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Removing development incentives in risky areas promotes climate adaptation

In the format provided by the authors and unedited

A Policy Background

A.1 The Coastal Barrier Resources Act

The Coastal Barrier Resources Act (CBRA) was enacted by Congress in 1982. Authored by Representative Thomas B. Evans, Jr. (R-DE) and Senator John Chafee (R-RI) and co-sponsored by a bipartisan group of legislators, it passed with overwhelming support in both the House of Representatives and the Senate, and was signed into law by President Ronald Reagan.

The goal of the CBRA is to minimize the cost of disasters to the federal government while preserving important natural resources in coastal areas. The law achieves this by identifying and designating CBRS units, which are areas that are relatively undeveloped and provide important ecological, recreational, and wildlife benefits. In these units, new federal expenditures or financial assistance are banned, as stated in the Act: "no new expenditures or new financial assistance may be made available under the authority of any Federal law for any purpose within the Coastal Barrier Resources System".[1] Most significantly, prohibited expenditures include post-disaster financial assistance and infrastructure spending, along with the provision of flood insurance through the NFIP. In addition to reducing costs to the federal government, the law was intended to create a disincentive for private landowners to develop in CBRS units. By using this approach, the CBRA encourages private landowners to make conservation-minded decisions without relying on government mandates or prohibitions or costly easement or land purchase programs. As such, the policy is often referred to as a "free-market approach to conservation".[2]

The CBRA is administered by the U.S. Fish and Wildlife Service (FWS) within the Department of the Interior. The FWS is responsible for maintaining maps and inventories of CBRS units, providing the information to the public, and for enforcing the restrictions on federal funding and programs within these areas. The agency also provides technical assistance and guidance to state and local governments, private landowners, and other stakeholders on how to comply with the CBRA regulations.

The original CBRS included 186 units and 450,000 acres of land. The law has been amended several times since its enactment, with the most significant amendments occurring in 1990 and 2000. These amendments expanded the scope of the CBRA, clarified certain provisions, and made changes to the mapping process for the CBRS. Today, the CBRS includes more than 3.5 million acres of land and encompasses over 580 separate units along the Atlantic, Gulf, and Great Lakes coasts.

A.2 State and Local Anticipation and Policy Responses

State and local governments can play key roles in determining the overall impacts and effectiveness of federal policies. There are two possible channels through which state and local actions might interact with the implementation of the CBRA. Firstly, states and localities might affect the delineation of units by either pushing back or welcoming proposed CBRS designations. Secondly, they might supplement or counteract the policy by providing or withdrawing financial support and other development incentives in CBRS units. Below, we discuss the implications of these potential State and local responses for our study.

As detailed in the 1982 "Undeveloped Coastal Barriers: Report to Congress" by the Department of the Interior, on January 15, 1982, the draft maps of 159 areas initially identified as undeveloped

[1] See https://www.congress.gov/97/statute/STATUTE-96/STATUTE-96-Pg1653.pdf.

[2] See https://www.fws.gov/sites/default/files/documents/coastal-barrier-resources-fact-sheet.pdf.

coastal barriers were released for public comments, and relevant documents were also provided to affected state and local jurisdictions.[3] Within the 60-day comment period, there were more than 500 comments relating to the delineation of specific coastal barrier units, with extensive follow-up discussions between the Department of the Interior and state and local stakeholders. The report pointed out that no units were removed from the original proposed set of designations after the public comment period, reflecting limited ability of localities to prevent CBRS designations. Rather, many of comments identified more areas that qualified as undeveloped coastal barriers, resulting in an addition of 55 areas. The proposed delineations were released on August 16, 1982, and the law went into effect on October 1, 1983.

The process aimed to designate a set of units that fit a clearly defined set of criteria based on only geomorphic and development features and not socioeconomic or political considerations. Importantly, the report noted that "Neither the specific language of the Reconciliation Act, nor its legislative history, support reliance on any development that is not visible on the ground", which precludes local jurisdiction from blocking a designation on grounds of intent to develop or approved development plans. Given the short timeline from the draft designation to implementation, it is unlikely that state and local jurisdiction could have affected development levels enough to prevent the designation of an area that fits the criteria based on observable features.

Once the CBRS was created, it is possible that state and local governments could either reinforce the federal restrictions on disaster aid and infrastructure spending by enacting their own policies to discourage development on CBRS lands or counteract the restrictions by substituting their own subsidies for those withdrawn by the federal government. For example, through interviews with stakeholders, Salvesan (2005) finds that inside a unit at North Topsail Beach, NC, development was facilitated by high density development zoning by the county and road investments by two local developers under a favorable agreement with the state [33]. He also finds the opposite at Dauphin Island, AL, where the state's construction setback policy and efforts by a local conservation group strengthened the CBRA, leaving the unit area mostly undeveloped. Motivated by these observations, we examine potential heterogeneous treatment effects by state and based on local political attitudes on environmental and conservation issues.

B Extended data and methods

B.1 Data sources and processing

Counterfactual construction. Data for regionalization and matching are collected from a number sources with different spatial geometries. Importantly, because the goal is to construct a set of controls that were comparable to CBRS treatment areas at the time of designation in 1982, all data comes from as close to this year as possible. Here, we provide an overview of the data sources used in this analysis and how these data are processed.

First, we construct a high-resolution gridded dataset on historical land cover, development levels, and elevation for use in the regionalization algorithm. Because only coastal lands are eligible for CBRS designation, we only include areas within 2 kilometers of the coastline in our sample. We use data on land cover from the Land Change Monitoring, Assessment, and Projection (LCMAP) database for the year 1985 [53]. These data are available at 30m resolution and include eight land cover classes: developed, cropland, grass/shrub, tree cover, water, wetland, barren, and ice/snow.

[3] `https://www.fws.gov/sites/default/files/documents/Undeveloped-Coastal-Barriers-Report-1982.pdf`

We aggregate this raster by a factor of 10 in order to construct a 300m resolution raster with information on the percent of each pixel covered by the eight land cover classes.[4] We also calculate elevation and distance to coast for each pixel. These comprise the set of characteristics we feed into the regionalization algorithm to identify spatially contiguous areas that share similar geomorphic and development features. This part of the process was designed to mimic the process by which natural resources hand-drew the boundaries of CBRS designations.

After we have identified spatial clusters using the regionalization algorithm, we apply the synthetic controls method to compute a set of weights that balances the pre-trends in development densities and pre-treatment characteristics of treatment and control areas. We expand our dataset to include measures of pre-treatment infrastructure and development pressures for each CBRS unit and candidate counterfactual area. These measures come from a wide variety of data sources with different native geometries (e.g. points, vectors, raster, census tracts). We implement standard geospatial processing techniques to aggregate these disparate geometries to CBRS treatment and counterfactual areas so that we can calculate synthetic control weights for each unit. Here, we describe the construction of each covariate used in the matching process.

Geography and natural resources:

- **Land cover.** We calculate the percent of area covered by each of the land cover classes included in the LCAMP database (developed, cropland, grass/shrub, tree cover, water, wetland, barren, ice/snow) for the year 1985.
- **Elevation.** We calculate average elevation using high resolution gridded data from the Altimeter Corrected Elevations, v2 (ACE2). Modern data is used as elevation is not expected to change substantially over time.
- **Barrier islands and capes.** For the purposes of controlling for whether the unit is located on a barrier island or cape in equations 2 and 3, we define a barrier island as a landmass disconnected from the mainland and a cape as an extension of land jutting out into water as a peninsula. Barrier islands are identified computationally. Capes were identified by hand.

Development pressures:

- **Pre-trends in built-up surface.** We calculate the percent of land area covered in built-up surface using the Historical Settlement Data Compilation for the United States (HISDAC-US). HISDAC-US contains historical gridded settlement layers derived from property records compiled in the Zillow Transaction and Assessment Dataset (ZTRAX). We use the historical building footprint area (BUFA) data layer, which estimates the total building footprint area (i.e., the built-up surface in m^2) across the contiguous United States at 250 meter spatial and 10 years temporal resolution, going back to 1900. We use estimates of built-up surface in 1960, 1970, and 1980 to match pre-trends in built-up surface, measured as a percent of land area, across treatment and control areas.
- **Socio-demographics.** We use sociodemographics at the block group level from 1990 U.S. Census data are accessed through the National Historical Geographic Information System

[4] We elect to aggregate the 30m LCMAP data to 300m resolution because the regionalization algorithm performs better with continuous land cover classes (shares) than discrete classes.

(NHGIS). We aggregate these data to the CBRS and counterfactual unit level using population weights calculated using gridded data at 1km resolution in year 2000 (earliest available) from Gridded Population of the World. The demographic variables measured include: median household income; per capita income; population below poverty line; educational attainment; employment status; race; median home value; home ownership; and population. Notably, we use sociodemographic data from the 1990 census because the 1980 census geographic information is badly incomplete ($> 30\%$ of blocks are missing) and data quality is poorest less developed regions; thus, it was not possible to link 1980 data with CBRS treatment areas.

- **Commuting distance urban population.** We use commuting distance urban population as a summary statistic for proximity to urban centers that takes into account the size of the urban center. To construct this variable, we sum the population of all urban clusters within a 20-mile buffer of each unit. Urban clusters are defined by groupings of RUCA code 1 counties, derived from USDA's Rural-Urban Commuting Area (RUCA) Codes and 1982 U.S. Census population data.
- **Pre-1982 Buildings.** We obtain data on parcel assessments from the Zillow Assessment and Transactions Database (ZTRAX). Using the geographic coordinates of the parcel centroids, we identify those in CBRS and counterfactual units and further filter for those with a structure built in or before 1982.

Flood risk in spillover areas:

- **Share of land area in flood zones.** We calcualte the share of land area in treatment and control spillover areas located in A and V zones as identified by the National Flood Hazard Layers from FEMA. These zones are included in the Special Flood Hazard Areas, or SFHAs, which are deemed the high flood-risk aras where flood insurance is required for properties with federally-backed mortgages.

Outcomes. We measure the direct effects of the CBRS within designated areas and the spillover effects in surrounding commmunities. Because we are interested in the long-term impacts of the policy, we measure all outcomes using the most recent data available. The full set of outcomes are geospatial processing techniques are described below.

- **Built-up surface.** We calculate the share of land area covered in building footprints (i.e. built-up surface) in 2010 using the BUFA layer from HISDAC-US, which is described above. Note that this measure differs considerably in magnitude from share of developed land as measured by land cover maps such as LCMAP or the NLCD, because it includes only the land area covered in building footprints (as computed from the square footage field in property assessment records) and does not include entire 30m grid cells that include a mix of vegetation, bare ground, roads and/or structures.
- **Buildings per acre.** We calculate the number of buildings per acre using building footprints from Microsoft Maps. These data are computer generated polygons derived from satellite imagery. We intersect them with CBRS and counterfactual unit boundaries to identify the number of structures in each unit. We then divide by total land area of the unit.

- **Property values.** We obtain information on property values from the Zillow Assessment and Transaction Database (ZTRAX). We construct four outcome variables from these data: average sales price, total assessed value per acre, land assessed value per acre, and improvement assessed value per acre. Measures of assessed value come from the most recent records available from the county as of 2021. To measure sales price within CBRS and spillover areas, we average the prices for all properties sold between 2010 and 2021. ZTRAX data are available at the parcel-level and geocoded using property centroids, so they can be easily spatially linked with CBRS and counterfactual units. ZTRAX contains close to the full universe of parcel assessment records. Data on assessment values are complete, but those on housing attributes have varying degrees of missingness depending on the county. ZTRAX also covers almost all transactions in U.S. states which require disclosure of sales prices during our sample period.[5] Therefore, our results on assessment values are from all treatment and control units, but those on sales prices and other attributes are subject to where transactions occurred and measurement issues in the original data. Nolte et al (2023) discuss these issues in more detail [54].

- **Flood insurance claims.** We measure flood damages using flood insurance claims from the National Flood Insurance Program (NFIP), the dominant insurer for flooding in the United States.[6] We construct two different measures of flood damages: NFIP claims per $1,000 of coverage and total NFIP claims per acre. Because flooding is an infrequent event, we average annual flood claims over the years 2009 to 2020. The most granular geographic identifier available in the NFIP claims and policies data is the property census tract. To estimate the value of NFIP claims in each CBRS spillover area, we aggregate the values from all census tracts that intersect a given spillover area, weighting by the number of buildings located in the FEMA-designated Special Flood Hazard Areas (the high flood-risk areas where flood insurance is required for properties with federally-backed mortgages). The intuition behind this approach is that the distribution of NFIP policies and claims over geographic space will likely resemble the distribution of structures in areas with high flood risk.

- **Population and housing units composition.** We use 5-year (2016-2020) estimates of demographics at the block group level from the American Community Survey (ACS) accessed through the National Historical Geographic Information System (NHGIS). The data is then aggregated in the same way as the 1990 Census data used in the matching process, the only difference being that we use gridded population data from 2020 to calculate the aggregation weights here. The variables measured include: share of White, Black, and Hispanic populations, median income, share of college graduates, share of housing units that are occupied by owners and renters, median rent, median rent as percent of income.

Summary Statistics. Table B1 provided summary statistics in CBRS treatment (column 1) and control areas (column 2). The data source for each variable is indicated in column 3.

[5] The nondisclosure states in our sample include Louisiana, Mississippi, and Texas.

[6] Homeowners within CBRS areas are not eligible to participate in the NFIP, so we do not look at the direct effect of CBRS designation on NFIP claims.

	CBRS (1)	Control (2)	Data source (3)
Sample for direct effects			
Built-up surface (%)	0.17	0.29	HISDAC-US
Buildings per acre	0.01	0.05	Microsoft
Total assessed value per acre	113,606	78,518	ZTRAX
Land assessed value per acre	47,523	37,574	ZTRAX
Improvement assessed value per acre	16,035	25,374	ZTRAX
Average property sales price	1,280,236	1,032,754	ZTRAX
Average lot size (acres)	6.24	4.97	ZTRAX
Average square footage	4,007	4,120	ZTRAX
Average bedrooms	3.35	3.31	ZTRAX
White share	0.91	0.88	ACS
Black share	0.04	0.06	ACS
Median household income	92,077	78,104	ACS
Median rent as % of income	32.63	31.07	ACS
Occupied housing units share	0.52	0.69	ACS
Sample for spillover effects			
Buildings per acre	0.67	0.49	Microsoft
Total assessed value per acre	332,275	171,314	ZTRAX
Land assessed value per acre	122,769	61,823	ZTRAX
Improvement assessed value per acre	97,424	63,516	ZTRAX
Average property sales price	535,050	405,762	ZTRAX
Average lot size (acres)	2.02	6.27	ZTRAX
Average square footage	3155	2514	ZTRAX
Average bedrooms	3.08	3.07	ZTRAX
White share	0.87	0.84	ACS
Black share	0.03	0.06	ACS
Median household income	91,829	77,617	ACS
Median rent as % of income	32.37	31.08	ACS
Occupied housing units share	0.53	0.68	ACS
Flood damages (NFIP claims) per acre	197.77	629.31	NFIP
Flood damages (NFIP claims) per $1000 coverage	95.99	119.15	NFIP
Buildings per acre in floodplains (SFHA)	0.17	0.12	NFHL

Table B1: **Outcome means within CBRS units and spillover areas, by treatment status.** All means (columns 1 and 2) are weighted by the synthetic control weights used in estimation. Data sources are given in column 3 and described in SI B.1.

B.2 Regionalization

We use a spatial clustering technique known as "regionalization" to separate all coastal areas into distinct regions that serve as the pool of potential counterfactual units for our analysis. This procedure is designed to mimic the process by which land use planners outlined CBRS units following geomorphic and development features.

In machine learning, clustering involves sorting observations into groups without any prior idea about what the groups are. These groups ("clusters") are delineated so that members of a group should be more similar to one another than they are to members of a different group. For example, observations in one group may have consistently high scores on some traits but low scores on others.

In spatial data science, clustering is widely used to provide insights on the geographic structure of complex multivariate spatial data. A "region" is similar to a cluster, in the sense that all members of a region have been grouped together, but a region also describes a clear geographic area. The process of creating regions is called "regionalization." Regionalization uses the same logic as standard clustering techniques, but also requires connectivity: two candidates can only be grouped together in the same region if there exists a path from one member to another member that never leaves the region [45].

We begin with a 300m resolution raster with information historical land use, elevation, and distance to coast. Each cell of the raster represents a distinct observation that will be grouped into a region. We only consider grid cells within 2 kilometers of the coast. We exclude any cell that is 100% water. We also exclude any cell that is within a CBRS unit (including both original units designated in 1982 and all units designated since then) or an otherwise protected area. Finally, in order to ensure that our counterfactual areas are not contaminated in the sense that they are treated by the spillover effects of CBRS units, we exclude all cells within 2km of a CBRS unit from the sample. We preprocess the data by normalizing all attributes before inputing them into the regionalization algorithm.

We use Agglomerative Clustering — one of the most common spatial clustering techniques. For computational feasibility, we implement the algorithm one state at a time, so that all regions contain pixels in the same state. We set the number of clusters (N) so that the average size of the resulting cluster equals the average size of the CBRS units in that state. Notably, not all clusters are required to be the same size. This produces counterfactual areas with a range of different geographic areas, just as CBRS units have a wide range of areas. We specify our Agglomerative Clustering algorithm using "rook" connectivity and "ward" linkage (which minimizes the variance of the clusters being merged).

C Results Based on Overlap Weighting

In this section, we demonstrate the robustness of our results to an alternative research design: propensity score weighting. While the main analysis constructs a control group using the synthetic control method, here we calculate overlap weights (a function of propensity scores) to bring the pre-treatment characteristics of CBRS and control areas into alignment. Overlap weights are proportional to the probability of an area belonging to the opposite treatment group. Specifically, CBRS units are weighted by the probability of not receiving the treatment, and counterfactual areas are weighted by the probability of receiving the treatment. These weights are intended to generate a sample that mimics the characteristics of a randomized experiment by maximizing the influence of areas that are compatible with treatment while minimizing the influence of outliers.

While both the synthetic controls and propensity score approaches identify a set of weights that balance the pre-treatment characteristics of CBRS and control areas, these two designs are complementary in our setting because they rely on different sets of matching variables. The synthetic control method largely relies on matching the development trajectories of treatment and control areas. In the propensity score approach, we match on a wider set of observable variables including all land cover types, measures of population and infrastructure density, proximity to urban centers and protected areas, and more sociodemographic characteristics (see below for a description of additional variables and their sources). Figure C2 shows that our treatment and control units are well balanced across this augmented set of variables in both the full sample and the ZTRAX sample. The summary statistics of the treatment and control samples based on the overlap weights are shown in Table C1.

The propensity score approach identifies different weights than the synthetic control method. Figure C1 shows the limited correlation ($R^2 = 0.47$) between the two sets of weights, with synthetic control weights on the x-axis and overlap weights on the y-axis. The differences in weights are driven by at least two factors. First, the two methods are matching on different sets of covariates. Second, synthetic controls assigns all CBRS units a weight of one (treats them all equally in estimation), while the propensity score approach down-weights CBRS units that are not well represented in the control group. This results in quite different samples, with the synthetic control treatment group being significantly less developed than the propensity score treatment group (Table B1 vs. Table C1). Because of these differences in sample, the point estimates should not necessarily be directly comparable. Instead, we will check whether the estimated relative effects are similar in magnitude.

Table C2 reports the estimates of the direct effects and Figure C3 displays the estimated spillover effects in spatial lags. The estimated relative effects are remarkably similar for many outcomes, including the development effects both inside CBRS units and in spillover areas, reduction in flood damages, and changes in socioeconomic characteristics. For example, using synthetic controls we estimate that CBRS designations reduce the number of buildings per acre by 83% and the percent of built-up surface by 41% and using propensity score matching we estimate that CBRS designations reduce the number of buildings per acre by 85% and the percent of developed land by 70%. The biggest difference lies in the effect on assessment values inside the units: while the effect is small and statistically insignificant under the synthetic control approach, here we see a large and significant decrease. This is likely because this method upweights units that saw larger reductions in assessment values.

Overall, these results are consistent with our main findings. Between the two methods, we prefer synthetic control for its ability to match based on historical development trajectory and the equal weights on treatment units. Nevertheless, the overlap weighting approach provides an informative robustness check and further supports our main findings.

Data Sources for Additional Variables Used in Matching

- **Distance to coast.** We calculate distance to coast using NOAA's medium resolution shoreline. Specifically, we take the minimum distance between the unit boundary and the shoreline. Modern data is used as distance to coast is not expected to change substantially over time.

- **Beach access.** Beach access is assessed using EPA's Beaches NHDPlus Indexed Dataset. Each unit is assigned a binary variable of 1 for intersecting with a beach, signifying beach access, or 0 for no intersection, and thus no access. Modern data is used as beach access is not expected to change substantially over time.

- **Proximity to protected area.** The percent of unit classified as protected land before 1982 is constructed using the United States Geological Survey's Protected Areas Database of the United States (PAD-US). Since 81.5% of protected areas are missing establishment dates, areas without dates are assumed to be from before 1982. If no percent of a land parcel is protected, the distance to the nearest pre-1982 PAD-US area in meters is also computed.

- **Roads.** Paved, unpaved, and unknown-surface road density is computed as the length of each road type in miles over unit area in acres using NASA's Global Roads Open Access Data Set (G-ROADS) database. We only include roads with construction dates prior to 1982.

- **Bridges.** We obtain information on the presence and size of bridges from the Federal Highway Administration's National Bridge Inventory (NBI). We use bridge density – calculated as bridge size ($length \cdot width$ in m^2) over the unit area in acres – as a summary statistic. Only bridges constructed before 1982 are included.

- **Dams.** Dam presence is from the U.S. Army Corps of Engineers' National Inventory of Dams (NID), with a binary indicator of a dam in each units. Only dams constructed before 1982 are included.

- Also note that the additional land cover types and socioeconomic variables are from the same sources as described in section B.1.

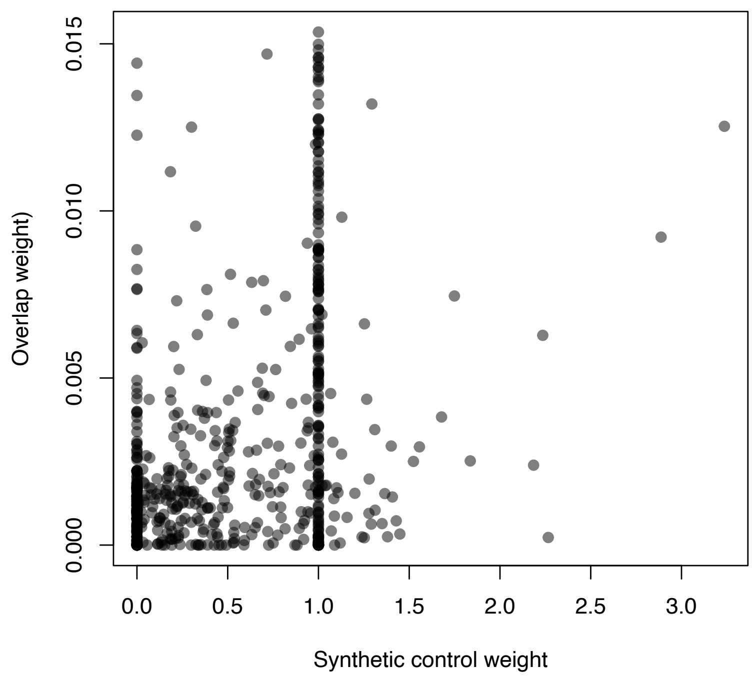

Figure C1: **Correlation between weights used in synthetic control and propensity score approaches.** X-axis shows synthetic control weights and y-axis shows overlap weights. The synthetic control method sets all treated unit weights to one. The correlation between the two sets of weights is $R^2 = 0.47$.

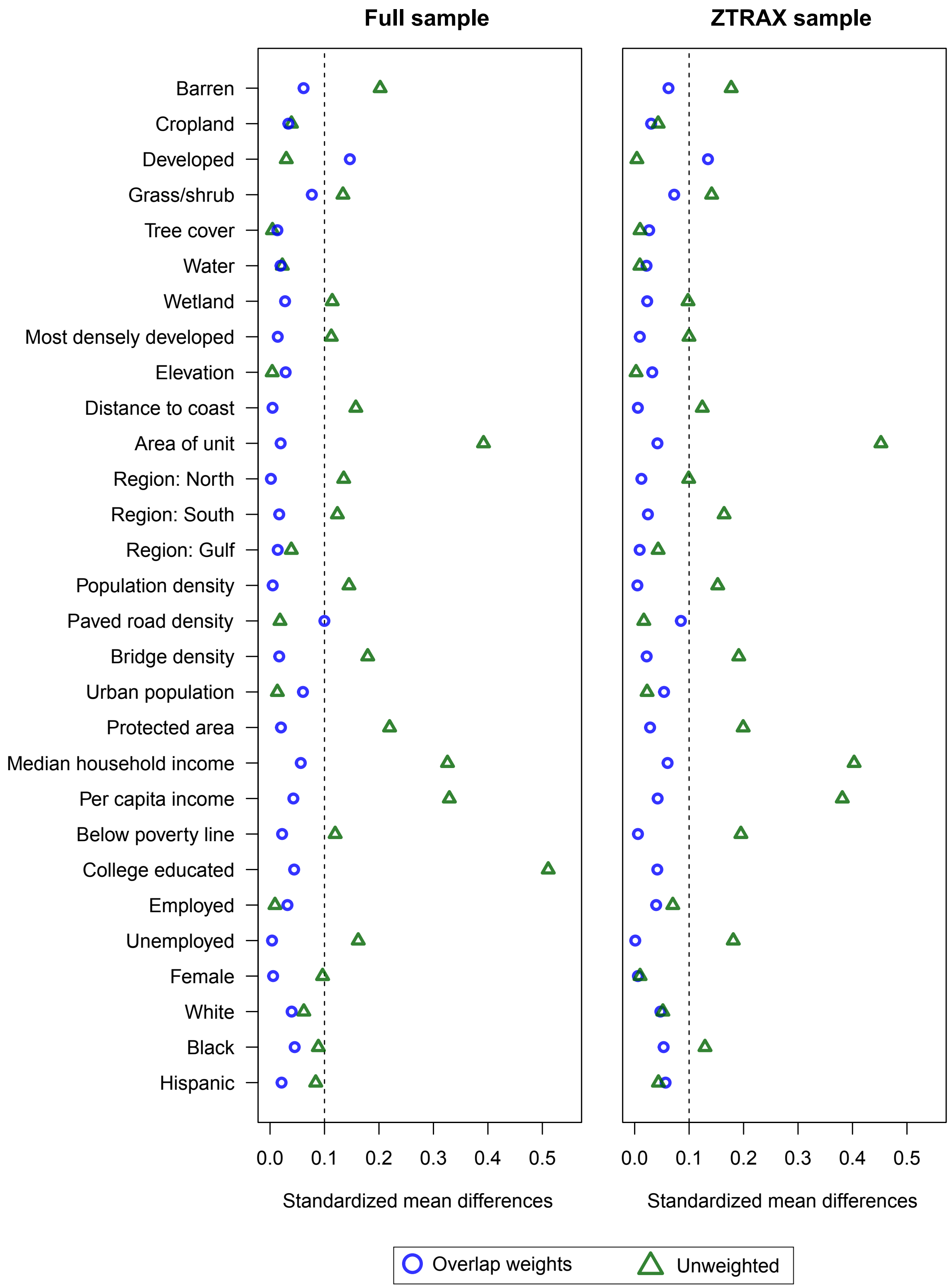

Figure C2: **Balance in unweighted and weighted samples using propensity score matching.** This figure shows the standardized mean differences of variables on land use, infrastructure, and demographics between CBRS and counterfactual units. The left panel features full sample and the right features the sub-sample with non-missing ZTRAX observations.

	Control (1)	CBRS (2)	Data source (3)
Sample for direct effects			
Built-up area (%)	0.211	0.798	HISDAC-US
Buildings per acre	0.128	0.019	Microsoft
Average property sales price	790,169	1,002,030	ZTRAX
Total assessed value per acre	340,546	153,513	ZTRAX
Land assessed value per acre	111,552	45,411	ZTRAX
Improvement value per acre	78,143	13,291	ZTRAX
Average lot size	11.6	10.1	ZTRAX
Average year built	1,979	1,982	ZTRAX
Average squared footage	3,104	3,780	ZTRAX
Average bedrooms	3.01	3.40	ZTRAX
Share White	0.894	0.904	ACS
Share Black	0.054	0.042	ACS
Share Hispanic	0.046	0.054	ACS
Share college graduate	0.304	0.358	ACS
Median household income	76,777	87,828	ACS
Share owner occupied	0.481	0.464	ACS
Share renter occupied	0.143	0.091	ACS
Share occupied	0.624	0.555	ACS
Median rent	1,153	1,325	ACS
Median rent as % of income	30.68	32.66	ACS
Sample for spillover effects			
Buildings per acre	0.485	0.590	Microsoft
Average property sales price	398,644	524,175	ZTRAX
Total assessed value per acre	260,203	335,687	ZTRAX
Land assessed value per acre	78,403	118,756	ZTRAX
Improvement value per acre	71,222	104,668	ZTRAX
NFIP claims per acre ($)	288.9	241.3	NFIP
NFIP claims per $1,000 coverage ($)	120.2	89.7	NFIP
Buildings per acre in SFHA	0.158	0.195	NFHL
Share White	0.873	0.897	ACS
Share Black	0.070	0.044	ACS
Share Hispanic	0.054	0.056	ACS
Share college graduate	0.279	0.344	ACS
Median household income	74,095	86,769	ACS
Share owner occupied	0.486	0.467	ACS
Share renter occupied	0.163	0.119	ACS
Share occupied	0.650	0.586	ACS
Median rent	1,206	1,282	ACS
Median rent as % of income	30.75	32.03	ACS
Observations	167	448	
Effective Sample Size (using overlap weights)	106	192	

Table C1: **Outcome means within CBRS units and spillover areas, by treatment status, using propensity score weights.** All means (columns 1 and 2) are weighted by the overlap weights used in estimation. Data sources are given in column 3 and described in SI B.1.

Outcome	Estimate	St. Err.	p-value	Relative effect	N
Development levels					
Built-up area (%)	−0.560	0.273	0.040	−70%	600
Buildings per acre	−0.110	0.032	0.001	−85%	612
Assessed value					
Total assessed value per acre	−190,763	83,095	0.022	−56%	314
Property characteristics					
Average property sales price	127,482	256,748	0.620	+16%	193
Average lot size (acre)	−0.997	6.968	0.886	−8.6%	309
Average year built	2.278	5.064	0.653		271
Average squared footage	601.7	438.4	0.171	+19%	261
Average bedrooms	0.381	0.184	0.040	+13%	228
Population demographics					
Median household income ($)	11,173	4,555	0.014	+15%	582
Share White	0.012	0.015	0.421	+1.4%	603
Share Black	−0.010	0.013	0.445	−14%	603
Share Hispanic	−0.003	0.010	0.767	−5.5%	603
Share college graduate	0.057	0.022	0.009	+20%	603
Share owner occupied	0.020	0.026	0.445	+4.1%	602
Share renter occupied	−0.044	0.014	0.002	−27%	602
Share occupied	−0.024	0.029	0.414	−3.7%	602
Median rent ($)	201.617	76.485	0.009	+17%	448
Median rent (% of income)	2.696	1.471	0.068	+8.8%	463

Table C2: **The effect of removing federal financial incentives for development within CBRS designations estimated using propensity score matching.** These effects are estimated as weighted differences between outcomes inside CBRS and control units. The estimation uses overlap weights constructed from land use, geography, development pressures, and sociodemographic variables (see Online Methods). Statistical significance is based on robust standard errors: *p < 0.1; **p < 0.05; ***p < 0.01

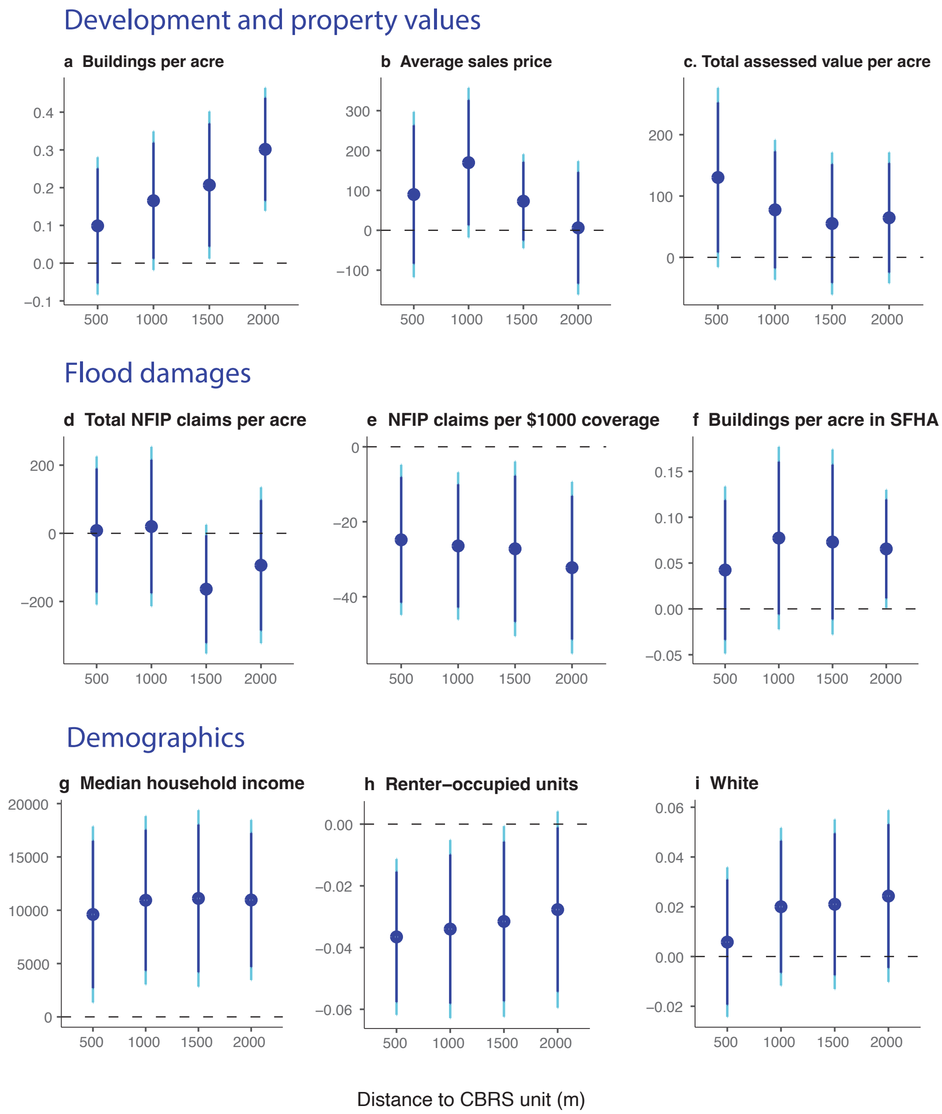

Figure C3: **Spillover effects on development and property values in neighboring communities estimated using propensity score matching.** This figure is the same as Figure 4, except estimated using propensity score matching instead of synthetic controls. It shows the spillover effects of CBRS designation in a 2km buffer area around CBRS units, estimated using a spatial lag model. Point estimates for each 500-meter band and the corresponding 90% confidence intervals are shown in dark blue, and the 95% confidence intervals are shown in light blue. The top panel shows three economic development outcomes, the middle panel shows three flood insurance outcomes, and the bottom panel shows three demographic outcomes.