Advancement to Candidacy Exam[1]

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[1] The views expressed in this presentation do not reflect the views of the National Science Foundation.

Outline

C.V.: Publications

- "Food Aid Cargo Preference: Impacts on the Efficiency and Effectiveness of Emergency Food Aid Programs." 2022. *Journal of Law & Economics* 65(2): 395–421. Joint with Vincent Smith (AEI, Montana State) and Stephanie Mercier (Agricultural Perspectives).
- "Moving to Density: Half a Century of Housing Costs and Wage Premia from Queens to King Salmon." 2023. *Journal of Public Economics* 222: 104906. Joint with Daniel Shoag (Case Western) and Stan Veuger (AEI, Harvard).
- "How Did Aid to State and Local Governments Affect Testing and Vaccine Delivery?" 2024. *Journal of Public Economics* 225: 104972. Joint with Jeffrey Clemens (UCSD), John Kearns (Boston Fed), and Stan Veuger (AEI, Harvard).
- "Was Pandemic Fiscal Relief Effective Fiscal Stimulus? Evidence from Aid to State and Local Governments." 2025. *Journal of Macroeconomics* 86: 103720. Joint with Jeffrey Clemens (UCSD) and Stan Veuger (AEI, Harvard).

C.V.: Active Projects

With draft:

- "Regulatory Risk and Firm Decision-Making: Evidence from the Waters of the United States and US Farms." Joint with Vincent Armentano (UCSD).
- "The Price of Growth: Urbanization in Texas After the Civil War." Joint with Bea Lee (Princeton).

Without draft:

- "Intergovernmental Grants to School Districts and Educational Outcomes During the COVID-19 Pandemic." Joint with Jeff Clemens (UCSD) and Stan Veuger (AEI, Harvard).
  - Two related papers also in the works.
  - Presented at the NBER and SREE this fall.
- "How Effective is Emergency In-Kind Food Aid? Evidence from USAID." Joint with Vincent Smith (AEI, Montana State) and Tonga Ahakovi (Stanford).
- "What is the Value of Federal Lands?" Joint with Jeff Clemens (UCSD), Fabian Eckert (UCSD), and Heidi Williams (Dartmouth, CBO).
- "How Can Access to Labor Impact Prices? Evidence from H2-A Farm Workers and the Adverse Effective Wage Rate." Joint with Ken Lee (UCSD).

C.V.: Teaching, Fellowships, and Grants

Fellowships:

- National Science Foundation Graduate Research Fellowship
  - Tenure used: AY 2023, AY 2024
  - Tenure planned: AY 2027
- National Bureau of Economic Research Graduate Fellowship for Fiscal and Economic Effect of Innovation and Productivity Policies
  - Support for AY 2026

Teaching:

- TA for ECON 250A in Fall 2024 and Fall 2025 for Gordon Dahl, Julian Betts, David Arnold, Eli Berman, and Clemence Idoux
- Visiting Lecturer at SDSU School of Public Health for Health Economics in Winter of 2025, co-teaching with Wilton Choi
- TA for ECON 140 in Spring 2025 (Jeff Clemens) and ECON 5 in Winter 2025 (Yinlin Dai)

Grants:

- Arnold Ventures Building Evidence Grant ($144,000)

Living with Density: The Impacts of By-Right Permitting Reform for ADUs in California

Joint with Gabriel Cañedo Riedel

Motivation: Housing Costs

Figure: Wages Less Housing Costs by Skill Group and CZ Density

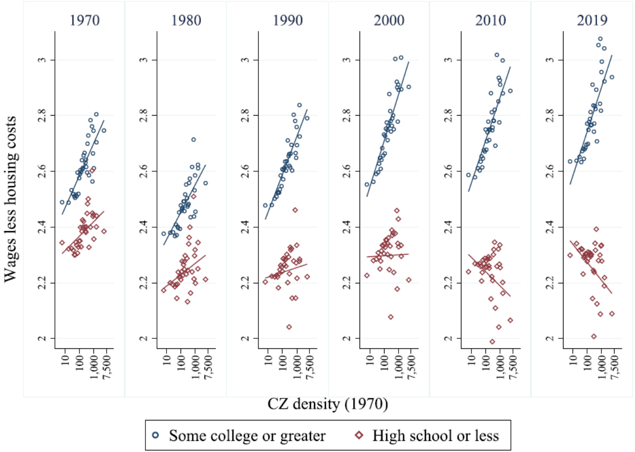


Figure from Hoxie, Shoag and Veuger (2023).

Motivation: Policy

- Several states have passed or considered bills to address housing costs by increasing supply
- Reforms to Accessory Dwelling Unit (ADU) permitting have been a popular tool, with several states passing and considering bills (Kahn and Furth, 2023; Schuetz, 2025):
  - Passed (14): (before 2020) CA, (after 2020) AR, AZ, CO, HI, ID, MD, ME, MT, NH, RI, UT, VT, WA
  - Considered (7): MA, MN, NC, NM, NY, TX, VA

Research Questions

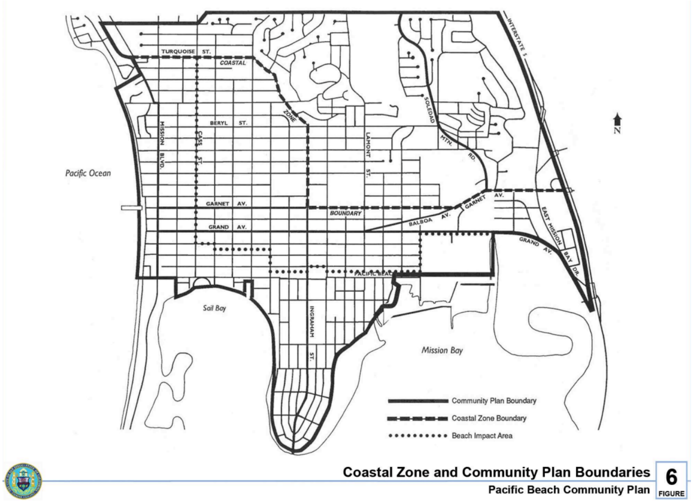
- What impact did 2016-2019 permitting reforms in California have on ADU permitting activity, land values, and home values?

CA ADU Reforms

- In 2016, CA undertook a multi-year project to reform zoning, with a focus on ADUs and smaller units (Gray, 2024)
- CA reforms were aimed to make ADU permits "by-right" and has passed several subsequent bills clarifying their initial reforms (California YIMBY, 2022*a*,*b*,*c*)
- The bulk of the reforms occurred between 2016 and 2019
- All residential lots were made eligible to have ADUs that met state-specified criteria of up to 1,200 square feet.
- These reforms will not go into effect within the coastal zone, which will maintain its restrictive zoning regime (California Coastal Commission, 2022*a*; Severen and Plantinga, 2018; Kahn, Vaughn and Zasloff, 2010; California Coastal Commission, 2022*b*)

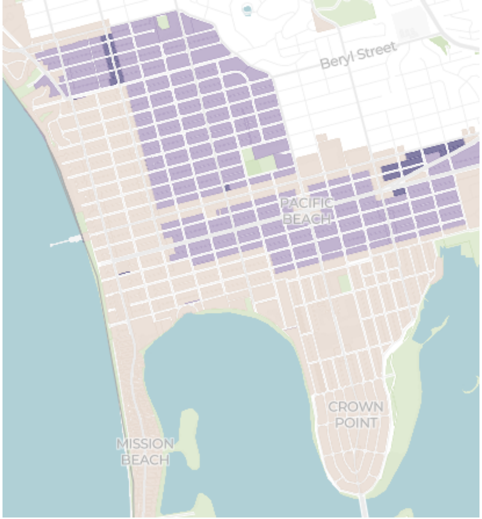
The California Coastal Zone

Figure: Map of Pacific Beach and the Coastal Zone



The California Coastal Zone

Figure: Map of Pacific Beach Where ADUs are Likely Prohibited (Land Use Atlas Inc., 2025)



Regulation of ADUs in CA

	Pre-2016	Post-2016
In CZ	Coastal Permit	Coastal Permit
Out CZ	City Permit	By-Right Permit

AV Pre-Analysis Plan

- As part of the grant from the Laura and John Arnold Foundation, we need to file a pre-analysis plan
- Now available on OSF

Methods: Conceptual Framework

$$\Delta Total = \Delta Land + \underbrace{\Delta Structure}_{\text{ADU + Non-ADU}} + \Delta Spillovers \tag{1}$$

- *Total* is the total sales price, which is observed directly
- *Land* is the value of the land
  - Area amenities / disamenities
  - Local regulations on use; option value
  - Local services (e.g. school quality)
- *Structure* is the value derived from what is built on the land
  - Characteristics of the house
  - ADU and non-ADU components, which may interact
- *Spillovers* captures how choices of nearby owners impacts the sale price
  - Quality of adjacent buildings
  - Availability of public spaces (such as street parking)

Methods: Conceptual Framework

$$\Delta Total = \Delta Land + \underbrace{\Delta Structure}_{\text{ADU + Non-ADU}} + \Delta Spillovers \tag{2}$$

- The change in land value comes from the option to redevelop
- The highest economic use of the land has increased with ADU reform in 2019
  - A SFR lot can increase from one unit to the original unit plus an ADU and JADU (1 unit $\rightarrow$ 3 units)
  - A duplex zoned lot can add an ADU and JADU (2 units $\rightarrow$ 4 units)
  - This applies to *all* residential lot types
- The option is valuable because the returns to building an ADU are uncertain and the landowner may wish to wait and see how demand conditions for ADUs develop over time
  - McMillen and O'Sullivan (2013) provide a simple framework that can be adapted to show this

Methods: Building Permits

$$\Delta Total = \Delta Land + \underbrace{\Delta Structure}_{\text{ADU + Non-ADU}} + \Delta Spillovers \tag{3}$$

Methods: Building Permits

$$
\begin{aligned}
Y_{its} = & \alpha + \beta_1(OutCZ_i \cdot Post_t) + \beta_2(f(DistCZ_i) \cdot Post_t) + X_{it}^{'}\gamma \\
& + \lambda_i + \tau_t + \varepsilon_{its}
\end{aligned} \tag{4}
$$

- Y_{its} is an indicator for whether or not a given lot i built an ADU in year t (direct permitting activity)
- i indexes lots, t indexes years, and s denotes border segments (zip codes)
- $OutCZ_i$ takes a value of 1 if a lot is outside the Coastal Zone
- $Post_t$ takes a value of 1 after 2016
- $f(DistCZ_i)$ is a distance function from the boundary
- $X_{it}^{'}$ are lot-level controls
- We include lot and time fixed effects
- We can swap in segment s by time t fixed effects
- We estimate these equations within a band from the coastal zone boundary

Methods: Land Values

$$\Delta Total = \Delta Land + \underbrace{\Delta Structure}_{\text{ADU + Non-ADU}} + \Delta Spillovers \tag{5}$$

Methods: Land Values

$$
\begin{aligned}
Y_{its} =& \alpha + \beta_1(OutCZ_i \cdot Post_t) + \beta_2(f(DistCZ_i) \cdot Post_t) + X_{it}^{'}\gamma \\
& + X_{is}^{'}\theta + \tau_t + \varepsilon_{its}
\end{aligned} \tag{6}
$$

- Y_{its} is the log of land value per acre of a transaction of lot i in year t
  - Land values are the transaction value multiplied by the land share in the next available assessment
- Transactions do not occur every year, so the lot fixed effect is dropped
- X_{is} are lot and / or segment controls
- Can swap in segment by time fixed effects
- This method is the same as Severen and Plantinga (2018)

Methods: Spillovers

$$\Delta Total = \Delta Land + \underbrace{\Delta Structure}_{\text{ADU + Non-ADU}} + \Delta Spillovers \tag{7}$$

Methods: Spillovers

$$
\begin{aligned}
Y_{its} = & \alpha + \sum_b \beta_b (I\{Bin = b\}_i \cdot Post_t) + X_{it}'\gamma \\
& + \phi_b + \tau_t + \sigma_s + \varepsilon_{its}
\end{aligned} \tag{8}
$$

- Y_{its} is the log of total sale value per acre of a transaction of lot i in year t
- Here, bins segment the distance from the CZ boundary for both plots inside and outside the CZ
- The omitted group should be inside the coastal zone and away from the border.
- Y_{its} is sale prices for plot i in year t
- Impacts just inside the coastal zone should indicate the presence of positive or negative spillovers
- This design is similar to those in Severen and Plantinga (2018) and Hornbeck and Kenniston (2017)

Measuring Land Values

$$LandValue_{it} = \underbrace{SalePrice_{it}}_{Transactions} \cdot \underbrace{\frac{AssessLand_{it+1}}{AssessTotal_{it+1}}}_{Assessment} \tag{9}$$

- Assessments only adjust after a sale in CA, but they provide a split of land and building values
- t is any period of sale, and $t+1$ denotes the very next available observation at any interval

Measuring Land Values

Alternatives to using assessments

- Using vacant lot sales and tear-downs
  1. For vacant lot and tear-down sales, estimate land values using a selection correction
  2. Use nearby vacant and tear-down estimates to interpolate the land values for a given lot based on observables (e.g. using Kriging)
- Use hedonics to difference out the structure value

Data Sources

Corelogic Historic Property Records

- County assessor records for *all* tax parcels
- Parcel ID and date geo-coded
- Semi-regular panel
- assessed values, building and lot characteristics, etc.

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Corelogic Transaction Records

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Coastal Zone Boundary File

- Polygon of the coastal zone

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Coastal Zone Boundary File

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Web-scraped Permit Data (not in this presentation)

- Building permits to attach to property records by APN and address
- Coverage varies by county

Data: What is Residential?

In Corelogic, two codes could identify a residential parcel:

- Land use code
  - Any residential use: (e.g. single family, duplex, apartment, mobile home lot, etc.)
- Property use code
  - 4 residential codes:
    - Single family
    - Condominium
    - Duplex
    - Apartment
- The law change applies to *all* residential land, so we will include all properties on residential land that don't have a designated commercial use
  - Just including vacant residential lots and lots in residential use

Data: Sample

To be included in the sample for value regressions, a parcel must have:

- 15 coastal counties of California
- Residential lots only
- A usable transaction date between 2010 – 2024
- Parcel or block latitude and longitude coordinates
- A land value ratio that is internally consistent (between 0 and 1)
- A lot acreage that is greater than 0
- A transaction to a non-family member and assessment afterwards
  - Assessments in California only truly update after a transaction
  - Assessments not around transactions are capped in many ways
- We will need to trim out outliers as many houses in the 15 coastal counties of CA are extreme outliers (e.g. Alicia Keys in La Jolla, Bill Gates in Del Mar, etc.)

Data: Comparison to ACS 5-Year

Corelogic

- County assessor filings for property taxes
- Transaction records from county clerks
- Admin data, with errors

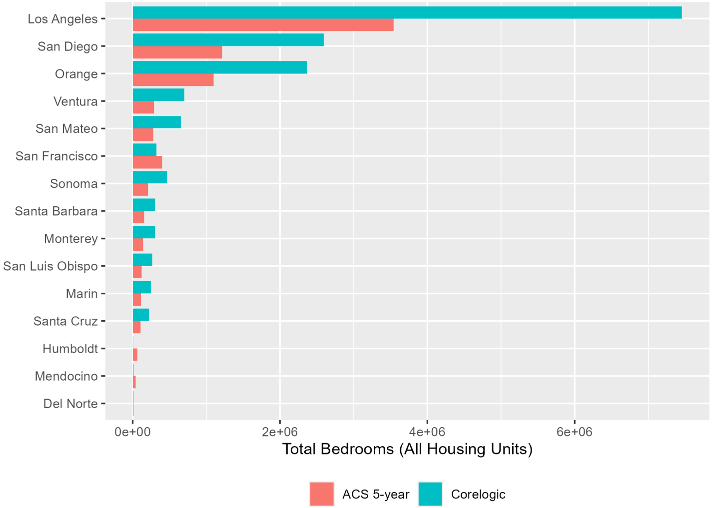
ACS 5-year
(2015-2019)

- A survey of respondents
- 5% sample
- Imperfect recall / misreporting

We will compare: the total number of housing units, build year distribution moments, and owner-occupied value moments by county (15 coastal)

Data: Comparison to ACS 5-Year

Figure: Total Bedrooms By County (2015-2019)

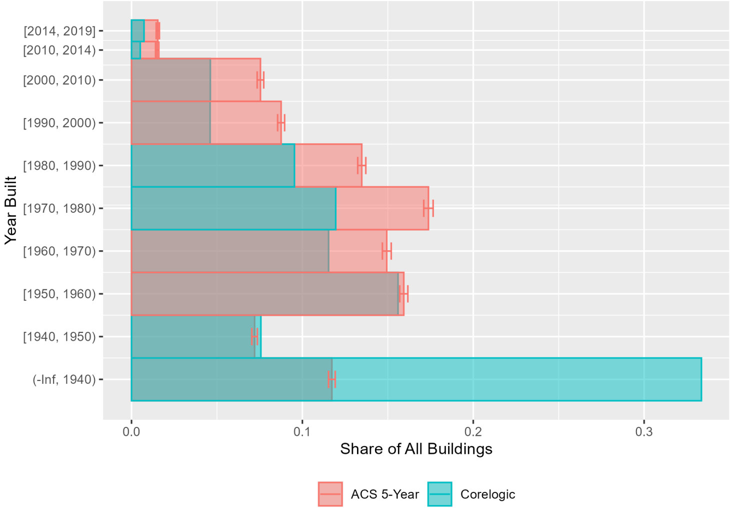


Data: Comparison to ACS 5-Year

- Known issue of duplicate parcels in Corelogic data (Diamond, Guren and Tan, 2020)
- Errors in Corelogic property attributes
  - Trimming data seems to be the most common practice
  - E.g. for units, single family residential lots sometimes have implausible number of units on them ($>$ 10 in some cases)
    - In communication with Corelogic

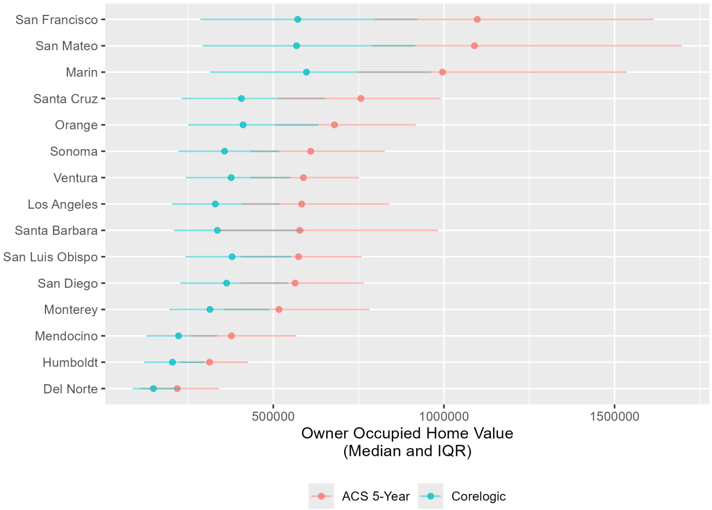
Data: Comparison to ACS 5-Year

Figure: Build Year (2015-2019)

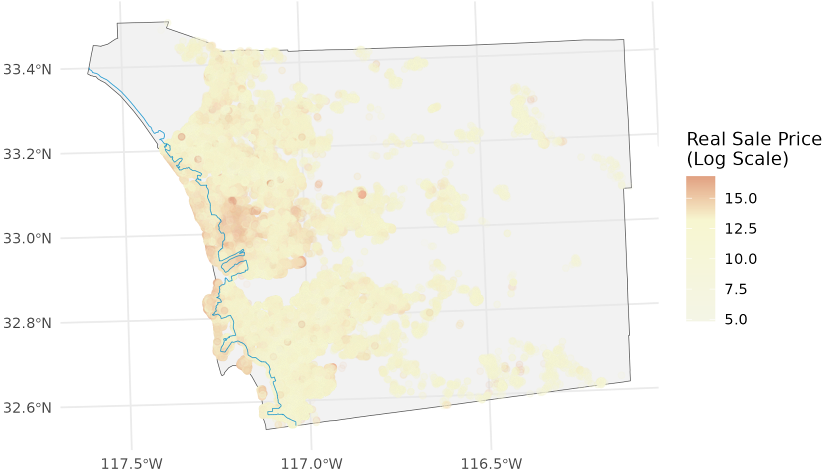


Data: Comparison to ACS 5-Year

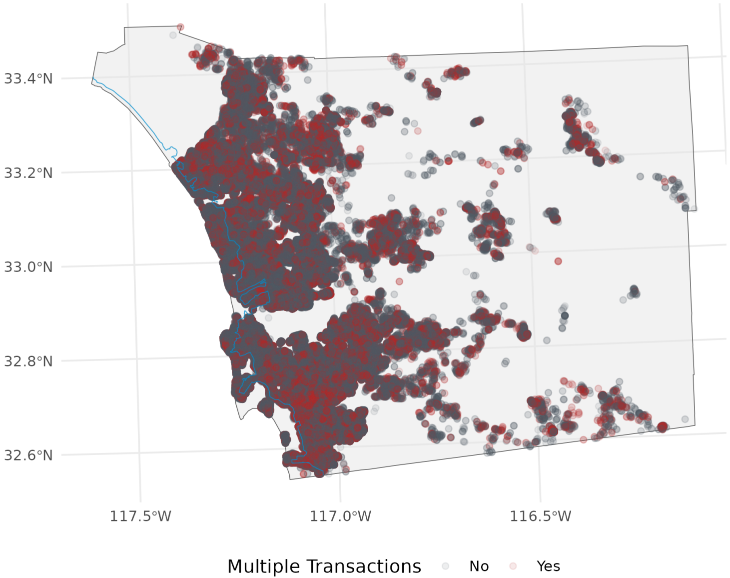
Figure: Owner Occupied Home Value (2015-2019)



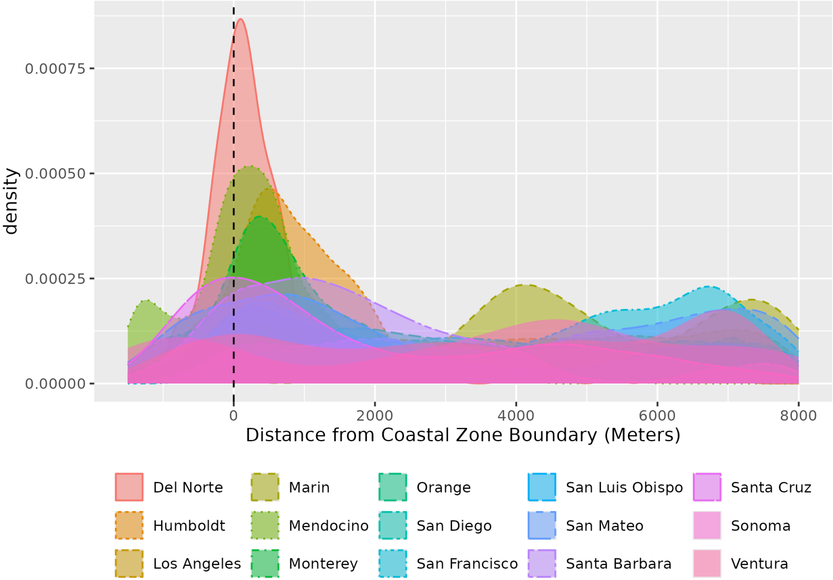
Total Sale Prices in San Diego (2010-2016)



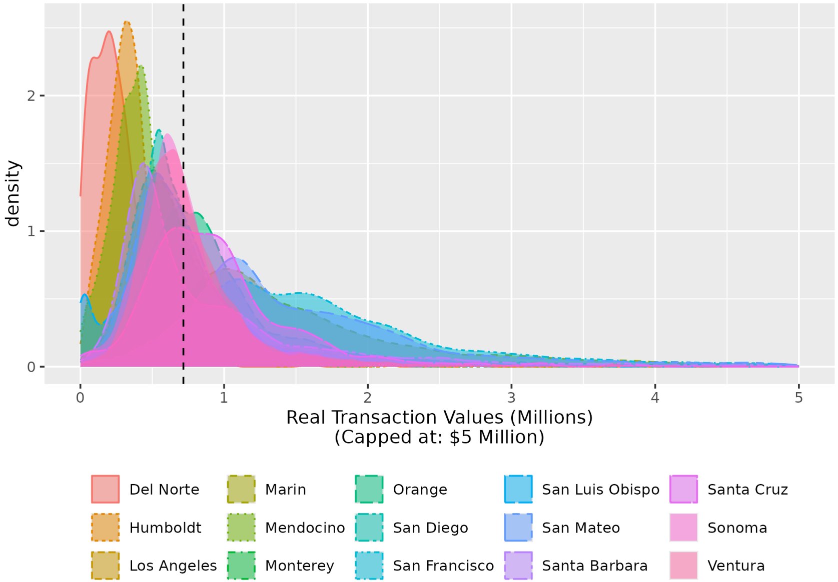
Multiple Transaction Parcels in San Diego (2010-2016)



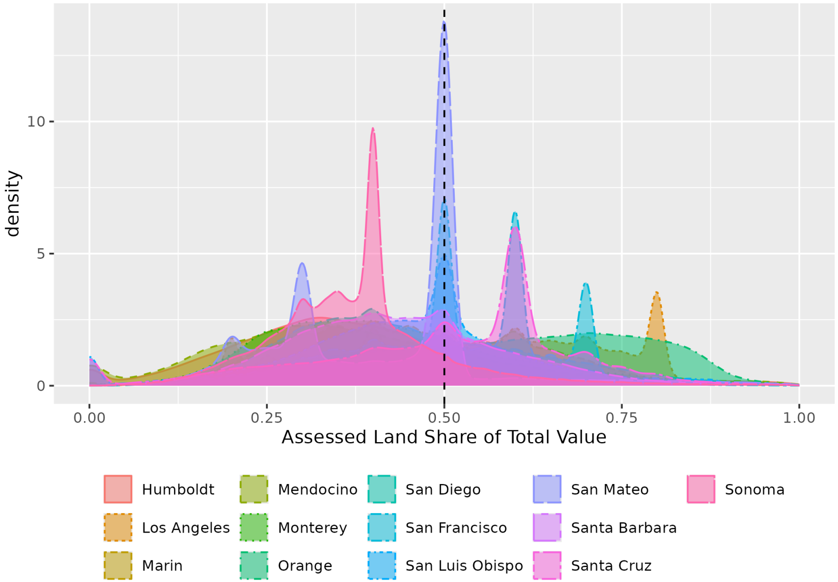
Distance to Coastal Zone Boundary by County



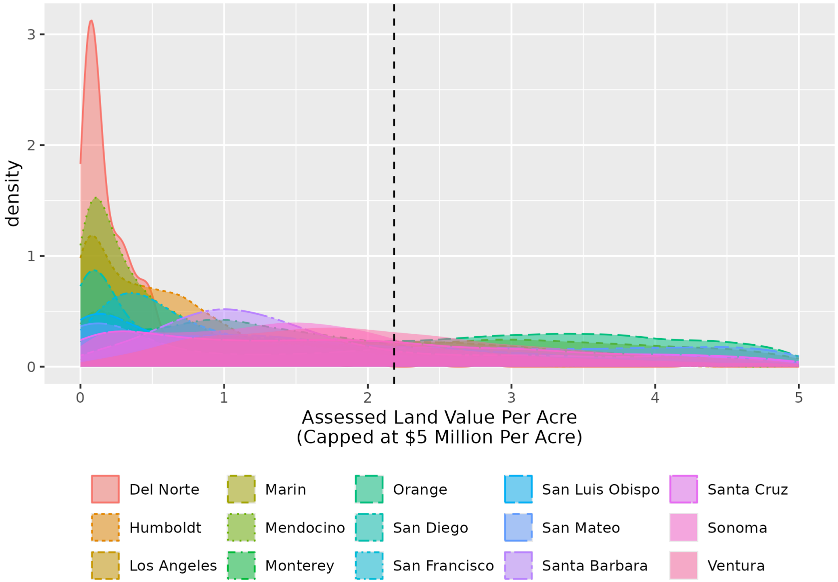
Transaction Values by County in 2016



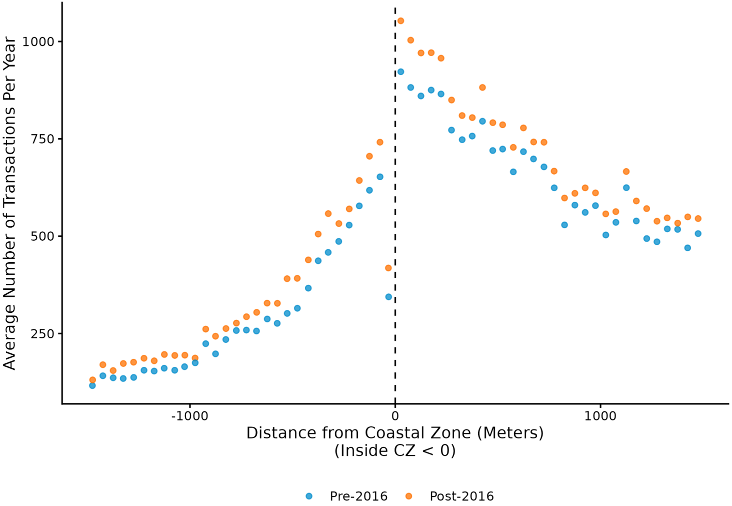
Assessed Land Value Share of Total Value by County in 2016



Land Value Per Acre by County in 2016



Transaction Count Per Year By Coastal Zone Distance Bin and Pre-Post ADU Reform



Land Value Regression

	Dep. Var: Log of Real Land Value Per Acre			
	(1)	(2)	(3)	(4)
$OutCZ_i \cdot Post_t$	0.338	0.385	0.141	0.103
	(0.020)	(0.029)	(0.021)	(0.029)
First Degree Polynomial	Y		Y	
Second Degree Polynomial		Y		Y
County Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y		
Zip by Year Fixed Effect			Y	Y
Adj. R^2	0.32	0.32	0.43	0.43
Obs	1,007,779	1,007,779	321,937	321,937
F-stat	298.8	177.5	46.7	12.2
Dep. Var. Mean Pre-2016	14.33	14.33	14.33	14.33
Dep. Var. Mean Pre-2016 in CZ	14.60	14.60	14.60	14.60
Band (Meters)	1,000	1,000	1,000	1,000

Concerns

- Bunching in the land share of total value densities
  - Should we use a hedonic model to estimate and remove the non-land share of value instead? (Rosen, 1974)
- Are there ways to limit comparisons along the coastal zone to only the "best" sections of clean overlap (e.g. Imperial Beach)
  - Identify segments with similar slopes on either side of the boundary
  - Limit comparisons to within zip codes
- Models (2) and (3) use transactions and therefore cannot have lot fixed effects
  - Should we use a re-sale model instead?

Selection into Sale

- Selling a home is *not* random
- Some descriptive papers do adjust for selection explicitly (McMillen and Singh, 2022)
- Causal papers view transaction volume as an outcome (Linden and Rockoff, 2008)
- I view transactions as potentially impacted by ADU reforms directly
  - ADUs may allow families to remain in their homes, decreasing transactions by reducing mismatch
  - ADUs may provide development opportunities that may be better exercised by a new-owner, increasing transaction volumes

Measuring ADUs

- I am including *permit* data, but this doesn't measure building
- ADUs can be built illegally (Jo et al., 2025)
- I can try and measure ADUs as changes in units and square footage in the Corelogic data
- Jo et al. (2025) provides a remote-sensing dataset of ADUs from 2016 to 2020 for San Jose and a method for expanding to other areas

Next Steps

- Match the ACS
- Data to add in
  - Permit data by APN
  - CZ segments for segment by time fixed effects
  - Property, neighborhood, city controls
- Data concerns to address
  - Hedonically estimate land values
  - Trimming the sample properly of outliers
    - Use pre-trends as a guide
- Anything else?

How Effective is In-Kind Food Aid? Evidence from USAID

Joint with Tonga Ahokovi and Vincent Smith

Food Aid

Photo from USAID Annual Report.

Background

- Since 1954 the US has made regular appropriations for in-kind emergency food aid shipments (Barrett and Maxwell, 2007; Hoxie, Mercier and Smith, 2022)
- In 2023, the US shipped just over 1 million metric tonnes of food at a total spend of $1.8 billion USD (Smith, 2025)
- In the 2^{nd} Trump administration, the value of providing in-kind food aid has been questioned by policymakers and USAID has been effectively shut down
- Future administrations will need to decide if in-kind food aid is a valuable use of government funds

Background

USAID's expenditures ($40B) largely cover 3 categories:

- Development aid
  - For example, agricultural extension programs
- Public health
  - For example, HIV vaccination campaigns
- Humanitarian aid
  - Disaster relief, including in-kind food aid
    - Title II in-kind food aid (about $2 billion)
    - Humanitarian aid has been estimated to save about 500,000 lives per year at a cost of $18,000 per life saved by Kenny and Sandefur (2025)
    - USAID estimates the cost of delivering one meal at about $38 (2012 USD) (Hoxie, Mercier and Smith, 2022)

Research Question

- How effective is USAID's in-kind food aid at achieving its policy goals?
- Specifically, does a country receiving more aid:
    1. have fewer excess deaths or better nutrition related outcomes? (Health)
    2. have a weaker market for agricultural producers and less agricultural trade? (Economic)
    3. have a more positive relationship with the United States? (Soft Power)

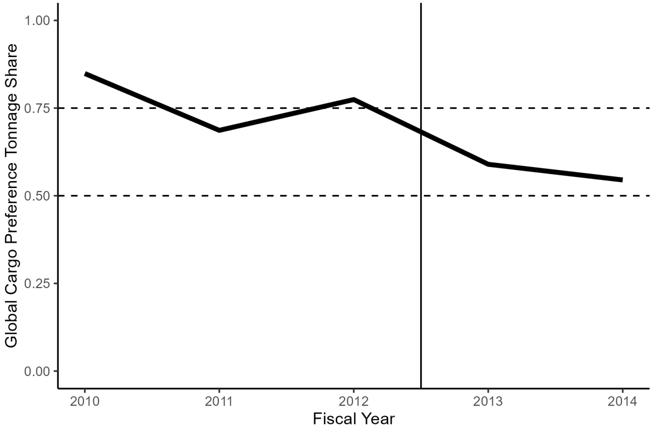
How USAID Delivers Food Aid (Lentz, Barrett and Mercier, 2017)

1. USAID decides to address a disaster
2. Food is purchased from US farms
3. The shipment is placed on a ship
   - Half of all tonnage must go on US ships (Hoxie, Mercier and Smith, 2022)
4. The shipment is loaded onto a truck and delivered

In 2012, the Moving Ahead for Progress in the 21^{st} Century Act (MAP-21) decreased cargo preference requirements from 75% down to 50% (current law) (Hoxie, Mercier and Smith, 2022)

USAID Cargo Preference

Figure: Reported Global USAID Cargo Preference Share by Fiscal Year



Data from MARAD FOIA.

In-Kind Aid: Pros and Cons

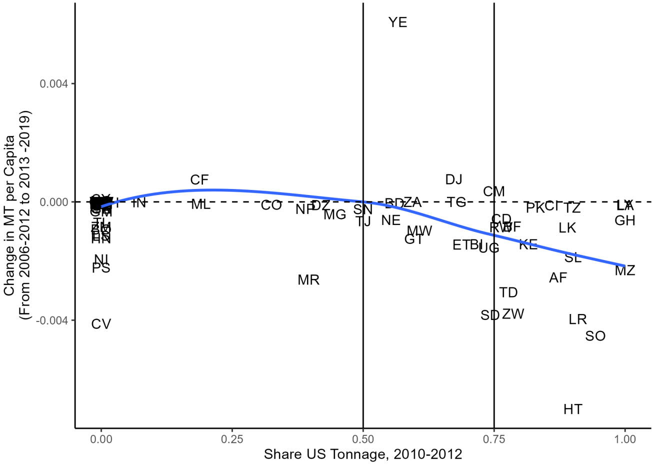
Benefits	Criticisms
Nutrition	Creates conflict
(Kenny and Sandefur, 2025)	(Nunn and Qian, 2014)
Spending on US agriculture	Swamps local markets
(Barrett and Maxwell, 2007)	(Cunha, De Giorgi and Jayachandran, 2019)
Spending on US shipping	Not cost effective / inefficient
(Barrett and Maxwell, 2007)	(Hoxie, Mercier and Smith, 2022)
Increases US soft power	
(Blair, Marty and Roessler, 2022)	

Methods

- Use the decrease in cargo preference requirement 2012 (effective FY 2013) to capture changes in aid to recipient countries
- Cargo preference increases ocean transportation costs on any given shipment from between 60% to 100%, and US ships are very limited (Hoxie, Mercier and Smith, 2022)
  - With a fixed budget, a decrease in spending on shipping likely leads to an increase in spending on aid
- Based on their proximity to US shipping routes, countries can be differentially effected by the decrease in cargo preference requirements

Change in MT of Aid

Figure: Change in Aid Delivered Before and After MAP-21 Reform



Data from MARAD FOIA and USAID reports.

Methods

$$
\begin{aligned}
Y_{it} =& \alpha + \beta(Aid_{it} - E_{2012}(Aid_{it})) + X_{it}'\gamma + \kappa_i + \tau_t + \varepsilon_{it} \\
(Aid_{it} - E_{2012}(Aid_{it})) =& \eta + \delta USFlag_{i,2012} + X_{it}'\theta + \psi_i + \zeta_t + v_{it}
\end{aligned}
\tag{10}
$$

- i indexes countries, t indexes years
- Aid_{it} are observed aid flows from USAID
- $E_{2012}(Aid_{it})$ is the Aid that would have been delivered based on USAID's pre-2012 delivery patterns
- $USFlag_{i,2012}$ is the US flag shipment share from 2010 to 2012

Methods

$$Aid_{it} = f_t(W_{it}, D_{it}, O_i) \tag{11}$$

- $f_t(\cdot)$ is an unknown function USAID uses to distribute food aid
- W_{it} are weather indicators
- D_{it} are disaster indicators
- O_i are other country observables
- We can estimate $f_{t \leq 2012}(\cdot)$ using machine learning in the years before the MAP-21 reform

Methods

$$E_{2012}(Aid_{it}) = \hat{f}_{t \leq 2012}(W_{it}, D_{it}, O_i), \forall t > 2012 \tag{12}$$

- The primary input that changes USAID's delivery function after 2012 is the relaxed cargo preference constraint enacted in MAP-21
- Weather, disaster, and country (fixed) variables are assumed to be exogenous (W_{it}, D_{it}, O_i)

Data

- Sample: 87 countries that have ever received USAID
- Digitized food aid reports from USAID
- FOIA'd cargo preference shares from MARAD
- Agricultural trade variables from FAO
- GDP and Pop from the World Bank
- Emergency data from EMDAT
- Weather variables from OECD
- Disaster declarations from the UN
- Health outcomes from Our World In Data
- Soft power outcomes from PEW, UN

Data: Digitized USAID Tables

Figure: USAID Annual Reports Data

Appendix 4: USAID Title II Emergency Activities: Summary Budget, Commodity, Recipient and Tonnage—Fiscal Year 2009

COUNTRY	AWARDEE	COMMODITY	RECIPIENTS (000s)	METRIC TONS	TOTAL COST (000s)
Africa					
Burundi	WFP	Cornmeal, Corn Soy Blend, Vegetable Oil, Yellow Peas	2	3,720	$4,101.7
Cameroon	WFP	Cornmeal, Vegetable Oil, Yellow Peas	170	4,690	$4,868.5
Central African Republic	WFP	Cornmeal, Corn Soy Blend, Kidney Beans, Rice, Vegetable Oil	367	3,430	$5,431.4
Chad	WFP	Cornmeal, Corn Soy Blend, Sorghum, Vegetable Oil, Yellow Peas, Yellow Split Peas	1,746	100,950	$138,482.2
Côte d'Ivoire	WFP	Cornmeal, Corn Soy Blend, Pinto Beans, Vegetable Oil	2	4,980	$6,608.1
Democratic Republic of the Congo	WFP	Cornmeal, Corn Soy Blend, Pinto Beans, Vegetable Oil, Yellow Split Peas	328	72,080	$111,654.1
	CARE	Vegetable Oil, Wheat, Yellow Split Peas, Lentils	202	19,180	$13,188.5
	CRS	Corn Soy Blend, Peas, Sorghum, Vegetable Oil, Wheat	26	168,790	$92,987.3

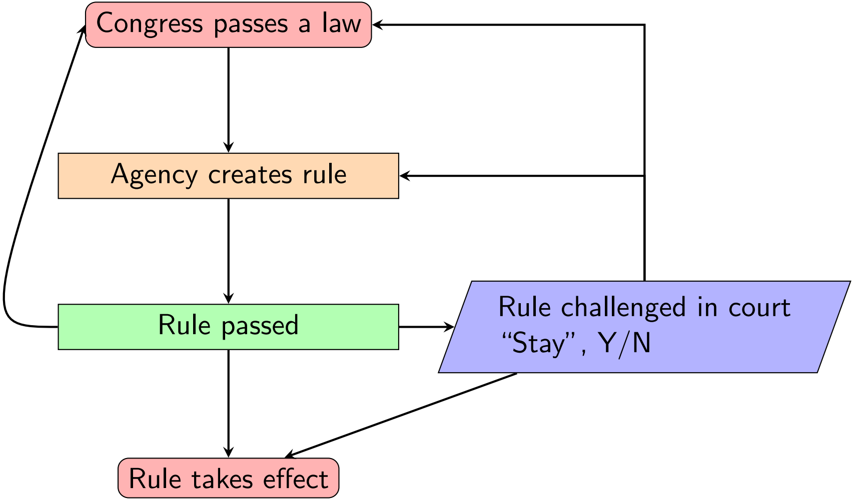
Next Steps

- Build an ML models for $f_{t \leq 2012}(\cdot)$
  - Two *excellent* undergrads are helping to clean the weather and disaster data (Minghao "Ryan" Zhao and Stephanie Hunt)
- Make sure the first stage and pre-trends look acceptable
- could do this in changes instead of with FEs

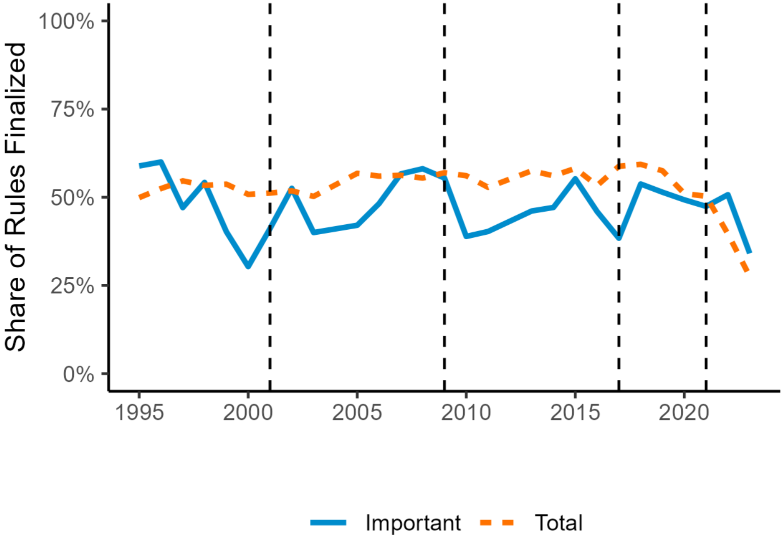
Regulatory Risk and Firm Decision-Making: Evidence from the Waters of the United States and US Farms

Joint with Vincent Armentano

Motivation: Rules, Congress, and the Courts



Motivation: Fraction of Rules Finalized



Motivation and Research Question

- Federal rule-making dictates how businesses interact with laws passed by Congress
- Congress occasionally writes vague laws that can be re-interpreted as presidential administrations turn-over

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- Federal rule-making dictates how businesses interact with laws passed by Congress
- Congress occasionally writes vague laws that can be re-interpreted as presidential administrations turn-over

- Use the Waters of the United States definition changes (geographical) to understand how regulatory risk from the rule-making process impacts firms (farms) investment choices
- Voluntary land conservation programs allow us to see how farmers' reservation price for farming changes with regulatory risk

Risk vs. Uncertainty

- Many different ways to conceptualize uncertainty, risk, ambiguity aversion, etc (Bloom, Bond and Van Reenen, 2007; Knight, 1921; Shoag and Veuger, 2016)

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- We view the changing probability of regulation as impacting firms' expectations over their future productivities
- This likely changes the first and second moments, which is unlike the pure-uncertainty literature (Bloom, Bond and Van Reenen, 2007)
- We view these changes as *regulatory risk*, which should generate wait-and-see behavior similar to a news shock as in Jaimovich and Rebelo (2009)

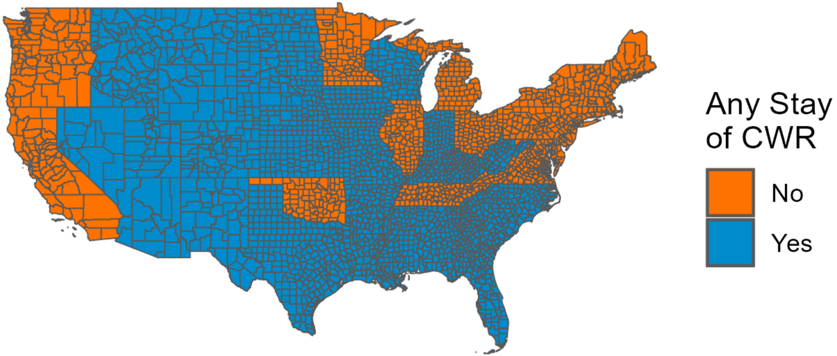
Background: Clean Water Act

- Regulates activities that may impact the environmental health of navigable waterways used in interstate commerce (WOTUS)
- Penalties for non-compliance with a strict permitting regime
- Ongoing farming that does not use fill material or dredging is exempt
- Commerce clause jurisprudence limits the EPA's ability to regulate the entire watershed
- Where does the EPA's authority to enforce the CWA start and stop?

Background: Timeline

	Rule in Effect		
Time	No-Stay	Stay	Action
Pre-2014	1988 (Rap.)	1988 (Rap.)	CWR Proposed in 2014
2014-2018	1988 (Rap.)	1988 (Rap.)	CWR Enjoined
2018-2020	CWR	1988 (Rap.)	SCOTUS Removes Injunction
2020-2022	1988 (Rap.)	1988 (Rap.)	Trump Proposes NWPR, Enjoined
2023-	2023	1988 (Rap.)	SCOTUS Decides *Sackett*

Background: Stays (Mulligan, 2019)



Background: Conservation Reserve Program (CRP) Hellerstein (2017)

- One of several voluntary land conservation programs
- Congress sets an acre target nationally
- USDA ERS sets maximum bids based on fair rental rates for each county
- Farmers make sealed bids with a rental rate and environmental benefit index (EBI) for offered land
- ERS selects a cutoff for cost-adjusted EBI and enrolls all bids above the cutoff
- No more than 25% of county land can be enrolled in CRP

Exposure DiD

$$y_{ct} = \alpha + \sum_{t \neq 2014} \beta_t \left(P_c \cdot T_t \right) + X_{ct} \cdot \gamma + \pi_c + \tau_t + \epsilon_{ct} \tag{13}$$

- Observations c, t is a county from [2009-2023]
- Outcomes include; CRP Acres, Avg CRP Price, N Adjudications
- Takes share sometimes in WOTUS (at-risk) of county cropland P_c, year dummies T_t
- Controls included are lagged CRP eligibility controls
- ID Assumption; percent of at-risk cropland is exogenous to regulatory changes (exogenous shares with common shock)
- County FE π_c & year FE τ_t

Data: Sources

- Predictions of the WOTUS jurisdiction under three rules (1988, CWR, and NWPR) from Greenhill et al. (2024)
- Conservation Reserve Program statistics on acres and rental payments from US Department of Agriculture (2024)
- Raster data on land cover from National Agricultural Statistics Service (2024)
- PCE deflator U.S. Bureau of Economic Analysis (2024)

Data: Defining Treatment Groups

Greenhill et al. (2024) use the following to predict regulatory topographies for $\sim 4,000,000$ points in the continental US

- Trained on Approved Jurisdictional Determinations from the USACE
- Predictors include:
  - Wetlands
  - Hydrology data
  - Elevation
  - Ecoregions
  - USACE Boundaries
  - State
  - Land cover classifications
  - Soil characteristics
  - Precipitation and other weather variables

Data: Defining Treatment Groups

- From the Greenhill et al. (2024) prediction points we've set up three groups.
  - Never treated (75%): no rule includes this land (e.g. the middle of the desert)
  - Always treated (8%): every WOTUS definition includes this land (e.g. farmland on the banks of the Potomac)
  - Sometimes treated (17%; 6% one rule, 11% two rules): some rules include this land, others don't
- WOTUS rules should roughly nest, with all rules classifying non-urban land next to rivers as regulated, and the middle of the desert as un-regulated
- We place the entirety of cropland ($30m^2$ grid cells), into one of the above categories to match the USDA Crop Data Layers

Data: Data Processing Greenhill et al. (2024)

Figure: 1988 (Rapanos) Regulatory Estimates from Greenhill et al. (2024)

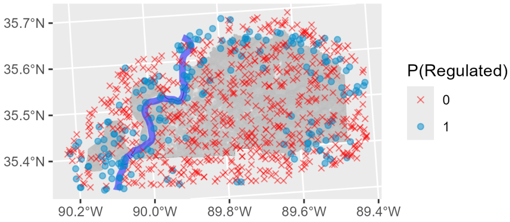
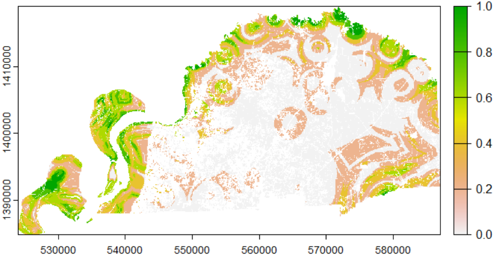


Figure: Resulting 1988 (Rapanos) Regulatory Topography from KNN



Data: Data Processing Greenhill et al. (2024)

Figure: Greenhill et al. (2024) Land Exposed to Changes in Jurisdiction (1988 and NWPR)

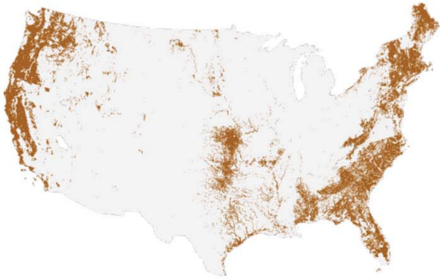
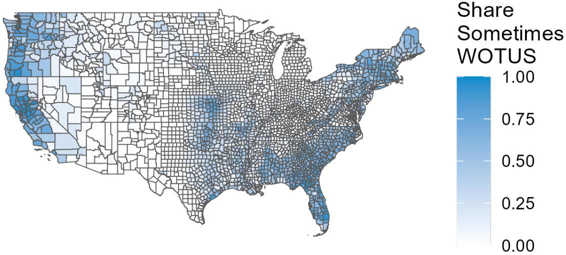


Figure: Our Measure of Cropland Share Sometimes WOTUS



Data: Data Processing Greenhill et al. (2024)

Figure: Sometimes Regulated Shares of Cropland in No-Stay States

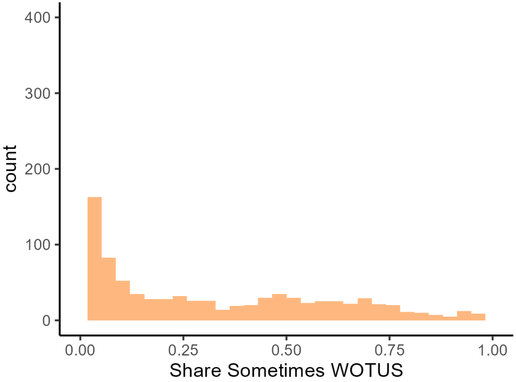
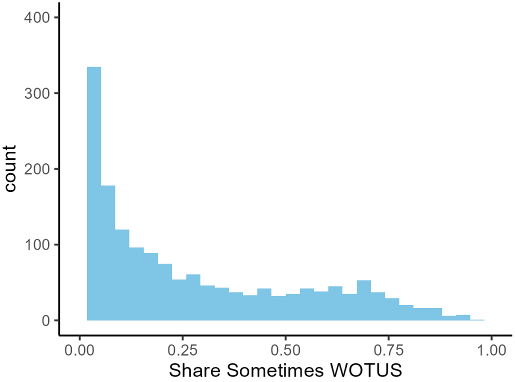


Figure: Sometimes Regulated Shares of Cropland in States with a Stay



Data: Other RHS Variables

- Controls for the CRP enrollment caps
  - Lagged eligible acres: $Cropland_{t-1} * 0.25 - CRPAcres_{t-1}$
  - Lagged dummy for over-enrollment in CRP
  - Lags to control for CRP contract expiration 10-15 years prior
  - Wetland-share bins by time FEs

Data: Outcomes

- Conservation reserve program average rents per acre enrolled
  - From county aggregate files, contains all contracts
    - General CRP (Auction)
    - Continuous CRP (Take-it-or-leave-it contract)
  - Acres of planted cropland

Results: CRP Rent Per Acre (2022 USD)

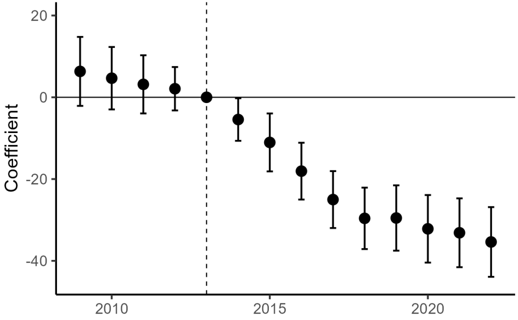


Figure: No-Stay States (Regulation)

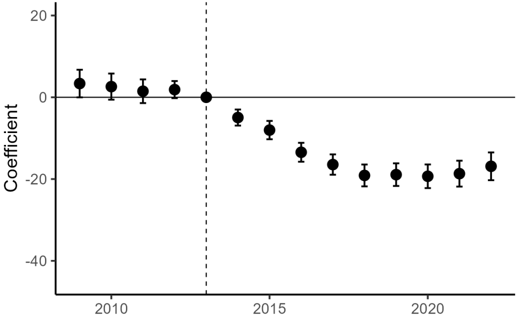


Figure: Stay States (risk)

No-Stay State Pre Mean: $66

Stay State Pre Mean: $50

Results: Cropland Acres

Figure: No-Stay States (Regulated)

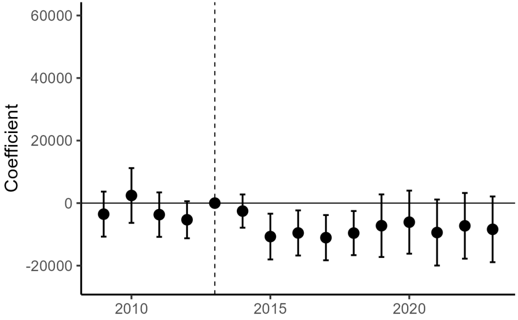
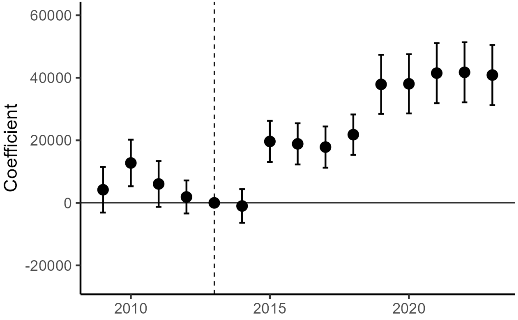


Figure: Stay States (risk)



No-Stay State Pre Mean: 171,595 acres

Stay State Pre Mean: 265,171 acres

Results: Total Costs

$$TotCost = N_n \cdot \underbrace{\overline{Cropland}_n \cdot \overline{ExpWOTUS}_n}_{\text{Avg. Exposed Acres to Regulation}} \cdot \beta_n + N_s \cdot \underbrace{\overline{Cropland}_s \cdot \overline{ExpWOTUS}_s}_{\text{Avg. Exposed Acres to Risk}} \cdot \beta_s \quad (14)$$

- N_g is the number of counties in state group g, no-stay and stay states
- $\overline{Cropland}_g$ is the average cropland across counties in group g
- $\overline{ExpWOTUS}_g$ is the average share of acres per county in group that is sometimes included in a WOTUS definition
- β_g is the coefficient from each regression for group g of the impact of exposure on CRP rents per acre
- National total cost estimate of $2.9 billion (2022 USD) annually

Referee Comments: AERI

- CRP includes both general (auction) and continuous (take-it-or-leave-it) contracts, how should we think of this?
  - General sign-ups only in 2010, 2015, 2016, 2019, 2021, 2023
- Cropland can be measured with a county-level survey from the FSA
- Asked for DDD
- Why not compare newly-exposed / at-risk areas after Rapanos instead of sometimes WOTUS?

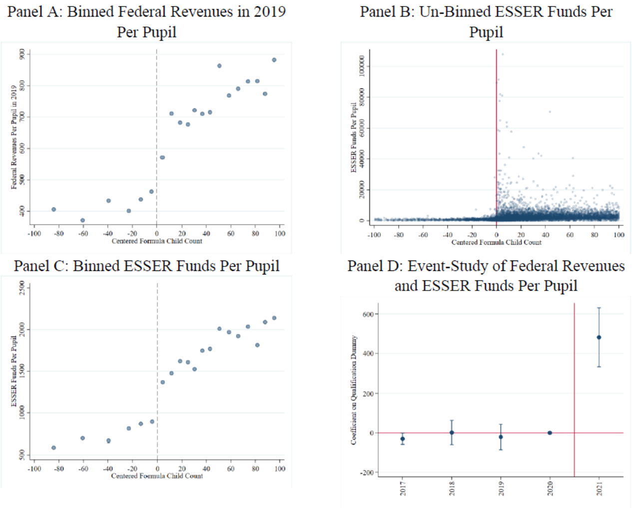
Other Projects

ESSER

- Joint with Stan Veuger and Jeff Clemens
- A group of projects that look at the impacts of intergovernmental grants to school districts during COVID on performance outcomes
- Three designs that exploit the Title 1-A formula used to deliver the funds
  - Qualification diff-in-discs (shown here)
  - Concentration grant hold harmless expiration
  - State matching

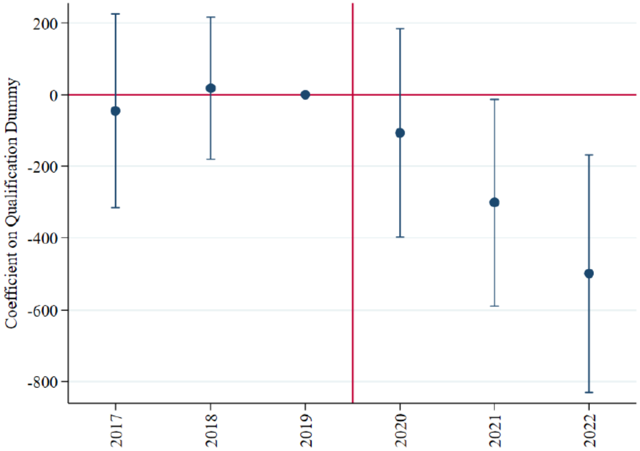
ESSER

Figure: First Stage Relationship Between Qualification and ESSER Funds Per Pupil



ESSER

Figure: Event Study of the Impact of Qualifying for Additional ESSER Funds on Local Revenues

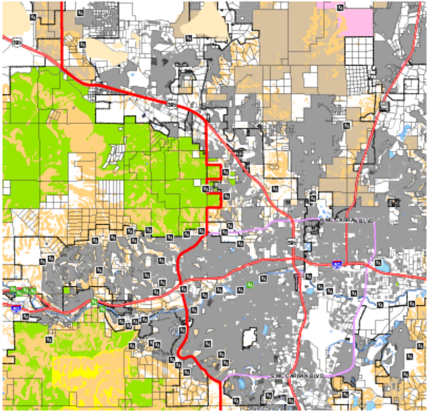


Federal Lands

- Joint with Heidi Williams, Jeff Clemens, and Fabian Eckert
- What is the value of selling federal land?
- OBBBA proposed (initially) to sell land in NV and UT to counties
- Could these sales help constrained western cities expand?
  - Reno, NV
  - Las Vegas, NV
  - St. George, UT
  - Others

Federal Lands

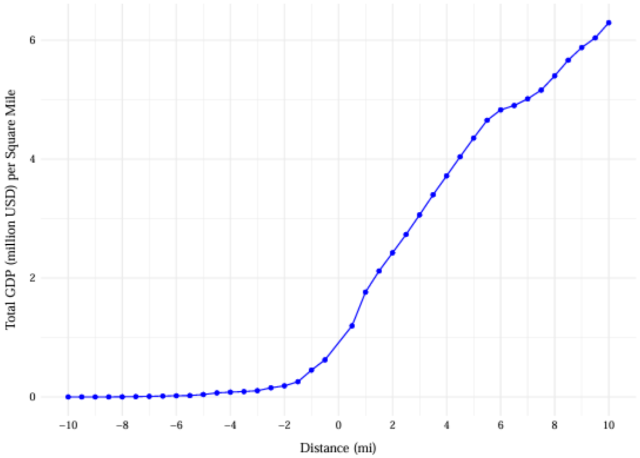
Figure: Federal Land Around Reno, NV



Federal lands shown in green and yellow.

Federal Lands

Figure: Change in GDP per Square Mile by Distance from Federal Land



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Appendix

Results:DiD Additional Variables

Controls to add:

- Components of the Environmental Benefit Index
  - Soil erosion
  - Soil moisture
  - Wind driven erosion
  - Wildlife/ habitat interaction
  - Wetland status
- Weather controls
- Crop prices
- Labor market tightness

Other Outcomes:

- Grid cell switching

Spatial RD - risk Threshold Boundary

$$y_{it} = \alpha + \Sigma_{t \neq 2014} \left[\beta_t (S_i \cdot T_t) + \gamma_t f(D_i) T_t + \delta_t f(D_i) T_t \cdot S_i \right] + \pi_i + \tau_t + \epsilon_{it} \quad (15)$$

- i, t is a 30m grid cell from [2007-2023]
- $\{Y\}$ = Cropland/Not, Crop Type, Evapotranspiration
- In stay states, this isolates risk between people who always have EPA risk to those that are uncertain about EPA risk
- In non-stay states, we get the direct effect of the regulation because the CWR takes effect
- D_i is distance from threshold, S_i is a dummy for risky side of the threshold, year dummies T_t, grid cell FE π_c & year FE τ_t

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1. For each rule (1988, CWR, and NWPR) get a set of $\sim 4,000,000$ points estimating if that rule applies from Greenhill et al. (2024)

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4. For each cell, calculate the distance to the nearest navigable water-way

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3. Set threshold for determining whether a point is regulated (we use 0.5)
4. For each cell, calculate the distance to the nearest navigable water-way
5. For each cropland cell, use the average of the nearest 4 points (by lat/lon and distance to navigable water) to guess whether or not that cell is regulated by each rule (KNN, $K = 11$)

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6. Assign a threshold to classify resulting KNN probabilities into regulatory groups (we use 0.5)

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6. Assign a threshold to classify resulting KNN probabilities into regulatory groups (we use 0.5)
7. Do this county by county

Results: Summary Statistics Stay vs. No-Stay States, 2009-2013

	Mean No-Stay (1)	Diff (2)		Mean No-Stay (1)	Diff (2)
Total Acres	550,098	106,062**	CRP Acres	6,478	4,996***
		(20,409)			(558)
Crop Land	171,595	93,576***	CRP Rent	66.27	-16.27***
		(6,398)			(1.2)
Share Cropland	0.36	0.09***	Some. WOTUS	0.27	-0.05**
		(0.01)			(0.01)
Share High Water	0.32	0.09***	Always WOTUS	0.18	-0.09***
		(0.01)			(0.01)
Conserv. Land	291,851	29,691	Conserv. Share	0.43	-0.03*
		(17,262)			(0.01)

$*p < 0.5; **p < 0.01; ***p < 0.001$

Results: Correlations with Sometimes WOTUS, 2009-2013

For each group of states (Stay and No-Stay), we run the following from 2009-2013:

$$y_{ct} = \alpha + \beta P_{ct} + \epsilon_{ct} \tag{16}$$

- y_{ct} is an outcome for county c at time t
- P_{ct} is the share of cropland that is sometimes included in WOTUS (risk)
- ϵ_{ct} is an error term

Results: Correlations with Sometimes WOTUS, 2009-2013

	No-Stay (1)	Stay (2)		No-Stay (1)	Stay (2)
Total Acres	416,085**	-726,682***	CRP Acres	-5,479*	-22,546***
	(50,531)	(37,462)		(1,466)	(1,175)
Crop Land	-7,201	-391,447***	CRP Rent	-23.21**	-30.49***
	(16,017)	(14989)		(4.42)	(1.87)
Share Cropland	-0.3***	-0.37***	CRP Open	3,823	-75141***
	(0.02)	(0.01)		(3,649)	(3285)
Sh. High Water	-0.32***	-0.37***	Always WOTUS	0.07**	0.26***
	(0.02)	(0.01)		(0.02)	(0.01)
Conserv. Land	424,615***	-445,556***	Conserv. Share	0.24***	0.06**
	(40,452)	(317,647)		(0.02)	(0.02)

$*p < 0.5; **p < 0.01; ***p < 0.001$