Can Removing Development Subsidies Promote Adaptation? The Coastal Barrier Resources Act as a Natural Experiment*

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Abstract

As natural disasters grow in frequency and intensity under climate change, limiting populations and properties in harm's way will be one important facet of adaptation. This study focuses on one approach to discouraging development in risky areas — eliminating public incentives for development, such as infrastructure investments, disaster assistance, and subsidized federal flood insurance. We examine the Coastal Barrier Resources Act of 1982, which eliminated federal incentives in designated areas along the Atlantic and Gulf coasts known as the Coastal Barrier Resources System (CBRS). We estimate the causal effect of CBRS designations by identifying plausible counterfactual areas using novel machine learning and matching techniques. Our results show that CBRS designations lower development density by 85% inside the designated areas but increase development in neighboring areas by 20%. We also show that the program capitalizes spillover benefits from natural amenities and flood protection services into property values in surrounding neighborhoods. We find that local property tax revenues are approximately unchanged. Finally, we present new evidence that the CBRS is associated with demographic change. These findings inform ongoing debates regarding cost-effective public policies to prevent over-development in risky areas.

Keywords: climate adaptation, land use, development incentives, regionalization, spillover effects, flood protection.

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1 Introduction

An important aspect of adaptation to climate change involves reducing exposure to climate risks. This is particularly true in coastal areas. As sea levels rise, tidal flooding worsens, and coastal storms become more frequent and severe, limiting the number of people and properties that lie in harm's way will be key to managing climate damages.

In the United States, local governments are primarily responsible for land use and zoning decisions that guide development, but a plethora of federal and state policies and programs also play important roles. Federal and state investments in roads, bridges, wastewater and drinking water systems, and other infrastructure lay the groundwork for development and population growth. Other government policies and programs, such as the federal government's National Flood Insurance Program (NFIP), which offers flood insurance for many properties at subsidized rates, and its disaster assistance programs, which provide funding for individuals and local governments after a disaster strikes, also affect development. By shifting some of the costs of floods and other disasters from property owners to the government, these programs remove many of the financial disincentives to development in risky areas.

Whether reducing some of these implicit subsidies would curb development, lower the costs of disasters, and help communities prepare for climate change is unclear. Many factors affect development decisions and these federal subsidies are only some of the factors at play. Empirical research is limited because few policy experiments exist where a clear comparison can be made of "treatment" settings, where incentives to development have been removed, and "control" settings, similar areas where such incentives remain.

One such experiment does exist, however, and has thus far received only limited attention from researchers. The 1982 Coastal Barrier Resources Act (CBRA) designated certain coastal areas along the Atlantic and Gulf Coasts as a Coastal Barrier Resources System (CBRS) within which federal funding for new roads, bridges, utilities, and other infrastructure, federal spending on post-storm disaster relief, and flood insurance under the NFIP are banned. The law's intended purpose is to transfer the cost of protecting and maintaining private development in these areas from federal taxpayers to individual property owners. Besides removing these federal incentives, CBRS designations do not otherwise prohibit development.

In this study, we leverage CBRA as a natural experiment to study the long-term economic impacts of removing federal assistance in areas at high risk of flooding and assess its efficacy as a land conservation and climate adaptation strategy. We address four main research questions:

1. Has CBRA been effective in discouraging development in the coastal areas designated as part of the CBRS and thereby lowering exposure to coastal flooding?

2. What are the long-term impacts of CBRA on development, flood damages, and land values in neighboring areas near CBRS lands?

3. What are the overall effects on property tax revenues for counties that include CBRS lands?
4. Has CBRA changed the demographics of households living in the CBRS and neighboring areas?

Through answering these questions, we aim to assess not only the *direct* effect of CBRA inside the designated areas, but also its *spillover* effects on neighboring areas. The spillover effect is a key component in a comprehensive evaluation of the program's benefits and costs. In particular, there is a longstanding tension between federal policies that affect development levels in certain risky areas and local governments' concerns over the impact on their tax base. The CBRA, for example, might reduce property tax revenues for counties that contain CBRS lands if it effectively discourages development in these areas. However, more undeveloped natural lands in CBRS areas could also provide flood protection benefits and other natural amenities to nearby areas, in turn boosting development and property values there. An extensive literature has documented the benefits of natural lands capitalized in property values (McConnell and Walls, 2005). Ignoring such spillover effects could bias our understanding of the local impacts of the program and even lead to resistance and counteracting policies by state and local governments.

Four studies of CBRA in the extant literature assess the effects of the program on development outcomes inside the designated areas.[1] Based on case studies of five regions, including interviews with state coastal managers, Salvesen (2005) finds that CBRA has had widely differing effects on development across regions and that state and local policies have played a large role in creating those differences. Some states have reinforced CBRA, Salvesen finds, by limiting state spending on infrastructure, but at the local level, development has sometimes been facilitated by local government spending on, for example, expanded public sewer service and developer-financed infrastructure. A 2007 report by the U.S. Government Accountability Office (GAO) estimated that 84 percent of CBRS units remained undeveloped at that time, mainly due to the units having a paucity of land suitable for development, the existence of state laws that discourage development, and the purchase of CBRS lands or easements by conservation organizations (Government Accountability Office, 2007). The GAO concluded that several factors explain why some units have seen development: (1) strong demand for beachfront residential sites and limited nearby supply; (2) support for development by local government; and (3) the availability of affordable private flood insurance.

Two studies have used regression techniques to compare CBRS development outcomes to other coastal lands. Onda et al. (2020) compare CBRS units to all non-CBRS coastal lands 2 kilometers (km) from the shore in a regression analysis of a single cross-section of 2016 data. They find that CBRS units, on average, have lower development density and higher proportions of vacant land than other coastal lands. The same authors, in a 2022 study, employ a spatial regression

[1] Two related studies estimates federal disaster expenditure savings as a result of lower development levels in CBRS (U.S. Fish and Wildlife Service, 2002; Coburn and Whitehead, 2019). However, both assume alternative scenarios for development rather than employing empirical estimation.

discontinuity design (RDD) to compare changes in development densities between 1980 and 2016 in CBRS units and areas just outside the CBRS boundaries in five states (Alabama, Delaware, Florida, North Carolina, and Texas) (Branham et al., 2022). The RDD approach can provide a causal interpretation to results as long as assignment to either side of the CBRS boundary—i.e., in the CBRS treatment or control area—is assumed to be random and there is no spillover effect of CBRS treatment on neighboring areas. Branham et al. (2022) find that growth in the number of built structures (measured from aerial photography) per hectare in non-CBRS areas was 4.4 times higher, on average, than in CBRS units.

Like these earlier studies, we estimate the effect that CBRS designation has had on the extent of development. Did these lands that were designated as the CBRS end up seeing less development than they otherwise would have in the absence of the program? We take a unique approach to construction of a control group to compare with the CBRS treatment group, which we consider a critical step in the analysis. Specifically, we use machine learning and matching techniques to mimic the process by which natural resource planners determined CBRS boundaries based on geomorphic and development features, allowing us to identify a set of coastal areas that could have been selected for CBRS designation in 1982 but were not. Figure 1 shows one example of a CBRS treatment area and constructed control area, overlaid with our parcel-level outcome data on the location and value of properties. Importantly, our research design does not require the assumption that CBRS boundaries were drawn without regard to development in order to interpret our results as causal.

To our knowledge, we are the first to analyze the effect the program has had on property values, development densities, and flood damages in areas adjacent to CBRS lands, which we refer to as spillover areas. We estimate these effects by comparing neighboring areas of CBRS units with neighboring areas of our counterfactuals. We then examine the overall effect the program has had on the property tax base of counties that include CBRS lands, including the direct and spillover effects, and calculate rough estimates of the program on annual property tax revenues. Finally, we look at demographic changes on CBRS lands and in spillover areas.

We find that CBRS designations lower average development density by 85% inside the unit but increase development densities in spillover areas by 20%. We document a similar pattern in assessed values of properties. Given that the spillover areas are generally larger than the units themselves, this represents a significant counteracting effect on the local property tax base. We also provide new findings on the effectiveness of CBRS designations in reducing flood damages to nearby proprieties, and on their impacts on local demographics as different households sort into these areas.

The analysis addresses several open questions about land-based climate adaptation. First, it has long been suggested that federal incentives, particularly the provision of subsidized federal flood insurance, play a significant role in encouraging development in risky areas, yet quantitative research on this question is limited (Bakkensen and Ma, 2020). Our study evaluates whether the removal of these incentives on certain coastal lands has been a cost-effective adaptation strategy.

Second, by examining the spillover effects of the CBRS on surrounding lands, we provide some of the first estimates of how natural infrastructure, which results from reduced development on CBRS lands, affects coastal property values, flood damages, and other outcomes. Third, our analysis sheds new light on how removing federal development subsides affects local government finances by providing some of the first estimates of the net effect this policy has on the local property tax base and revenues.

Our results also have broader applicability to climate adaptation policy questions. A current bill in the US Congress, the Build for Future Disasters Act (H.R. 2632), proposes removing NFIP subsidies for new construction in Special Flood Hazard Areas (FEMA-designated 100-year floodplains) beginning in 2025. State policies and programs are also being revisited. The question of whether and for how long state governments should maintain roads and bridges that repeatedly flood, for example, versus abandoning the infrastructure altogether, is a matter of ongoing debate (Jones et al., 2019; Thompson et al., 2019). The results of our analysis shed light on some of the outcomes that can be expected if these changes are made. Similarly, as wildfire risk is increasing drastically in recent years, our findings on CBRA provide valuable policy lessons on managing development in the wildland-urban interface.[2]

[2] See https://www.resources.org/common-resources/does-coastal-barrier-resources-act-provide-policy-template-address-wildfire-risk/ for a detailed discussion.

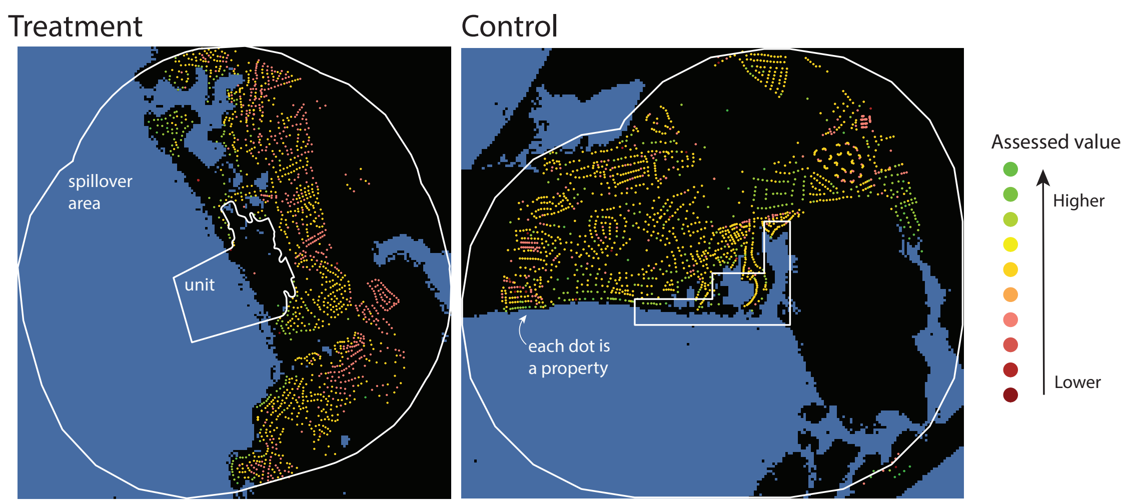

Figure 1: **Overview of research design.** Left: an example CBRS (treatment) area, with its spillover area (2km buffer). Right: same, but for a control area. Properties from the Zillow Transactions and Assessment Database (ZTRAX), which comprises one set of outcomes studied in the paper, are overlaid on the maps as points. The color of the points corresponds to the total assessed value of the home.

2 Methods

2.1 Counterfactual construction

The goal of our empirical strategy is to identify the causal effect of CBRS designation. The core challenge is identifying a set of appropriate counterfactual units to serve as "control" areas for CBRS "treatment" areas. The CBRA encourages the conservation of biologically rich, underdeveloped, and hurricane-prone coastal areas. Therefore, we cannot simply compare our outcomes of interest in CBRS units to those in all other coastal areas; we must identify comparable areas that could have been selected for CBRS designation but were not. We do so using a novel procedure designed to mimic the process by which natural resource planners defined CBRS boundaries. Intuitively, our method for finding counterfactual treatment areas relies on finding locations that are indistinugishable (to the algorithm) from CBRS lands at the time of designation (Englander, 2021; Pollmann, 2020).[3]

CBRS boundaries do not follow traditional administrative boundaries; they were hand drawn to follow geomorphic and development features (U.S. Fish and Wildlife Service, 2022).[4] Our first step is to trace out potential counterfactual areas using an automated procedure that closely resembles this process. Informed by the delineation criteria for the CBRS set out in the August 16, 1982 Federal Register (Steel, 1982), we begin with 300m resolution gridded data on historical land cover, development levels, 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, within a CBRS unit (including both original units designated in 1982 and all units designated since then) or an otherwise protected area, and all grid cells within two kilometers (2km) of a CBRS unit (to avoid selecting control areas that may be "treated" by spillover effects of CBRS units). We then apply a machine learning technique known as regionalization to group these pixels into spatially contiguous areas that share similar attributes (Guo, 2008).[5] The resulting spatial clusters serve as the pool of potential counterfactual units.

[3] Pollmann (2020) proposes a similar method for identifying counterfactual locations for spatial treatments that take the form of points. However, while his approach uses convolutions neural networks to identify candidate counterfactual point locations that are statistically indistinguishable from treatment locations, our approach is concerned with developing an algorithm that mimics the process of drawing the boundaries of place-based treatments by outlining contiguous areas that resemble treated locations. In this sense, our design is more closely related to Englander (2021), who uses spatial clustering to identify potential fishing closures in an assessment of a policy aimed to reduce the harvest of juvenile fish in Peru's anchoveta fishery.

[4] The August 16, 1982 Federal Register sets out the definition and delination criteria for CBRS units. Only "undeveloped coastal barriers" were eligible for inclusion in the CBRS. The document reads, "A coastal barrier or any portion thereof shall be treated as an undeveloped coastal barrier... only if there are few manmade structures on the barrier or portion thereof and these structures and man's activities on the barrier do not significantly impede geomorphic and ecological processes" (Steel (1982), page 35701). Importantly, the definition includes the phrase "any portion thereof", meaning "the statutory definition does not require an entire coastal barrier be included" (Steel (1982), page 35708). This implies that natural resource managers could manipulate the boundaiares of CBRS units to exclude developed areas.

[5] See Appendix B for additional details on the regionalization procedure.

We narrow down the pool of potential counterfactual units using propensity score (PS) matching, a technique designed to reduce selection bias in observational studies by balancing covariates across treatment and control groups. First, we limit our sample to coastal areas that would have met the basic requirements for inclusion into the CBRS by conducting a three-to-one match based on land cover, development levels, and elevation. The results of this procedure are illustrated in Figure 2, where CBRS areas (left) are shown beside matched counterfactuals (right). The algorithm effectively acts as a natural resource planner would have — tracing out low elevation coastal lands that had high shares of wetlands and beaches (barren), while avoiding highly developed areas.

Next, to ensure that the counterfactual areas closely resembled the treatment areas at the time of CBRS designation in 1982, we conduct a second match on a wide range of observable socioeconomic characteristics around the time of designation, including measures of infrastructure density, proximity to urban centers and protected areas, and sociodemographic characteristics. This allows us to determine a set of propensity score weights that balances the treatment and counterfactual areas across a wide range of observable characteristics (see Table 1 for the full set of characteristics). We find that overlap weights are best suited to our context (Figure A2). Overlap weights are proportional to the probability of an area belonging to the opposite treatment group (Li et al., 2018). 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 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.[6]

Our empirical strategy requires ensuring that CBRS and control areas were comparable at the time of designation, while allowing for, and measuring, divergence in outcomes over the four decades since based on treatment status. We therefore limit our sample to the original set of CBRS units designated in 1982, and all data used in the process of generating counterfactuals comes from as close to this year as possible (and no later than the year 1990). Data sources and processing techniques are described in detail in Appendix A.

The locations of all CBRS and counterfactual units included in our sample are shown in Figure A1. We include control areas in all 18 Atlantic and Gulf coast states, although four of these states (MD, NH, NJ, and VA) did not have any units in the original CBRS. Because some states had a limited pool of undeveloped coastal areas in 1982, our procedure does not require that the distribution of control units matches the distribution of treatment units across states. However, we do balance treatment and control units across three broad regions — the North Atlantic, South Atlantic, and Gulf Coast — to avoid making inappropriate comparisons between, for example,

[6]Because outcome data from the Zillow Transactions and Assessment (ZTRAX) Database (property sales prices and characteristics) are incomplete — only about half of treatment and control units have one or more parcels in the database — we calculate a separate set of overlap weights for the ZTRAX outcomes. Balance is shown in the right panel of Figure A2 in the Appendix.

	CBRS (1)	**Controls** (2)	**Coastal** (3)	**SMD** (4)
Land cover & geography:				
Elevation (m)	1.8	1.8	6.3	0.029
Distance to coast (m)	46	56	1002	0.005
Beach/barren (%)	22.3	30.1	1.4	0.062
Cropland (%)	0.4	0.5	10.6	0.034
Developed (%)	6.8	7.2	18.4	0.147
Grass/shrub (%)	3.0	3.0	2.8	0.013
Tree cover (%)	3.6	3.4	14.4	0.019
Water (%)	28.6	24.9	11.2	0.028
Wetland (%)	35.2	30.9	41.3	0.014
Development pressures:				
Population density (persons/km2)	0.19	6.30	1.16	0.005
Commuting-distance urban population (millions)	1.7	1.7	1.4	0.060
Road density (km/acre)	0.11	0.12	0.89	0.100
Bridge density (m2/acre)	0.19	0.04	0.29	0.017
Protected area (%)	11.2	18.3	12.5	0.020
Socio-demographics:				
Median household income (thousand USD)	35.4	27.8	29.1	0.056
Below poverty line (%)	10.0	11.7	20.1	0.022
Female (%)	48.2	49.3	51.4	0.006
White (%)	89.5	91.2	59.7	0.040
Black (%)	4.1	5.6	22.5	0.045
Hispanic (%)	2.5	1.6	24.8	0.021
College degree (%)	21.0	12.5	15.5	0.044
Employed (%)	44.0	43.8	44.7	0.032
Unemployed (%)	2.3	2.8	4.3	0.004
Observations	167	448		
Effective Sample Size (using overlap weights)	106	192		

Table 1: **Covariate balance across CBRS treatment units and constructed controls.** We assess the success of our procedure for identifying counterfactual areas by comparing the unweighted mean characteristics of CBRS units (column 1) and counterfactual units (column 2). For comparison, we also show the mean characteristics of all areas within 2 km of the coastline (column 3). Data are for all US states on the Atlantic and Gulf Coasts. Column 4 shows the standardized mean difference (SMD) between treatment and control areas using overlap propensity score weights.

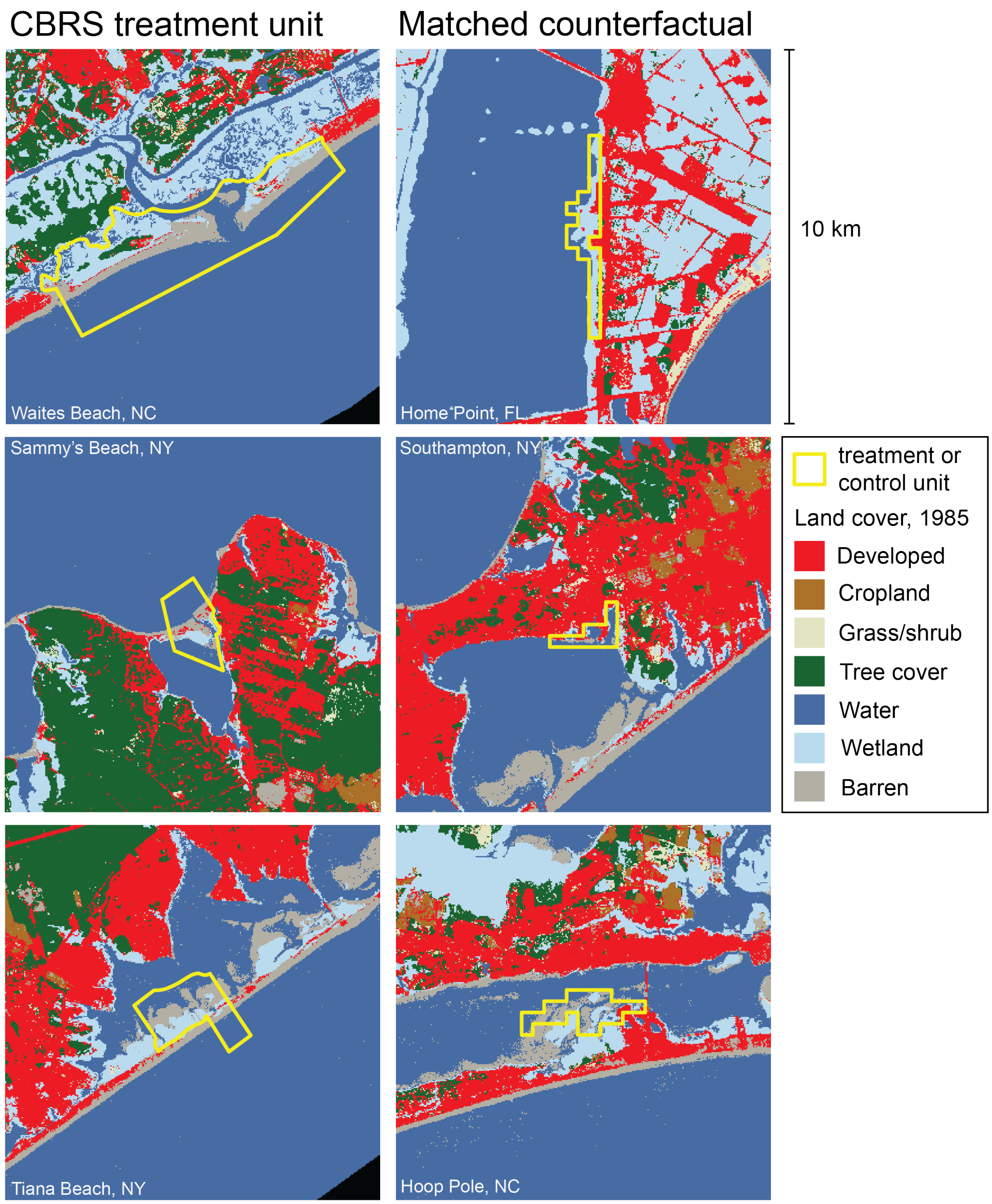

Figure 2: **Example treatment and control areas.** Here we show three CBRS units (left column) beside matched counterfactual areas (right column). Counterfactual units are constructed using a spatial clustering algorithm based on land cover, elevation, and distance to coast. We then match with CBRS treatment units based on development pressure.

coastal areas in Maine and Mississippi.

Table 1 assesses the success of our procedure for constructing counterfactual areas by comparing the mean characteristics of CBRS treatment (column 1) and counterfactual areas (column 2). For comparison, we also show the mean characteristics of all areas within 2km of the coastline (column 3). CBRS units are significantly different than the average coastal area in 1982, with less developed area, lower populations, and less infrastructure. Encouragingly, the matching procedure brings the observable characteristics of CBRS treatment and counterfactual areas into alignment. With the use of overlap weights, the standardized mean difference between CBRS and counterfactual areas is at or below 0.1 (the commonly used threshold for accessing balance) across more than 20 covariates.

2.2 Outcomes

We examine two sets of outcomes related to the removal of development subsidies: direct effects within CBRS units and spillover effects in neighboring communities. All outcomes are measured using the most recent data available (2010 onwards) such that we capture the long-term effect of CBRS designation.

Direct effects include impacts on development levels, land values, and composition of the housing stock and population. We measure development levels using two different data sources. The first measure is the number of structures per acre, calculated from Microsoft Map's Building Footprint database. This dataset provides approximately 130 million computer generated building footprints derived from satellite imagery for the entire United States. The second measure is the percent of land classifed as "developed" according to the USGS's Land Change Monitoring, Assessment, and Projection (LCMAP) data product. LCMAP defined developed land as "areas of intensive use with much of the land covered with structures (e.g., high-density residential, commercial, industrial, mining, or transportation), or less intensive uses where the land cover matrix includes vegetation, bare ground, and structures (e.g., low-density residential, recreational facilities, cemeteries, transportation/utility corridors, etc.)" (USGS, 2022). We measure land values using property sales prices and assessment values from the Zillow Transactions and Assessment Database (ZTRAX). The ZTRAX dataset also provides information on the composition of the housing stock (e.g. lot size, year built, square footage, number of bedrooms). We evaluate the composition of the population using census block-group-level 5-year estimate (2016-2020) from the American Community Survey (ACS). Building footprints and ZTRAX data points are assigned to CBRS units by intersecting the geocoded polygons and points with CBRS boundaries. To calculate census observations for each CBRS area, we aggregate the values from all census block groups that intersect a given CBRS unit using population weights calculated from high resolution gridded population data.

We also examine the effects of CBRS areas on neighboring communities. To do so, we draw a two-kilometer (2km) buffer around each CBRS unit and counterfactual area. In addition to

	Control (1)	CBRS (2)	Data source (3)
Sample for direct effects			
Buildings per acre	0.128	0.019	Microsoft
Percent developed area	0.092	0.040	LCMAP
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 2: **Outcome means within CBRS units and spillover areas, by treatment status.** 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 section 2.2.

the outcomes described above, we measure the impact of CBRS designation on flood damages in order to test whether preserving natural lands provides protective services from flooding. We measure flood damages using flood insurance claims from the National Flood Insurance Program (NFIP), the dominant insurer for flooding in the United States.[7] 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.

Summary statistics for our outcome measures are provided in Table 2. Column (1) shows the mean values in counterfactual areas and column (2) shows the mean values in CBRS units. All means are weighted by the overlap weights used in estimation.

2.3 Estimating equations

We estimate the direct effect of CBRS designation on our outcomes of interest using a simple weighted regression:

$$Y_i = \alpha + \beta T_i + \gamma R_i + \epsilon_i \tag{1}$$

where i indexes the CBRS or counterfactual area, Y corresponds to one of our outcome variables, T is an indicator equal to one if the unit is treated as part of the CBRS, and R is an indicator equal to one if the unit is located on a barrier island or cape. We weight each observation by the overlap weight, which is a function of its estimated propensity score determined following the matching procedure described in section 2.1. The treatment effect of interest, β, captures any systematic differences between the outcomes in CBRS and counterfactual areas.

To estimate the spillover effects of CBRS designations on neighboring communities, we turn to a spatial lag model. This allows us to capture heterogeneity in spillover effects by distance to the unit. The estimating equation is:

$$Y_{i,b} = \sum_{b=1}^{4} \beta_b \mathbf{1}[B = b] \times T_i + \gamma R_i + \epsilon_{i,b} \tag{2}$$

where the indicator $\mathbf{1}[B = b]$ is equal to one if the observation falls within distance band b relative

[7]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.

to the CBRS or counterfactual unit boundary. We use four distance bands, in increments of 500 meters, out to a total distance of 2km.

2.4 Impacts on local property tax revenue

We calculate the approximate impact of CBRS designation on county revenues from property taxes using the equation:

$$R_c = t_c \times \big(\beta_d^{AV} A_{c,d} + \sum_{b=1}^{4} \beta_b^{AV} A_{c,b}\big) \tag{3}$$

where R_c denotes the estimated effect of CBRS designation on property tax revenue in county c. The parameter β_d^{AV} is our estimated effect of CBRS designation on total assessed value per acre within the CBRS unit and β_b^{AV} is the estimated effect on assessed value within each distance band b of the CBRS unit. We multiply these estimated effects by the total acreage within the unit, $A_{c,d}$, and in each distance band, $A_{c,b}$, respectively. Summing these values gives us an estimate of the effect of CBRS designation on total assessed value within the county (the term in parentheses). Notably, this estimate captures the direct effects within CBRS units and the spillover effects on neighboring properties, both in number and value of developed properties. To estimate the effect on property tax revenue, we then multiply by the county tax rate, t_c. This tax rate is derived from SmartAsset, which quantifies a county-level "effective property tax rate" using median property taxes.

3 Results

3.1 The direct effects of CBRS designations

As the primary goal of the CBRA was to discourage development within designated areas, we first examine the direct effect of the program on development and property characteristics on CBRS lands. Our results are shown in Table 3.[8]

We find that CBRS designation has a quantitatively large and statistically significant impact on building density. The number of buildings per acre is 0.11 lower in CBRS units than control areas. Taking the outcome mean in the counterfactual units as the baseline (Table 2), CBRS treatment reduces development density by about 85% below the levels in the counterfactual areas.[9] Consistent with fewer structures, we also find that CBRS units have 5 percentage points less land classified as developed area in the 2018 LCMAP. Overall, our results are consistent with prior work that

[8] In our primary specification we calculate heteroskedasticity robust standard errors. Table A1 shows the same estimates with bootstrapped standard errors.

[9] We use the overlap weights to calculate control means in order to ensure comparability with treatment areas.

Outcome	**Estimate**	**Standard error**	**p-value**	**Observations**
Buildings per acre	-0.110^{***}	0.032	0.001	612
Percent developed land	-5.0^{***}	1.6	0.002	612
Total assessed value per acre	$-190,763^{**}$	$83,095$	0.022	314
Land assessed value per acre	$-74,465^{**}$	$37,260$	0.047	314
Improvement value per acre	$-69,303^{***}$	$17,699$	< 0.001	314
Average property sales price	127,482	$256,748$	0.620	193
Average lot size (acre)	-0.997	6.968	0.886	309
Average year built	2.278	5.064	0.653	271
Average squared footage	601.7	438.4	0.171	261
Average bedrooms	0.381^{**}	0.184	0.040	228

Table 3: **The effect of CBRS designation on development and property values.** The direct effects are estimated as weighted differences of outcomes inside CBRS and counterfactual units. The estimation uses overlap weights constructed from land use, geography, development pressures, and sociodemographic variables. Statistical significance is based on robust standard errors: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

finds CBRS designations have been effective in curbing development inside the units. Compared to Branham et al. (2022), our estimate of the reduction in average development density is larger—85% versus 75%. This difference might be attributed to different research designs: Branham et al. (2022) compares narrow areas across CBRS unit boundaries to estimate a treatment effect local to these areas, whereas our estimate captures the treatment effect on all CBRS areas. We might expect the policy to have a smaller effect at boundary because the cost of extending existing infrastructure, such as roads and sewage lines, is less costly at smaller distances. Another key difference lies in the study area, which in this paper consists of all original units along the Gulf and Atlantic coasts, compared to five states in the previous study.

The lower development on CBRS lands might have implications for county property tax base. To understand these implications, we examine property assessment values and find that CBRS designation reduces total assessed value by approximately $191,000 per acre, which is more than 50% of the baseline and statistically significant. We also see similar levels of relative reductions when we break down the assessed value by land and improvement components. All three estimates suggest CBRS designations substantially decrease the property tax base on lands within the units.

It is notable that the relative decrease in assessed value is lower than that in building density, suggesting there could also be changes in the composition of homes inside the units. Next, we assess the effect of CBRS designation on property values. Our estimated effect suggests the average CBRS property sells for over $127,000 more than the average control property. However, the estimate is noisy and statistically insignificant. Notably, it is based on only 193 units with non-missing values and could be subject to selection issues (e.g., only the nicest properties are sold) or biased because the overlap weights might not produce a balanced treatment-control comparison in this subsample. We also examine whether the CBRS has an effect on the characteristics of properties. We find limited evidence of systematic differences in the characteristics of properties in CBRS and counterfactual areas, with CBRS homes having 0.4 more bedrooms on average than those in the counterfactual areas, but no significant difference in lot size, year built, or square footage.

Overall, our findings show that withdrawing federal incentives through CBRS is effective in pre-empting development on designated lands. As discussed by Bagstad et al. (2007), our nation's existing structure of taxes, subsidies, and insurance leads to implicit subsidies that have encouraged the over-development of disaster-prone coastal areas, degraded natural capital, and fostered economic inequality. A small but growing body of studies have provided empirical evidence of perverse incentives associated with the federal flood insurance provision and wildfire suppression efforts (Cordes and Yezer, 1998; Kousky and Olmstead, 2010; Peralta and Scott, 2019; Craig, 2019; Browne et al., 2019). Our findings provide some of the first causal evidence on the efficacy of removing such financial incentives. Importantly, the magnitude of our estimates highlights the central role of these federal incentives — without them, most development would not have occurred.

While CBRS has been effective so far, it is unclear whether the it will continue to stave off development in risky areas as demand for coastal properties continues to grow in the United States. It is also of interest whether new CBRS designations in areas under high development pressure would be effective. To provide some insight into this question, we re-estimate the effect of CBRS designation on buildings per acre and percent developed land separately for CBRS lands under low versus high development pressure. We define high development pressure as those areas most likely to see large increases in development based on pre-policy observable characteristics (see Appendix C for details). Our results suggest that the policy is highly effective at limiting development in both lands with high and low development pressure. We estimate that CBRS designation reduces the number of buildings per acre by 0.05 in low development pressure areas and 0.41 in high development pressure areas. When viewed in the context of overall development levels, which are greater in areas with high development pressure, the relative magnitude of the effects is similar. Across both low and high development pressure areas, the CBRS designation eliminates nearly all new buildings. A similar pattern holds for percent developed area; we find that CBRS designation virtually eliminates developed land in low development pressure areas and reduces it by more than 50% in high development pressure areas. One possible explanation for the discrepancy between the effect sizes for buildings per acre and percent developed land in areas with high development pressure is the construction of infrastructure other than properties, such as public beach facilities and parking lots.

3.2 The spillover effects of CBRS designations

Our results above show that lands designated as part of the CBRS have seen far less development than they otherwise would have in the absence of the program. In this section, we look at whether the program impacts extend to neighboring areas. More open space and natural lands in CBRS units might create spillover benefits such as amenity values and flood attenuation benefits. These benefits, in turn, might have encouraged development in spillover areas, which we will examine through three outcomes: building density, average home prices, and assessed values. We will also explicitly assess any potential flood protection benefits through two measures of flood damages based on claims in the National Flood Insurance Program: total claims per acre and total claims per $1000 coverage.

The results are shown in Figure 3. The top panel shows development and property value outcomes, most of which are positive. Specifically, CBRS units cause more dense development, higher property sales prices, and higher assessed values per acre in neighboring areas. In the case of development density, the effect is not statistically significant closest to the CBRS unit (within 500m), but becomes significant and increasing as distance increases. Specifically, within 1000-1500m and 1500-2000m of CBRS units, we estimate an additional 0.2 and 0.3 buildings per acre, respectively, representing 42% and 62% increases relative to the counterfactual means. Average sales prices and assessed values are highest closer to the CBRS units and decline with distance. Properties in the 0-500m and 500-1000m bands, for example, sell at a $90,000 and $170,000 premium, respectively, which is 23% and 43% of the counterfactual mean. Properties in the 1500-2000m distance band have average price effects that are close to zero. The assessed values of properties are about $130,000 higher in the 0-500m spillover distance band, which is about 50% of the baseline. The magnitude of the effects on assessed values decreases gradually with distance.

Impacts of the CBRS on flood damages in spillover areas are shown in the second panel of Figure 3. We find no impacts on flood insurance claims per acre within 1000m of the CBRS units, but a reduction at greater distances. In the 1000-1500m distance band, for example, the annual insurance claims are $164 less per acre and are statistically significant at the 10% level.

The per-acre measure of flood damages is influenced by the increase in development that we observe in spillover areas. In other words, flood damages per property may be lower but there are more properties per acre. The center (e) and the right-most panel (f) in the second panels of Figure 3 decompose these effects. Consistent with the increased development effect above, panel (f) shows that there are more buildings per acre in the Special Flood Hazard Areas of CBRS spillover areas compared to areas near our counterfactual units. On the other hand, panel (e) shows that CBRS indeed reduces flood claims by about $25-32 per $1000 of coverage, which represents a 21-27% reduction in flood damages, accounting for flood insurance uptake. This result suggests that at the property level, the CBRS is providing flood protection benefits to properties in the spillover area. The protection effect is likely generated by more natural lands inside the units acting as natural

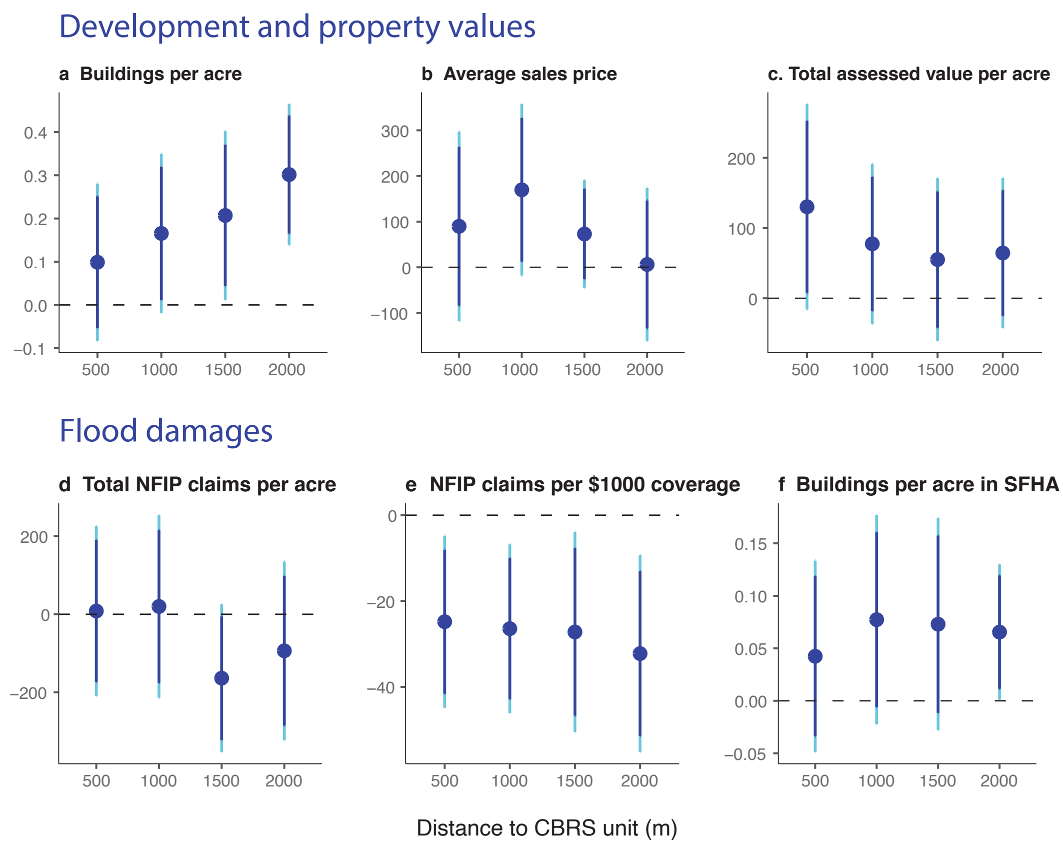

Figure 3: **Spillover effects on development and property values in neighboring communities.** This figure shows the spillover effects of CBRS designation in a 2km buffer area around CBRS units, estimated using a spatial lag model. Point estimates for each 500-meter band and the corresponding 90% confidence intervals are shown in dark blue, and the 95% confidence intervals are shown in light blue. The top panel shows three economic development outcomes, and the bottom panel shows three flood insurance outcomes.

barriers to dissipate and absorb waves before they reached the spillover areas, also in line with prior findings that wetlands are associated with reductions in damages from coastal storms and flooding (Costanza et al., 2008; Narayan et al., 2017; Sun and Carson, 2020; Taylor and Druckenmiller, 2022).

A back-of-the-envelope calculation based on these estimates shows that the original system of CBRS units designated in 1982 generates $46.6 million per year in savings for the NFIP in terms of reduced flood insurance claims, over 85% of which is from the spillover areas.[10] To provide a sense of magnitude, this figure represents approximately 3% of average annual NFIP claims in Atlantic and Gulf coast counties over the period 2009-2021.[11] For further context, the original units make up only 0.46% of land areas in these counties. If we assume the CBRS units added later along the Gulf and Atlantic coasts generate similar benefits, the total saving in the current system (excluding the Great Lakes region) would be $112 million per year, a 7% saving in average annual NFIP claims generated from removing federal financial incentives for development on only 1% of coastal lands in these counties.[12] With the caveat that these numbers are based on noisy estimates, we note that this finding complements the two existing studies of federal savings from CBRA, which focus on post-disaster assistance but not NFIP savings (Coburn and Whitehead, 2019; U.S. Fish and Wildlife Service, 2002). Coburn and Whitehead (2019), for example, estimate an average annual savings in disaster aid expenditures over the 1989 to 2013 period of approximately $396 million.

Overall, we find increased development levels and flood damage reduction for properties in the spillover areas. This is consistent with that natural hazards such as flood, wind, and erosion risk (e.g. Beltran Hernandez et al. (2018); Hino et al. (2017); Below et al. (2015); Zhang et al. (2010)) affect the desirability of coastal locations. It is important to note that the positive development effect might also be driven by natural amenities provided by CBRS lands beyond flood protection. A large hedonic literature on coastal housing markets have shown that environmental amenities, such as beach access, water views and water quality (e.g. Landry et al. (2022); Bin et al. (2008); Kuwayama et al. (2022)) also capitalize into property values. Our results add to the literature by demonstrating that natural lands need not be explicitly conserved to provide such benefits; it can be enough to simply not subsidize development in environmentally sensitive areas.

[10]To calculate NFIP savings, we follow equation (3) for the spillover areas by multiplying the point estimates of claims per acre by distance band with the acres of land areas in each band. For savings within the CBRS units, we calculate the average claims per acre across all counterfactual areas and multiply it by CBRS land areas.

[11]We adopt NOAA's definition of coastal shoreline counties: https://coast.noaa.gov/data/digitalcoast/pdf/defining-coastal-counties.pdf. Average annual NFIP claims in these 185 Atlantic and Gulf Coast counties over the period 2009 to 2021 was $1.85 billion.

[12]This number is calculated by separately scaling the saving within unit and that in spillover areas by overall unit and spillover areas and then summing them up.

Outcome	**Estimate**	**Standard error**	**p-value**	**Observations**
Share White	0.012	0.015	0.421	603
Share Black	-0.010	0.013	0.445	603
Share Hispanic	-0.003	0.010	0.767	603
Median household income ($)	$11,173^{***}$	$4,555$	0.014	582
Share college graduate	0.057^{***}	0.022	0.009	603
Share owner occupied	0.020	0.026	0.445	602
Share renter occupied	-0.044^{***}	0.014	0.002	602
Share occupied	-0.024	0.029	0.414	602
Median rent ($)	201.617^{***}	76.485	0.009	448
Median rent (% of income)	2.696^{*}	1.471	0.068	463

Table 4: **Effects on of socio-demographics of the population within CBRS lands.** The direct effects are estimated as weighted differences of outcomes inside CBRS and counterfactual units. The estimation uses overlap weights constructed from land use, geography, development pressures, and sociodemographic variables. Statistical significance is based on robust standard errors: *p < 0.1; **p < 0.05; ***p < 0.01

3.3 Demographic changes

The previous sections have shown that CBRS designations have significantly dampened development inside the units. Because CBRS designations transfer the costs of development and disasters to state and local governments and private property owners, the policy may attract homeowners who are more able to bear these costs. In neighboring areas, we find that CBRS designations have stimulated development and generated positive flood protection benefits. We also find higher prices for homes located close to CBRS lands, reflecting both the flood protection services and environmental amenities. We may expect these changes to alter the characteristics of the populations both inside the units and in the spillover areas. We analyze these changes using the 2016-2020 5-year ACS estimates aggregated from block groups to our study areas.

Table 4 reports the estimates on the effects of CBRS designations inside the units. There are no statistical differences in race and ethnicity between treatment and counterfactual units, but large and significant differences in income and education level. On average, the population in CBRS units earns $11,000 more in annual household income, which represents a 15% increase. The share of individuals with a college degree is 5.7 percentage points higher from a baseline share of 30.4 percent. When we turn to the characteristics of housing units, we find further that the share of rental units decrease by 4.4 percentage points. The median rent is $201 higher, and while income is also higher, the rent-to-income ratio increased by 2.7 percentage point. Again, all of these results are economically meaningful when compared to the counterfactual mean. Together, these results suggest that CBRS areas tend to attract affluent and educated homeowners and have become less affordable for renters. In general, this is consistent with the objective of CBRA to transfer costs in risky areas to those homeowners who can afford them.

Next, we turn to the spillover areas and estimate the effect of CBRS designations on population and housing characteristics using a spatial lag model. These results are shown in Figure 4. Panels (a) and (b) show that there is a slight increase in the share of White population around 2 percentage points and a decrease in Black population of similar magnitude, although these estimates are not statistically significant.[13] In panels (c) and (d), we find a large increase in the share of college graduates of more than 5 percentage points and an average increase in median household income of over $10,000. These demographic changes are similar to those in CBRS lands and appear to slightly increase with distance to the unit boundary, suggesting that the impacts might extend even beyond the 2km spillover distance. Also similar to the direct effect, we find that median rent increases by around $100 and the share of renter-occupied units decreases by 3-4 percentage points. Overall, it appears that the neighboring areas of CBRS also attract wealthier and more educated homeowners.

Given the evidence presented above that CBRS lands generate natural amenities and flood attenuation services, this demographic change could be interpreted as environmental gentrification (Fox, 2019). Environmental gentrification is a process in which reducing pollution or providing environmental amenities increases local property values and attracts wealthier residents. Several studies, almost exclusively in urban settings, find that community greening projects in less affluent neighborhoods can contribute to the displacement of existing residents and businesses (Maantay and Maroko, 2018; Crouch, 2012). Notably, in the spillover areas, unlike in the CBRS, flood insurance and disaster aid are still provided by the federal government. This highlights a policy tension. On one hand, the CBRS is effective in transferring the cost of developing in high risk areas to wealthier individuals who are better able to bear this cost. On the other, the policy raises environmental justice concerns because existing lower-income residents may be displaced after CBRS designation and the natural amenity and flood protection benefits generated by the program may then flow disproportionately to well-off individuals.

3.4 Fiscal impacts on counties

As described in section 2.4, we calculate the overall effect of CBRS designations on property tax revenues by combining the estimated effects on total assessed property values in both CBRS units and their spillover areas with current average county property tax rates. We find that decreased development in CBRS units results in a property tax revenue loss of $510 million per year. This decrease is largely offset by an increase in revenues in the spillover areas of $489 million per year, leading to a net loss of $21 million.

One concern that local governments may have is that they bear the cost of the CBRS in terms of lost revenues from less development, while neighboring jurisdictions may capture the benefits,

[13] We do not find any notable patterns in the share of Hispanic population. These results are not presented but are available upon request.

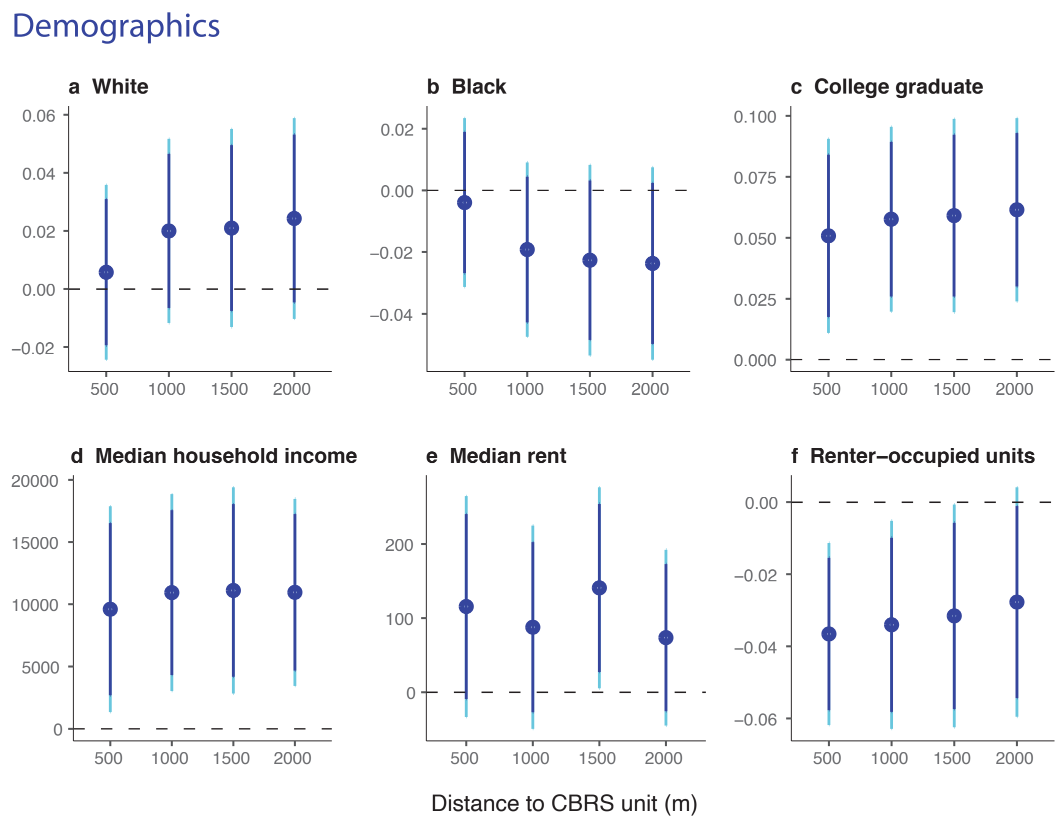

Figure 4: **Spillover effects on demographics in neighboring communities.** This figure shows the spillover effects of CBRS designation on a 2km buffer area around the units, estimated using a spatial lag model. Point estimates for each 500-meter band and the corresponding 90% confidence intervals are shown in blue, and the 95% confidence intervals are shown in light blue. The outcomes in panels (a)-(c) are the share of population that are White, Black, and college graduates, respectively. The outcome is median household income in panel (d), median rent in panel (e), and the share of housing units occupied by renter in panel (f).

the increases in revenues in spillover areas. We find this largely not to be the case. Of the $489 million increase in revenues in spillover areas, $425 million accrues within the same county where the CBRS unit was designated; only $64 million goes to neighboring counties. Overall, 54 of the 80 counties with CBRS units experience a net positive fiscal effect. We note that these estimates are based on average effective tax rates that might have some inaccuracies and thus should be viewed as approximate. Nevertheless, the calculations provide some evidence that the program likely does not have large negative fiscal impacts on local governments, and may even have benefits.

These findings are informative for coastal communities caught between, on one hand, increasing disaster costs, and on the other, the fiscal implications of limiting development in risky areas. Our calculation suggests that there is not necessarily a hard trade-off between the two objectives. Since conserving or restoring natural lands might provide positive benefits and raise property values in adjacent lands in the same jurisdiction, the pro-active land-use choices to limit exposure to natural hazards might not, as in conventional views, carry a high price in terms of fiscal impact.

4 Discussion

Coastal communities in the US are centers of economic development and home to critical natural resources but face significant threats from climate change and human development. Sea level rise and more frequent and severe coastal flooding threaten people, infrastructure, and ecosystems. At the same time, coastal environments are increasingly subject to development pressures, such as land use change, pollution and resource harvesting, that can interact with climate-driven changes to increase their vulnerability. These challenges are of particular concern since more than 40% of Americans and over $1 trillion in real estate value are located in coastal areas (Dahl et al., 2018). Policies that prevent damages to coastal communities and natural resources will be key to mitigating direct damages from climate hazards as well as their cascading economic impacts.

This paper investigates the efficacy of one approach to limiting populations and properties in harm's way — withdrawing the availability of federal funding and financial assistance. We find compelling evidence that in the case of the CBRS, this approach has been highly effective in achieving its primary objective of limiting development in disaster-prone coastal areas. We also find that CBRS units cause statistically significant and economically meaningful spillover effects in neighboring communities. We show that CBRS designation increases development levels and property values in adjacent lands, increasing the overall property tax base. We also provide quantitative evidence that by preserving natural ecosystems such as wetlands, CBRS lands provide protective services from flooding to nearby properties. To our knowledge, we are the first to document such spillover effects.

Methodologically, we contribute to the literature by developing a novel approach for identifying the causal effect of land use policies. Our approach uses machine learning to mimic the process by which natural resource planners designated CBRS boundaries in combination with matching techniques to ensure that CBRS units and our constructed control areas were comparable at the time of designation. We argue that this approach allows for causal interpretation of our results, lending confidence to their use in decision-making. Importantly, the procedure we develop can be applied more generally to other land use policies for which it is notoriously difficult to establish causal effects, such as the establishment of protected areas.

Our study has a few important limitations. First, although we believe our empirical approach represents a significant step forward in this literature, this is ultimately a retrospective analysis that relies on selection on observables. We cannot observe all factors that influenced CBRS designation in the early 1980s. Second, we estimate the average treatment effect of CBRS designation across all original units designated in 1982. However, we recognize that there is likely significant heterogeneity in the efficacy of the policy depending on surrounding social and natural systems, as well as the presence of state and/or local policies that either enhance or detract from the the policy. Third, our estimates do not capture the full range of benefits and costs associated with CBRS designation. Additional costs may include distortions to the spatial allocation of economic growth (Hsieh and Moretti, 2019), while benefits may include the provision of wildlife habitat, water filtration services, or recreation opportunities. While some environmental benefits may be captured in our estimates of the effect of the CBRS on local property values, it is reasonable to assume that not all benefits fully capitalize into property values (Keiser and Shapiro, 2019). Finally, we acknowledge that our back-of-the-envelope calculation of the impact of the CBRS on local property tax revenues is constrained by the difficulty of collecting accurate data on the property tax rates used by local governments.

Overall, our results indicate that the removal of federal incentives for development can be a cost-effective policy option for preventing over-development in risky areas. The CBRA is far less restrictive than many other land use policies; private development can still occur within the CBRS, as long as developers, homeowners, and other non-federal parties bear the full cost. It is also less costly, since the government does not invest in conservation but rather reduces expenditures on federal outlays for infrastructure and disaster assistance. It might therefore present a politically feasible policy option for limiting the number of people and properties in harm's way. Our results not only support the efficacy of the removal of federal funds in limiting development, but also indicate that such an approach can have a positive financial impact on local government revenues and provide co-benefits such as increased amenity value and protection from natural hazards in surrounding communities.

Our findings have the potential to inform a number of ongoing policy discussions. In April 2022, the U.S. Fish and Wildlife Service recommended that Congress add over 277,000 acres to the CBRS along nine states most impacted by Hurricane Sandy. Our estimates could serve as inputs into the cost-benefit analysis of this proposal. More generally, our estimates can inform state- and local-level decisions about zoning practices and government support for infrastructure development and repair in high risk coastal areas. Notably, our results apply to risky areas beyond just coastlines; a similar approach to managing development could be taken in inland floodplains or in wildfire-prone areas.

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Supplemental Information

A Data

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 an overview of the data sources used in this analysis and how these data are processed.

A.1 Regionalization

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 (USGS, 2022). 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. 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. 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.[14]

A.2 Matching

After we have identified spatial clusters using the regionalization algorithm, we must identify which regions were comparable to areas selected for CBRS designation in 1982. We expand our dataset to include measures of natural resources, 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 propensity scores for each unit. Here, we describe the construction of each covariate used in the matching process.

<u>Geography and natural resources:</u>

- **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.

[14] Although we have access to assessment data from ZTRAX, we are not able to include pre-1982 buildings in the regionalization process as there widespread missingness in these data, both in the presence of properties and the completeness of the year built variable.

- **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.

- **Barrier islands and capes.** For the purposes of controlling for whether the unit is located on a barrier island or cape in equations 1 and 2, 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.

- **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.

Infrastructure:

- **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.

Development pressures:

- **Socio-demographics.** We use sociodemographics at the block group level from 1990 U.S. Census data accessed through the National Historical Geographic Information System (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.

- **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.

A.3 Outcomes

- **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. 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.

- **Flood insurance claims.** We measure flood damages using the value of insurance claims paid by the National Flood Insurance Program between 2009 and 2021. These data are available at the claim-level from the NFIP Redacted Claims Dataset and the NFIP Redacted Policies Dataset. We construct a number of different measures of flood damages and flood insurance uptake: total NFIP claims per acre, NFIP claims per policy, NFIP claims per $1,000 of coverage, and NFIP policies per structure. The most granular geographic identifier available in these data is the property census tract. We aggregate the NFIP data to the unit level by weighting by number of buildings in SFHAs. This aggregation method is based on the assumption that the spatial distribution of NFIP policies and claims resembles the distribution of buildings in high flood risk areas.

- **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.

B 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" (Duque et al., 2007). 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 (Guo, 2008).

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 Heterogenity by development pressure

In this section, we test whether the impact of CBRS designation varies by the local degree of development pressure. To do so, we must first classify CBRS lands and counterfactual ares as being under low or high development pressure at the time of designation in 1982. Because we are unaware of any existing development pressure index that we could compute at a local level using the data we have available from the pre-policy period, we generate our own development pressure index that relies only on these data.

Intuitively, we classify an area as under high development pressure if, in the absence of policy intervention, it experiences large increases in the percent of developed area over our study period. To operationalize this concept, we build a simple model to predict which counterfactual areas undergo the largest increases in development over the period 1985 to 2020 based on their characteristics around 1985. We use a linear regression where the outcome variable is an indicator for whether the area is in the highest quintile (top 20%) of change in developed area and the predictors are the historical measures of land cover, geography, population density, infrastructure, proximity to urban centers, protected areas, and socio-demographics described in Section A. In the sample the model is trained on, we predict which areas experience the greatest increases in development with 83% accuracy (true positives = 57% accuracy, true negatives = 90% accuracy). Performance is similar in a held-out test set (overall = 86% accuracy, true positives = 60% accuracy, true negatives = 92% accuracy). Satisfied with model performance, we then apply this model to CBRS and control areas to predict which areas are under the highest levels of development pressure at the time of CBRS designation.

Next, we estimate heterogeneous effects of CBRS designation in areas with high versus low levels of development pressure. This requires re-estimating propensity score weights to ensure that our sample is balanced overall and within subgroups. To do so, we follow Yang et al. (2021) and expand the propensity score model to include interactions of all covariants with our indicators of development pressure. In order to allow for these interaction terms, we use a more parsimonious propensity score model. Specifically, we include the following pre-policy characteristics in the model: percent developed area, percent wetland, percent barren, percent water, elevation, distance to coast, area, region, population density, road density, percent protected area, proximity to urban center, median household income, and percent white. Covariate balance for this model is shown in Figure A3. We then estimate the heterogeneous effect of CBRS designation in areas with high versus low development pressure by interacting the CBRS treatment indicator T in equation (1) with our indicator for high development pressure.

Our results are shown in Table A2. We find that the absolute value of the effect of CBRS designation on development levels is smaller in low development pressure areas. We estimate that CBRS designation reduces the number of buildings per acre by 0.05 in low development pressure areas and 0.41 in high development pressure areas. The same pattern holds if we instead measure development using percent developed land cover from LCMAP. However, when viewed in the context of overall development levels, the relative magnitude of the effects is similar because areas with high development pressure have significantly higher average development levels. Indeed, we estimate that CBRS designation effectively eliminates nearly all new buildings in both low and high development pressure areas. Turning to percent developed area, we find that CBRS designation virtually eliminated developed land in low development pressure areas and reduces it by more than 50% in high development pressure areas.

D Supplemental Figures and Tables

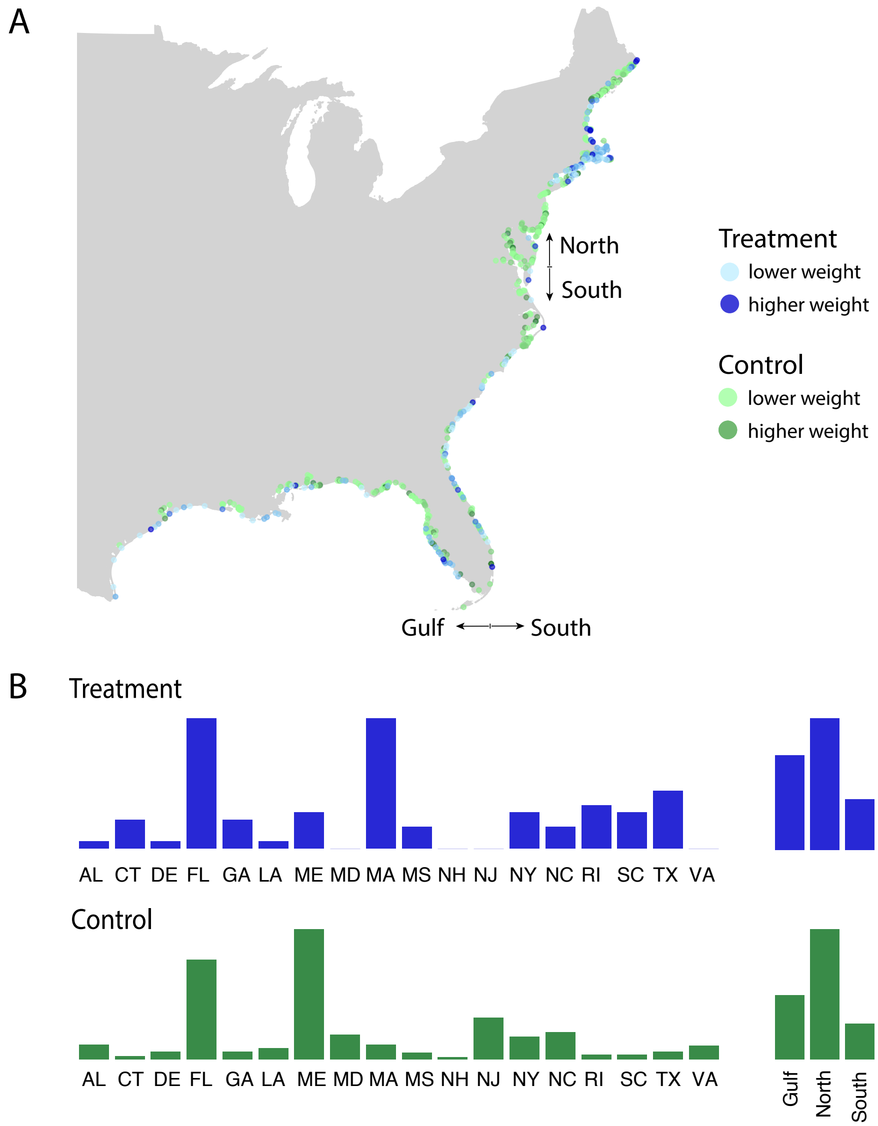

Figure A1: **Geographic distribution of treatment and control units.** Panel A maps CBRS treatment units (blue) and constructed controls (green). The shading of the point corresponds to the overlap weights used in our regression analysis, with lower weights (less relevant observations) indicated by lighter shades and higher weights (more relevant observations) indicated by darker shades. Panel B shows the distribution of treatment and control units across states (left) and regions (right).

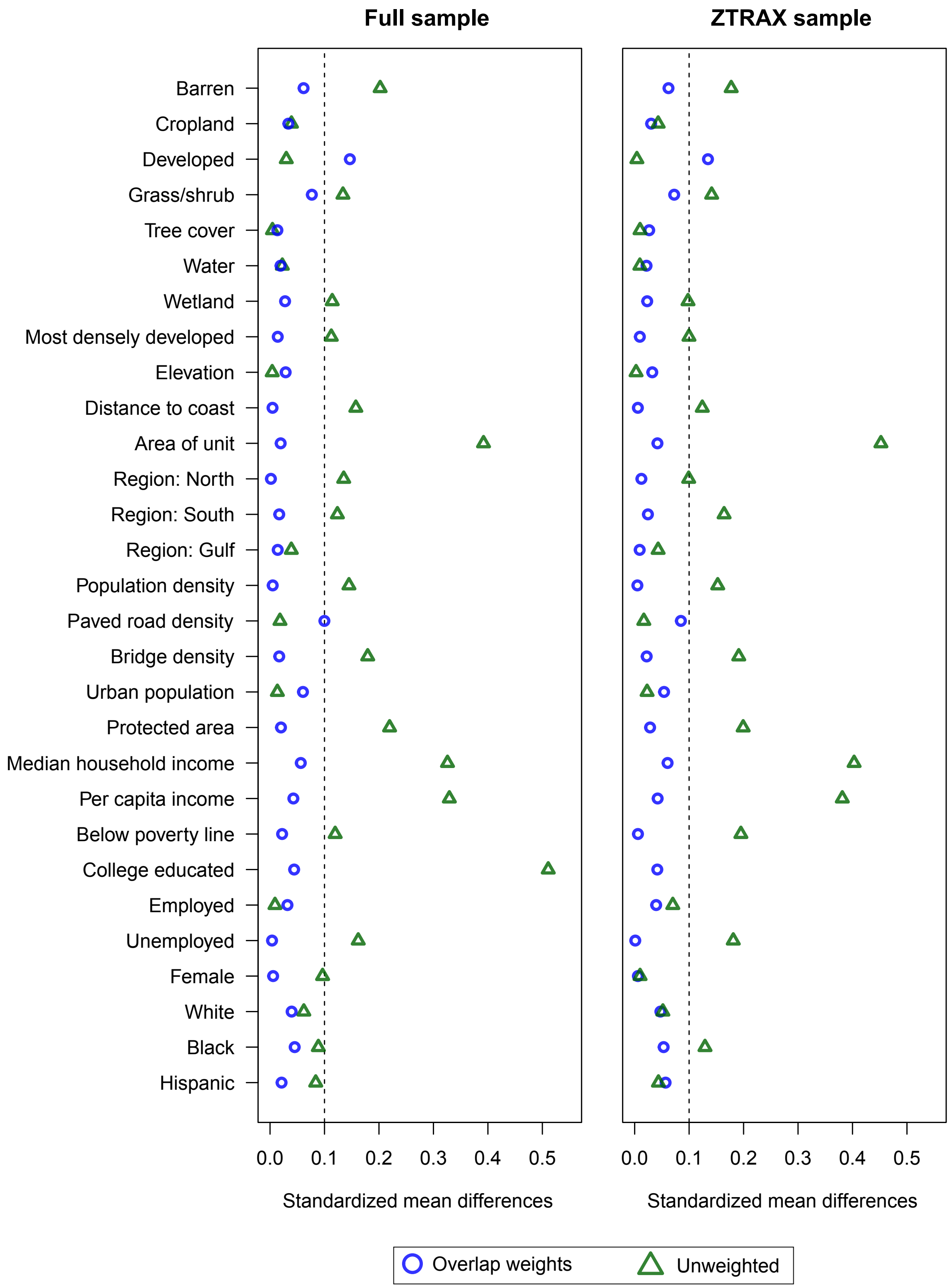

Figure A2: **Balance in weighted and unweighted samples.** This figure shows the standardized mean differences of variables on land use, infrastructure, and demographics between CBRS and counterfactual units. The left panel features full sample and the right features the sub-sample with non-missing ZTRAX observations.

Outcome	**Estimate**	**Standard error**	**p-value**
Buildings per acre	-0.110^{***}	0.031	0.000
Property sales per acre	-0.063^{**}	0.028	0.024
Average property sales price	127,482	248,276	0.608
Total assessed value per acre	$-190,763^{**}$	82,875	0.022
Land assessed value per acre	$-74,465^{**}$	36,534	0.042
Improvement value per acre	$-69,303^{***}$	17,869	0.000
Average lot size	-0.997	6.780	0.883
Average year built	2.278	5.253	0.665
Average squared footage	601.7	434.2	0.167
Average bedrooms	0.381^{**}	0.187	0.043
Share White	0.012	0.016	0.430
Share Black	-0.010	0.013	0.444
Share Hispanic	-0.003	0.010	0.767
Share college grad	0.057^{***}	0.021	0.008
Median HH income	$11,173^{**}$	4,368	0.011
Share owner occupied	0.020	0.026	0.444
Share renter occupied	-0.044^{***}	0.014	0.002
Share occupied	-0.024	0.029	0.410
Median rent	201.6^{***}	74.5	0.007
Median rent (% of inc.)	2.696^{*}	1.433	0.061

Table A1: **Estimation of direct effects with bootstrap standard errors.** This table reports the bootstrapped standard errors of estimates in Table 3. Statistical significance: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

	Estimate	St. Err.	p-value	N	Control mean
Buildings per acre					
Low development pressure CBRS units	-0.05	0.01	0.00	596	0.06
High development pressure CBRS units	-0.41	0.09	0.00	596	0.37
Percent developed land					
Low development pressure CBRS units	-0.04	0.01	0.02	596	0.04
High development pressure CBRS units	-0.13	0.04	0.00	596	0.25

Table A2: **Heterogenous effects of CBRS designation by local levels of development pressure.** See above text for details. Statistical significance is based on robust standard errors: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

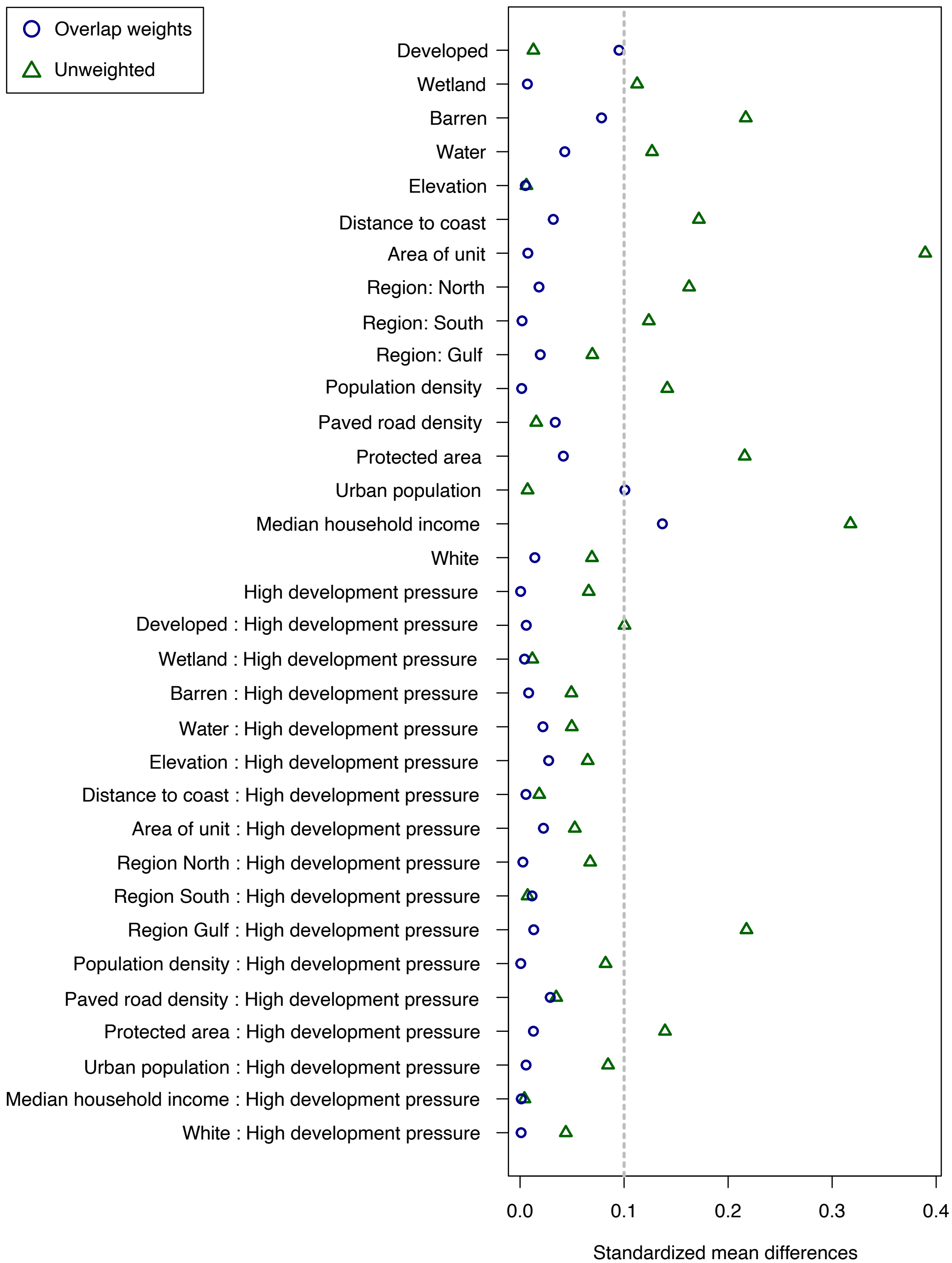

Figure A3: **Balance in low and high development pressure subgroups.** This figure shows the standardized mean difference of variables on land use, infrastructure, and demographics between the CBRS and counterfactual units in the model designed to achieve balance both in the overall sample and within high and low development pressure subgroups.