Transformation in US Agriculture: Insights from Energy Price Shocks, Ecosystem Service Enhancements, and Renewable Energy Developments

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ACADEMIC ABSTRACT

Agriculture in the US is undergoing significant transformation in response to shifting energy markets, environmental challenges, and renewable energy policies. Using economic simulation and econometric models, this dissertation explores how changes in energy prices, renewable energy policies, and conservation programs influence agricultural production, land use, and environmental outcomes across the country.

In the first chapter, the focus is on the impacts of energy price shocks and ethanol policy changes. Since agriculture relies heavily on energy, from fuel to fertilizers, changes in energy prices can significantly affect farming operations. The findings show that higher energy prices tend to increase the costs of production, leading to reduced output. A 40 percent increase in energy prices leads to crop output reductions of up to 13.7 percent for rice, 12.1 percent for corn, and 12.0 percent for oats, while prices increase by 9.6 percent, 6.8 percent, and 7.4 percent, respectively. Livestock output falls modestly, but higher prices offset these losses as pork and beef values increase by 13.1 percent and 3.1 percent, respectively. Conversely, a 40 percent drop in energy prices boosts crop output (e.g., corn +6.4 percent) and lowers prices (corn -3.9 percent), leading to only a 1.3 percent gain in value. Livestock value increases slightly (about 0.27 percent) due to higher output but falling prices. The study also evaluates the effects of increased ethanol demand. In the highest-demand scenario (increasing the blend wall, the allowable proportion of ethanol

that can be added to gasoline, to 20 percent and quadrupling exports), corn production jumps by 44.8 percent, and processing for ethanol grows by 151.1 percent. This expansion reduces livestock feed costs by increasing the feed supply, thereby boosting pork, poultry, and beef output. However, the resulting increase in meat supply pushes prices downward, especially for pork (-6.2 percent), leading to a 3.4 percent decline in the total livestock sector value.

The second chapter compares two agricultural conservation programs for reducing water pollution from nitrogen (N) runoff: (i) a Yield Reserve Program, which pays farmers to reduce fertilizer use; and (ii) an expanded Conservation Reserve Program (CRP), which pays farmers to take land out of production. The research finds that the Yield Reserve Program is generally more cost-effective at excess N reduction, reducing N loads by up to 771 million pounds under a 2 percent corn yield reserve scenario. However, it also causes a “rebound effect”, increasing corn acreage by 9.2 million acres because lower per-acre fertilizer use combined with subsidies encourages more planting. The CRP shows a much stronger “slippage effect” as up to 76-79 percent of retired land is offset by marginal land brought into production, diluting the environmental benefits. Despite this, both programs show promise in excess N reduction, especially when targeted to high-output regions like the Corn Belt and Northern Plains.

The third chapter shifts to a rapidly evolving issue in the energy transition: the siting of large-scale solar photovoltaic (LSSPV) facilities. Although solar energy is key to decarbonizing the power sector, new solar developments increasingly face community opposition. This study combines a nationwide property sales dataset with solar site locations to measure the impact of LSSPV proximity and visibility on nearby property values. Difference-in-differences estimates show that LSSPV significantly increases agricultural or vacant land value by about 19.4 percent within a 2-mile radius, while simultaneously reducing residential property values within 3 miles by about 4.8 percent. The estimated average negative impact on home values is primarily driven by site proximity and diminishes with both distance and time. Effect estimates are more robust to alternative specifications when proximity pairs with visibility rather than invisibility, but no evidence suggests visibility significantly amplifies the proximity effect. Heterogeneous effect estimates indicate that high solar lease potential, being in heavily Democratic-leaning counties, and brownfield redevelopment largely mitigate the negative residential value impact. The analysis reveals no significant heterogeneity of price impact across a few factors, including varying site visibility, directional orientation of properties relative to the LSSPV site, and different tracking systems. Evidence indicates that the negative impact on residential values might mostly stem from negative perceptions, but channels through physical conditions cannot be entirely dismissed. Our assessment provides benchmark information for local externality mitigation plans, potentially reducing community opposition and expediting the renewable energy transition.

Together, these three studies offer a forward-looking view of the potential for US agriculture and rural economies to adapt to shifting energy landscapes, conservation needs, and renewable energy development. The findings provide valuable guidance for farmers, planners, and policymakers working to ensure sustainable and inclusive rural futures in a changing world.

GENERAL AUDIENCE ABSTRACT

Agriculture in the US is rapidly evolving in response to volatile energy markets, environmental concerns, and the expansion of renewable energy. This dissertation uses economic simulation and statistical methods to explore how changes in energy prices, renewable energy policies, and conservation programs influence agricultural production, land use, and environmental outcomes across the country.

The first chapter examines how energy price and ethanol demand changes influence crop and livestock production. Since farming is energy-intensive, a 40 percent rise in energy prices increases production costs and reduces crop output, up to 13.7 percent for rice and 12.1 percent for corn. Livestock output falls slightly, but higher prices offset much of the loss. Conversely, falling energy prices raise output and lower prices. When ethanol demand rises, such as through higher blending requirements and increased exports, corn production and ethanol processing expand significantly. While this reduces livestock feed costs and boosts meat production, it also pushes meat prices down.

The second chapter compares two conservation programs designed to reduce nitrogen runoff: a Yield Reserve Program, which pays farmers to use less fertilizer, and an expanded Conservation Reserve Program (CRP), which pays them to retire land. The Yield Reserve is more cost-effective for reducing nitrogen loads, but it encourages more planting (a rebound effect). The CRP, while effective, shows a stronger slippage effect, much of the retired land is replaced by new cropland.

The third chapter investigates how large-scale solar developments (LSSPV) affect nearby property values. By analyzing property sales across the country, the study finds that solar facilities increase farmland value by 19.4 percent within 2 miles but reduce residential

home values by about 4.8 percent within 3 miles. These effects are stronger when sites are visible. Factors such as high solar lease potential, being in heavily Democratic-leaning counties, and brownfield redevelopment largely mitigate the negative residential value impact. The findings suggest that local concerns may be driven more by perception than by physical impacts.

Together, these studies offer insights into how US agriculture can adapt to renewable energy transitions and environmental policy while minimizing trade-offs and maximizing sustainability.

Dedication

To my beloved grandmother, whose strength and kindness continue to inspire me.

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Chapter 1

Impacts of Energy Price and Ethanol Demand Shocks on US Agriculture: A Partial Equilibrium Approach

Abstract

Agriculture is an energy-intensive industry while the energy markets have experienced significant volatility since the 21st century. This study examines possible implications of energy price and ethanol demand shocks for US agriculture using the REAP (Regional Environment and Agriculture Programming) model, a partial equilibrium framework. The analysis updates the model baseline to 2030 USDA projections and evaluates a broad range of scenarios, including both rising and falling energy prices (±20 percent and ±40 percent) and four alternative ethanol demand scenarios. Higher energy prices lead to higher crop prices and lower crop output in most farm regions, and vice versa. Livestock declines are generally offset by price increases, leading to a modest rise in total livestock value. Higher ethanol demand leads to expansion of corn production. Findings highlight the vulnerability of US agriculture to energy price volatility and biofuel policy shifts. The analysis underscores the need for adaptive strategies among farmers, policymakers, and stakeholders, especially in regions and sectors with high energy or feed input intensity.

1.1 Introduction

Energy serves as an indispensable input in U.S. agricultural production, influencing nearly every facet of farm operations. While direct energy inputs such as diesel fuel for machinery, heating fuels, and electricity for irrigation are readily observable, indirect energy inputs are equally significant. Agricultural inputs like fertilizers, pesticides, and other agrochemicals require substantial amounts of energy for their manufacturing, transportation, and application. Collectively, these indirect costs substantially amplify agriculture's total energy dependence.

According to Hitaj and Suttles (2016), indirect energy-related expenses constituted approximately 16 percent to 36 percent of total cash expenditures for U.S. crop producers in 2014. Among these indirect inputs, fertilizers are particularly sensitive to fluctuations in global energy markets due to their heavy reliance on natural gas and petroleum products as feedstocks. Fertilizer production, particularly nitrogen-based fertilizers such as ammonia and urea, is directly linked to energy costs because the synthesis process involves substantial amounts of natural gas. Empirical research highlights this strong linkage, with estimates suggesting that approximately 33 percent of changes in crude oil prices directly influence fertilizer prices (Baffes, 2007).

Energy markets have experienced significant volatility since the beginning of the 21st century (Figure 1.1), with prices fluctuating in response to geopolitical events, technological advancements, regulatory changes, and shifts in global demand. Between 2001 and 2024, the standard deviation of the price index of crude oil was 28.22 compared to 4.82 for the 1987-2000 period. Energy prices may continue to be volatile in the future for several reasons. First, there is growing pressure for reducing carbon emissions which may drive up energy prices. Burning of fossil fuels is estimated to comprise 80 percent to 95 percent of global greenhouse gas (GHG) emissions (Schmalensee, et al. 1998; Pepper et al. 1992; Wang and Ye, 2017). The Paris Agreement calls for reducing net anthropogenic GHG emissions to zero during the second half of this century (Oberthur and Groen, 2018). On the other hand, the Trump administration implemented several measures aimed at reducing regulatory barriers to enhance U.S. oil and gas production, with the objective of lowering energy prices (Davenport, 2025). Moreover, rapid progress in renewable energy technologies (such as solar, wind, and battery storage) could significantly lower their production costs, increasing competitiveness and market penetration (Nemet, 2006; Nikolina, 2020). Improved efficiency and lower-cost renewables would reduce dependence on fossil fuels, creating downward pressure on energy prices as supply expands and diversifies. This volatility has far-reaching consequences for various economic sectors, particularly agriculture, which relies heavily on stable energy inputs for production, processing, and transportation.

Studies on the impacts of energy price on agriculture, such as Konyar and Howitt (2000) and Edwards, et al. (1996), were limited to the effects of rising energy prices in the U.S. crop sector only and did not provide regional analysis of impacts. Zhang (2021) evaluated how an increase in the price of energy affects California's dairy manufacturing industry. Hu et al. (2021) conducted a partial equilibrium study that assesses regional impacts on the crop and livestock sector and found that higher energy prices lead to higher crop prices in most cases, and decreased crop output with the exception of corn and soybeans, which benefit from higher ethanol and biodiesel prices. Livestock production declined although total livestock value increased as price increases offset the effects of reduced output. The analysis by Hu et al. (2021) was conducted based on 2007 price and production values. Hu et al. also assumed that a 'blend wall' limits ethanol production to 10 percent of retail gasoline sales and a constant export demand for ethanol. While extensive research has examined the impacts of rising energy prices on U.S. agriculture, there is limited empirical evidence on how declining energy prices affect the agricultural sector. This gap is especially relevant given recent technological and policy developments that could exert downward pressure on energy prices over the long term.

This study extends the analysis of the impacts of energy price shocks on U.S. agriculture by 1) updating the baseline to 2030 projected prices and production (US Department of Agriculture, 2021) to better evaluate the consequences of future changes in energy prices; 2) including the scenarios of declining energy prices; 3) relaxing the blend wall constraint and relaxing the assumption of constant export demand for ethanol to reflect recent and potential expansion of the Renewable Fuel Standard Program and international trading of ethanol (https://www.whitehouse.gov/briefing-room/statements-releases/2022/04/12/fact-sheet-using-homegrown-biofuels-to-address-putins-price-hike-at-the-pump-and-lower-costs-for-american-families/).

This study provides a comprehensive analysis of how energy price volatility and ethanol demand shocks affect the entire US agricultural sector. Unlike prior research that focused narrowly on specific crops or regions, this study employs a nationally representative model that captures the diversity of agricultural production across the US. By incorporating detailed agricultural activities such as crop rotations and region-specific land use dynamics, the analysis generates nuanced insights into sector-wide and regional responses.

This study finds that higher energy prices lead to higher crop prices and lower crop output in most farm regions, while lower energy prices have the opposite effect. Livestock declines are generally offset by price increases, leading to a modest rise in total livestock value, and vice versa. Higher ethanol demand (both domestic and export) leads to expansion of corn production but reduction of sorghum, a minor feed grain. These findings have important implications for national policy and regional planning in the face of future energy and biofuel market developments.

1.2 Materials and Methods

1.2.1 The REAP Model

We examine the effects of energy price and ethanol demand shocks employing the REAP (Regional Environment and Agriculture Programming) model, a partial equilibrium simulation model developed by USDA's Economic Research Service. The REAP framework leverages nonlinear mathematical programming methods to simulate and analyze complex interactions between agricultural production systems, environmental impacts, and potential policy interventions (Johannson et al., 2007). As a result, the model provides critical insights and quantitative assessments that help inform and guide effective agricultural and environmental policy decisions.

Recent applications of the REAP model have addressed several critical agricultural and environmental challenges. For instance, Marshall et al. (2018) employed the model to evaluate policy measures aimed at reducing hypoxia, an oxygen deficiency detrimental to aquatic ecosystems, in the Gulf of Mexico. Malcolm et al. (2015) utilized REAP to assess strategies for climate change adaptation within U.S. agriculture. Additionally, several studies have used REAP to explore the environmental implications of biofuel production.

Marshall et al. (2011) examined the potential trade-offs between expanding biofuel cultivation, such as corn-based ethanol, and the associated environmental impacts like soil erosion and fertilizer runoff. Sands et al. (2017) further extended this research by analyzing how biofuel policies, including Renewable Fuel Standards, affect agricultural land use, commodity markets, and regional environmental quality, emphasizing the importance of understanding these interactions when designing sustainable bioenergy strategies.

As a partial equilibrium model, REAP explicitly captures the price formation process endogenously, meaning that commodity prices within the model are derived through equilibrium between agricultural supply and demand curves (Sands et al. 2017) (See *1.SI1* for more details). However, as a partial equilibrium framework, REAP does not explicitly simulate input markets such as labor or capital markets; instead, it takes input prices as given and concentrates on direct agricultural commodity and production dynamics. REAP establishes a carefully calibrated baseline scenario to reflect the existing and projected agricultural conditions and subsequently evaluates various alternative scenarios. These scenarios may involve changes in market conditions, agricultural policies, biofuel mandates, or shifts in energy prices. Outputs from the model provide comprehensive regional analyses of agricultural outcomes, including land use allocations, cropping patterns, livestock production levels, commodity pricing, farm incomes, and various environmental outcomes like soil erosion, nutrient runoff, pesticide loadings, and impacts on biodiversity (Sands et al. 2017).

Geographically, the REAP model segments the contiguous United States into ten major farm production regions (FPRs), each reflecting distinct agricultural practices, climatic conditions, and resource availabilities. Within each region, livestock production, including dairy cattle, poultry (layers, broilers, turkeys), swine, and cattle grazing, is assumed to have homogeneous production practices and economic conditions. These regions are further divided into smaller subregions formed through the intersection of FPR boundaries and USDA-defined land resource regions (LRRs) (Sands et al., 2017). To capture the finer-scale environmental interactions, these subregions are further partitioned by overlaying watershed boundaries defined by Hydrologic Unit Codes (HUCs). Within many of these units, land is further categorized based on soil erosion susceptibility, distinguishing highly erodible lands (HEL) from non-highly erodible (non-HEL) lands. This comprehensive regionalization results in 456 distinct subunits, which enables the REAP model to conduct precise and environmentally differentiated crop production analyses.

Crop production activities within the REAP model are simulated based on realistic crop rotation practices involving ten major field crops (corn, soybeans, wheat, barley, cotton, oats, sorghum, rice, hay, and silage). Initial crop rotation patterns are informed by empirical data derived from the USDA's National Resources Inventory (USDA, no date). These rotations are calibrated meticulously to align with historical and projected acreage information reported by the USDA's National Agricultural Statistics Service (NASS). To more accurately reflect farmer behavior and avoid overly specialized or unrealistic model predictions, REAP utilizes constant elasticity of transformation (CET) functions. These functions help determine the distribution of agricultural land across different crop rotations and tillage practices, promoting more plausible and diversified cropping outcomes that reflect actual farm management decisions under changing economic and environmental conditions.

The baseline scenario within REAP is calibrated to match USDA Agricultural Projections for the year 2030 (USDA, 2021), ensuring the relevance and applicability of the model's outcomes to contemporary and near-future agricultural and environmental challenges. Detailed supplementary information, including comprehensive assumptions about commodity demand elasticities, specific livestock production practices, cropland availability, and crop-specific yields and input cost structures, are fully documented in the accompanying technical appendices. Appendix 1.SI.2 provides further information on commodity demand elasticities (Table 1.A1), crop acreage and production (Table 1.A2), livestock production activities (Table 1.A3), cropland supply (Table 1.A4), and major crops' yields and production costs (Table 1.A5 and 1.A6) that are used in the REAP model. These rigorous calibration procedures and detailed assumptions ensure that REAP's projections and analyses realistically portray the potential impacts of shifts in energy prices, agricultural practices, and environmental policies on the U.S. agricultural sector.

1.2.2 Energy Price Shocks

Table 1.1 presents the breakdown of energy inputs for corn, wheat, soybeans, and rice production, as described by Pimentel (2009). For these crops, approximately 60 percent of total energy-related expenditures are due to diesel fuel, fertilizers, lime, and agrochemicals, all highly sensitive to energy price fluctuations. Thus, increases in energy prices directly influence these input costs proportionally.

In this study, scenarios involving both increases and decreases in energy prices are simulated relative to a baseline aligned with the USDA's 2030 agricultural projections (USDA, 2021). Changes in energy costs are introduced through weighted pass-through rates specific to crop production (Table 1.A7), livestock operations (Table 1.A8), and agricultural processing industries (Table 1.A9). The definitions and calculations for these pass-through rates are detailed in Table 1.A7 (note b). Variations in energy costs influence agriculture primarily through changes in prices of fuel, electricity, fertilizers, lime, and agrochemicals.

A meaningful analysis of energy price impacts on crop production must account for how much of total variable costs these energy-intensive inputs represent. Across all crop rotations modeled in REAP, inputs such as fuel, lubricants, electricity, and energy-intensive materials (fertilizer, lime, chemicals) collectively represent an average of 31.8 percent of total variable operating costs (Table 1.A7). Sorghum demonstrates the highest sensitivity to energy cost changes (45.9 percent of operating costs), whereas cotton has the lowest sensitivity (20.7 percent) (Figure 1.2, Table 1.A7).

Livestock production expenses are notably dominated by feed-related costs, which themselves are energy-intensive. Consequently, energy price volatility is likely to significantly influence overall livestock operating costs. Within the REAP model, direct energy inputs (fuel, lubricants, electricity) and indirect energy impacts (feed, transport, machinery operation) together average 32.1 percent of total livestock operational expenditures (Table 1.A8). Poultry sectors (eggs, broilers, turkeys) show the greatest sensitivity to energy cost changes (48.6 percent), while swine finishing demonstrates the least sensitivity (20.8 percent) (Figure 1.2, Table 1.A8).

For agricultural processing activities within REAP, input costs primarily stem from raw material purchases, while fuel and electricity expenditure remain relatively minor, averaging only 1.7 percent of total costs (Table 1.A9). Energy price shocks in the model are operationalized by adjusting crop, livestock, and processing expenses based on their specific energy intensity. Illustratively, a 10 percent rise in energy costs increases corn production costs by 3.07 percent, broiler production costs by 4.86 percent, and processing costs by only 0.17 percent (Tables 1.A7, 1.A8, 1.A9). Energy price increases and declines of 20 percent and 40 percent were evaluated accordingly.

1.2.3 Ethanol Scenarios

Changes in energy prices also directly affect ethanol market dynamics, influencing both demand and supply aspects. Rising energy prices typically reduce gasoline demand and consequently ethanol usage, given ethanol's complementary role once it surpasses a certain blending threshold, specifically, around 4.5 percent of total fuel content (Wang et al., 2016). Higher energy prices also elevate ethanol production costs, primarily via increased costs for corn, its main feedstock, reducing overall ethanol supply.

The Renewable Fuel Standard (RFS), an ethanol mandate, initially set a goal of 36 billion gallons by 2022, with post-2020 targets being at the EPA's discretion (Bracmort, 2020). However, current ethanol blends in gasoline rarely surpass 10 percent, constrained by existing infrastructure limits, a barrier known as the 'blend wall' (Bracmort, 2020). In practice, U.S. ethanol production peaked at 16 billion gallons in 2018 but dropped to around 14 billion gallons by 2020, falling significantly below the mandated RFS levels. Meanwhile, the EPA has investigated higher ethanol blends (20 percent to 30 percent) to reduce greenhouse gas emissions (USEPA, 2018).

The U.S. accounts for approximately 20 percent of global petroleum consumption and around half of the global ethanol consumption, implying substantial potential for export growth given that many international markets have not yet approached similar blend wall constraints. This analysis presumes ethanol demand elasticity closely mirrors gasoline demand elasticity, with ethanol supply closely linked to corn prices.

This study examines four distinct ethanol market scenarios projected for 2030. Scenario one maintains domestic ethanol consumption at the 10 percent blend wall level with stable export levels. Scenario two keeps the 10 percent blend wall but assumes ethanol exports double. Scenario three raises the domestic blend wall to 20 percent while doubling exports, and scenario four similarly adopts the 20 percent blend wall but quadruples export volumes. Although USDA's 2030 agricultural projections do not explicitly include baseline energy prices, the USDA ERS provides detailed cost breakdowns for fuels and other energy-intensive agricultural inputs for crops and livestock, informing our scenario simulations (Tables 1.A7, 1.A8).

1.3 Results

1.3.1 Energy price change scenarios

Results show how U.S. agriculture reacts to energy price increases and declines of 20 and 40 percent accordingly.

1.3.1.1 Crop output and prices

With increased energy prices of 20 and 40 percent, the production of all ten crops declines (Figure 1.3, Table 1.A10). The decline in production of crops reflects the effects of leftward supply shifts as a result of increased energy prices combined with downward sloping demand. Reductions vary among crops for energy price increases of 20 and 40 percent with larger percentage reductions for rice, sorghum, corn, and oats, which have either relatively high energy costs or are mainly used as feed grains. Conversely, when energy prices fall, crop production generally increases, highlighting the responsiveness of agricultural output to energy costs.

Conversely, when energy prices decrease by 20 and 40 percent, crop production generally rises. This occurs as lower energy costs shift supply curves to the right, encouraging greater output at lower marginal cost. The production gains are particularly notable for rice, sorghum, oats, and corn, which show increases exceeding 8 percent in the case of a 40 percent energy price reduction. This asymmetry in response highlights the strong link between energy input costs and agricultural output decisions, especially for energy-intensive crops.

Crop prices follow a similar but inverse pattern. As energy prices rise, crop prices also tend to increase, reflecting the passthrough of higher production costs to market prices (Figure 1.4, Table 1.A11). Rice, oats, and silage show the largest percentage increases. However, percentage increases are less than the percentage increase in crop operating costs reflecting the downward sloping demand for crops. For example, while corn operating cost increases by 6.14 percent and 12.28 percent across the two positive energy price shocks, corn prices only rise by 2.51 percent and 4.99 percent, respectively.

When energy prices decline, crop prices fall as well, reflecting lower production costs and an outward shift in supply. The largest price decreases occur for rice, silage, and oats, the same crops that show the strongest production increases. This responsiveness of crop prices to energy price reductions suggests that energy prices play a critical role in shaping both supply and price outcomes in agricultural markets.

1.3.1.2 Livestock output and prices

With increased energy prices of 20 and 40 percent, production of beef, pork, milk, broilers, turkey, and eggs declines (Figure 1.5, Table 1.A12). These declines reflect the effects of leftward shifts in supply due to higher input costs, interacting with downward-sloping demand functions. The largest percentage reductions are observed for turkey, broilers, and eggs, followed by beef, milk, and pork. Conversely, when energy prices decrease by 20 and 40 percent, production levels rise across all livestock categories, though the increases are relatively small in scale. Livestock production increases only between 1 and 2 percent under a 40 percent energy price reduction.

Livestock prices generally increase in response to rising energy prices, as producers pass along some of the higher costs (Figure 1.6, Table 1.A13). The largest price increases under a 40 percent energy price rise are seen for turkey (11.53 percent), broilers (10.87 percent), and pork (9.63 percent). Other livestock categories show more modest price increases, including milk (2.23 percent), beef (3.32 percent), and eggs (5.55 percent). When energy prices decline, livestock prices fall, reversing the earlier trend. The largest price decrease is concentrated in pork, reflecting its greater responsiveness to energy-related production costs.

Trends in the total value of livestock output reflect the combined effects of both price and production changes (Figure 1.7, Table 1.A14). With energy price increases, the total value of output generally rises, as the reduced supply is more than offset by higher prices. Pork and broilers show the largest value gains, ranging from 4.82 percent to 8.11 percent for pork and 2.20 percent to 6.08 percent for broilers. Milk, beef, and eggs exhibit more modest increases, generally under 2 percent. Under energy price declines, total livestock values tend to fall slightly. Price declines outweigh production increases, especially for pork and broilers, where value gains from increased output are offset by falling market prices. This asymmetry highlights the complex interaction between cost shocks, producer behavior, and consumer demand in determining overall market outcomes for livestock.

1.3.1.3 Ethanol output

Ethanol production declines as energy prices rise, reflecting the effects of a leftward shift in the supply of corn grain, its primary input, and ethanol's role as a complement to gasoline, which has a downward-sloping demand curve (Wang et al., 2016). As energy prices increase by 20 percent and 40 percent, ethanol production falls from 18.4 billion gallons in the baseline to 17.2 and 16.5 billion gallons, representing declines of approximately 6.7 percent and 10.6 percent, respectively. Conversely, when energy prices fall by 20 percent and 40 percent, production rises to 20.0 and 21.6 billion gallons, an increase of 8.6 percent and 17.2 percent over the baseline.

Ethanol prices ($/gallon) decrease from $1.29 in the baseline to $1.26 and $1.16 under the 20 percent and 40 percent energy price increases, showing a non-monotonic response likely influenced by shifts in both supply and complementary fuel demand. When energy prices fall, ethanol prices decrease slightly to $1.27 and $1.25, suggesting some downward pressure from increased production.

1.3.1.4 Regional crop distribution

When energy price increases 40 percent, total acres of crops decrease by 16.5 million acres (Table 1.A15), declining in all regions except Northern Plains. Southern Plains has the largest reduction of 4.3 million acres followed by Appalachia and Northeast.

The changes in crop acres are mainly caused by the changes in corn acres. Corn acres decrease by 7.1 million acres in the U.S. (Table 1.A16) declining in all regions except for modest increases in Delta and Northern Plains. The largest reductions occur in the Appalachia, Northeast, and Mountain States. Corn acres in Appalachia have the largest reduction of 2.86 million acres followed by Northeast and Mountain States (Table 1.A16). Correspondingly, total crop value falls by approximately $9.5 billion (Table 1.A17). Regions with the largest acreage contractions, particularly Appalachia and the Southern Plains, also experience the greatest declines in crop value.

When energy price declines by 40 percent, total U.S. crop acreage expands by approximately 18.2 million acres relative to the baseline (Table 1.A15). This expansion is observed across all farm production regions except Northern Plains, with the largest increase of 5.0 million acres in Appalachia, followed by 4.2 million acres in Northeast and 3.7 million acres in Southern Plains. The increase in total crop acreage is largely driven by changes in corn acreage, which rises by 7.9 million acres nationwide (Table 1.A16). Most regions experience increases in corn planting, with the most significant gains in Appalachia, Northeast, and Northern Plains. These shifts reflect the lower cost of energy-intensive inputs, encouraging expanded production, particularly of corn, which is sensitive to energy price changes due to its high input requirements. As a result, total crop value rises by about $10.4 billion, reflecting the combined effects of increased acreage and production volume across major commodities (Table 1.A17).

1.3.1.5 Regional livestock distribution

Total value of livestock output (milk, pork, beef, turkey, broilers, and eggs) increases by about $2.7 billion (2.24 percent) with the energy price increase by 40 percent

(Table 1.A18). Regional changes reflect similar increasing trends. Regions with large increases of the total value of livestock production are Appalachia followed by Pacific States, Northern Plains, and Southern Plains (Table 1.A18). When energy price declines by 40 percent, total value of livestock output increases by 0.27 percent, which indicates that the decrease in livestock prices is offset by the increase in output.

1.3.2 Ethanol Scenarios

Results show how U.S. agriculture reacts to ethanol demand shocks across the three scenarios comparing to the first scenario. Scenarios 2, 3 and 4 are labeled exp*2, dom*2 & exp*2, and dom*2 & exp*4, respectively, in the figures below.

1.3.2.1 Crop output and prices

With increased ethanol demand across Scenarios 2, 3, and 4, the production of sorghum declines while the production of corn, oats, soybeans, and wheat increases (Figure 1.8, Table 1.A.19). The highest increase of corn production reflects the effect of rightward demand curve shifts combined with upward sloping supply. Relaxing the blend wall constraint in scenarios 3 and 4 is the major driver of crop acreage changes, while changes in export demand have smaller effects because ethanol export only accounts for approximately 10 percent of total domestic ethanol production.

With increased ethanol demand across Scenarios 2, 3, and 4, changes in crop prices are similar to the change in crop production (Figure 1.9, Table 1.A.20). The major driver of price changes is the shift in blend wall constraint while export demand shifts have smaller effects. Soybeans, wheat, and oats show the largest price decreases. Corn, sorghum, and silage show the largest price increases. The increases in corn, silage and sorghum prices reflect the effect of rightward demand curve shifts combined with upward sloping supply. The large decreases in prices of soybeans, wheat, and oats show a second-round leftward shift of demand curve, reflecting the decline in feed use of soybeans, wheat, and oats due to an increased use of DDG (dried distillers grains), a co-product of ethanol production that is used as a high-protein animal feed.

Table 1.A21 describes changes in corn supply and use as ethanol demand increases. Production expands by 2.74 to 31.14 percent across the three scenarios. Feed use, export, commercial ending stock, and explicit demand (domestic use excluding processing for ethanol and feed use) all decline. These reductions are more than offset by increased processing for ethanol, which increases by 8.37 percent to 104.63 percent across the three ethanol scenarios. Relaxing the blend wall constraint is the major driver of changes in corn supply and use while export changes have smaller effects.

1.3.2.2 Ethanol output

With increased ethanol demand across Scenarios 2, 3, and 4, ethanol domestic use declines modestly in Scenario 2 from 16.1 to 16.0 billion gallons reflecting increased export demand, increases dramatically in Scenario 3 to 30.6 billion gallons reflecting increased use in domestic fuel as the blend wall constraint is relaxed, and declines modestly relative to Scenario 3 to 30.5 billion gallons reflecting further export demand increases. Ethanol export changes across Scenarios 2, 3, and 4 from 1.9 to 3.6, 3.5, and 6.8 billion gallons, respectively, reflecting the effects of increased export demand. Prices ($/gallon) increase from $1.29 in the base to $1.31, $1.38, and $1.39, respectively, under the three scenarios. Larger increases under Scenarios 3 and 4 indicate that relaxing the blend wall constraint has the largest impact on ethanol price and the domestic use of ethanol is more important than export.

1.3.2.3 Livestock output and prices

Changes in ethanol scenarios impact the livestock sector through shifts in feed availability and prices, particularly the increased availability of by-products from ethanol processing that are used for animal feed. Production of pork, broilers, and turkey modestly increase while production of beef, eggs, and milk decline slightly, which are all less than 1 percent changes (Figure 1.10, Table 1.A22). Accordingly, the prices of livestock commodities change modestly except pork, which declines by more than 6 percent under the two scenarios that include the 20 percent blend wall (dom*2) (Figure 1.11, Table 1.A23).

1.3.2.4 Regional crop distribution

With the exception of Delta and Southern Plains, total acres of crops increase under ethanol scenarios (Table 1.A24). Under ethanol scenario 4, Corn Belt has the largest expansion of 13.2 million acres followed by Appalachia and Northeast. The changes in crop acres are mainly caused by the changes in corn acres. Corn acres increase by 27.9 million acres in the U.S. (Table 1.A25) under ethanol scenario 4 with the major driver of the increase being the shift to the 20 percent blend wall (dom*2). Corn acres in Corn Belt have the largest expansion of 10.7 million acres followed by Appalachia, Northern Plains, and Northeast (Figure 1.12, Table 1.A25).

With the exception of Delta and Southern Plains, gross value of crop output increases across the U.S. but increases vary among regions (Table 1.A26). For the U.S., crop value increases by 13.2 percent with ethanol scenario 4. The largest driver of the increase is the increase in blend wall to 20 percent (dom*2). Corn Belt sees the largest increase in crop value followed by Appalachia, Northeast, and Northern Plains.

1.3.2.5 Regional livestock distribution

Total value of livestock output (milk, pork, beef, turkey, broilers, and eggs) declines modestly across ethanol scenarios, with a decrease of approximately $0.4 billion (0.36 percent) under Scenario 4. Under Scenario 2, the decline is more limited at roughly $0.1 billion (0.10 percent), while Scenario 3 sees a moderate drop of about $0.3 billion (0.30 percent). These declines are primarily driven by lower prices, especially for pork. Regionally, reductions in livestock value are most pronounced in Appalachia, followed by the Corn Belt and Southeast across all scenarios. The pattern of regional decline remains relatively consistent, indicating that areas with concentrated livestock operations are more exposed to ethanol-driven shifts in feed prices and co-product availability (Table 1.A27).

1.3.3 Sensitivity Analysis

We conducted a sensitivity analysis on the energy passing-through rate, a key parameter that governs the degree to which changes in energy prices affect agricultural production costs, to evaluate the robustness of our model's baseline calibration. Specifically, we simulated two alternative scenarios in which the energy passing-through rate was reduced by 20 percent and increased by 20 percent and compared these against the baseline energy passing-through rate.

The results show that adjustments to the energy passing-through rate meaningfully influence crop-level production balances, especially for energy-intensive commodities (Table 1.A28, Table 1.A29). When the passing-through rate is reduced by 20 percent, the cost pressure on producers diminishes, resulting in slightly higher production levels for major field crops such as corn, soybeans, and wheat. Conversely, a 20 percent increase in the energy passing-through rate amplifies cost burdens, leading to marginal reductions in production, particularly in energy-intensive processing and input-heavy supply chains.

Despite these directional effects, the overall pattern of commodity balance responses remains consistent across scenarios, indicating that the model's core conclusions are not overly sensitive to moderate variation in the energy cost parameter. This sensitivity check reinforces the reliability of our findings under a plausible range of energy market conditions.

1.4 Summary

The US agricultural sector is highly sensitive to energy markets due to its dependence on energy-intensive inputs such as fuel, fertilizer, and electricity. Volatile energy prices, alongside evolving biofuel policies, present both risks and opportunities for crop and livestock producers. This study uses the REAP model to assess how energy price changes and ethanol demand shocks influence agricultural production, prices, and economic value across US regions. The analysis extends previous work by incorporating both rising and falling energy prices, updating baseline projections to 2030, and relaxing constraints on ethanol exports and domestic blending.

This study finds that higher energy prices lead to higher crop prices, lower crop output, and lower crop values. Crop acres decrease in most farm regions with the exception of Northern Plains. Corn acres follow a similar pattern. Conversely, falling energy prices lead to expanded production, reduced prices, and higher crop values, especially for energy-intensive crops, underscoring the sensitivity of agricultural output to energy costs. Livestock production tends to decline in response to higher energy costs. Total livestock value tends to increase reflecting that the decreased outputs are more than offset by higher prices. The regional distribution of the value of livestock changes very little (less than one percent) in response to energy price increases. Conversely, lower energy prices reverse these trends, modestly increasing production but reducing prices, leaving overall value changes minimal or slightly negative.

Higher ethanol demand (both domestic and export) leads to expansion of corn production but reduction of minor feed grain sorghum. Corn supply surges by 26.5 percent with the highest ethanol demand in scenario 4 with most of the increased supply going into ethanol production. Crop output increases the most in Corn Belt which has the largest share of corn. Livestock production tends to change modestly in response to higher ethanol demand. Accordingly, the prices of livestock commodities change modestly except pork, which declines by more than 6 percent in response to higher ethanol demand.

The vulnerability of agricultural enterprises to volatile energy price varies by enterprise and region depending on their energy intensity and region where production occurs. Potential ethanol demand shocks have important direct effects by expanding corn acreage. Farmers, farm advisors, lenders, input suppliers, and policymakers need to be aware of these effects and be well prepared to anticipate the effects of possible volatile energy prices and ethanol policy changes.

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Tables and Figures

Table 1.1 Energy Inputs into Crop Production (Pimentel, 2009)

	Energy input per hectare of crop (thousand kcal)							
	Corn	Percent of total	Soybeans	Percent of total	Wheat	Percent of total	Rice	Percent of total
Labor[a]	462	6%	240	9%	312	8%	462	2%
Machinery	1,018	14%	360	14%	925	24%	703	4%
Diesel	405	6%	444	18%	1,000	26%	3,730	19%
Nitrogen	2,480	34%	59	2%	1,094	29%	2,576	13%
Phosphorus	328	5%	156	6%	143	4%	156	1%
Potassium	274	4%	48	2%	6	0%	94	0%
Lime	315	4%	562	22%		0%	560	3%
Seeds	520	7%	450	18%	218	6%	560	3%
Irrigation	320	4%		0%		0%	9,877	50%
Herbicides	620	9%	170	7%	5	0%	280	1%
Insecticides	280	4%	0	0%	0	0%	10	0%
Electricity	34	0%	29	1%	12	0%	728	4%
Transport	169	2%	16	1%	67	2%	150	1%
Total	7,225		2,534		3,782		19,886	

[a]It is assumed that a person works 2,000 hours per year and utilizes an average of 8,000 liters of oil equivalents per year.

Figure 1.1 Brent Crude Oil Price index—1987-2024. Source: U.S. Bureau of Labor Statistics. Displayed in Federal Reserve Economic Data, Federal Reserve Bank of St. Louis, fred.stlouisfed.org

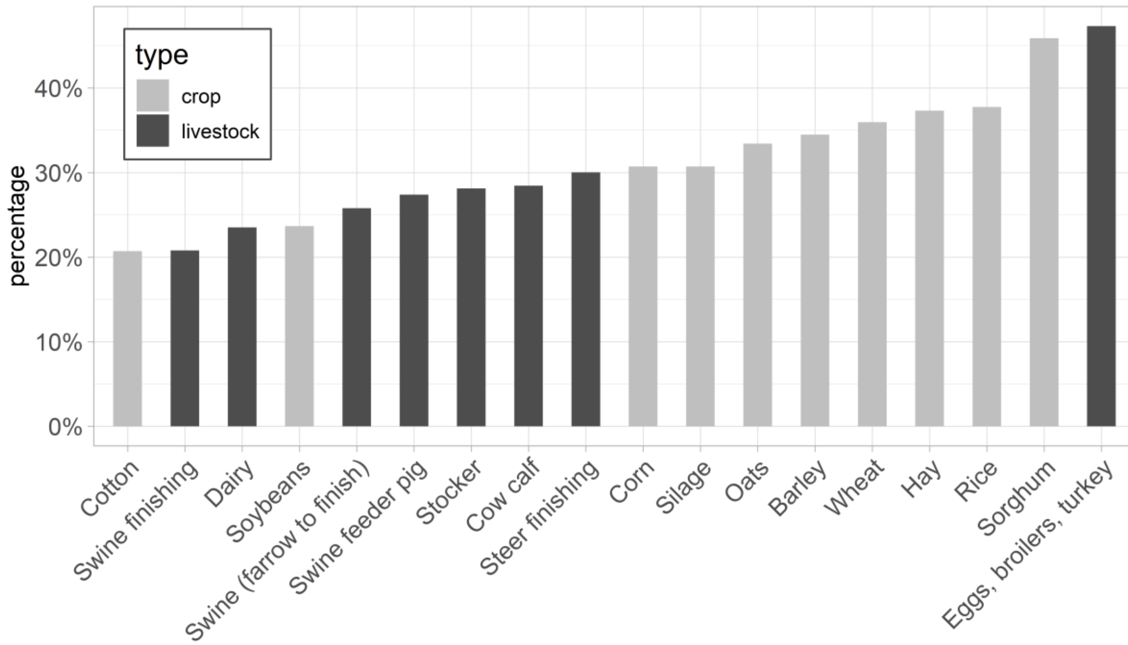

Figure 1.2 Weighted pass-through rate of energy costs in crops and livestock

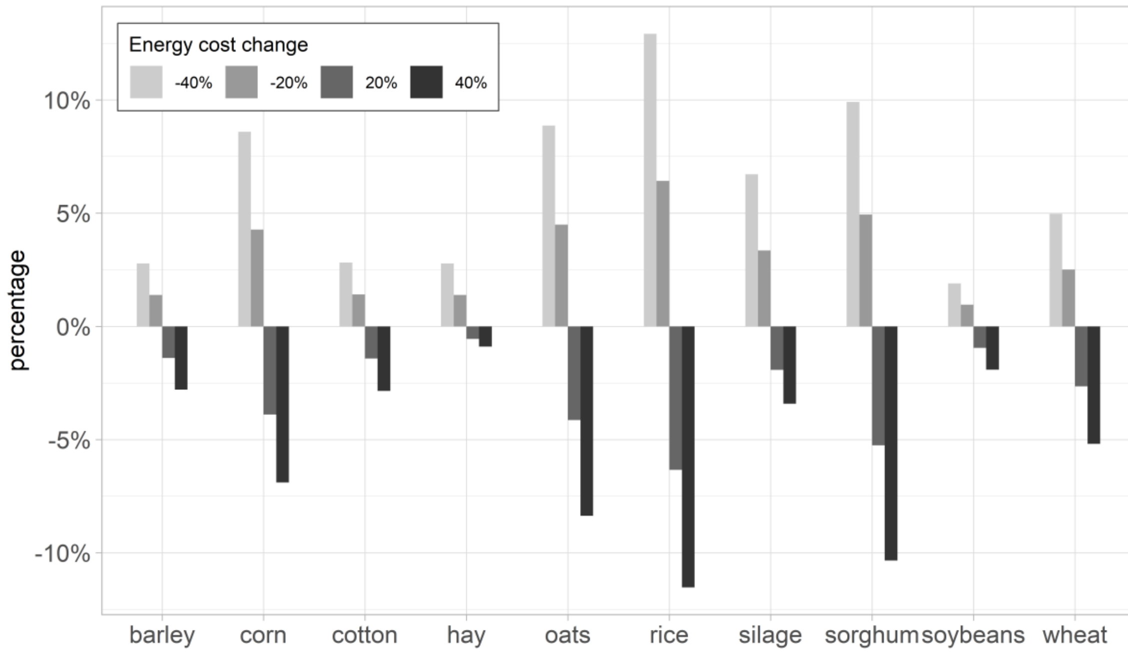

Figure 1.3 Crop commodity output change by energy cost change

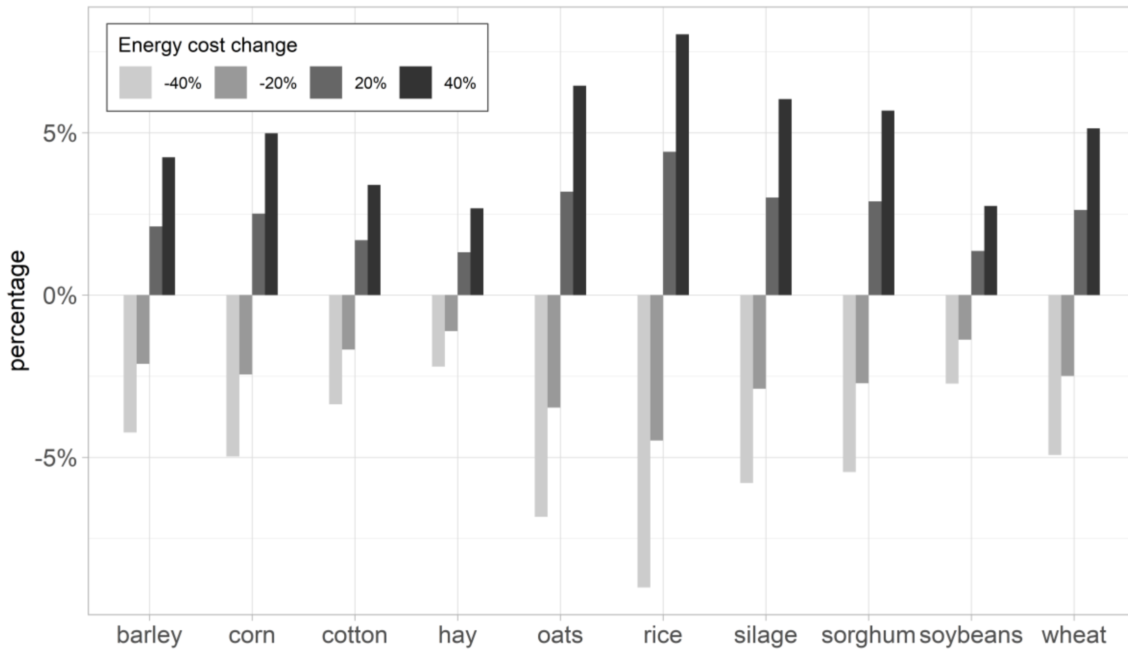

Figure 1.4 Crop commodity price change by energy cost change

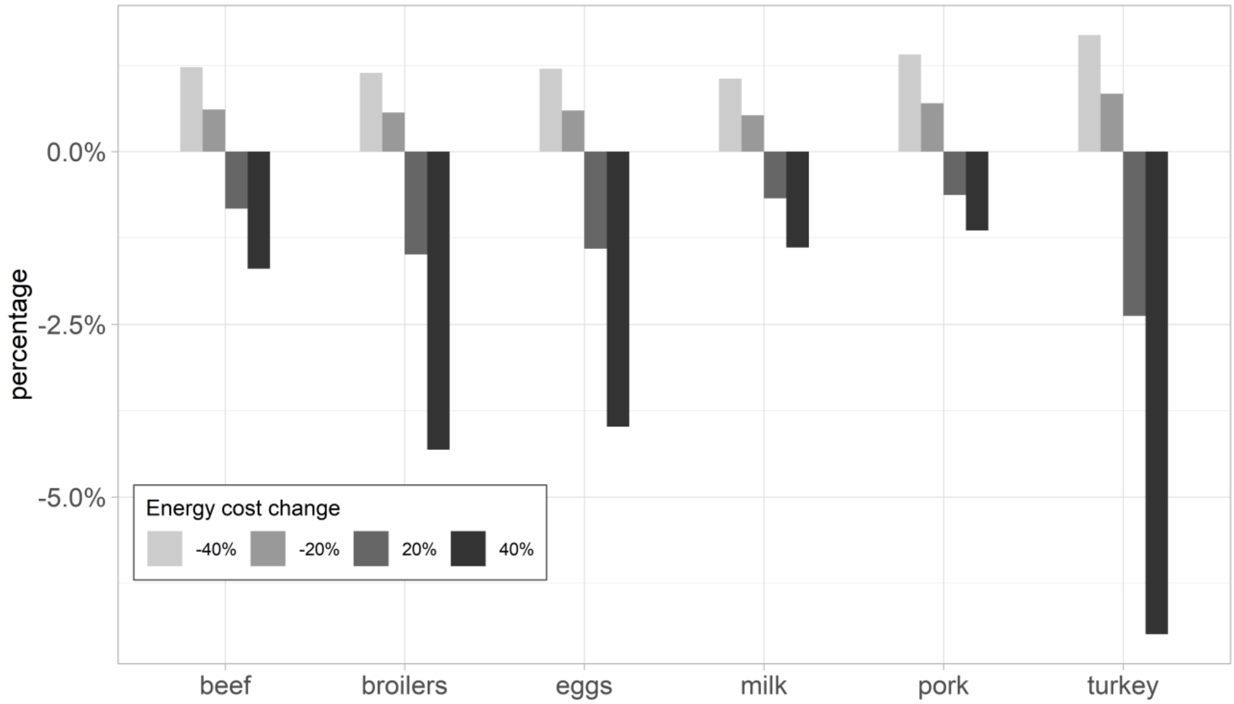

Figure 1.5 Livestock output change by energy cost change

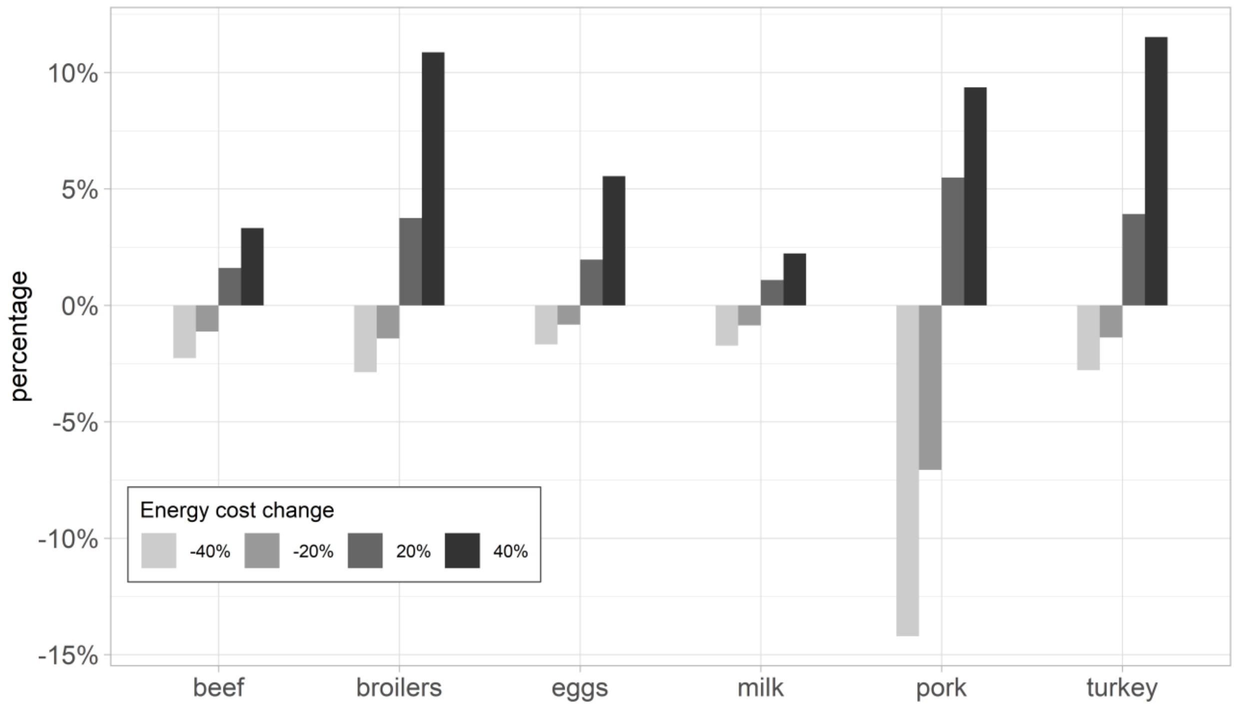

Figure 1.6 Livestock price changes by energy cost change

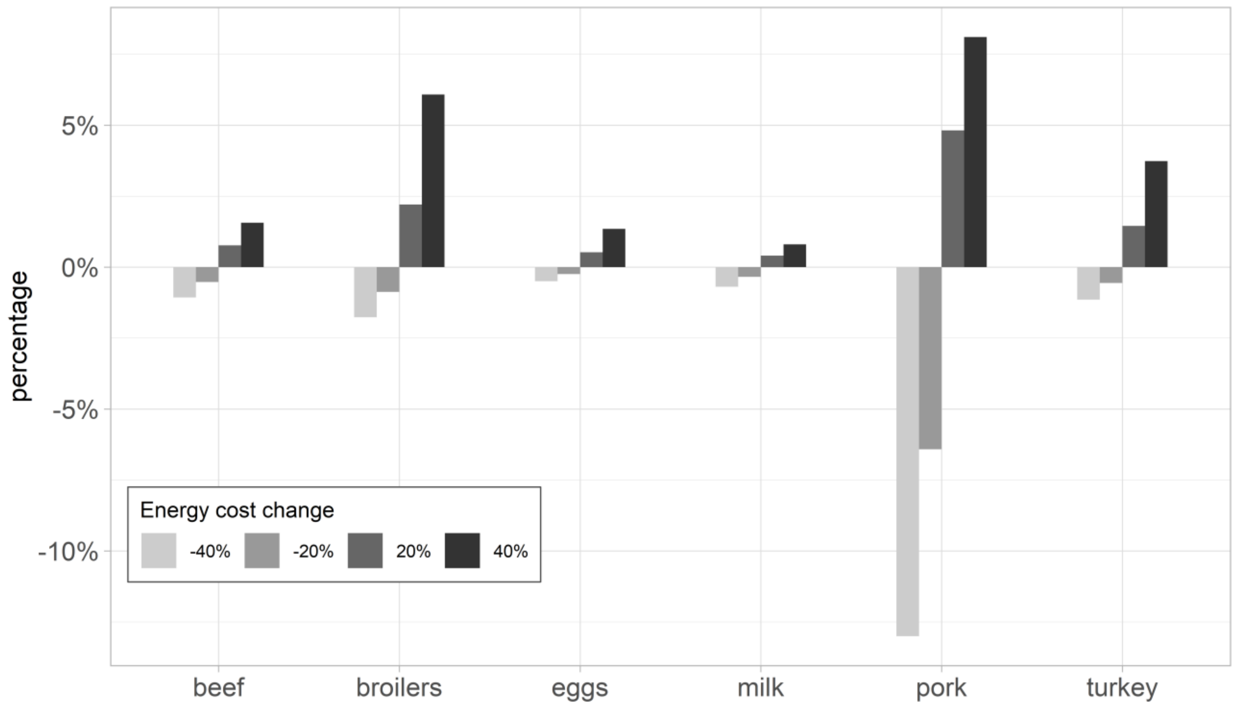

Figure 1.7 Livestock value changes by energy cost change

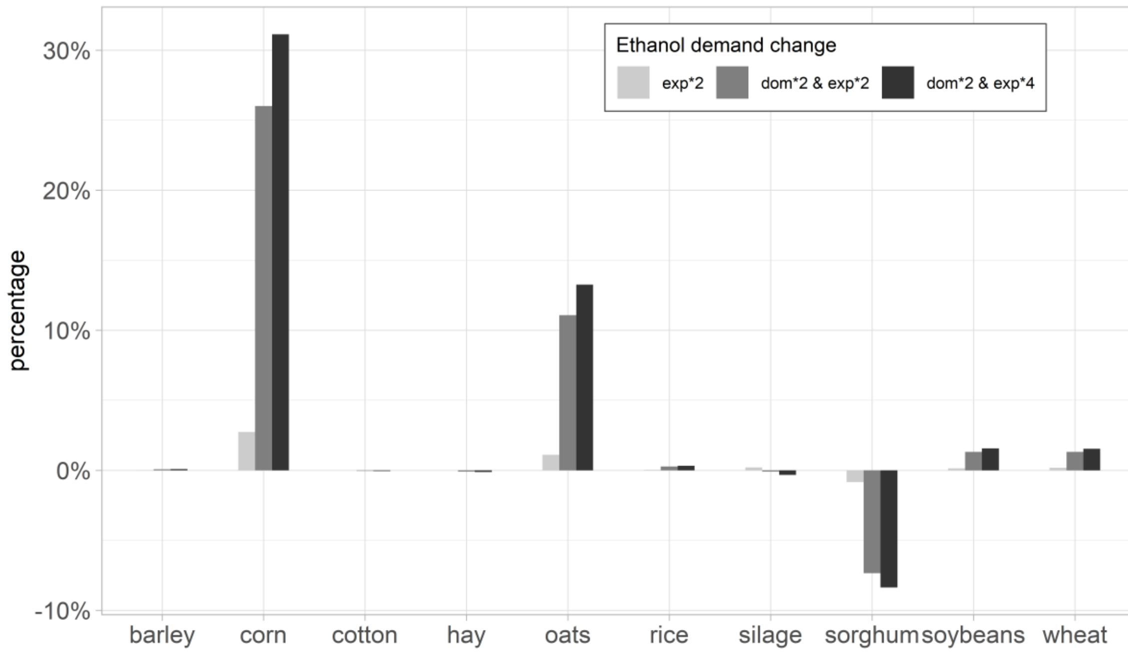

Figure 1.8 Crop commodity output change by ethanol scenarios

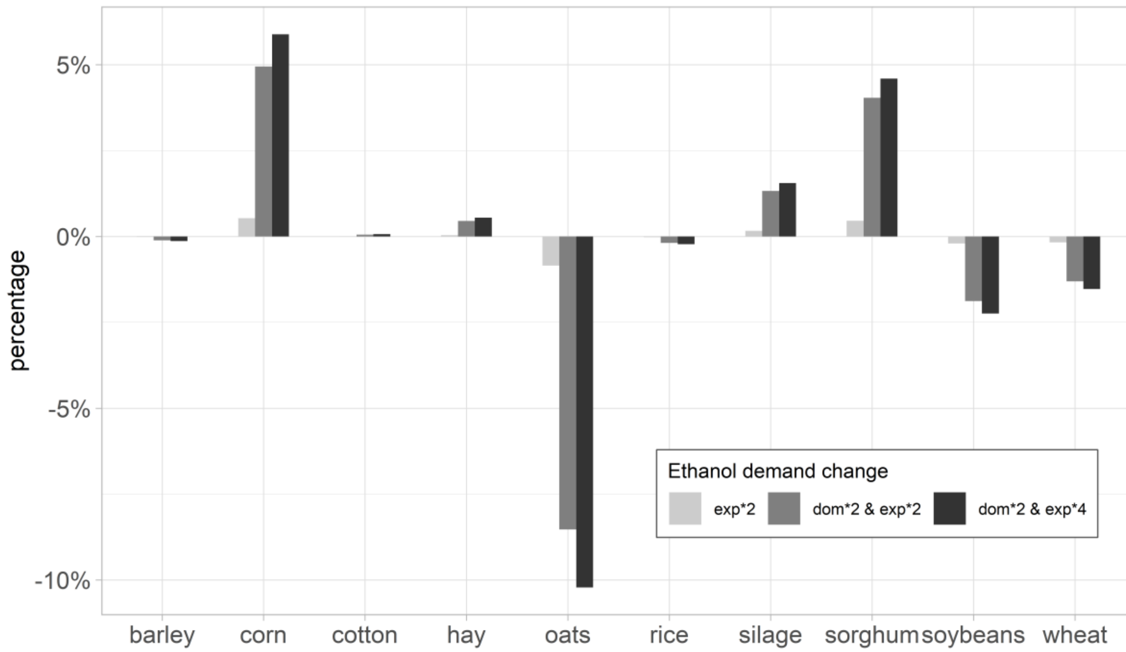

Figure 1.9 Crop commodity price change by ethanol scenarios

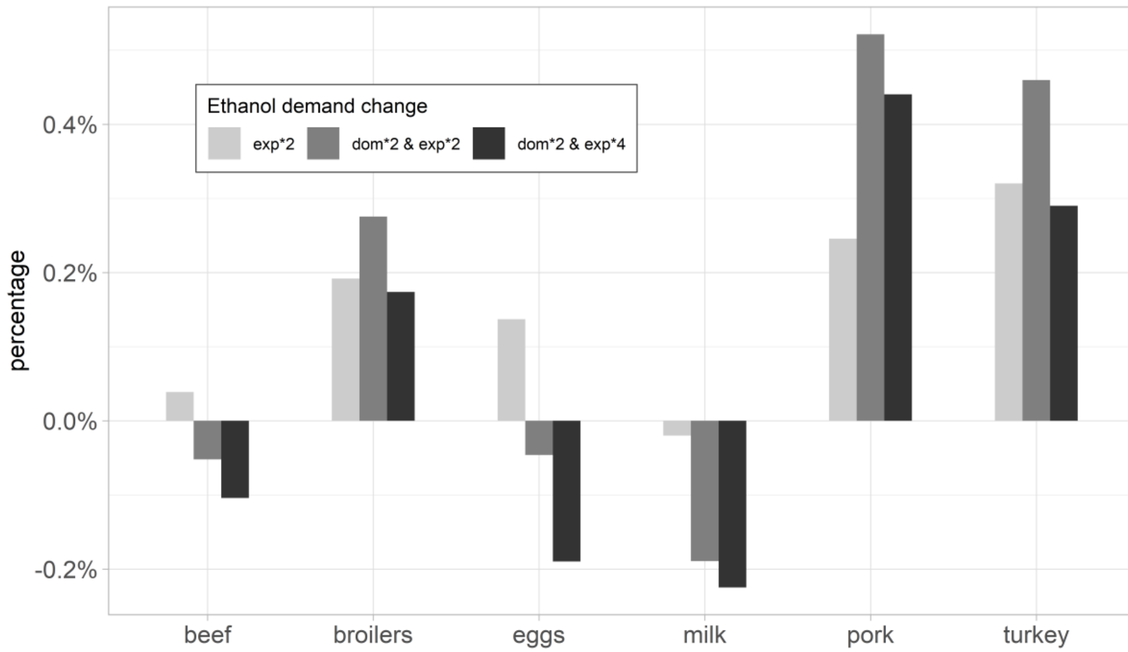

Figure 1.10 Livestock output change by ethanol scenarios

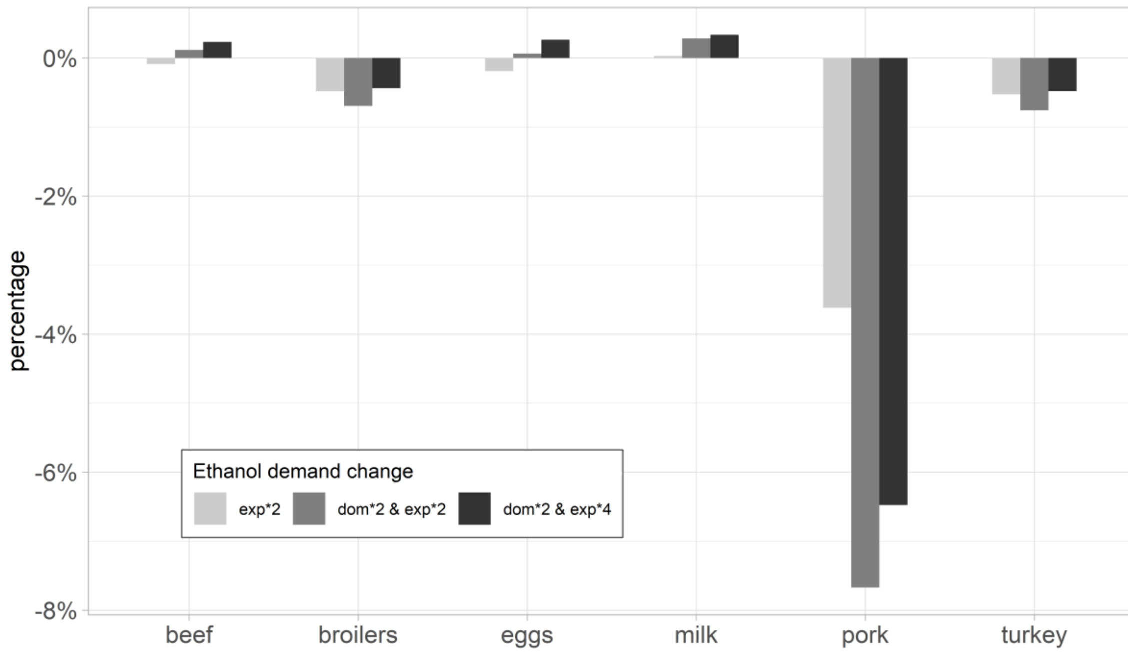

Figure 1.11 Livestock price changes by ethanol scenarios

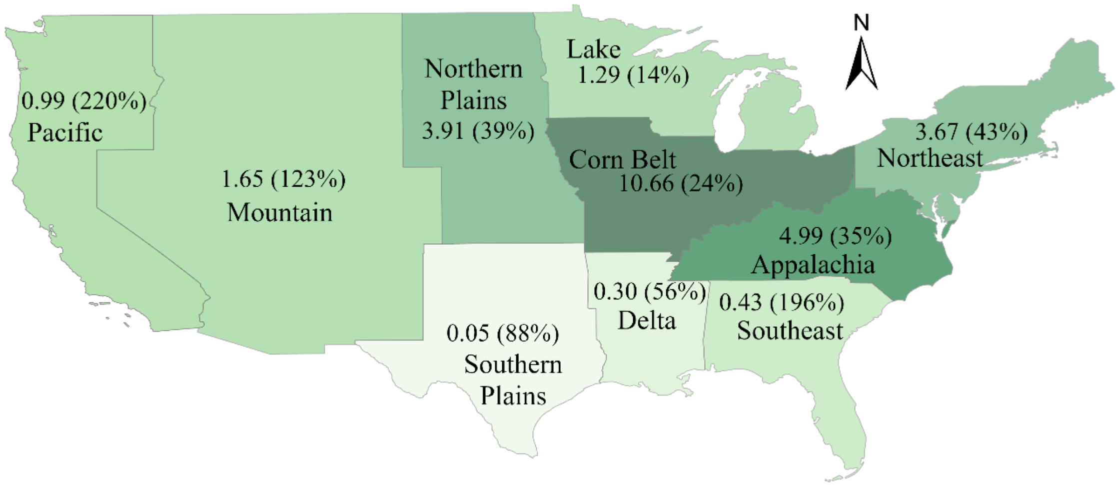

Figure 1.12. Corn acre change (million acres) under ethanol scenario 4

Chapter 2

Improving ecosystem services from US agriculture: yield reserve vs. land retirement

Abstract

Pressure for protecting and restoring water quality requires more reduction in nitrogen (N) loads from agriculture. Researchers have been evaluating agricultural production choices along both the extensive and intensive margins to improve ecosystem services. This study examines and compares the cost-effectiveness of a government budget-equivalent Yield Reserve Program and an expansion of land retirement program (CRP) on revenues, costs, output, and potential reductions in N loads from the production of 10 major crops, both nationally and regionally. Findings indicate that the Yield Reserve Program outperforms the CRP in terms of achieving N reduction under equivalent government budget expenditures. However, the N reduction under the Yield Reserve Program is partially offset by the "rebound effect" on corn acreage whereby corn acreage increases with the subsidized N reduction. The CRP expansion demonstrates a strong "slippage effect", where the expansion of CRP acreage simply brings marginal land into crop production resulting in a smaller-than-expected N reduction. Sensitivity analysis shows that higher percentage of Yield Reserve per acre tends to be more cost-effective in excess N reduction, and more inelastic land supply tends to reduce the "slippage" of CRP expansion.

2.1 Introduction

Water pollution resulting from anthropogenic sources of nutrients, specifically nitrogen (N), is an escalating environmental issue in the United States. The US Environmental Protection Agency (EPA) reveals that only 38% of US rivers and streams meet good water quality standards for N, indicating that nearly half are in poor biological condition (U.S. EPA 2016). Agricultural activity is the largest source of nutrient runoff to streams in the US (Alexander et al., 2008; Goolsby, 2000; U.S. EPA 2017). This negative externality is directly linked to the significant technological advancements in fertilizer production and seed hybridization during the Green Revolution, which dramatically increased crop and livestock yields in the US and many other parts of the world (Evenson and Gollin 2003; Stewart et al., 2005). However, excess fertilizer not utilized by crops can accumulate in the soil and enter the environment through runoff, leaching into groundwater, or converting into gaseous forms, thus contributing to pollution (Alexander et al., 2008). Research has estimated that agricultural activities from the Mississippi/Atchafalaya River Basin (MARB) contribute approximately 60 percent of N and nearly half of P loadings into the Mexico Gulf (Marshall et al., 2018). For the Chesapeake Bay watershed, agricultural activities produced 117.06 million pounds of N load, accounting for 46 percent of total simulated N load to the Bay (Chesapeake Progress, 2022).

Row-crop agriculture, particularly corn, is a major contributor to nutrient pollution (Alexander et al., 2008). Despite agronomic recommendations, farmers often apply more fertilizers than necessary, leading to nutrient runoff (USDA ERS, 2022; Sheriff, 2005). It is estimated that U.S. average N fertilizer applications to corn field increased from 58 pounds per acre in 1964 to 149 pounds per acre in 2018 (USDA ERS, 2022). Data estimated by the US Department of Agriculture (USDA) indicates that, on average, 34 pounds of N per acre per year are lost from crop fields to waterways through various pathways (USDA NRCS, 2017). Additionally, long-term fertilization practices have resulted in a significant accumulation of nutrients in soils, lakes, riverbeds, and groundwater (Van Meter et al. 2017). VanMeter et al. (2016) estimated the legacy accumulation of N varies from 22 to 62 pounds per acre per year in cropland in the Mississippi River basin.

Federal and state governments have taken actions to protect and restore water quality, but progress is not satisfactory. For example, the U.S. Environmental Protection Agency (EPA) extended the time for reaching its original goal of reducing the areal extent of the hypoxic zone in the Gulf of Mexico from 2015 to 2035, recognizing the enormity of the task of reducing nutrient loads on a subcontinental scale (U.S. EPA, 2022). As of 2023 in the Chesapeake Bay watershed, the adoption of water quality protection practices including agricultural best management practices (BMPs) is projected to achieve only 57% of the N reductions needed to achieve the Chesapeake Bay's Total Maximum Daily Load (TMDL) standards by 2025 (Chesapeake Progress, 2024).

The U.S. Geological Survey (USGS) calculated that the total N load from the MARB to the Gulf in Water Year 2017 was approximately 3,320 million pounds and the action plan requires a cut in N load to the Gulf by 45 percent or more (U.S. EPA, 2022). The total simulated N load to Chesapeake Bay in 2023 was 248 million pounds while the 2025 target of N load is 210 million pounds, which means 38 million pounds (15.3 percent) of 'excess N' needs to be removed annually (Chesapeake Progress, 2024). Achieving these targets requires a huge reduction in N loads from agriculture, which could have significant economic impacts on producers and consumers.

Researchers have been evaluating agricultural production choices along both the extensive and intensive margins to improve ecosystem services while considering the cost-effectiveness of these choices (Hellerstein et al., 2015; Marshall et al., 2018; Metcalfe et al., 2007; Miao et al., 2016; Kirwan et al., 2005; US Farm Service Agency, 2015). The extensive margin is response of crop production and associated changes in environmental impacts to changes in cropland area while the intensive margin is response of crop production and environmental impacts to changes in other production inputs (Babcock, 2015; Earnhart and Hendricks, 2023). One widely discussed intensive margin approach is the Yield Reserve Program (Chesapeake Bay Commission, 2004; Metcalfe et al., 2007; Henry A. Wallace Center, 2001; US Congress, Senate, 2002a, 2002b), an innovative proposal made to reduce nutrient applications and nutrient pollution potential by compensating farmers to reduce their N applications below standard agronomic recommendations. One widely discussed and implemented extensive margin approach is land retirement, such as the Conservation Reserve Program (Fleming, 2014; Hansen, 2007; Morefield et al., 2016; Wu, 2000; Wu, 2005). Wu (2000) discussed the slippage effect of the Conservation Reserve Program (CRP), whereby retiring cropland may bring non-cropland into crop production. Wu found that for each one hundred acres of cropland retired under CRP in the central United States, twenty acres of non-cropland were converted to cropland, offsetting the water and wind erosion reduction benefits of CRP, respectively. Fleming (2014) modeled county-level slippage empirically using satellite imagery and the results also suggested the existence of CRP slippage, although at a rate lower than the 20 percent reported by Wu (2000). However, most analyses of these approaches are conducted at the regional level, few if any studies have compared these two approaches in terms of their impacts on the whole US agriculture sector as well as their potential ecosystem benefits.

We examine the national and regional effects of a government budget-equivalent Yield Reserve Program and an expansion of a land retirement program (CRP) on revenues, costs, output, and potential reductions in N loads from the production of 10 major crops in the US. We also test the sensitivity of the Yield Reserve program through different levels of yield reserve (the amount of subsidized N reduction), extra subsidies, and enrollment rates, and the sensitivity of CRP expansion through different levels of marginal land supply elasticities. We find that the Yield Reserve Program outperforms the CRP in terms of achieving N reduction under equivalent government budget expenditures. Sensitivity analysis indicates that a higher percentage of Yield Reserve in terms of the amount of subsidized N reduction tends to be more cost-effective, and that a more inelastic land supply tends to reduce the "slippage effect" of CRP expansion.

2.2 Materials and Methods

2.2.1 REAP model

This study uses the Regional Environment and Agriculture Programming (REAP) model, a partial equilibrium model implemented using nonlinear mathematical programming. The REAP model was developed by USDA's Economic Research Service to analyze the intersection of agriculture and the environment for policy applications (Johannson et al., 2007). Recent issues analyzed using the REAP model include policies to reduce hypoxia in the Gulf of Mexico (Marshall et al. 2018), climate change adaptation

(Malcolm et al., 2015) and environmental implications of biofuels (Marshall et al., 2011; Sands et al., 2017).

REAP models crops, livestock, and crop processing activities. For this application we simplify the REAP model to a crop-only model. Appendices provide further information on model objective function (1.SI1, 1.SI2) and data input to the model including commodity demand elasticities (Table 1.A1), crop acreage and production (Table Table 1.A2), cropland supply (Table 1.A3), and major crop yields and production costs (Table 1.A4 and Table 1.A5).

The 2022 USDA Budget includes $4.6 billion for the Farm Bill Conservation Programs including $2.3 billion for the CRP. In this study, we simulate three scenarios of increasing subsidy payments of approximately $500 million, $750 million, and $1 billion to farmers to achieve N load reductions from all US croplands. We model the three scenarios under two program implementations, CRP and Yield Reserve, as described below that would reduce the N load from cropland while maximizing net welfare (producer plus consumer surplus) of 10 major crops.

2.2.2 Land Supply Function

The cropland supply function in the REAP model was originally formulated as a kinked linear function. This specification allocates the initial X percent of cropland (fixed land) at a constant price, with any additional cropland (variable land) supplied at a higher price along an upward-sloping linear curve. While this approach facilitates model convergence during the calibration of a baseline scenario, it fails to adequately capture realistic land market dynamics under external shocks. To address this limitation, we revised the specification of the variable land supply function to an exponential form (Figure 2.A1).

This modification better reflects the increasing marginal cost of land as cropland expands, thereby improving the model's ability to simulate realistic market responses to exogenous changes.

2.2.3 Yield Reserve Program in REAP

The basic decision unit of crop production in REAP is the crop rotation made up of some combination of 10 field crops (barley, corn, cotton, hay, oats, rice, silage, sorghum, soybeans, and wheat). We model a Yield Reserve Program that would compensate farmers for reducing N applications in corn production given that corn typically has the highest N fertilizer applications among the 10 field crops. Assuming that farmers currently follow Extension recommendations in applying N, subsidies are designed to compensate farmers for the opportunity cost of foregone net revenues from the N that is not applied. Foregone net revenues, ΔNR, are calculated from the loss of yield net of the savings in N and yield-related costs relative to those that would have been obtained prior to the Yield Reserve Program:

$$\Delta NR = P_c\left(Y_{base} - Y_{yr}\right) - P_N\left(N_{base} - N_{yr}\right) \qquad (2.1)$$

where P_c is the price of crop; P_N is the price of N fertilizer; Y_{base} is the crop yield under the baseline condition; Y_{yr} is the yield obtained with the N application mandated by the Yield Reserve Program; N_{base} is the amount of N applied under the baseline condition; and N_{yr} is the amount of N applied under the Yield Reserve Program.

Yield loss in response to reduced N applications is estimated using empirical studies of the response of crop yield to N applications. Most studies found similar patterns of corn yield response to N (Huang and LeBlanc, 1994; Vanotti and Bundy, 1994). We assume that N applications are based on the general ratio of 1 pound of N per bushel of expected corn grain yield. Since US average corn yield is projected to be 196.5 bushels per harvested acre in 2030 (USDA, 2021), we adjusted the general corn yield function estimated for the Corn Belt (Huang and LeBlanc, 1994; Vanotti and Bundy, 1994):

$$Yield\ (corn) = 96.57 + 0.73N - 0.001127N^2 \qquad (2.2)$$

where the application of 196.5 pounds of N fertilizer per acre would yield 196.5 bushels of corn grain per acre in this corn yield response function.

The reduction in N load is estimated as the reduction in excess N from corn production. Excess N is defined as the total amount of N fertilizer applied to corn minus the amount of N removed by corn (Heckman et al., 2003; Ribaudo et al., 2017). The assumed N removal by corn varies by state. In Virginia and Michigan, the estimated N removed by corn is approximately 0.90 pound per bushel (Virginia Cooperative Extension Service, 2000; Michigan State University Extension, 2017). In California, the estimated N removed by corn is approximately 0.81 pound per bushel (University of California, Davis, 2009). We take the average of the three states and use a rate of 0.87 pound per bushel to count the N removed by corn. The total reduction in excess N from corn production under Yield Reserve is estimated as:

$$\Delta Excess\ N = (N_{base} - 0.87 * Y_{base}) * A_{base} - (N_{yr} - 0.87 * Y_{yr}) * A_{yr} \qquad (2.3)$$

where A_{base} is the corn acreage under the baseline condition; and A_{yr} is the corn acreage obtained under the Yield Reserve Program. The excess N per acre from corn production at baseline is estimated to be approximately 25.55 pounds according to the baseline corn yield of 196.5 bushels per acre and N application of 196.5 pounds per acre.

Scenarios of the Yield Reserve Program were introduced in REAP as follows: First we estimate foregone net revenues as represented in equation (2.1) for each of the three scenarios of approximately $500 million, $750 million, and $1 billion. Second the subsidies of estimated foregone net revenues are added back to the corresponding rotations containing corn production. The estimated yield losses and foregone net revenues depend on the total subsidy amount available for the program as described below.

To simulate the appropriate percentage of yield reserve that would lead to the foregone net revenues from the program equal to the three scenarios of approximately $500 million, $750 million, and $1 billion, we assume the price of corn in the US is unchanged with the minor decrease of yield in the Yield Reserve Program. Hence the US average revenue of corn per acre is $3.55 times the US average corn yield response function (equation (2.2)) (Figure 2.1). The US average cost of corn per acre is the sum of average land cost of $163.41 per acre, average variable cost (excluding N fertilizer cost) of $276.56 per acre, and the N fertilizer cost of $0.39 per pound (Schnitkey et al., 2022; USDA ERS, 2023) (Figure 2.1). For example, for the first scenario ($500 million subsidy) in Yield Reserve Program, using the US average corn yield response function (equation (2.2)), a 3.41 percent reduction of N application will lead to a 1 percent yield loss relative to the baseline yield that would have been obtained prior to the Yield Reserve Program. We assume that the N fertilizer accounts for 22 percent of the total variable cost of corn production based on the estimate from the Commodity Cost and Return (USDA ERS, 2023), therefore, a 3.41 percent reduction of N application will also lead to an average 0.75 percent reduction in variable costs of corn production relative to those that would have been incurred prior to the Yield Reserve Program. Using the foregone net revenue function (equation (2.1)), the loss of 1 percent yield net of the savings in N and yield-related costs relative to those that would have been obtained prior to the Yield Reserve Program is approximately \$4.37 per acre on average for the US (Figure 2.1). The total US corn acreage is 99 million leading to an estimated expenditure of \$4.37 times 99 million acres = \$433 million. The simulated subsidy per acre varies among REAP regions because of the regional variations of yield response and variable cost. Additionally, the subsidies from the Yield Reserve Program would cause a rebound effect on corn acreage as the simulated result showed an expansion of 4.35 million acres, which is likely because the Yield Reserve tends to reduce N applications and move the production closer to the profit maximizing point, therefore, the subsidy from the simulation is approximately \$501 million if applying 1 percent yield reserve on all US corn land.

For the second scenario (\$750 million subsidy), a 5.04 percent reduction in N application leads to a 1.5 percent yield loss and a 1.11 percent reduction in variable costs of corn production. This results in a foregone net revenue of approximately \$6.58 per acre, and with a rebound effect expanding corn acreage by 6.72 million acres, the total subsidy is approximately \$772 million.

For the third scenario (\$1 billion subsidy), a 6.62 percent reduction in N application results in a 2 percent yield loss and a 1.46 percent reduction in variable costs, with a foregone net revenue of about \$8.80 per acre. Factoring in the rebound effect and acreage expansion of 9.19 million acres, the total subsidy is approximately \$1,058 million.

2.2.4 CRP Program in REAP

Land retirement shocks are implemented as changes of CRP acreage. We evaluated three scenarios of uniform expansion of CRP acreage across all REAP regions that would cost additional payments of approximately \$500 million, \$750 million, and \$1 billion to farmers. The total acreage enrolled in CRP is projected to be 26.9 million acres in the baseline year 2030 (USDA, 2021), which is almost 10 million acres less than the modern peak of 36.8 million acres in 2007. We assume the supply of cropland for CRP is perfectly elastic. The total payment to CRP land is estimated to be $2,057 million, therefore, a 37 percent uniform expansion of CRP land in the baseline year would cost approximately an additional $750 million and restore the acreage of CRP land to its peak. We found that 25 percent and 50 percent uniform expansions of CRP land in the baseline year would cost approximately an additional $500 million and $1 billion, respectively. Therefore, to be budget equivalent to the three scenarios in the Yield Reserve Program, three scenarios of uniform expansion of CRP land by 25 percent, 37 percent, and 50 percent across all REAP regions were introduced in REAP with corresponding additional CRP payments of approximately $515 million, $762 million, and $1,029 million added into the total welfare.

2.3 Results and Discussion

2.3.1 Yield Reserve Program

Results from the simulated three scenarios of Yield Reserve Program show how the total N reduction from corn production and total welfare from the 10 crops react to corn yield reserves of 1 percent, 1.5 percent, and 2 percent (Table 2.1). A yield reserve subsidy which represents an income transfer from taxpayers to agricultural producers results in a much smaller increase in net welfare from the agricultural sector but also a substantial reduction in “excess N” which represents an environmental benefit.

2.3.1.1 Crop output and prices under Yield Reserve Program

Under Yield Reserve, with N fertilizer reductions of 3.41 percent, 5.04 percent, and 6.62 percent and corresponding yield losses of 1 percent, 1.5 percent, and 2 percent, the production of seven major crops in the US declines while that of corn, soybeans and sorghum increases (Figure 2.2, Table 2.A1). The increase in corn production reflects the rebound effect of yield reserve subsidies, in which the savings from lower N application per acre alongside the incentive of receiving subsidies bring more cropland into corn production. Initially farmers are overapplying N fertilizer and losing profits, a reduction in N application moves the production of corn closer to the point of maximum net revenue. A subsidy to compensate for foregone net revenue, which "overshoots" the estimated losses from reduced yield and results in a net profit, provides additional incentives for farmers to expand corn production. The increase in production of soybeans and sorghum along with corn occurs mainly because the expansion of corn production happens in rotations of corn and soybeans and rotations of corn and sorghum, which have higher profitability than other rotations containing corn. The decline in production of the other seven crops reflects the effects of leftward supply shifts as a result of increased production of corn, soybeans, and sorghum combined with downward sloping demand. Reductions vary among crops with a larger percentage reduction for barley and oats, which are less profitable or are mainly used as feed grains.

The change in crop prices is opposite to the change of crop production reflecting the downward sloping demand for crops (Figure 2.3, Table 2.A2). Corn shows the largest percentage price decreases. However, percentage price decreases are more than the percentage increase in production of corn reflecting the downward sloping demand for corn with its low domestic demand elasticity of -0.23. For example, while corn production increases by 2.96, 4.47, and 6.01 percent across the three yield reserve scenarios, corresponding corn price decreases are 6.15, 9.31, and 12.50 percent.

2.3.1.2 Regional crop distribution under Yield Reserve Program

With corn yield reserves of 2 percent, total acres of 10 major crops increase by 9.02 million acres (Table 2.A3), which indicates that the total expansion of corn, soybeans, and sorghum production offsets the decline in the other seven major crops (Figure 2.A2). With corn yield reserves of 2 percent, total acres of corn increase by 9.19 million acres in the US (Table 2.A4) with the biggest expansion of 7.42 million acres in Northern Plains followed by Corn Belt and Lake States. The change of total acres of 10 major crops shows a similar pattern to that of the corn acreage change at the farm production region level (Table 2.A3, Table 2.A4, Figure 2.A3, Figure 2.A4), which indicates the changes of total acres of 10 major crops are dominated by corn acreage changes.

2.3.1.3 Regional N reduction under Yield Reserve Program

With a corn yield reserve of 2 percent, the simulated N reduction across the US totals approximately 771 million pounds. As illustrated in Figure 2.4, the most significant N reductions are concentrated in the Corn Belt, Lake States, and the southern portion of the Northern Plains, where the implementation of Yield Reserves has a substantial impact. In these regions, there is a notable decrease in excess N even with a slight rebound in corn acreage, demonstrating that the Yield Reserve approach effectively reduces N loads despite potential increases in corn production. However, the map also reveals areas in the northern portion of the Northern Plains where N levels have increased, as indicated by the dark shading. This suggests that, in these regions, the expansion of corn acreage has partially or completely offset the N reduction benefits associated with the Yield Reserve. This pattern highlights the spatial variability in the effectiveness of Yield Reserves, emphasizing that while Yield Reserves can lead to significant reductions in certain areas, the outcome may differ where corn expansion is prevalent. This nuanced spatial response points to the need for region-specific considerations when implementing N reduction strategies tied to Yield Reserve.

2.3.1.4 Sensitivity of Yield Reserve Program

Evidence from the existing conservation programs suggests that the overall enrollment rate of Yield Reserve program is unlikely to be 100 percent due to incentives, qualifications, and restrictions (Barnes et al., 2020; Institute for Agriculture and Trade Policy, 2024). A past study estimated that Yield Reserve implementation would cost $2 to $3 per acre to make sure that the program is appropriately placed, and any losses are documented (Metcalfe, 2006).

We tested the sensitivity of the Yield Reserve program through different levels of yield reserve, extra subsidies, and enrollment rates. The heatmaps in Figure 2.5 show the results of varying extra subsidies (dollars per acre) and percent enrollment rates on program cost, N reduction, cost-effectiveness, and corn acreage expansion for Yield Reserve 1 percent and 2 percent scenarios. Each heatmap represents different scenarios by adding extra subsidies and varying enrollment levels, where the highlighted black or red boxes represent the realistic scenarios within the budget constraint of $500 million to $1 billion. The black or red boxes follow a downward slope indicating that with a fixed budget, higher subsidies per farmer can only be accomplished with lower enrollment rates. Assuming higher enrollment rates are associated with increased extra subsidies, the most realistic scenarios are most likely to be around the positively-sloped 45-degree line across each heatmap. In the N reduction heatmap, the black-boxed scenarios show that the achievable

N reduction levels within the given budget under 2 percent Yield Reserve are higher than 1 percent Yield Reserve.

Correspondingly, in the cost-effectiveness heatmap, the red-boxed scenarios show that the cost-effectiveness within the given budget under 2 percent Yield Reserve is better than under 1 percent Yield Reserve as indicated by the darker color of the graph. This is also reflected by the heatmap of corn acreage expansion, where the black-boxed scenarios show that there is less corn acreage expansion under 2 percent Yield Reserve as indicated by the lighter color of the graph. Evidence suggests that farmers frequently overapply N fertilizers relative to the amount required for profit maximization (Del Rossi et al., 2023; Ribaudo et al., 2011). Implementing a 1 percent Yield Reserve could potentially align corn production more closely with its economic optimum compared to a 2 percent Yield Reserve leading to more pressure to expand corn acreage (rebound effect), as reflected by the scenarios around the positively sloped 45-degree line across the heatmaps of cost-effectiveness and corn acreage expansion.

In summary, the highlighted black or red boxes provide different possible scenarios of farmers' participation in the Yield Reserve program within a budget of $500 million to $1 billion. They point to combinations of Yield Reserve levels, subsidy levels, and enrollment rates that balance cost-effectiveness with significant N reduction and minimal corn acreage expansion. The higher percentage of Yield Reserve (2 percent vs. 1 percent) tends to be more cost-effective, which is likely because the 2 percent Yield Reserve tends to reduce N applications below and further away from the profit maximizing point, and therefore, diminishes the "rebound effect". These scenarios emphasize that strategic funding allocations can achieve meaningful environmental outcomes without compromising budgetary constraints, offering a pragmatic approach to N reduction through the Yield Reserve program.

2.3.2 Conservation Reserve Program

Results from the three scenarios of CRP expansion show how the 10 major crops in the US react to a uniform expansion of CRP land by 25 percent, 37 percent, and 50 percent across all REAP regions (Table 2.2). The estimated slippage effect of the CRP is approximately 78.5 percent, 77.2 percent, and 75.7 percent across the three scenarios of CRP expansion, which means for each one hundred acres of cropland retired under CRP in the US, approximately 76 to 79 acres of non-cropland would be converted to cropland, partially offsetting the N reduction benefits of CRP. For example, the total corn acreage decreases by 0.70 percent, 1.03 percent, and 1.41 percent across the three scenarios of CRP expansion (Table 2.A8), however, the simulated excess N decreases only 0.32 percent, 0.48 percent, and 0.68 percent, respectively. The CRP expansion retires relatively low yield corn land and pushes the corn production to marginal cropland which requires more N application. As a result, the N reduction from corn production under CRP expansion scenarios is approximately 2 percent of the simulated N reduction from corn production under Yield Reserve scenarios (Table 2.1, Table 2.2).

2.3.2.1 Crop output and prices under CRP Program

With the uniform expansion of CRP land by 25 percent, 37 percent, and 50 percent across all REAP regions, the production of crops declines except oats (Figure 2.6, Table 2.A5). The decline in crop production reflects the effects of leftward supply shifts as a result of increased acreage of CRP land combined with downward sloping demand. Output reductions vary among crops with the largest in sorghum, followed by wheat, barley, and hay.

The change in crop prices is opposite to the change in crop production reflecting the downward sloping demand for crops (Figure 2.7, Table 2.A6). Barley shows the largest percentage increase in price, followed by hay, wheat, and sorghum.

With the exception of hay and silage, the change in crop acreage shows a similar pattern to the change of crop production (Figure 2.6, Figure 2.A6, Table 2.A7). The acreage of hay and silage increases but the output declines, which means the expansion of CRP land takes over the land originally planted to high yield hay and silage and pushes the production of hay and silage to lower yield land.

2.3.2.2 Regional crop distribution under CRP Program

With the uniform expansion of CRP land by 50 percent across all REAP regions, total acres of 10 major crops decrease by 3.14 million acres (Table 2.A7), which indicates the total decline in other seven major crops offset the total expansion of oats, hay, and silage (Figure 2.A6). With the uniform expansion of CRP land by 50 percent across all REAP regions, the biggest decline in crop acreage is in Pacific States, followed by Appalachia, Delta States, and Southeast (Table 2.A7, Figure 2.A5).

2.3.2.3 Sensitivity of CRP Program

We tested the sensitivity of the CRP program through different levels of land supply elasticities to understand how land supply elasticity influences slippage rates and the overall effectiveness of CRP in reducing N loads. Land supply elasticity reflects the responsiveness of landowners in converting non-cropland into cropland in response to economic incentives, such as payments under CRP. When land supply is inelastic (low elasticity), landowners are less likely to convert additional land into cropland, resulting in lower slippage and thus greater net environmental benefits. Figure 2.8 illustrates an inverse relationship between slippage and land supply elasticity: as land supply becomes more inelastic, slippage decreases, and more effective N reduction is achieved through CRP. This relationship can be represented by the following equations for land supply elasticity:

$$Elas_{land} = \frac{\Delta Q/Q}{\Delta P/P} \quad (2.4)$$

$$\beta_{land} = \frac{P/Q}{Elas_{land}} \quad (2.5)$$

Where $\frac{\Delta Q}{Q}$ is the percentage change in the quantity of land supply, and $\frac{\Delta P}{P}$ is the percentage change in land rental price. This means that when β_{land} is low, a small increase in price leads to a large increase in land conversion (high slippage). Conversely, when β_{land} is high (inelastic), land conversion is limited even with price changes, reducing slippage.

Despite CRP's improved performance under more inelastic land supply, the total N reduction achieved is still significantly lower than what is possible under the Yield Reserve Program, as demonstrated in Figure 2.8, Table 2.1, and Table 2.2. This underscores the limitations of CRP in achieving large-scale N reductions, especially compared to input-focused strategies like Yield Reserve.

2.4 Summary

This study finds that the Yield Reserve Program outperforms the CRP in terms of achieving N reduction under equivalent government budget expenditures. The CRP shows strong "slippage effect", where the expansion of CRP acreage simply brings marginal land into crop production resulting in small excess N reductions. These findings suggest that subsidizing adoption of conservation practices such as Yield Reserve on cropland may be more cost effective than land retirement in reducing N loadings. Further research is needed to compare the cost effectiveness of Yield Reserve with other working land conservation practices such as nutrient management, reduced tillage, and cropland buffers.

The N reduction under the Yield Reserve Program is partially offset by the expansion of corn acreage. The increase in corn acreage under Yield Reserve Program reflects the rebound effect where the yield reserve subsidies plus savings in N application costs outweigh the losses in revenue causing corn acreage to increase. The expansion of corn acreage under the Yield Reserve Program is mainly in the Northern Plains, followed by Corn Belt and Lake States, which are all regions with high corn acreage.

This study finds that the slippage effect of the CRP is approximately 77 percent across the three scenarios of CRP expansion, which offsets the N reduction benefits of CRP. In corn production, we find that the CRP expansion retires existing relatively low yield corn land and pushes the corn production to marginal cropland which requires more N application per unit of yield. As a result, the N reduction from corn production under CRP expansion scenarios is almost negligible. Sensitivity analysis of the CRP program through different marginal land supply elasticities shows that more inelastic land supply tends to reduce the "slippage" of CRP expansion. Further research on land supply elasticities is needed to provide more accurate estimates of the effects of land retirement programs on slippage and achievement of environmental goals.

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Tables and Figures

Table 2.1: Simulated results under Yield Reserve scenarios

		Corn Yield Reserve Scenario		
	baseline	1%	1.5%	2%
N fertilizer application on corn (pound per acre)	196.5	189.8	186.6	183.5
% change		-3.41%	-5.04%	-6.62%
% change of corn variable cost		-0.75%	-1.11%	-1.46%
Corn yield (bushel per acre)	196.5	194.5	193.5	192.6
Forgone net revenue (dollar per acre)		4.37	6.58	8.80
Simulated Yield Reserve subsidy (million dollars)	0	501	772	1058
Simulated excess N (million pounds)	2388	2019	1823	1618
Simulated excess N reduction (million pounds)		369	565	771
Total welfare of 10 crops (billion dollars)	414.6	419.5	422.0	424.6
% change		1.18%	1.78%	2.41%

Table 2.2: Simulated results of CRP and total crop acreage under CRP expansion scenarios

		CRP expansion		
	baseline	25%	37%	50%
CRP land (million acres)	25.92	32.40	35.51	38.88
CRP payment (million dollars)	2,057	2,572	2,819	3,086
Total crop acreage (million acres)	325.0	323.6	322.8	321.8
Slippage[a]		78.5%	77.2%	75.7%
Total corn acreage (million acres)	99.2	98.5	98.2	97.8
Simulated N reduction from corn production (million pounds)		7.6	11.6	16.1
Total welfare (billion dollars)	414.6	413.9	413.5	413.9
% change		-0.17%	-0.26%	-0.36%

[a]Slippage = 100% - (ΔCrop acreage /ΔCRP acreage). For example, the slippage of 25% CRP expansion scenario is 100% - (325.0-323.6) / (32.40-25.92) = 78.5%.

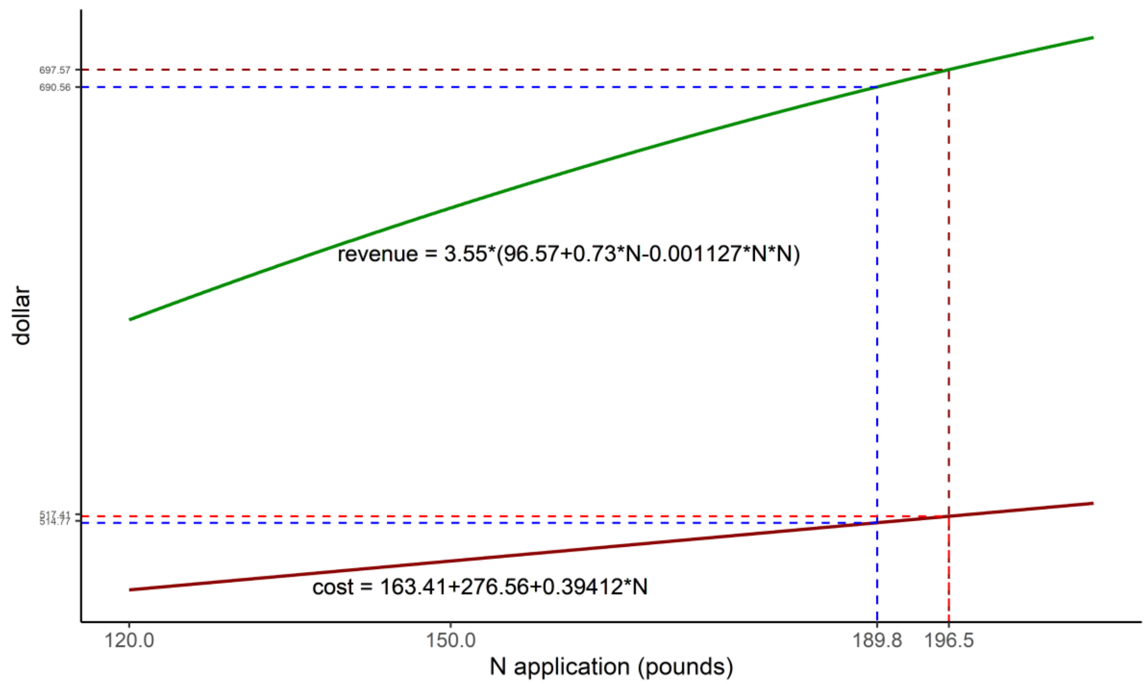

Figure 2.1 Average revenue and cost of corn production at baseline and first Yield Reserve scenario of $501 million

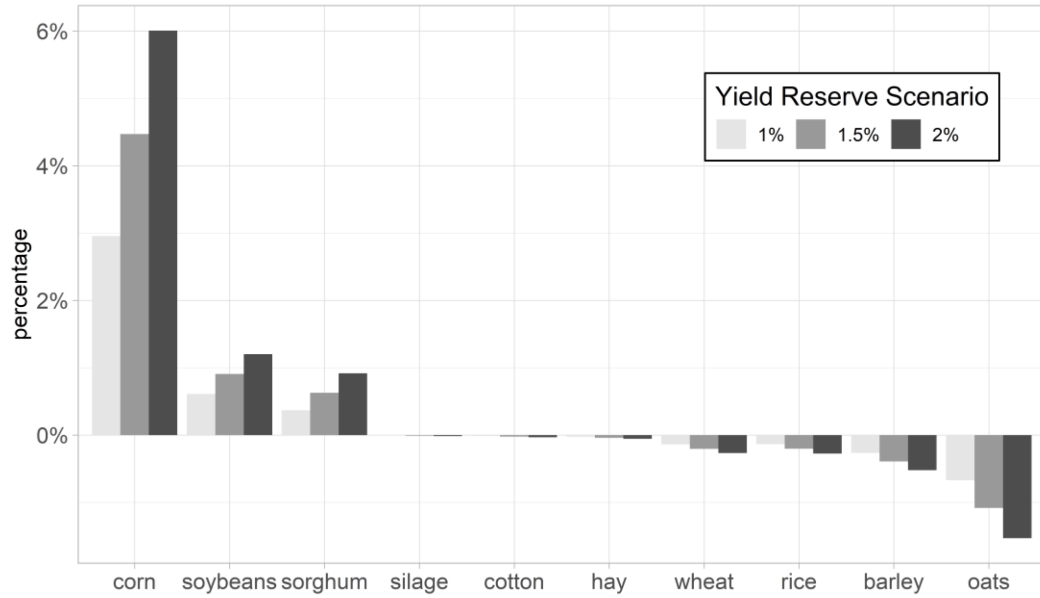

Figure 2.2 Crop commodity output change by Yield Reserve scenarios

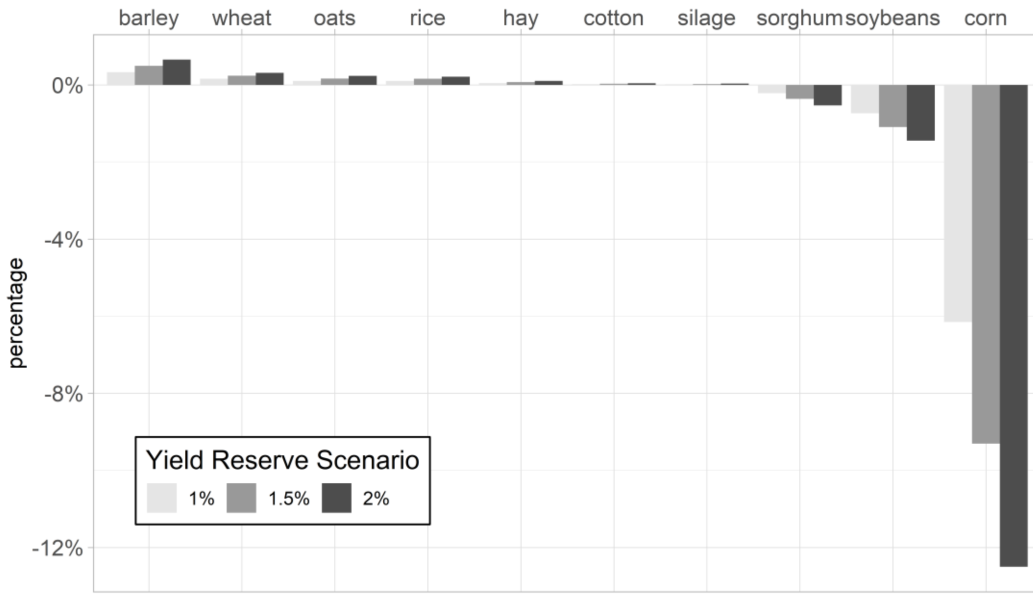

Figure 2.3 Crop commodity price change by Yield Reserve scenarios

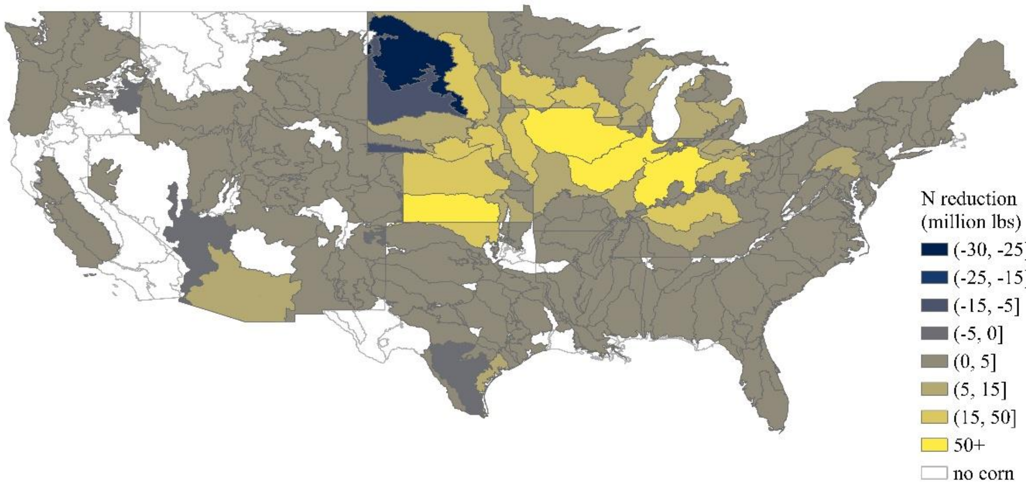

Figure 2.4 N reduction by REAP region under 2 percent Yield Reserve scenario

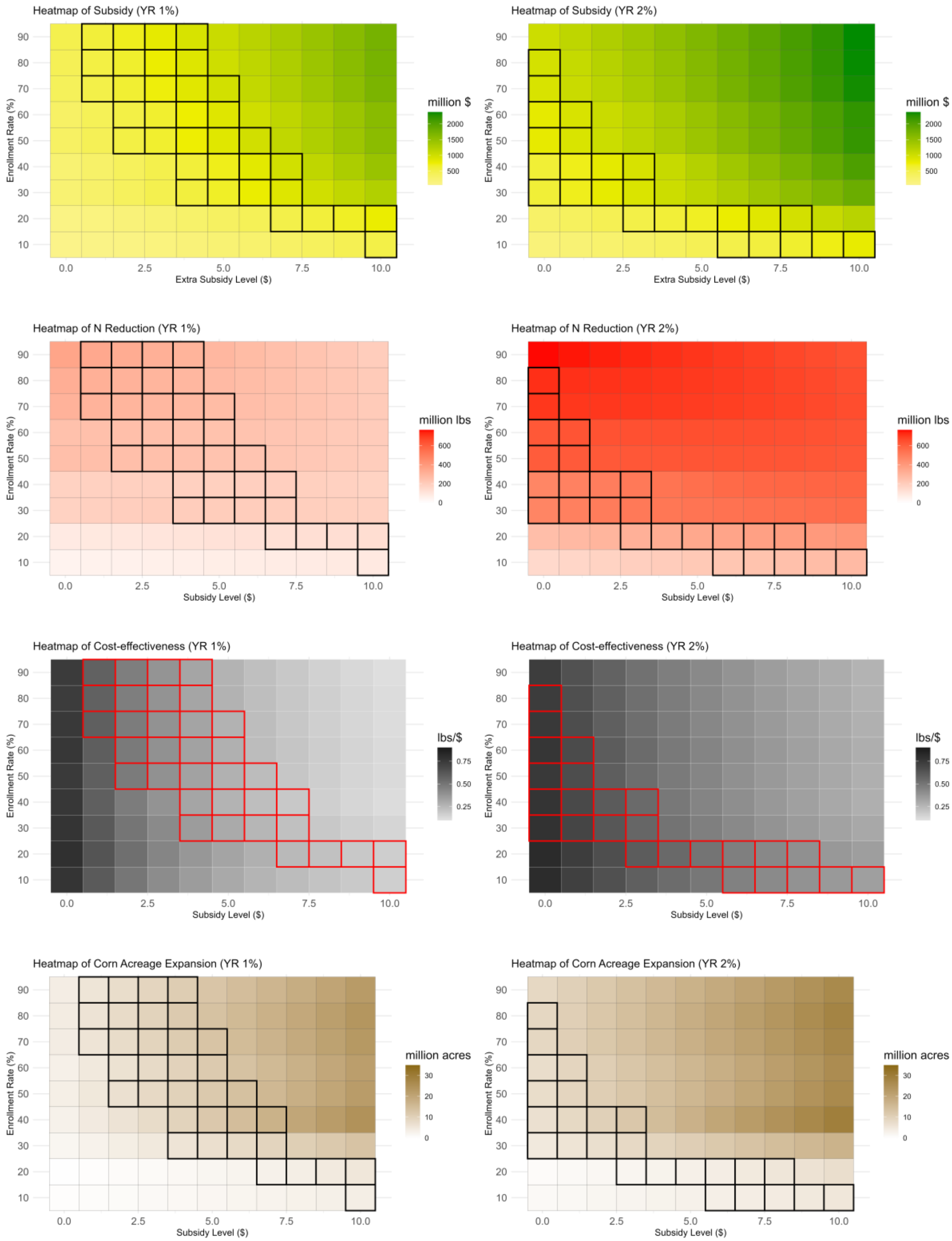

Figure 2.5 Sensitivity of Yield Reserve with different enrollment rates and extra subsidies

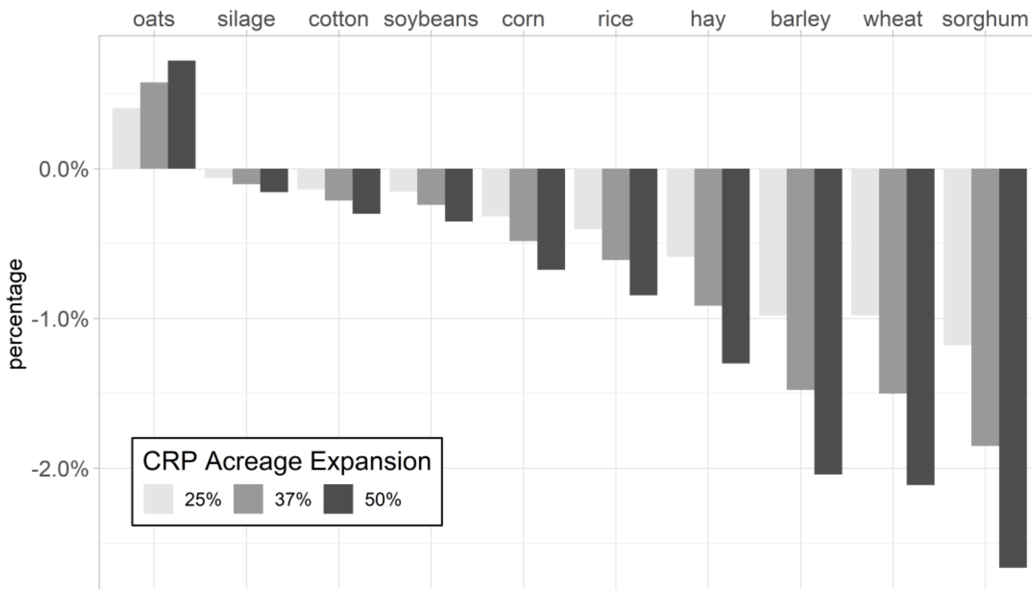

Figure 2.6 Crop commodity output change by CRP scenarios

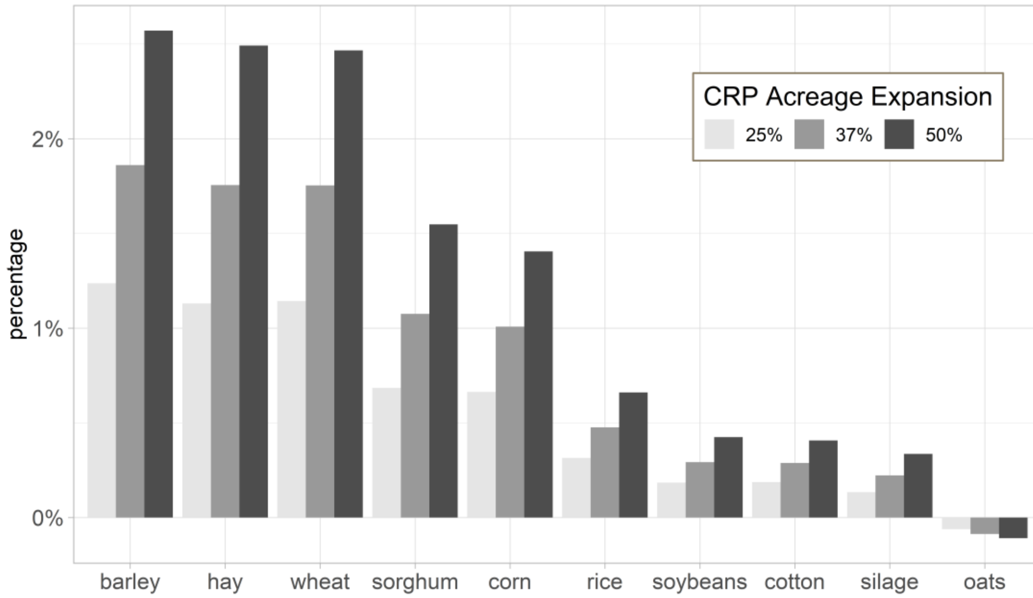

Figure 2.7 Crop commodity price change by CRP scenarios

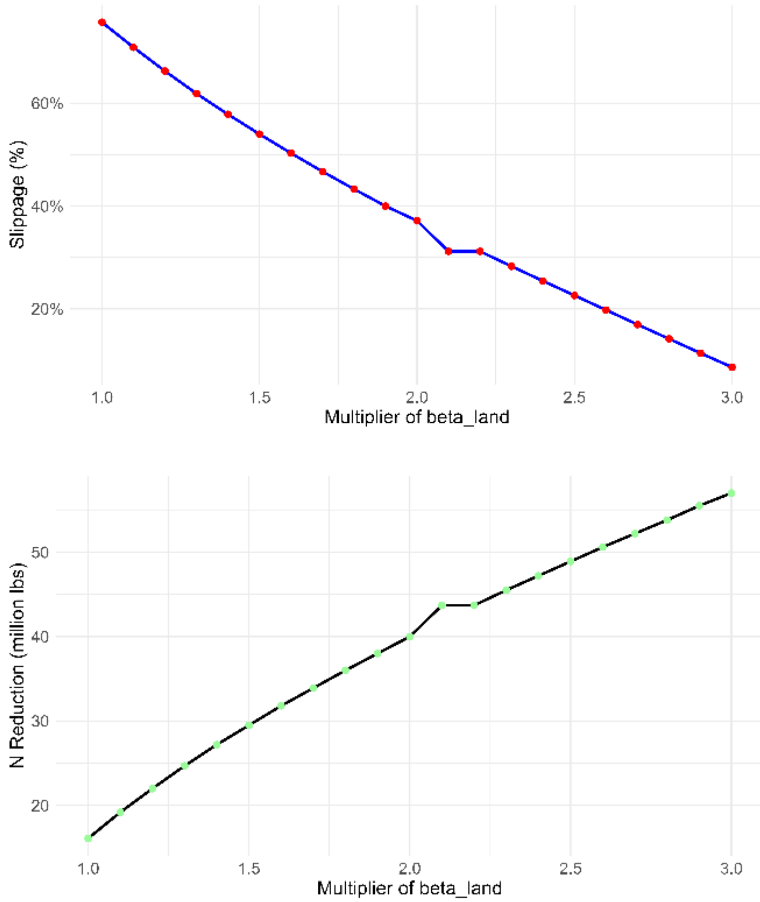

Figure 2.8 Slippage rate and N reduction under decreased land supply elasticity scenarios

Chapter 3

Impact of Large-scale Solar on Property Values in the US: Diverse Effects and Causal Mechanisms

Abstract

As the renewable energy transition continues into less receptive communities, local opposition is expected to intensify, potentially slowing the process. Since the local impacts are neither well quantified nor widely recognized, we lack policies and common practices to mitigate the potential associated welfare loss in affected communities. Based on a nationwide dataset combining property transactions and large-scale solar photovoltaic (LSSPV) sites, we analyze the heterogeneous effects of LSSPV on property prices and the associated causal pathways. Difference-in-differences estimates show that LSSPV significantly increases agricultural or vacant land value by about 19.4 percent within a 2-mile radius, while simultaneously reducing residential property values within 3 miles by about 4.8 percent. The estimated average negative impact on home values is primarily driven by site proximity and diminishes with both distance and time. Effect estimates are more robust to alternative specifications when proximity pairs with visibility rather than invisibility, but no evidence suggests visibility significantly amplifies the proximity effect. Heterogeneous effect estimates indicate that high solar lease potential, being in heavily Democratic-leaning counties, and brownfield redevelopment largely mitigate the negative residential value impact. The analysis reveals no significant heterogeneity across a few factors, including varying site visibility, directional orientation of properties relative to the LSSPV site, and different tracking systems. Evidence indicates that the negative impact on residential values might mostly stem from negative perceptions, but channels through physical conditions cannot be entirely dismissed. Our assessment provides benchmark information for local externality mitigation plans, potentially reducing community opposition and expediting the renewable energy transition.

3.1 Introduction

As the cost of solar energy continues to decline, its role in the US energy system is becoming increasingly prominent. According to the US Energy Information Administration (2022), technological advancements and economies of scale have driven substantial reductions in large-scale solar photovoltaic (LSSPV) installation costs over the past decade. Building on this trend, the U.S. Energy Information Administration (2024) projects that solar will remain the leading source of renewable electricity generation in the United States over the next several decades. These developments have positioned LSSPV systems as central to the country's decarbonization strategy.

While the environmental and climate benefits of LSSPV systems are widely recognized, including their contribution to greenhouse gas reduction and air quality improvement, the expansion of solar infrastructure has increasingly met with local opposition. Recent research highlights this growing resistance. For example, Crawford et al. (2022) analyzed public hearings and planning processes to show how aesthetic concerns, land use conflicts, and perceived exclusion from decision-making processes fuel opposition to LSSPV. Eisenson et al. (2024) further underscored how the lack of procedural justice and inadequate community engagement in siting decisions intensify conflict. Mulvaney (2017) documented a range of community-level concerns in California, including environmental justice issues and perceived threats to local identity and heritage. As solar development pushes into areas previously less receptive to utility-scale renewable energy, this opposition is expected to intensify, potentially slowing the overall pace of the energy transition.

Anecdotal and qualitative evidence suggests that local concerns about LSSPV are driven by a set of commonly cited disamenities. These include negative visual impacts, loss of property values, diminished local environmental quality, and adverse effects on agricultural operations (Crawford et al., 2022; Sharpton et al., 2020; Nilson and Stedman, 2023). Sharpton et al. (2020), through stakeholder interviews in the Southeastern U.S., revealed how solar siting processes can exacerbate rural-urban divides and generate long-term resentment when local input is ignored. Nilson and Stedman (2023) used survey-based methods to demonstrate that the perception of fairness and inclusion in energy decision-making strongly predicts local support for solar projects. Despite these insights, the economic and social costs associated with LSSPV siting remain poorly quantified in the literature, and no standard policy frameworks currently exist to compensate communities for potential welfare losses associated with these installations.

The most prominent concern among communities near LSSPV facilities relates to changes in local amenities. Recent empirical studies support the idea that LSSPV proximity can reduce residential property values. For instance, Elmallah et al. (2023) analyzed transaction data from several Northeastern states and find statistically significant reductions in home prices near solar sites. Gaur and Lang (2023) similarly reported declines in property values in Massachusetts, particularly where solar installations are visible from residential properties. Nilson et al. (2024) emphasized the role of visual impact, showing that site characteristics such as size, elevation, and reflectivity influence residents' perception of harm. Sánchez-Pantoja et al. (2018) explained that the geometric uniformity and highly reflective surfaces of solar panels can appear disruptive or out of place, especially in scenic or rural settings. These aesthetic effects can reduce neighborhood desirability and, in turn, affect real estate markets.

Beyond visual concerns, LSSPV facilities may generate other disamenities that are less immediately visible. Lovich and Ennen (2011) highlighted that utility-scale solar development can fragment wildlife habitats and alter ecosystem functions in arid and semi-arid environments. Sawyer et al. (2022) examined land use transitions and show that poorly planned solar development can disrupt pollinator habitats and alter soil and hydrological dynamics. Additionally, solar installations may increase soil erosion and water runoff or degrade local air quality during construction and maintenance (Bastida et al., 2006). While these physical effects may vary in severity and visibility, perceptions of them can significantly influence market behavior. As McCluskey and Rausser (2003) and Taylor et al. (2016) discussed, real estate markets are often subject to "stigma effects," where the perception of harm, regardless of actual physical risks, can lead to property value declines.

Solar development also affects land values, particularly in agricultural settings. LSSPV projects typically require 5 to 10 acres per MWac of generating capacity, making them one of the most land-intensive forms of energy production. Hernandez et al. (2015) identified agricultural lands as the most common sites for LSSPV due to their flat topography, minimal vegetation, and proximity to grid infrastructure. Katkar et al. (2021) found that these same attributes not only reduce installation costs but also make farmlands particularly vulnerable to conversion pressure. A recent projection from the American Farmland Trust (2023) estimated that over 7 million acres could be occupied by solar installations by 2040, with 83 percent of this development occurring on working farmland

and ranchland. Notably, over half of this land is classified as "nationally significant" due to its high productivity. These trends suggest increasing competition between food and energy production, particularly near urban boundaries, where land values are already elevated.

In the short term, solar lease payments often offer landowners higher returns than conventional farming, which can inflate agricultural land prices and increase the cost of entry for new farmers. In the long run, this land competition may have broader implications for food systems and rural land markets, especially as energy demand surges in response to electric vehicle adoption and the growing power requirements of AI data centers. As LSSPV expands into agriculturally productive areas, the economic trade-offs associated with solar development will become more acute.

Among the various community concerns, visual impact and property value loss are consistently ranked as the most salient drivers of opposition (Crawford et al., 2022; Nilson et al., 2024). These effects represent classical negative externalities, uncompensated harms borne by nearby residents for the benefit of a broader public good. Because no standard mechanisms currently exist to offset these harms, addressing them is critical to improving the equity and political feasibility of LSSPV expansion. Indeed, as Mulvaney (2017) and Nilson et al. (2024) reported, a substantial proportion of proposed solar projects have been delayed, withdrawn, or rejected due to community resistance. By rigorously quantifying these externalities, policymakers can design more equitable solar siting frameworks that include compensation mechanisms and community benefits agreements.

This study contributes to this goal by conducting a nationwide analysis of property-level transaction data combined with detailed geospatial information on LSSPV site characteristics. We estimate the causal impact of LSSPV proximity and visibility on property values using a Difference-in-Differences (DID) identification strategy. Previous studies have employed similar empirical frameworks but were typically limited in geographic scope. For example, Abashidze and Taylor (2023) focused on North Carolina, while Elmallah et al. (2023) examined six states in the Northeast and Gaur and Lang (2023) examined two states in the Northeast. Our study builds upon and extends this literature by not only incorporating visibility analysis using high-resolution viewshed modeling, but also by evaluating the interaction between proximity and visibility on housing prices. Specifically, we generate a national-scale geospatial database that captures whether each residential home in the contiguous U.S. has line-of-sight exposure to a nearby LSSPV facility (Figure 3.A2, see *Data* for details).

Our study builds on and extends this literature in several ways. First, we consider both proximity and visibility, leveraging a national-scale viewshed analysis to determine whether and how residential properties are visually exposed to LSSPV facilities. This visibility layer, constructed using Digital Elevation Model data, allows us to differentiate between properties that are near solar sites and those that can actually see them, two dimensions that may have distinct effects on property values.

Second, we disaggregate our analysis by property type: (1) residential properties (hereafter "residential homes" or "residential") on parcels under five acres (i.e., the typical minimum acreage requirement for a solar lease), where LSSPV effects primarily stem from impacts related to residential amenities; (2) agricultural or vacant land above five acres (hereafter "agricultural land" or "ag-land"), where LSSPV effects mainly result from potential solar lease-induced land use value changes; and (3) properties over five acres with residential structures (hereafter “large-lot homes”), where LSSPV effects may include both residential amenity and land use value impacts. Each of these property types is exposed to different dimensions of LSSPV impacts, ranging from residential disamenities to changes in land lease potential.

Lastly, we further investigate the impact heterogeneity across a range of dimensions, including rural-urban status, census region, lot size, county political leaning, median household income, solar site scale, site historical land use, state siting regulation, among others. To make sure our estimates are not specific to the five-acre segregation criterion, we conducted robustness checks in *Appendix*.[1]

3.2 Data

The analysis primarily utilizes data of four categories: the US large scale solar photovoltaic data (LSSPV data), the real estate transaction and assessment records (Property Transaction Data), geospatial data, and visibility data.

3.2.1 LSSPV Data

The LSSPV data acquired from the US Large Scale Solar Photovoltaic Database (USPVDB) (Fujita, et al., 2023) contains 3,699 LSSPV facilities investigated in the study. This dataset provides detailed information on LSSPV site footprint, area, capacity, and installation year, spanning from 1986 to 2021 (Figure 3.A1 shows the total acreage developed per year and Table 3.A1 shows the summary statistics of LSSPV projects). The

[1] The results are presented in *Appendix Table 3.A5*, which suggest that the main estimates are robust to alternative acreage thresholds for segregating the small-lot properties and large-lot properties (e.g., 5 miles to 0.3 miles for small-lot properties and 5 miles to 9 miles for large-lot properties). Therefore, the main conclusions of this study are not sensitive to changes in the five-acre threshold.

facility polygons are digitized along the boundaries of the solar arrays, within an accuracy of 10 meters.

3.2.2 Property Transaction Data

The property data is purchased from CoreLogic through a data agreement. CoreLogic data contains comprehensive information on property and transactions from the whole US and enables researchers to work on property-level research questions. We developed a process to exclude non-arm's-length transactions (i.e., purging price outliers, foreclosure sales, multiple sales, sales between relatives, sales involving institutional buyers or sellers, and others as detailed in 3.SI.1) so that our analyses only include transactions reflecting fair market values. The transaction prices are adjusted for inflation to reflect their values in 2017 dollars using the Consumer Price Index data from the US Bureau of Labor Statistics. We also exclude potential home flipping events by removing transactions of the same property that occur within 120 days of each other. As the majority of LSSPV sites have been developed within the past decade, we keep transactions up to 15 years before the installation of nearest LSSPV to make the time frame generally centered around the LSSPV development. The final dataset for analysis comprises both single-family residential properties and agricultural or vacant land, spanning 40 states[2] from 1993 to 2020. To avoid the potential impact from market disequilibrium, we drop observations during the Great Recession (i.e., 2008 to 2010). Tables 3.A2 to 3.A4 show the summary statistics of residential homes, agricultural and vacant land, and large-lot homes, respectively. Figure 3.A3 to Figure 3.A5 illustrated the distribution of post-LSSPV-

[2] The other ten states (i.e., Alaska, Hawaii, Idaho, Kansas, Louisiana, Maine, Mississippi, Montana, Utah, and Wyoming) are excluded from the final analysis due to the absence of LSSPV sites, a lack of available transactions near LSSPV sites, or their non-continental status.

installation transactions of residential homes, agricultural or vacant land, and large-lot homes, respectively, across different proximity bins.

3.2.3 Geospatial Data

The geospatial data consists of a collection of geographic layers obtained from the US Census Bureau TIGER/line geodatabase (USCB TIGER) and US Energy Information Administration (EIA), which includes shapefiles of primary roads, transmission lines, and metropolitan areas. To support heterogeneity analyses, we also collected data on median household income, median land values, political leanings, and state-level siting policies, among other factors (see *Appendix* for details).

To acquire solar site proximity and other (dis)amenities, we generated geographic variables that represent the Euclidian distance between a property and the boundary of the nearest five solar sites, transmission line, primary road, and metropolitan area. The geographic variables were then matched with the property data. To alleviate identification concerns that attributes of control observations (i.e., properties far away from sites) might considerably deviate from treated observations (i.e., properties with solar site exposure), we only kept residential homes that are less than or equal to 6 miles away from the nearest solar sites. For properties above five acres (i.e., agricultural land or large-lot homes), we use a 20-mile radius inclusion criterion due to the general low density and low transaction volumes of such properties. The final sample includes 8.3 million transactions for residential homes, 68 thousand transactions for agricultural or vacant land, and 416 thousand transactions for large-lot homes.

3.2.4 Data for Heterogeneity Analysis

We conduct heterogeneity analyses for residential homes and agricultural land. In this subsection, we present the exact definitions and data sources of the factors investigated in our heterogeneity analyses.

We utilized the shapefile of metropolitan areas from the US Census Bureau TIGER/line geodatabase (USCB TIGER) to compute the Euclidian distance between each property and the boundary of the nearest metropolitan area. Properties were categorized as urban or rural, depending on whether their distances from the nearest metropolitan area were zero (i.e., in the metropolitan areas) or greater than zero, respectively.

Properties were divided into big-lot and small-lot categories by comparing each property's lot size to the median lot size within our final dataset. Similarly, LSSPV projects were classified into big-USS and small-USS groups based on whether their lot sizes exceeded the median LSSPV lot size in the dataset.

Data from the 2020 American Community Survey were employed to obtain estimated median household incomes at county level. Counties were divided into high-income and low-income groups by comparing their median income against the national average. Properties were assigned into one of four regional groups (US Northeast, US South, US West, and US Midwest) following the region categories defined by the US Census Bureau.

Political leanings of counties were determined based on the outcomes of the 2016 presidential election, as reported by the MIT Election Data and Science Lab (MIT Election Data and Science Lab, 2018). A county is defined as heavily Democratic leaning if more than 65 percent of its votes were cast for the Democratic presidential candidate, which is represented by Dem-leaning in Figure 3.3, Figure 3.6, and Figure 3.7, where Non-Dem means Dem-leaning = 0.

Public involvements were determined using the data from Energy Markets & Policy (EMP) department of Lawrence Berkeley National Laboratory (Enterline et al., 2024), which indicates 34 states have statutory or regulatory requirements mandating some form of public meeting or hearing during the site permitting phase.

Residential properties (below five acres) were classified into high-view and low-view (including no view properties) groups by comparing the visibility index from each property to the median of positive visibility indices (See the definition of visibility index in Visibility Analysis under Data & Methods). As the control group cannot be classified into high-view and low-view subgroups, we use interaction specifications to investigate heterogeneity in visibility level. For all other dimensions, we use separate models for corresponding subgroups.

Residential properties were also categorized as facing and not-facing groups, depending on whether they are located on the south side of an LSSPV site.

Using the USPVDB data, LSSPV sites were classified as either greenfield or brownfield. Greenfield sites represent the majority of LSSPV facilities and occupy land that may have previously been wildland, urbanized, cultivated, or reclaimed. Brownfield sites include facilities that treat, store or dispose of hazardous waste and that require cleanup, and inactive or abandoned contaminated facilities or locations where there is an active release or threatened release into the environment of hazardous substances that have been dumped, discharged, emitted or otherwise improperly managed.

We also check the heterogeneity of site tracking systems (i.e., tracking or fixed) based on USPVDB data. The tracking system of solar panels is a mechanical setup that adjusts the angle of the panels throughout the day to follow the sun's movement, maximizing energy capture. Tracking systems can affect visibility because they often require taller mounting structures and continuous motion, making the panels more prominent and noticeable from different vantage points compared to fixed systems. This increased visual profile may raise concerns about aesthetic impacts in residential or scenic areas.

3.2.5 Visibility Database

We establish a visibility database for LSSPV across the continental US and investigate the property value effect of LSSPV visibility. We calculate the visibility from residential properties to large-scale solar sites within 6 miles. This visibility analysis proceeds in three steps. First, we acquire Digital elevation models (DEMs) of the continental US from the Shuttle Radar Topographic Mission (SRTM) produced by NASA.[3] Our analysis uses the 2018 version of SRTM DEMs at a resolution of 90 m by 90 m. The DEMs employed reflect terrain elevation but may not capture structures (e.g., houses or trees), and hence could overstate visibility especially when the viewpoint and the target are close (Lang et al., 2024). Nonetheless, the employed DEMs are the best available public data for our analysis, as structural elevation data (e.g., Light Detection and Ranging, or LiDAR, data) are not available for most solar sites and their neighborhoods.

[3] DEMs provide crucial information on the ground topography of the study area. The Shuttle Radar Topographic Mission by NASA employs remote sensing technology to gather laser light measurements of the earth's surface. The mission started in 2000, with a goal to create the first near-global topographical map of Earth and collect data on nearly 80 percent of the planet's land surfaces. Data are available at https://srtm.csi.cgiar.org/.

Second, we calculate the viewsheds from solar sites to decide the areas from which the sites are visible, utilizing the duality of vision following Guo et al. (2024) (i.e., if and only if viewpoint A has a view on target B and a viewpoint on B has a view on target A). This approach greatly reduces computational effort since the number of solar sites (3,699) is much smaller than the number of properties (about 5.9 million). Unlike the wind turbines that require height specifications for accurate viewshed analyses, LSSPV sites span broad areas, necessitating a proper way to account for partial views of a large solar site. Specifically, we set viewpoints along the perimeter of each site, where the viewpoints are defined with a random start point, an interval distance D, and a height of two meters. In practice, D is set at 500 meters to balance the computation workload and the accuracy of partial view accounting.

Third, we aggregate the viewsheds from all site perimeter viewpoints and overlay the aggregated viewshed layer with properties to calculate the visibility variables. The aggregation of viewsheds will generate the visibility index (Figure 3.A7) for each geographic unit defined by the raster resolution (90 m by 90 m). Overlaying with the property layer, the visibility index will represent the number of perimeter viewpoints that can see a property, or the number of solar site perimeter points that the property has view on based on the duality of vision. This property-specific visibility index quantifies the extent of solar site visibility for each property and can be converted into a binary visibility variable that serves as the treatment variable in a DID model. For more details of the visibility analysis, refer to 3.SI.2 section in *Appendix*.

3.2.6 Materials and Data Availability

Our replication package provides all code used in this study, including Stata and Python code for raw data processing, geospatial variable processing, viewshed analysis, data aggregation, and estimation analysis. All analyses are conducted in Stata 18MP (https://www.stata.com/order/) and Python 3.9.18 https://www.python.org/downloads/release/python-3918/). The replication package also shares datasets that are from unrestricted data sources.

The property transaction data are acquired from CoreLogic Solutions, LLC (https://www.corelogic.com/360-property-data). Restricted by contract with CoreLogic, all variables derived from raw CoreLogic data will not be shared. To replicate our study, we recommend acquiring CoreLogic national-level property data with transactions from 1993 to 2020 and applying the data processing code in the replication package.

Other raw data are from publicly available sources. The large-scale solar site data is available at the US Large Scale Solar Photovoltaic Database webpage: https://eerscmap.usgs.gov/uspvdb. Digital Elevation Models in the viewshed analysis are produced by NASA's Shuttle Radar Topographic Mission and available at https://srtm.csi.cgiar.org. Geospatial data on states, counties, census tracts, primary roads, and metropolitan areas are from US Census Bureau TIGER/line geodatabase, available at https://www.census.gov/geographies/mappingfiles/time-series/geo/tiger-geodatabase-file.html. Geospatial data on transmission lines are obtained from US Energy Atlas hosted by Energy Information Administration, available at https://atlas.eia.gov/search. Data for heterogeneity analysis are drawn from multiple public sources, with details described in the *Appendix*.

3.3 Econometrics: Property Value Effect Models

Previous studies have used econometric models to analyze and identify a variety of characteristics that could consistently influence property values, such as the productivity of the farmland (Chen et al., 2023), the influences of urbanization (Livanis et al., 2006), and environmental factors (Chen and Towe, 2024; Melstrom, 2021; Towe and Chen, 2023). To estimate the impact of solar projects on nearby property values, it is crucial to control for potential confounders. We employ a DID approach to investigate the effects of LSSPV installation on nearby property values. Intuitively, this approach compares the change in property values before and after installation for properties close to the LSSPV site against the value change for properties farther away but still within the defined vicinity.

3.3.1 Analyses for Residential Homes

The general DID framework of our residential home study is as follows:

$$\begin{aligned} \ln(P_{it}) = \beta_0 + \beta_1 Post_{it} + \beta_2 T_i + \beta_3 Post_{it} \times T_i \\ +\delta_k \sum_{k=1}^{K} X_{it}^{k} + \gamma_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^{k}) + \tau_{ct} + \varepsilon_{it}. \end{aligned} \tag{3.1}$$

In Eq. (3.1), each observation corresponds to a transaction of residential home i that occurred in year t, with the dependent variable being the natural logarithm of transaction price $\ln(P_{it})$. $Post_{it}$ is a binary indicator that denotes whether the transaction of residential home happened after the LSSPV installation. T_i is the binary indicator that denotes whether a residential home was assigned to a treatment group, and the exact definition of treatment is explained below. The coefficient β_3 associated with the interaction term between $Post_{it}$ and T_i captures the impact of LSSPV installation on the outcome variable, which resembles a proportional change in the residential home prices. Previous studies show that the proximity to transmission lines could have an impact on the value of nearby property (Lu et al., 2023), and this impact could change after an LSSPV installation in the vicinity (Abashidze and Taylor, 2023). To account for housing and lot characteristics that could affect home values and the estimation of β_3, we include property-level control variables X_{it}^k and $Post_{it} \times X_{it}^k$ (Banzhaf, 2021; Keiser and Shapiro 2019), where X_{it}^k include total bedroom number, total bathroom number, building age, and natural logarithms of distances to the nearest transmission line, the nearest primary road, and the nearest metropolitan area. To absorb the time-varying external location-specific shocks in the housing market, we incorporate fixed effects on the census tract by year level, denoted as τ_{ct}. All standard errors are two-way clustered at the census tract and year level.

To detect the proper site-proximity treatment in the average effect models (i.e., Eq. (3.1)), we employed a distance decay version of the DID approach, as shown in Eq. (3.2). The distance decay study uses proximity intervals ($T_i^m, \forall m \leq M-1$) as the treatment variables instead of a single binary treatment (as T_i in Eq. (3.1)). The distance-decay model shown in Figure 3.1 uses 0.5-mile intervals from 0 to 6 miles, with properties in the 5-6 mile ring (i.e., T_i^M) serving as the control group. To investigate the role of visibility, we further interact the proximity intervals with a binary visibility variable to produce the results in Figure 3.1 (i.e., the treatment variables become $T_i^m \times 1(View = 1)$ and $T_i^m \times 1(View = 0)$). The model specifications in Eq. (3.2) are identical to Eq. (3.1) except for differences in the treatment variables,

$$\ln(P_{it}) = \beta_0 + \beta_1 Post_{it} + \sum_{m=1}^{M-1} \beta_2^m \, T_i^m + \sum_{m=1}^{M-1} \beta_3^m \, Post_{it} \times T_i^m$$
$$+\delta_k \sum_{k=1}^{K} X_{it}^k + \gamma_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it}. \tag{3.2}$$

Based on the proximity cut-off point suggested in the distance decay results, we specify a proximity treatment (i.e., results suggest properties within 3 miles) for the average treatment model in Eq. (3.1). Moreover, we can test the average treatment effect of the interaction between visibility and proximity, by slightly modifying Eq. (3.1) to allow for two treatment groups (i.e., effects shown as β_3^{view} and $\beta_3^{no\_view}$ in Table 3.1 column (2)). The empirical results of these specifications decide the appropriate treatment to use for subsequent studies, where the control group specification will also be consistent with the exploratory specifications.[4]

Our DID model relies on the assumption that the LSSPV siting process is independent of the price trends over time conditional on the covariates (i.e., the parallel trends assumption). We conduct pre-trend tests with placebo treatments by setting a pseudo-post variable mimicking a fake installation event six years before the actual installation and dropping observations that are actually treated after the actual site installation. Null effect estimates from the placebo tests support the plausibility of the parallel trends assumption. Moreover, the event study model could also display pre-treatment effects where pre-treatment trend differences would show up and suggest a violation of the parallel trends assumption.

3.3.2 Analyses for Agricultural or Vacant Land

In our analysis, ag-land is defined as agricultural or vacant land above five acres, where LSSPV effects mainly result from potential solar lease-induced land use value

[4] This is to say, if pure proximity with a 3-mile cut-off point is decided as the most meaningful treatment to use, the control group in the main average effect model will be properties within the 5-to-6-mile proximity bin. This would involve the exclusion of properties within the 3-to-5-mile bin from the analyses. The subsequent event study and heterogeneity analysis models will follow the same sample and covariate specifications as the main model.

changes. The DID model detecting effect of distance decay for the ag-land study is specified as follows:

$$\ln(PperAcre_{it}) = \beta_0 + \beta_1 Post_{it} + \sum_{m=1}^{M-1} \beta_2^m T_i^m + \sum_{m=1}^{M-1} \beta_3^m Post_{it} \times T_i^m$$
$$+\delta_k \sum_{k=1}^{K} X_{it}^k + \gamma_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it} \tag{3.3}$$

In Eq. (3.3), each observation corresponds to a transaction of ag-land i that occurred in year t, with the dependent variable being the natural logarithm of ag-land price per acre $\ln(PperAcre_{it})$. $Post_{it}$ is a binary indicator that denotes whether the transaction of ag-land happened after the LSSPV installation. The proximity intervals ($T_i^m, \forall m \leq M - 1$) are the variables that denote whether an ag-land site was assigned to a treatment group. The distance-decay model shown in Figure 3.4 uses 2-mile intervals from 0 to 20 miles, with properties in the 18-to-20 mile proximity bin (i.e., T_i^M) serving as the control group. The coefficient β_3^m for the interaction term between $Post_{it}$ and T_i^m captures the impact of LSSPV installation on the outcome variable, which resembles a proportional change in the ag-land price per acre. Previous studies show that the proximity to transmission lines could have an impact on the value of nearby property (Lu et al., 2023), and this impact could change after an LSSPV installation in the vicinity (Abashidze and Taylor, 2023). Therefore, we include the nearest distance to transmission line $\ln(DistLine_i)$ in X_{it}^k, and the interaction term between $Post_{it}$ and $\ln(DistLine_i)$ is also added to capture this potential confounding effect. To account for land characteristics that could affect ag-land values, we also include other property-level control variables in X_{it}^k, including natural logarithms of distances to the nearest primary road and the nearest metropolitan area. To absorb the time-varying location-specific shocks in the land market, we incorporate fixed effects at the county-site by year level, denoted as τ_{ct}. County-site is an interaction between county and the nearest site indicator that captures county-specific policy shocks and external shocks unique to the site locale. All standard errors are two-way clustered at the county-site and year level.

3.3.3 Analyses for Large-lot Homes

In our analysis, large-lot homes are defined as properties over five acres with residential structures, where LSSPV effects may involve impacts via changes in both residential amenities and land use potential. The DID model detecting effect of distance decay for large-lot homes is as follows:

$$\ln(P_{it}) = \beta_0 + \beta_1 Post_{it} + \sum_{m=1}^{M-1} \beta_2^m T_i^m + \sum_{m=1}^{M-1} \beta_3^m Post_{it} \times T_i^m + \delta_k \sum_{k=1}^{K} X_{it}^k + \gamma_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it} \tag{3.4}$$

In Eq. (3.4), each observation corresponds to a transaction of large-lot-home i that occurred in year t, with the dependent variable being the natural logarithm of large-lot-home price $\ln(P_{it})$. $Post_{it}$ is a binary indicator that denotes whether the transaction of large-lot-homes happened after the LSSPV installation. The proximity intervals $(T_i^m, \forall m \leq M-1)$ are the variables that denote whether a large-lot-home was assigned to a treatment group. The distance-decay model shown in Figure 3.4 uses 2-mile intervals from 0 to 20 miles, with properties in the 18-to-20-mile ring (i.e., T_i^M) serving as the control group. The coefficient β_3^m for the interaction term between $Post_{it}$ and T_i^m captures the impact of LSSPV installation on the outcome variable. Similar to specifications for other property types, we include the nearest distance to transmission line $\ln(DistLine_i)$ and the interaction term between $Post_{it}$ and $\ln(DistLine_i)$ in control terms X_{it}^k and $Post_{it} \times X_{it}^k$. To account for other housing and lot characteristics that could affect large-lot-home values, we also include in X_{it}^k variables such as the total number of bedrooms, total number of bathrooms, building age, and natural logarithms of distances to the nearest primary road and the nearest metropolitan area. To absorb the time-varying external location-specific shocks in the large-lot-home market, we incorporate fixed effects on the county-site by year level, denoted as τ_{ct}. All standard errors are two-way clustered at the county-site and year level.

3.3.4 Event Study Model

We conduct event studies to explore the timing of the LSSPV exposure effect. Event studies are only conducted for residential homes and ag-land, as the distance decay study shows no effect for large-lot-homes. The regression model is generally specified as:

$$\ln(P_{it}) = \alpha_0 + \alpha_1 T_{it} + \sum_{j \neq -1} \beta_j YearR_{jt} + \sum_{j \neq -1} \gamma_j (T_{it} \times YearR_{jt}) + \delta_k \sum_{k=1}^{K} X_{it}^k$$

$$+\eta_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it} \tag{3.5}$$

In Eq. (3.5), T_i is the binary indicator that denotes whether a property was assigned to the treatment group, where the treatment definition depends on the distance decay studies for each property type (i.e., site within 3 miles for residential homes and below 2-mile proximity for ag-land). $YearR_{jt}$ are the event study dummies, including "leads" and "lags" of the event indicator (i.e., year j relative to the year of LSSPV installation), and a certain lead year in j (e.g., $j = -1$) is excluded as a normalization. $T_{it} \times YearR_{jt}$ is the interaction term between the treatment and the dummy of the event study year j. The coefficient γ_j for the interaction term captures the LSSPV exposure effect in event study year j. The property-level control variables X_{it}^k include housing and lot characteristics (same as Eq. 3.2) for the residential-home model but lot characteristics only for the ag-land model. The fixed effects and standard error specifications match those used in the distance decay model for the corresponding property type.

3.4 Results

3.4.1 LSSPV Impact on Residential Home Value

We first present the results for residential properties under five acres, which include approximately 8.3 million property transactions within a 6-mile radius of LSSPV sites from 15 years before the installation of each site through 2020.

3.4.1.1 Residential Proximity and Visibility

We first use distance decay specifications within the DID framework to decide the proper treatment variable, assuming solar site exposure is determined by proximity and visibility. The view-specific distance decay results (Figure 3.1) show that proximity is the major driver of the negative residential value impact. We find that, without LSSPV view, LSSPV proximity reduces residential sales price by up to 7.2 percent within a 0.5-mile radius, and the bin-specific estimates gradually decrease with distance and remain statistically significant up to 3 miles from the LSSPV site. Having LSSPV in the viewshed of a home incurs slightly more negative effects (i.e., up to 7.9 percent within 0.5 miles) compared to the pure proximity effects,[5] and the bin-specific effects also diminish with distance. Beyond 3 miles, both the proximity effect and the visibility effect become indistinguishable from zero, suggesting that visibility does not independently generate negative impacts in the absence of proximity.

3.4.1.2 Residential Treatment - Site within 3 Miles

As shown in Table 3.1 column (1), when examining the average treatment effect of proximity within 3 miles (regardless of visibility), the estimate is 4.8 percent and statistically significant at the 5 percent level. We further investigate the interaction between proximity and visibility in column (2). When the solar site is visible and within 3 miles, property values, on average, decrease by about 5.2 percent. The corresponding effect of an invisible site is estimated at 4.6 percent. While both estimates are statistically significant at the 5 percent level, a statistical test shows that the difference between them is not significant at all (test p-value =0.746), indicating that site visibility may not impose a significant additional average effect beyond proximity and supporting the validity of proximity-based specifications in prior studies (Elmallah et al., 2023; Gaur and Lang 2023). We also checked an alternative specification that excludes no-view properties within the 3-mile radius in column (3) of Table 3.1, which provides a similar interaction effect of visibility and proximity. These average effect analyses, combined with the distance decay results, suggest that site proximity alone largely drives the residential home

[5] As pointed out in the Data & Methods section below, our visibility measure potentially overrepresents the true visibility especially when the viewpoint and the target are close, limited by structural elevation data availability (21). This measurement bias introduces attenuation in the treatment variable, potentially leading to an underestimation of the visibility impact (and hence the difference between visibility and proximity impact in Figure 3.1).

effect. Consequently, site proximity within a 3-mile radius (as presented in Table 3.1 column (1)) will serve as the principal treatment variable, representing LSSPV exposure, in subsequent event study and heterogeneity analyses. Examining the sensitivity of estimates to alternative control group specifications in Table 3.3, we find that the interaction effect of visibility and proximity remains robust across the board, while the pure proximity effect becomes insignificant in some of the alternative specifications. This implies that site visibility appears to reinforce the proximity effect in the sense that it improves the robustness of the home value effect estimate across various alternative control group specifications. To provide a comprehensive view of the proximity effect, we present both the specifications from column (1) and column (2) in the pre-trend tests and robustness checks in Appendix Section 3.SI.3. Pre-trend tests with placebo treatments in Table 3.2 show that the parallel trend assumptions are satisfied for all specifications in Table 3.1. More robustness checks in Table 3.A5 and 3.A6 confirm that all estimates in Table 3.1 remain consistent when applying alternative sample selection criteria based on acreage and the number of observations per tract-year cluster.

3.4.1.3 Residential Event-study Results

We explore the timing of the LSSPV exposure effect (i.e., site visible within 3 miles) based on an event study where the base year is specified as three years prior to the LSSPV installation[6] (Figure 3.2). The average negative price impact on residential homes is minor after the base year but becomes pronounced following the installation. The effect generally maintains its magnitude over time and fades after the ninth year post-installation.

[6] This approximately represents the time when some residents may become aware of the upcoming LSSPV site through permitting, contracting, community engagement, or other site preparation activities.

There are potential explanations for the observed effect dynamics. Right after the base year, the gradual dissemination of the LSSPV site information may not have reached many home buyers or led them to fully realize the potential negative price impact of the site, but the installation event makes the impacts clear and manifested in the market. The diminishing effect after nine years might come from the shrinking sample size as most of the LSSPV sites were developed after 2010. However, if the diminished effect is true, it does not necessarily imply that the negative amenity impacts disappear after nine years since many of the negative impacts, such as soil erosion and dust pollution, may take a long time to manifest (Bastida et al., 2006; Hernandez, et al., 2014; Li et al., 2007). A more plausible explanation of the fading price impact may be linked to residential sorting and demographic shifts (Banzhaf and Walsh, 2008; Bernstein et al., 2022; Shertzer and Walsh, 2019), as individuals less concerned about LSSPV facilities move into the affected neighborhoods. This indirectly suggests that the negative price impact might be more closely related to psychological factors than to the amenities themselves, which will be explored further in subsequent analyses and discussions.

3.4.1.4 Residential Effect Heterogeneity

We explore the heterogeneity of LSSPV exposure effect on residential homes across various dimensions, as shown in Figure 3.3. [7] We observe noticeable heterogeneity across census regions, county political leaning, county median household income, and historical land use of the LSSPV sites. Statistical tests results are available in Table 3.A7. LSSPV sites in the Northeast region impose significantly more negative impacts than those

[7] We also investigate the heterogeneous pure proximity and visible proximity effects in Figure 3.7. The results show that both effects have very similar heterogeneities as the main results in Figure 3.3: the negative property value impact is significantly higher in more politically conservative counties, and brownfield sites may have a positive property value impact.

in other regions. Heavily Democratic-leaning counties (over 65 percent Democratic votes in 2016) experience a positive LSSPV effect (+0.0374, insignificant), which is significantly different from more politically conservative (Non-Dem) counties (-0.0538, significant at the 5 percent level). Greenfield LSSPV development leads to a negative effect (-0.0466, significant at the 10 percent level), while brownfield redevelopments lead to a positive residential value effect (+0.225, significant at the 10 percent level), significantly different from the effect of Greenfield LSSPV.[8] Observed differences along other dimensions are not statistically significant. Moreover, we observe almost zero heterogeneity across different rural status, different lot sizes, different site capacities, and different levels of site visibility. A higher level of visual exposure ("High View" in Figure 3.3) or directly facing the solar panels (i.e., in the south of the solar panels, "Facing" in Figure 3.3) does not lead to a more negative residential value effect, providing further evidence that more view exposure may not lead to significantly more negative impacts. While we lack direct data on glint and glare effects, indirect evidence suggests they may not be a primary mechanism, as we find no evidence to support that being exposed to a site with tracking systems (i.e., potentially more susceptible to glare impacts, "Tracking" in Figure 3.3) or facing the solar panels lead to more negative impacts. Instead of visual levels or details, impacts appear to stem from psychological factors, such as negative perceptions of industrialization and altered scenic views. These negative perceptions are expected to be amplified by conservative ideology or mitigated by progressive ideology, aligning with the empirical

[8] Brownfields include sites such as hazardous waste facilities, abandoned contaminated areas, and inactive mines (USEPA, 2024). Solar projects on brownfields often require site cleanup, which can reduce negative externalities and undesirability of these sites and positively affect property values. This aligns with Gaur et al. (2023), who found that residents are willing to pay more for solar projects on brownfields, as these sites are otherwise undesirable. Meanwhile, respondents in Gaur et al. request compensation for solar projects developed on greenfields, suggesting that they perceive brownfields as the more appropriate land type for LSSPV development than greenfields.

finding that more politically conservative counties are associated with more negative impacts.

3.4.2 LSSPV Impact on Agricultural Land Value

Our Ag-land analyses show that having LSSPV sites within 2 miles of agricultural or vacant land increases the sales price per acre by an average of 19.4 percent,[9] which is statistically significant at the 5 percent level (Figure 3.4). The positive effect rapidly declines and becomes insignificant beyond 2 miles, similar to estimates in Li et al. (2024). This positive effect is likely due to the demand increase from potential solar leases, as further expansion of existing LSSPV sites is less costly than constructing new sites and likely involve nearby agricultural or vacant land. Pre-trend tests in Table 3.2 show that the parallel trend assumptions are satisfied since the estimated coefficients for the pre-treatment periods are small in magnitude and statistically insignificant. This indicates that there were no systematic differences in trends between treated and control groups before the LSSPV sites were installed, suggesting that any observed post-treatment differences can more plausibly be attributed to the treatment itself rather than pre-existing trends. Robustness checks in Table 3.4 show that across different control group definitions such as using alternative distance bands, excluding nearby treatment sites, or adjusting for regional characteristics, the estimated treatment effects on ag-land values remain similar in size and statistically significant. This consistency across specifications suggests that the positive impact is not driven by a particular control group selection method, supporting the robustness of the main ag-land estimate. Event-study results in Figure 3.5 show that the

[9] The coefficient estimate is 0.177, which reflects the effect on the logarithm of price. When this is converted to the actual proportional price effect, the result is $e^{0.177} - 1$ = 19.4%.

positive land value effect manifests three years after the site installation and fades away six years later. Figure 3.6 presents our analysis of heterogeneous ag-land effects. We find that LSSPV sites of larger than-median scale have virtually zero effect on land value, while sites of smaller scale display a positive effect on land value (significant at the 10 percent level). Considering that smaller sites have a larger potential for expansion, this observation seems to confirm our speculation that the nearby land value increase is mainly driven by the potential of future solar lease. We also find that agricultural or vacant lots of large acreage bears virtually zero effect while smaller lots show a significant (at the 5 percent level) positive effect. However, these differences are not statistically significant. More robustness checks in the Panel B of Table 3.A5 suggest that our land value estimates remain consistent when applying alternative sample selection criteria based on acreage. Finally, robustness checks in the Panel B of Table 3.A6 reveal that when focusing solely on county-site-year clusters containing more than a few sales, the land price effect of LSSPV rises dramatically, reaching 86.1 percent when excluding less-than-20-land-sales clusters (corresponding to a coefficient of 0.621). Given that we have excluded sales of land hosting LSSPV sites, the mechanism behind this substantial effect on land prices remains unclear but warrants further investigation.

3.4.3 LSSPV Impact on Large-lot Home Value

Our empirical results show that LSSPV sites have a dual effect: they decrease residential property values via reduced residential amenity, while simultaneously increasing nearby land prices due to enhanced land use potential. For large-lot residential homes with over five acres of land, we expect the LSSPV to impact property values through both channels. Our distance decay analysis (Figure 3.4) suggests that the overall LSSPV impact on large-lot home price is close to zero and statistically insignificant for all nearby proximity bins. Robustness checks in Table 3.A5 and Table 3.A6 confirm that these large-lot-home estimates remain small and insignificant when applying alternative sample selection criteria based on acreage and the number of observations per tract-year cluster. Therefore, the LSSPV property value impacts via amenity reduction and increased land use potential seem to offset each other in residential homes with over five acres of land.

3.4.4 Benefits and Costs of LSSPV Sites

Our findings highlight the complex interplay between the benefits and costs of LSSPV development. In Table 3.A8, we performed a back-of-the-envelope calculation to estimate the benefits and costs of LSSPV solar sites included in our analysis, including the mitigation value (i.e., avoided social cost of carbon emission), the appreciation of nearby agricultural or vacant land value, the value loss of nearby residential properties, and the agricultural production loss on land utilized for hosting LSSPV. The results suggest that the assessed benefits of existing LSSPV significantly outweigh the assessed total costs. The carbon mitigation benefit is the major benefit (about $22.2 billion annually), while the loss in residential home value is the dominant cost (about -$4.1 billion annually). Therefore, property value losses constitute a major proportion of negative externalities of LSSPV. While the expansion of solar energy is crucial for the renewable energy transition, it is imperative to address the localized externalities to ensure equitable outcomes for affected communities. Quantitative evidence, such as that generated by this study, can inform policymakers and stakeholders in designing compensation mechanisms and siting strategies that mitigate negative impacts while promoting the broader adoption of solar energy.

To illustrate how our results or similar studies could be used to develop a community compensation plan, we designed a prototype evidence-based community compensation plan for a site proposal in (Figure 3.A10). First, property value impact studies should be carefully conducted with empirical data from comparable solar sites (e.g., similar size, similar demographics, in counties or states of similar regulations, etc.), where the effect of distance decay, dynamics, and heterogeneities across a wide range of dimensions should be analyzed. The sample choice of LSSPV sites needs to balance site similarity and statistical power of analysis. Second, based on the property value study, compensation specifics should be decided for different properties in the neighborhood. Taking our main results as an example, compensation rates could be set at 5.2 percent of the annualized property value for ten years for residential homes within 3 miles of the LSSPV site with a site view, and 4.8 percent for those without a view. Third, the community compensation plan can involve communication with stakeholders ahead of the permitting process, and stakeholders' input should be involved in the revision process before reaching a final plan. A comprehensive compensation plan should also consider local externalities that might not visibly manifest in property prices. We would like to stress that the specific community compensation plan developed based on our nationwide study here should be merely taken as an example, and we recommend conducting targeted studies to determine appropriate community compensation plans for a specific LSSPV site.

3.5 Discussion

Our analyses and heterogeneity checks indicate that a nearby solar site may act as a stigmatizing nuisance (i.e. a psychological disamenity) (Goffman, 2009; Link and Phelan, 2001; McCluskey and Rausser, 2003; Taylor et al., 2016). Evidence supporting this claim includes the minimal variation in effects across different levels of site visibility, in effects across properties to the south and to the north of the site, and in effects across sites with different tracking systems, as they suggest that the view details of solar sites (including view extent, the exact view composition, and potential difference in glare effects) do not significantly impact residential values. The negative impact on nearby residences appears to operate primarily through psychological channels rather than through the degree of visibility or specific visual details. Considering disamenities other than visual impact, the scale of the site likely results in different disamenity levels and impacts, but this is also not observed (i.e., "Big USS" vs. "Small USS" in Figure 3.3). One explanation can be linked to negative perceptions that solar sites are industrial/commercial uses that alter rural land use and scenic views (Taylor et al., 2016). The disparities in effects between brownfield and greenfield sites align with this mechanism. Another piece of evidence is the significantly higher property value loss in more conservative counties compared to Democratic-leaning counties. This disparity is likely due to solar sites being more aligned with progressive values prevalent in Democratic-leaning counties and less frequently associated with negative perceptions. However, we cannot entirely rule out causal channels related to actual disamenity variations. First, our nationwide analysis may obscure heterogeneities under certain conditions, for example, sites with a larger scale may have a stronger negative effect in one region but a weaker one in another region, potentially canceling out in a pooled sample. Second, unexplored physical channels, such as vegetation and soil management practices (Elmallah et al.,2023; Hernandez, et al., 2014), might also contribute to the negative LSSPV impact on residential values.

3.6 Summary

This study provides a comprehensive nationwide assessment of the externalities associated with LSSPV installations in the US, focusing on their impacts on property values. We leverage a rich property transaction dataset with detailed geospatial information of LSSPV sites to estimate the effects on both residential properties and agricultural/vacant land. We apply advanced geospatial methods to overcome computational challenges and develop a comprehensive nationwide database on LSSPV visibility.

Our findings reveal that while LSSPV installations tend to decrease the value of nearby residential properties by approximately 4.8 percent within a 3-mile radius, they increase agricultural and vacant land values by about 19.4 percent within 2 miles. The analysis suggests that residential property value losses are predominantly driven by proximity to the site rather than specific visual factors such as site visibility, direction, or tracking systems, indicating that psychological disamenities, rather than tangible physical nuisances, are the primary drivers of negative valuation.

Further heterogeneity analysis highlights that residential value losses are more pronounced in conservative (non-Dem) counties, suggesting socio-political attitudes influence perceptions of LSSPV developments. Moreover, the study observes no significant difference in property impacts between large and small solar sites, nor between sites with or without public involvement, reinforcing the idea that general negative perceptions, rather than specific site characteristics, dominate.

Despite localized negative externalities, a cost-benefit analysis concludes that the overall societal benefits of LSSPV installations, primarily through carbon mitigation valued at approximately $22.2 billion annually, outweigh the total estimated costs, which include residential value losses of about $4.1 billion annually.

This study[10] also proposes a framework for community compensation plans, advocating for empirical, site-specific impact assessments and stakeholder involvement in the design and implementation of mitigation strategies, ensuring equitable outcomes for affected communities.

[10] A later version of this study is published at the *Proceedings of the National Academy of Science.*

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Tables and Figures

Table 3.1: Difference-in-Differences Estimates for Residential Homes

	(1)	(2)	(3)
	ProxT	ProxT × ViewT	ProxT × ViewT
ProxT	-0.076**		
	(0.022)		
β_3: ProxT × Post	-0.048*		
	(0.020)		
ProxT × 0.ViewT		-0.078**	
		(0.022)	
ProxT × 1.ViewT		-0.070**	-0.044
		(0.023)	(0.029)
$\beta_3^{no\_view}$: ProxT × 0.ViewT × Post		-0.046*	
		(0.020)	
β_3^{view}: ProxT × 1.ViewT × Post		-0.052*	-0.046+
		(0.020)	(0.023)
N	4975808	4975808	2444983
Covariates	Yes	Yes	Yes
Census Tract×Year	Yes	Yes	Yes
Test (H_0: $\beta_3^{no\_view} = \beta_3^{view}$):	z-Statistic = 0.324		p-value =0.746

Note: In Column (1), ProxT, standing for site proximity below 3 miles, is used as the treatment. In Column (2), proximity without view (ProxT×0.ViewT) and proximity with view (ProxT×1.ViewT) are used as treatment. In Column (3), properties that satisfy ProxT=1 and ViewT=0 are excluded. β_3s represent the treatment effects specified in Section 4.5.1. Standard errors, two-way clustered at census tract and year level, are reported in parentheses: + $p < 0.1$, $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$. Census tract by year fixed effects and property-level covariates are included in all specifications but not displayed. The control group is properties in the 5-to-6-mile proximity bins of the LSSPV sites, and properties located within 3 to 5 miles from the LSSPV sites are excluded. The number of observations, N, is calculated excluding singleton observations on the census-tract by year level. The coefficient for Post is omitted due to collinearity with fixed effects.

Table 3.2: Placebo Test Results

	Placebo Tests			
	(1)	(2)	(3)	(4)
	Residential ProxT	Residential ProxT × ViewT	Residential ProxT × ViewT	Ag Land ProxT
T	-0.040***	-0.034**	-0.026	0.069
	(0.011)	(0.011)	(0.016)	(0.054)
T × Pseudo-post	0.0026	0.0012	0.0091	-0.092
	(0.010)	(0.012)	(0.016)	(0.12)
N	3656813	3656813	2413556	42637

Note: T stands for the treatment variable. The column titles include the treatment variables actually employed in each specification. ProxT stands for using site proximity (less than 3 miles for Residential and 2 miles for Ag Land) as the treatment. ProxT×ViewT represents using the visibility within 3 miles as the treatments, where Column (2) includes the no-view properties within 2.5 miles with control variables addressing them while Column (3) exclude the no-view properties within 2.5 miles. Therefore, Column (1) through (3) correspond to the same columns in main text Table 1. The Pseudo-post variable indicates a post variable based on pseudo treatment events, specified at 6 years prior to the actual LSSPV installation. The time frame for these placebo tests is specified as 12 years through 2 years prior to the actual LSSPV installation. Standard errors are two-way clustered at census tract and year level, reported in parentheses: + $p < 0.1$, $* \, p < 0.05$, $** \, p < 0.01$, $*** \, p < 0.001$. Census tract by year fixed effects and property-level covariates are included in all specifications but not displayed.

Table 3.3: Robustness Check on Residential Home Analysis

	(1) Main C: 5-to-6 mi	(2) R1 C: 5-to-5.5 mi	(3) R2 C: 5.25-to-5.75 mi	(4) R3 C: 4.75-to-5.75 mi	(5) R4 C: 4-to-5 mi	(6) R5 C: 4-to-6 mi
Panel A						
β_3: ProxT × Post	-0.0476*	-0.0386+	-0.0499*	-0.0292	-0.0240	-0.0285+
	(0.0199)	(0.0223)	(0.0241)	(0.0188)	(0.0156)	(0.0142)
Panel B						
$\beta_3^{no\_view}$: ProxT × 0.ViewT × Post	-0.046*	-0.0371	-0.0481+	-0.0278	-0.0228	-0.0271+
	(0.020)	(0.0224)	(0.0242)	(0.0188)	(0.0156)	(0.0142)
β_3^{view}: ProxT × 1.ViewT × Post	-0.052*	-0.0425+	-0.0549*	-0.0331+	-0.0276+	-0.0326*
	(0.020)	(0.0222)	(0.0239)	(0.0187)	(0.0158)	(0.0145)
N	4975808	4233376	4230993	4987151	5061577	6560201

Note: The main purpose of these analyses is to check the robustness of our main estimates for residential homes against different control group and sample selection criteria. Panel A results use proximity as the treatment, corresponding to Column (1) in main text Table 3.1. In Panel B, proximity without view (ProxT×0.ViewT) and proximity with view (ProxT×1.ViewT) are used as treatment, corresponding to Column (2) in Table 3.1. Our main specification estimates are presented as Column (1), where the control group is properties in the 5-to-6-mile proximity bin. The control groups in Column (2) to (6) are properties in the 5-to-5.5-mile proximity bin, the 5.25-to-5.75-mile proximity bin, the 4.75-to-5.75-mile proximity bin, the 4-to-5-mile proximity bin, and the 4-to-6-mile proximity bin, respectively. Standard errors are two-way clustered at census tract and year level, reported in parentheses: + $p < 0.1$, $* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$. Census tract by year fixed effects and property-level covariates are included in all specifications.

Table 3.4: Robustness Check on Agricultural or Vacant Land Analysis

	(1) Main C: 18-to-20 mi	(2) R1 C: 17-to-19 mi	(3) R2 C: 18-to-21 mi	(4) R3 C: 18-to-22 mi	(5) R4 C: 18-to-23 mi
T × Post	0.177*	0.158+	0.189*	0.199*	0.187*
	(0.0764)	(0.0838)	(0.0744)	(0.0746)	(0.0790)
N	60024	57141	62534	64978	67420

Note: The main purpose of these analyses is to check the robustness of our main estimate for agricultural or vacant land, as shown in Figure 3.4, against different control group and sample selection criteria. In all columns, T denotes properties that are within 2 miles of LSSPV sites, used as the treatment variable. The main estimate is presented in Column (1), where the control group is properties in the 18-to-20-mile ring. The control group in Column (2) is properties in the 17-to-19-mile ring, the control group in Column (3) is properties in the 18-to-21-mile ring, the control group in Column (4) is properties in the 18-to-22-mile ring, and the control group in Column (5) is properties in the 18-to-23-mile ring. Standard errors are two-way clustered at county and year level, reported in parentheses: + $p < 0.1$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$. County by year fixed effects and property-level covariates are included in all specifications but not displayed.

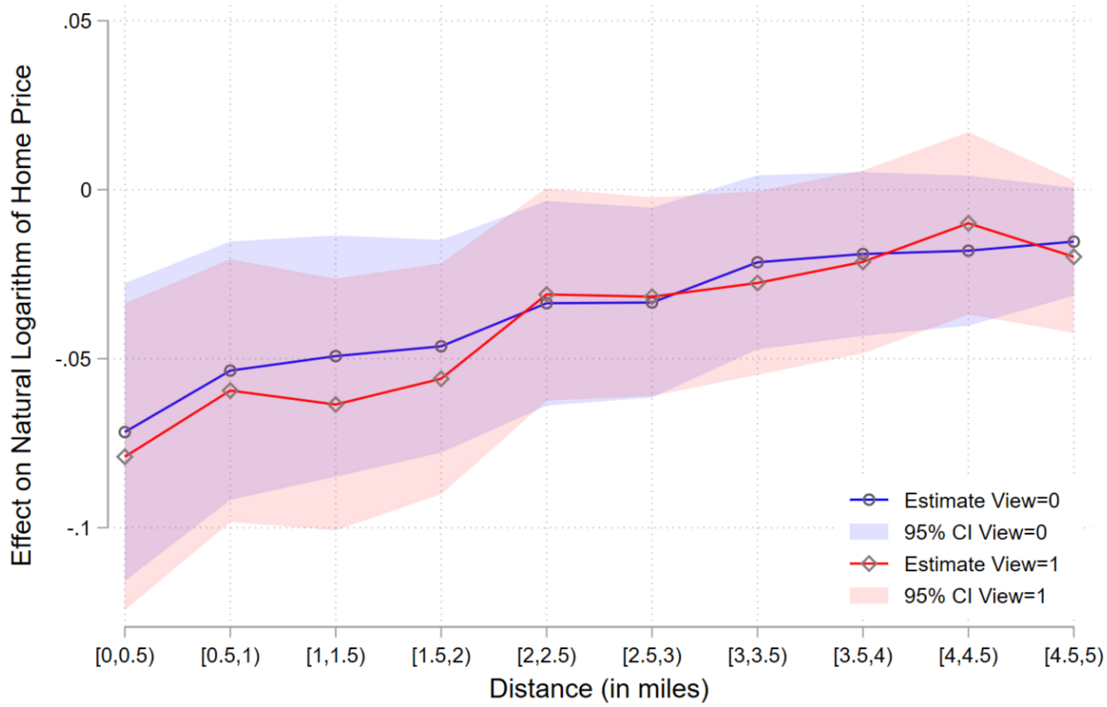


Figure 3.1 Effects of proximity and view on residential home value. The blue line connects the coefficient estimates of proximity bins without view, obtained by interacting with the proximity bins, the binary post-treatment indicator, and the no-visibility indicator (i.e., equals 1 if no site view). The red line connects coefficient estimates of proximity bins with view, obtained by interacting the proximity bins, the binary post-treatment indicator, and the visibility indicator (i.e., equals 1 if with site view). The number of observations (N) in this analysis is 8,303,074, excluding singleton observations on the census-tract by year level. The 95% CIs are constructed with two-way clustered SEs at the census tract and year level. The control group is properties in the 5-to-6-mile proximity bin.

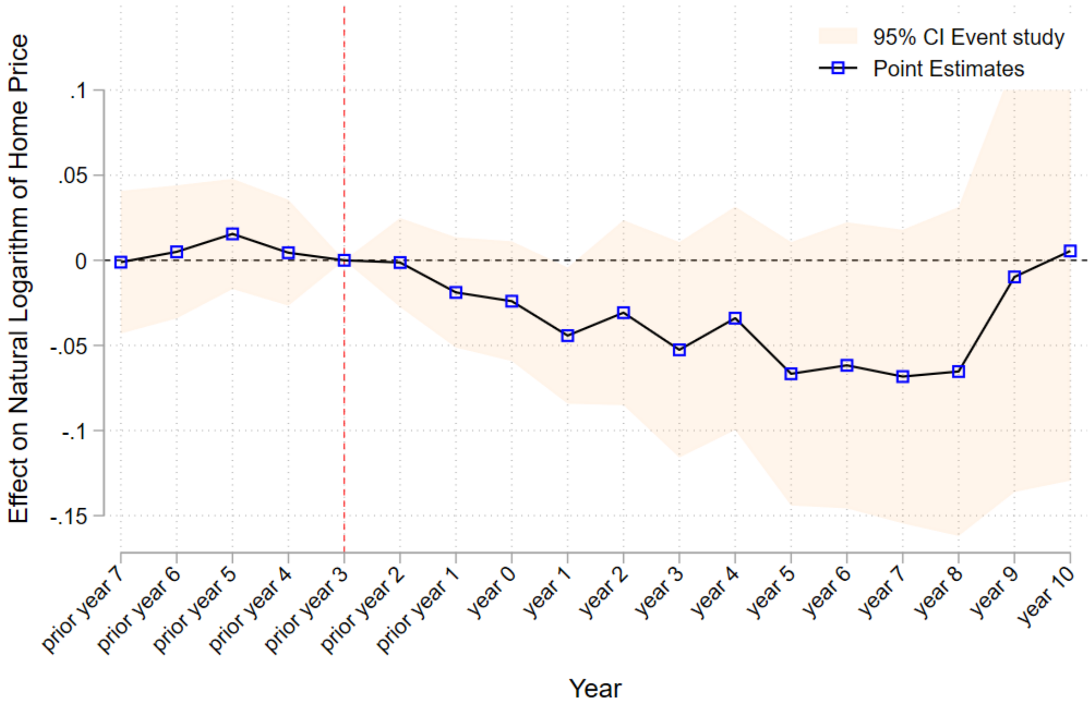


Figure 3.2 Event study on residential home value. The treatment (LSSPV site within 3 miles) effect on residential home values is illustrated across different years relative to the year of LSSPV installation. The blue squares on the black line indicate the coefficient estimates, obtained by interacting the treatment variable with year indicators. The reference year is defined as three years before the LSSPV installation, and the control group is properties in the 5-to-6-mile proximity bin. The shaded areas represent the 95% CIs, constructed using two-way clustered SEs at the census tract and year level.

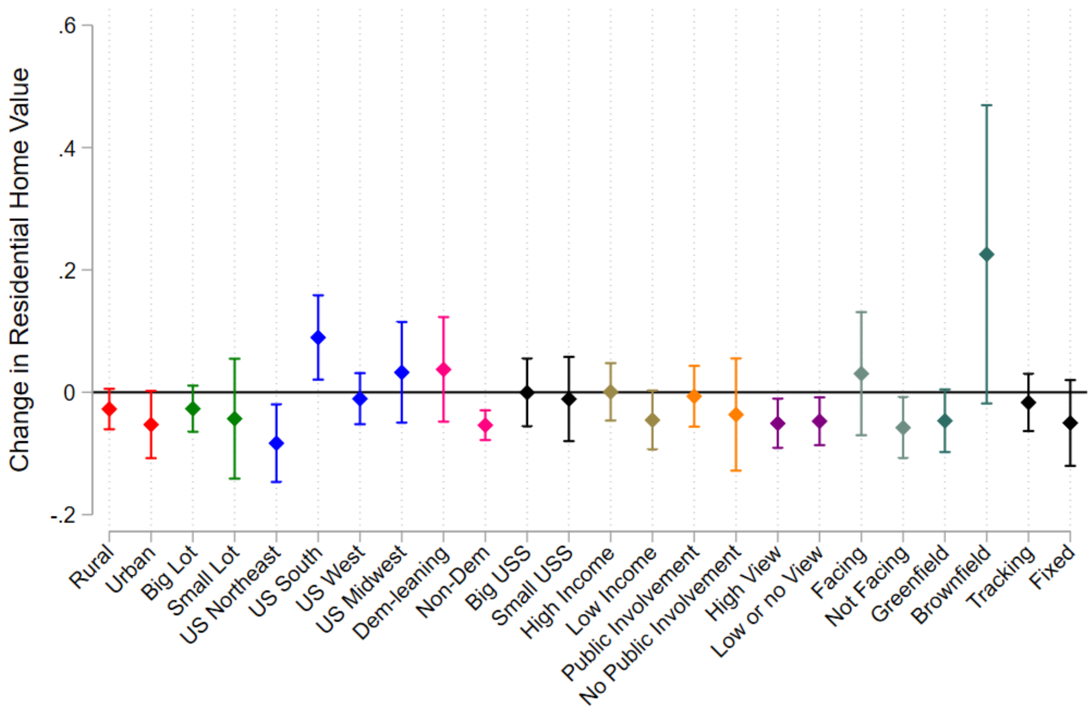


Figure 3.3 Heterogeneous effects of LSSPV exposure by different dimensions. Diamonds are the point estimate of the effect of LSSPV on nearby residential home values based on DID models. The treatment is LSSPV within 3 miles, and the control group is properties in the 5-to-6-mile proximity bin of the LSSPV site. The 95% CIs of the estimates are shown as bars, having clustered SEs at the census tract and year level. Check *SI Appendix* for the details of all factors investigated here. More heterogeneity checks differentiating visible and invisible sites are available in Figure 3.7.

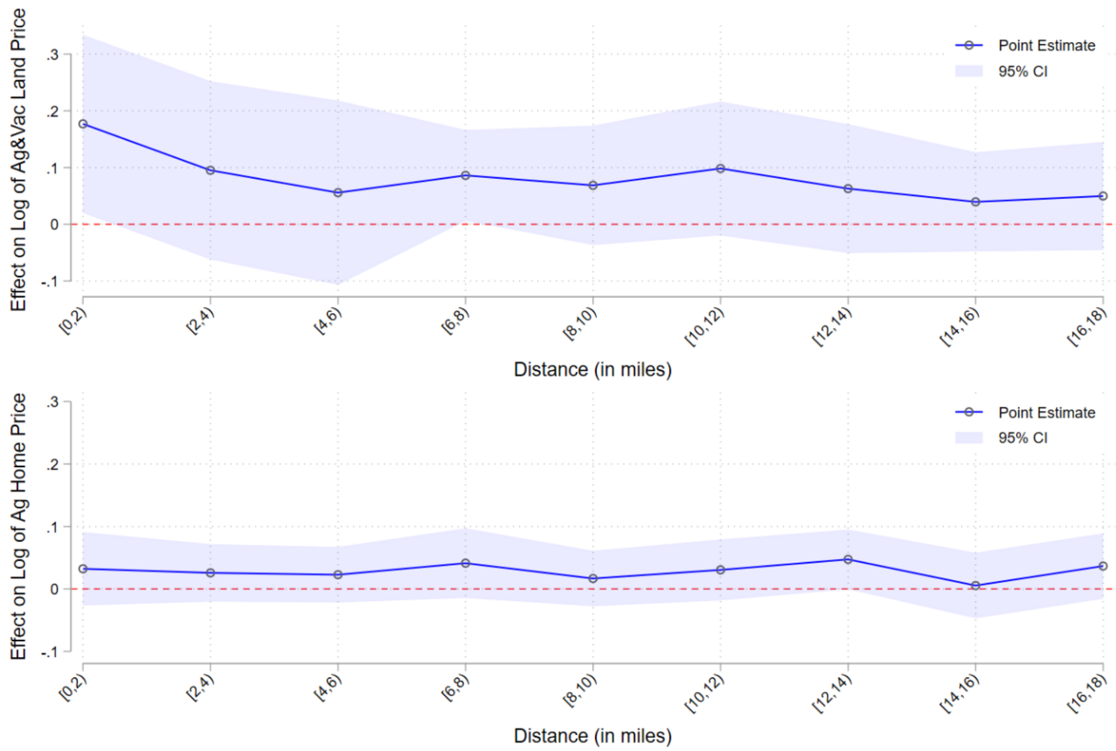


Figure 3.4 Distance decay results for agricultural/vacant land and large-lot homes. The top sub-figure shows estimates for agricultural and vacant land above five acres. The bottom sub-figure shows estimates for large-lot homes, defined as properties over five acres with residential structures. The results show the value effects of LSSPV for a range of proximity bins, defined with 2-mile intervals. The blue line connects the coefficient estimates of proximity bins, obtained by interacting the proximity-bin indicators with the binary post-treatment indicator. The treatment groups are properties within these proximity bins, while the control group is properties within the 18-to-20-mile proximity bin. The 95% CIs are constructed with two-way clustered SEs at the county-site and year level.

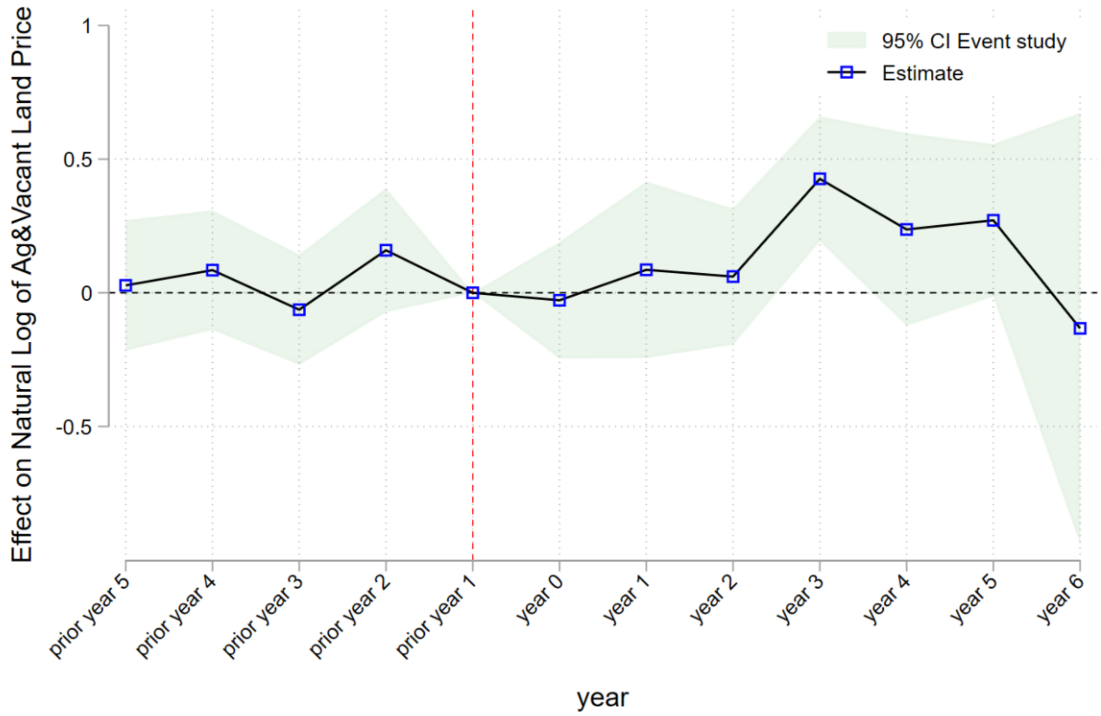


Figure 3.5 Event Study Result for Agricultural or Vacant Land Value. In this figure, the treatment (LSSPV site within 2 miles) effect on ag-land value is illustrated across different years relative to the year of LSSPV installation. The blue squares on the black line indicate the coefficient estimates, obtained by interacting the treatment variable with year indicators. The shaded areas represent the 95% CIs, constructed using two-way clustered SEs at the county-site and year level.

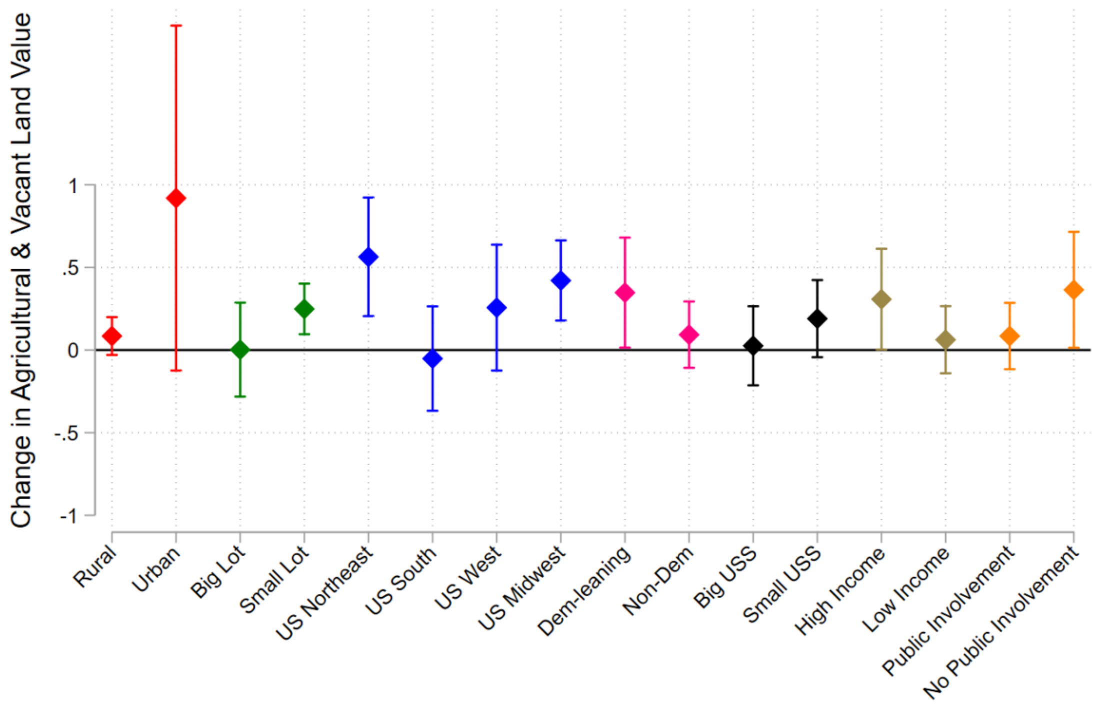
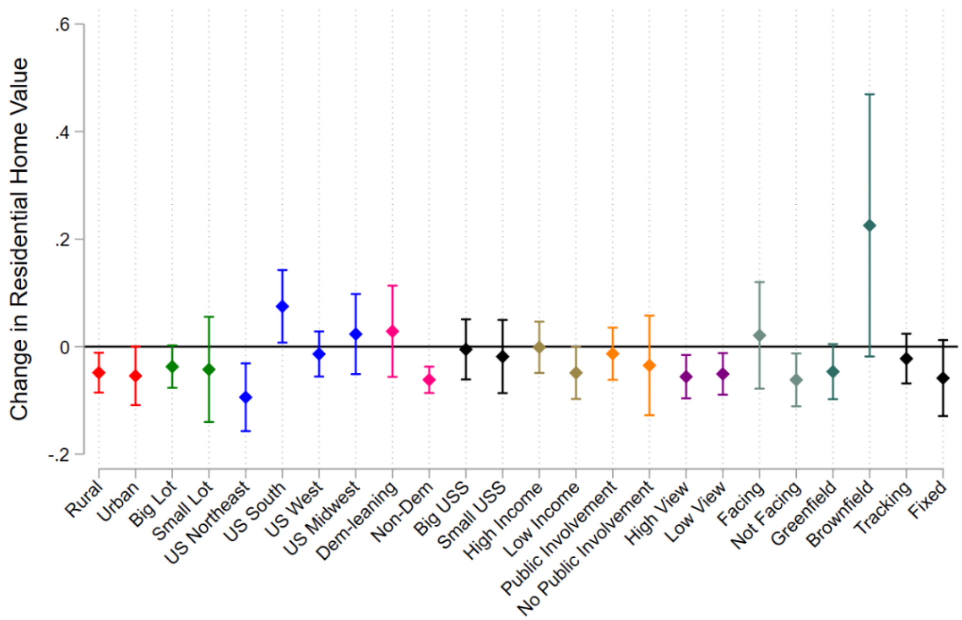
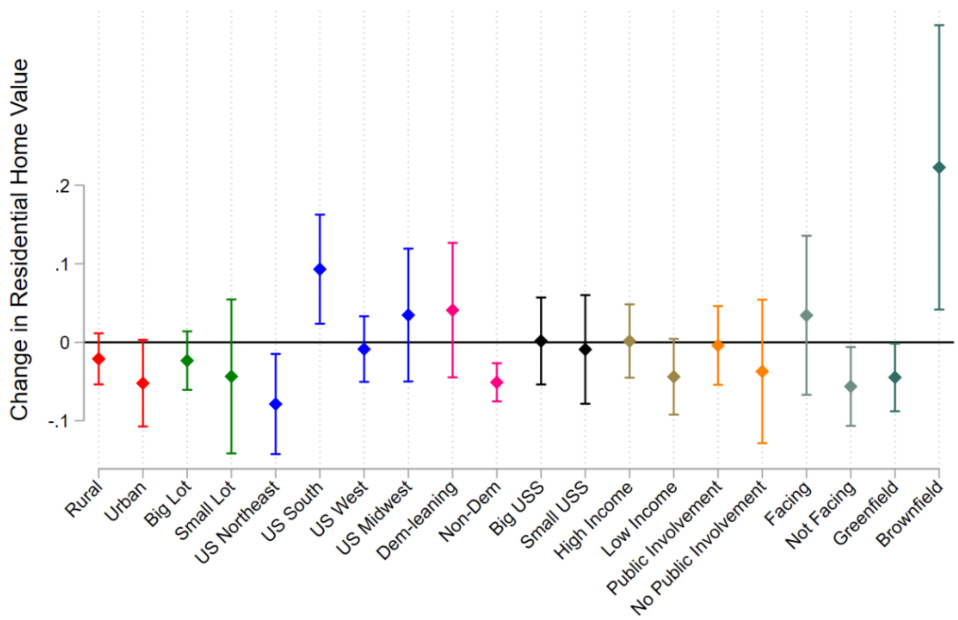


Figure 3.6 Heterogeneous Effects of LSSPV on Ag-land by Different Dimensions (see the definition of variables in Main Text 3.2.4)



(a) Treatment: Visible LSSPV within 3 miles



(b) Treatment: Invisible LSSPV within 3 miles

Figure 3.7 Heterogeneous Effects on Residential Home Values (Alternative Treatment). Unlike the main results in Figure 3.3, the treatment here is visible (for subfigure a) or invisible (for subfigure b) LSSPV within 3 miles. Except the differences in treatment assignment, all other aspects of these heterogeneity analyses are identical to the main analysis. The 95% CIs of the estimates are shown as bars, calculated from clustered SEs at the census tract and year level.

Appendix

Supporting Information Text

1.SI.1 Objective Function in the crop-only REAP Model

The objective function represents the net social benefit of the US agricultural sector, encompassing both consumer and producer surplus (CPS). This net social benefit is calculated as the sum of the areas under the crop demand curves, along with government payments such as Conservation Reserve Program (CRP) rental payments. From this total, the areas under the supply curves for quasi-fixed regional inputs, crop-specific PMP cost functions, CRP land supply curves, and production costs are subtracted. The objective function is written as:

$$\begin{aligned} Max\ \text{CPS} = {} & \sum_m \sum_p \alpha_{m,p} Z_{m,p} + \frac{1}{2} \sum_m \sum_p \beta_{m,p} Z_{m,p}^2 + \sum_{rl} \sum_{ec} PMT_{rl,ec}^{crp} CRP_{rl,ec} \\ & - \sum_{xccrop(b,rl,h.tl.ec)} w_{xccrop}^{vc} X_{xccrop} - \sum_{rl} \sum_{ec} \alpha_{rl,ec}^{cland} LCF_{rl,ec} \\ & - \left(\sum_{rl} \sum_{ec} \alpha_{rl,ec}^{cland} LCV_{rl,ec} + \frac{1}{2} \sum_{rl} \sum_{ec} \beta_{rl,ec}^{cland} LCV_{rl,ec}^2 \right) \\ & - \left(\sum_{rl} \sum_{ec} \sum_c \alpha_{rl,ec}^{ac} \Delta AC_{rl,ec} + \frac{1}{2} \sum_{rl} \sum_{ec} \sum_c \beta_{rl,ec}^{ac} \Delta AC_{rl,ec}^2 \right) \end{aligned}$$

The first and second terms in the objective function, $\sum_m \sum_p \alpha_{m,p} Z_{m,p} + \frac{1}{2} \sum_m \sum_p \beta_{m,p} Z_{m,p}^2$, represent the sum of the area under market demand and supply curves. The parameters for these curves are derived from the demand or supply for each commodity p in each market m in the base year ($Z_{m,p}^0$), the commodity price in the base year (P_p^0), and the price elasticity of demand or supply ($\varepsilon_{m,p}$). The formula for deriving the slope parameter is $\beta_{m,p} = (P_p^0 / Z_{m,p}^0) * (1/\varepsilon_{m,p})$. The intercept is then obtained from the equation $\alpha_{m,p} = P_p^0 - \beta_{m,p} * Z_{m,p}^0$. The third term, $\sum_{rl} \sum_{ec} PMT_{rl,ec}^{crp} CRP_{rl,ec}$, is the sum of rental payments for CRP land. The fourth term, $\sum_{xccrop(b,rl,h.tl.ec)} w_{xccrop}^{vc} X_{xccrop}$, is the sum of the variable production costs for the primary crop production activities, where w_{xccrop}^{vc} represents the sum of all the cost of the inputs. The implicit assumption underlying this specification is that the prices of these inputs are constant. The fifth term, $\sum_{rl}\sum_{ec}\alpha_{rl,ec}^{cland}LCF_{rl,ec}$, is the sum of the fixed cropland costs for the primary crop production activities. The sixth term, $\sum_{rl}\sum_{ec}\alpha_{rl,ec}^{cland}LCV_{rl,ec}+\frac{1}{2}\sum_{rl}\sum_{ec}\beta_{rl,ec}^{cland}LCV_{rl,ec}^{2}$, is the sum of the variable cropland costs for the primary crop production activities. The seventh term, $\sum_{rl}\sum_{ec}\sum_{c}\alpha_{rl,ec}^{ac}\Delta AC_{rl,ec}+\frac{1}{2}\sum_{rl}\sum_{ec}\sum_{c}\beta_{rl,ec}^{ac}\Delta AC_{rl,ec}^{2}$, is the sum of the areas under the PMP supply functions for crops, where the $\Delta AC_{rl,ec}$ is the difference between simulated crop acreage in the each REAP region ($AC_{rl,ec}$) and the supply of crop acreage in each REAP region in the base year ($AC_{rl,ec}^{0}$). The parameters for these PMP functions are derived from the supply of crop acreage in each REAP region in the base year ($AC_{rl,ec}^{0}$). The PMP supply functions for crops are part of a nested system of CET functions that determine the substitution behavior among crop rotations and tillage practices. The CET functions aggregate individual production activities that differ by crops produced, rotations used, and tillage practices employed into a crop production index that is used in the PMP function for crops. The PMP supply functions for crops avoid the problems of overspecialization and corner solutions, in accordance with our neoclassical economic behavioral expectation of profit maximization.

1.SI.2 Elasticities of Demand and Supply in the REAP Model

The elasticities of demand and supply (Table 1.A1) used in the REAP are updated through multiple sources. The elasticities under attribute IMP are updated according to the Table 3 in Regional Environment and Agriculture Programming Model (Johannson et al. 2007). The own price elasticities of demand (DOM) are updated according to the Demand Elasticities from Literature accessed from the website of USDA Economic Research Service. (https://www.ers.usda.gov/data-products/commodity-and-food-elasticities/download-the-data/) The elasticities of DOM, EXP, and SCE are negative reflecting downward sloping demand. The elasticity of IMP is positive reflecting upward sloping supply. The demand elasticity of ethanol is set to the same as gasoline.

Table 1.A1: Elasticities[a, b] used in REAP model

	DOM[c]	EXP	SCE	IMP
Corn	-0.2	-0.5	-0.8	0.201
Sorghum	-0.84	-1.17	-0.44	
Barley	-0.26	-0.65	-0.81	0.201
Oats	-0.1	-0.65	-1.53	0.201
Wheat	-0.09	-1.44	-0.37	0.201
Rice	-0.33	-2.41	-0.63	0.201
Soybeans	-0.38	-0.73	-6.67	0.201
Cotton	-1.02	-1.26	-0.89	0.201
Silage	-0.5			
Hay[d]	-0.5			
Eggs	-0.72	-0.601	-0.201	0.201
Broilers	-0.3	-0.86	-0.201	
Turkey	-0.553	-0.945	-0.201	
Fluidmlk[e]	-0.2588			
Butter[e]	-1.132	-0.068	-0.201	0.201
Nfdmilk[e]	-1.49	-0.601	-0.201	0.201
Amcheese	-0.122	-0.1723	-0.201	0.01
Otcheese	-0.287	-0.601	-0.201	0.201
Icecream	-0.504			0.01
Evdrymlk[e]	-1.49	-0.601	-0.201	0.201
Milk[e]	-0.243			0.201
Hogslaugh	-0.076	-0.201		0.201
Livcalf				0.201
Bfyrlings		-0.201		0.201
Nonfdsl				0.201
Fedsla		-0.201		0.201
Fedbeef	-0.75	-0.78	-0.201	0.201
Nonfdbeef	-0.48		-0.201	0.201
Veal	-3.12	-0.601	-0.201	0.201
Pork	-0.773	-0.601	-0.201	0.201
Glutmeal		-2.5		0.201
Glutfeed		-3.5		0.201
Beanmeal		-1.02	-0.21	0.201
Beanoil	-0.46	-1.34	-0.26	0.201
Ddg		-3.5		
Ethanol	-0.58	-1		1

[a]Source: Johannson, R., M. Peters and R. House 2007. Regional environment and agriculture programming model, U.S. Department of Agriculture, Economic Research Service: 1-111.
[b]The absence of an elasticity indicates that no explicit supply or demand curve is specified for that particular commodity in that particular market—i.e., the price remains constant.
[c]DOM (domestic consumption, explicit demand that excludes PRPC), EXP (exports, explicit demand, excluding exports under export enhancement program), IMP (imports, explicit supply), SCE (ending commercial stocks, explicit demand), PRPC (production & processing use, implicit derived demand).

[d]We updated the DOM elasticity of Hay. Source: Konyar, K., & Knapp, K. (1986). Demand for Alfalfa Hay in California (No. 1575-2016-133992).
[e]We updated the elasticities of Fluidmlk, Butter, Nfdmilk, Evdrymlk, and Milk from the Commodity and Food Elasticities retrieved from USDA ERS website (https://www.ers.usda.gov/data-products/commodity-and-food-elasticities/).

Table 1.A2: Crop acreage and production[a] in baseline year 2030

	Acres (million)	Production[b]
Corn	89.0	16,180
Sorghum	7.0	427
Barley	2.6	183
Oats	2.7	69
Wheat	44.5	1,969
Rice	2.7	210
Soybeans	90.0	4,955
Cotton	12.8	20
Silage[c]	7.1	102
Hay[c]	59.4	358

[a]Source: US Department of Agriculture, USDA Agricultural Projections to 2030. Retrieved Feb 20, 2021 from https://usda.library.cornell.edu/concern/publications/qn59q396v?locale=en
[b]The production unit of Corn, Sorghum, Barley, Oats, Wheat, and Soybeans is million bushels. The production unit of Rice is million hundredweight. The production unit of Cotton is million bales. the production unit of Silage and Hay is million tons.
[c]There is no projection of Silage and Hay. Considering that Hay and Silage are both forages and that Corn may be harvested for either grain or silage, the updating method we applied for the acreage and production of Silage and Hay is:
$Silage_{2030} = Silage_{2007} * (Corn_{2030} / Corn_{2007})$
$Hay_{2030} = Hay_{2007} * (Corn_{2030} / Corn_{2007})$

Table 1.A3: Livestock production activities[a] in baseline year 2030

	dairy[b]	bfcowen	bfcowcf	feedlot[c]	cfeedlot	stocker
Appalachia	0.75		3.39			
Corn Belt	0.93		4.87	30.84	9.25	11.15
Delta States	0.16		1.93			
Lake States	2.20		2.94	11.29	3.08	
Mountain States	0.83	6.25		1.37	58.83	11.15
Northern Plains	0.30	6.55		20.31	139.62	11.15
Northeast	1.73		1.85			
Pacific States	1.75	3.62			19.92	11.15
Southeast	0.31		2.50			
Southern Plains	0.47	7.28			104.16	66.92
U.S.	9.43	23.70	17.48	63.81	334.86	111.53

	farofin[d]	feedrpig	pigfin	eggs[e]	broilers	turkey
Appalachia	9.48	2.22	7.45	689	11651	1763
Corn Belt	11.42	0.43	1.58	4090	2146	1088
Delta States	0.47			563	11206	547
Lake States	3.76	0.15	0.56	901	0	1120
Mountain States	0.63			595	0	1
Northern Plains	5.32	0.09	0.34	425	0	165
Northeast	1.06			1481	3934	234
Pacific States	0.21			657	1464	507
Southeast	0.44	0.01	0.02	891	14722	284
Southern Plains	0.70			677	5045	330
U.S.	33.50	2.90	9.94	10968	50167	6040

[a]Source: US Department of Agriculture, USDA Agricultural Projections to 2030. Retrieved Feb 20, 2021 from https://usda.library.cornell.edu/concern/publications/qn59q396v?locale=en

[b]The unit of DAIRY (dairy cow), BFCOWEN (cow-calf, 17 western states), and BFCOWCF (cow-calf, 31 eastern states) is million head.

[c]The unit of FEEDLOT (farmer cattle feeding), CFEEDLOT (commercial feedlot), and STOCKER (beef calf to yearling) is million CWT.

[d]The unit of FAROFIN (farrow to finish hogs), FEEDRPIG (feeder pig production), and PIGFIN (feeder pig finishing) is 10 million CWT.

[e]The unit of EGGS (egg production) is million dozen eggs. The unit of BROILERS (broiler carcass) and TURKEY (turkey carcass) is million pounds.

Table 1.A4: Cropland supply[a] in REAP model

	QBASE[b, c, d]	PBASE[c]	ELAS[c]	FIXED[b, c, d]	MAXIMUM[b, c, d]
Appalachia	12.53	93	0.3	9.71	42.81
Corn Belt	40.45	183	0.3	31.35	129.01
Delta States	92.53	240	0.3	71.71	303.48
Lake States	91.52	122	0.3	70.93	205.72
Mountain States	17.69	118	0.3	13.71	57.17
Northern Plains	7.10	103	0.3	5.50	25.59
Northeast	15.23	130	0.3	11.80	44.29
Southeast	42.62	45	0.3	33.03	110.22
Southern Plains	33.34	107	0.3	25.84	84.08
Pacific States	15.02	313	0.3	11.64	28.26

[a]Source: The FPR level data is aggregated from state level data retrieved from 2020 USDA NASS Survey.

[b]The unit of quantity (QBASE, MAXIMUM, and FIXED) is million acres. The unit of price (PBASE) is dollar/acre.

[c]The QBASE is the cultivated cropland quantity in baseline year 2030. The FIXED is the quantity of cropland supplied at the base price (PBASE). The MAXIMUM is the maximum quantity of cropland supply. The ELAS, QBASE, and PBASE together define the variable cropland supply curve slope.

[d] We assumed that quantities (QBASE, MAXIMUM, and FIXED) do not change from 2020 to 2030. We assumed that PBASE will change at the same rate as the predicted GDP Implicit Price Deflator from 2020 to 2030.

Table 1.A5: Yields[a] of corn and soybeans in REAP model

	Corn (bushels/acre)	Soybeans (bushels/acre)
Appalachia	147.9	47.9
Corn Belt	199.3	65.1
Delta States	215.9	52.1
Lake States	217.1	59.5
Mountain States	231.1	
Northern Plains	182.3	55.2
Northeast	174.6	58.8
Southeast	158.9	42.3
Southern Plains	188.6	30.0
Pacific States	268.6	

[a]Source: Adjusted yields calibrated by REAP model based on the yield results from Environmental Policy Integrated Climate (EPIC) model.

Table 1.A6: Production costs[a, b] of corn and soybeans in REAP model

	Corn[c] (dollars/acre)	Soybeans[d] (dollars/acre)
Appalachia	454.1	156.0
Corn Belt	433.7	103.5
Delta States	499.5	109.3
Lake States	389.9	116.8
Mountain States	323.2	
Northern Plains	359.8	94.7
Northeast	381.4	131.2
Southeast	391.6	132.8
Southern Plains	448.2	97.6
Pacific States	493.3	

[a]Source: the inputs table in REAP model.

[b]Production costs here are updated to the baseline year of 2030 according to the USDA Agricultural Projections to 2030. Therefore, the crop production costs here are different from Table A7 below, which has a baseline year of 2021.

[c]Average production costs of continuous corn rotation (RCCC) on non-irrigated, non-highly erodible land with conventional tillage.

[d]Average production costs of continuous soybeans rotation (RBBB) on non-irrigated, non-highly erodible land with conventional tillage.

Table 1.A7: Energy inputs into crop operation and pass-through rates of energy prices (dollars per planted acre)

	Fertilizer	Chemicals	Fuel, lube, and electricity	Total operating costs[a]	Weighted Pass-through rates[b]
Corn	93.13	24.38	31.58	228.99	30.7%
Sorghum	30.11	18.15	43.15	128.70	45.9%
Barley	33.38	13.11	22.84	110.67	34.5%
Oats	28.16	2.29	17.24	81.61	33.4%
Wheat	32.69	8.78	19.77	93.03	36.0%
Rice	66.96	66.16	105.6	395.96	37.8%
Soybeans	15.31	15.0	15.23	106.63	23.7%
Cotton	62.81	63.35	48.86	436.86	20.7%
Silage[c]	93.13	24.38	31.58	228.99	30.7%
Hay[d, e]	118.07	38.14	24.05	202.56	37.3%
Average					31.8%

[a]Source: USDA Economic Research Service. Commodity Costs and Returns. https://www.ers.usda.gov/data-products/commodity-costs-and-returns/ Accessed May 24, 2021.

[b]Assume the pass-through rate of energy price change to fertilizer and chemicals is 33% (Baffes, 2007) and the pass-through rate of energy price change to fuel, lube, and electricity is 100%. Given corn as an example, the weighted pass-through rate is: [(93.13+24.38)*33%+31.58*100%]/228.99=30.7%.

[c]There is no USDA cost and return data on silage, we assume it is same as corn.

[d]There is no USDA cost and return data on hay. We used Iowa State University Extension and Outreach. Estimated Costs of Pasture and Hay Production: Ag Decision Maker. https://www.extension.iastate.edu/agdm/crops/html/a1-15.html.

[e]The costs of energy inputs in hay are the average of costs in seeding year and established year.

Table 1.A8: Livestock energy costs

Item	Energy costs ($)[a]	Total variable costs ($)	Energy costs as % of total variable costs (%)
Dairy[b, c]	830	3,529	23.5
Swine (farrow to finish)[d, e]	256	995	25.8
Swine feeder pig[d]	25	90	27.4
Swine finishing[d, f]	43	205	20.8
Cow calf[d]	200	704	28.5
Steer finishing[d, g]	199	663	30.0
Stocker[d, h]	71	252	28.1
Egg, broilers, turkey[i]	39,486	81,270	48.6
Average			32.1

[a]Energy related expenses include feed costs, machinery variable costs, utilities, and hauling costs.

[b]Source: University of Missouri Cooperative Extension. Missouri Dairy Confinement Planning Budget for 2021. https://extension.missouri.edu/media/wysiwyg/Extensiondata/Pub/pdf/agguides/agecon/g00676.pdf Accessed May 24, 2021.

[c]Average of 20,000 lb milk production and 24,000 lb milk production.

[d]Source: Iowa State University Extension and Outreach. Livestock Enterprise Budgets for Iowa-2021. https://www.extension.iastate.edu/agdm/livestock/html/b1-21.html.

[e]Farrow to finish is for one litter.

[f]Variable cost does not include cost of purchasing feeder pig.

[g]Variable cost does not include cost of purchasing feeder steer.

[h]Backgrounding a calf on winter corn and hay to produce 300 lbs. of gain (from 450 to 750 lbs). Cost does not include cost of purchasing feeder animal.

[i]Source: Rhodes et al. (2017). College Park, MD: University of Maryland Extension. Broiler production management for potential and existing growers. https://extension.umd.edu/sites/extension.umd.edu/files/2021-07/Broiler_Production_Management_Extn_Bulletin.pdf Accessed Jun 27, 2022. Cost is for four broiler houses totaling 144,000 square feet and 1,224,000 birds/year.

Table 1.A9: Processing Costs and Share of Costs Devoted to Fuel and Electricity for Industries Contained in REAP

	Cost of purchased fuels consumed ($1,000)[a]	Cost of purchased electricity ($1,000)[a]	Total cost of supplies and/or materials ($1,000)[a]	% of total cost for purchased fuels and electricity[a]
Animal slaughtering & processing	602,468	1,350,293	147,843,239	1.32
Dairy product manufacturing	411,432	777,745	78,621,941	1.51
Soybean and other oilseed processing	249,356	208,773	33,949,202	1.35
Grain and oilseed milling	668,433	848,875	63,947,190	2.37
Wet corn milling	261,957	282,627	6,300,724	8.64
Weighted average				1.71

[a]Source: U.S. Census Bureau. Annual Survey of Manufactures: Summary Statistics for Industry Groups and Industries in the U.S.: 2019 and 2018. https://data.census.gov/cedsci/table?q=&text=AM1831BASIC01&tid=ASMAREA2017.AM1831BASIC01.

Table 1.A10: Crop commodity output by energy price scenario

	Energy price change (%)				
	-40	-20	0	20	40
Barley (million bu)	188	185	182	180	177
% change	2.8%	1.4%		-1.4%	-2.8%
Corn (million bu)	17,633	16,931	16,237	15,605	15,117
% change	8.6%	4.3%		-3.9%	-6.9%
Cotton (million bales)	21	21	20	20	20
% change	2.8%	1.4%		-1.4%	-2.8%
Hay (million tons)	291	287	283	282	281
% change	2.8%	1.4%		-0.6%	-0.9%
Oats (million bu)	57	54	52	50	48
% change	8.9%	4.5%		-4.1%	-8.4%
Rice (million cwt)	238	225	211	198	187
% change	12.9%	6.4%		-6.3%	-11.5%
Silage (million tons)	51	50	48	47	46
% change	6.7%	3.4%		-1.9%	-3.4%
Sorghum (million bu)	472	451	429	407	385
% change	9.9%	4.9%		-5.3%	-10.3%
Soybeans (million bu)	5,075	5,028	4,981	4,934	4,885
% change	1.9%	1.0%		-0.9%	-1.9%
Wheat (million bu)	2,043	1,995	1,946	1,894	1,845
% change	5.0%	2.5%		-2.6%	-5.2%

Table 1.A11: Crop commodity price by energy price scenario

	Energy price change (%)				
	-40	-20	0	20	40
Barley ($/bu)	4.33	4.42	4.52	4.62	4.71
% change	-4.23%	-2.12%		2.12%	4.25%
Corn ($/bu)	3.37	3.46	3.54	3.63	3.72
% change	-4.97%	-2.45%		2.51%	4.99%
Cotton ($/bale)	671.58	683.28	694.97	706.74	718.58
% change	-3.36%	-1.68%		1.69%	3.40%
Hay ($/ton)	105.69	106.87	108.07	109.49	110.96
% change	-2.20%	-1.11%		1.32%	2.68%
Oats ($/bu)	1.78	1.84	1.91	1.97	2.03
% change	-6.83%	-3.46%		3.18%	6.45%
Rice ($/cwt)	12.25	12.86	13.46	14.05	14.54
% change	-9.01%	-4.48%		4.42%	8.04%
Silage ($/ton)	25.88	26.68	27.48	28.30	29.13
% change	-5.79%	-2.88%		3.00%	6.04%
Sorghum ($/bu)	3.49	3.59	3.69	3.80	3.90
% change	-5.45%	-2.72%		2.89%	5.68%
Soybeans ($/bu)	9.56	9.69	9.83	9.96	10.10
% change	-2.73%	-1.38%		1.36%	2.75%
Wheat ($/bu)	4.85	4.98	5.11	5.24	5.37
% change	-4.93%	-2.49%		2.62%	5.14%

Table 1.A12: Livestock commodity output by energy price scenario

	Energy price change (%)				
Commodity	-40	-20	0	20	40
Milk (million cwt)	1,946	1,935	1,925	1,912	1,898
% change	1.06%	0.53%		-0.68%	-1.39%
Pork (million cwt)	425	422	419	417	414
% change	1.41%	0.70%		-0.63%	-1.14%
Beef (million cwt)	404	401	399	395	404
% change	1.22%	0.61%		-0.82%	1.22%
Eggs (million dozen)	11,100	11,033	10,968	10,814	10,531
% change	1.20%	0.59%		-1.41%	-3.98%
Broilers (million lbs)	50,739	50,451	50,167	49,420	50,739
% change	1.14%	0.57%		-1.49%	1.14%
Turkeys (million lbs)	6,142	6,091	6,040	5,896	6,142
% change	1.69%	0.84%		-2.38%	1.69%

Table 1.A13: Livestock commodity prices by energy price scenario

	Energy price change (%)				
Commodity	-40	-20	0	20	40
Milk ($/cwt)	16.78	16.93	17.08	17.27	17.46
% change	-1.73%	-0.86%		1.09%	2.23%
Pork ($/cwt)	13.10	14.19	15.27	16.10	16.70
% change	-14.21%	-7.06%		5.49%	9.36%
Beef ($/cwt)	120.76	122.17	123.56	125.55	127.66
% change	-2.26%	-1.13%		1.61%	3.32%
Eggs ($/dozen)	1.20	1.21	1.22	1.24	1.29
% change	-1.67%	-0.83%		1.96%	5.55%
Broilers ($/lb)	0.42	0.43	0.43	0.45	0.48
% change	-2.87%	-1.43%		3.75%	10.87%
Turkeys ($/lb)	0.68	0.69	0.69	0.72	0.78
% change	-2.79%	-1.38%		3.92%	11.53%

Table 1.A14: Livestock commodity value (millions of dollars) by energy price scenario

	Energy price change (%)				
Commodity	-40	-20	0	20	40
Milk	32,655	32,771	32,882	33,015	33,148
% change	-0.69%	-0.34%		0.40%	0.81%
Pork	5,568	5,990	6,401	6,709	6,920
% change	-13.00%	-6.41%		4.82%	8.11%
Beef	48,734	49,002	49,260	49,639	50,032
% change	-1.07%	-0.52%		0.77%	1.57%
Eggs	13,304	13,338	13,370	13,441	13,550
% change	-0.49%	-0.24%		0.53%	1.35%
Broilers	21,388	21,583	21,772	22,253	23,097
% change	-1.76%	-0.87%		2.20%	6.08%
Turkeys	4,150	4,174	4,198	4,259	4,355
% change	-1.14%	-0.56%		1.45%	3.74%

Table 1.A15: Total (millions of acres) and relative (%) crop production by farm production region and energy price scenario[a]

	Energy price change (%)				
Region	-40	-20	0	20	40
Appalachia	37.51	35.01	32.55	30.41	28.41
% of total	11.85%	11.39%	10.91%	10.51%	10.08%
Corn Belt	132.50	130.91	129.29	128.21	127.37
% of total	41.87%	42.58%	43.35%	44.30%	45.20%
Delta States	25.81	24.98	24.14	23.32	22.56
% of total	8.15%	8.13%	8.09%	8.06%	8.01%
Lake States	38.76	38.57	38.38	38.34	38.28
% of total	12.25%	12.55%	12.87%	13.25%	13.58%
Mountain States	7.74	7.25	6.68	5.72	5.46
% of total	2.45%	2.36%	2.24%	1.98%	1.94%
Northern Plains	29.03	29.98	30.82	31.51	32.14
% of total	9.17%	9.75%	10.33%	10.89%	11.40%
Northeast	21.86	19.79	17.70	15.71	13.84
% of total	6.91%	6.44%	5.94%	5.43%	4.91%
Pacific States	6.23	6.09	5.96	5.88	5.74
% of total	1.97%	1.98%	2.00%	2.03%	2.04%
Southeast	3.97	3.69	3.40	3.12	2.96
% of total	1.26%	1.20%	1.14%	1.08%	1.05%
Southern Plains	13.07	11.15	9.34	7.16	5.04
% of total	4.13%	3.63%	3.13%	2.47%	1.79%
US total	316.50	307.44	298.27	289.38	281.80

[a]Crops include corn, sorghum, barley, oats, wheat, rice, soybeans, cotton, silage, and hay.

Table 1.A16: Total (millions of acres) and relative (%) corn production by farm production region and energy price scenario

	Energy price change (%)				
Region	-40	-20	0	20	40
Appalachia	17.36	15.73	14.09	12.64	11.24
% of total	17.96%	16.95%	15.87%	14.91%	13.75%
Corn Belt	45.70	45.08	44.44	44.01	43.71
% of total	47.27%	48.58%	50.06%	51.94%	53.49%
Delta States	0.48	0.52	0.55	0.58	0.62
% of total	0.50%	0.56%	0.62%	0.69%	0.75%
Lake States	9.61	9.44	9.25	9.08	8.92
% of total	9.94%	10.17%	10.42%	10.72%	10.91%
Mountain States	2.23	1.83	1.34	0.43	0.25
% of total	2.30%	1.97%	1.51%	0.51%	0.30%
Northern Plains	9.03	9.48	9.95	10.33	10.68
% of total	9.34%	10.21%	11.21%	12.19%	13.07%
Northeast	10.85	9.65	8.44	7.27	6.15
% of total	11.23%	10.40%	9.51%	8.58%	7.52%
Pacific States	0.78	0.62	0.45	0.28	0.10
% of total	0.81%	0.67%	0.51%	0.34%	0.12%
Southeast	0.57	0.40	0.22	0.05	0.00
% of total	0.59%	0.43%	0.25%	0.06%	0.00%
Southern Plains	0.07	0.06	0.05	0.05	0.05
% of total	0.07%	0.07%	0.06%	0.06%	0.07%
US total	96.69	92.81	88.79	84.74	81.71

Table 1.A17: Value of crop production (millions of dollars) by farm production region and energy price scenario[a]

	Energy price change (%)				
Region	-40	-20	0	20	40
Appalachia	19,433	18,588	17,713	16,972	16,271
% of total	11.47%	11.02%	10.56%	10.14%	9.73%
Corn Belt	73,741	74,110	74,424	75,071	75,864
% of total	43.53%	43.93%	44.35%	44.86%	45.35%
Delta States	15,320	15,072	14,759	14,412	14,100
% of total	9.04%	8.93%	8.80%	8.61%	8.43%
Lake States	21,371	21,636	21,885	22,232	22,570
% of total	12.62%	12.82%	13.04%	13.29%	13.49%
Mountain States	5,997	5,949	5,866	5,659	5,707
% of total	3.54%	3.53%	3.50%	3.38%	3.41%
Northern Plains	10,698	11,412	12,114	12,787	13,429
% of total	6.31%	6.76%	7.22%	7.64%	8.03%
Northeast	10,257	9,515	8,755	8,019	7,295
% of total	6.05%	5.64%	5.22%	4.79%	4.36%
Pacific States	7,105	7,248	7,431	7,698	7,875
% of total	4.19%	4.30%	4.43%	4.60%	4.71%
Southeast	2,617	2,529	2,432	2,331	2,301
% of total	1.54%	1.50%	1.45%	1.39%	1.38%
Southern Plains	2,865	2,647	2,430	2,148	1,887
% of total	1.69%	1.57%	1.45%	1.28%	1.13%
US total	169,403	168,707	167,809	167,328	167,299
	0.95%	0.54%		-0.29%	-0.30%

[a]Crops include corn, sorghum, barley, oats, wheat, rice, soybeans, cotton, silage, and hay.

Table 1.A18: Total (millions of dollars) and relative (%) value of livestock output by farm production region and energy price scenario[a]

	Energy price change (%)				
Region	-40	-20	0	20	40
Appalachia	13,231	13,337	13,435	13,625	13,892
% of total	10.86%	10.96%	11.05%	11.11%	11.18%
Corn Belt	17,047	16,898	16,739	16,751	16,803
% of total	13.99%	13.88%	13.77%	13.66%	13.52%
Delta States	7,394	7,367	7,338	7,414	7,590
% of total	6.07%	6.05%	6.04%	6.05%	6.11%
Lake States	12,252	12,211	12,166	12,214	12,251
% of total	10.05%	10.03%	10.01%	9.96%	9.86%
Mountain States	10,003	9,941	9,878	9,975	10,122
% of total	8.21%	8.17%	8.13%	8.13%	8.15%
Northern Plains	14,084	14,105	14,123	14,295	14,502
% of total	11.56%	11.59%	11.62%	11.66%	11.67%
Northeast	11,075	11,036	10,995	11,044	11,142
% of total	9.09%	9.07%	9.05%	9.01%	8.97%
Pacific States	11,796	11,860	11,925	12,114	12,353
% of total	9.68%	9.74%	9.81%	9.88%	9.94%
Southeast	9,845	9,828	9,808	9,906	10,129
% of total	8.08%	8.07%	8.07%	8.08%	8.15%
Southern Plains	15,144	15,143	15,137	15,276	15,479
% of total	12.43%	12.44%	12.45%	12.46%	12.46%
US total	121,870	121,725	121,544	122,615	124,263
	0.27%	0.15%		0.88%	2.24%

[a]Livestock output includes milk, beef, pork, eggs, broilers, and turkeys.

Table 1.A19: Crop commodity output by ethanol scenarios

		Ethanol domestic use and export		
	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Barley (million bu)	182	182	183	183
% change		0.01%	0.07%	0.09%
Corn (million bu)	16,237	16,682	20,460	21,293
% change		2.74%	26.01%	31.14%
Cotton (million bales)	20	20	20	20
% change		0.00%	-0.05%	-0.06%
Hay (million tons)	283	283	283	283
% change		-0.01%	-0.10%	-0.12%
Oats (million bu)	52	53	58	59
% change		1.10%	11.07%	13.26%
Rice (million cwt)	211	211	212	212
% change		0.03%	0.27%	0.32%
Silage (million tons)	48	48	48	48
% change		0.21%	-0.10%	-0.34%
Sorghum (million bu)	429	426	398	393
% change		-0.84%	-7.35%	-8.37%
Soybeans (million bu)	4,981	4,988	5,046	5,059
% change		0.14%	1.31%	1.56%
Wheat (million bu)	1,946	1,949	1,972	1,976
% change		0.17%	1.32%	1.54%

Table 1.A20: Crop commodity price by ethanol scenarios

		Ethanol domestic use and export		
	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Barley ($/bu)	4.52	4.52	4.52	4.51
% change		-0.02%	-0.11%	-0.13%
Corn ($/bu)	3.54	3.56	3.72	3.75
% change		0.53%	4.95%	5.89%
Cotton ($/bale)	694.97	695.00	695.35	695.45
% change		0.01%	0.06%	0.07%
Hay ($/ton)	108.07	108.11	108.56	108.66
% change		0.04%	0.45%	0.55%
Oats ($/bu)	1.91	1.89	1.75	1.71
% change		-0.85%	-8.53%	-10.22%
Rice ($/cwt)	13.46	13.46	13.43	13.43
% change		-0.02%	-0.19%	-0.22%
Silage ($/ton)	27.48	27.52	27.84	27.90
% change		0.17%	1.33%	1.56%
Sorghum ($/bu)	3.69	3.71	3.84	3.86
% change		0.46%	4.04%	4.60%
Soybeans ($/bu)	9.83	9.81	9.64	9.61
% change		-0.20%	-1.88%	-2.24%
Wheat ($/bu)	5.11	5.10	5.04	5.03
% change		-0.17%	-1.31%	-1.53%

Table 1.A21: Corn supply and use (millions of bushels) by ethanol scenarios

		Ethanol domestic use and export		
	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Beginning stocks	2847	2847	2847	2847
Production	16,237	16,682	20,460	21,293
% change		2.74%	26.01%	31.14%
Imports	25	25	26	26
Total supply	19,109	19,554	23,333	24,166
% change		2.33%	22.11%	26.47%
Explicit demand[a]	1,762	1,760	1,742	1,738
% change		-0.12%	-1.14%	-1.35%
Feed use	6,086	6,015	4,918	4,638
% change		-1.17%	-19.19%	-23.80%
Processing	6,574	7,124	12,280	13,452
% change		8.37%	86.79%	104.63%
Exports	2,782	2,763	2,603	2,569
% change		-0.69%	-6.45%	-7.68%
Ending stocks	2,882	2,869	2,768	2,746
% change		-0.42%	-3.95%	-4.69%
Total use	19,109	19,554	23,333	24,166
% change		2.33%	22.11%	26.47%

[a]Domestic use excluding processing for ethanol and feed use.

Table 1.A22: Livestock commodity output by ethanol scenarios

		Ethanol domestic use and export		
Commodity	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Milk (million cwt)	1,925	1,925	1,922	1,921
% change		-0.02%	-0.19%	-0.22%
Pork (million cwt)	419	420	421	421
% change		0.25%	0.52%	0.44%
Beef (million cwt)	399	399	398	398
% change		0.04%	-0.05%	-0.10%
Eggs (million dozen)	10,968	10,983	10,963	10,947
% change		0.14%	-0.05%	-0.19%
Broilers (million lbs)	50,167	50,263	50,305	50,254
% change		0.19%	0.28%	0.17%
Turkeys (million lbs)	6,040	6,059	6,068	6,058
% change		0.32%	0.46%	0.29%

Table 1.A23: Livestock commodity prices by ethanol scenarios

Commodity	baseline	Ethanol domestic use and export exp*2	dom*2 & exp*2	dom*2 & exp*4
Milk ($/cwt)	17.08	17.08	17.13	17.14
% change		0.03%	0.28%	0.34%
Pork ($/cwt)	15.27	14.71	14.10	14.28
% change		-3.62%	-7.67%	-6.47%
Beef ($/cwt)	123.56	123.45	123.70	123.85
% change		-0.09%	0.12%	0.23%
Eggs ($/dozen)	1.22	1.22	1.22	1.22
% change		-0.19%	0.06%	0.26%
Broilers ($/lb)	0.43	0.43	0.43	0.43
% change		-0.48%	-0.69%	-0.44%
Turkeys ($/lb)	0.69	0.69	0.69	0.69
% change		-0.53%	-0.76%	-0.48%

Table 1.A24: Total (millions of acres) and relative (%) crop production by farm production region and ethanol scenario[a]

		Ethanol domestic use and export		
Region	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Appalachia	32.55	33.08	37.62	38.61
% of total	10.91%	10.99%	11.65%	11.78%
Corn Belt	129.29	130.39	140.32	142.52
% of total	43.35%	43.32%	43.44%	43.47%
Delta States	24.14	24.10	23.77	23.69
% of total	8.09%	8.01%	7.36%	7.23%
Lake States	38.38	38.53	39.86	40.13
% of total	12.87%	12.80%	12.34%	12.24%
Mountain States	6.68	6.87	7.93	8.16
% of total	2.24%	2.28%	2.46%	2.49%
Northern Plains	30.82	31.25	33.95	34.54
% of total	10.33%	10.38%	10.51%	10.54%
Northeast	17.70	18.11	21.48	22.21
% of total	5.94%	6.02%	6.65%	6.78%
Pacific States	5.96	6.06	6.84	7.00
% of total	2.00%	2.01%	2.12%	2.14%
Southeast	3.40	3.43	3.66	3.71
% of total	1.14%	1.14%	1.13%	1.13%
Southern Plains	9.34	9.15	7.59	7.27
% of total	3.13%	3.04%	2.35%	2.22%
US total	298.27	300.97	323.03	327.86

[a]Crops include corn, sorghum, barley, oats, wheat, rice, soybeans, cotton, silage, and hay.

Table 1.A25: Total (millions of acres) and relative (%) corn production by farm production region and ethanol scenario

	Ethanol domestic use and export			
Region	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Appalachia	14.09	14.53	18.28	19.08
% of total	15.87%	15.91%	16.29%	16.35%
Corn Belt	44.44	45.34	53.34	55.10
% of total	50.06%	49.63%	47.54%	47.21%
Delta States	0.55	0.57	0.80	0.85
% of total	0.62%	0.63%	0.71%	0.73%
Lake States	9.25	9.36	10.34	10.54
% of total	10.42%	10.25%	9.21%	9.03%
Mountain States	1.34	1.55	2.74	2.99
% of total	1.51%	1.70%	2.44%	2.56%
Northern Plains	9.95	10.36	13.24	13.86
% of total	11.21%	11.34%	11.80%	11.87%
Northeast	8.44	8.77	11.51	12.11
% of total	9.51%	9.60%	10.26%	10.38%
Pacific States	0.45	0.54	1.28	1.44
% of total	0.51%	0.59%	1.14%	1.23%
Southeast	0.22	0.26	0.59	0.65
% of total	0.25%	0.28%	0.52%	0.56%
Southern Plains	0.05	0.06	0.09	0.10
% of total	0.06%	0.06%	0.08%	0.09%
US total	88.79	91.35	112.21	116.72

Table 1.A26: Value of crop production (millions of dollars) by farm production region and ethanol scenario[a]

		Ethanol domestic use and export		
Region	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Appalachia	17,713	18,003	20,612	21,205
% of total	10.56%	10.61%	11.07%	11.17%
Corn Belt	74,424	75,241	82,919	84,694
% of total	44.35%	44.34%	44.55%	44.60%
Delta States	14,759	14,749	14,688	14,675
% of total	8.80%	8.69%	7.89%	7.73%
Lake States	21,885	22,030	23,297	23,564
% of total	13.04%	12.98%	12.52%	12.41%
Mountain States	5,866	5,947	6,466	6,584
% of total	3.50%	3.50%	3.47%	3.47%
Northern Plains	12,114	12,371	14,253	14,680
% of total	7.22%	7.29%	7.66%	7.73%
Northeast	8,755	8,976	10,903	11,344
% of total	5.22%	5.29%	5.86%	5.97%
Pacific States	7,431	7,510	8,200	8,354
% of total	4.43%	4.43%	4.41%	4.40%
Southeast	2,432	2,451	2,621	2,660
% of total	1.45%	1.44%	1.41%	1.40%
Southern Plains	2,430	2,402	2,181	2,138
% of total	1.45%	1.42%	1.17%	1.13%
US total	167,809	169,679	186,141	189,899
% change		1.11%	10.92%	13.16%

[a]Crops include corn, sorghum, barley, oats, wheat, rice, soybeans, cotton, silage, and hay.

Table 1.A27: Total (millions of dollars) and relative (%) value of livestock output by farm production region and ethanol scenario[a]

		Ethanol domestic use and export		
Region	baseline	exp*2	dom*2 & exp*2	dom*2 & exp*4
Appalachia	13,435	13,330	13,216	13,253
% of total	11.05%	11.00%	10.92%	10.94%
Corn Belt	16,739	16,682	16,607	16,614
% of total	13.77%	13.76%	13.73%	13.72%
Delta States	7,338	7,319	7,290	7,295
% of total	6.04%	6.04%	6.03%	6.02%
Lake States	12,166	12,150	12,150	12,161
% of total	10.01%	10.02%	10.04%	10.04%
Mountain States	9,878	9,863	9,855	9,863
% of total	8.13%	8.14%	8.15%	8.14%
Northern Plains	14,123	14,080	14,065	14,090
% of total	11.62%	11.62%	11.63%	11.63%
Northeast	10,995	10,982	10,965	10,969
% of total	9.05%	9.06%	9.06%	9.06%
Pacific States	11,925	11,924	11,984	12,003
% of total	9.81%	9.84%	9.91%	9.91%
Southeast	9,808	9,783	9,740	9,743
% of total	8.07%	8.07%	8.05%	8.04%
Southern Plains	15,137	15,103	15,098	15,120
% of total	12.45%	12.46%	12.48%	12.48%
US total	121,544	121,214	120,969	121,112

[a]Livestock output includes milk, beef, pork, eggs, broilers, and turkeys.

Table 1.A28: Sensitivity of energy passing-through rate under energy price decreases 40% scenario

Crop	baseline*0.8	baseline[a]	baseline*1.2
Barley (million bu)	187	188	189
% change[b]	2.23%	2.8%	3.33%
Corn (million bu)	17,506	17,633	17,760
% change	7.82%	8.6%	9.38%
Cotton (million bales)	21	21	21
% change	2.26%	2.8%	3.39%
Hay (million tons)	290	291	293
% change	2.22%	2.8%	3.34%
Oats (million bu)	56	57	57
% change	7.52%	8.9%	10.21%
Rice (million cwt)	233	238	244
% change	10.34%	12.9%	15.51%
Silage (million tons)	51	51	52
% change	5.44%	6.7%	8.00%
Sorghum (million bu)	462	472	482
% change	7.64%	9.9%	12.20%
Soybeans (million bu)	5,059	5,075	5,091
% change	1.58%	1.9%	2.22%
Wheat (million bu)	2,025	2,043	2,060
% change	4.07%	5.0%	5.88%

[a]baseline of energy passing-through rate is in Table 1.A7.

[b]% change relative to constant energy price baseline scenario (see Table 1.A10 Column 3).

Table 1.A29: Sensitivity of energy passing-through rate under energy price increases 40% scenario

Crop	baseline*0.8	baseline[a]	baseline*1.2
Barley (million bu)	178	177	176
% change[b]	-2.24%	-2.8%	-3.33%
Corn (million bu)	15,224	15,117	15,011
% change	-6.24%	-6.9%	-7.55%
Cotton (million bales)	20	20	20
% change	-2.27%	-2.8%	-3.43%
Hay (million tons)	281	281	280
% change	-0.76%	-0.9%	-1.03%
Oats (million bu)	48	48	47
% change	-6.77%	-8.4%	-10.00%
Rice (million cwt)	190	187	185
% change	-10.13%	-11.5%	-12.44%
Silage (million tons)	47	46	46
% change	-2.81%	-3.4%	-4.04%
Sorghum (million bu)	394	385	376
% change	-8.24%	-10.3%	-12.43%
Soybeans (million bu)	4,904	4,885	4,866
% change	-1.54%	-1.9%	-2.30%
Wheat (million bu)	1,864	1,845	1,826
% change	-4.21%	-5.2%	-6.16%

[a]baseline of energy passing-through rate is in Table 1.A7.

[b]% change relative to constant energy price baseline scenario (see Table 1.A10 Column 3).

Table 2.A1: Crop commodity output by yield reserve scenario

	Yield reserve (%)			
	0	1.0	1.5	2.0
Barley (million bu)	165	165	164	164
% change		-0.26%	-0.39%	-0.52%
Corn (million bu)	18,372	18,915	19,193	19,476
% change		2.96%	4.47%	6.01%
Cotton (million bales)	21	21	21	21
% change		-0.01%	-0.02%	-0.03%
Hay (million tons)	299	299	299	299
% change		-0.02%	-0.04%	-0.05%
Oats (million bu)	20	20	20	20
% change		-0.67%	-1.08%	-1.53%
Rice (million cwt)	229	228	228	228
% change		-0.13%	-0.20%	-0.27%
Silage (million tons)	103	103	103	103
% change		-0.01%	-0.01%	-0.01%
Sorghum (million bu)	442	443	444	446
% change		0.37%	0.63%	0.92%
Soybeans (million bu)	5,337	5,370	5,386	5,401
% change		0.61%	0.91%	1.20%
Wheat (million bu)	2,153	2,150	2,148	2,147
% change		-0.14%	-0.20%	-0.27%

Table 2.A2: Crop commodity price by yield reserve scenario

	Yield reserve (%)			
	0	1.0	1.5	2.0
Barley ($/bu)	4.70	4.72	4.72	4.73
% change		0.33%	0.49%	0.66%
Corn ($/bu)	3.33	3.13	3.02	2.92
% change		-6.15%	-9.31%	-12.50%
Cotton ($/bale)	643.29	643.41	643.48	643.55
% change		0.02%	0.03%	0.04%
Hay ($/ton)	117.32	117.37	117.40	117.44
% change		0.04%	0.07%	0.10%
Oats ($/bu)	3.26	3.26	3.26	3.27
% change		0.10%	0.16%	0.23%
Rice ($/cwt)	13.02	13.04	13.04	13.05
% change		0.10%	0.16%	0.21%
Silage ($/ton)	28.28	28.28	28.28	28.28
% change		0.01%	0.02%	0.03%
Sorghum ($/bu)	3.53	3.52	3.52	3.51
% change		-0.22%	-0.37%	-0.53%
Soybeans ($/bu)	10.15	10.08	10.04	10.00
% change		-0.74%	-1.09%	-1.45%
Wheat ($/bu)	4.78	4.78	4.79	4.79
% change		0.16%	0.24%	0.31%

Table 2.A3: Total (million acres) and relative (%) crop production by farm production region and yield reserve scenario

	Yield reserve (%)			
Region	0	1.0	1.5	2.0
Appalachia	18.47	17.78	17.43	17.08
% of total	5.68%	5.40%	5.26%	5.12%
Corn Belt	80.98	82.66	83.47	84.28
% of total	24.92%	25.11%	25.18%	25.23%
Delta States	14.19	14.01	13.92	13.84
% of total	4.37%	4.25%	4.20%	4.14%
Lake States	30.88	31.66	32.03	32.39
% of total	9.50%	9.62%	9.66%	9.70%
Mountain States	37.26	37.57	37.73	37.88
% of total	11.47%	11.41%	11.38%	11.34%
Northeast	78.97	81.06	82.33	83.73
% of total	24.30%	24.62%	24.83%	25.07%
Northern Plains	7.34	7.46	7.52	7.58
% of total	2.26%	2.27%	2.27%	2.27%
Pacific States	4.39	4.35	4.33	4.31
% of total	1.35%	1.32%	1.31%	1.29%
Southeast	27.78	27.78	27.76	27.73
% of total	8.55%	8.44%	8.37%	8.30%
Southern Plains	24.71	24.93	25.05	25.17
% of total	7.60%	7.57%	7.55%	7.54%
US total	324.97	329.25	331.57	333.99

Table 2.A4: Total (million acres) and relative (%) corn production by farm production region and yield reserve scenario

	Yield reserve (%)			
Region	0	1.0	1.5	2.0
Appalachia	5.60	5.11	4.85	4.60
% of total	5.65%	4.93%	4.58%	4.24%
Corn Belt	33.44	34.39	34.84	35.28
% of total	33.70%	33.20%	32.88%	32.54%
Delta States	0.61	0.57	0.56	0.55
% of total	0.61%	0.55%	0.52%	0.51%
Lake States	11.82	12.28	12.50	12.71
% of total	11.91%	11.85%	11.79%	11.72%
Mountain States	2.50	2.52	2.52	2.52
% of total	2.52%	2.43%	2.38%	2.33%
Northeast	3.71	3.84	3.90	3.97
% of total	3.74%	3.71%	3.68%	3.66%
Northern Plains	35.22	38.64	40.60	42.65
% of total	35.50%	37.30%	38.31%	39.33%
Pacific States	1.22	1.32	1.38	1.43
% of total	1.23%	1.28%	1.30%	1.32%
Southeast	0.22	0.23	0.24	0.24
% of total	0.22%	0.22%	0.22%	0.22%
Southern Plains	4.88	4.69	4.59	4.48
% of total	4.92%	4.53%	4.33%	4.14%
US total	99.24	103.59	105.96	108.43

Table 2.A5: Crop commodity output by CRP expansion scenario

	CRP expansion			
	0	25%	37%	50%
Barley (million bu)	165	163	163	162
% change		-0.98%	-1.48%	-2.04%
Corn (million bu)	18,372	18,313	18,283	18,248
% change		-0.32%	-0.48%	-0.68%
Cotton (million bales)	21	21	21	21
% change		-0.14%	-0.21%	-0.30%
Hay (million tons)	299	297	296	295
% change		-0.59%	-0.91%	-1.30%
Oats (million bu)	20	21	21	21
% change		0.40%	0.58%	0.72%
Rice (million cwt)	229	228	227	227
% change		-0.40%	-0.61%	-0.85%
Silage (million tons)	103	103	103	103
% change		-0.06%	-0.10%	-0.16%
Sorghum (million bu)	442	436	433	430
% change		-1.18%	-1.85%	-2.66%
Soybeans (million bu)	5,337	5,329	5,324	5,318
% change		-0.15%	-0.24%	-0.35%
Wheat (million bu)	2,153	2,132	2,120	2,107
% change		-0.98%	-1.50%	-2.11%

Table 2.A6: Crop commodity price by CRP expansion scenario

	CRP expansion			
	0	25%	37%	50%
Barley ($/bu)	4.70	4.76	4.79	4.82
% change		1.24%	1.86%	2.57%
Corn ($/bu)	3.33	3.36	3.37	3.38
% change		0.66%	1.01%	1.40%
Cotton ($/bale)	643.29	644.49	645.14	645.90
% change		0.19%	0.29%	0.41%
Hay ($/ton)	117.32	118.64	119.38	120.24
% change		1.13%	1.75%	2.49%
Oats ($/bu)	3.26	3.26	3.26	3.25
% change		-0.06%	-0.09%	-0.11%
Rice ($/cwt)	13.02	13.06	13.08	13.11
% change		0.31%	0.48%	0.66%
Silage ($/ton)	28.28	28.31	28.34	28.37
% change		0.13%	0.22%	0.34%
Sorghum ($/bu)	3.53	3.55	3.57	3.58
% change		0.68%	1.08%	1.55%
Soybeans ($/bu)	10.15	10.17	10.18	10.19
% change		0.18%	0.29%	0.42%
Wheat ($/bu)	4.78	4.83	4.86	4.89
% change		1.14%	1.75%	2.47%

Table 2.A7: Total crop acreage (million acres) by farm production region and CRP expansion scenario

	CRP expansion			
Region	0	25%	37%	50%
Appalachia	18.47	17.99	17.77	17.53
% change		-2.60%	-3.80%	-5.05%
Corn Belt	80.98	81.38	81.51	81.60
% change		0.49%	0.66%	0.77%
Delta States	14.19	13.86	13.69	13.51
% change		-2.37%	-3.53%	-4.80%
Lake States	30.88	31.53	31.85	32.21
% change		2.12%	3.16%	4.32%
Mountain States	37.26	38.19	38.64	39.12
% change		2.48%	3.69%	4.98%
Northeast	7.34	7.41	7.44	7.47
% change		0.84%	1.26%	1.73%
Northern Plains	78.97	77.67	77.02	76.31
% change		-1.65%	-2.48%	-3.38%
Pacific States	24.71	23.39	22.74	22.04
% change		-5.35%	-7.95%	-10.81%
Southeast	4.39	4.29	4.24	4.20
% change		-2.31%	-3.30%	-4.31%
Southern Plains	27.78	27.89	27.88	27.83
% change		0.39%	0.37%	0.19%
US total	324.97	323.58	322.78	321.83

Table 2.A8: Crop acreage (million acres) by CRP expansion scenario

	CRP expansion			
	0	25%	37%	50%
Barley	1.46	1.44	1.44	1.43
% change		-0.87%	-1.25%	-1.64%
Corn	99.24	98.55	98.21	97.84
% change		-0.70%	-1.03%	-1.41%
Cotton	11.62	11.61	11.60	11.59
% change		-0.10%	-0.15%	-0.22%
Hay	63.95	64.12	64.13	64.10
% change		0.26%	0.27%	0.23%
Oats	0.43	0.44	0.44	0.44
% change		0.87%	1.29%	1.72%
Rice	2.88	2.87	2.86	2.85
% change		-0.52%	-0.79%	-1.08%
Silage	6.45	6.50	6.53	6.56
% change		0.84%	1.24%	1.69%
Sorghum	5.48	5.40	5.36	5.31
% change		-1.34%	-2.10%	-3.01%
Soybeans	96.52	96.17	96.00	95.80
% change		-0.35%	-0.54%	-0.74%
Wheat	36.96	36.48	36.22	35.91
% change		-1.28%	-1.99%	-2.84%

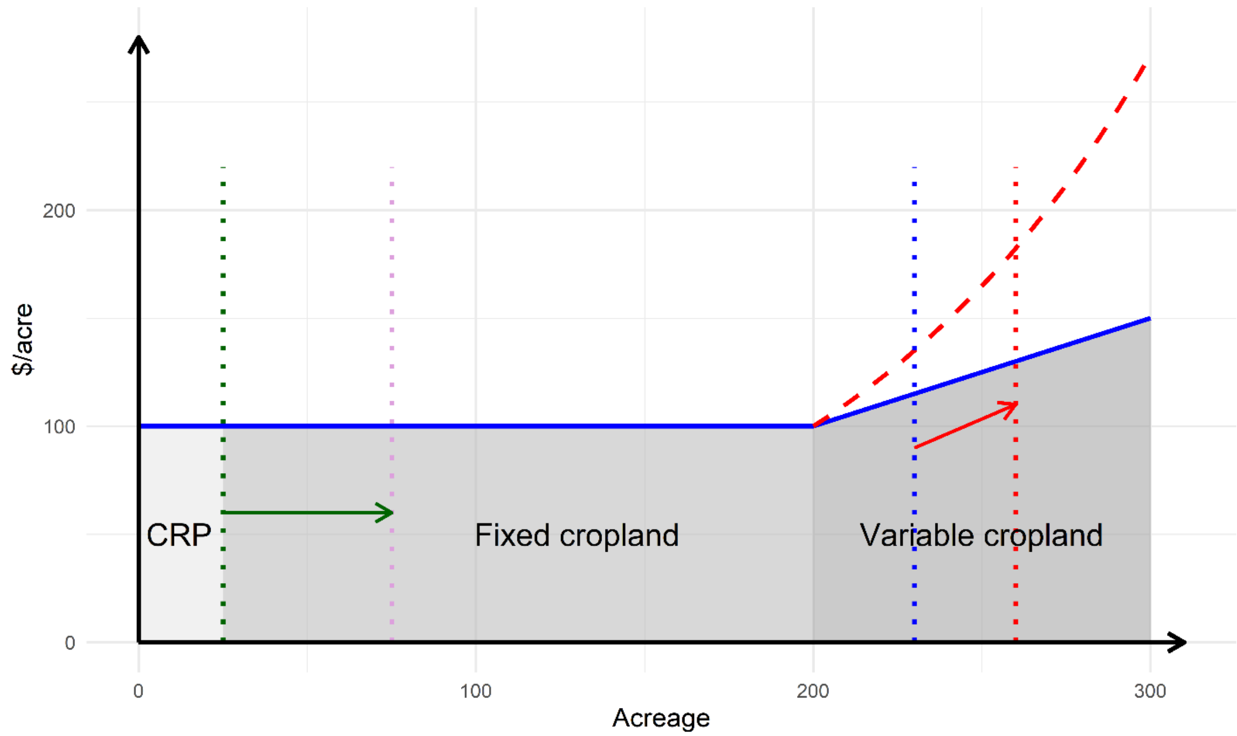


Figure 2.A1. Land Supply in REAP and demonstration of slippage effect

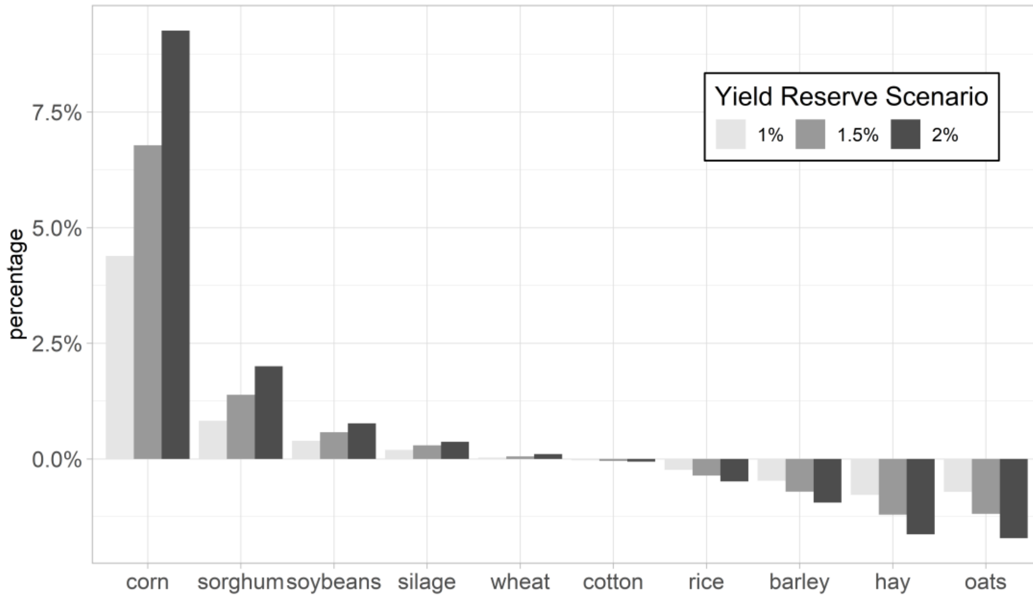


Figure 2.A2. Crop acreage change by Yield Reserve scenarios

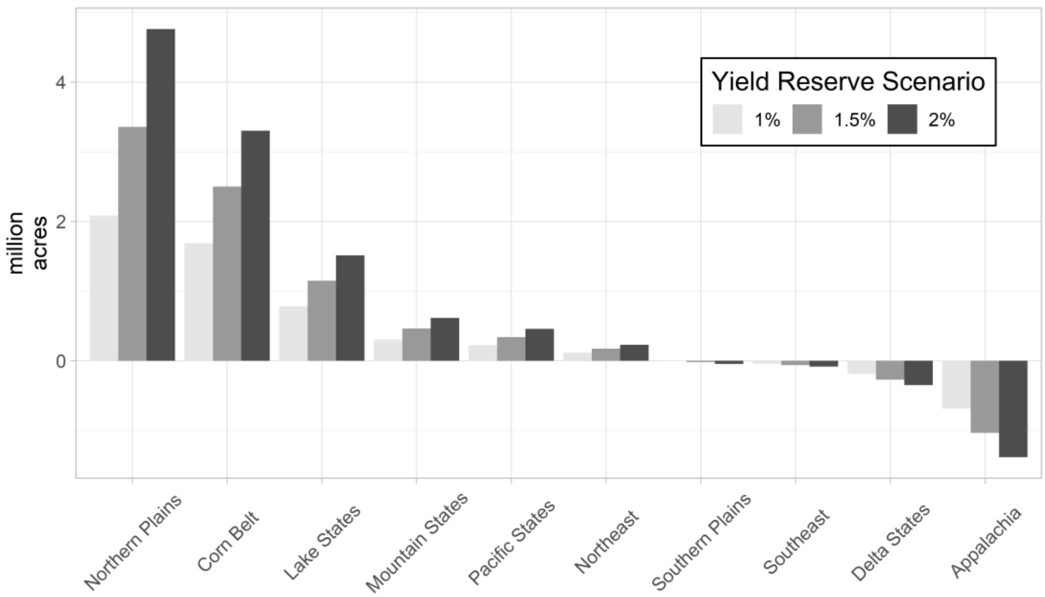


Figure 2.A3. Crop acreage change at farm production region level by Yield Reserve scenarios

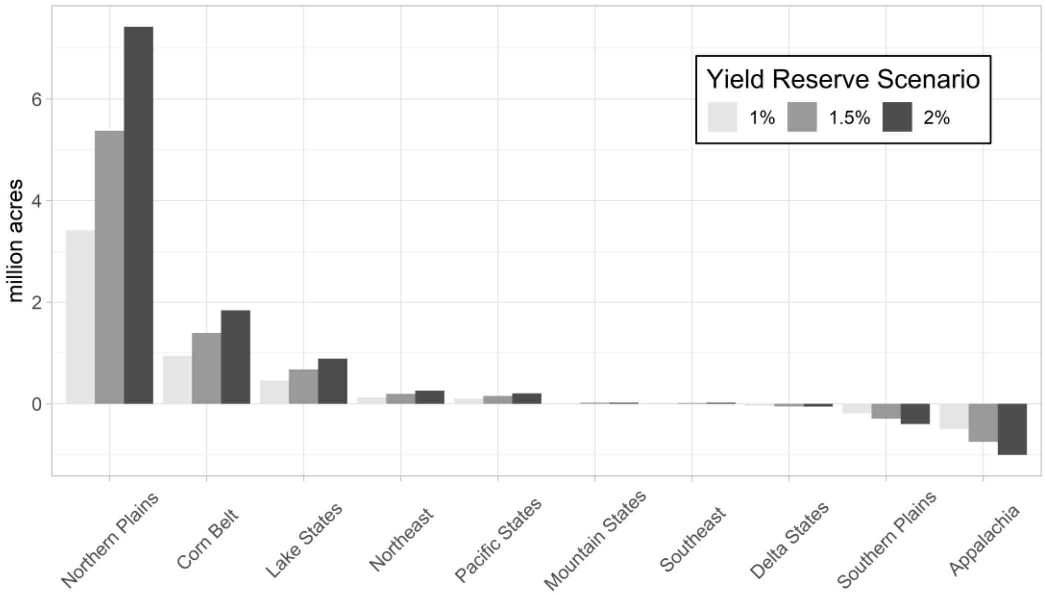


Figure 2.A4. Corn acreage change at farm production region level by Yield Reserve scenarios

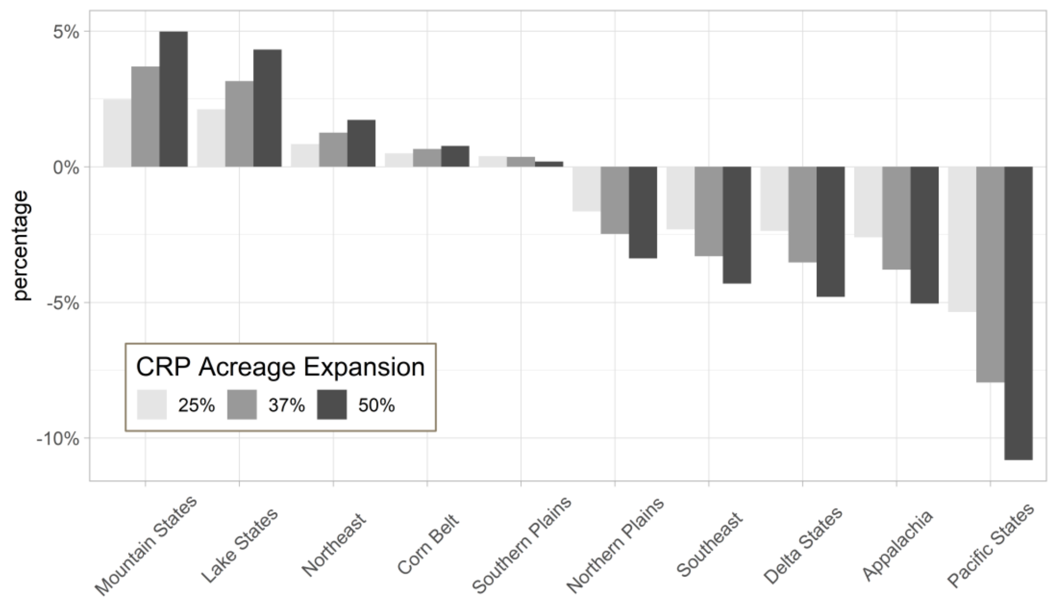


Figure 2.A5. Crop acreage change at farm production region level by CRP scenarios

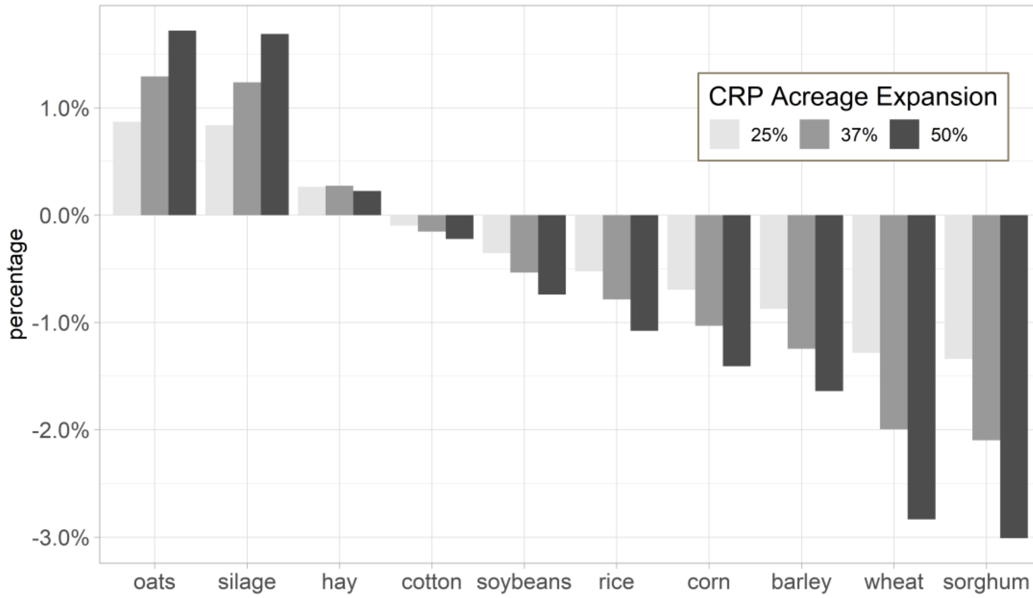


Figure 2.A6. Crop acreage change by CRP scenarios

Supporting Information Text

3.SI More Details for Data & Methods. We provide additional details of the data cleaning process and methods in this section.

3.SI.1 Purging Non-arms' length transactions.

The non-arm's length transactions are identified via the following process and dropped from the analysis. CoreLogic's owner transfer data provides a range of indicators for transactions that may not reflect fair market values, and quoted phrases below are variable names in the CoreLogic dataset.

1. Transactions are dropped if they are not identified as non-arm's length by CoreLogic's direct indicator (i.e., "PRIMARYCATEGORYCODE" is not A);

2. Transactions are dropped if they are not identified as deeds (i.e., could be quit claims, foreclosures, open-end mortgages, or others, where DEEDCATEGORYTYPECODE is not G);

3. Transactions that cannot be matched with tax rolls are dropped (i.e., "PENDINGRECORDINDICATOR" is positive);

4. When "SALETYPECODE" clearly suggests that the price is not the full price (i.e., SALETYPECODE is something other than F);

5. Transactions with positive status in "SHORTSALEINDICATOR" "FORECLOSUREREOINDICATOR", "FORECLOSUREREOSALEINDICATOR", "NEWCONSTRUCTIONINDICATOR", "INVESTORPURCHASEINDICATOR", or "INTERFAMILYRELATEDINDICATOR" are dropped;

6. After all the previous steps and a deflation process, transactions with extremely low prices (i.e., less than $1000) are dropped. To diminish the influence from outliers, we then drop transactions with prices in the two extreme percentiles (i.e., price less than the 1st percentile and price larger than the 99th percentile).

3.SI.2 Visibility Analysis Details.

In the visibility analysis, we use the perimeter points as the viewpoints, calculate the view from each of them, and overlay their viewsheds with the property map. We take the number of perimeter points that are visible from a property as the visibility index of it (Figure 3.A7, Figure 3.A8). Based on this visibility index, we generate a <u>binary visibility variable</u>, with 1 indicating at least one perimeter point is visible. The binary visibility variable is used in the main analysis. Also, for heterogeneity analysis to show whether the extent of solar view matters (Figure 3.3), we generate a <u>categorical visibility variable</u> further differentiating high and low view (based on sample median visibility index).

This approach relies on a key assumption: there are no obstructions within the solar site that block the view. In other words, the solar site is assumed to be flat: if a person can see the nearest edge, they can see the panels; if the central part of the site is visible, the farthest edges are also visible. A flat surface is a technical requirement to build a utility-scale solar site, and the solar panels are generally low and have the same heights. Therefore, we believe this assumption holds in reality.

The continuous visibility index (i.e., the number of perimeter points) itself may not precisely represent the proportion of visible area in one case, as shown in Figure 3.A9. The viewshed of a property could “start” from the middle of a site and extend to the farther edges, as shown in subfigure (B) – but it doesn't cover the closer edge. In this situation, the viewshed may cover about the same proportion of area as in subfigure (A) but will incorporate fewer perimeter points (and hence a low visibility index). The situation in subfigure (B) exists only when the view obstruction exactly blocks the closer edge while not blocking the farther edge, which is rarely the case when the property is moderately far away from the site. Thus, we believe that, in general, the continuous visibility index can approximately reflect how much view a property has on a solar site. This caveat is less concerning for the variables in the analysis (the binary visibility variable or the categorical visibility variable), as the aggregation will mute much of the inaccuracy in exact visibility index numbers. Therefore, we believe the binary and categorical visibility measures used in the analysis do not carry major errors from using the perimeter points.

Since LiDAR data is not available for the majority of solar sites, we have to use surface elevation in the viewshed analysis instead of structural elevation. This approach might overestimate the visibility, and our binary or categorical visibility variables may overestimate the actual visibility of the solar sites (and hence underestimate the visibility effect). As utility-scale solar sites are typically very large and located in rural settings, the major concern here are vegetations (i.e., scattered buildings are unlikely to block the whole site). The obstruction from vegetations is much less effective in the winter, so the visibility calculated from the terrain elevation can be considered as a good approximation (i.e., a slight overrepresentation) of the winter view.

3.SI.3 Robustness Check on the Five-acre Segregation Criterion. To make sure the main conclusions are not specific to the five-acre segregation threshold defining properties with small lots and large lots, we conduct robustness checks. The five-acre threshold is used in the main analysis because a standard utility scale solar site requires at least 5 acres of land, and therefore it is much easier for homes with above-five-acre land to obtain potential future solar lease. To avoid conflict with this widely used standard, we set alternative selection criteria for small lots and large lots separately (i.e., 4, 3, 2, 1, 0.5, 0.3 acres for small lots, and 6, 7, 8, 9, 10 acres for large lots).

The results are presented in Table 3.A5, which suggests that our main estimates hold across a wide range of alternative acreage thresholds around 5 acres. When the land acreage threshold rises to 10 acres, the LSSPV effect on land price becomes insignificant, suggesting heterogeneity starts to dominate the estimation (as suggested by the "Big Lot" versus "Small Lot" comparison in Figure 3.6). For very big lots, the solar lease potential may have lower impact since the outcome is the average land price per acre and the potential solar lease may not apply to the entire lot. In conclusion, these robustness check results suggest that our main estimates are robust to alternative sample inclusion criteria, unless it deviates so much from 5 acres that the effect heterogeneity across acreage becomes dominant.

3.SI.4 Robustness Check: Excluding Clusters with Few Transactions.

In the analysis, some clusters (e.g., defined by the census tract by year fixed effects for residential analysis) contain a few transactions, as shown in Figure 3.A6. Singelton observations, where the underlying subgroups (defined by the fixed effects) only have one observation, are dropped automatically in our regressions. Throughout our estimates, we report the number of observations (N) excluding singletons. However, when an underlying subgroup contains only a few transactions, it also may not contribute good enough information (i.e., treated and control pairs) to the analysis. Therefore, to evaluate whether these sparsely populated clusters are the main drivers of our findings, we conduct robustness checks excluding clusters with fewer than M sales per year, where M changes from 5 to 20. The results are presented in Table 3.A6, suggesting that the main estimates for the residential analysis are robust against the exclusion with tract-year clusters containing low numbers of sales.

However, the robustness check for agricultural or vacant land reveal an important heterogeneity: if we focus on county-site-year clusters containing more than five sales, the land price effect of LSSPV rises dramatically, from 57.1% (corresponding to a coefficient of 0.452 for excluding less-than-5-sales clusters) to 86.1% (corresponding to a coefficient of 0.621 for excluding less-than-20-sales clusters). Given that we have excluded sales of land hosting LSSPV sites, the mechanism behind this substantial effect on land prices remains unclear but warrants further investigation.

3.SI.5 Evidence-based Community Compensation Plan

We provide a detailed concept map of a prototype evidence-based community compensation plan for a proposed LSSPV site in Figure 3.A10. The full process is clarified, including the potential initial input data, the study sample selection process, the studies needed, the study outcomes, the possible compensation scheme, the potential compensation principles, and the stakeholder feedback process.

Study like ours covers the property value impact of LSSPV, and similar studies with alternative outcomes related to the land or residential rent impacts of LSSPV. If certain impact channels do not manifest in property or rent values, more research is needed to determine the value of these impacts, which may include investigating environmental changes in ecosystem services and applying stated preference studies (or benefit transfer studies) to estimate the corresponding changes in dollar value.

We clarify the preferred recipients of the compensation and the principle of no-double-dipping. Compensation for a negative environmental change should be provided for the entity that directly bears the impact, i.e., the reduction in ecosystem services. Therefore, in the case of residential property owners and renters, renters should be compensated if the property is typically leased (obviously, the owner is to be compensated if she is the resident). In the case of landowners and tenant farmers, tenant farmers directly bear the change in land rent (presumably change in the same direction and rate as land prices) and should be compensated. If the agricultural operator is the owner, she might not be compensated if no net loss is found for her. For the large-lot home (home with above 5 acres of land), the situation is more complicated. If the whole property is owner occupied and operated, the owner might be compensated when a net loss is found, and should not be compensated otherwise (i.e., she always simultaneously enjoys the land value increase and bears the residential value loss). If either the land or the home is leased, the renters or tenant farm should be compensated similarly to the previous cases, while the property owner (as the resident or operator) might be compensated when a net loss in total property value is found. If both the land and the home are leased, the property owner is irrelevant for a compensation plan.

3.SI.6 Back-of-the-envelope Calculation of Benefits and Costs of LSSPV Sites

We performed a back-of-the-envelope calculation to estimate the benefits and costs of all solar sites included in our analysis. The benefits considered include: the mitigation value (i.e., avoided social cost of carbon emission) and the appreciation of nearby agricultural or vacant land value. The costs considered include: the value loss of nearby residential properties and the loss of agricultural production on land utilized for hosting LSSPV. These calculations are intended to serve as an approximation of the total value of specific benefits or costs associated with LSSPV development, providing an intuitive comparison between the magnitude of property value loss and the scale of other benefits and costs. We do not claim that this calculation represents a comprehensive benefit-cost analysis of LSSPV.

The results are presented in Table 3.A8. The total value of the assessed benefits of existing LSSPV significantly outweighs the total costs. The benefits considered in Table 3.A8 amount to $22,163 million, with the mitigation value accounting for the vast majority at $22,156 million. The total costs add up to $4,152 million, with the loss in residential home value dominating at $4,106 million. Therefore, the carbon mitigation benefit is the major benefit of LSSPV, while the loss in residential home value represents the most significant community cost at this stage.

Table 3.A1: Summary Statistics of LSSPV Projects

	Mean	S.D.
Project Area (Acres)	85.755	246.671
Capacity (MWac)	14.911	37.355
Battery Storage (Yes/No)	0.028	0.164
Greenfield (Yes/No)	0.952	0.213
Visibility: Site Visible from # Properties (Count)	858.360	2171.250
Tracking System (Yes/No)	0.466	0.499
Year of Installation	2016.836	2.997
Observations	3699	

Table 3.A2: Summary Statistics of Residential Homes

	Mean	S.D.
Sales Price (2017 USD)	327443.690	241624.926
Lot Size (Acres)	0.383	0.566
Distance to Nearest LSSPV (Miles)	3.374	1.494
Distance to Nearest Power Line (Miles)	0.941	0.965
Distance to Nearest Road (Miles)	2.572	4.093
Distance to Nearest Metro Area (Miles)	0.302	1.792
Solar Site Visible (Binary)	0.214	0.410
Total Number of Bedrooms	2.732	1.140
Total Number of Bathrooms	1.919	0.957
Building Age (Years)	40.365	28.201
Observations	8318704	

Note: The summary statistics are generated from the sample that is ready for analysis, on which the distance (i.e., less than 6 miles from the nearest site) and time filters (i.e., not in the Great Recession period) have already been applied.

Table 3.A3: Summary Statistics of Agricultural and Vacant Land

	Mean	S.D.
Sales Price per Acre (USD)	13945.193	19246.926
Lot Size (Acres)	29.630	45.154
Distance to Nearest LSSPV (Miles)	10.472	5.208
Distance to Nearest Power Line (Miles)	2.022	2.075
Distance to Nearest Road (Miles)	10.205	9.751
Distance to Nearest Metro Area (Miles)	5.980	5.736
Observations	67920	

Note: The summary statistics are generated from the sample that is ready for analysis, on which the distance (i.e., less than 20 miles from the nearest site) and time filters (i.e., not in the Great Recession period) have already been applied.

Table 3.A4: Summary Statistics of Large-lot Homes

	Mean	S.D.
Sales Price (USD)	315805.302	243368.571
Lot Size (Acres)	25.529	1145.660
Distance to Nearest LSSPV (Miles)	12.170	7.458
Distance to Nearest Power Line (Miles)	1.592	1.777
Distance to Nearest Road (Miles)	5.944	7.190
Distance to Nearest Metro Area (Miles)	3.030	4.472
Total Number of Bedrooms	2.937	0.918
Total Number of Bathrooms	2.184	0.899
Building Age (Years)	33.862	49.443
Observations	416167	

Note: The summary statistics are generated from the sample that is ready for analysis, on which the distance (i.e., less than 20 miles from the nearest site) and time filters (i.e., not in the Great Recession period) have already been applied.

Table 3.A5: Robustness Check on the Five-acre Criterion

Panel A: Residential Analysis (< 5 Acres) [a]	(1) Main	(2) R1	(3) R2	(4) R3	(5) R4	(6) R5
Alt. Inclusion Criteria	< 5 Acres	<= 4 Acres	<= 2 Acres	<= 1 Acres	<= 0.5 Acres	<= 0.3 Acres
β_3: ProxT × Post	-0.0476*	-0.0482*	-0.0487*	-0.0504*	-0.0612*	-0.0733+
	(0.0199)	(0.0201)	(0.0215)	(0.0236)	(0.0284)	(0.0360)
$\beta_3^{no\_view}$: ProxT × 0.ViewT × Post	-0.0459*	-0.0465*	-0.0472*	-0.0493*	-0.0610*	-0.0736+
	(0.0200)	(0.0202)	(0.0216)	(0.0236)	(0.0285)	(0.0361)
β_3^{view}: ProxT × 1.ViewT × Post	-0.0524*	-0.0527*	-0.0529*	-0.0532*	-0.0618*	-0.0726+
	(0.0199)	(0.0201)	(0.0214)	(0.0235)	(0.0284)	(0.0358)
N	4975808	4953841	4833576	4595344	4102825	3444395
Panel B: Ag-Land Analysis (>= 5 Acres) [b]	(1) Main	(2) R1	(3) R2	(4) R3	(5) R4	(6) R5
Alt. Inclusion Criteria	>= 5 Acres	>= 6 Acres	>= 7 Acres	>= 8 Acres	>= 9 Acres	>= 10 Acres
T × Post	0.177*	0.231**	0.192*	0.241*	0.196+	0.138
	(0.0764)	(0.0751)	(0.0815)	(0.0938)	(0.101)	(0.113)
N	60024	49813	45881	42989	40533	37950
Panel C: Large-Lot-Home Analysis (>= 5 Acres) [c]	(1) Main	(2) R1	(3) R2	(4) R3	(5) R4	(6) R5
Alt. Inclusion Criteria	>= 5 Acres	>= 6 Acres	>= 7 Acres	>= 8 Acres	>= 9 Acres	>= 10 Acres
T × Post	0.0345	0.0331	0.0522	0.0306	0.0437	-0.0124
	(0.0280)	(0.0346)	(0.0342)	(0.0369)	(0.0374)	(0.0418)
N	329719	249146	210358	183510	162912	144006

Note: [a] The main purpose of analyses in Panel A is to check the robustness of our main estimates for residential homes against different sample selection criteria based on acreage. β_3 results use proximity as the treatment, corresponding to Column (1) in main text Table 3.1. $\beta_3^{no\_view}$ and β_3^{view} results use proximity without view (ProxT×0.ViewT) and proximity with view (ProxT×1.ViewT) as different treatment groups, corresponding to Column (2) in Table 3.1. The robustness checks follow all specifications of the main estimate, except changing the acreage inclusion criteria. Standard errors are reported in parentheses: + p < 0.1, $*$ p < 0.05, $**$ p < 0.01, $***$ p < 0.001. [b] Panel B checks the robustness of our main estimate for agricultural or vacant land, presented in Figure 5, against different sample selection criteria based on acreage. The main specification estimates are presented as Column (1), where T denotes properties that are within 2 miles of LSSPV sites. The other columns follow all specifications of the main estimate, except changing the acreage inclusion criteria. [c] Panel C checks the robustness of our main estimate for large-lot homes, presented in Figure 5, against different sample selection criteria based on acreage. The main specification estimates are presented as Column (1), where T denotes properties that are within 2 miles of LSSPV sites. The other columns follow all specifications of the main estimate, except changing the acreage inclusion criteria.

Table 3.A6: Robustness Check Excluding Clusters with Few Transactions

Panel A: Residential Analysis [a]	(1) Main	(2) R1	(3) R2	(4) R3	(5) R4
Excluding cluster if Sales Count < M	M = 1	M = 5	M = 10	M = 15	M = 20
β_3: ProxT × Post	-0.0476*	-0.0463*	-0.0442*	-0.0439+	-0.0441+
	(0.0199)	(0.0204)	(0.0213)	(0.0224)	(0.0244)
$\beta_3^{no\_view}$: ProxT × 0.ViewT × Post	-0.0459*	-0.0445*	-0.0426+	-0.0425+	-0.0428+
	(0.0200)	(0.0205)	(0.0214)	(0.0225)	(0.0244)
β_3^{view}: ProxT × 1.ViewT × Post	-0.0524*	-0.0513*	-0.0484*	-0.0476*	-0.0475+
	(0.0199)	(0.0203)	(0.0212)	(0.0223)	(0.0243)
N	4975808	4859725	4631826	4334746	3995840
Panel B: Ag-Land Analysis [b]	(1) Main	(2) R1	(3) R2	(4) R3	(5) R4
Excluding cluster if Sales Count < M	M = 1	M = 5	M = 10	M = 15	M = 20
T × Post=1	0.177*	0.452***	0.600***	0.536***	0.621**
	(0.0764)	(0.0814)	(0.0972)	(0.121)	(0.172)
N	60024	39760	27117	19077	14457
Panel B: Large-Lot-Home Analysis [c]	(1) Main	(2) R1	(3) R2	(4) R3	(5) R4
Excluding cluster if Sales Count < M	M = 1	M = 5	M = 10	M = 15	M = 20
T × Post=1	0.0345	0.0490	0.0457	0.0500	0.0587
	(0.0280)	(0.0299)	(0.0316)	(0.0352)	(0.0377)
N	329719	287035	244803	213192	188717

Note: [a] The main purpose of analyses in Panel A is to check the robustness of our main estimates for residential homes against the exclusion of clusters (defined by the census-tract-by-year fixed effects) with low transaction numbers. β_3 results use proximity as the treatment, corresponding to Column (1) in main text Table 3.1. $\beta_3^{no\_view}$ and β_3^{view} results use proximity without view (ProxT×0.ViewT) and proximity with view (ProxT×1.ViewT) as different treatment groups, corresponding to Column (2) in Table 3.1. The main specification estimates are presented as Column (1), where only singletons are dropped. The robustness checks follow all specifications of the main estimate, except changing the exclusion criterion on transaction numbers per cluster, M. Standard errors are reported in parentheses: + $p < 0.1$, $* \; p < 0.05$, $** \; p < 0.01$, $*** \; p < 0.001$. [b] Panel B checks the robustness of our main estimate for agricultural or vacant land, presented in Figure 5, against the exclusion of clusters (defined by the county-site-by-year fixed effects) with low transaction numbers. In all Panel B columns, T denotes properties that are within 2 miles of LSSPV sites, used as the treatment variable. The main specification estimates are presented as Column (1), where only singletons are dropped. The other columns follow all specifications of the main estimate, except changing the criterion on transaction numbers per cluster, M. [c] Panel B checks the robustness of our main estimate for agricultural or vacant land, presented in Figure 5, against the exclusion of clusters (defined by the county-site-by-year fixed effects) with low transaction numbers. In all Panel C columns, T denotes properties that are within 2 miles of LSSPV sites, used as the treatment variable. The main specification estimates are presented as Column (1), where only singletons are dropped. The other columns follow all specifications of the main estimate, except changing the criterion on transaction numbers per cluster, M.

Table 3.A7: Tests of the Heterogeneous Effects of LSSPV on Residential Home Value

Subgroup 1	Effect Estimates 1	S.E.1	Subgroup 2	Effect Estimates 2	S.E.2	Z-stat (Null: left=right)	P-value
Rural	-0.0275	0.0169	Urban	-0.0527	0.0280	0.773	0.439
Dem-leaning	0.0374	0.0436	Non-Dem-leaning	-0.0538	0.0124	2.011	0.044
Public Involve	-0.0065	0.0253	No Public Involve	-0.0364	0.0468	0.563	0.573
High View	-0.0507	0.0205	Low View	-0.0473	0.0199	0.166	0.868
Greenfield	-0.0466	0.0261	Brownfield	0.2254	0.1244	2.141	0.032
Tracking	-0.0167	0.0238	Fixed	-0.0501	0.0358	0.779	0.436
Facing	0.0304	0.0513	Not Facing	-0.0577	0.0254	1.540	0.124
High Income	0.0007	0.0239	Low Income	-0.0453	0.0246	1.342	0.180

Note: This table reports statistical tests for the heterogeneous effect results in Figure 3.4, including only the dimensions where the test outcome is not readily apparent from Figure 3.4. The estimates are reported with two-way clustered standard errors at census tract and year level.

Table 3.A8: Estimated Benefits and Costs of LSSPV Sites

Category	Annual Amount
Climate change mitigation benefits [a]	$22,155,900,000
carbon emissions offset (metric tons annually)	116.6 million
social cost of carbon (2020 value) at a 2% discount rate	$190 per metric ton
Appreciation of agricultural land within 2-mile radius [b]	$7,012,986
Land parcels within 2-mile	
Average price	$271,392
Estimated number affected	2664
Impact of LSSPV on agricultural land price	19.4%
Annualized Value/Total Price	5%
Depreciation of residential home within 3-mile radius [b]	-$4,106,283,025
Residential home within 3-mile	
Average house price	$323,746
Estimated number affected with LSSPV view	1,436,278
Impact of LSSPV on price	-5.2%
Estimated number affected without LSSPV view	3,728,889
Impact of LSSPV on price	-4.8%
Annualized Value/Total Price	5%
Agricultural production loss [c]	-$45,741,277
Annual net cash farm income per acre	$206
Total LSSPV acreage	317,207
percentage of LSSPV on agricultural land	70%
Sum of annual benefits and costs	$18,010,888,684

Note: [a] The total climate change mitigation benefits are calculated based on the following factors: The Solar Energy Industries Association estimated the US solar industry offset 169 million metric tons of carbon emissions annually in 2022, in which utility-scale solar power accounted for approximately 69% of the total installed solar capacity. The EPA has set the social cost of carbon at $190 (2020 value) using a 2% discount rate (Rennert et al., 2022). [b] The ratio between annualized property value and total property value is set at 5%, following the common practice in housing studies (Bayer et al., 2016). [c] The annual agricultural production loss is calculated based on the following factors: The 2022 US Census of Agriculture reported the net cash farm income of operations is $151,639,741,000, the market value of crops accounts for 52% of total market value, the total cropland is 382,356,350 acres (USDA, 2022). The net cash farm income per acre is $206. USDA ERS reported more than 70% of LSSPV development occurred on agricultural land.

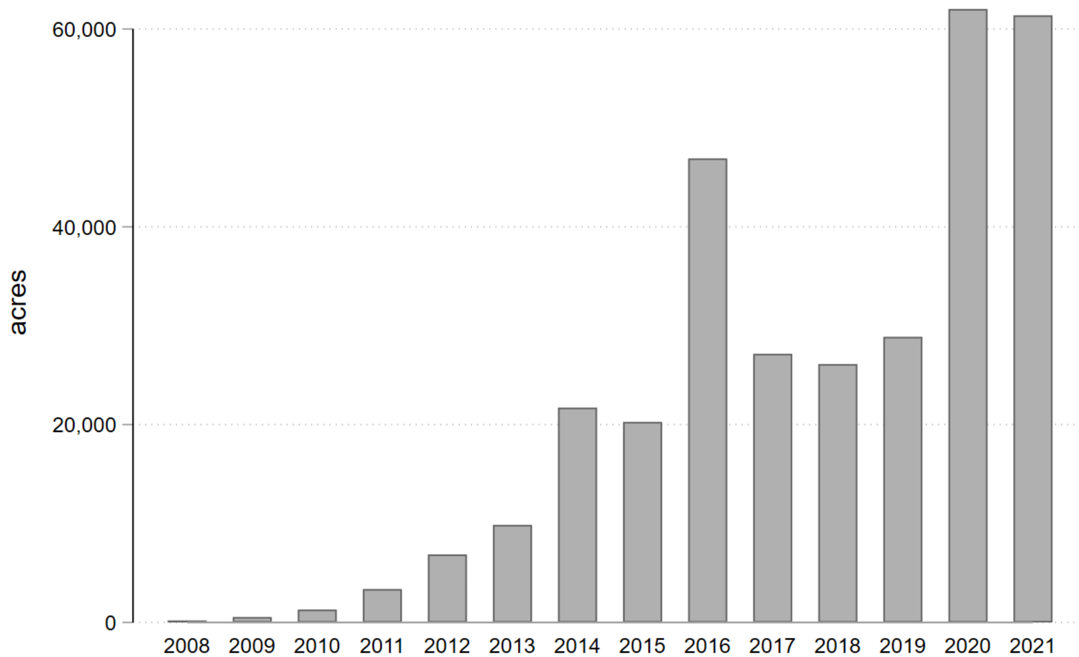


Figure 3.A1. Newly Added Acreage of U.S. LSSPV Facilities by Year

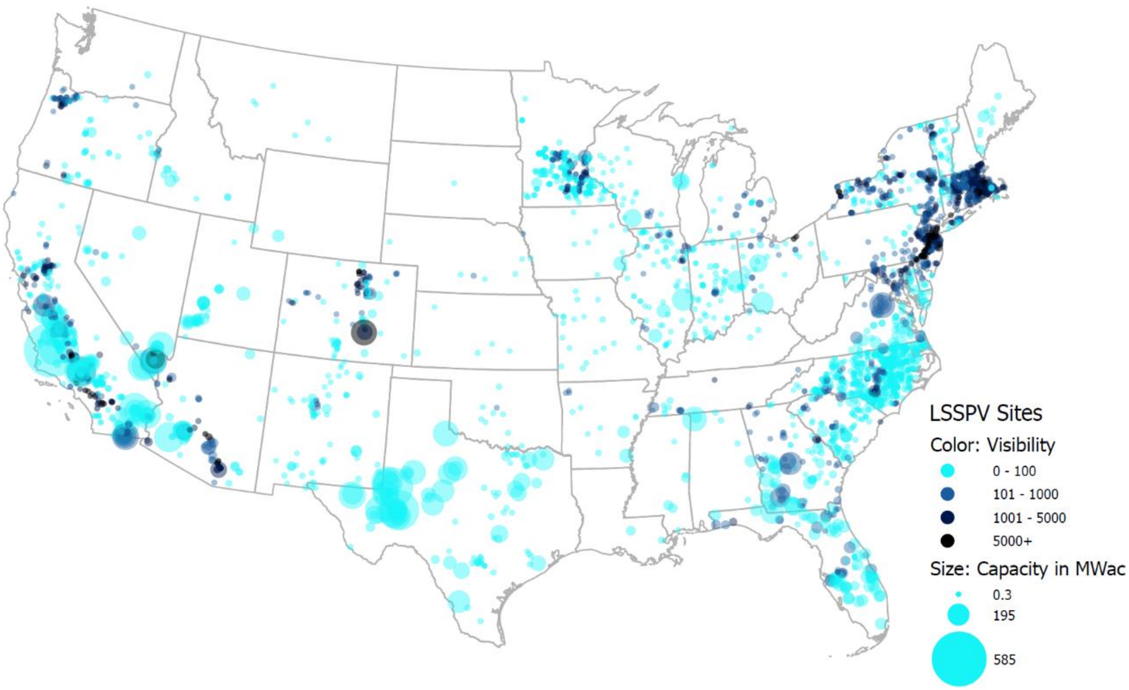


Figure 3.A2. Map of LSSPV locations, capacity, and visibility. The size of circles indicates the capacity of each LSSPV site. The colors represent the visibility of each site. Visibility is measured in the number of local (<6 miles) residential homes with a view of that LSSPV site.

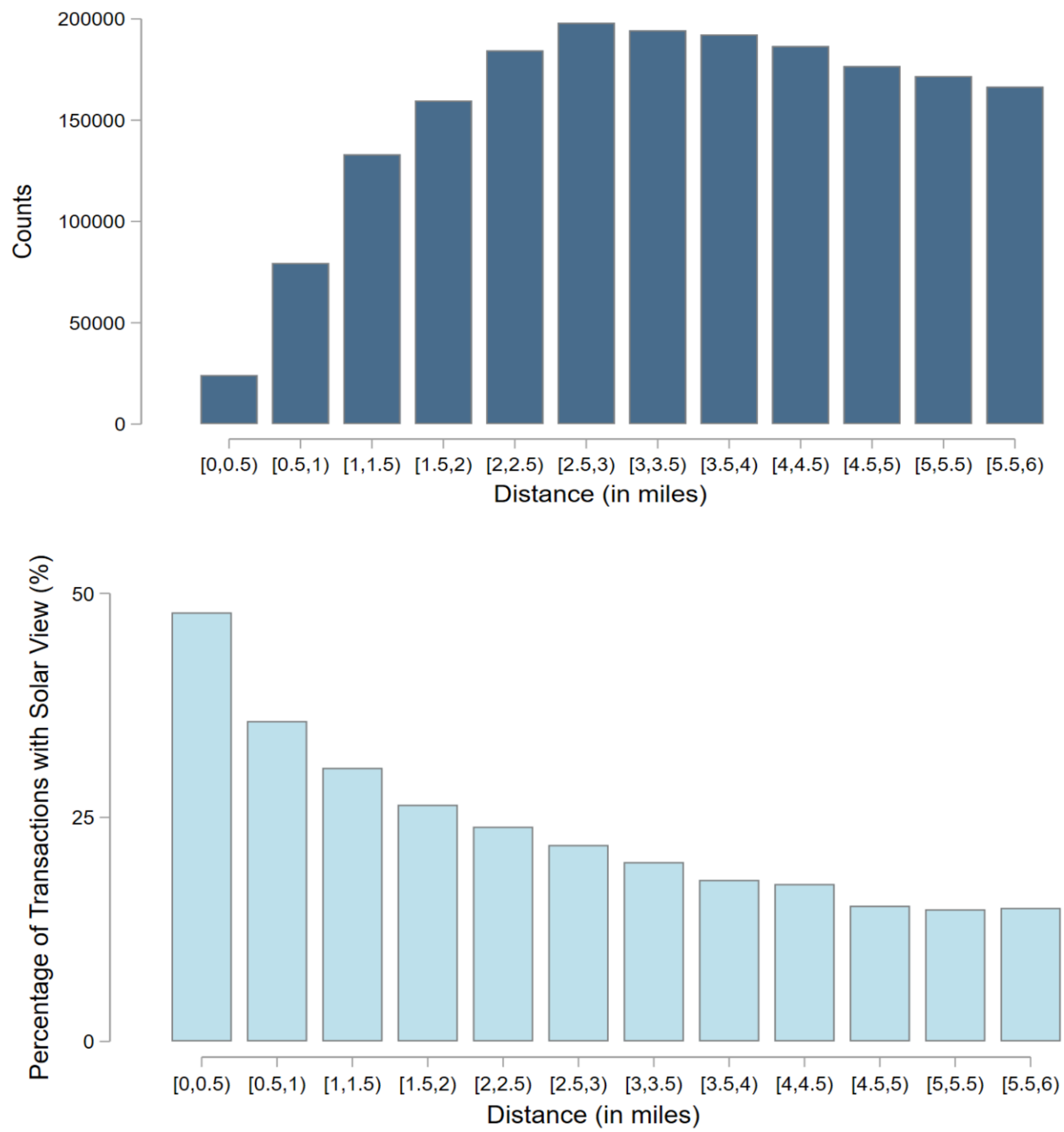


Figure 3.A3. Number of Residential Transactions Post-LSSPV-installation and Percentage with Solar View

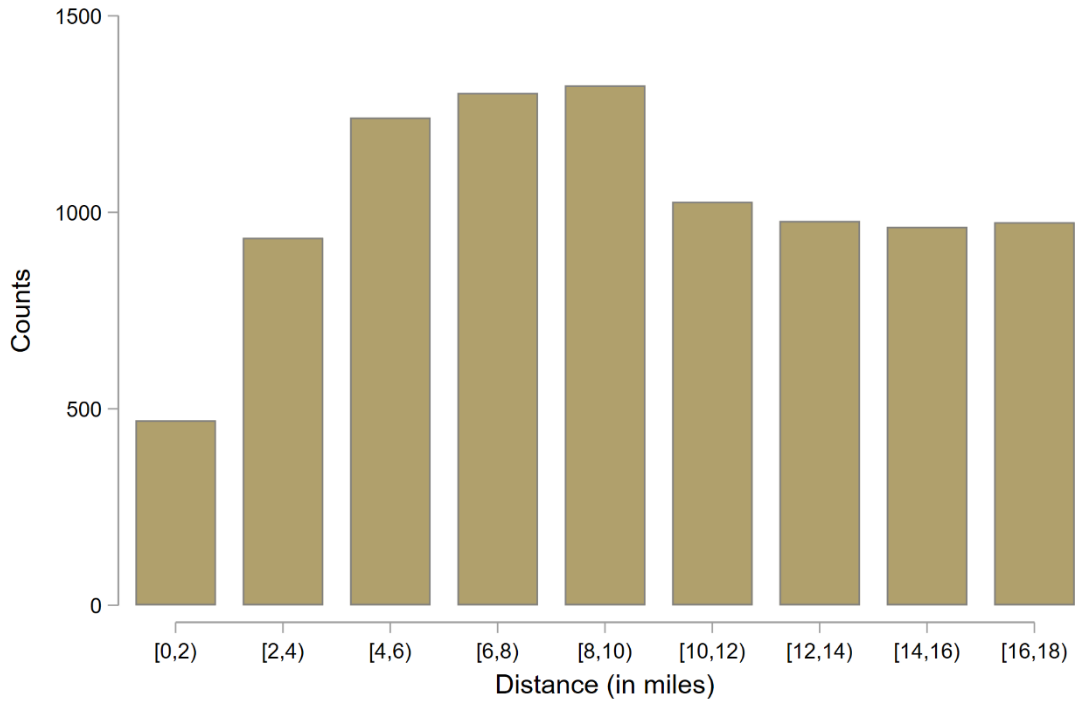


Figure 3.A4. Number of Agricultural & Vacant Land Transactions Post-LSSPV-installation

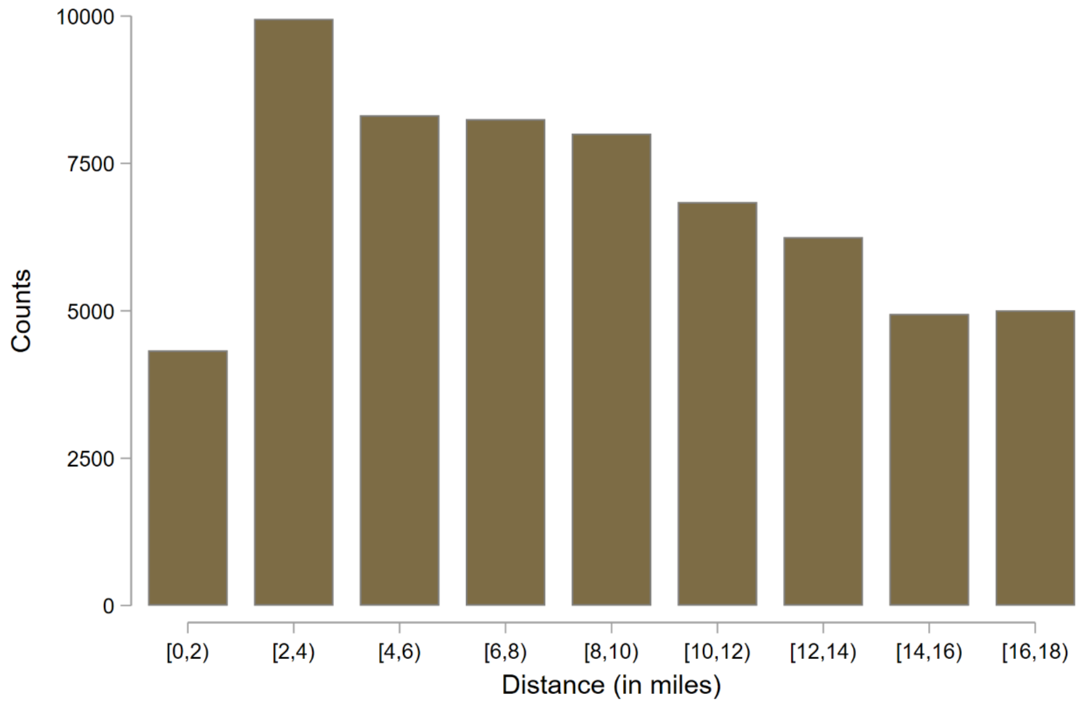


Figure 3.A5. Number of Large-Lot Home Transactions Post-LSSPV-installation

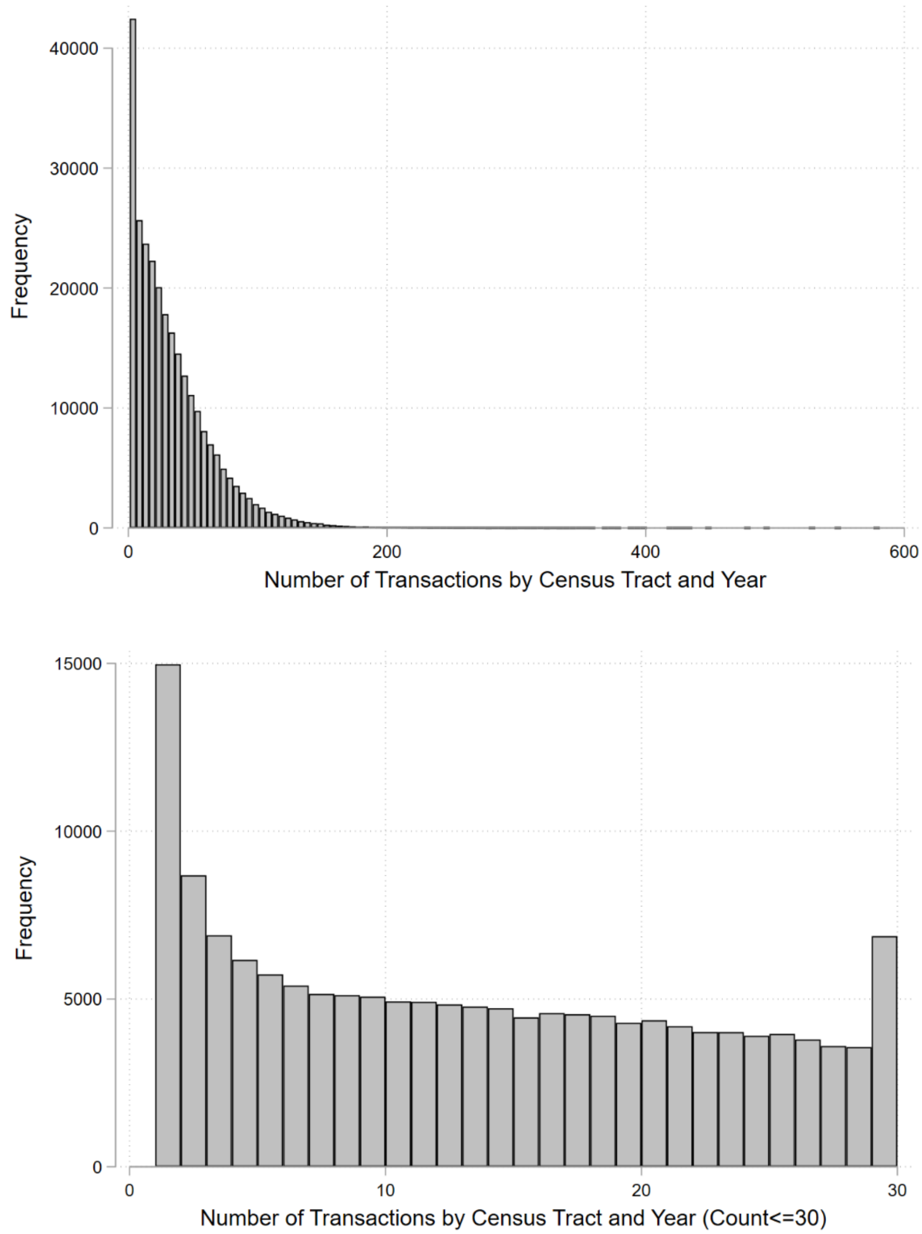


Figure 3.A6. Distribution of Transaction Counts for Residential Homes at the Census Tract-Year Level

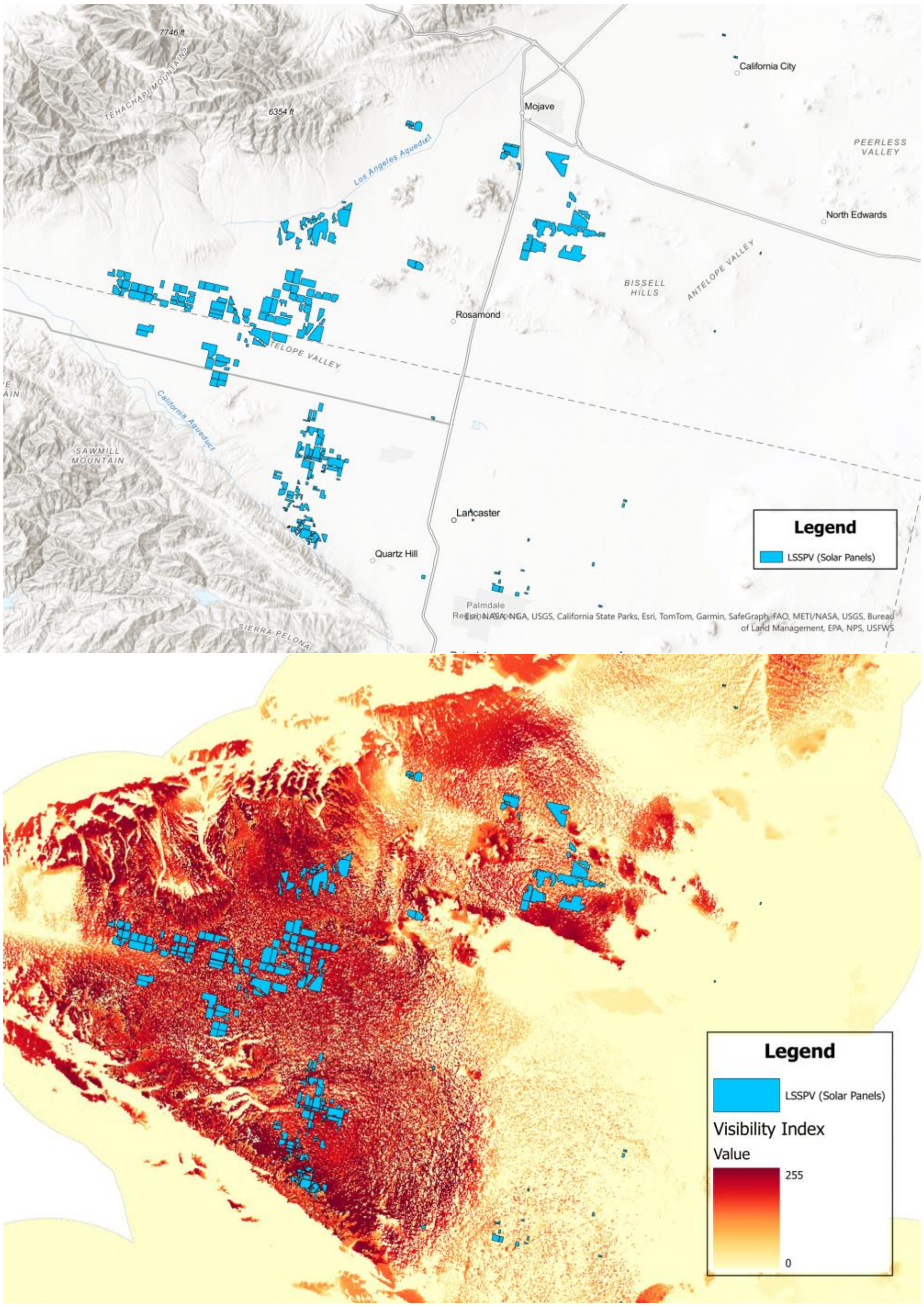


Figure 3.A7. LSSPV Visibility Index with Terrain Comparison Example One. The visibility index measures the number of visible perimeter points of nearby solar sites. Intuitively, the red color denotes regions with solar view, and regions in darker red can see a larger area of solar panels.

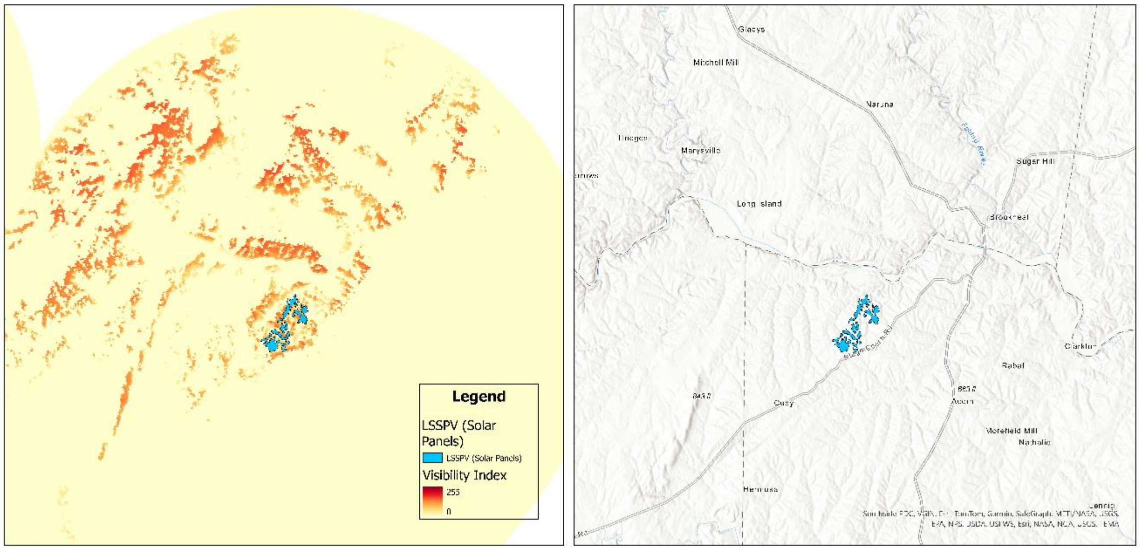


Figure 3.A8. LSSPV Visibility Index with Terrain Comparison Example Two

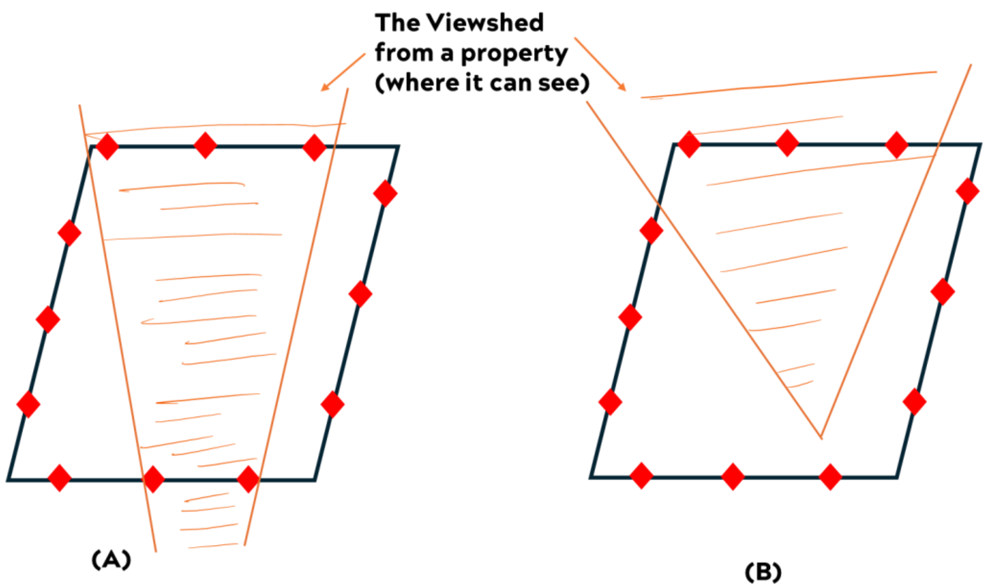


Figure 3.A9. Illustration of Viewshed Variability and the Impact on Continuous Visibility Index

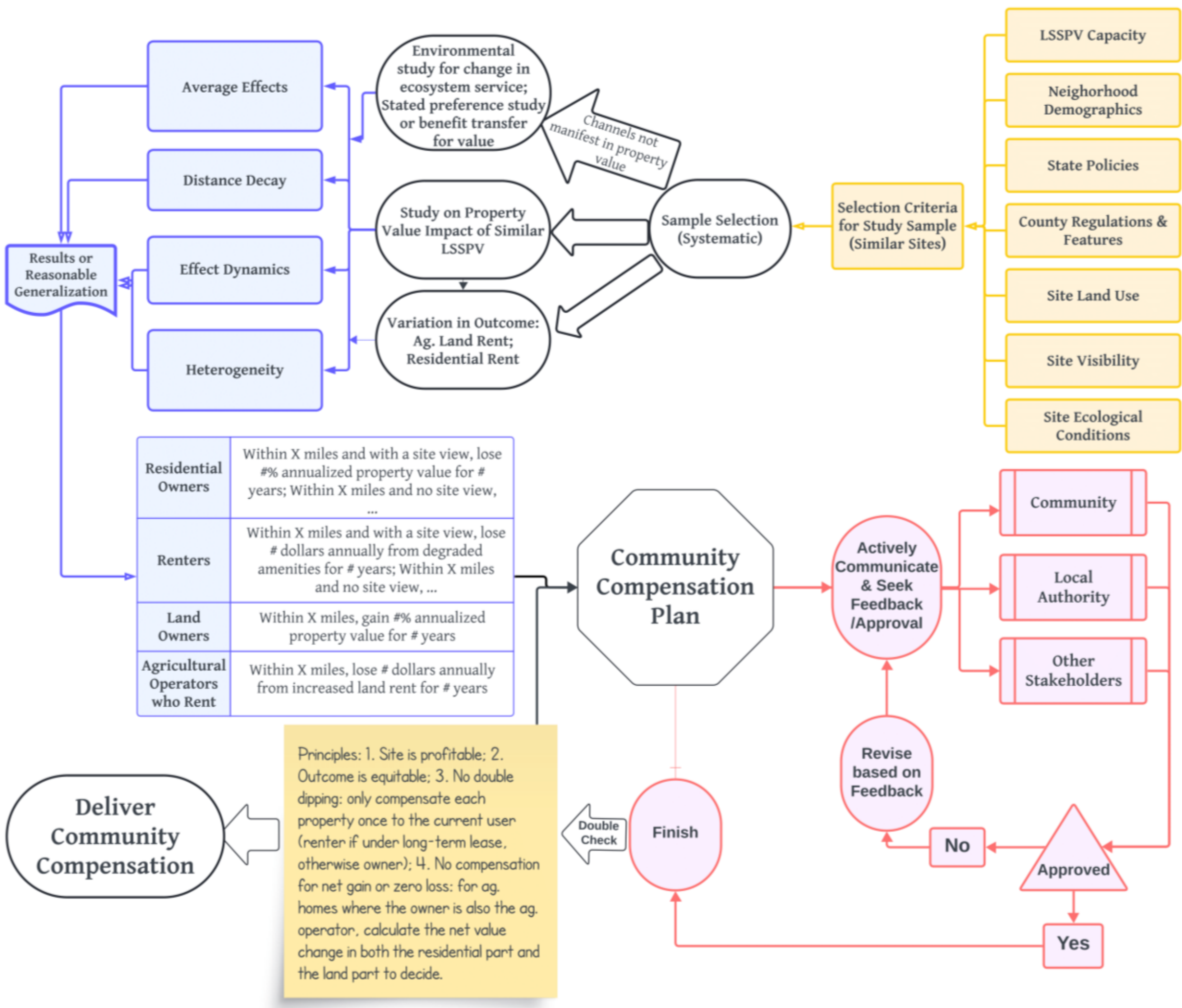


Figure 3.A10. A Prototype Evidence-based Community Compensation Plan

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