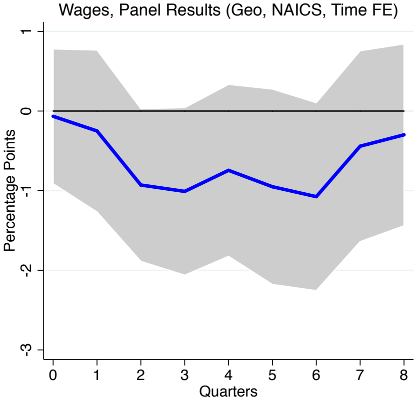
$$\Delta X_{i,t+k} = \alpha^k + \gamma_i^k S_t + \beta^k \Delta X_{t+k}^{AGGR} + \delta_m(\delta_q) + \epsilon_{i,t+k}, \tag{2}$$

- $\Delta X_{i,t+k} \equiv \log X_{i,t+k} - \log X_{i,t-1}$.
- Our object of interest: γ_i^k is the response of X_i at horizon k to a disaster shock at time t.
- X_i: Employment (monthly) or Average Weekly Wage (quarterly).
- S_t: population-weighted average of S_{ct}
- X^{AGGR} is a measure of the aggregate counterpart of X.
- δ_m (δ_q) are monthly (quarterly) dummies to control for seasonal effects.

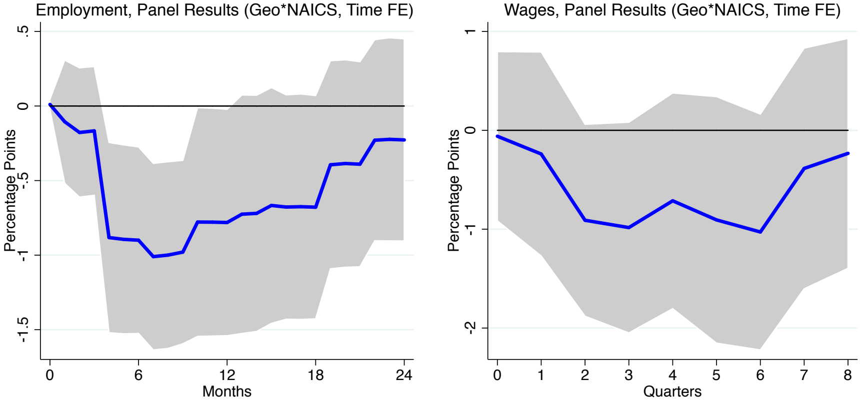
Main Results

GEO NAICS3, and DATE FE

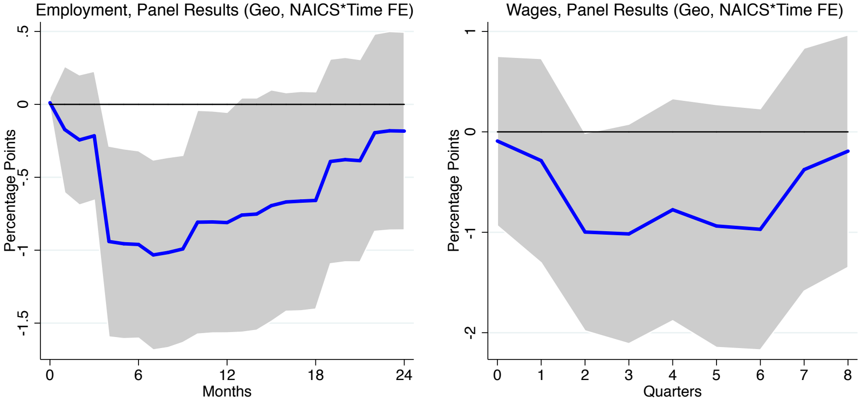




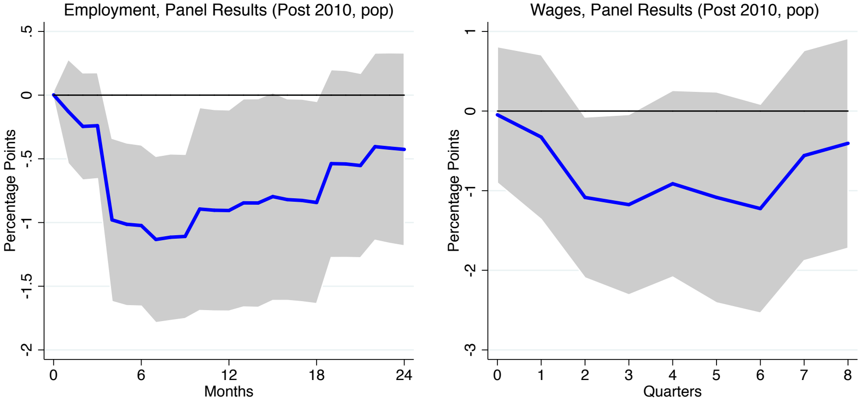
GEO*NAICS3, and DATE FE



DATE*NAICS3, and GEO FE

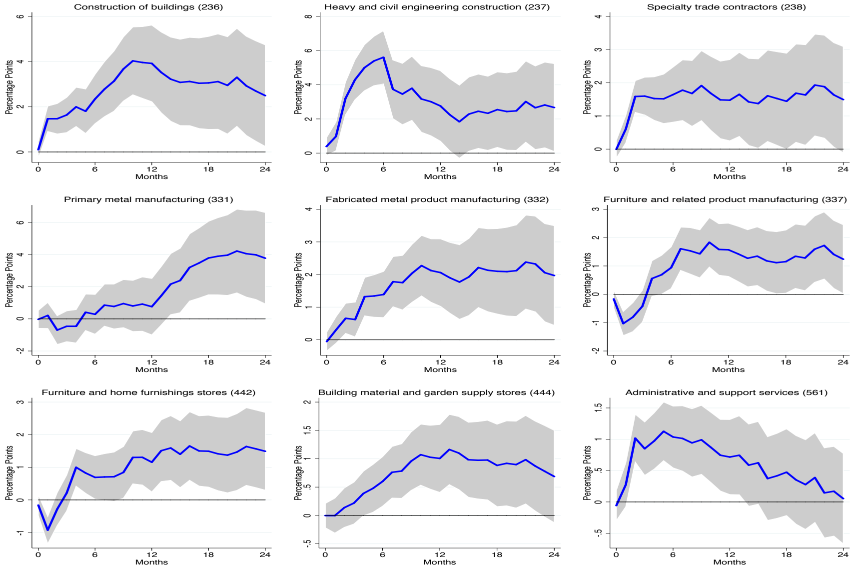


DATE, NAICS3, and GEO FE, Post 2010, Pop

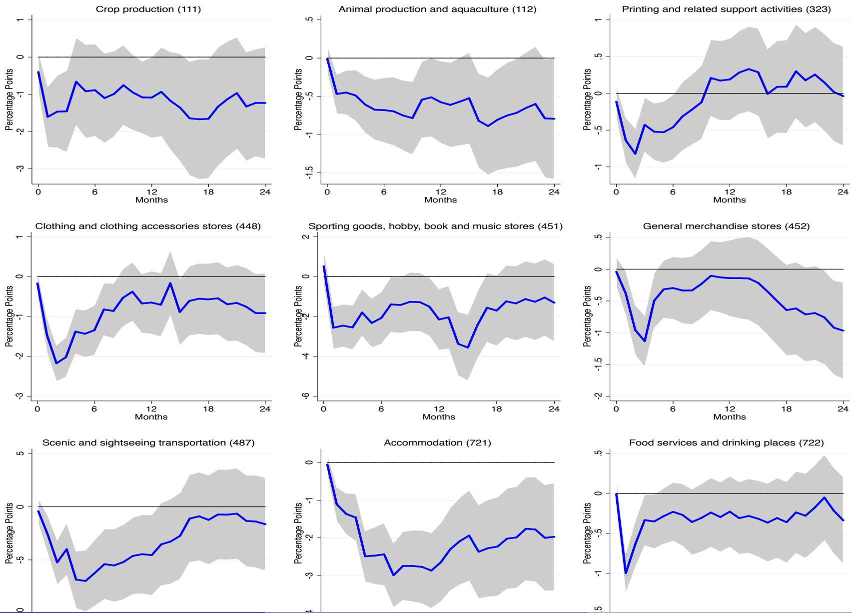


Industry Heterogeneity

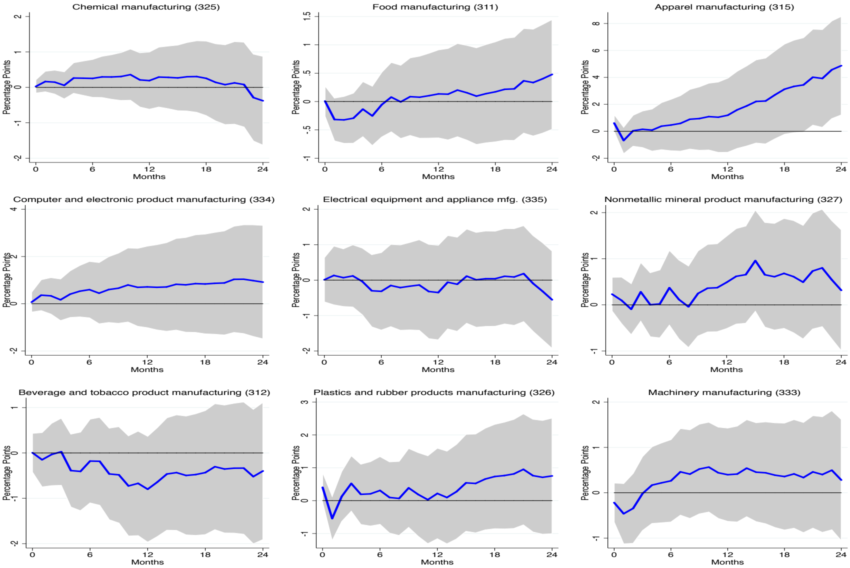
Strengthened Industries



Weakened Industries



Neutral Industries



Robustness

- Our results are **robust to the use of several alternative measures** of exposure to natural disasters:

  1. Using a **higher threshold for** x_{cHt} (64 knots instead of 33),
  2. Using a **different formula** to compute the wind speed (Depperman, 1947)
  3. Using **geographical centroids** of each counties instead of the population-weighted ones.

Discussion

- **Some results are intuitive**: a disaster shock generates a construction boom and affects negatively retail, transport and accommodation industries.

- Some **other results can be explained by input-output linkages**:

  - According to US IO tables, construction sectors are the most important buyers of both furniture manufacturing (absorbing 52% of total sales) and fabricated metal product manufacturing (absorbing 26% of total sales).

  - Retail and accommodation sectors are important buyers of printing activities (absorbing 10% of total sales).

Conclusion

- We studied the **short-run employment effects of natural disaster** using disaggregated data for Puerto Rico and an exogenous measure of exposure.
- Disaster shocks cause a **temporary decrease in employment and wages**.
- A lot of **heterogeneity across industries**. Some results are obvious, some explained by I-O linkages.
- **Policy Implications**:
  - A new concept of resilience to natural disaster shocks: *adaptability-driven employment resilience*, defined as the **potential ability of workers to rapidly reallocate from the contracting to the expanding industries** in the aftermath of a natural disaster.
  - *Adaptability-driven employment resilience* could be achieved (or enhanced) by introducing **new and different vocational training programs.**

Thank You !!!

For info, questions, complaints:
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Up next – 3:30-5pm PT

SESSION 4.1

The Effects of Temperatures on Behavior

SESSION 4.2

Adaptation at Home: Consumption, Building Codes, and Insurance

SESSION 4.3

Quantifying and Minimizing Water Quality Impacts

SESSION 4.4

Integrating Climate and Transportation Planning

Thanks for tuning in!