CLIMATE ADAPTATION
RESEARCH SYMPOSIUM

MEASURING & REDUCING SOCIETAL IMPACTS

Adaptation at Home: Consumption, Building Codes, and Insurance

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The session will begin shortly.

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Yanjun Liao

Resources for the Future and U Penn

Judson Boomhower

UC San Diego

Wangyang Lai

Shanghai University of Finance and Economics

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What's at Stake? Understanding the Role of Home Equity in Flood Insurance Demand

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Yanjun (Penny) Liao [1,2] Philip Mulder [2,3]

[1] Resources for the Future

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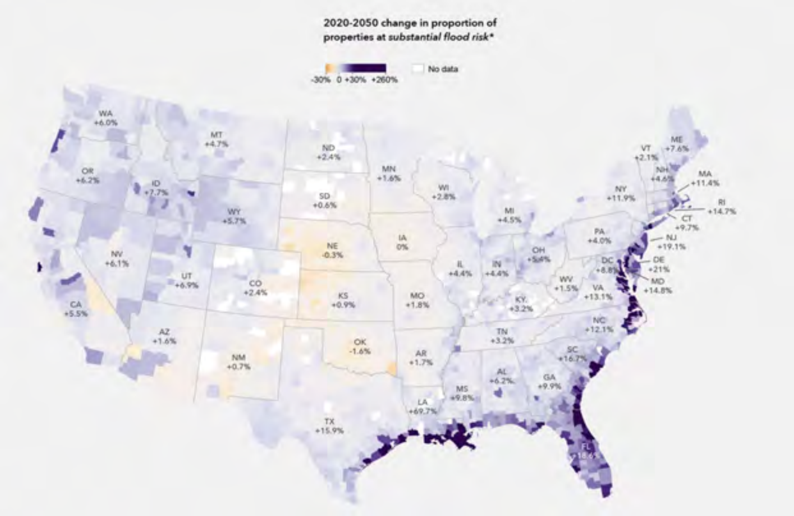
Sep 8, 2021
UCLA Climate Adaptation Symposium

Millions of homes are exposed to increasing flood risk



Source: The First Street Foundation

Flood Risk and the Mortgage Market

- Flooding increases displacement, delinquencies, and foreclosures
- Flood insurance protects against these outcomes
- Yet, millions of risky properties uninsured - why?
- Conventional explanations: imperfect information, behavioral bias
- This Paper: low stakes in property leads to under-insurance

Rising Seas Threaten an American Institution: The 30-Year Mortgage

Climate change is starting to transform the classic home loan, a fixture of the American experience and financial system that dates back generations.

Homes in Nags Head, N.C., as Hurricane Florence approached in September 2018.

Source: The New York Times

Research Question and Approach

How and why does home equity affect flood insurance demand?

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- The implicit insurance value is higher for homeowners with lower home equity

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Model

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Empirical Analysis

1. A positive causal relationship between home equity and flood insurance demand
2. Mechanism tests support the role of default incentive (vs. liquidity constraints)

Research Design

Setting: Flood insurance demand in the National Flood Insurance Program (NFIP)

- Quarterly panel of 271 MSAs, 2001-2017

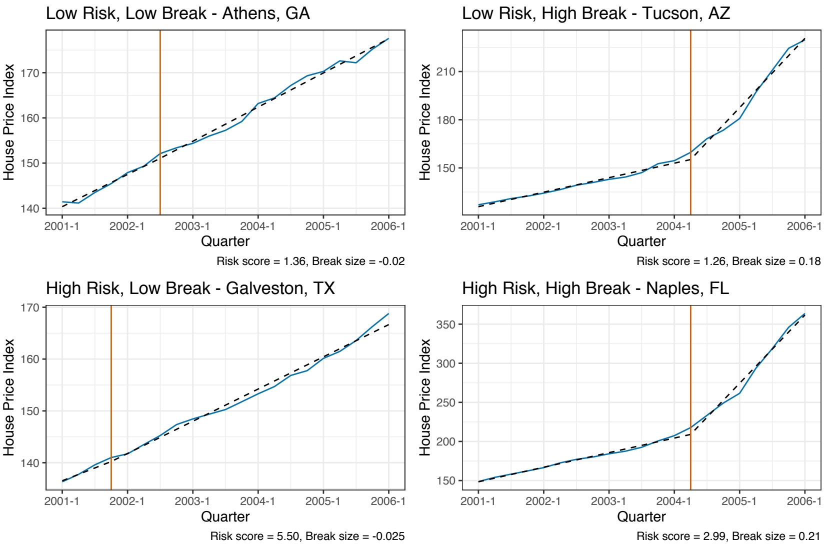
Challenge: Home equity correlated with other determinants of flood insurance demand

Solution: Use sudden price variation in the housing booms of early 2000s as instruments

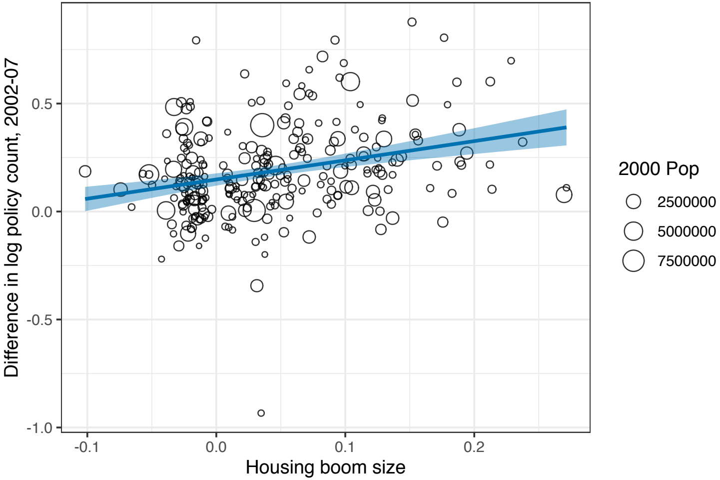
- Rapid land value appreciation caused increase in equity ▸ Home Prices & Equity

Econometrics: Instrumental variable + Difference-in-differences

The Housing Booms



The Housing Booms and Flood Insurance



Empirical Strategy

Continuous treatment event study:

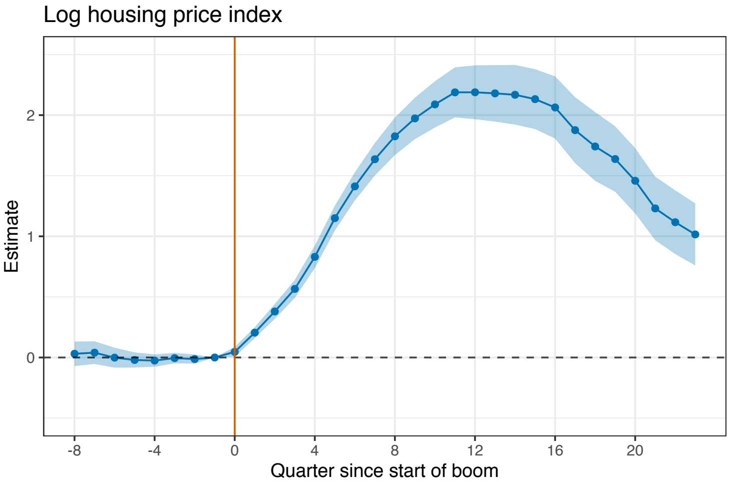
$$Y_{mt} = \sum_{\tau=-9}^{24} \boldsymbol{\alpha_\tau} (Post_{mt}^{\tau} \times \Delta P_m) + \delta' X_{mt} + \gamma_m + \gamma_t + \varepsilon_{mt}$$

- Y_{mt}: outcome of interest (e.g. log housing price index, log policy count)
- $Post_{mt}^{j}$: event time indicator, the j-th quarter after housing boom
- ΔP_m: structural break instrument
- Controls: income, home sales volume, population growth, employment rate, dynamic effects of risk, recent flood claims, MSA and year fixed effects

⇒ $\boldsymbol{\alpha_\tau}$'s flexibly capture the trajectory of the outcome of interest relative to the boom size and start time in each MSA

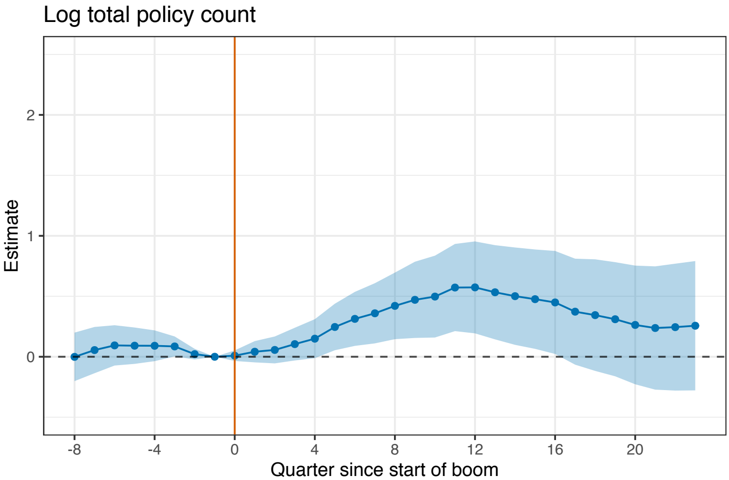
- Identification relies on parallel trends in outcome absent the booms

Structural Breaks and Home Price Dynamics



+1 SD boom size ⇒ +15% home prices at peak

Structural Breaks and NFIP Take-Up



$+1$ SD boom size $\Rightarrow$ $+5\%$ take-up at peak

Raw pre-trends

Other Findings

- This effect is not driven by
  - SFHA insurance purchase mandate ▸ Non-SFHA Take-Up
  - New construction ▸ Pre-2003 Buildings
  - Renovations to existing buildings ▸ Coverage
- Other choice margins remain stable: deductible ▸ Show, contents ▸ Show
  - Risk preferences and perceptions are stable across the boom-bust cycle

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$\Rightarrow$ Housing booms affect flood insurance take-up primarily through housing prices

2SLS Estimation

Policy Sample	Dependent variable: log NFIP policy count		
	All	SFHA	Non-SFHA
	(1)	(2)	(3)
$\log(\widehat{\text{HomePrice}})$	0.307^{***}	0.213^{***}	0.483^{***}
	(0.077)	(0.061)	(0.154)
First-stage F-stat	39.10	52.59	36.76
Observations	15,112	15,112	15,112
Adjusted R^2	0.991	0.992	0.979
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Magnitude:

- Effect of home prices $\uparrow$ 1% $\approx$ Effect of premium $\downarrow$ 2%
- Effect from a hurricane hit $\approx$ Effect of home prices $\uparrow$ 4.8%

A much larger effect for non-SFHA policies

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Boom vs. Bust: First-Difference Regressions

	Boom (2002-07)		Bust (2007-12)			
	All	Non-SFHA	All	Non-SFHA	All 2003-05	Non-SFHA 2003-05
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\widehat{HomePrice})$	0.334***	0.364**	0.384***	0.731***	1.369***	1.452***
	(0.110)	(0.178)	(0.117)	(0.243)	(0.302)	(0.416)
Observations	250	250	250	250	250	250
First-stage F-stat	33.75	33.34	11.96	11.40	11.96	11.40
Adjusted R2	0.024	0.034	0.170	0.126	0.147	0.123
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Why does higher home equity increase insurance take-up?

Insurance demand model suggests two potential economic mechanisms and their predictions

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Default Incentive: Lower implicit insurance value from defaulting

- Prediction 1: a larger effect in MSAs with lower transaction costs of default
- Prediction 2: a larger effect in MSAs with greater non-SFHA tail risk exposure Result

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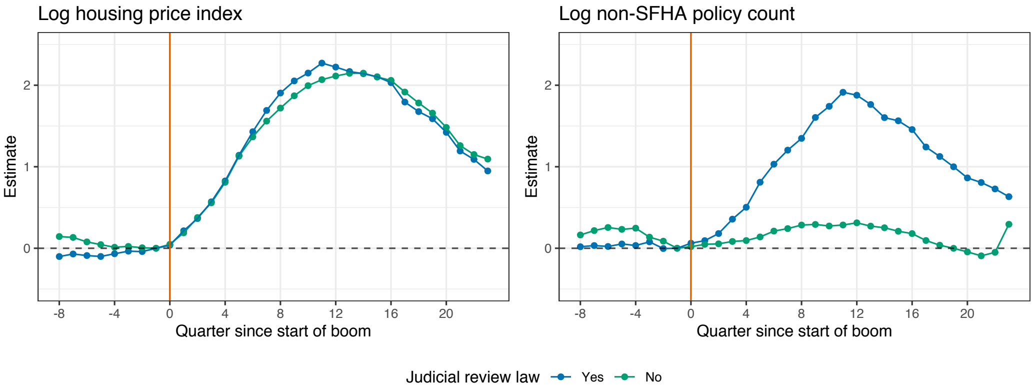
Liquidity: Higher home equity provides greater liquidity with refinancing

- Prediction: an increase in 1-year renewal rate at the beginning of the boom

The Default Incentive Mechanism

- Prediction 1: a larger effect in states with judicial foreclosures



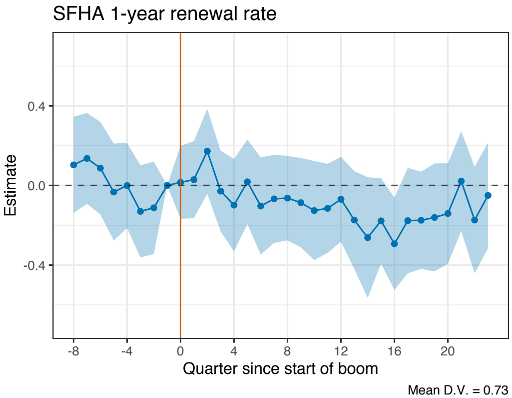
Mechanism: 2SLS Estimates

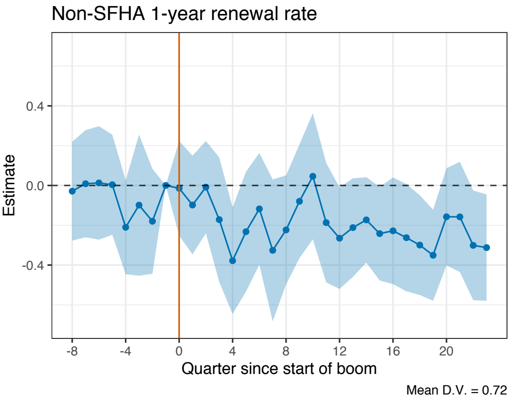
	Dependent variable: log NFIP policy count			
Policy Sample	**Non-SFHA**		**SFHA**	
	(1)	(2)	(3)	(4)
$\log(\widehat{\text{HomePrice}})$	0.355**	0.493***	0.231***	0.285***
	(0.147)	(0.161)	(0.067)	(0.066)
$\log(\widehat{\text{HomePrice}}) \times$ Judicial	**0.383***		**−0.067**	
	(0.122)		**(0.067)**	
$\log(\widehat{\text{HomePrice}}) \times$ HighTailRisk		**0.337**		**0.107**
		(0.154)		**(0.078)**
First-stage F-statistic	(40.83, 94.55)	(36.09, 92.43)	(45.86, 93.88)	(46.68, 86.08)
Observations	15,572	15,572	15,572	15,572
Adjusted R^2	0.979	0.979	0.992	0.992

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The Liquidity Mechanism

- Prediction: an increase in 1-year renewal rate at the beginning of the boom





Conclusion

Findings

- New incentive-based explanation of the flood insurance gap: homeowners rely on mortgage default as an implicit insurance
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Implications for Disaster Risk Management

- Some disaster risk gets transferred from homeowners to lenders, and ultimately to taxpayers
- Moral hazard: distorted incentives to insure, adapt, and develop in risky areas
- Risk-induced property value depreciation can lower insurance demand
- Potential solutions should focus on reflecting the risk in the mortgage system, particularly for homes outside 100-year floodplains

Home Prices and Equity Comovement

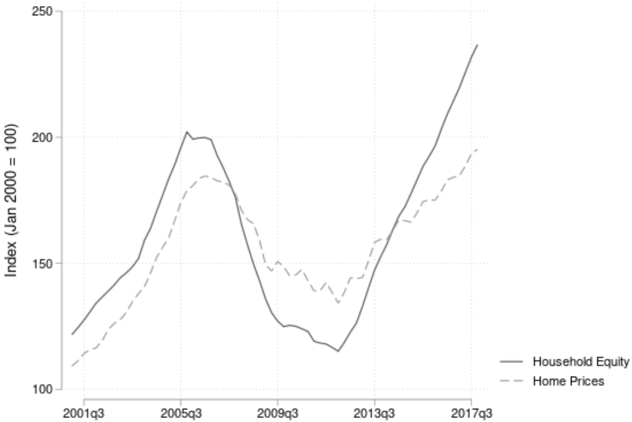

Figure: Time series of national home prices and household home equity

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Insurance Demand: Baseline Model

- Properties values structure S, land L, mortgage M and equity $E = S + L - M$
- Disaster probability $1 - p$, damages $R \in \mathbb{R}^+$ distributed $f(R)$
- Household income W, quasi-linear utility:

$$\underbrace{U(C)}_{\text{consumption}} + \underbrace{W + E - R - C}_{\text{period-end asset}}$$

- WTP for insurance $\widehat{P}$ is not affected by home equity:

$$\widehat{P} = (1 - p) \cdot \mathbb{E}(R)$$

Insurance Demand **With** Liquidity Constraint

- Liquidity constraint on consumption and insurance spending

$$C + I \cdot P_I \leq W + \delta E$$

- New WTP when the constraint is binding:

$$\widehat{P} \approx \underbrace{\Delta C \cdot (1 - U'(C'))}_{\text{liquidity effect } <0} + (1 - p) \cdot \mathbb{E}(R)$$

$\Rightarrow$ The liquidity effect alleviates (WTP $\uparrow$) as equity increases

Insurance Demand **With** Default

- Uninsured households can avoid paying R by giving up E and paying $\widehat{M}$
  - Optimal for households with $R > E + \widehat{M}$

- New WTP:

$$\widehat{P} = (1-p) \cdot \left(E - \int_0^{E+\widehat{M}} (E-r) f(r) dr + \int_{E+\widehat{M}}^{\infty} \widehat{M} f(r) dr \right)$$

$\Rightarrow$ WTP increases with equity:

$$\frac{d\widehat{P}}{dE} = (1-p) \cdot \left(1 - F(E+\widehat{M})\right) > 0$$

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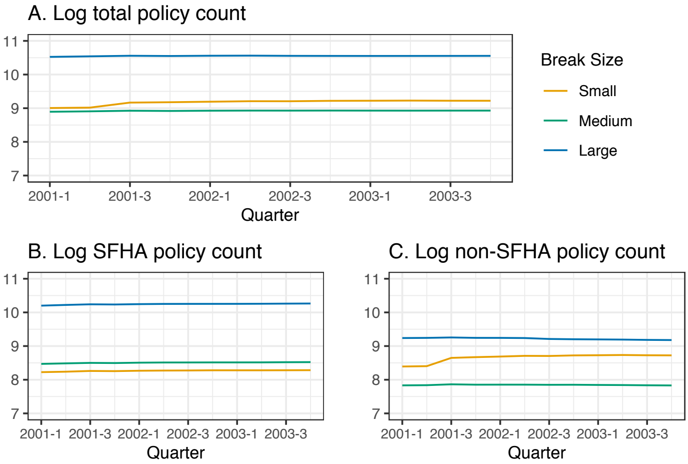
Results: Pre-Trend in Raw Data



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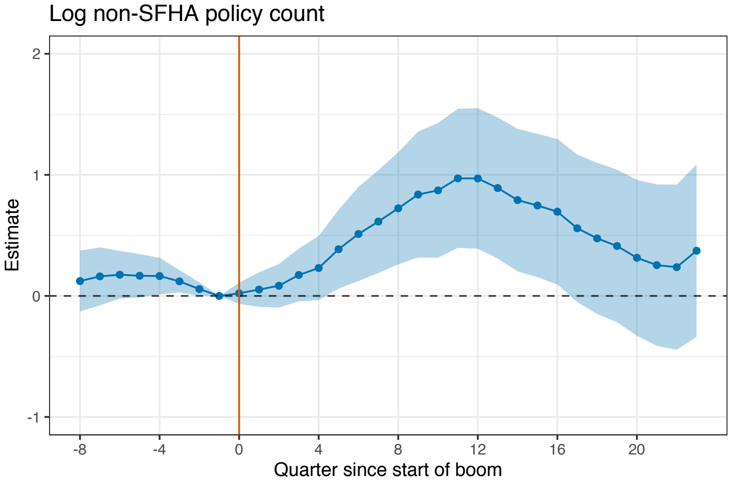
Results: Non-SFHA Take-Up



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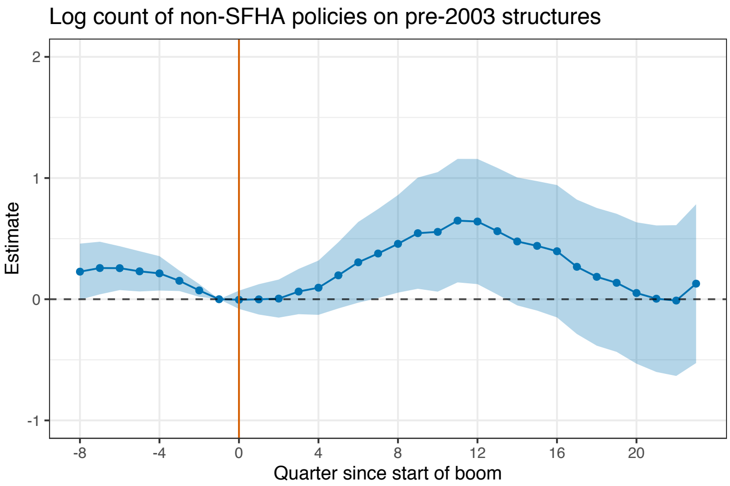
Non-SFHA Take-Up Among Pre-2003 Buildings



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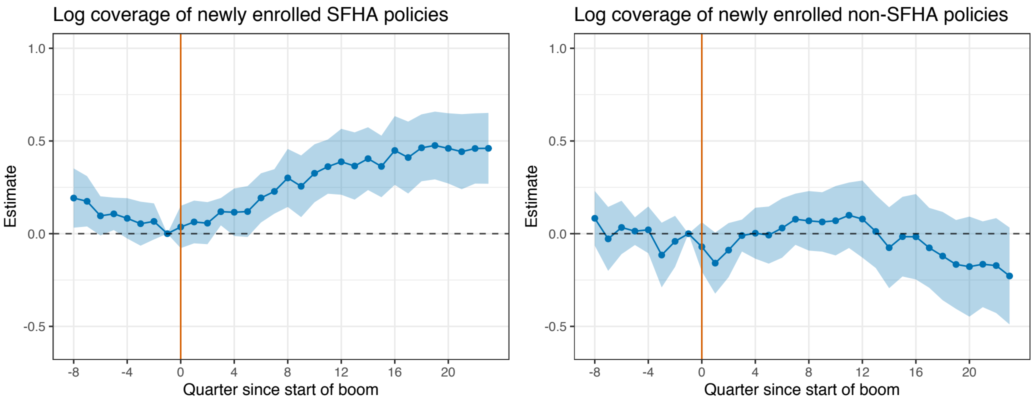
Results: Coverage



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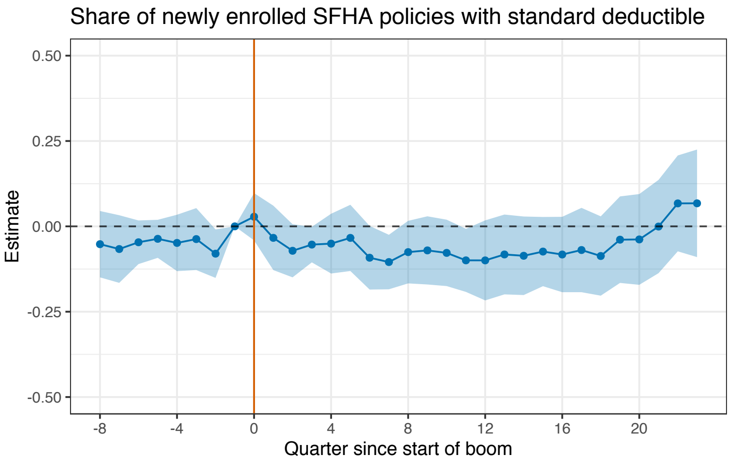
Results: Deductible



Mean D.V. = 0.703

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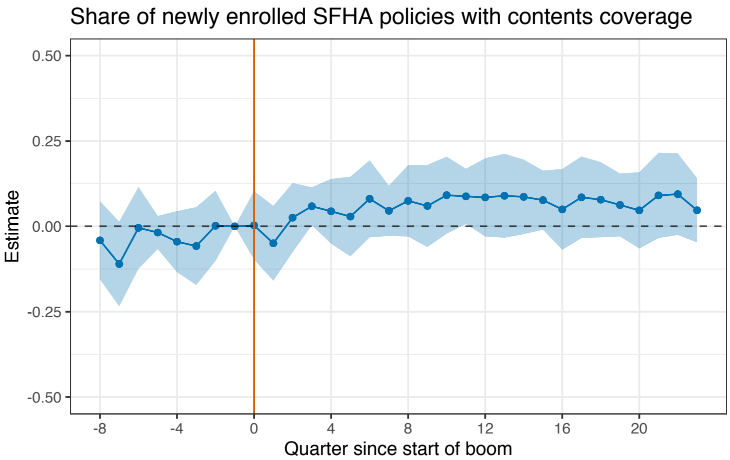
Results: Contents Coverage



Mean D.V. = 0.318

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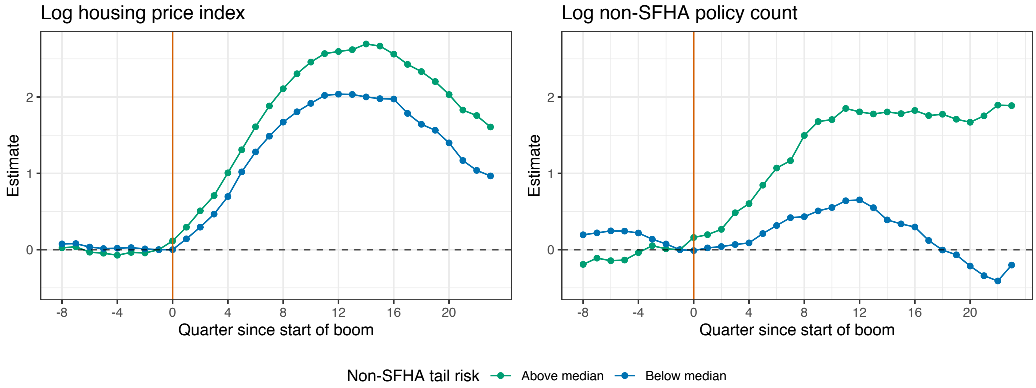
The Default Incentive Mechanism

- Prediction 2: a larger effect in MSAs with higher non-SFHA risk
  (# non-SFHA properties at 1% annual risk/# of non-SFHA properties at any risk)



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Judson Boomhower

Assistant Professor, UC San Diego

Building Codes and Community Resilience to Natural Disasters

Building Codes and Community Resilience to Natural Disasters

Patrick Baylis[1] Judson Boomhower[2]

[1]University of British Columbia

[2]University of California San Diego and NBER

September 8, 2021

Adapting to natural disasters: voluntary action vs. mandated resilience

- Large-scale disasters are becoming more frequent due to climate change and other factors.
- Losses can be reduced through adaptive investments, but takeup may be complicated by risk misperception, spatial spillovers, and emphasis on post-disaster aid.
- Growing federal and state initiatives to require or subsidize takeup of mitigation investments.

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- Large-scale disasters are becoming more frequent due to climate change and other factors.
- Losses can be reduced through adaptive investments, but takeup may be complicated by risk misperception, spatial spillovers, and emphasis on post-disaster aid.

- Growing federal and state initiatives to require or subsidize takeup of mitigation investments.
- Limited evidence about the degree to which these programs increase resilience relative to a counterfactual of voluntary adoption.

We consider wildfire building codes in California

- Wildfires have caused $40 billion of property damage in the United States in the past 5 years, mostly in California.

Tubbs Fire, Santa Rosa, CA. Aerial imagery from NearMap.

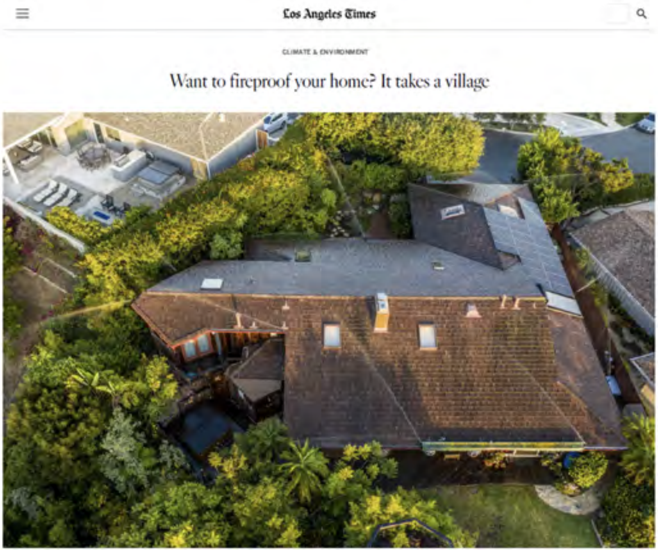
We evaluate the effect of building codes on survival of own- and neighboring structures.

- Assemble parcel-level damage data representing almost all U.S. homes destroyed by wildfire since 2003.
- Merge to the universe of assessor data for destroyed and surviving homes inside fire perimeters.
- Use differences in code requirements to measure the effects of building codes on structure survival.
- Measure spillover benefits of mitigation for neighboring properties due to reduced structure-to-structure spread.

This study advances our understanding of disaster mitigation in four ways.

1. We estimate policy effects.
   - Previous literature measures technology effects (e.g., Gibbons et al, 2012; Syphard et al 2012; Syphard et al 2017).
2. First estimates of spatial externalities from mitigation.
3. Scale: Our estimates are based on data for almost all U.S. homes experiencing wildfires since 2007.
   - This new dataset is useful beyond this study.
4. We deploy an explicit empirical design.
   - Previous literature is descriptive or relies on regression adjustment.

Spatial externalities and myopia may limit investment



Los Angeles Times

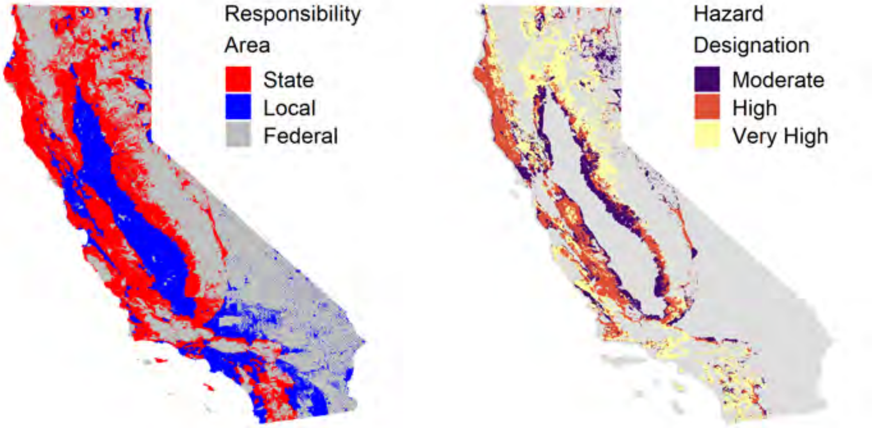
CLIMATE & ENVIRONMENT

Want to fireproof your home? It takes a village

Local governments may also face split incentives

- Hazard designations are unpopular with incumbent homeowners
- Local governments internalize a small share of mitigation benefits (Baylis and Boomhower, 2019).
- Incomplete adoption of local govt FHSZ maps (Troy, 1998; Miller et. al., 2020)

California's WUI code requirements depend on jurisdiction and mapped fire hazard



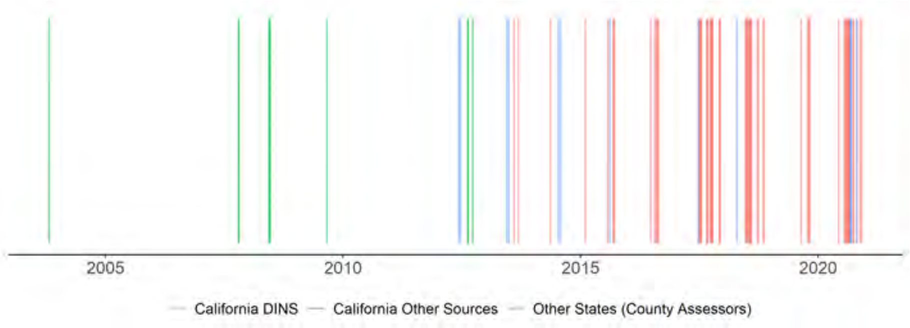
Mandatory codes in all state-managed areas, with opt-in adoption in local government areas (hundreds of municipalities and counties).

The 1991 Oakland Firestorm catalyzed important changes

- Mid-1990's building code reforms
  - A.B. 337, 1992 ("Bates Bill")
  - A.B. 3819, 1995 (Class A/B roofs required in high-hazard zones)
  - A.B. 423, 1999 (outlaws untreated wood shingles on all homes)
- Strengthened via "Chapter 7A" requirements in 2008
- Standards have been mandatory in SRA, and opt-in in LRA

We compile near-comprehensive data on U.S. homes destroyed by wildfire over two decades.

- Censuses of damaged homes for 112 wildfires, 2003–2020.
- APN, street address, extent of damage.
- CAL FIRE for California 2013–2020.
- Individual county assessors for pre-2013 and other states.



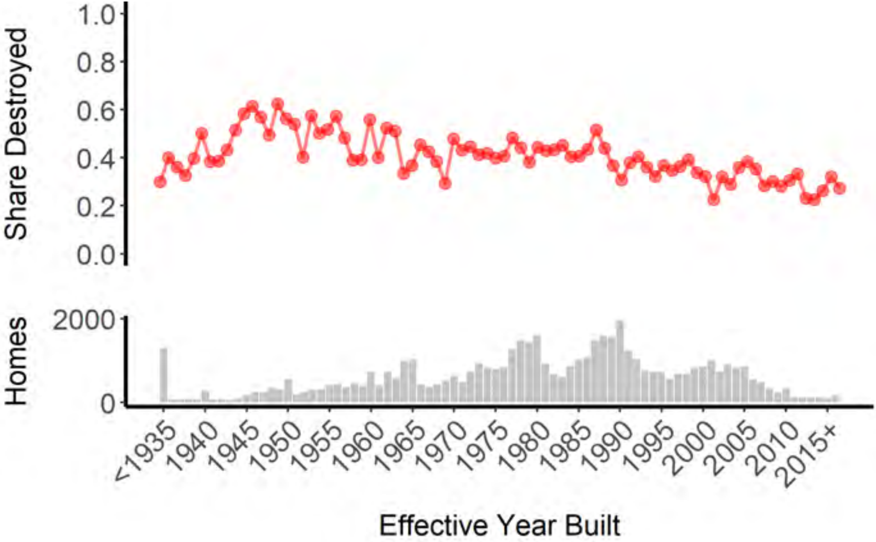
We merge to the universe of properties inside wildfire perimeters and leverage additional spatial data.

- Property tax assessment data (ZTRAX)
  - Universe of U.S. properties
    - Year built, effective year built, assessed value by year, etc.
    - Limit to single family homes inside wildfire perimeters.
  - Merge to damage data based on assessor parcel number.

- Additional spatial datasets
  - Parcel boundaries (county assessors).
  - High-res aerial imagery to validate locations & damage reports.

Summary of the final merged dataset (all states)

- 51,530 homes exposed to wildfires in CA, OR, WA, AZ.
- 41% destroyed.



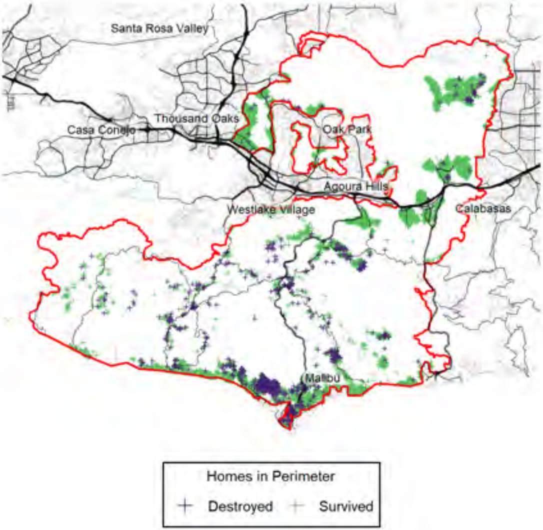
Aerial imagery validates rooftop locations.

Redding, CA before the Carr Fire (2018)

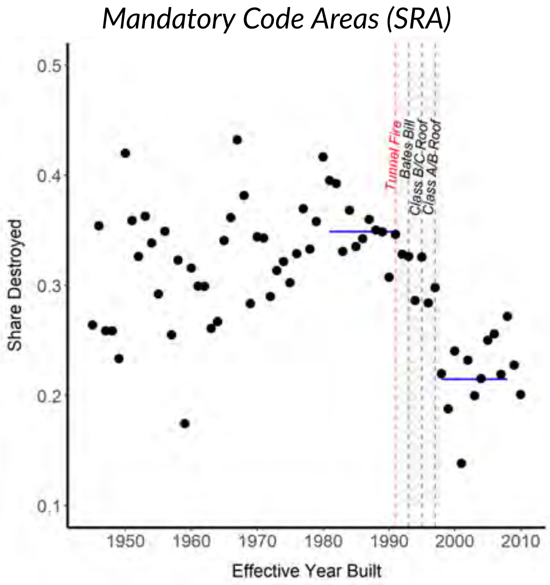
Post-fire imagery validates damage reports.

Redding, CA after the Carr Fire (2018)

Woolsey Fire (2018)

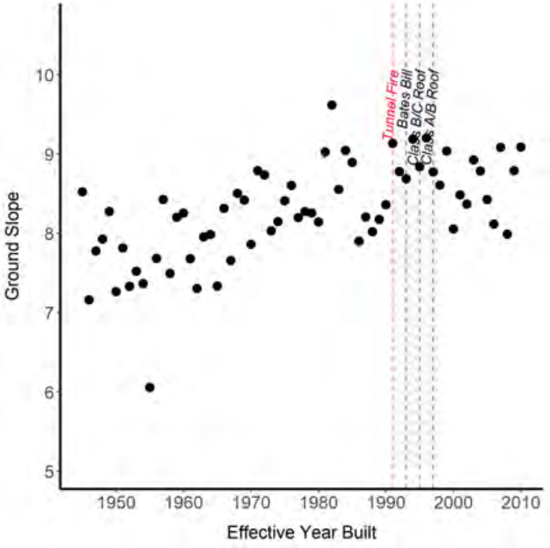


Homes built after 1995 in mandatory code areas are more likely to survive.



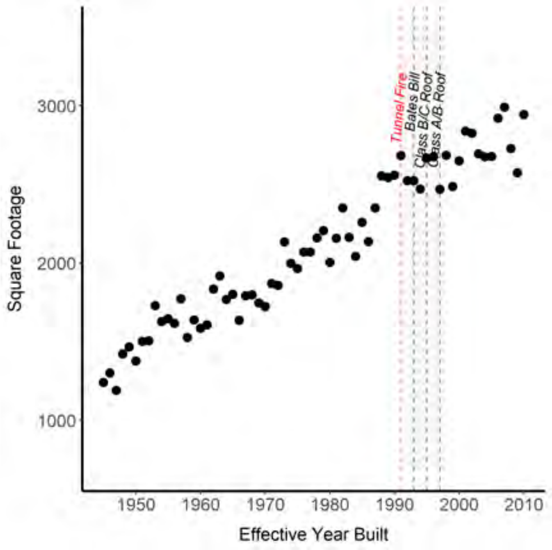
Other home characteristics do not change in 1995.

Ground Slope



Other home characteristics do not change in 1995.

Building Square Footage



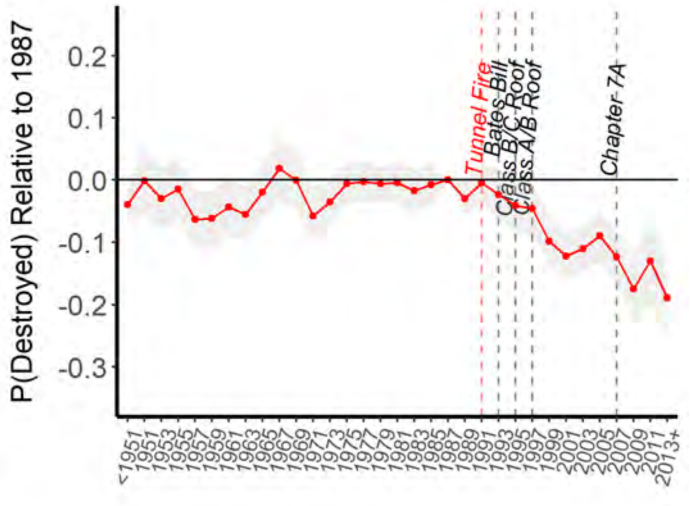
The empirical strategy compares survival for homes on the same street built in different years.

$$1[Destroyed]_{isf} = \sum_{v=v_0}^{v=V} \beta_v D_i^v + \gamma_{sf} + X_i\alpha + \epsilon_i \tag{1}$$

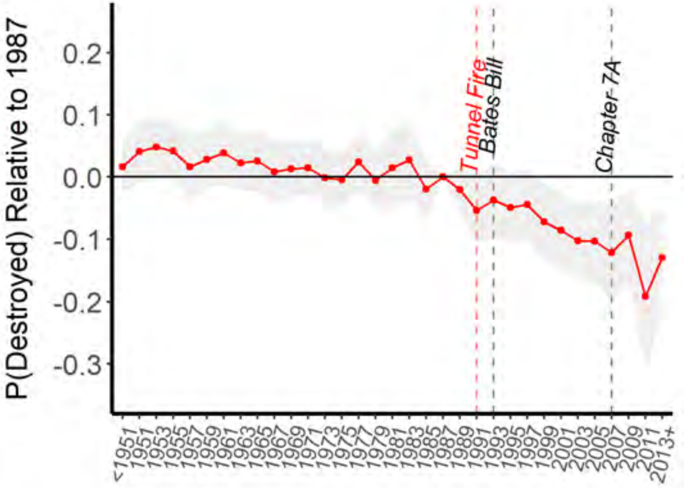
- V vintage bins
- γ_{sf} are street-by-fire fixed effects
- X_i includes controls for ground slope, vegetation, building square footage, and number of bedrooms.

1. Estimate Equation 1 separately by jurisdiction.
2. DiD specification that interacts vintage bins with jurisdiction.

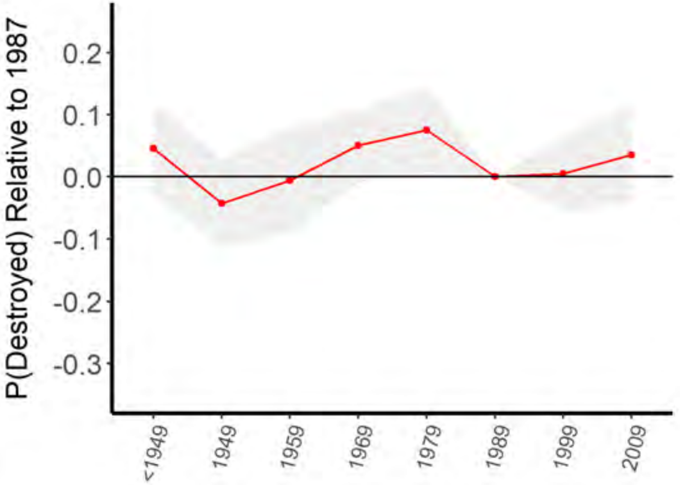
Vintage effects in mandatory code areas (SRA)



Vintage effects in opt-in code areas (LRA-VHFHSZ)



Vintage effects for other CA areas plus OR, WA, AZ



Difference in differences estimates

	(1)	(2)
Comparison Group × 1998–2007	-0.023	-0.009
	(0.026)	(0.026)
Comparison Group × 2008–2016	-0.003	0.019
	(0.033)	(0.038)
SRA × 1980–1997	-0.007	-0.046
	(0.033)	(0.041)
SRA × 1998–2007	-0.096***	-0.137***
	(0.034)	(0.042)
SRA × 2008–2016	-0.137***	-0.187***
	(0.036)	(0.043)
LRA VHFHSZ × 1980–1997	-0.024	-0.049
	(0.032)	(0.049)
LRA VHFHSZ × 1998–2007	-0.108***	-0.140***
	(0.033)	(0.048)
LRA VHFHSZ × 2008–2016	-0.144***	-0.176***
	(0.037)	(0.050)
Ground slope (deg)		0.005***
		(0.001)
Lot Size (Acres)		-0.000
		(0.000)
Building Square Feet		-0.000
		(0.000)
Bedrooms		-0.000
		(0.003)
Street FEs	Yes	Yes
Fuel Model FEs	No	Yes
Aspect FEs	No	Yes
Observations	48,213	38,386
R^2	0.62	0.63

Evaluating effects on structure to structure spread

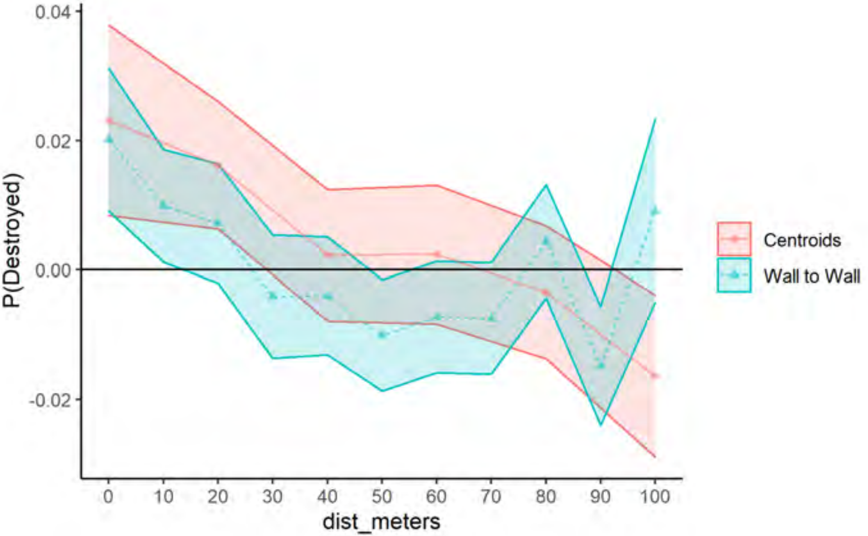
Redding, CA: Carr Fire (2018)

Evaluating effects on structure to structure spread

Santa Rosa, CA: Tubbs Fire (2017)

Nearby pre-code neighbors increase loss risk

Regression estimates controlling for own structure age and street fixed effects.



Total benefits calculation *(Preliminary)*

- We find a ~15-ppt decrease in own-structure risk and a ~2-ppt decrease for near neighbors.
- Given existing estimates of mitigation costs and the value of avoided damages, we can benchmark the cost effectiveness of universal mitigation.
- Thought experiment: "What is the minimum annual probability of wildfire exposure that makes WUI building codes cost effective?"

Conclusion

- We assembled data on nearly all homes exposed to wildfires in the United States during 2003–2020.
- We identify remarkable, non-linear vintage effects in survival for California homes.
- We show that these effects are due to state and local building code changes following the 1991 Oakland Firestorm.
- These preventive investments improve survival for neighboring homes.
- Preliminary calculations suggest the building code mandate was likely cost-effective.

Wangyang Lai

Assistant Professor, Shanghai University of Finance and Economics

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Adaptation Mitigates the Negative Effect of Temperature Shocks on Household Consumption

Adaptation Mitigates the Negative Temperature Shock on Household Consumption

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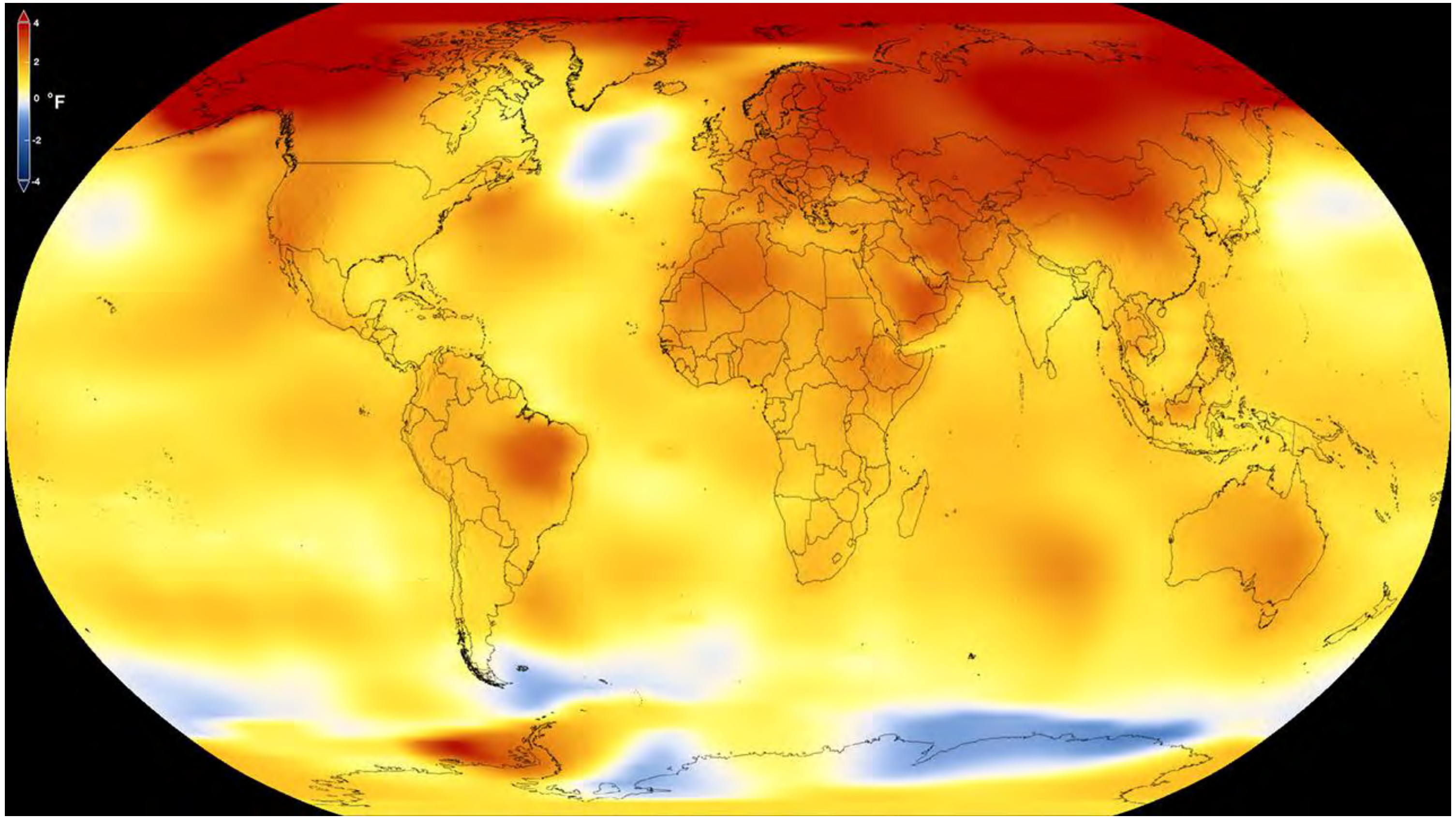
[1]Shanghai University of Finance and Economics

[2]Cornell University

[3]International Food Policy Research Institute

UCLA's Climate Adaptation Research Symposium 2021

Motivation



- NASA: Average temperature from 2013 to 2017, as compared to a baseline average from 1951 to 1980.

- As the world has warmed, that warming has triggered many other changes to the Earth's climate.
- Over the last 50 years, the world has seen increases in prolonged periods of excessively high temperatures, heavy downpours, and in some regions, severe floods and droughts.

Motivation

- Existing studies document the negative impacts of temperature on economic growth as well as various channels of impacts.
- However, previous studies mostly focus on impacts from production sides and few studies explore the direct impact on consumption.
- The importance of consumption function in the macroeconomic literature.

Objective

- Quantify the direct impacts of temperature on consumption
- Identify the patterns of adaptation
- Predict the future impacts.

Selected Literature

- **Economic growth**: Nordhaus (2006) and Dell et al. (2012)
- **Agriculture**: Mendelsohn et al. (1994), Schlenker et al. (2005), Deschenes and Greenstone (2007) and Burke and Emerick (2016)
- **Education**: Zivin et al. (2020), Goodman et al. (2018) and Garg et al. (2018)
- **Labor supply and productivity**: Zivin and Neidell (2014), Sudarshan (2017) and Park and Behrer (2018)
- **Mortality**: Deschenes and Moretti (2009), Deschenes and Greenstone (2011), Barreca et al. (2016) and Heutel et al. (2020).
- **Social conflict/civil war**: Miguel et al. (2004), Jia (2014) and Hsiang et al. (2016)

Data

- **Consumption**: transactions of credit and debit cards in China from the *UnionPay* network from 2013 to 2018.
- The data are aggregated at the city by date level.

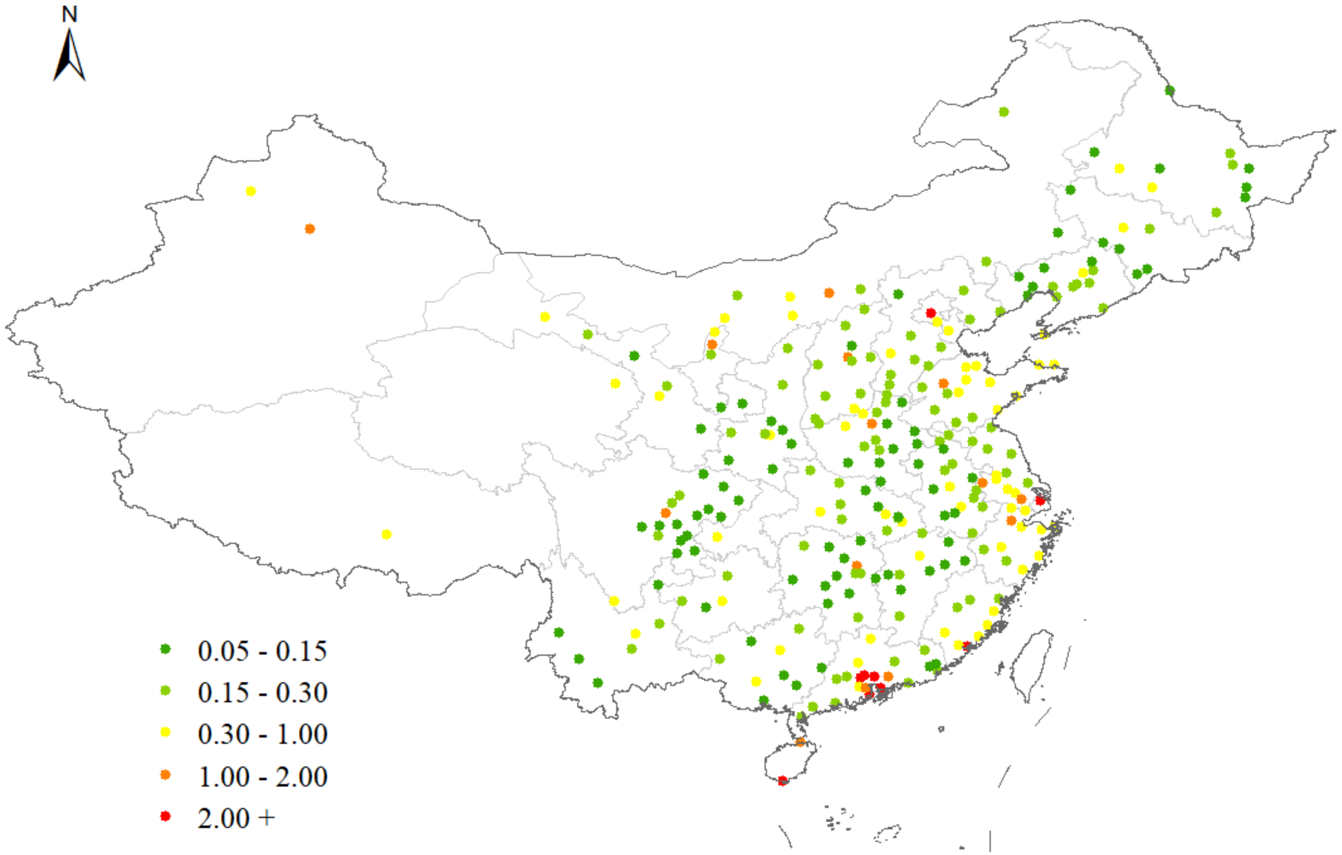
- **Weather**: ERA-Interim products from European Center for Medium-Range Weather Forecasts (ECMWF).
- It provides daily weather information from 1979 to present at 79km-grid resolution.

- **Climate Projections**: NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), 21 GCM models at a spatial resolution of 0.25 degrees.

- **Socioeconomic Projections**: Shared Socioeconomic Pathways (SSPs).

Data

Card Coverage: No. of Active Cards per Capita 2015



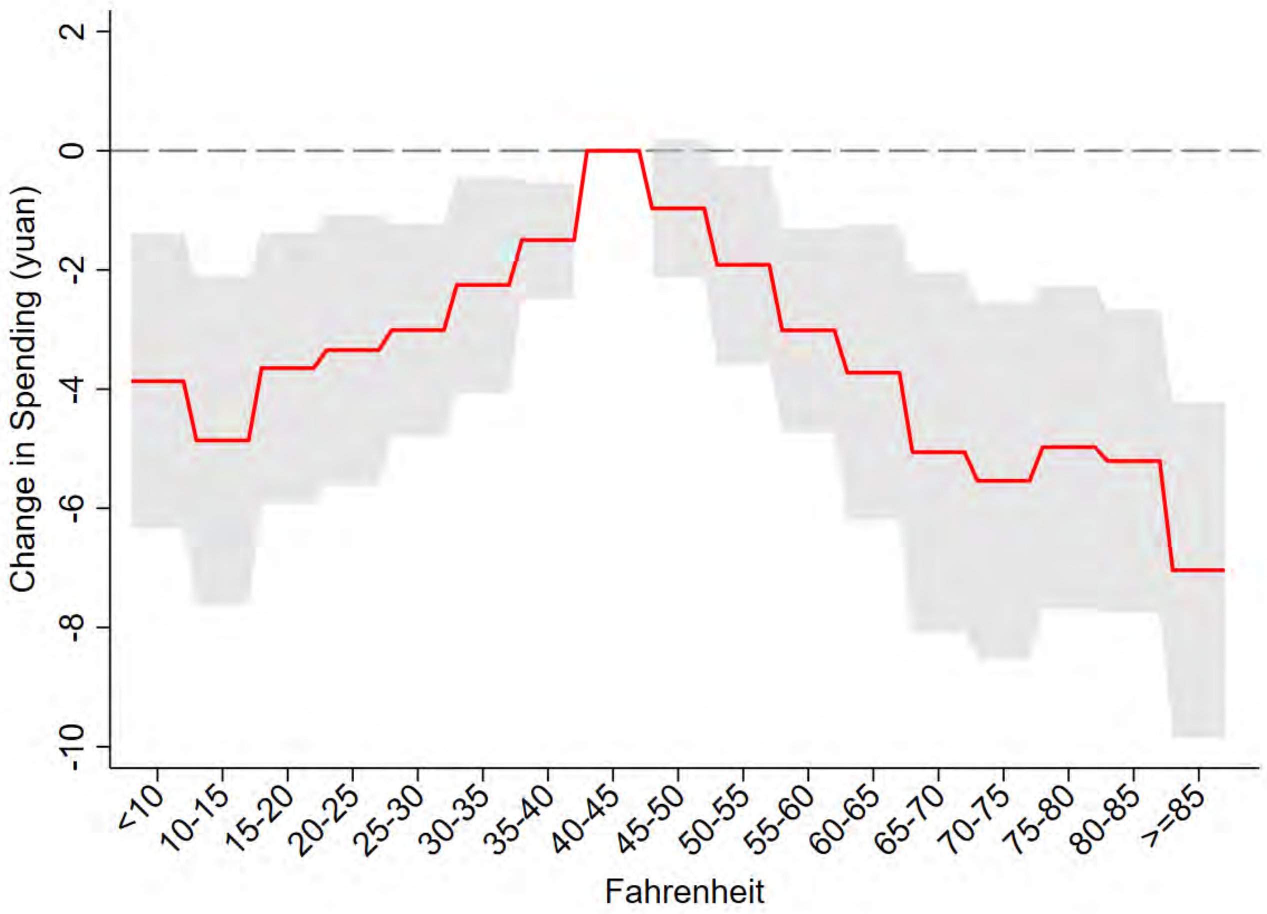
Baseline Model

$$y_{c,t} = \sum_{j=0}^{J} \beta_j TP^{j}_{c,t} + x_{c,t}\rho + \eta_t + \kappa_{c,s} + \varepsilon_{c,t} \qquad (1)$$

- *y* is the value of transactions per card in city *c* at time (day) *t*.
- *TP* is separate indicators for each 5 F bin for average temperature from last 10 days (*t* to *t-9*). The reference categories are the bins that minimize/maximize the response function.
- Control for air pollution and other weather conditions, as well as city FE, date FE, city-by-year-quarter FE, city-by-holiday FE.
- Standard errors are cluster at the city level.

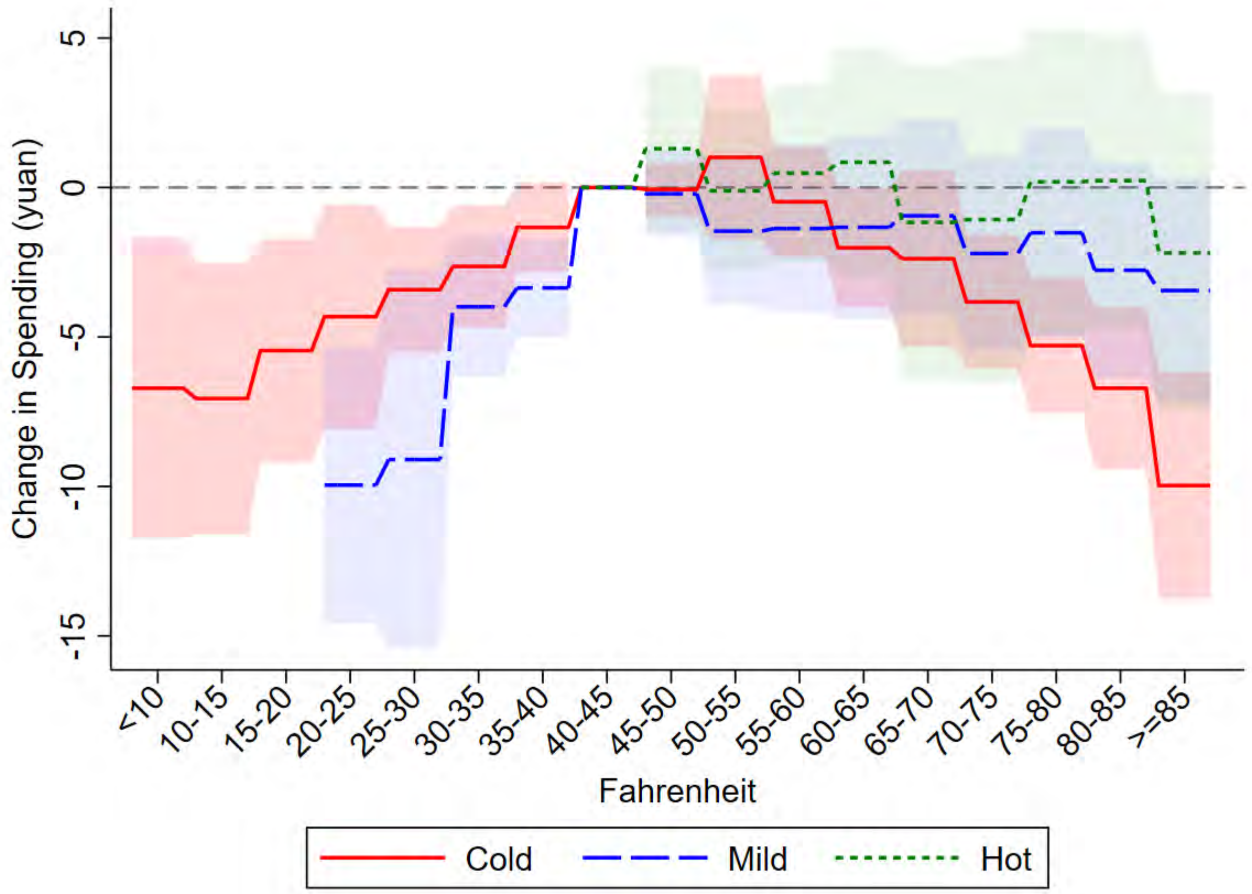
Temperature Impact

Consumption Responses to Temperature Shocks



Temperature Impact

Consumption Responses by Hot, Mild, and Cold Regions



Long-run Projections with Adaptation

Model

$$y_{c,t} = f(TP_{c,t}, CM_c, GDP_c; \theta) + x_{c,t}\rho + \eta_t + \kappa_{c,s} + \epsilon_{c,t}, \text{where} \qquad (2)$$

$$\begin{aligned} f(TP_{c,t}, CM_c, GDP_c; \theta) = & \alpha_0 TP_{c,t} + \alpha_1 TP_{c,t} \cdot \mathbb{1}(TP_{c,t} \in [40, 60)) + \alpha_2 TP_{c,t} \cdot \mathbb{1}(TP_{c,t} \geqslant 60) \\ & + [\beta_0 TP_{c,t} + \beta_1 TP_{c,t} \cdot \mathbb{1}(TP_{c,t} \in [40, 60)) + \beta_2 TP_{c,t} \cdot \mathbb{1}(TP_{c,t} \geqslant 60)] \cdot CM_c \\ & + [\gamma_0 TP_{c,t} + \gamma_1 TP_{c,t} \cdot \mathbb{1}(TP_{c,t} \in [40, 60)) + \gamma_2 TP_{c,t} \cdot \mathbb{1}(TP_{c,t} \geqslant 60)] \cdot GDP_c. \end{aligned}$$

CM_c: 30-year average temperature from 1981 to 2010;

GDP_c: GDP per capita in 2010;

Carleton et al. (2020): Climate captures the adaptive behaviour through various channels and income reflects the budget constraint governing adaptation.

Long-run Projections with Adaptation

- ***Intuitively,***

Beijing's climate $\Longrightarrow$ Shanghai's climate

Beijing's CT relationship $\Longrightarrow$ Shanghai's CT relationship.

- ***No Adaptation,***

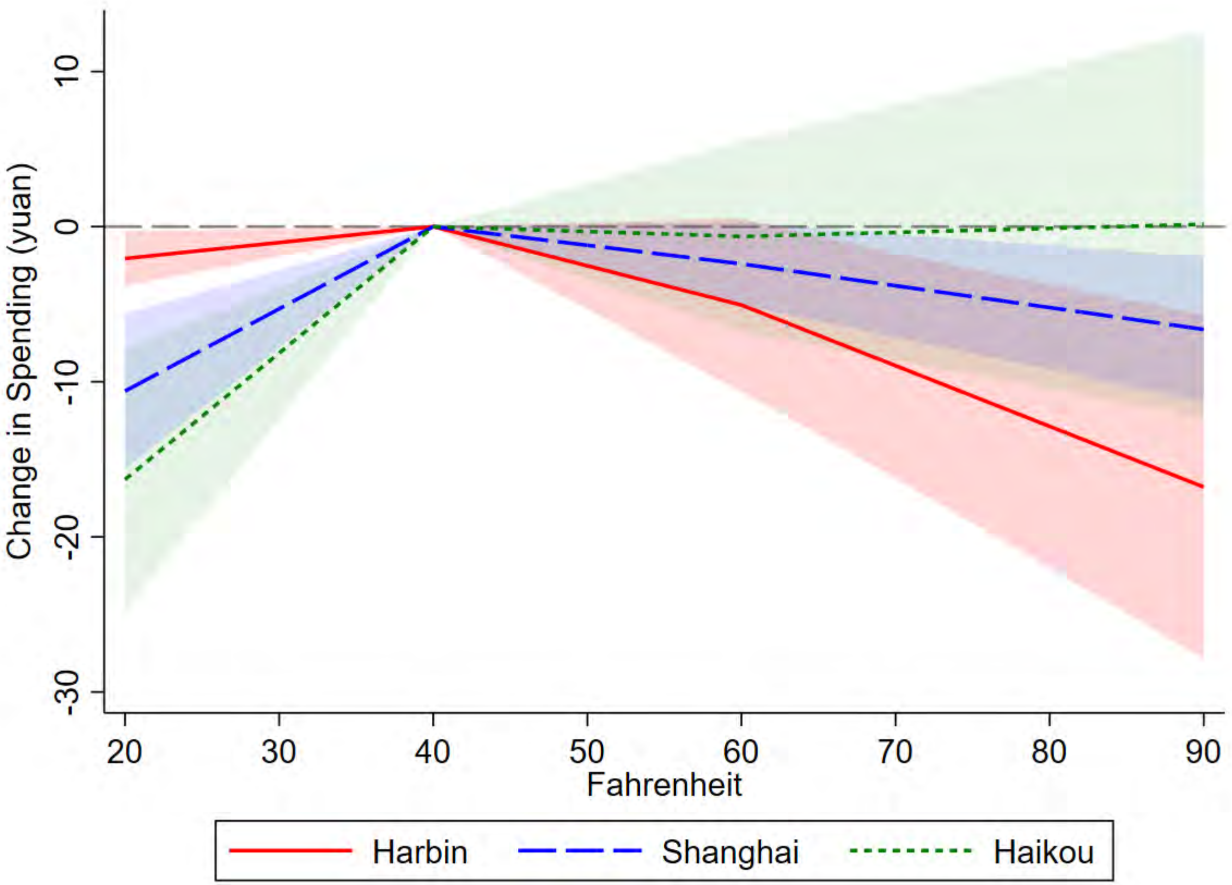
$$\Delta\hat{y}_{c,\tau}^{NoAdapt} = f(TP_{c,\tau}, CM_{c,2018}, GDP_{c,\tau}; \hat{\theta}) - f(TP_{c,2018}, CM_{c,2018}, GDP_{c,\tau}; \hat{\theta})$$

- ***Adaptation,***

$$\Delta\hat{y}_{c,\tau}^{Adapt} = f(TP_{c,\tau}, CM_{c,\tau}, GDP_{c,\tau}; \hat{\theta}) - f(TP_{c,2018}, CM_{c,2018}, GDP_{c,\tau}; \hat{\theta})$$

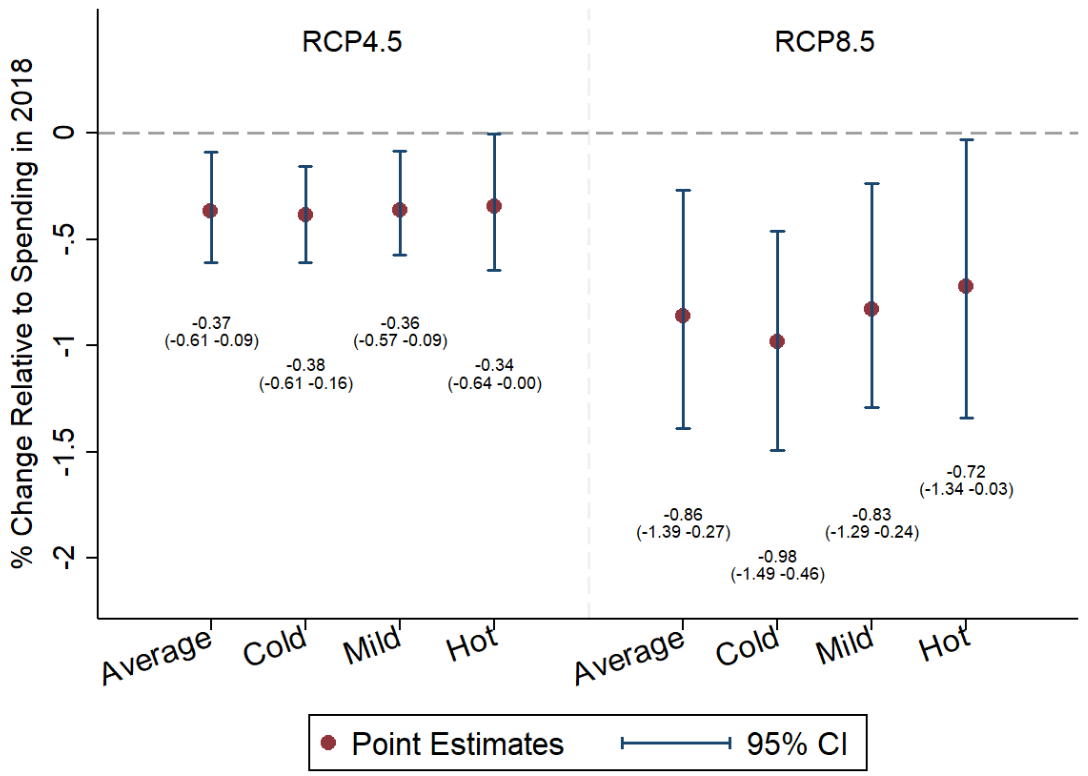
Long-run Projections with Adaptation

Current Consumption-temperature Relationship by City

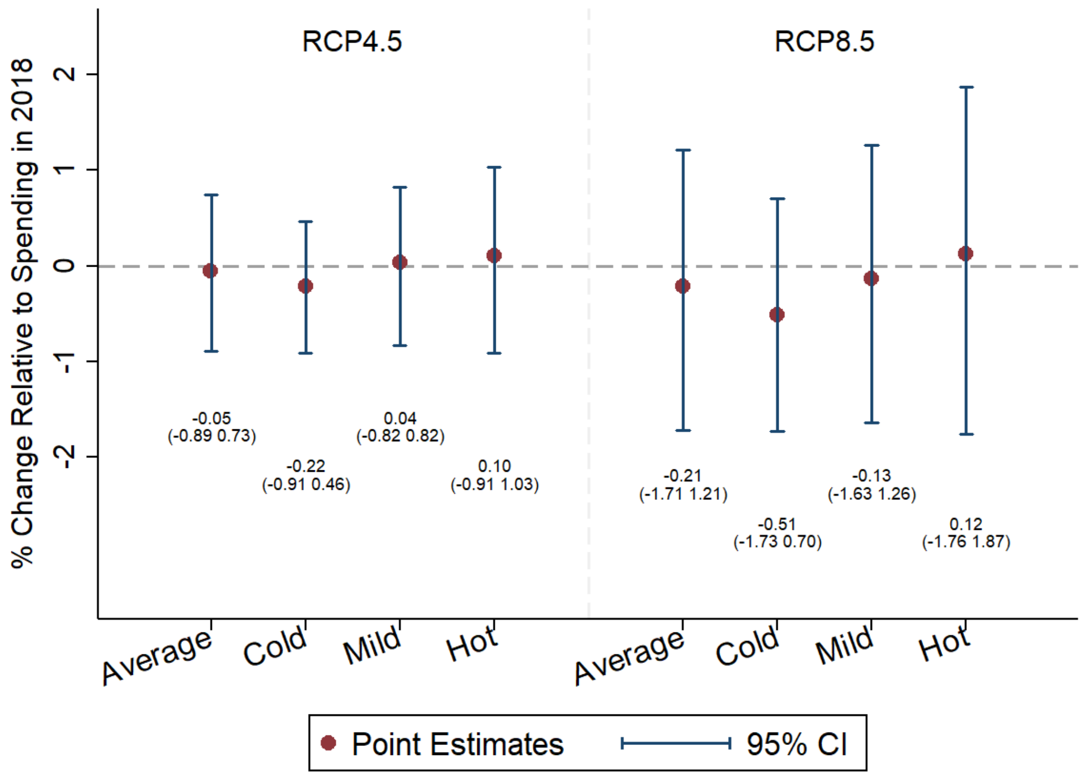


End-of-Century Projections (2080-2099)

No Adaptation

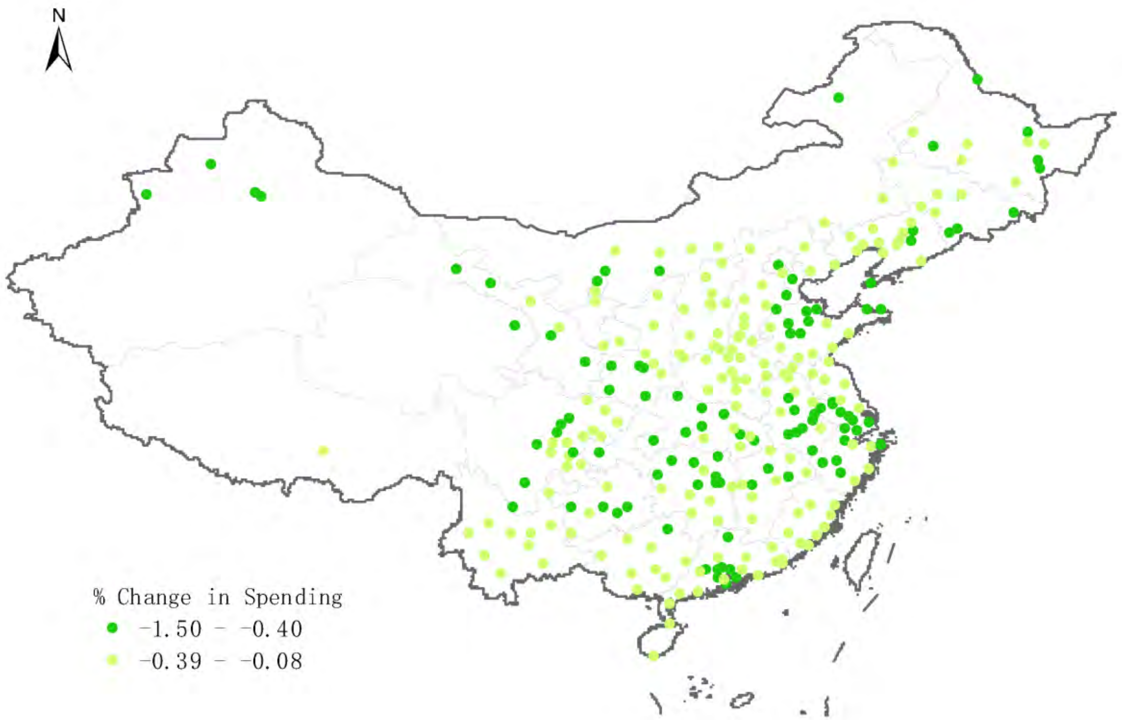


Adaptation

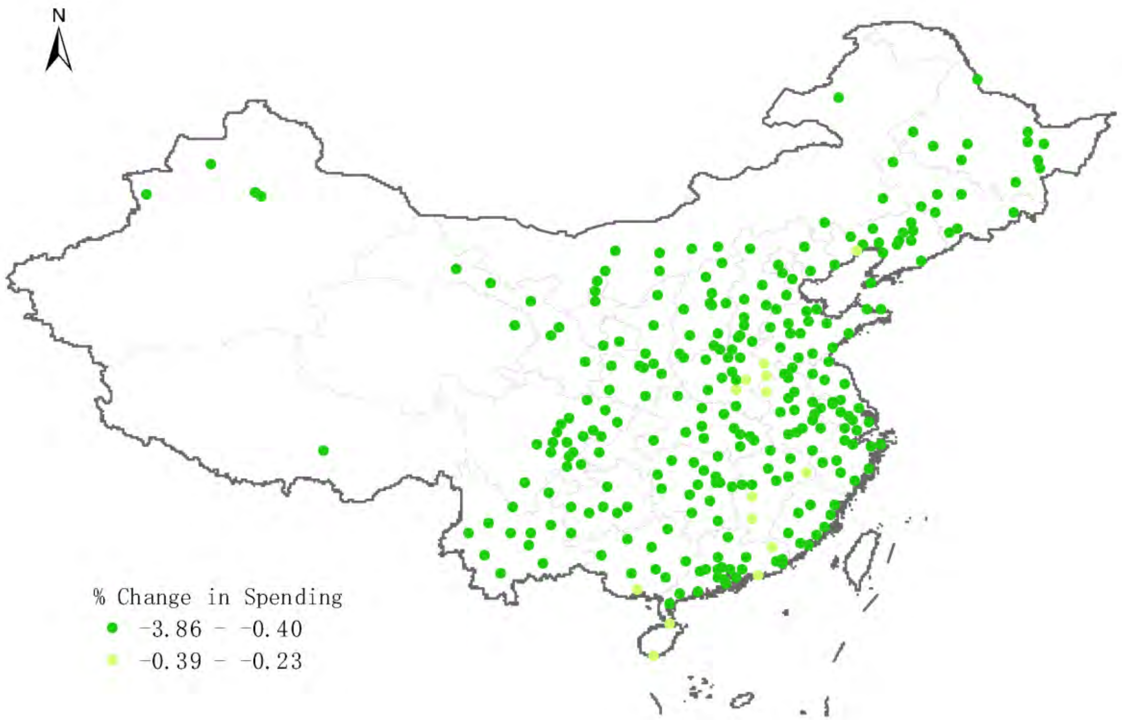


End-of-Century Projections, No Adaptation

RCP 4.5

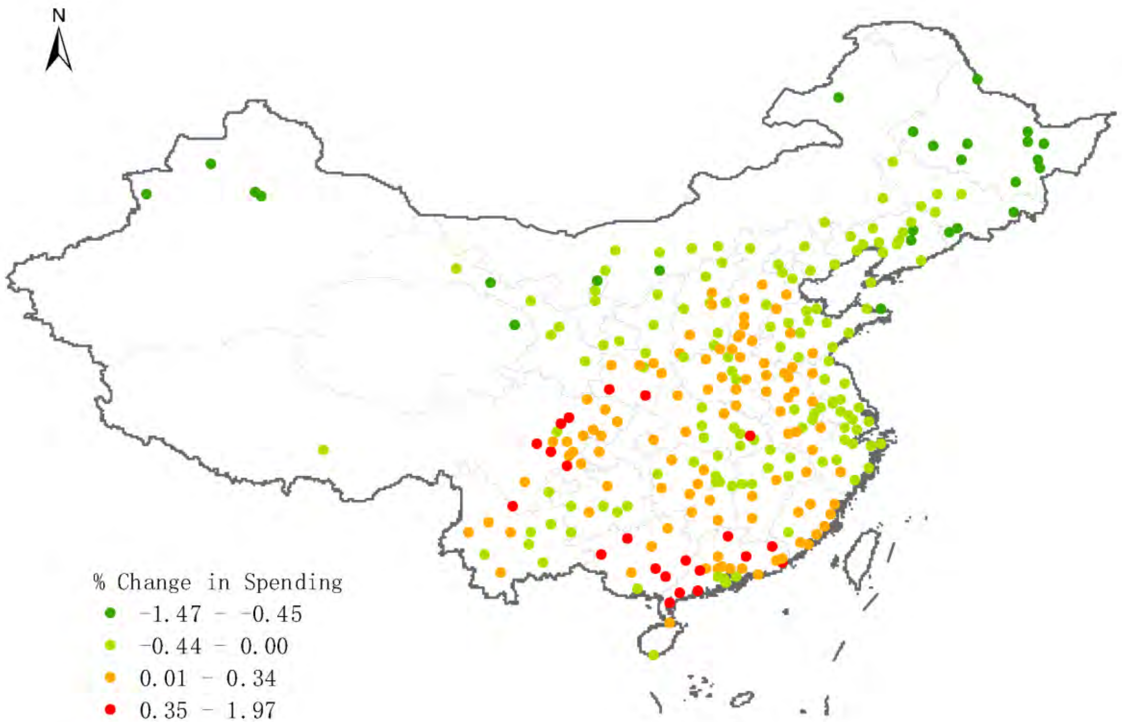


RCP 8.5

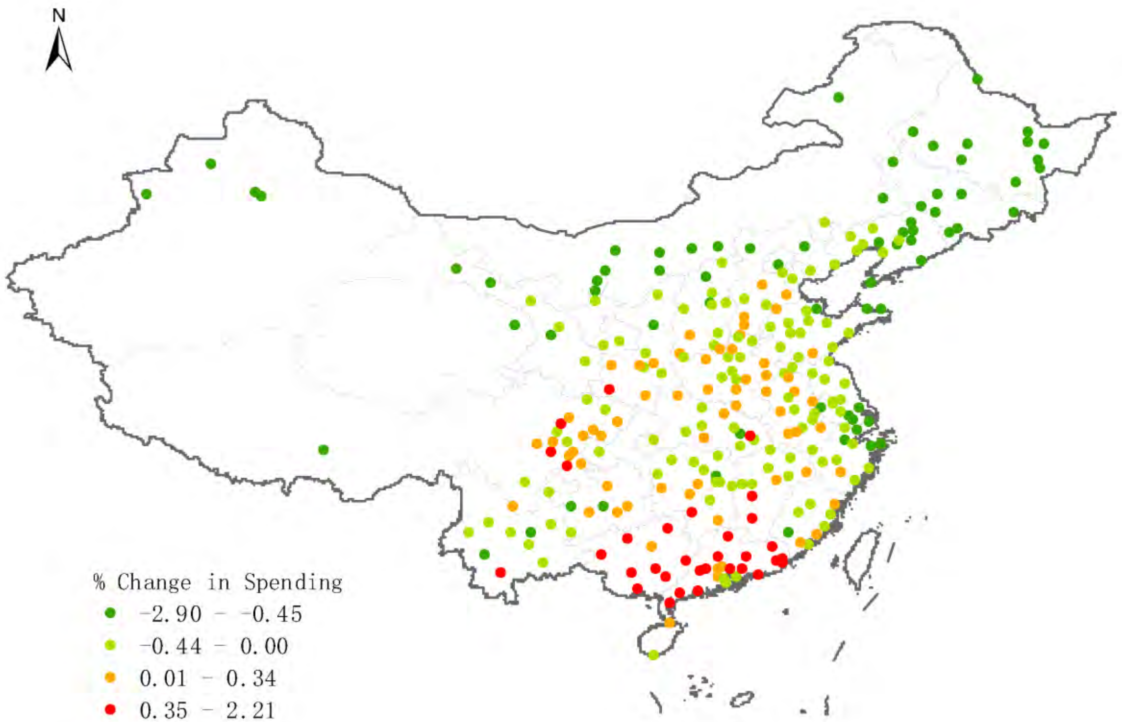


End-of-Century Projections, Adaptation

RCP 4.5



RCP 8.5



Conclusions

Temperature Impacts:

- Excess heat and cold have a direct and immediate negative effect on household consumption.

Adaptation Impacts:

- Excess heat has the largest effect in cold regions but the smallest in hot regions. The opposite is true for excess cold.

Future Impacts (2080-2099):

- Without adaptation, the end-of-century (2080-2099) consumption would observe a statistically and economically significant decrease under both RCP4.5 and RCP8.5 scenario on an annual basis.
- With adaptation, the consumption impact is closer to zero and not statistically significant.

Coming up Tomorrow!

Break-out 5 | 8:30-10am PT

SESSION 5.1

The Cumulative Costs of Climate Change

SESSION 5.2

Heat Vulnerability Affecting Workers, Healthcare, and Neighborhoods

SESSION 5.3

Innovative Toolkits for Urban Heat Adaptation

SESSION 5.4

Housing and Hazards: How Should We Protect Vulnerable Homes?

Break-out 6 | 10:15-11:45am PT

SESSION 5.1

Emerging Research on Financial Adaptations to Climate Impacts

SESSION 5.2

Wading into the Economic Impacts of Climate Change on Water

SESSION 5.3

Equitable Adaptation to Climate-Related Flood Risks: Part 2

CLIMATE ADAPTATION
RESEARCH SYMPOSIUM

MEASURING & REDUCING SOCIETAL IMPACTS

Thanks for tuning in!

UCLA Luskin Center for Innovation