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The Impact of the Conservation Reserve Program on Nearby Property Values

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The Impact of the Conservation Reserve Program on Nearby Property Values*

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Abstract

Conservation programs are often viewed as competing with local economic activity, yet they may also generate environmental amenities for nearby communities. We estimate how land enrolled in the Conservation Reserve Program (CRP)—the largest US payments-for-ecosystem-services program—affects residential property values. Using nationwide field-level CRP data from 2012–2022 linked to residential property transactions, we apply a repeat-sales hedonic framework to identify how changes in nearby CRP land influence home values. We find that CRP enrollment meaningfully raises residential property values: a 10-hectare increase in CRP land within 1,000 meters raises home values by about 1.6 percent, with especially strong effects for land converted to tree cover. Placebo and robustness tests indicate that results are not driven by county-level economic trends or development pressure. In aggregate, our estimates imply that property value benefits attributable to CRP lands are equivalent to \$775-900 million per year, highlighting local benefits beyond payments to participating landowners.

Classification: Social Sciences; **Keywords:** Payments for Ecosystem Services, Land Conservation, Environmental Amenities, Hedonic Pricing

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1 Introduction

Conservation is often perceived to be at odds with economic activity. Payments-for-ecosystem-services (PES) programs have been promoted as a way to ease this tension by providing landowners with financial compensation for setting aside land or adopting environmentally beneficial practices. Because participation is voluntary, those who enroll do so only if it improves—or at least does not reduce—their own welfare. However, PES programs can have spillover effects beyond those who participate directly. Using land for conservation may depress rural economies by reducing outputs, employment, and demand for support services from agriculture, forestry, or other land-based industries. These potential harms may be offset by diffuse local benefits, including improved environmental quality, recreational amenities, and landscape resilience to erosion, extreme weather, and ecological disturbances. We estimate the effect of the Conservation Reserve Program (CRP), the largest and most longstanding US PES program, on nearby property values. We show that CRP enrollments generate measurable financial benefits for the broader community, not only participating landowners.

CRP pays farmers in ecologically sensitive areas to remove land from production and replace crop cover with native vegetation for 10–15 years to provide environmental benefits. Since the program was inaugurated in 1985, it has faced concerns that such removal may negatively impact rural economies. Areas with high CRP enrollment may see reduced demand for agricultural labor and for the products and services of farm-related businesses. CRP could also lead to outmigration if enrollment increases absentee land ownership.

On the other hand, successful PES programs may generate ecosystem services that enhance agricultural productivity or local amenity values, which could benefit local economies. One of CRP’s primary objectives is to limit erosion on marginal croplands. A large scientific literature demonstrates that taking marginal, degraded, or otherwise environmentally sensitive cropland out of production and establishing perennial, often native, vegetation in its place delivers a host of ecosystem services, including reductions in sediment loss, runoff, and flood damage to crops (Benayas et al., 2009; Zhou et al., 2014; Li et al., 2017; Kim, 2023). Moreover, CRP creates or restores wildlife and pollinator habitat, enhancing local recreational opportunities, and it may have aesthetic value (Fields et al., 2018; Ricigliano et al., 2019; Quinlan et al., 2021).

Whether the local benefits of PES programs outweigh any local economic harms is ultimately an empirical question; we seek to add to the evidence on this question for CRP. CRP effects on

amenities and local economic activity could have consequences both for home and land prices and for local wages (Roback, 1982). We specifically focus on consequences for nearby residential home prices, an outcome that has not yet been carefully studied. In the hedonic framework, these estimates capture how households implicitly value the environmental amenities (and disamenities) generated by CRP land, such as changes in landscape aesthetics, wildlife abundance, or air quality, through their willingness to pay for housing. We use comprehensive national data on residential home sales coupled with administrative data on field-level CRP enrollment to study the effects of changes in nearby CRP land on home sales prices.

Most studies quantifying the costs and benefits of CRP have relied on publicly available county-level data on enrollment. Field-level CRP data allow us to estimate regressions at the individual property level, enabling more credible causal identification of CRP’s effects. They also let us detect highly local effects, operating within a kilometer, that a county-level regression would obscure. Specifically, we use a repeat-sales framework, identifying the effects of CRP land on home prices based on properties that experienced changes in the amount of nearby CRP land over the study period (2012–2020). Cross-sectional hedonic regressions could be biased due to correlation between unobserved home attributes and CRP land area nearby; the repeat-sales strategy avoids such bias by identifying effects from within-property variation in home prices and nearby CRP land over time.

We find that CRP land has a significant positive effect on home prices. For each additional hectare of CRP land within a 1 kilometer (km) radius of the home, home prices increase by approximately 0.16 percent. This effect size more than doubles for increases in CRP land within 500 meters (m). We implement several tests to explore the internal validity of our estimates. First, we include time-varying controls that proxy for development pressure, a factor that could influence changes in both CRP enrollment and home values. Second, to test whether our estimates could be driven by unobserved time-varying variables correlated with CRP enrollment, such as local economic conditions, we construct a placebo test in which we reassign CRP land to properties within the same county that are not close to CRP lands. CRP effects estimated from these placebo regressions are small and statistically insignificant. Heterogeneity analyses provide further evidence of the plausibility of our estimates. CRP contracts specify what land cover type to convert enrolled land to. When we distinguish by land cover type, we find that the largest increases in property values are associated with CRP lands that are contracted to be converted to tree cover—highly visible and known to significantly boost nearby property values (Kovacs et al., 2022). Moreover,

the effect of changes in CRP land on property values is stronger for properties with longer between transactions, consistent with gradual establishment of vegetation on enrolled CRP land. Our estimates imply that one acre of CRP land increases nearby home values by \$1,000, on average. Across the universe of US properties, we estimate that CRP increases home values by \$6–7 billion.

Rather than conducting a comprehensive benefit–cost analysis for CRP, we seek to provide one critical input into such an analysis—a measure of the local amenity value generated by CRP lands. The benefits we report represent only a subset of the environmental benefits of CRP: local amenity values associated with improved views and recreation that are capitalized into nearby property values. For a comprehensive accounting of CRP benefits, ecosystem services that manifest farther downstream or more diffusely, such as wildlife habitat, water quality, air quality, and carbon storage, need also be considered. While this change in property values also factors into the net economic impact of CRP on rural communities, increased amenities must be weighed against any potential negative consequences for wages, although this may be due to a displacement of economic activity to other areas, rather than simply a reduction.

Much of the literature on economic consequences of PES programs has focused on poverty alleviation (e.g., IIED 2002)¹ and consequences for participating households. CRP is an important exception: extensive work dating to early in its history has the spillover effects of the program for communities, including effects on agricultural production, employment, and population. Early input–output modeling tended to find that economic activity in agricultural counties with high CRP enrollment would decline (e.g., Hyberg et al., 1991; Mortensen et al., 1990). However more recent econometric studies have found more mixed results, with effects varying by industry and negative local economic effects dissipating over time (Li and Ando, 2023; Sullivan et al., 2004). China’s Sloping Land Conversion Program,² another large land retirement PES program, has also been widely studied, with limited evidence of its consequences for regional economies (Liu et al., 2021) and off-farm employment (e.g., Liu et al., 2018).

A complementary gap exists with respect to the environmental benefits of PES programs: although the environmental benefits of PES programs have been extensively studied, post hoc monetary valuations remain rare.³ A few studies have evaluated CRP’s consequences for land values (e.g., Shoemaker, 1989; Wu and Lin, 2010), but they have tended to emphasize capitalization

¹However, an inherent trade-off between poverty reduction and environmental goals has been noted. For example, see Jayachandran (2023) and Alix-Garcia et al. (2015).

²It is also known as the “Grain for Green Program.”

³On the other hand, stated preference studies have frequently estimated prospective monetary values of hypothetical PES programs.

of option value of CRP participation into agricultural land values rather than the value of amenities to nearby residential properties. Studies have also used county-level data for both land values and CRP enrollment, which may attenuate estimates. Our study also relates to the broader literature valuing land conservation and especially to work using hedonic methods to measure conservation benefits, which includes studies focusing on the value of tree cover (see [Siriwardena et al., 2016](#), for a review), open space (see [McConnell et al., 2005](#)), and role of development rights (e.g., [Chamblee et al., 2011](#)). Furthermore, as our findings highlight the value of improved environmental amenities as part of the CRP’s benefits, our paper also connects to the literature on how environmental amenities relate to economic and population impacts (e.g., [Banzhaf and Walsh, 2008](#); [Gillespie et al., 2024](#); [Weber et al., 2026](#)).

2 Background

CRP was established by the Food Security Act of 1985 (the “Farm Bill”) to assist cropland owners and operators in conserving soil and water resources on their lands. In exchange for a rental payment—which today averages about \$72 per acre nationwide ([USDA FSA, 2025](#))—the landowners would enter into 10–15-year contracts in which they would agree to forgo agricultural production, harvesting, and grazing on the land and establish an approved vegetative cover, specified within each contract by a “practice number.” To be eligible, fields must have been planted in at least four of the previous six crop years and be “environmentally vulnerable.”⁴ When CRP was first established, it focused on erosion control by establishing perennial cover. Later farm bills approved practices related to establishing riparian buffers, wetland conservation, and wildlife habitat. An extensive literature has uncovered a variety of ecosystem benefits created by CRP, including reduced soil erosion ([US Department of Agriculture, 2025](#)), increased soil carbon and nutrient retention ([Li et al., 2017](#); [Zhou et al., 2014](#)), and improved wildlife and pollinator habitat ([Fields et al., 2018](#); [Ricigliano et al., 2019](#); [Quinlan et al., 2021](#)). The most common conservation practices on CRP land during the study period are summarized in Table B.2.

Landowners can enter into CRP contracts in three ways: the General Sign-Up, Continuous Sign-Up, or Grassland Sign-Up. The General Sign-Up, held annually, is competitive; land is assigned an Environmental Benefits Index score, which weighs cost and the environmental benefits, and bids above a cutoff determined by available acreage capacity are accepted ([Hellerstein, 2017](#)).

⁴Such land either scores eight or more on USDA’s Erodibility Index or lies in a designated conservation priority area, such as the Prairie Pothole waterfowl region across most of the Midwest ([Stubbs, 2022](#)).

The Continuous Sign-Up, established in 1996, allows enrollment at any point in time, but applies more stringent eligibility criteria focused on high-priority lands such as riparian buffers, grassed waterways, filter strips, and wetland restoration. The Grassland Sign-Up, the most recent mechanism, focuses on conserving existing native grasslands; however, because it does not require a landcover change, we omit its land from this study. Today, CRP is roughly evenly split across the three enrollment mechanisms.⁵

CRP participation, particularly in terms of whole-field enrollment, tends to be highest in areas where cropland is marginal and the returns are more favorable than cropping. Panel (a) of Figure 1 shows that counties with highest shares of CRP land are concentrated in the Great Plains, especially in the southern Plains region and Dakotas, as well as in Iowa, Missouri, Minnesota, and eastern Washington also have high participation. To minimize impacts on rural economies, the program limits enrollment to at most 25 percent of cropland in a county at any time, though this constraint rarely binds in practice (U.S. Department of Agriculture, Farm Service Agency, 2024). Enrollment peaked in 2007, when 36.7 million acres were included within the contiguous United States (Figure B.1), declined through the 2010s due to a combination of rising crop prices and decreased enrollment caps⁶ Since reaching a low of 18.3 million acres (not including acres enrolled in the Grassland CRP program) in 2021, enrollment has recovered slightly, perhaps in part due to modest increases in incentives.

3 Data

We obtained geospatial data of all CRP parcels through collaboration with USDA. Files contain the boundaries of all Common Land Units—individual contiguous farming parcels delineated by the Farm Service Agency—actively enrolled in CRP nationwide each year from 2012 to 2022. Attributes for each observation include contract number, expiration date, and practice number, which describes the specified conservation practice agreed to within each contract. We dropped parcels in the Grassland CRP program because it does not change land cover. For each enrollment year, we removed parcels with duplicate records or implausible contract expiration dates and created persistent parcel identifiers to track enrolled fields consistently through time (see Appendix section A.1.1 for more details). The lower panels of Figure 1 illustrates the field-level CRP data. Whereas

⁵As of June 2025, 7.8, 8.4, and 9.7 million acres were enrolled via the General Sign-Up, Continuous Sign-Up, and Grassland Sign-Up, respectively (US Department of Agriculture, Farm Services Agency, 2025).

⁶The 2008 farm bill reduced the enrollment cap to 32 million acres, and the 2014 farm bill reduced it to 24 million acres (Congressional Research Service, 2019).

most empirical studies of CRP used county-level data (e.g., the upper panels of Figure 1), Panel (c) of Figure 1 shows transactions of residential properties and subcounty geographic variation in the locations of enrolled fields (as of 2018). Panel (d) zooms in to a portion of the county to show the field-level polygon data, which indicate precisely which areas were enrolled in a given year.

Within CRP, specific land management practices are assigned to each contract in accordance with environmental goals and outcomes. We use information from the CRP data on the land management practice (“practice number”) associated with the contract to identify the land cover outcome of each parcel. We classified each practice into grass, trees, wetland, and “various,”⁷ based on the most common resulting land cover.

We combined data on enrolled CRP land with data on residential property transactions 2012–2022. From CoreLogic, Inc., we obtained property transaction and county assessors’ data for individual parcels across the United States. Before analysis, we filtered the owner transfer dataset to retain only residential property transactions and merged the owner transfer and assessors’ datasets using a property identifier.⁸ We then cleaned the merged dataset to remove transactions with unusual or outlier sales prices or price changes. First, we removed any transactions of a given property occurring before records of any significant property changes (i.e., new construction or new buildings). Second, to eliminate speculation-driven transactions, we removed any records that occurred within 365 days of another transaction record for the same property. Third, we removed sets of transactions with average jumps in price per year of more than 50 percent. Finally, we removed transactions with sale prices in the top and bottom 1 percent within each state.

For each transaction, we then calculated a series of variables describing changes in CRP enrollment and land cover nearby (see Appendix A.1.2 for more details). First we calculated total enrolled CRP within 500 m and 1,000 m using versions of the annual CRP data sets rasterized at a 50 m resolution to improve computational speed. We also calculated CRP within each transaction’s county in each year. Next, we classified CRP parcels based on the outcome land cover class specified by each contract’s conservation practice code, and we measured CRP land within

⁷Practice numbers associated with legacy practices that involved few enrollments and de minimis acreage at the field level, such as erosion control structures, were dropped from analyses that categorize CRP land by outcome land cover.

⁸The owner transfer dataset includes transaction-level records for real estate sales; the property characteristics dataset contains detailed parcel attributes, including geographic coordinates, structural details, and assessed values. To create a comprehensive dataset, we first filtered the owner transfer data to retain only arm’s-length residential transactions, identified using property classification codes. We merged these records with the property characteristics data at the county level using a CoreLogic proprietary property identifier, ensuring that each transaction was linked to its corresponding property attributes.

500 m and 1,000 m contracted to be converted to grassland, trees, wetland, and various.⁹ Finally, to measure broader land cover changes beyond CRP parcels, we used the USDA Cropland Data Layer data set (USDA National Agricultural Statistics Service, 2022) to calculate land area in three broad landcover classes (agricultural, natural, and developed) within 500 m and 1,000 m of each property in each transaction year (see Appendix A.1.3 for more details).

Summary statistics for property transactions by the amount of CRP land within 1,000 m are presented in Table B.1. The first column describes properties with no CRP land within 1,000 m. The next four columns are by quartile of CRP land nearby, defined over properties with any CRP land nearby. Sales prices are lower and lot sizes greater among properties with nearby CRP land, likely because they are more likely to be in rural areas. The spatial distribution of transacted properties with enrolled CRP nearby is shown in Panel B of Figure B.1. Whereas CRP land is most concentrated in the western Great Plains region, our transactions of properties with CRP land nearby are more concentrated in the more densely populated region between Ohio and southern Minnesota.

4 Methods

We estimate the effects of CRP enrollment on residential property values using a repeat-sales hedonic approach. For each property i transacted in year t , we use OLS to estimate

$$\log(P_{it}) = \beta^d CRP_{it}^d + X'_{it}\theta + \alpha_i + \gamma_{s(i),y(t)} + \delta_{m(t)} + \varepsilon_{it}, \quad (1)$$

where P_{it} is the observed sales price, CRP_{it}^d is the number of acres of enrolled CRP land within distance d in year t , and X_{it} is a set of time-varying controls. The property fixed effect α_i controls for the effects of time-invariant property characteristics (e.g., lot size, square footage, number of bedrooms) on price. It can only be identified for properties with multiple observed sales, and its inclusion is the key feature of a repeat-sales hedonic model. Our main specification also includes state-by-year effects, which control for price shocks common to properties within a given state in a given year, and month-of-year fixed effects, which account for seasonal variation in home prices.

The coefficient of interest β^d is identified based on variation in prices of homes that experience changes in the amount of enrolled CRP land nearby between transactions. The identifying assump-

⁹ CRP contracts assigned to the “various” land cover category were participants in the State Acres for Wildlife Enhancement (SAFE) program. The SAFE program includes CRP parcels converted to various landcover types depending on habitat needs.

tion is that, conditional on the included controls and fixed effects, changes in CRP enrollment are uncorrelated with other factors that could affect changes in price. Factors violating this assumption would need to vary within state and over time in a way that is correlated with both home prices and nearby CRP enrollment.

We use several approaches to test the possibility that such endogenous factors, rather than CRP enrollment, could drive our results. First, we include controls for potential time-varying confounding factors. Because the presence of CRP may be correlated with that of other open space, we control for non-CRP natural lands within the same buffer distance d , which isolates the marginal contribution of enrolled land above and beyond the baseline amenity environment. We additionally control for development pressure, as areas experiencing rapid development may be less likely to see increases in CRP enrollment, and homes may face greater upward price pressure. For this, we include county-level annual residential building permits from the US Census Building Permits Survey in X_{it} . Second, we employ a placebo test to assess whether unobserved county-level factors could explain the observed effects, described in detail in the following section. Third, in robustness specifications, we additionally control for CRP enrollment in the property’s county outside the buffer distance d , addressing potential bias from correlation between local and county-wide enrollment patterns.

We also use heterogeneity analyses to further explore the plausibility that CRP is driving our estimates and explore possible mechanisms. First, we examine how effects differ between positive and negative changes in nearby CRP land. Second, as the benefits of CRP enrollment may take time to fully materialize, we explore heterogeneous effects by time elapsed between home sales. Third, we examine how effects vary across CRP practices by outcome land cover category, as different cover types (e.g., wetlands, grasslands, forest) likely generate distinct amenity and ecosystem service profiles that buyers may value differently. Finally, we examine regional heterogeneity.

5 Results

5.1 Effects of CRP on Property Values

Our main findings regarding the effects of CRP enrollment on nearby property values are shown in Table 1. Column 1 of Panel A indicates, for example, that increasing the area of enrolled CRP land within 500 m of a given property by 10 hectares increases its property value by approximately 4.1 percent on average. Column 1 of Panel B indicates that increasing the amount of CRP land

within 1,000 m of a given property by 10 hectares increases its property value by about 1.6 percent on average.

As discussed in Section 4, these estimates could be biased if factors exist that both affect property values and vary over properties and time in ways that are correlated with the amount of nearby CRP land, such as population and economic growth and development pressure. Therefore, in Column 2 of Table 1, we add time-varying controls for population, income, total employment, and building permits, measured at the county level. After including controls in the regressions, our estimates of the effect of CRP enrollment on property values barely changed, suggesting that these factors are not driving our results.

We hypothesize that if other factors are correlated with CRP and not accounted for by our county-level control variables or property, state-by-year, and month-of-year fixed effects, they may also be correlated with changes in CRP land in the same county over time. Therefore, in addition to the controls included in Column 2, Column 3 includes a control for total county CRP land, from which we subtracted the corresponding CRP land nearby for the given property. After including county CRP, the estimated effects of nearby CRP decline only slightly and remain statistically significant. The coefficient on county CRP land is also positive and statistically significant; on its face, the magnitude of the coefficients indicate that increasing CRP in the same county by 10 hectares increases property values by about 0.001 percent.¹⁰ Plausible channels exist through which more distant CRP land could increase property values—for example, by improving water or air quality or supporting wildlife habitat. Although the county-level CRP variable likely captures some of these effects, we are cautious in interpreting the estimate as a causal effect of county CRP, as our identification strategy is primarily designed to capture the effects of nearby CRP on individual properties. We prefer to view county CRP as another control variable intended to capture factors that vary across counties and years in ways that are correlated with CRP; our coefficients of interest, the effects of nearby CRP land, are robust to its inclusion.

Notably, the CRP and non-CRP natural land coefficients are strikingly similar. That the CRP coefficients are slightly larger suggests that while the bulk of CRP’s amenity value is shared with natural land generally, enrollment generates an additional premium. This is consistent with CRP’s targeting of environmentally sensitive parcels and the management obligations that enrolled land must satisfy, which may produce higher-quality conservation outcomes than unmanaged natural

¹⁰Put another way, the estimates suggest increasing CRP in the same county by 10 sq. km increases property values by 0.1 percent.

land alone. It is also worthwhile to note that a fraction of the non-CRP natural land may have transitioned from crop production through virtue of earlier enrollment in CRP. While this does not affect our model specification; it does have implications for the cumulative benefits of the program.

5.2 Tests of Validity

To further explore whether unobserved county-level conditions could be driving our estimates, we perform a placebo test. For every property in the repeat-sales sample that experienced a change in CRP land nearby, we search for properties in the same county that sold in the same years and had no CRP land within 5,000 m in either year. When more than one match is found, we choose one at random. In the placebo regressions, these “control” observations, which have no CRP land nearby, are assigned the CRP changes of their matched “treated” observations, and the true treated observations are dropped.

Results from the placebo regressions are given in Columns 1 and 2 of Table 2. If unobserved factors varying at the county level were driving our estimates, we would expect these placebo estimates to be similar to our main results. However, the coefficients decline substantially in magnitude and become statistically insignificant. These regressions are based on a smaller sample whose treatment units have a slightly different geographic composition, because some treated observations could not be matched and were dropped from the sample. To confirm that the placebo assignment, rather than the change in sample, drives the diminished estimates, we re-estimate the model from Table 1 after dropping the treated observations that could not be matched, so that the treatment units have the same geographic composition as the placebo sample. Both are statistically significant and similar in magnitude to those in Table 1. Together, these results provide some confidence that unobserved county-level variables are not driving our estimated effects of CRP enrollment on property values.

We next perform a series of robustness tests and heterogeneity analyses to further check the validity of our estimates and better understand mechanisms underlying them. Table B.3 includes CRP within 500 m and 500–1,000 m in the same regression. The second column also includes county CRP (net of CRP within 1,000 m). Our estimates of the effect of CRP land within 1,000 m on property values are very similar to those reported in Table 1. Estimates of the effects of CRP land within 500 m decline but remain statistically significant, possibly due to correlation with CRP within 1,000 m.

Because the amenity benefits of CRP may take time to materialize as vegetation becomes

established, we examine how effects vary by time between sales in Table B.4, using a distance band of 1,000 m. Columns 1–3 correspond to intervals of 0–3, 4–6, and 7+ years, respectively. The estimated effect is positive and statistically significant across all columns and increases monotonically with the length of the interval. This pattern is consistent with gradual vegetation establishment and is difficult to attribute to confounding, which would not predict effects that systematically grow as enrolled land matures.

5.3 Heterogeneity

CRP contracts outline conservation practices required for each enrolled parcel, including the land cover to which land will be converted. Table 3 explores heterogeneity in the effects of CRP land across CRP parcels contracted to implement various land covers. Across the 500 and 1,000 m bandwidths, and across specifications that do and do not include county CRP land, nearby CRP most strongly increases property values when the contracted land cover is trees. We estimate that increasing CRP land with trees within 1,000 m by 10 hectares increases property value by approximately 3 percent on average. This estimate is about twice the overall average effect of CRP land on property values reported in Table 1. However, CRP contracts specifying tree cover are relatively uncommon. CRP land with grass cover within 1,000 m also has a positive and statistically significant effect, whose magnitude is slightly smaller than the average effect. We find positive but statistically insignificant effects for CRP lands converted to wetland or the “various” land cover category, the latter comprising parcels enrolled in the State Acres for Wildlife Enhancement program (see footnote 9). Both are relatively uncommon land cover outcomes in the program, which likely limits the statistical power of these estimates.

We also split the sample based on USDA Economic Research Service Farm Production Regions to consider heterogeneity across regions in the effect of CRP on property values (Figure B.5). CRP land within 1,000 m has strongest effects are observed in the South within the Southeast and Delta regions. This result is consistent with heterogeneity across land cover types in Table 3 since although CRP enrollment is relatively uncommon in the South (Figure 1), CRP parcels in the region are disproportionately converted to tree cover (Appendix Figure B.4).

In Table B.5, we examine differences between the effects of increases and decreases in CRP land nearby using separate terms in the regressions. Columns (1) and (2) show that within 500 m, increases in CRP land raise property values while decreases lower them, with the effect of

increases slightly larger in magnitude.¹¹ Similarly, columns (3) and (4) show that within 1,000 m, increases in CRP increase property values while decreases lower them, but in this case only the effect of decreases is statistically significant. This likely reflects the overall decline in CRP enrollment during our sample period, which produces more properties experiencing decreases than increases and thus greater statistical power for the former. Together, these results suggest that both increases and decreases in nearby CRP land contribute to the relationship observed in our main estimates.

5.4 Implications for Property Values

Finally, we put our main estimates into perspective by calculating the implied effects of CRP on prices of US homes in monetary terms. In Table 4, the first row of each panel calculates the average price effect for homes with CRP nearby using the difference between predicted prices based on the actual amount of CRP nearby and predicted prices assuming no CRP nearby.¹² Among properties with CRP nearby, Panels A and B imply that nearby CRP land results in an approximately \$2,000–2,500 increase in property values on average. Within our repeat-sales data set, approximately 3 percent of properties have CRP within 1,000 m. Consistent with this, the average price effect across all properties in the repeat-sales data set is significantly lower: \$30–35 for CRP land within 500 m and \$70–80 for CRP land within 1,000 m. Row 3 aggregates price effects of CRP land across all transacted properties in the Corelogic data set 2012–2022. We find that CRP has increased transaction prices by \$850–950 million when considering only CRP lands within 500 m. For those within 1,000 m, CRP lands have boosted transaction prices by \$1.8–2.1 billion. Not all single-family residential US properties were transacted during the study period; therefore, the final row in each panel of Table 4 extends our estimates to the full single-family set within the current CoreLogic property assessment data set. Because values of transacted homes may differ systematically from values of homes overall, we calculate a series of county-specific adjustment factors equal to the ratio of average assessed values among homes overall and homes for which we observe transactions. On average, this equals 0.815. We estimate total effects of CRP on each county’s property values as the average property value impact (from Row 2) multiplied by the adjustment factor and total number of properties in the county. The final row in each panel of Table 4 reports total impacts across all counties. Using this back-of-the-envelope calculation, we find that CRP land within 1,000 m may

¹¹Note that decreases in CRP land are recorded as negative values in this regression. Therefore, a positive coefficient indicates that a decrease is associated with a negative effect.

¹²Averages are calculated based on values and nearby CRP land for each property at the time of its most recent sale.

increase the values of US properties overall by around \$6–7 billion. Assuming a discount rate of 5 percent and that these impacts persist indefinitely implies annual flow benefits of \$300–350 million; assuming benefits are capitalized benefits over only a ten-year CRP contract horizon implies annual benefits of approximately \$775–900 million per year.

6 Discussion

A longstanding concern regarding CRP is that by removing land from agricultural production, it may result in lost jobs and perhaps even outmigration. Most evidence suggests that CRP enrollment results in employment declines within the agricultural sector, at least temporarily ([Sullivan et al., 2004](#); [Li and Ando, 2023](#)). However, PES programs can affect the welfare of participating communities in ways beyond their direct implications for the economic base. First, payments may more than compensate landowners for participation; to the extent that this is true, payments may provide an influx of income that benefits local economies. Second, if PES programs have their intended effect, they will increase production of ecosystem services, which can increase local amenity values.

We evaluate how increased amenity values due to CRP, the largest PES program in the US, are capitalized into nearby home prices. We find that CRP land significantly increases the price of nearby homes: a 10-hectare increase in enrollment results in an approximately 4 and 1.6 percent increase in the value of homes within 500 and 1,000 m, respectively. Our results have comparable magnitudes with recent estimates for permanent land conservation. For example, [Lang et al. \(2023\)](#) estimate that a 1-acre increase in conserved land within one-quarter mile of a home raises its value by 0.018 percent using Massachusetts data, implying a 0.44 percent increase per 10 hectares, which is closely aligned with our Northeast regional estimate (Figure B.5). Nationwide, our estimates imply that nearby CRP increases property values by \$775–900 million per year. For context, CRP’s 2023 budget was approximately \$1.8 billion, though most of that is a transfer to landowners rather than real resource costs, so the relevant social costs (e.g., administrative expenses) are substantially smaller.

These figures represent capitalization of local CRP amenities into housing prices, which is distinct from but informative about the program’s total social welfare effects. Our repeat-sales estimates identify the movement along the ex post hedonic price function, which [Banzhaf \(2021\)](#) shows is a lower bound on the sum of Hicksian equivalent surplus and the change in landowner

profits, under general-equilibrium price adjustment and household re-sorting. In his simulations, the bound recovers about three-quarters of true surplus, approaching it in the [Palmquist \(1992\)](#) local-externality limit, where treatment is too geographically isolated to shift the price function. Because only a small share of properties (about 3%) have any nearby CRP lands, our setting is close to this limit. The measure is nonetheless partial: it omits wage adjustment and incidence in a full Rosen-Roback system, as well as ecosystem services that are not capitalized into nearby homes, such as carbon storage and downstream water quality.

The amenities we capture are tied most directly to the immediate vicinity of CRP lands, such as aesthetic values, and only partially reflect the ecosystem services valued at broader scales (e.g., improved air and water quality, recreation opportunities, and wildlife habitat). Our regressions also suggest increases in CRP land farther than 1 km away but within the same county also increase property values. We are cautious in our interpretation of the effects of county-level CRP variables, as these could be correlated with other variables that vary at the county level over time. Taken at face value, they would raise the implied amenity benefits of CRP land considerably.

Like other PES programs, CRP has faced concerns regarding additionality (i.e., whether enrolled lands would have been left fallow even without the program). These concerns underscore a broader tension in PES design between targeting environmentally meaningful acreage and enrolling landowners who are willing to participate at feasible payment levels. Using regression discontinuity designs rooted in CRP’s competitive auction enrollment mechanism, [Aspelund and Russo \(2025\)](#) and [Rosenberg and Pratt \(2024\)](#) find that only 25–30 percent of CRP lands would have otherwise been cropped. However, their results can be more precisely interpreted as reflecting both additionality associated with the initial enrollment and practice persistence. Re-enrollments, which comprise most of the land in the program at any given time, have low additionality; however, this is not relevant to cumulative benefits as they typically accrue with initial enrollment and persist over time. The findings of both [Aspelund and Russo \(2025\)](#) and [Rosenberg and Pratt \(2024\)](#) may thus speak more to the cost effectiveness of re-enrollment than the benefits we estimate here. Moreover, even were additionality a concern, CRP requires land management practices beyond simply land retirement; ecosystem service flows for land retired absent the program may be lower than for the more intensive CRP-funded conservation practices.

Our results have direct implications for the ongoing debate regarding CRP’s future. Some lawmakers have proposed shifting conservation funding to other farm bill programs, but others seek to strengthen the program. Project 2025 proposed eliminating CRP altogether ([Dans and Groves,](#)

eds, 2023). A recent bipartisan bill, the “CRP Improvement and Flexibility Act,” was introduced in the Senate in July 2025 and the House in September to expand key provisions, including protecting wildlife habitat, improving grazing access, increasing payment limit, and allowing for emergency haying in response to drought. As these debates continue, our findings underscore the importance of accounting for CRP’s broader socioeconomic effects. In particular, its payment structure is still anchored in the opportunity cost of alternative land uses, with essentially no consideration of benefits, including amenities that accrue to rural communities. Recognizing and incorporating these local welfare gains along with conservation benefits more generally could help CRP become a bonafide PES program responsive to rural development objectives.

More generally, our results illustrate how PES programs can generate meaningful place-based value beyond their direct environmental outcomes. This is particularly relevant given the persistent tension in PES design between setting land aside for conservation and maintaining the economic uses that land might otherwise support. These insights suggest opportunities to design PES programs that better leverage amenity benefits to ease that tension.

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Table 1: Estimated Effect of Changes in Nearby Enrolled CRP Land on Residential Property Values

<i>A. CRP within 500 m</i>			
	(1)	(2)	(3)
CRP nearby (hectares)	0.0041*** (0.0006)	0.0040*** (0.0006)	0.0037*** (0.0006)
Non-CRP nat. land (ha)	0.0032*** (0.0002)	0.0032*** (0.0002)	0.0032*** (0.0002)
County CRP (ha)			4.53×10^{-6} *** (1.34×10^{-6})
Controls	No	Yes	Yes
Bandwidth (m)	500	500	500
Observations	12,057,806	12,057,806	12,057,806
R ²	0.95292	0.95300	0.95301
Mean property value (CRP nearby)	183,201.6	183,201.6	183,201.6
Mean property value	302,013.4	302,013.4	302,013.4
<i>A. CRP within 1,000 m</i>			
	(1)	(2)	(3)
CRP nearby (hectares)	0.0016*** (0.0002)	0.0016*** (0.0002)	0.0014*** (0.0002)
Non-CRP nat. land (ha)	0.0011*** (7.44×10^{-5})	0.0011*** (7.55×10^{-5})	0.0011*** (7.54×10^{-5})
County CRP (ha)			4.44×10^{-6} *** (1.33×10^{-6})
Controls	No	Yes	Yes
Bandwidth (m)	1,000	1,000	1,000
Observations	12,057,806	12,057,806	12,057,806
R ²	0.95291	0.95299	0.95300
Mean property value (CRP nearby)	185,667.4	185,667.4	185,667.4
Mean property value	302,013.4	302,013.4	302,013.4

Note: All columns include property fixed effects, state-by-year effects, and month-of-year effects. Standard errors are clustered by county. Columns with controls include controls for county population, income, total employment, and residential building permits. County CRP measures total CRP land in each property's county, net of CRP land within 1,000 m of that property.

Table 2: Placebo Test Results

Dep. var: log(Price)	Placebo regressions		Base regressions, adjusted sample	
	(1)	(2)	(3)	(4)
CRP (sq. km)	0.0002 (0.0007)	0.0002 (0.0002)	0.0038*** (0.0009)	0.0015*** (0.0003)
County CRP	4.58×10^{-6} *** (1.35×10^{-6})	4.47×10^{-6} *** (1.37×10^{-6})	4.59×10^{-6} *** (1.35×10^{-6})	4.47×10^{-6} *** (1.38×10^{-6})
Non-CRP nat. land	0.0032*** (0.0002)	0.0011*** (7.74×10^{-5})	0.0032*** (0.0002)	0.0011*** (7.68×10^{-5})
Controls	Yes	Yes	Yes	Yes
Bandwidth (m)	500	1,000	500	1,000
Observations	11,974,205	11,800,645	11,976,561	11,807,481
R ²	0.95316	0.95335	0.95311	0.95322

Note: All columns include property fixed effects, state-by-year effects, and month-of-year effects. Standard errors are clustered by county. All columns include controls for county population, income, total employment, and residential building permits.

Table 3: Heterogeneity in the Effects of CRP Enrollment, by Outcome Landcover Class

	(1)	(2)	(3)	(4)
CRP (grass) nearby	0.0032*** (0.0009)	0.0028*** (0.0009)	0.0013*** (0.0003)	0.0012*** (0.0003)
CRP (trees) nearby	0.0084*** (0.0012)	0.0081*** (0.0012)	0.0031*** (0.0004)	0.0030*** (0.0004)
CRP (wetland) nearby	0.0018 (0.0023)	0.0016 (0.0023)	0.0006 (0.0007)	0.0005 (0.0007)
CRP (various) nearby	0.0032 (0.0021)	0.0033 (0.0021)	0.0005 (0.0007)	0.0005 (0.0007)
Non-CRP nat. land (ha)	0.0032*** (0.0002)	0.0032*** (0.0002)	0.0011*** (7.54×10^{-5})	0.0011*** (7.53×10^{-5})
County CRP (ha)		4.54×10^{-6} *** (1.34×10^{-6})		4.45×10^{-6} *** (1.33×10^{-6})
Controls	Yes	Yes	Yes	Yes
Bandwidth (m)	500	500	1,000	1,000
Property effects	Yes	Yes	Yes	Yes
Observations	12,057,806	12,057,806	12,057,806	12,057,806
R ²	0.95300	0.95301	0.95299	0.95300
Mean property value (CRP nearby)				
Mean property value	302,013.4	302,013.4	302,013.4	302,013.4

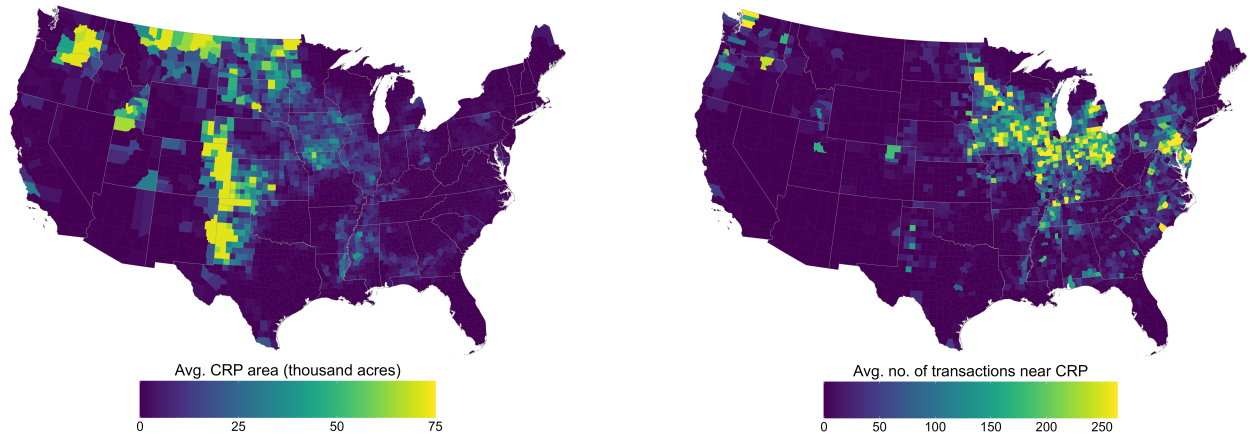
Note: CRP area variables are measured in hectares. All columns include property fixed effects, state-by-year effects, month-of-year effects, and controls for county population, income, total employment, and residential building permits. Standard errors are clustered by county.

Table 4: Implied Total Effects of CRP on US Property Values

<i>A. CRP within 500 m</i>	Specification		
	(1)	(2)	(3)
Avg. price effect, transacted properties near CRP	2,644.5	2,561.1	2,356.1
Avg. price effect, all transactions	35.9	34.7	32.0
Total price effect, all transactions (USD millions)	951.5	921.5	847.8
Total price effect, all properties (USD millions)	3,233.8	3,131.9	2,881.3
<i>B. CRP within 1,000 m</i>	Specification		
	(1)	(2)	(3)
Avg. price effect, transacted properties near CRP	2,238.4	2,162.5	1,944.4
Avg. price effect, all properties	80.9	78.1	70.2
Total price effect, all transactions (USD millions)	2,144.7	2,072.0	1,863.0
Total price effect, all properties (USD millions)	7,161.0	6,918.2	6,220.5

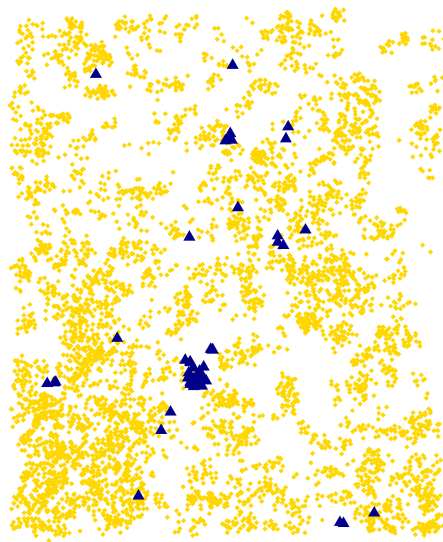
Note: Price effects in Columns 1–3 are calculated based on specifications in Columns 1–3 of Table 1, respectively. The total price effect across all transactions is calculated by applying estimates from Table 1 to the most recently observed transaction price for each property in the CoreLogic transactions data set and enrolled CRP land at the time of the transaction. The total price effect across all properties is calculated by multiplying each county’s average calculated price effect by the total number of properties observed within the CoreLogic assessors’ data set and an adjustment factor equal to the ratio of the mean assessed value for all properties and that among properties for which we observe transactions.

Figure 1: Overview of CRP and Property Transactions Data

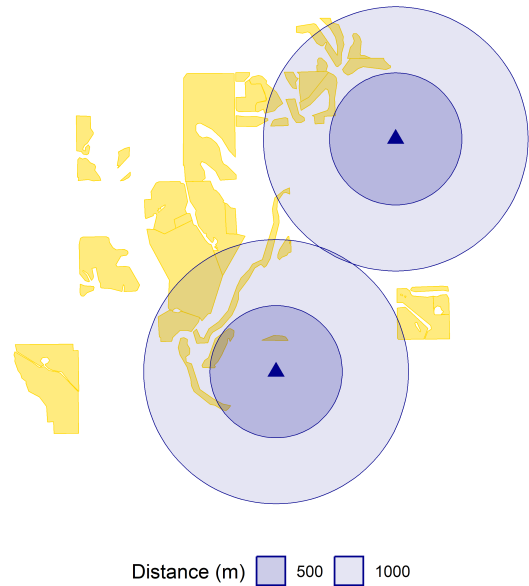


(a) Average CRP area by county

(b) Average number of transactions near CRP land by county



(c) Field-level CRP data and property transactions



(d) Zoomed view of the area outlined in panel (c)

Note: For panels (a) and (b), averages are over 2012–2022. Average CRP area and average number of transactions near (within 1,000 m of) CRP are top-coded at the 98th percentiles: 9.75 percent and 270 transactions, respectively. The variables' true maximums are 262,043 acres and 331 transactions. Panel (c) displays the locations of CRP fields and transactions of residential properties from one US county in 2018. To preserve anonymity, the coordinates of CRP fields are jittered by up to 500 m, coordinates of property transactions are jittered by up to 100 m, and the county is not identified. Panel (d) zooms in on a portion of the county in Panel (c) and illustrates the field-level CRP data and the 500 m and 1,000 m buffers around each transaction within which we calculate total area enrolled in CRP.

A Extended Data and Methods

A.1 Data Appendix

A.1.1 CRP Data Cleaning and Processing

CRP parcel data were shared via geodatabase, with one feature class for each year 2012 through 2022 (R. Iovanna, April 2024). Parcel units were Common Land Units (CLUs), and included columns for contract number, expiration date, and practice number. Column names and formats were standardized across annual datasets, and state and county identifiers were assigned to each parcel. As described in the main text, records with implausible expiration dates were removed using year-specific lower and upper date limits. Specifically, observation dates with expiration dates prior to October 1 of the previous year (before the current fiscal year) or September 30 of the calendar year 15 years later (assuming a maximum contract length of 15 years) were assumed to be erroneous and removed. We also removed very small polygons (less than 10 square meters).

The datasets did not contain a persistent CLU identifier that could be used to track parcels longitudinally. Contract numbers were not suitable for this purpose because contracts may change over time, and parcel geometries were not always identical across annual datasets due to changes in CRP delineation and geoprocessing procedures. To create a consistent time series of enrolled parcels, we generated a persistent parcel identifier (`crp_keyid`) and reconciled duplicate and near-duplicate parcel geometries across years.

Initial `crp_keyid` values were assigned based on parcel geometry, state location, and approximate parcel area, allowing parcels with identical geometries to be tracked through time regardless of contract number. Duplicate records associated with the same parcel geometry within a single year’s dataset were removed. When multiple observations shared a parcel identifier, we retained the record with the most recent contract expiration date and removed the remaining duplicates, assuming the most recent expiration date reflected the current enrollment record.

Additional processing was required for parcels representing the same underlying field but whose geometries differed across years due to boundary adjustments, changes in coordinate precision, revisions to delineation methods, or parcel splits and merges. We compared parcel geometries across years using relative area differences and spatial overlap metrics. Parcels with area differences of less than 1 percent and spatial overlap exceeding 80 percent were considered to represent the same field and were assigned a common identifier. These thresholds were selected after evaluating alternative parameter values and choosing the combination that minimized matching errors while

resolving the greatest number of geometry inconsistencies.

Following cross-year reconciliation, duplicate observations associated with the same `crp_keyid` were removed. When records sharing a parcel identifier contained conflicting information, the observation with the most recent valid expiration date was retained. The resulting dataset provides a harmonized longitudinal inventory of CRP parcels that can be tracked consistently across enrollment years.

A.1.2 Construction of Parcel-Level CRP Exposure Measures

This appendix describes the three-step procedure used to construct parcel-level measures of CRP land within 500 meters and 1,000 meters of each property transaction.

Step 1: Rasterization of CRP Polygons

Computing the area of CRP land within a circular buffer around each of millions of property transactions using vector-on-vector overlay operations would be computationally prohibitive at national scale. We therefore converted the polygon data to raster format as an intermediate step.

For each year from 2012 to 2022 and each of the 48 contiguous states, we rasterized the CRP polygon layer at 50-meter resolution using the `fasterize` package in R. To ensure that CRP land near state borders is correctly captured for properties on either side, we defined each state’s raster extent using a 10-kilometer buffer around the state boundary and include CRP polygons from all counties overlapping that buffered area. This produced 11 annual binary rasters per state, stored as GeoTIFF files.

Step 2: Extraction of CRP Area for Each Parcel

Using the annual raster layers, we computed the area of CRP land within circular buffers around each property in the transactions data. For each parcel, we draw circular buffers at 500 meters, 1,000 meters, and 5,000 meters and use the `exact_extract` function to sum the number of CRP-covered raster cells falling within each buffer.

The resulting cell counts were converted to areas in hectares by multiplying by 0.25 (the area in hectares of a 50m $\times$ 50m cell). The output for each state is a parcel-level dataset with CRP exposure measures across all three buffer distances and all eleven years.

Step 3: Merging with Transaction Data

The parcel-level CRP exposure dataset is merged with the CoreLogic transaction records. After reshaping the CRP data from wide to long format by year, we merged on parcel identifier and transaction year, attaching the CRP exposure measure for the year of sale.

A.1.3 Land Cover Data Cleaning and Processing

Annual land-cover conditions in the area surrounding residential properties were derived from the Cropland Data Layer (CDL) ([USDA National Agricultural Statistics Service, 2022](#)). We used the CDL rather than the National Land Cover Database (NLCD) because the CDL data were available annually throughout the study period. CDL rasters were reclassified into natural land (forest, grassland/pasture, wetland, shrubland, water, barren), agricultural (crop classes), and developed. We include grassland/pasture in the natural category because it represents a non-developed vegetative cover that may contribute to environmental amenities valued by nearby residents. Reclassified rasters were overlaid with 500 m and 1,000 m buffers around each residential property to calculate the area of surrounding developed, agricultural, and natural land. With these results, we constructed a measure of non-CRP natural land by subtracting the area of enrolled CRP land from the total area classified as natural land in the CDL for each buffer distance. These variables were used as controls for land-cover composition surrounding each property.

To characterize baseline county-level land-cover composition at the beginning of the study period, we used the 2011 NLCD ([U.S. Geological Survey, 2024](#)). NLCD land-cover classes were aggregated into three categories: natural land (forest, shrub/scrub, nonpasture grasslands, wetlands, open water, and perennial ice/snow), agricultural land (cropland and pasture), and developed or barren land (all remaining classes). For each county, we calculated the percentage of land area in each category [Figure B.2](#).

A.2 Regression specification

Our preferred specification ([Equation 1](#) includes fixed effects at the property, state-by-year, and month-of-year levels. A natural concern is that state-by-year effects leave time-varying confounders that operate at finer spatial scales—county-level demand shocks, development pressure, or local economic conditions—which, if correlated with nearby CRP enrollment, could bias $\hat{\beta}^d$. Replacing state-by-year with county-by-year fixed effects would absorb any such shock common to a county

in a given year. We considered this specification and report here why we do not adopt it: in our setting county-by-year effects remove almost all of the identifying variation in treatment while purging little, if any, confounding that is not already addressed by our research design.

The identifying variation in nearby CRP is sub-county and spatially clustered. CRP enrollment is concentrated in particular regions, and within a given county and year relatively few properties experience changes in nearby CRP; among those that do, the changes tend to be correlated because field-level enrollment decisions cluster geographically. As a result, county-by-year fixed effects absorb nearly all of the within-property variation that identifies our coefficient. After partialling out fixed effects and controls, the standard deviation of residual nearby-CRP variation falls by more than two orders of magnitude, from 0.203 to 0.0012 hectares for CRP within 500 m and from 0.714 to 0.0027 hectares for CRP within 1,000 m.

Figure B.3 maps the county-level standard deviation of residual treatment under each specification. Under state-by-year fixed effects, residual variation is broadly distributed across the country; under county-by-year fixed effects it collapses to near zero everywhere except a handful of counties. With virtually no identifying variation remaining, the coefficient would be identified from a small, geographically unrepresentative set of properties. The county-by-year specification is therefore uninformative.

Crucially, the confounding that motivates county-by-year fixed effects is already addressed by our placebo test (Table 2). Because placebo “treatments” are assigned to properties in the same county transacting in the same years as treated units, any county-by-year shock correlated with CRP changes would generate a spurious placebo effect of comparable magnitude to our main estimates. Instead, the placebo coefficients are small and statistically insignificant. This is direct, within-county-year evidence that local time-varying confounders are not driving our results.

B Additional Tables & Figures

Table B.1: Summary Statistics for Properties With Multiple Sales, 2012–2022

Variable	No CRP land	1st quartile	2nd quartile	3rd quartile	4th quartile
Sale amount (thousands USD)	309.04 (275.69)	187.97 (129.34)	189.61 (131.01)	185.60 (128.88)	179.72 (128.02)
Enrolled CRP within 500 m (sq. km)	0.00 (0.00)	0.04 (0.15)	0.22 (0.52)	0.73 (1.41)	3.97 (5.95)
Enrolled CRP within 1000 m (sq. km)	0.00 (0.00)	0.46 (0.30)	1.97 (0.61)	5.46 (1.59)	21.93 (16.85)
Natural land within 500 m (hectares)	19.49 (20.96)	24.15 (20.08)	25.59 (20.39)	28.69 (20.75)	33.84 (20.64)
Natural land within 1000 m (hectares)	91.29 (83.23)	105.22 (74.14)	110.59 (74.84)	123.20 (75.23)	145.29 (71.99)
Year built	1,979.69 (29.79)	1,973.23 (35.89)	1,973.06 (36.30)	1,973.65 (35.68)	1,974.05 (35.61)
No. of bedrooms	3.27 (1.49)	3.14 (0.80)	3.14 (0.84)	3.17 (2.87)	3.16 (0.95)
No. of bathrooms	2.44 (1.15)	2.19 (1.01)	2.21 (1.00)	2.23 (1.67)	2.19 (1.04)
Building square feet	2,389.86 (1,259.19)	2,443.39 (1,120.67)	2,461.69 (1,141.40)	2,493.44 (1,156.32)	2,457.48 (1,163.25)
Lot size (acres)	0.67 (4.95)	1.31 (4.72)	1.47 (5.51)	1.78 (7.39)	2.39 (7.72)
No. of observations	12,438,391	108,723	104,016	106,509	106,232

Note: Columns show means for each variable among transacted properties with no CRP land within 1,000 m and within the first, second, third, and fourth quartiles of CRP area within 1,000 m, respectively. Standard deviations are in parentheses.

Table B.2: Common CRP Practices

CRP Practice	Avg. acres per year (millions)	Percent of total
Establishment of permanent native grasses (CP02)	5.84	25.2
Grass already established (CP10)	3.34	14.4
Establishment of permanent introduced grasses and legumes (CP01)	3.21	13.8
Permanent wildlife habitat (CP04D)	1.69	7.3
SAFE—grass (CP38E)	1.47	6.3
Rare and declining habitat (CP25)	1.38	6.0
Filter strips (CP21)	0.78	3.4
Wetland restoration (CP23)	0.76	3.3
Riparian buffer (CP22)	0.71	3.1
Other (less than 3 percent of total acres)	3.98	17.2

Note: The “Avg. acres per year” column shows the average acres enrolled in each practice between 2012 and 2022. Other practices are those that average less than 3 percent of total acreage per year.

Table B.3: Property Value Regressions Including Multiple CRP Distance Bandwidths

Model:	log(Price)	
	(1)	(2)
<i>Variables</i>		
CRP within 500 m	0.0017*** (0.0006)	0.0017*** (0.0006)
CRP within 1000 m	0.0012*** (0.0003)	0.0010*** (0.0003)
Non-CRP natural land within 500 m	0.0019*** (0.0001)	0.0019*** (0.0001)
Non-CRP natural land within 1000 m	0.0005*** (7.36×10^{-5})	0.0005*** (7.36×10^{-5})
County CRP (ha)		4.48×10^{-6} *** (1.33×10^{-6})
Controls	Yes	Yes
Observations	12,057,806	12,057,806
R ²	0.95301	0.95302

Note: CRP areas are measured in hectares. All columns include property fixed effects, state-by-year effects, month-of-year effects, and controls for county population, income, total employment, and residential building permits. Standard errors are clustered by county.

Table B.4: Differences in the Effect of Changes in CRP Land Nearby Across Properties with Varying Time Between Sales

	(1)	(2)	(3)
CRP nearby (hectares)	0.0012*** (0.0003)	0.0016*** (0.0003)	0.0017*** (0.0003)
Non-CRP nat. land (ha)	0.0008*** (5.66×10^{-5})	0.0012*** (7.66×10^{-5})	0.0013*** (9.36×10^{-5})
Years between obs.	0-3	4-6	≥ 7
Controls	Yes	Yes	Yes
Bandwidth (m)	1,000	1,000	1,000
Observations	4,119,675	4,902,870	3,134,566
R ²	0.96431	0.95148	0.94307
Mean property value (CRP nearby)	188,467.8	186,087.1	181,327.0
Mean property value	305,302.5	302,310.6	301,188.1

Note: CRP area variables are measured in hectares. All columns include property fixed effects, state-by-year effects, month-of-year effects, and controls for county population, income, total employment, and residential building permits. Standard errors are clustered by county.

Table B.5: Differences between the Effects of Positive and Negative Changes in CRP Land Nearby

Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
CRP nearby (increase)	0.0031** (0.0015)	0.0029** (0.0015)	0.0006 (0.0005)	0.0005 (0.0005)
CRP nearby (decrease)	0.0024*** (0.0009)	0.0024*** (0.0009)	0.0009*** (0.0003)	0.0008*** (0.0003)
Non-CRP nat. land (ha)	0.0015*** (0.0002)	0.0015*** (0.0002)	0.0005*** (7.38×10^{-5})	0.0005*** (7.38×10^{-5})
County CRP (ha)		$2.62 \times 10^{-6**}$ (1.12×10^{-6})		$2.61 \times 10^{-6**}$ (1.12×10^{-6})
<i>Fixed-effects</i>				
Mean property value (CRP nearby)	203,761.5	203,761.5	202,833.3	202,833.3
Mean property value	348,511.1	348,511.1	348,511.1	348,511.1
Controls	Yes	Yes	Yes	Yes
Bandwidth (m)	500	500	1,000	1,000
Property effects	Yes	Yes	Yes	Yes
State $\times$ year effects	Yes	Yes	Yes	Yes
Month-of-year effects	Yes	Yes	Yes	Yes
<i>Fit statistics</i>				
Observations	6,155,705	6,155,705	6,155,705	6,155,705
R ²	0.99252	0.99252	0.99252	0.99252

Note: CRP area variables are measured in hectares. All columns include property fixed effects, state-by-year effects, month-of-year effects, and controls for county population, income, total employment, and residential building permits. Standard errors are clustered by county.

Figure B.1: CRP Enrollment Over Time

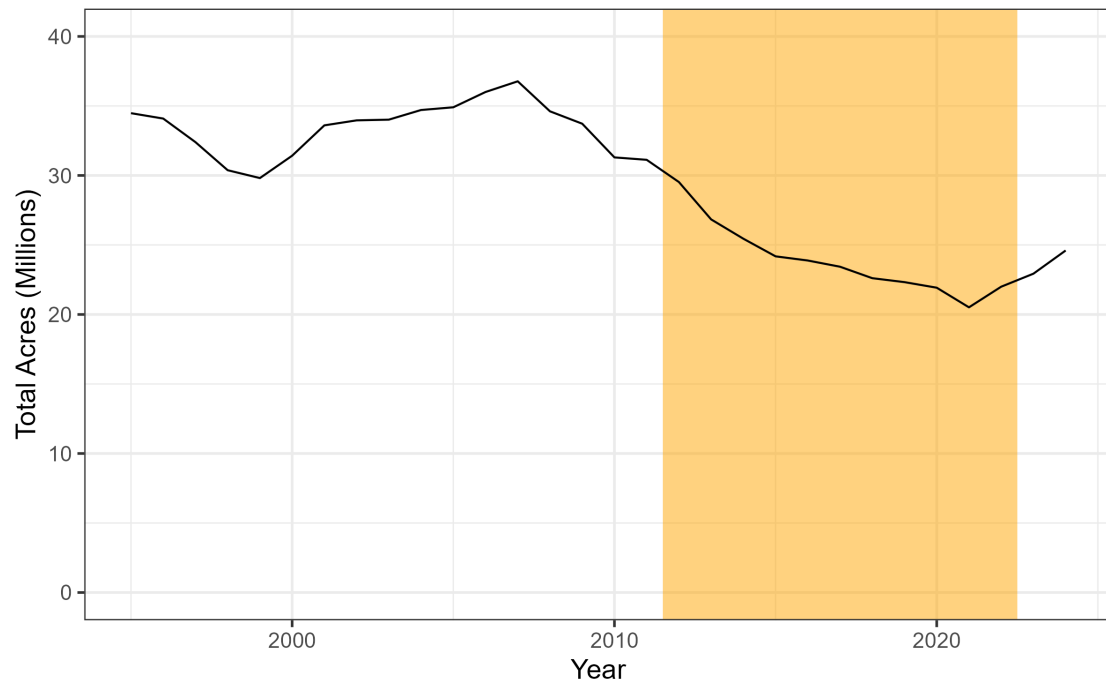
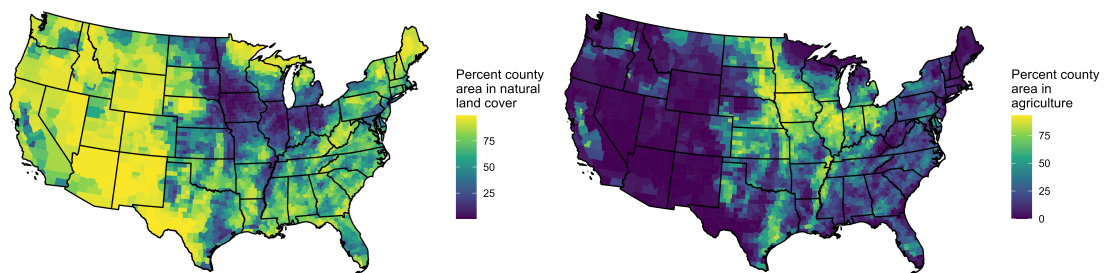
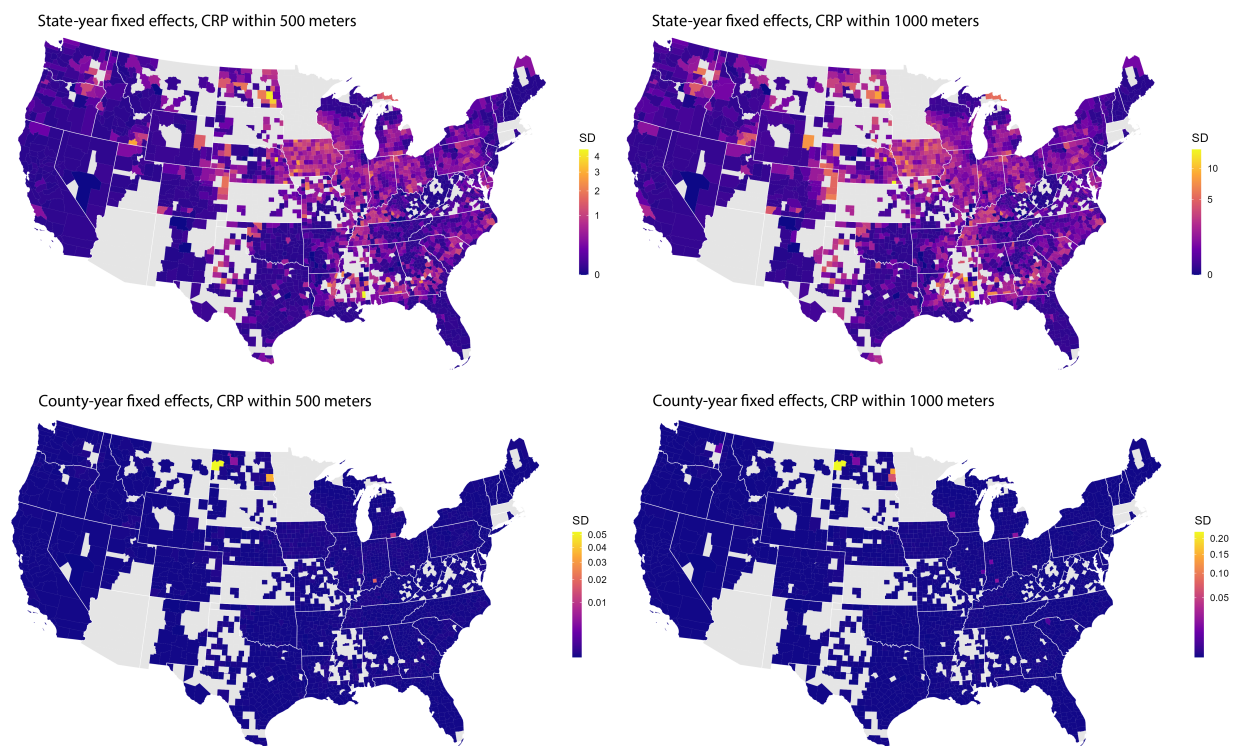


Figure B.2: Percent County in Natural Lands (Panel A) and Agriculture (Panel B)



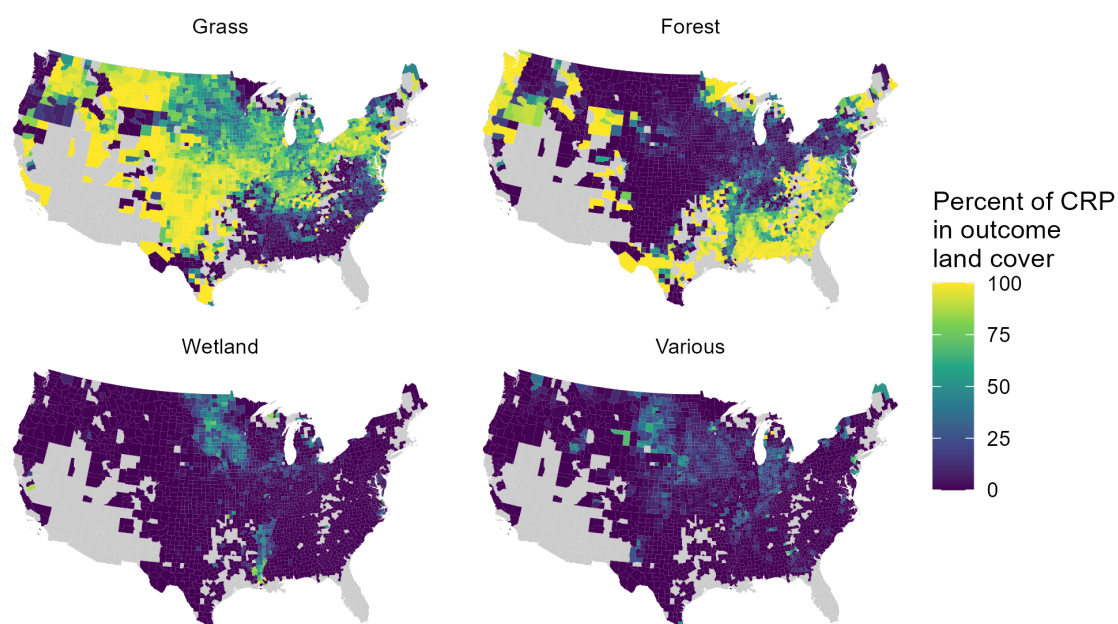
Note: Percentages are calculated from 2011 NLCD data. Natural lands include all forest, shrub and scrublands, nonpasture grasslands, wetlands, open water, and perennial ice/snow. Agricultural lands are cropland and pasture.

Figure B.3: Residual variation in Nearby CRP After Removing Fixed Effects



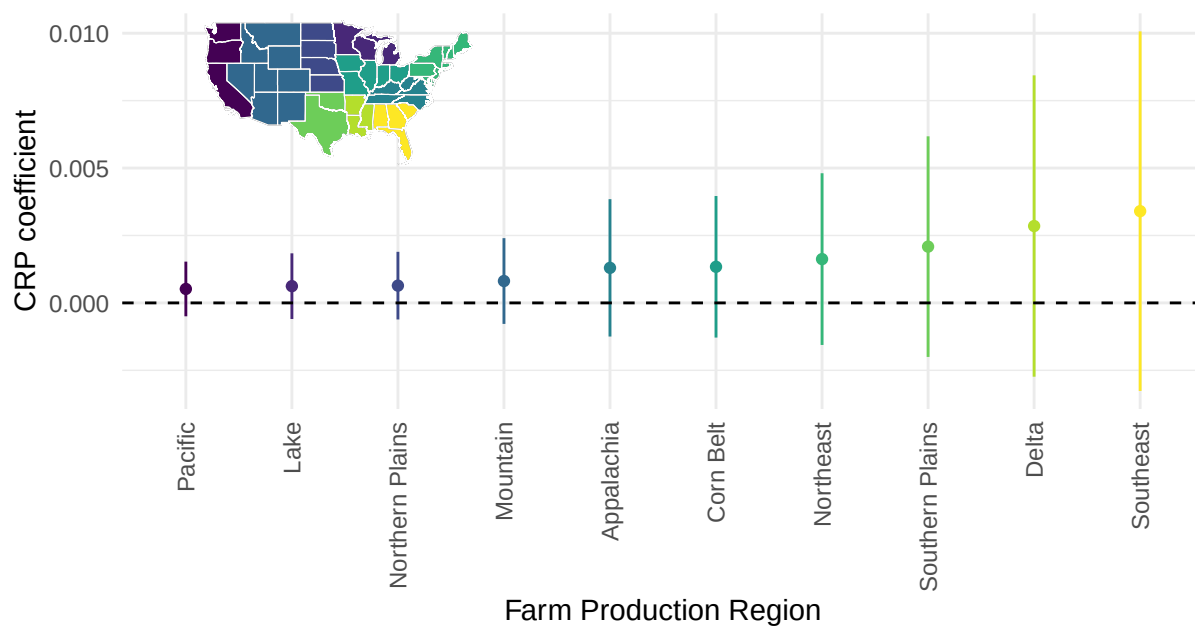
Note: Plots the standard deviation of the variation in the treatment variable, nearby CRP measured in hectares, after conditioning on the controls and fixed effects in Equation 1, which include time-varying controls at the county-year level, parcel fixed effects, month-of-year fixed effects, and state-by-year fixed effects (top panel). Bottom panel shows the same, but conditioning on county-by-year fixed effects in place of state-by-year fixed effects. Color scales change across all four panels.

Figure B.4: CRP land Cover Types, by County



Note: Percentage in each land cover type is averages of the percentage CRP in each land cover category in each county across the study period. Counties shaded in grey have no enrolled CRP land during the study period.

Figure B.5: Estimates of the Effect of CRP Land Within 1 km on Property Values, by Farm Production Region



Note: Regions are ordered by coefficient estimate magnitude. States corresponding to each Farm Production Region are shown in the same color in the inset map as in the coefficient plot.

