Three Chapters In Applied Economics

by

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Abstract

This dissertation comprises three chapters that address significant issues in applied economics, with a focus on energy, agricultural trade, and environmental conservation.

The first chapter, "The Impact of Small Refinery Exemptions on Renewable Fuel Market Factors in the United States," investigates the effects of regulatory exemptions on the renewable fuel industry. Small refinery exemptions (SREs) have been a contentious topic, as they allow certain refineries to bypass Renewable Fuel Standard (RFS) obligations. This chapter employs econometric models to analyze the influence of SREs on biofuel production, prices, and agricultural feedstock markets.

The second chapter, "China’s Changing Demand for U.S. Agricultural Commodities: Structural Change in China’s Import Demand for Meat, Grains, and Oilseed Crops," explores the evolving trade dynamics between China and the United States. With China's rapid economic growth and shifting dietary preferences, there has been a notable increase in its demand for imported agricultural commodities. This chapter utilizes a structural change framework to assess how China's import patterns for meat, grains, and oilseeds have transformed in recent times.

The third chapter, "Mitigating Climate Change with the Conservation Reserve Program (CRP): The Role of Carbon Credits and CRP Redesign," examines the potential of the CRP in contributing to climate change mitigation. This chapter evaluates the effectiveness of CRP in sequestering carbon and proposes redesigns to enhance its climate benefits. The study also explores the integration of carbon credits into the CRP, providing a market-based mechanism to incentivize greater participation and maximize environmental gain.

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List of Abbreviations

RFS	Renewable Fuel Standard
RIN	Renewable Identification Number
SVAR	Structural Vector Auto Regression
SRE	Small Refinery Exemption
EPA	Environmental Protection Agency
RVO	Renewable Volume Obligation
BDI	Baltic Dry Index
IAIDS	Inverse Almost Ideal Demand System
CRP	Conservation Reserve Program
EBI	Environmental Benefits Index

Impact of Small Refinery Exemptions on Renewable Fuel Market Factors in the United States

Abstract: The Renewable Fuel Standard (RFS) in the United States mandates blending biofuels into gasoline, while Small Refinery Exemptions (SREs) enable select refiners to bypass these requirements. This study assesses the impact of SREs on factors in the corn-based fuel ethanol market such as ethanol and corn prices, ethanol renewable identification number (RIN) prices, ethanol production, and corn prices. Using a structural vector autoregression (SVAR) model, our findings suggest a limited influence of SREs on these variables. Our variance decomposition analysis reveals that only 3.8% of annual and 8% of five-year ethanol price fluctuations can be attributed to SREs. Furthermore, SREs explain less than 3% of the variations in ethanol RIN prices. Within 12 and 60 months, SREs account for 16% and 19% of the fluctuations in ethanol production, respectively. This research provides insights into the limited impact of SREs on the U.S. corn ethanol fuel industry, shedding light on the complex dynamics of this policy within the broader context of biofuel blending and its economic implications.

Keywords: Corn, Ethanol, Renewable Fuel Standard, Renewable Identification Numbers, Small Refinery Exemptions

JEL classification: Q41, Q48

1. Introduction

The Renewable Fuel Standard (RFS) program, established by the Energy Policy Act of 2005, is instrumental in shaping the United States' renewable energy landscape. The RFS mandates the inclusion of a substantial volume of conventional biofuel, primarily starch-based ethanol, into transportation fuel to enhance sustainability and mitigate the energy sector's environmental impact. This requirement, capped at 15 billion gallons annually, positions corn-based ethanol as a primary contributor, consuming over 40% of domestic corn production in recent years (McConnell, 2021).

The RFS regulations oversight falls within the Environmental Protection Agency (EPA) jurisdiction, which enforces compliance through Renewable Volume Obligations (RVOs) imposed on oil refiners. The initial aim of the RFS was to achieve a total renewable fuel volume of 36 billion gallons by 2022. However, a growing concern has emerged as RVO mandates have been inconsistently met since 2010 (Miao et al., 2012; Bracmort, 2019). The final RVOs significantly fell short of the desired goals, particularly in 2022, achieving only 20 billion gallons against the 36-billion-gallon target. This shortfall is primarily attributed to challenges meeting cellulosic biofuel production targets specified in the RFS statutes (Gerveni et al., 2023).

Moreover, the E10 "blend wall," restricting ethanol content in gasoline to 10%, has played a pivotal role in causing gasoline consumption to fall below projections (Strogen et al, 2012,). Addressing these challenges has intensified the conflict between petroleum refiners and biofuel producers, centered around compliance costs and the reluctance to invest in higher ethanol blends such as E15 and E85 (Gerveni et al., 2023).

Additionally, the global COVID-19 pandemic significantly impacted domestic gasoline and diesel consumption, prompting the EPA to reduce annual RVOs in 2020 and 2021, much to the dissatisfaction of biofuel producers, during this time conventional biofuel RVOs experienced the most substantial reductions in response to the pandemic's impact on fuel demand (Skor, 2022). Under its authority, the EPA is responsible for establishing final renewable fuel volume targets considering factors such as costs, air quality, climate change policy, program implementation, energy security, infrastructure, commodity prices, water quality, and supply.

As recent as June 21, 2023, the EPA unveiled a new ruling outlining biofuel volume requirements and percentage standards for consistent biofuel growth for various renewable fuel categories over 2023–2025. Following a court remand of the 2016 annual rule, the latest ruling had established a target volume amount of 250 million gallons of renewable fuel for 2023, with the specific volume targets including cellulosic biofuel, biomass-based diesel (BBD), advanced biofuel, and total renewable fuel (US EPA, 2023).

2. Small Refinery Exemption Waiver (SREs)

One factor that has also contributed to the discrepancy in meeting RVO requirements in the renewable fuel sector is the utilization of Small Refinery Exemption (SRE) waivers, which have provided small refineries with flexibility in meeting their renewable fuel blending obligations. These waivers have also sparked significant controversy within the corn-based renewable fuel industry. According to the EPA, small refineries are defined as refineries who have average crude oil input capabilities of less than 75,000 barrels per day (equivalent to 3,150,000 gallons or 11,907,315 liters per day). As of January 1, 2019, 53 small refineries were among the 132 operating refineries across the United States (EIA, 2019).

Under the SRE policy, Small refiners can request SREs from the EPA by demonstrating "disproportionate economic hardship" in meeting the mandated blending volumes. Their argument often concerns higher compliance costs, which exceed the industry average and threaten their refinery operations (DOE, 2011) [1]. Regarding the application process for refiners, In order to be excluded from the RFS requirements, small refineries in the United States must submit an annual application and show "disproportionate economic hardship." Every year, the EPA has different deadlines for applications; typically, submissions must be made by the end of the current year in order to allow for consideration. The EPA then evaluates the operational data and economic circumstances of each refinery in collaboration with the Department of Energy (DOE). For every application, the DOE offers a thorough study and recommendation, assisting the EPA in determining whether to grant the exemption. Refineries that have been approved are subject to specific reporting requirements and modified commitments. Given this process, refineries must carefully consider the timing of these decisions because it affects their financial and operational plans for the next compliance year.

Notably, 108 SRE waivers were granted to oil refiners during 2013-2018, with the majority being issued in 2017 and 2018 (see Figure 1). From 2013 to 2018, the study period, we witnessed fluctuations in corn ethanol RIN (D6 RIN) prices, particularly corn ethanol RIN prices coinciding with a broader trend of declining prices in ethanol, corn, and gasoline (see Figure 1). The EPA granted 31 Small Refinery Exemption waivers in 2018 (see Figure 2). These 31 waivers led to the exemption of approximately 13.4 billion gallons of gasoline and diesel and 1.43 billion RINs from mandated volume compliance (Hansen & Hill, 2019). Notably, 2017 marked a significant period with the issuance of 35 exemption waivers to refiners, resulting in the exemption of approximately 1.82 billion RINs from mandated compliance.

At the core of the RFS lies Renewable Identification Numbers (RINs), which serve as a crucial compliance metric. The Environmental Protection Agency (EPA) employs RINs to

[1] For context, the Energy Policy Act 2005 initially allowed temporary exemption status for small oil refineries until 2011.

meticulously monitor the compliance of obligated parties, which encompasses fuel refiners and blenders, with their designated volume obligations. Each RIN is linked to a physical gallon of renewable fuel produced and transferred to a blender. Obligated parties use these RINs to demonstrate their fulfillment of the RFS-prescribed sale volumes of renewable fuel following the blending process.

From 2013 to 2018, the study period, we witnessed fluctuations in corn ethanol RIN (D6 RIN) prices, particularly corn ethanol RIN prices coinciding with a broader trend of declining prices in ethanol, corn, and gasoline (see Figure 1). The EPA granted 31 Small Refinery Exemption waivers in 2018 (see Figure 2). These 31 waivers led to the exemption of approximately 13.4 billion gallons of gasoline and diesel and 1.43 billion RINs from mandated volume compliance (Hansen & Hill, 2019). Notably, 2017 marked a significant period with the issuance of 35 exemption waivers to refiners, resulting in the exemption of approximately 1.82 billion RINs from mandated compliance.

The substantial volume of renewable fuel exempted due to SREs has raised considerable concern within the biofuel production sector regarding the potential impact and role of SREs in influencing the demand for renewable fuels. This research sheds light on the multifaceted consequences and the SREs' role in this intricate energy policy landscape.

This study aims to contribute to the existing body of literature on the impact of Small Refinery Exemptions (SREs) by analyzing their effects on crucial variables in the U.S. renewable energy sector. These variables include the prices of corn, ethanol, corn ethanol Renewable Identification Numbers (RINs), and ethanol production. Notably, concerns have arisen from biofuel producers and farmers who argue that SREs have created conditions enabling oil refiners to evade their renewable fuel blending requirements, thus negatively affecting the demand for ethanol and corn.

Geoff Cooper, the president of the Renewable Fuel Association (RFA), emphasized the detrimental impact of SREs in his testimony to the House Energy and Commerce Committee in 2019, stating that:

> *"EPA's mismanagement of the SRE program has rendered EPA's annual Renewable Volume Obligation rule meaningless, introduced tremendous uncertainty into the marketplace, and significantly undermined demand for renewable fuels" (Cooper, 2019).*

While the impact of SREs on renewable fuel markets remains controversial, it is worth noting that only a limited number of studies have delved into this matter. For instance, Irwin (2018) analyzed ethanol RIN price data from 2008 to 2018 but found little evidence that physical ethanol demand decreased with the increasing approval of SRE waivers. Irwin's focus on consumption and price trends provided valuable insights concerning higher-level ethanol-blended fuels like E15 and E85. Additionally, Lade (2019) examined the relationship between SREs and E15 but did not quantitatively assess their impact on ethanol production, ethanol prices, corn-based ethanol RIN prices, or corn prices. While contributing to understanding the effects of SREs, these previous studies did not comprehensively analyze the broader renewable fuel sector.

This study employs a structural vector autoregression (SVAR) model to investigate the relationship between SRE waivers and their impact on price and quantities in the renewable fuel sector. By offering a more comprehensive assessment, the results of this research will provide valuable insights into the ongoing debate surrounding the impact of SREs on the renewable fuel sector.

3. Data and Methodology

Data Collection

Our study utilizes a dataset comprising crucial variables related to the renewable fuel sector. The dataset includes records of Renewable Volume Obligations (RVOs) that were not fulfilled due to the retroactive granting of exemption waivers, as well as the potential volume of ethanol that could have been blended in gasoline without the issuance of Small Refinery Exemptions (SREs) to oil refiners. The dataset spans seventy-two monthly observations from 2013 to 2018.

Data related to corn-based ethanol Renewable Identification Number (RIN) prices and SRE waiver decisions were sourced from the Environmental Protection Agency (EPA) (US EPA, 2022). The EPA's dataset provides historical weekly volume-weighted average RIN prices for segregated RINs, information on annual SRE waiver determinations, and estimates for gasoline and diesel fuel volume exempted from mandated blending requirements.

To align with our monthly data framework, we aggregate the EPA's weekly RIN price data into monthly records. In our analysis, we address the challenge of integrating annual exempted volumes of gasoline and diesel, as reported by the EPA, into our monthly data framework. Due to the lack of monthly granularity in the exemption data, we adopted a simplified approach by evenly distributing the annual exempted volumes across all twelve months of the respective year. This assumes that SRE impacts are uniformly distributed throughout the year, which, while a simplification, allows us to proceed with a consistent monthly analysis framework.

Data on ethanol fuel production, motor gasoline refinery production, and blender production were obtained from the U.S. Energy Information Administration (EIA), measured in barrels per day. Monthly pricing data for corn, ethanol, and gasoline was procured from the

Economic Research Service's Bioenergy Statistics (U.S. Bioenergy Statistics, 2022). The Baltic Dry Index (BDI) was incorporated as an indicator of global demand for corn, following a similar SVAR methodology as outlined by McPhail et al. (2012). The BDI, administered by the London Baltic Exchange, measures shipping rates for bulk commodities and raw materials. The inclusion of the Baltic Dry Index (BDI) in our analysis serves as a proxy for global economic activity, particularly in the bulk commodities market, which directly impacts the demand for corn. The BDI measures the shipping costs of major raw materials and is often interpreted as a indicator of commercial demand, including for agricultural products like corn. Given that a significant portion of the U.S. corn production is exported, fluctuations in the BDI provide insights into potential shifts in global demand pressures, which, in turn, could influence corn prices and, consequently, ethanol production costs. By integrating the BDI, we aim to capture these broader economic dynamics that could indirectly affect the renewable fuel sector, particularly under the RFS mandates.

All prices and index values were adjusted to 2015 using the U.S. Consumer Price Index (CPI) for consistency. Descriptive statistics for all variables are presented in Table 1.

Significance of Selected Variables

The variables considered in this study play a pivotal role in elucidating the impact of Small Refinery Exemptions (SREs) in the renewable energy sector. Each variable offers a unique perspective on the complex dynamics at play.

For instance, The prices of corn are fundamental within the biofuel industry, reflecting not only the agricultural landscape but also the economic viability of ethanol production. SREs, potentially influencing ethanol demand, may potentially have some impact on corn price. As an indicator of demand and value for renewable fuels, ethanol price provide insights into the economic implications of SREs on the broader renewable fuel industry. Corn ethanol Renewable Identification Numbers (RINs) are key compliance instruments under the Renewable Fuel Standard (RFS) and are closely tied to SREs. Ethanol production levels serve as a barometer for the industry's health and sustainability. SREs may directly influence production by affecting the demand for renewable fuels, indicating their operational and economic implications for biofuel facilities.

Together, these variables offer invaluable insights into the multifaceted effects of SREs, encompassing economic, regulatory, and operational aspects. They are instrumental in addressing our central research question pertaining to the overarching impact of SREs on the renewable energy sector.

Structural Vector Autoregression (SVAR) Model

In this study, we employ the SVAR model, a widely used method for examining the effects of economic shocks on economic variables (Zivot & Wang, 2006). This approach is rooted in identifying the associated parameters based on underlying economic theory, encompassing expected contemporaneous interactions and structural relationships among the variables integrated into the model. The SVAR approach equips us with tools to analyze our focal variables' impulse responses and variance decompositions, allowing us to assess the overall significance of shocks on each variable.

A Structural Vector Autoregression (SVAR) model is primarily used to assess causal relationships among variables informed by economic theory. Unlike standard VAR models, SVARs incorporate a priori theoretical constraints to elucidate structural relationships, distinguishing causal impacts from simple correlations. These models employ impulse response functions to trace the effects of one-time shocks on variables over time, enhancing our understanding of dynamic interactions.

Although not designed to test Granger causality directly, SVARs align with its principles by analyzing how past values influence future outcomes, assuming the model's structure accurately reflects real-world dynamics. Additionally, variance decomposition within SVARs helps quantify the contribution of each variable to others in the system, providing insights into their directional influences. These models are particularly effective for analyzing the impacts of economic policies on critical economic variables, offering more credible causal interpretations than purely descriptive models.

We justify using a SVAR model over VAR or ARDL for several reasons. SVAR models are particularly advantageous when a theoretical foundation for causality exists, setting them apart from VAR models, which lack explicit causal assumptions and primarily focus on contemporaneous relationships. On the other hand, ARDL models, tailored for cointegration and error correction, emphasize long-term relationships. The selection among SVAR, VAR, or ARDL models primarily hinges on the research objectives, data availability, the nature of the research study, and whether the focus of the study is on structural shocks and causality, long-term dynamics, or contemporaneous relationships.

Based on our discussion, the preference for SVAR over the other two models is motivated by the explicit causal assumptions provided by SVAR models, which align with the theoretical foundation of our study. This emphasis on structural shocks and causality makes SVAR more suitable for our particular research objectives and our decision in model selection.

The general SVAR equation can be represented as:

$$A_0 x_t = \alpha + \sum_{i=1}^{p} A_i x_{t-i} + \varepsilon_t, \tag{1}$$

where x_t represents variables of interest to be included in the model; A_0 represents the offdiagonal matrix which captures the contemporaneous relationships across the variables included in the model; p represents the lag order which is to be determined based on Schwarz Information Criterion (SIC); A_i reflects the effects of the lagged endogenous variables included in x_t; and ε_t represents a vector of serially uncorrelated structural shocks. From equation (1) we can specify the reduced form of our model as:

$$x_t = A_0^{-1}\alpha + \sum_{i=1}^{p} A_0^{-1} A_i x_{t-i} + e_{t.} \tag{2}$$

For the reduced form VAR specification when A_0^{-1} is known, the dynamic structure of the SVAR can be estimated through equation (2). When A_0^{-1} is unknown, we identify our structural parameters through economic intuition and by imposing theoretical restrictions that reduce the number of unknown structural parameters to be less than or equal to the number of estimated parameters in the VAR residual variance-covariance matrix. In our SVAR model, the variables are ordered as follows:

$$\begin{aligned} x_t &= (\ln SRE_t, \ln BDI_t, \ln Gas\,\mathrm{Pr}_t, \ln GasPd_t, \\ &\ln Corn\,\mathrm{Pr}_t, \ln Eth\,\mathrm{P}\,d_t, \ln D6RIN\,\mathrm{Pr}_t, \ln Eth\,\mathrm{Pr}_t), \end{aligned} \tag{3}$$

In our SVAR model, we hypothesize that ethanol prices are influenced by a series of interrelated variables, including the volume of gasoline and diesel fuel exempt from blending requirements due to Small Refinery Exemptions (SRE), global corn demand indicated by the Baltic Dry Index (BDI), monthly wholesale prices for gasoline (GasPr) and ethanol (EthPr), gasoline production by refiners and blenders measured in thousands of barrels per day (GasPd), corn prices received by farmers ($/bushel) (CornPr), fuel ethanol production (EthPd), and corn ethanol Renewable Identification Number prices (D6RINPr). These variables are ordered in the model based on their expected influence on ethanol prices, reflecting theoretical and empirical considerations about how each shock might affect the ethanol market. This ordering is crucial as it determines how we interpret the causal relationships and dynamic interactions within the model, assuming that ethanol prices react to shocks across all these listed variables. The natural logarithmic transformation (ln) of these variables helps in stabilizing variance and interpreting results in terms of percentage changes.

In constructing the SVAR model, the ordering of variables is meticulously chosen based on a combination of economic theory and empirical precedence to reflect the underlying causal relationships accurately. At the forefront, Small Refinery Exemptions (SREs) are posited to directly influence fuel production metrics, as regulatory changes often precede market and production responses, aligning with the theory of regulatory impact on economic sectors. Following SREs, global demand indicators like the Baltic Dry Index (BDI) and wholesale fuel prices are positioned, recognizing their role in signaling shifts in economic activity and input costs that subsequently affect production decisions. Production volumes of gasoline and ethanol precede price responses in the commodity markets, such as corn and ethanol prices, consistent with supply-side economic theory, where production changes impact prices through market balance mechanisms. This ordering mirrors the natural sequence of economic responses from regulatory impacts to market dynamics and also adheres to empirical observations noted in existing literature, where regulatory and global economic shifts precipitate adjustments in production and pricing structures.

The structural parameters of the SVAR model are imposed as follows:

$$e_t = \begin{pmatrix} e_t^{SRE} \\ e_t^{BDI} \\ e_t^{Gas\,Price} \\ e_t^{Gas\,Prod} \\ e_t^{Corn\,Price} \\ e_t^{Eth\,Prod} \\ e_t^{D6RIN\,Price} \\ e_t^{Eth\,Price} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & 0 & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} & 0 \\ a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} & a_{87} & a_{88} \end{pmatrix} \times \begin{pmatrix} \varepsilon_t^{SRE\_shock} \\ \varepsilon_t^{BDI\_shock} \\ \varepsilon_t^{Gas\,Price\_shock} \\ \varepsilon_t^{Gas\,Prod\_shock} \\ \varepsilon_t^{Corn\,Price\_shock} \\ \varepsilon_t^{Eth\,Prod\_shock} \\ \varepsilon_t^{D6RIN\,Price\_shock} \\ \varepsilon_t^{Eth\,Price\_shock} \end{pmatrix} \quad (4)$$

In the SVAR framework, model variables are considered endogenous, reflecting their interdependence and mutual influence (Gottschalk, 2001). This gives the SVAR framework an advantage in its ability to confine policy effect estimates by establishing identifying assumptions about the variables. Additionally, orthogonality restrictions are imposed to ensure that structural shocks are uncorrelated. Achieving orthogonality is often facilitated by forming an uncorrelated error term through a Cholesky decomposition ordering of the variables (Fernández-Villaverde & Rubio-Ramírez, 2010).

In our SVAR analysis, we first ensure that all model variables are stationary to prevent spurious results and enable reliable interpretation. Stationarity in time series data means that statistical properties such as mean, and variance do not change over time (Hamilton, 1994). To test for stationarity, we employ the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, which are designed to detect the presence of a unit root—a condition indicating non-stationarity.

The null hypothesis for both the ADF and PP tests is that the variable has a unit root. Rejecting this hypothesis implies the variable is stationary. Table 2 summarizes these results, showing that all tested variables become stationary after differencing once. This ensures that the relationships among variables in our SVAR model are stable over time. Additionally, based on the Schwarz Information Criterion (SIC), we determine that our model requires one lag, optimizing model complexity and explanatory power.

4. Results

Impulse Response Analysis

The responses of ethanol prices, ethanol production, D6 RIN prices (Ethanol RIN price), and corn prices to a positive one standard deviation shocks from the initial impact of SRE, BDI, Gasoline price, and Gasoline production are depicted in impulse response function (IRF) graphs for a period of up to 12 months (Figure 3). Based on the variable ordering provided in equation (3), the columns show the responses of the ethanol price, D6 RIN price, ethanol production, and corn prices to our model variables.

For instance, the first row of graphs in Figure 3 displays how the ethanol price, ethanol RIN price, ethanol production, and corn price responded to a positive one standard deviation shock in SREs. From the first row, we can see how SREs affected the price of ethanol, the price of ethanol RINs, the volume of ethanol produced, and the price of corn over a year. The impulse response analysis reveals statistically negligible effects, indicating no enduring impact of Small Refinery Exemptions (SREs) on the four variables. The lack of persistence in the graphs suggests that shocks related to SREs may not persist long enough to significantly influence ethanol prices, production levels, ethanol RINs, or corn prices over an extended period. While acknowledging the absence of long-term effects, this analysis zooms in on the short-term impact of SREs. Examination of the initial months following a positive one standard deviation shock in SREs shows minor fluctuations in ethanol prices, ethanol RIN prices, ethanol production, and corn prices. Despite these short-term variations, the overall response remains statistically insignificant, suggesting that SRE shocks do not substantially influence these variables in the short run.

Variance Decomposition

The utilization of variance decomposition aids in comprehending the impact of different shocks on relevant variables. Through variance decomposition our study aims to assess the significance of each shock in elucidating changes in ethanol prices and other model variables.

According to our findings, Small Refinery Exemption (SRE) shocks initially constitute 1% of the fluctuations in ethanol prices within a month (refer to Table 3). Over a year, this influence escalates to approximately 4%, and at the five-year mark, SRE shocks contribute around 8% to the long-term variability in ethanol prices. Notably, at the five-year point, gasoline prices and ethanol production emerge as more influential, explaining 16% and 13% of the changes in ethanol prices, respectively. Furthermore, 5% of the ethanol price variance in the long run can be attributed to shocks in Renewable Identification Number (RIN) prices for ethanol. Regarding ethanol RIN prices, SRE shocks account for less than 3% of the variability from 1 month to 5 years. Regarding ethanol production, SREs contribute to about 5% of the monthly fluctuations. However, their significance becomes more pronounced over the long term, explaining approximately 16% and 19% of the variations at 1 and 5 years, respectively. Gasoline production is a substantial factor, responsible for 38% of the changes over 5 years and 66% of the short-term variation within a month in ethanol production. Lastly, SREs contribute about 7% to the fluctuations in corn prices over 1 month to 5 years.

Discussion of Market and Policy Implications of SREs

Impulse Response Analysis results indicate minimal long-term impact from SRE shocks on ethanol prices, production, and corn prices. The minor fluctuations observed in the short term also suggest a limited impact from these exemptions on market dynamics. This suggests that the market either quickly adjusts to the shocks or that the size of the shocks is not substantial enough to cause significant long-term changes. An Analysis of variance decomposition reveals that while SREs have a growing influence over time on ethanol prices, they remain a smaller factor than gasoline prices and ethanol production. This gradual increase in influence could indicate accumulating effects that might become more significant over an extended period. It is essential to highlight the substantial role of gasoline production in influencing ethanol production, suggesting solid linkages between these fuel markets.

Although SREs do not show a significant impact currently, there is still a need to carefully monitor their influence. Policymakers should regularly review the impact of SREs to ensure they do not inadvertently lead to larger market distortions over time. Adjustments may be necessary if their cumulative effect significantly alters market dynamics. Our analysis indicates market resilience to shocks from SREs. However, to safeguard against potential vulnerabilities, policies could be crafted to enhance the biofuel industry's adaptive capacity. This might include supporting technological innovations in ethanol production or diversifying feedstock sources beyond corn. Given the negligible short-term effects but potential long-term impacts, policies should focus on ensuring long-term stability in the ethanol market. This could involve creating more robust mechanisms for adjusting RVOs (Renewable Volume Obligations) in response to market conditions or enhancing ethanol blending and distribution infrastructure. Government investment in diversifying biofuel sources could be increased to reduce dependency on corn-based ethanol and mitigate any future impacts of SREs. Exploring second-generation biofuels from non-food biomass could provide a more sustainable and less market-sensitive alternative.

Regular engagement with stakeholders, including small and large refineries, biofuel producers, and agricultural sectors, is crucial. These discussions can provide deeper insights into market dynamics and help tailor policies that address specific industry challenges without causing adverse effects. In the context of evolving market conditions and the potential influence of SREs, periodic reviews of the Renewable Fuel Standard should continue to align with market realities while pursuing environmental and energy security goals.

Recognizing the multifaceted nature of these influences is crucial for policymakers, industry stakeholders, and researchers to develop effective strategies that promote a sustainable and resilient biofuel sector. As we navigate the intricate landscape of biofuel dynamics, understanding the broader context in which SREs operate provides a foundation for crafting robust policies that address the challenges and opportunities in the renewable energy landscape. Periodic reviews of policies, consideration of global and domestic factors, and a focus on long-term strategies are essential to ensure the stability and growth of the biofuel sector.

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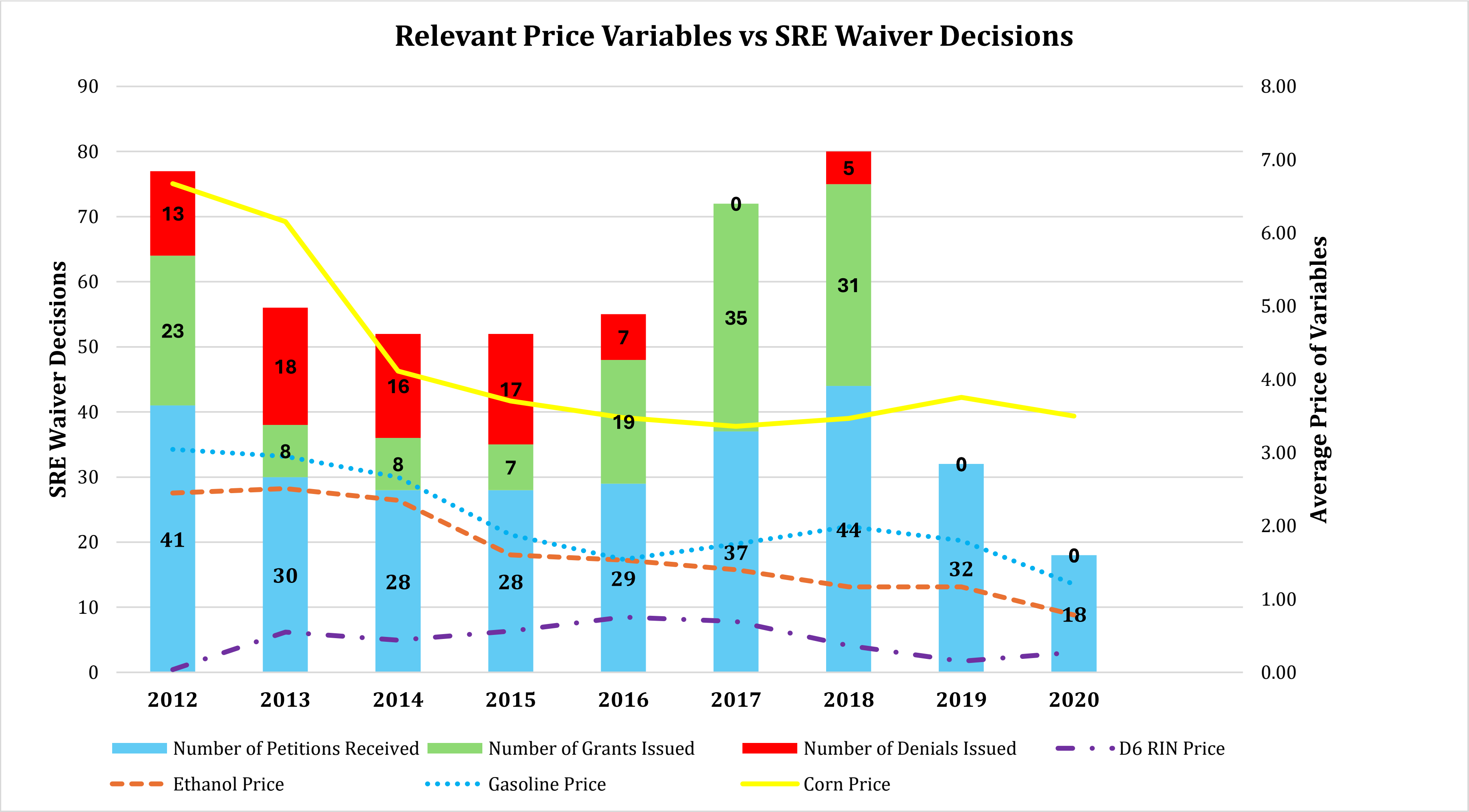


Note: In addition to Number of Petitions Received, Number of Grants Issued, and Number of Denials Issued, The EPAs data page also reports The Number of Petitions declared ineligible, The Number of Petitions Withdrawn, and the Number of Petitions Pending which are not included in the figure.

Figure 1. Price Variables and SRE Waiver Decisions

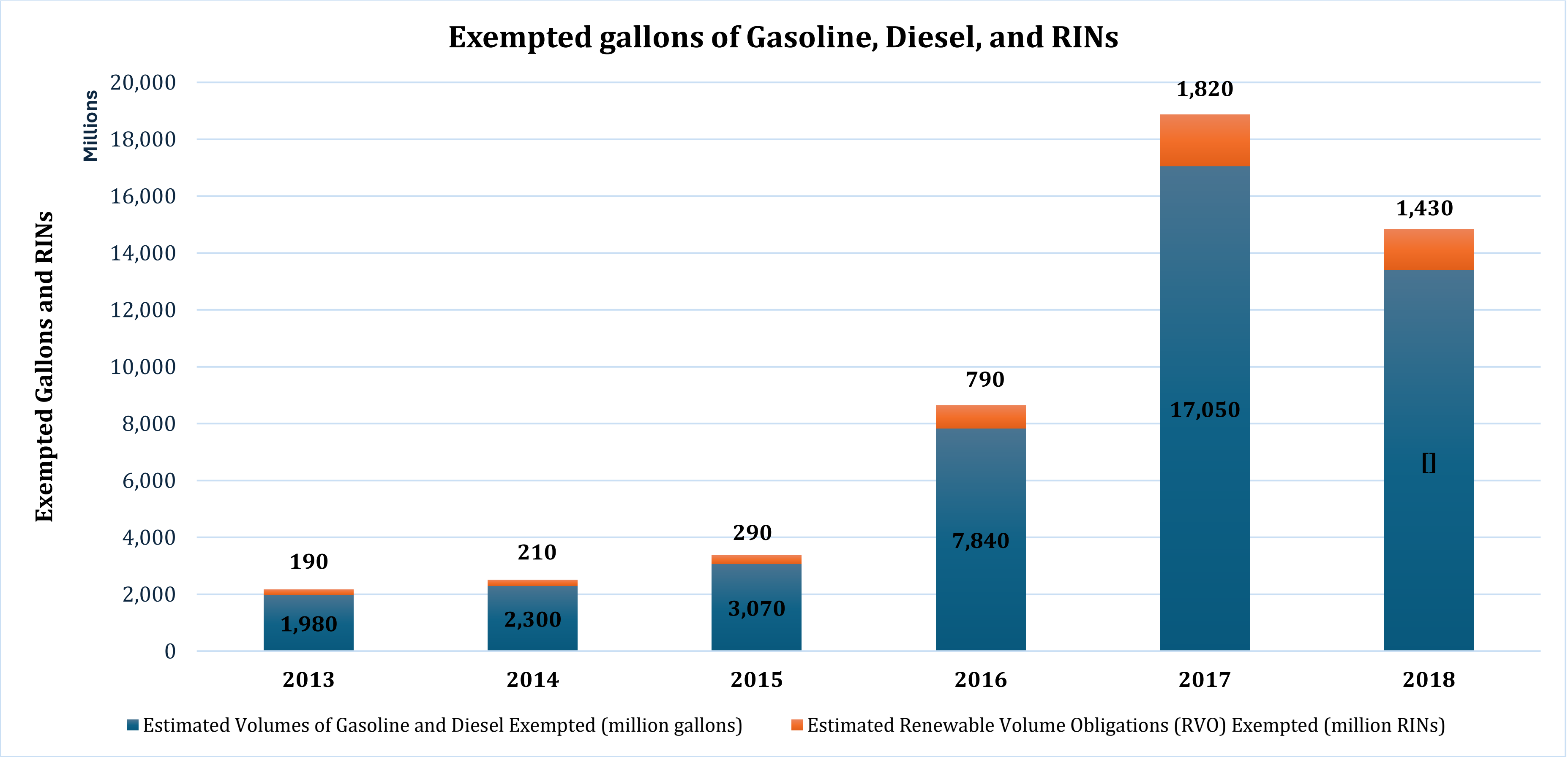
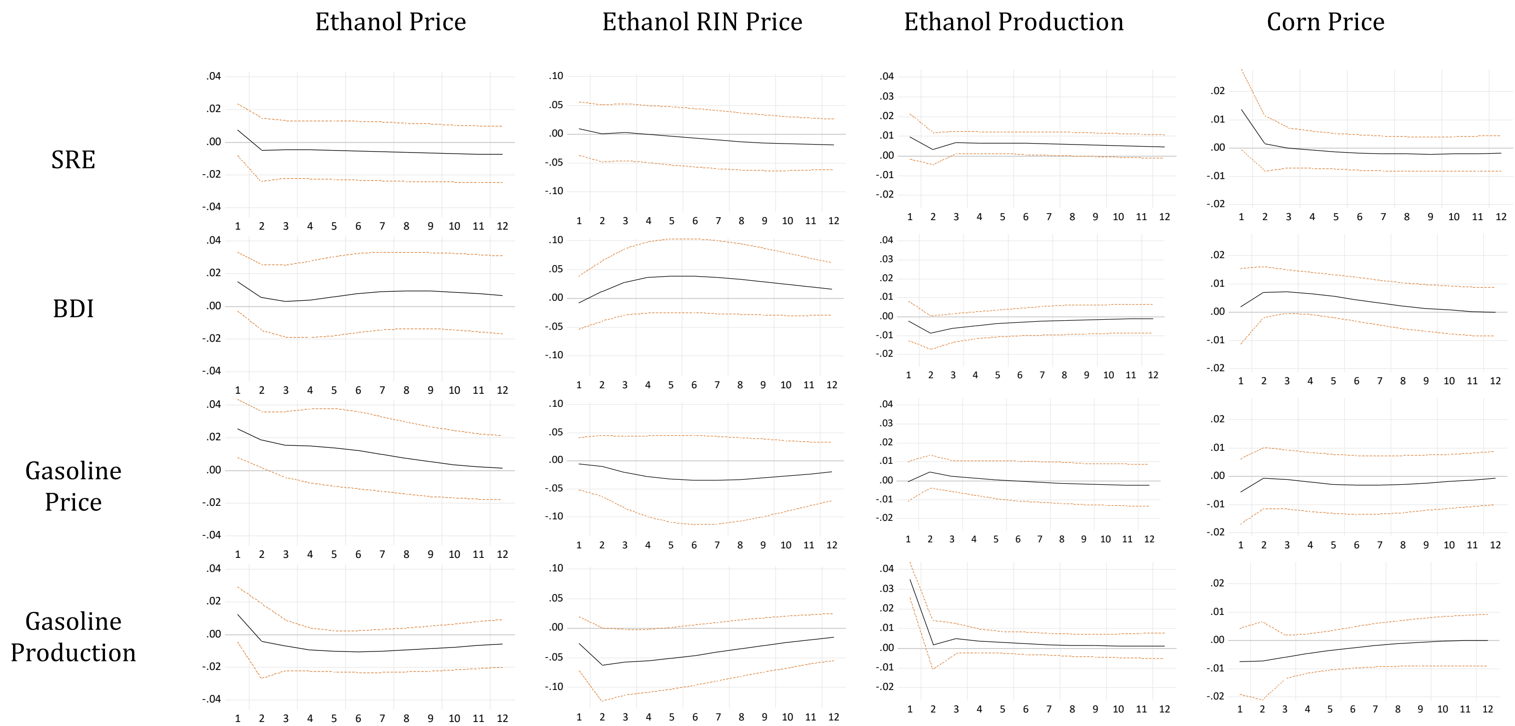


Figure 2. Exempted gallons of Gasoline, Diesel, and RINs



Note: Monte Carlo standard errors are used for each set of impulse response graphs. For our IRF graphs, the solid line of the graph represents a one standard deviation magnitude of the shock, and the dotted lines represent the standard error confidence bands at a 95% significance level.

Figure 3. Impulse Response graphs for SVAR

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev	Minimum	Maximum
Ethanol price ($/gal)	1.56	0.17588	1.03	2.05
Gas price ($/gal)	2.43	0.25325	2.02	2.82
Corn price ($/bushel)	3.73	0.22299	3.35	4.37
D6 (corn ethanol) RIN price	0.55	0.20059	0.07	0.99
Gas production (Thousand barrels/day)	278517	14326.7	235070	303123
Ethanol production (Thousand barrels/day)	29713	2322.08	22494	33773
Baltic Dry Index	109.14	26.4482	82.89	200.14
SRE (Exempted volumes million gallons)	634.17	488.635	165.00	1420.83

Table 2. Unit Root Tests

Variable	ADF level	PP level	ADF 1st - diff	PP 1st - diff
SRE waiver	-1.464	-1.473	-10.216***	-10.216***
Baltic Dry Index (BDI)	-2.869	-2.812	-10.969***	-11.017***
Gas Price	-0.700	-3.885**	-4.366***	-6.006***
Gas Production	-2.361	-5.023***	-7.626***	-20.835***
Ethanol Price	-3.826**	-3.831**	-11.757***	-12.718***
Ethanol Production	-5.004***	-4.971***	-3.916***	-32.039***
D6 RIN Price	-2.013	-2.026	-7.125***	-7.241***
Corn Price	-5.912***	-5.885***	-4.574***	-51.584***

Note: The null hypothesis of ADF and PP test is there is a unit root in an AR model, the alternative hypothesis is that variable was generated by a stationary process.

Table 3. Variance Decomposition of Ethanol Price

Variance Decomposition								
Period	S.E.	**SRE**	**BDI**	**Gasoline Price**	**Gasoline Production**	**Corn Price**	**Ethanol Production**	**Ethanol RIN Price**
Ethanol Price:								
1	0.07	**1.14**	**4.48**	**12.97**	**2.98**	**0.22**	**5.02**	**8.27**
		(3.58)	(4.85)	(7.02)	(4.16)	(2.07)	(4.08)	(5.02)
12	0.11	**3.74**	**7.01**	**17.02**	**7.61**	**1.99**	**14.15**	**4.27**
		(4.09)	(5.94)	(9.44)	(5.48)	(3.43)	(7.45)	(4.00)
60	0.12	**8.34**	**7.18**	**15.98**	**7.57**	**1.95**	**13.44**	**5.36**
		(9.85)	(7.55)	(9.74)	(5.74)	(4.29)	(7.55)	(7.13)
Ethanol RIN Price:								
1	0.05	**0.26**	**0.13**	**0.08**	**1.77**	**0.80**	**2.41**	
		(2.70)	(2.57)	(1.89)	(3.27)	(2.82)	(3.99)	
12	0.11	**0.76**	**5.02**	**4.22**	**10.12**	**7.13**	**13.71**	
		(5.22)	(7.83)	(8.07)	(8.01)	(6.75)	(9.56)	
60	0.11	**2.36**	**5.04**	**4.49**	**9.96**	**7.12**	**13.41**	
		(10.98)	(8.14)	(8.96)	(7.83)	(6.54)	(9.43)	
Ethanol Production:								
1	0.08	**5.25**	**0.26**	**0.01**	**66.30**	**2.50**		
		(4.85)	(2.35)	(1.73)	(6.77)	(2.27)		
12	0.14	**15.52**	**5.56**	**1.68**	**42.54**	**9.87**		
		(8.24)	(5.98)	(4.84)	(8.78)	(5.33)		
60	0.14	**18.95**	**5.30**	**3.52**	**37.79**	**8.64**		
		(13.62)	(6.73)	(7.85)	(11.66)	(5.73)		
Corn Price:								
1	0.14	**7.57**	**0.17**	**1.20**	**2.23**			
		(7.51)	(2.11)	(3.34)	(3.13)			
12	0.47	**6.65**	**6.82**	**2.47**	**5.75**			
		(5.74)	(6.63)	(4.74)	(5.29)			
60	0.61	**7.09**	**6.74**	**2.63**	**5.69**			
		(7.89)	(6.80)	(6.41)	(5.71)			

Note: This table depicts results of variation decomposition of our SVAR model based on Cholesky Ordering. The table shows decomposition results for 1 month, 12 months, and 60 months (5 years). Values in parentheses indicate standard error estimates.

China’s Changing Demand for U.S. Agricultural Commodities: Structural Change In China’s Import Demand for Meat, Grains, and Oilseed Crops

Abstract: This study examines the shifts in China's import demand for key agricultural commodities—soybeans, pork, poultry, corn, and cotton—following significant trade policy changes, including the imposition of retaliatory tariffs by China and the subsequent Phase One Trade Agreement with the United States. Employing an Inverse Almost Ideal Demand System (IAIDS) model, we analyze the price and scale flexibilities to understand the commodities' demand responsiveness. The results reveal a nuanced picture of demand shifts, suggesting both immediate and potentially enduring changes in China's import patterns, with significant increases in market shares for alternative suppliers like Brazil, Argentina, and Ukraine during the tariff period, some of which persist post-agreement. The findings suggest realignments in global trade networks, altering traditional supply chains. The commodities are identified as necessities, indicating that increased spending in China does not proportionally increase quantity demanded, affecting global agricultural markets and trade policies. Structural changes assessed via Likelihood Ratio Test show varied impacts across commodities and periods.

Keywords: International Trade, Tariffs, Phase One Trade Agreement, Demand Analysis
JEL classification: Q17, Q18

1. Introduction

The trade relationship between China and the United States, in the agricultural sector, has been both significant and complex. In 2017, U.S. agricultural exports to China surpassed $20 billion, underscoring the critical role these exports play in the U.S. economy. This relationship, however, faced substantial disruptions in 2018 when China implemented retaliatory tariffs on a wide range of U.S. food and agricultural exports. This move was in response to the U.S. imposing tariffs under Section 232 of the Trade Expansion Act and Section 301 on Chinese goods. The ensuing trade tensions had profound implications for U.S. agriculture, affecting not only farmers but also the broader network of businesses involved in the agricultural supply chain, including processors, distributors, and shippers.

The imposition of retaliatory tariffs led to reduced demand and lower prices for U.S. agricultural products, significantly impacting the sector's revenue and contributing to broader economic challenges within rural communities. In January 2020, a pivotal shift occurred with the Phase One Trade Agreement, marking a commitment by China to increase its purchases of U.S. agricultural commodities. This development presents a critical juncture to assess the impact of trade policies on agricultural trade flows between the two nations.

This paper seeks to evaluate the dynamics of China's import demand for key U.S. agricultural commodities—grains, oilseeds, and meats—across three distinct periods: prior to the imposition of retaliatory tariffs, during the tariff period, and following the initiation of the Phase One Trade Agreement. Employing the Inverse Almost Ideal Demand System (IAIDS) model, this study aims to identify import demand flexibilities for these commodities and to detect any structural changes in China's import demand for U.S commodities over these intervals. The novelty of this research lies in its detailed examination of the shifts in trade dynamics and demand responsiveness to price and income changes, facilitated by the IAIDS model's robust analytical framework.

By shedding light on the impact of retaliatory tariffs and subsequent trade agreements on China's import demand for U.S. agricultural commodities, this analysis should offer valuable insights for policymakers, industry stakeholders, and those interested in international trade relationships. It aims to contribute to a deeper understanding of the evolving U.S.-China trade relationship and its implications for the agricultural sector, highlighting the importance of policymaking in navigating these complex international trade interactions.

2. Background

U.S – China Trade War

In 2018, the United States imposed trade actions on China, leading to retaliatory trade restrictions and a significant decline in trade between the two countries. Talks of a trade war with China began when former U.S. President Donald Trump imposed tariffs on steel and aluminum imports in March 2018, followed by tariffs on selected imports from China in July 2018. China responded with retaliatory tariffs on nearly all U.S. imports, including agricultural products. By September 2019, China had imposed tariffs on 1,053 different U.S. food and agricultural tariff lines (Regmi, 2019).

Historically, China had become a significant export market for U.S. agricultural commodities before the restrictions. Figure 1 shows the total value of U.S. agricultural product exports to five different trade partners—China, Mexico, Canada, Japan, and the EU28 from 2000 to 2023. China showed a relatively rapid growth in terms of the value of U.S. agricultural exports, starting from around 2006. We observe the substantial decline in U.S. exports to China around 2018, primarily influenced by the trade war and retaliatory tariffs, explaining the volatility. The peak we observe in 2023 might be an indicator of recovery from these trade disruptions as a result of the Phase One trade agreement. Overall, we can clearly see the impact that the tariffs had on U.S. agricultural exports to China. The value of exports fell from around $19 billion in 2018 to around $9 billion, dropping China to the fifth largest importer of U.S. agricultural products in 2019. U.S. agricultural exports towards other trading partners such as Canada, Mexico, Japan, and the European Union showed more steady growth suggesting consistent growth in trade among trade partners in the North American Free Trade Agreement (NAFTA).

In January 2020, the U.S. and China signed the Phase One trade agreement, requiring structural reforms and changes in China's economic and trade arrangements, including its agriculture sector. The goal under the agreement is to increase American farm and fishery income, generate economic activity in rural communities, and promote job growth. Specifically, China's commitment to substantial purchases of U.S. goods and services was vital to the deal. Despite trade tensions and the history of trade disputes, the economic interdependence between the U.S. and China has shown resilience and growth. In 2022, it was reported that trade between the U.S. and China reached nearly $690 billion. This record-setting trade volume occurred amidst continuing tariffs, showing the enduring connection between the two countries despite efforts to decouple their economies (Palmer, 2023). Moreover, the U.S. regained its status as China's largest export market towards the end of 2023, indicating gradual stabilization in trade relations (Weiwen, 2023). These developments in trade behavior between the two countries reflect dynamic adjustments and recalibration within the global trade dynamics between the U.S. and China.

China Import, Export, and Domestic Trends

China became a member of the World Trade Organization (WTO) in December 2001. The WTO both regulates and facilitates international trade between countries. The organization's primary role is to establish and enforce international trade laws and regulations. For the past decade, China has been the world's largest exporter of goods. This expansion in exports by China started largely after China acceded to the WTO and has continued today. There has also been an expansion in imports from many countries to China. The accession of China to the WTO also reduced their tariffs, with many countries opening market access to China.

Figure 2 shows the value, in U.S. dollars, of various agricultural commodities imported by China from the United States over 2000 to 2023.We see general upward trend in the total value of agricultural commodities imported by China from the U.S. from 2000 to around 2014 followed by a period of volatility. From the figure, we see that soybeans have been a prominent agricultural import from the U.S. by China and the most significant portion of the imports for the entire period. We also observe a sharp decline around 2018, corresponding to the period of retaliatory tariffs imposed by China. The subsequent recovery around 2020 could be linked and attributed with start of the Phase One trade agreement with China purchasing certain amounts of U.S. agricultural products as agreed upon in the deal.

Additionally, there have been other contributing factors driving agricultural and economic expansion in China. For meat products, changes in consumer preferences, movement of people to urban centers, eating out more in restaurants, and growing consumer incomes, have been key contributing factors to this growth (Zhang et al. 2018, Zhang et al. 2020). For grains and oilseeds, growth in imports was likely due to increased demand for feed due to China's growing livestock sector (Bai et al., 2020, Gale et al., 2019, Sheng et al., 2019). China's livestock sector has grown exponentially in the past few decades and has seen much expansion, especially in the dairy, hog, and poultry sectors (Patton 2017, Qian et al. 2018, Hu et al. 2017, Fuller et al. 2006, Mo et al. 2012).

China has also experienced economic shocks within its agricultural markets in recent years, specifically in the pork sector. China is the world's largest pork consumer, and African swine fever in the domestic market caused significant disruptions in the country's pork sector (Ma et al., 2021, Mason-D'Croz et al., 2020). In August 2018, China lost a significant portion of its domestic pork supply due to African swine fever. With the losses suffered in the domestic pork market, China was forced to import pork from other countries, such as countries in the European Union, Brazil, and the U.S. (Haley and Gale 2020). Analyzing structural change in China's pork imports is of interest because even with the implementation of the retaliatory tariff, imports of U.S. pork to China remained steady.

Regarding other prominent commodities such as soybeans, the U.S. has been the second-largest exporter of soybeans to China, following Brazil, exporting more than a third of its soybean production to China. Theoretically, China's imposition of a tariff on U.S. soybeans should result in the Chinese consumers paying a higher price for soybeans imported from the United States. Regarding other essential agricultural commodities, the U.S. is the largest producer of corn globally, and China has been a large importer.

General Overview of Grain and Oilseed Crop Import Trends

China's import trends for corn, cotton, and soybeans have also seen notable shifts over the past few decades, influenced primarily by expansion of domestic production capacities, global market dynamics, changing consumer preferences, and the demands of its growing livestock sector. China's escalating demand for corn is primarily driven by its expanding livestock industry, which relies heavily on corn as a key feed component. Despite being a significant producer, domestic restrictions on production and the necessity to ensure a stable feed supply have led to a growing trend in corn imports. This may reflect broader shifts in agricultural practices and consumer trends, highlighting the strategic adjustments made by China to meet its domestic demands.

Additionally, China stands as the world's foremost producer and consumer of cotton, however the landscape of its cotton imports has evolved in response to domestic needs, fluctuations in global cotton prices, and shifting demands within the country's vast textile industry contributing to the need to engage with international markets to stabilize its textile sector. Lastly, the surge in soybean imports into China is largely attributed to the country's robust livestock industry and an increasing demand for high-protein animal feed. This surge has positioned China as the largest global importer of soybeans, with a significant share of its imports sourced from countries like Brazil and the United States. The expansion in soybean imports exemplifies the strategic initiatives to support the country's agricultural sector and meet the nutritional requirements of its livestock industry.

Overall, the dynamics of China's import trends for grains and oilseed crops are shaped by a multifaceted array of factors, including domestic agricultural capabilities, consumer dietary shifts, global market conditions, and the evolving needs of its livestock and textile industries. Trends like this reflect the country's adaptability to changing domestic and international landscapes and its growing influence on global agricultural markets.

General Overview of Meat Import Trends

China's meat import trends have also undergone significant transformations over recent decades, driven by factors including evolving consumer preferences, domestic production adjustments, economic growth, and health crises. For pork, traditionally the most consumed meat in China, has seen substantial changes in its import patterns. To meet the surging domestic demand, China has increased its pork imports from countries such as the European Union, the United States, Canada, Brazil, and Chile. The domestic pork industry faced significant challenges, particularly when the outbreak of African Swine Fever (ASF) occurred over 2018-2021, which decimated China's pig population, leading to shortages and heightened pork prices. Consequently, the ASF outbreak has profoundly influenced China's pork import strategy in recent years.

Additionally, the poultry sector has also witnessed a consistent rise in consumption, attributed to its affordability. However, the domestic poultry industry has also faced challenges, outbreaks of diseases such as avian influenza, have hampered production and increased reliance on imports. Key suppliers of poultry to China include Brazil, the United States, and Argentina. Overall, these shifts in meat import patterns reflect China's evolving dietary landscape, marked by increased meat consumption and global trade dynamics within the domestic livestock industry.

3. Literature Review

Previous studies have examined China's import demand for various commodities, including grains, oilseeds, and meats, to understand the factors influencing China's import trends, the impact of trade policies and tariffs, and changes in consumer preferences. Carvalho et al. (2018) investigated the impact of China's retaliatory tariffs on the United States, specifically focusing on the agricultural sector. They found that these tariffs significantly reduced U.S. agricultural exports to China, negatively impacting the U.S. agricultural economy and highlighting the immediate economic pressures faced by U.S. farmers due to decreased access to one of their largest export markets. Similarly, Li et al. (2018) examined the effects of trade tensions on China's soybean imports from the United States, indicating a strategic shift in China's import behavior towards alternative sources like Brazil to mitigate the tariff impact on its soybean supply chain.

Taheripour et al. (2018) assessed the broader implications of trade disputes on global agricultural markets, concluding that such disputes could lead to significant disruptions, affecting not only direct participants but also other countries through changes in global trade flows and prices. Waugh (2019) explored the consequences of trade policies on U.S. soybean exports to China, revealing considerable losses in export revenue for U.S. soybean farmers and underscoring the vulnerability of agricultural exports to geopolitical tensions. Zheng et al. (2018) analyzed the effects of China's retaliatory tariffs on agricultural products, including grains and oilseeds, finding that these tariffs would lead to a reconfiguration of global agricultural trade patterns, potentially disadvantaging U.S. producers while benefiting those from non-tariffed countries.

Bai et al. (2020) focused on the increase in China's grain and oilseed imports, attributing this growth to the rising demand for feed due to the country's expanding livestock sector. They predicted that China's continued economic development and dietary shifts towards more meat consumption would sustain high levels of import demand for these commodities. Collectively, these studies provide a comprehensive overview of the factors influencing China's import trends and the consequences of trade policies on global agricultural markets, highlighting the adjustments made by China in response to trade tensions, and the economic fallout for U.S. agricultural exporters.

Additionally, studies have analyzed China's import trends for meats like beef, pork, and poultry. Hu et al. (2017) delved into the expansion of China's livestock sector, noting significant growth in the dairy, hog, and poultry sectors, which has increased China's demand for meat imports due to urbanization, rising incomes, and changing dietary preferences. Zhang et al. (2018) aimed to understand the dynamics behind China's growing meat imports, finding that consumer preferences, urbanization, and increasing incomes play critical roles in driving the demand for meat imports, particularly pork.

Focusing on the impact of the African swine fever (ASF) outbreak in 2018, Ma et al. (2021) analyzed the substantial disruptions it caused to China's pork sector. The outbreak led to a sharp decline in hog inventory, resulting in significant price increases and a push for government interventions. The study suggested that diversifying subsidies to include chicken farms could reduce pork prices more efficiently and save government expenditure, highlighting the significant disruptions caused by the disease and the increased reliance on imports from countries such as the European Union, Brazil, and the United States. These studies help us gain a meaningful overview of the factors influencing China's meat import trends by identifying the role and importance of understanding consumer behavior, economic policies, and health crises in shaping the global meat trade. The study performed in this paper seeks to elaborate on and further expand work done in this area to gain better understanding of these changing market dynamics especially for U.S. commodities.

4. Methodology

Modeling Import Demand

Studies analyzing import demand often employ a range of econometric models, among which the Almost Ideal Demand System (AIDS), introduced by Deaton and Muellbauer (1980), has been widely used due to its proven utility in various applications. The model is often used to estimate key elasticity measures, such as price and income elasticities, making it foundational in trade analysis research (Kiawu & Jones, 2013; Baldwin & Jones, 2013; Prokeinova et al., 2016).

Building on this approach, the Inverse Almost Ideal Demand System (IAIDS) was developed by Moschini and Vissa (1992) and expanded by Eales and Unnevehr (1993). IAIDS modifies the AIDS framework to provide a more nuanced specification tailored for detailed import demand analysis. This model enhances methodological flexibility, facilitating the estimation of own- and cross-price flexibility and scale flexibility, thus offering a comprehensive view of market responses to economic changes.

IAIDS is adept at directly incorporating external economic variables like exchange rates into demand equations, enriching the analysis of macroeconomic impacts on source-specific import demand (Jones, Muhammad, & Mathews Jr., 2013). Its non-linear specification captures the complex responses of import demand to price and income variations effectively, also allowing for the consideration of seasonal demand fluctuations (Baldwin & Jones, 2013).

In the case for our analysis the IAIDS approach is particularly suited for analyzing China's agricultural import demand under varying trade policies. IAIDS focuses on direct quantity modeling, which is useful for examining how China's import quantities respond to price changes and policy shifts. It enhances the ability to differentiate sources and incorporate additional economic variables such as exchange rates and tariffs directly into the demand equations, offering a more nuanced analysis of source-specific import dynamics. Furthermore, IAIDS's capability to handle non-linear responses and seasonal variations provides a comprehensive view of the complex market behaviors induced by trade policies, making it a more ideal choice than the standard AIDS approach for our in-depth analysis of structural changes in China’s import patterns in response to regulatory tariffs and trade agreements.

To provide some insights, we will examine changes in U.S. commodity exports to China relative to major competitors' pre-retaliatory tariff, following the imposition of the tariffs, and after the start of the Phase One trade agreement. Following (Eales and Unnevehr 1994, Nguyen, 2012, Jones, Muhammad, & Mathews Jr., 2013) We develop the model as follows.

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln q_j + \beta_i \ln Q \qquad (1)$$

where wi is the expenditure share of the ith commodity, qj is the demanded quantity of commodity j, and ln(Q) is the logarithm of the quantity index which is defined by the equation (2).

$$, \ln Q = \alpha_0 + \sum_j \alpha_j \ln q_j + 0.5 \sum_i \sum_j \gamma_{ij} \ln q_i \ln q_j \qquad (2)$$

which aggregates the demanded quantities into a single index. Here equation (1) is represented as the non-linear inverse AIDS specification, and utility maximization requires that the estimated coefficients and parameters satisfy certain restrictions. These restrictions on the demand system (adding up, homogeneity, and symmetry) are expressed as follows:

Adding up, $\sum_i \alpha_i = 1, \sum_i \gamma_{ij} = 0, \sum_i \beta_i = 0$, restriction satisfied

Homogeneity, $\sum_j \gamma_{ij} = 0$, restriction satisfied.

Symmetry, $\gamma_{ij} = \gamma_{ji}$ for any $i \neq j$, restriction satisfied.

Together both equations (1) and (2) determine the nonlinear structure of the inverse demand system. The structure of the quantity index mirrors that of the price index as originally proposed by Deaton and Muellbauer. When applied within the AIDS framework for pricing and within the Inverse AIDS (IAIDS) for quantities, these indices facilitate the creation of entirely linear models, simplifying the estimation process. The estimation of inverse demand systems quantifies the relationship between price and quantity through the concept of flexibilities, as introduced by (Houck1966). Flexibilities serve a similar interpretative purpose to elasticities, as discussed by (Eales and Unnevehr 1994). Specifically, price flexibility in inverse demand models indicate the percent change in prices resulting from a 1% change in the supplied quantity of country i. The derivation of these flexibilities comes from differentiating equation (1) with respect to the natural logarithm of quantity j resulting in the following flexibilities:

own and cross price flexibility: $f_{ij} = -\delta_{ij} + \frac{\{\gamma_{ij} + \beta_i(w_j - \beta_j \ln Q)\}}{w_i}$, (3)

scale flexibility: $f_i = -1 + \frac{\beta_i}{w_i}$ (4)

where fij and fi are price and scale flexibilities, respectively; δij is the Kronecker delta (δij=1 for i=j, and δij=0 otherwise); the terms on the right-hand side are taken from equations (1) and (2).

From (Eales and Unnevehr 1994; Park and Thurman 1999), a commodity is called "inflexible" when a 1% increase in its consumption leads to less than a 1% increase in the marginal value of that consumption. This concept is similar to the idea of inelastic demand, where quantity demanded is not very responsive to price changes. A commodity's demand is considered to be inelastic when its own-price flexibility does not exceed 1 in absolute value. Furthermore, commodities are identified as gross quantity substitutes if their cross-price flexibilities register as negative. In contrast, they are considered gross quantity complements when their cross-price flexibilities are positive. Cross price flexibility measures how the quantity demanded of one good (a commodity) responds to the price change of another good. If cross price flexibility is negative, the two goods are "gross substitutes" so an increase in the price of one decrease demand for the other. If positive, they are "gross complements" an increase in the price of one increase demand for the other.

Scale flexibility pertains to how expenditures affect consumption when consumer preferences are homothetic. Homothetic preferences mean that the consumer's preferences remain proportionally consistent as their income or total expenditure changes. When the expenditure increases by 1%, the amount spent on each good should also increase by 1% for the consumer to achieve a new consumption bundle that maintains the same proportion of spending on each good. This requires scale flexibilities to be -1, reflecting a proportional change in quantity demanded across all goods relative to the change in income or expenditure. In terms of scale flexibility, when the absolute value of the flexibility is greater than 1, the commodity is considered a necessity. However, if the flexibility is less than 1 in absolute terms, the commodity is classified as a luxury good. Observing scale flexibilities will help us understand the change in the consumer's budget allocation to different goods as their total expenditure changes.

One key component in our analysis into China's import demand involves incorporating two dummy variables into the IAIDS model to account for structural changes during specific periods. These variables include a policy dummy for the time frame when retaliatory tariffs were in effect (Dummy variable D1) and another for the duration of the Phase One trade agreement (Dummy variable D2). By including these dummy variables, we aim to control for structural shifts that occurred over these distinct periods. To evaluate structural changes associated with both the retaliatory tariff and Phase One trade agreement phases, we conduct comparisons between models capturing the log-likelihood values in the model results across each specification. Specifically, we contrasted a unrestricted models, incorporating the dummy variables for the specified periods, against a restricted model that excludes these variables. For the retaliatory tariff phase, the analysis involved comparing the unrestricted model, containing dummy variable D1, against the restricted model devoid of dummy variables. Similarly, for the Phase One trade agreement phase, we compared the unrestricted model, inclusive of dummy variable D2, against the restricted model lacking dummy variables. Additionally, to assess structural changes encompassing both periods simultaneously, we juxtaposed the unrestricted model, which includes both D1 and D2 dummy variables, against the restricted model that omits these variables.

We obtain the full information maximum likelihood values from the models to collect the log-likelihood function information in our results. These values help us facilitate the use of the log-likelihood ratio test to compare the fit of the unrestricted models against the restricted model, thereby determining the presence of structural changes. Following (Kiawu and Jones 2013) the likelihood ratio test can be used to determine if the model including dummy variables is significantly different from that of the restricted model and is given as:

$$LR = -2[L(\tilde{\beta},\tilde{\sigma}^2) - L(\hat{\beta},\hat{\sigma}^2)] \sim X_m^2 \qquad (5)$$

where $L(\tilde{\beta},\tilde{\sigma}^2)$ is the maximum of the log likelihood function when the restriction is imposed, $L(\hat{\beta},\hat{\sigma}^2)$ is the maximum of the log likelihood function when the restrictions are not imposed, and *m* is the number of restrictions.We will test to see whether the calculated or observed values are statistically significant by comparing it with the tabular value in the Chi-square chart. Based on these results we are able to infer whether a structural change in China's import demand for U.S commodities has occurred.

5. Data

We use price and quantity data on pork, poultry, corn, cotton, and soybean imports to China for this study. Quarterly data for each commodity is collected over the pre-tariff, retaliatory tariff, and post tariff (Phase One trade agreement) periods. In addition to U.S. exports, we identify two significant exporters for each commodity and include estimates for the rest of the world (ROW). Harmonized System (HS) of each commodity classification is in parentheses. Quarterly Import data for corn (1005) and pork (203) starts from 2012. For cotton (52), soybeans (1201) quarterly import data starts from 2000, and poultry (105, 207) quarterly import data starts from 1995. In addition to the U.S., For pork, we include import estimates for Brazil and Chile. For poultry, we include Argentina and Brazil. For corn, we identify Ukraine and Argentina as exporters. For cotton, we include Australia and India, and for soybeans, we include Brazil and Argentina. We obtained data from Trade Data Monitor, which collects import and export data and statistics from customs agencies and institutes worldwide and represents trade values at the wholesale level.

Descriptive statistics for China's import share for each commodity over the pre-tariff, retaliatory tariff, and post-tariff periods are presented in Table 1. For our study, we identify the pre-retaliatory tariff period as the years prior to March 2018. We identify the period that the retaliatory tariffs imposed by China on the U.S. to be between April 2018, when the tariffs began up to when the Phase One Trade Agreement began in January 2020.

Table 1 presents the landscape of China's agricultural imports, focusing on the import shares of the commodities of interest across three distinct time periods the pre-retaliatory tariff phase, retaliatory tariff phase, and Phase One trade agreement phase. These periods mark significant shifts in trade policy and reflect the periods where structural change in Chinas import demand have likely taken place. From Table 1 we observe fluctuations in trade dominance among exporting countries before and after China's imposition of retaliatory tariffs and the subsequent trade agreement. For instance, in the pork sector, the United States experienced a decline from a modest 17% to 10% during China's retaliatory tariffs against the United States. It then slightly improved to 12% following the Phase One trade agreement. Meanwhile, Brazil, another key player in the pork market, saw its share rise significantly from 2.61% to 11.68% during the tariff period, maintaining a solid presence of 16.54% after the agreement.

In the poultry and soybean markets, similar patterns emerge. The U.S. poultry market share decreased from 56.42% to 25.81% under retaliatory tariffs, with a negligible recovery to 25.86% post-agreement. Brazil, conversely, increased its share considerably from 27.16% to 43.34% and slightly declined to 45.49% after the Phase One trade agreement. In the soybean market, the U.S. witnessed a dramatic fall from 40.17% to 19.02% during the retaliatory phase, which then rose to 28.57% post-agreement. Brazil's soybean share ascended from 41.65% to a dominant 70.10%, slightly receding to 64.03% following the agreement.

Corn and cotton markets also displayed shifts, with Ukraine gaining an impressive lead in corn exports to China during the tariff period and India seeing an increased share in cotton imports. Overall, these shifts seem to highlight the significant impact that trade agreements and tariffs can have on global trade dynamics. Particularly, it is interesting to observe how retaliatory measures like the tariffs imposed on the U.S. by China can redirect trade flows towards alternative sources, adjusting shares across different commodities in response to changing trade landscapes.

6. Results

Table 2 presents uncompensated price flexibilities (Marshallian) from our restricted Inverse Almost Ideal Demand System model; the flexibilities can essentially be interpreted similar to that of price elasticities of demand that measure how the quantity demanded of a good respond to a change in its own price and the price of other goods. For the U.S. we observe an own-price flexibility of -0.948 suggesting that a 1% increase in the price of U.S. soybeans leads to a decrease in demand by approximately 0.948%. This shows a nearly proportional but slightly inelastic response. Brazil and Argentina are substitutes for U.S. soybeans since their flexibilities are positive when the price of U.S. soybeans changes. Brazil, with a cross-price flexibility of

0.0130, shows a small positive relationship with the U.S. soybean price. The estimate for ROW (Rest of the World) appears to be a strong substitute for U.S. soybeans, given the higher positive cross-price flexibility of 0.75 with Brazilian soybeans. It means if the price of Brazilian soybeans increases by 1%, the demand for soybeans from other countries increases by 0.75%.

In terms of cotton, the U.S. own-price flexibility is -1.011, indicating that demand is responsive and nearly proportionately elastic to price changes. Australia shows a high degree of substitution with the U.S., as indicated by the high positive cross-price flexibility of 2.254. However, the own-price flexibility of -4.726 suggests a very elastic demand for Australian cotton; if its price rises by 1%, the demand falls by 4.726%. For corn the U.S. has a slightly less than proportional own-price flexibility of -0.930. This implies a decrease in the quantity demanded by 0.930% for every 1% price increase, indicating an inelastic demand. For Ukraine corn has a substantial negative cross-price flexibility with respect to Argentinian corn (-0.875), suggesting that they are strong substitutes. However, Ukrainian corn has a positive cross-price flexibility with ROW, indicating a complementary relationship.

For meats starting with poultry, we observe that the U.S. own-price flexibility is -1.272, indicating a responsive and elastic demand. It implies a 1% increase in the price would lead to a 1.272% decrease in demand. Argentina, Brazil, and ROW show varying degrees of substitution and complementary relationship with U.S. poultry based on their positive and negative flexibilities. Lastly for pork, Brazil shows very high own-price elasticity of -4.806, indicating demand for Brazilian pork is highly sensitive to price changes. Additionally, ROW shows a very high cross-price flexibility with Brazil at 4.684, suggesting that if Brazilian pork becomes more expensive, consumers will substantially increase their demand for pork from ROW countries like Spain for instance.

Overall, our estimates indicate that the demand for U.S. soybeans is nearly proportional but slightly inelastic, indicating that price increases will slightly decrease demand but not drastically. Brazil and Argentina act as substitutes for U.S. soybeans, with Brazil showing a small positive relationship and ROW showing a stronger substitution effect. This implies that if U.S. soybean prices increase, some demand will shift to these other sources. The demand for U.S. cotton is nearly proportionately elastic, suggesting that price increases will significantly reduce demand. Australia's cotton acts as a strong substitute for U.S. cotton, which could be strategically important for exporters. The highly elastic demand for Australian cotton indicates that price increases would lead to substantial reductions in the quantity demanded. The demand for U.S. corn is inelastic, meaning price increases will not heavily reduce demand. Ukraine and Argentina show strong substitution effects, indicating competitive relationships in the global corn market. The elastic demand for U.S. poultry suggests that price increases will lead to notable reductions in demand. Varying degrees of substitution and complementary relationships with Argentina, Brazil, and ROW suggest complex competitive dynamics. The highly elastic demand for Brazilian pork means that price increases will significantly reduce demand. ROW pork acts as a strong substitute, indicating that price increases in Brazilian pork will lead to substantial increases in demand for ROW pork.

Scale Flexibility Calculations

Table 3 presents scale flexibility estimates for China's import demand for agricultural commodities. Scale flexibilities measure how the quantity demanded of a commodity responds to proportional changes in total expenditure. For soybeans the U.S., Brazil, and Argentina have scale flexibility measures of -1.0669, -0.8892, and -1.0369, respectively, while the Rest of the World (ROW) stands at -1.5014. We can interpret these results as all soybean sources are considered necessities, as all values are less than -1. This means that an increase in China's total expenditure on soybeans leads to a less than proportionate increase in the quantity demanded. The ROW's value suggests a stronger necessity relative to others due to the higher absolute value. For cotton the scale flexibility for the U.S. is -1.1576, indicating that U.S. cotton is a necessity in China. Australia and India present values close to -1, suggesting a similar categorization. However, ROW has a higher absolute value, implying a stronger response to changes in expenditure for cotton. Regarding corn all sources show scale flexibilities less than -1, categorizing them as necessities. The U.S. and ROW's values are closer to -1, with Ukraine and Argentina showing slightly lower values, indicating a relatively stronger necessity status. For poultry, all sources show values less than -1, with Argentina's elasticity being significantly lower, implying a greater necessity status. In contrast, for pork, U.S. pork is considered a necessity. The U.S. pork has a higher necessity character with a scale flexibility less than -1. Overall, the findings seem to imply that for most commodities, an increase in China's total expenditure does not lead to a proportionate increase in the quantity demanded for these imports, signaling their status as necessities rather than luxuries in China. These trade and import patterns are likely to persist unless there are significant changes that occur in China's economy preferences, or the relative prices of these goods. For policymakers, recognizing these patterns can be beneficial to help guide and influence trade agreements and domestic agricultural policies.

Overall, the results indicate that soybeans from the U.S., Brazil, Argentina, and ROW are considered necessities in China. This implies that increases in China's total expenditure on soybeans will lead to less than proportional increases in the quantity demanded. We determine that U.S. cotton and cotton from Australia and India are necessities, with ROW showing a stronger response to expenditure changes. This suggests stable demand patterns regardless of expenditure increases. Corn from all sources is considered a necessity, indicating stable demand even with changes in total expenditure. All sources of poultry are necessities, with Argentina showing a particularly strong necessity status. This implies that demand will not rise proportionately with increased expenditure, additionally for the U.S. pork is considered a necessity, indicating stable demand patterns, and highlighting its essential role in China's import basket.

Structural Change Calculations

Table 4 details the outcomes of the Likelihood Ratio Test conducted to evaluate whether structural change occurred in China's import tariffs on the demand over the Retaliatory Tariff Period, the Phase One Trade Agreement period, and both periods combined. The LR tests are used to compare the fit of two competing models, one that is nested within another, to determine if the more complex model significantly improves the fit.

For soybeans, there is strong evidence of the tariff impact. The highly significant LR values across all stages (Retaliatory Tariff Period, Phase One Trade Agreement period, and both periods combined) indicate that tariffs have significantly impacted soybean import demand in China. With cotton there is significant evidence of structural change during the Retaliatory Period and when both periods are combined suggesting that tariffs during these periods affected China's import demand for cotton. For corn, the lack of statistically significant results indicates that there were no substantial structural changes in China's imports of corn due to tariffs over the specified periods. in contrast, poultry saw significant results across all stages, particularly during the Phase One Agreement period, suggesting that tariff changes had a strong impact on poultry import demand. The test results for pork are mixed, there is evidence of tariff impact during the Retaliatory Period and when both periods are combined. However, the Phase One Agreement period alone does not show significant results, indicating that other factors might have influenced pork import demand during this time.

Looking at U.S. commodities specifically, the results indicate varying impacts of tariffs on U.S. exports of these commodities to China. For instance, tariffs did not significantly impact U.S. pork exports to China based on the LR test results. Similar to pork, U.S. corn exports to China are not significantly affected by tariffs. With U.S. poultry we see significant effects in certain periods. There are significant effects of tariffs on U.S. poultry exports during the retaliatory period and over both periods retaliatory tariff and phase one combined, indicating sensitivity to tariff changes. results for U.S. cotton indicate exports are not significantly affected by the tariffs. Additionally, U.S. soybeans display no impact from tariffs, suggesting that other factors (e.g., non-tariff barriers, domestic policies, or global market conditions) might have influenced import demand more significantly.

7. Discussion

The post-WTO era marks a notable increase in China's agricultural imports, demonstrating the critical role of globalization and policy decisions in transforming trade dynamics. Our analysis highlights immediate shifts in import shares during the retaliatory tariff period, such as the decline in the U.S. market share for pork and soybeans and the increase for Brazil and other countries reflecting tariffs' direct, short-term impact. Post-tariffs into the Phase One trade agreement phase suggest that some changes were more enduring than just responses to tariffs. For example, Brazil's increased share in the soybean and pork markets suggests that Chinese importers have established more robust supply chains with Brazil, potentially a longer-term realignment in global trade dynamics. This could be due to supply reliability during the tariff periods and better trade terms or relationships developed over this time.

Additionally, the degree of dependency China has on certain commodities from the U.S., such as soybeans and pork, where significant market share shifts were observed. The observed shifts in import shares and the identification of alternative suppliers like Brazil and Argentina for soybeans or Brazil and Chile for pork underscore attempts to reduce dependency on U.S. commodities. A key takeaway from our analysis reveals how trade realignments might become permanent if these new relationships are reliable and cost-effective when fueled by or influenced by ongoing geopolitical tensions. The increase in market share for countries like Brazil in the soybean market and Ukraine in the corn market during the retaliatory tariff period suggests that these countries have successfully capitalized on the opportunity to fill the gap left by the U.S. This points to the adaptability of global trade networks and markets, where alternative suppliers can quickly step in to meet demand.

The slight recovery in U.S. market shares over the Phase One agreement, although not to pre-tariff levels, coupled with the sustained presence of other competitors in the market, indicates resilience. This suggests that while China might revert some of its sourcing to the U.S., the diversification of its supply chain during the tariff period could help withstand future policy changes. Ultimately, our study demonstrates that short-term trade policy changes can lead to lasting shifts in global trade dynamics by forcing importers to explore and solidify new supply relationships. The degree of dependency on particular trade partners influences how dramatically these shifts might occur, and the adaptability and resilience of the global trade network play crucial roles in how effectively the market can respond to such changes.

8. Conclusion

The recalibration of China's import patterns in response to the retaliatory tariffs and Phase One trade agreement offers a unique learning opportunity for policymakers. For China, diversification of import sources, including Brazil and Argentina for soybeans and pork and Ukraine for corn, indicates a strategic shift to mitigate risks associated with over-reliance on any single foreign supplier. For U.S. policymakers, this shift underscores the need for creating more resilient trade relations that can withstand political and economic fluctuations. The shift in China's import sources can profoundly impact global commodity markets. Moving away from U.S. suppliers in favor of others not only influences market shares but also has the potential to alter global pricing mechanisms and supply chain structures. This realignment may induce greater competition among exporting countries, leading to price adjustments and changes in global supply and demand dynamics.

As China's trade policies evolve, considering a robust theoretical framework adds depth to the empirical findings. The theory of comparative advantage helps us to understand and explain the efficiency of trade based on specialization; however, tariffs can alter this landscape significantly. For instance, while the U.S. may have a comparative advantage in soybean production, tariffs have encouraged China to seek alternative sources like Brazil. In the wake of China's retaliatory tariffs and subsequent Phase One Trade Agreement, exploring the underlying economic theories may enrich our understanding of the shifts observed in import patterns and their broader implications. Theoretically, countries stand to gain by specializing in producing goods they can produce more efficiently and engaging in trade for other goods. However, tariffs disrupt this equilibrium. For example, tariffs may elevate the cost of imported goods, so the effects of tariffs may potentially erode the comparative advantage of trading partners, leading to market inefficiencies and potential increases in domestic prices.

Additionally, the impact of trade barriers like tariffs varies with the size of the economy. Large economies like China can leverage tariffs to influence global commodity prices and secure favorable trade conditions. By integrating economic theories like this into the paper's analytical framework, perhaps we can better grasp the comprehensive implications of China's trade policies on global trade dynamics. The theories provide the context for the empirical data and offer insight for how similar policies may unfold in other global contexts.

Lastly, future investigations to further address implications of this research topic will aim to dissect the varying impacts of tariffs and the Phase One agreement on different commodity markets. For instance, one thought is to explore the use of Smooth Transition Regression (STR) models to calculate the speed of adjustment of policy changes. A deeper understanding in this area could yield more profound insights into the economic and policy mechanisms influencing trade, thereby aiding the development of more informed and effective trade policies and negotiation strategies.

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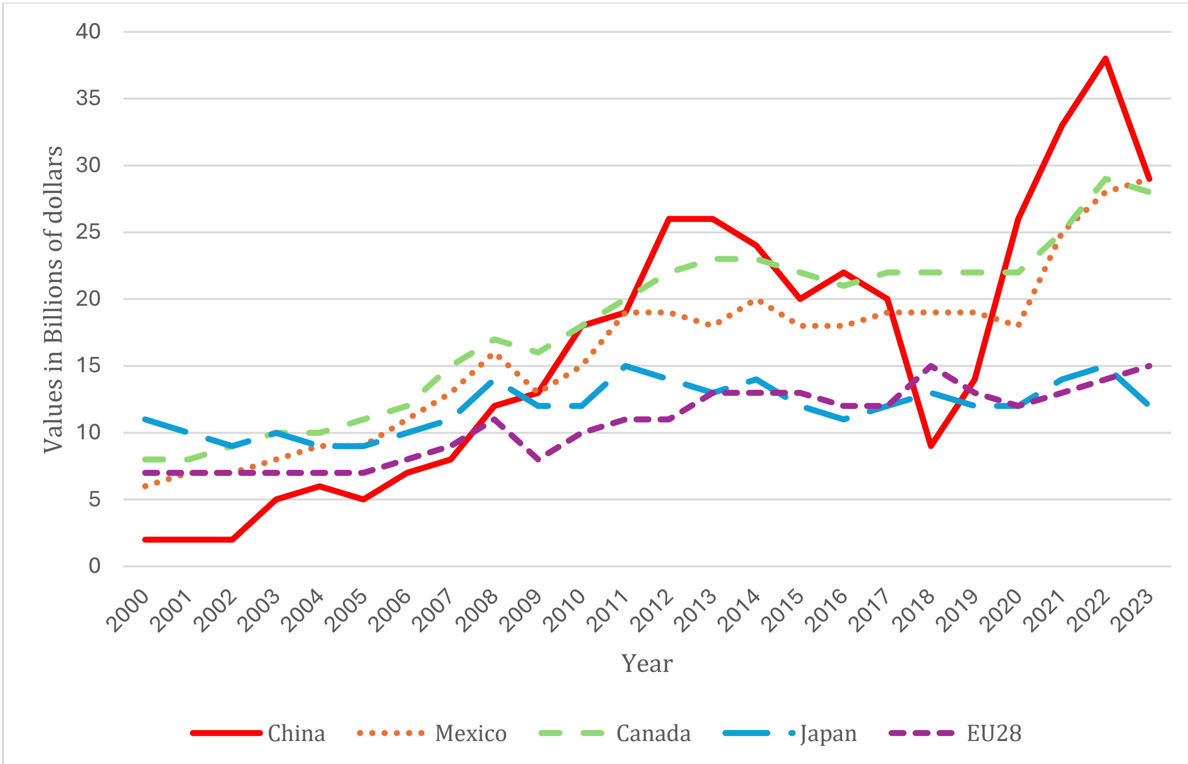

Figure 1. U.S. Total Agricultural Product Exports 2000-2023

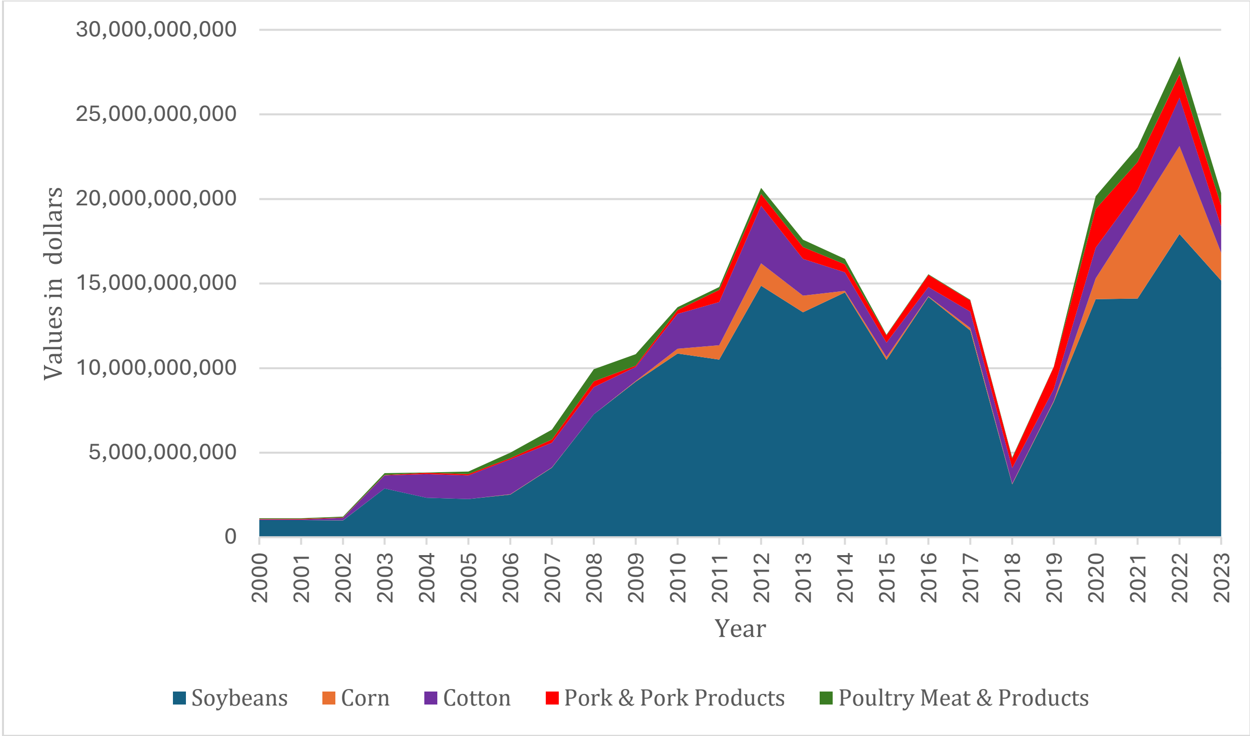

Figure 2. U.S. Agricultural Commodity Imports China 2000-2023

Table 1. China Import Share Statistics:

Period:	**Pre-Retaliatory Tariff Period**				**Retaliatory Tariff Period**				**Phase One Trade Agreement**			
Pork	**USA**	**Brazil**	**Chile**	**ROW**	**USA**	**Brazil**	**Chile**	**ROW**	**USA**	**Brazil**	**Chile**	**ROW**
Share	17.14	2.61	3.28	76.96	10.37	11.68	3.86	74.08	12.03	16.54	4.11	67.32
Poultry	**USA**	**Argentina**	**Brazil**	**ROW**	**USA**	**Argentina**	**Brazil**	**ROW**	**USA**	**Argentina**	**Brazil**	**ROW**
Share	56.42	7.37	27.16	9.06	25.81	5.83	43.34	25.01	25.86	5.76	45.49	22.89
Corn	**USA**	**Ukraine**	**Argentina**	**ROW**	**USA**	**Ukraine**	**Argentina**	**ROW**	**USA**	**Ukraine**	**Argentina**	**ROW**
Share	43.12	47.52	0.85	8.51	7.58	85.02	1.30	6.10	52.87	28.92	0.71	17.50
Cotton	**USA**	**Australia**	**India**	**ROW**	**USA**	**Australia**	**India**	**ROW**	**USA**	**Australia**	**India**	**ROW**
Share	36.59	11.84	21.67	29.90	25.99	24.02	11.05	38.95	45.11	5.43	8.92	40.54
Soybean	**USA**	**Brazil**	**Argentina**	**ROW**	**USA**	**Brazil**	**Argentina**	**ROW**	**USA**	**Brazil**	**Argentina**	**ROW**
Share	40.17	41.65	14.78	3.40	19.02	70.10	5.81	5.07	28.57	64.03	4.34	3.06

Table 2: Uncompensated Price Flexibilities

Soybeans	*USA*	*Brazil*	*Argentina*	*ROW*	***Poultry***	USA	*Argentina*	*Brazil*	ROW
USA	**-0.948**	0.0130	-0.066	-0.065	*USA*	**-1.272**	0.160	-0.003	0.290
Brazil	0.085	**-1.102**	0.0613	0.06	*Argentina*	0.808	**-0.895**	-0.271	-1.079
Argentina	-0.182	0.121	**-0.937**	-0.038	*Brazil*	-0.089	-0.026	**-0.863**	-0.027
ROW	-1.152	0.75	-0.262	**-0.841**	*ROW*	0.722	-0.522	-0.179	**-1.371**
Cotton	*USA*	*Australia*	*India*	*ROW*	***Pork***	USA	*Brazil*	Chile	ROW
USA	**-1.011**	0.617	-0.112	-0.651	*USA*	**-0.100**	-0.063	-0.021	-0.792
Australia	2.254	**-4.726**	0.270	2.151	*Brazil*	0.064	**-4.806**	0.137	4.684
India	-0.28	0.130	**-0.605**	-0.297	*Chile*	-0.101	0.308	**-0.123**	-1.177
ROW	-0.707	0.646	-0.127	**-0.968**	*ROW*	-0.176	0.561	-0.057	**-1.487**
Corn	*USA*	*Ukraine*	*Argentina*	*ROW*					
USA	**-0.930**	0.111	-0.023	-0.225					
Ukraine	0.170	**-1.252**	-0.031	0.274					
Argentina	-0.407	-0.875	**-0.354**	0.896					
ROW	-0.694	0.644	0.091	**-1.429**					

Table 3. Scale Flexibilities: China Import Demand

Soybean		*Cotton*		*Corn*	
US	-1.0669	US	-1.1576	US	-1.0676
Brazil	-0.8892	Australia	-0.0502	Ukraine	-0.8383
Argentina	-1.0369	India	-1.0536	Argentina	-0.7413
ROW	-1.5014	ROW	-1.1567	ROW	-1.3886
Poultry		***Pork***			
US	-0.8243	US	-0.9781		
Argentina	-1.4380	Brazil	0.0795		
Brazil	-1.0069	Chile	-1.0941		
ROW	-1.3523	ROW	-1.1596		

Table 4. Likelihood Ratio Test Results

China Import Demand	**Pork**	**Poultry**	**Corn**	**Cotton**	**Soybeans**
Stage	LR Test	LR Test	LR Test	LR Test	LR Test
Retaliatory Period	**2.454**	**12.933****	**2.141**	**1.984**	**20.291*****
Phase One Agreement	**1.612**	**3.0448***	**0.693**	**5.612***	**4.992***
Both Periods Combined	**4.909***	**21.796*****	**2.292**	**12.929****	**24.772*****
China Import Demand (U.S Only)	**U.S Pork**	**U.S Poultry**	**U.S Corn**	**U.S Cotton**	**U.S Soybeans**
Stage	LR Test	LR Test	LR Test	LR Test	LR Test
Retaliatory Period	**0.2246**	**6.289***	**2.6554**	**0.0788**	**1.2686**
Phase One Agreement	**0.0036**	**3.0448**	**0.2586**	**1.1974**	**1.3234**
Both Periods Combined	**0.696**	**6.334***	**3.7752**	**2.8458**	**1.7654**

**To determine the significance of this LR value, we compare it against the critical values from the chi-square (χ^2) distribution with 1 degree of freedom at each specified significance level: For $\alpha = 0.05$, the critical χ^2 value is approximately 3.841.For $\alpha = 0.01$, the critical χ^2 value is approximately 6.635.For $\alpha = 0.001$, the critical χ^2 value is approximately 10.827.*

Appendix

One consideration to further explore this research topic is by incorporating a Logistic Smooth Transition Autoregressive (LSTAR) model, a specification of the Smooth Transition Regression (STR) model, into our import demand analysis. We will incorporate the smooth transition model in our analysis, following a similar approach used by Teräsvirta (1994), Lin and Teräsvirta (1994), and Holt and Balagtas (2009). In order to further examine structural change in China's import demand for U.S. commodities, the following specification may be helpful:

$$w_{it} = f(X_t, \theta^*) + e_{it}$$

where,

$$\theta^* = \theta_1 + \theta_2 D(t)$$

Where D(t) is a variable that indicates structural change and *t* represents the transition variable. If structural change is assumed to be a discrete one-time event at t^*, then D(t) can be specified to equal one if $t > t^*$ and zero otherwise, where the assumption made is that parameters included the model undergo structural change that reflects an underlying smooth and continuous process which can be modeled as:

$$w_{it} = f(X_t, \theta_1)(1 - G(t^*; \gamma, c)) + f(X_t, \theta_2)G(t^*; \gamma, c) + e_{it}$$

where θi is the set of parameters explaining meat demand for two different regimes determined by a transition variable t^*, according to the transition function, *G*, a transition occurs from regime one to regime two, a function of t^*. γ and c are parameters that describe the characteristics of the transition function. The model above is an offshoot of the time-varying regression models considered in a univariate context by Terasvirta. These are known as Smooth Transition Regression (STR) models. A standard specification of the transition function is the first order logistic function:

$$G(t^{*};\gamma,c) = 1/(1+e\frac{-\gamma(t^{*}-c)}{\sigma_{t^{*}}}), \gamma > 0$$

where γ is the speed of adjustment parameter determining how quickly the model shifts from one regime to another. The centrality parameter, c, determines at what point in the sample the structural change is fifty percent complete (Holt and Balagtas). $\sigma_{t^{*}}$ is the standard deviation of the normalized trend variable. Dividing γ by $\sigma_{t^{*}}$ makes the speed-of-adjustment parameter unit free.

When using first-order logistic function as the transition function, the STR model nests a two-regime threshold regression model as a special case (Dijk, Franses, and Terasvirta). As γ approaches zero, the transition function becomes almost linear in *t*. Using time as a transition variable, *t* equals $\frac{t}{T}$ where *t* is the individual time period and *T* is total time. This makes the transition variable a normalized index that can be representative of time, between zero and one. Models that use this transition function are typically referred to in literature as Logistic Smooth Transition Autoregressive (LSTAR) models. Overall, more analysis will help to develop a clearer picture of structural change in China's import demand. As more data is collected over the Phase One trade agreement period, we will be able to produce more concise estimates for structural change.

Mitigating Climate Change with the Conservation Reserve Program (CRP): The Role of Carbon Credits and CRP Redesign

Abstract: This paper assesses the impact of adding carbon sequestration incentives to the U.S. Conservation Reserve Program (CRP). We use a comprehensive dataset from the USDA Economic Research Service to model how changes in the Environmental Benefits Index (EBI) for carbon sequestration affect CRP enrollments, budget allocations, and environmental outcomes. Our findings indicate that while prioritizing carbon storage enhances the program's benefits in terms of enduring environmental gains, it could reduce attention to other critical areas like wildlife habitat and soil erosion. This study highlights the trade-offs involved in adjusting conservation policies to incorporate climate change objectives.

Keywords: Conservation Reserve Program, carbon sequestration, caron credit payment, land conservation
JEL classification: Q15, Q24

1. Introduction

The resurgence of dialogue around the development of carbon credit markets in the United States coincides with the nation's renewed commitment to the Paris Agreement, a global initiative aimed at curtailing greenhouse gas emissions. Since rejoining the treaty in February 2021, the U.S. has embarked on ambitious objectives to abate greenhouse gas (GHG) emissions, drawing significant attention to the agricultural sector's role in climate mitigation efforts (Bonnie et al., 2020; Elder, 2021).

The Conservation Reserve Program (CRP), administered by the Farm Service Agency (FSA) of the USDA and covering 20.7 million acres as of May 2021, stands as a cornerstone in the U.S. agricultural conservation strategy. It aims to bolster the sector's capacity for climate change mitigation (FSA, 2021a,b). The FSA's initiative to offer up to a 10% increase in rental payments for CRP lands employing climate-smart practices marks a progressive step towards this goal (FSA, 2021a,c). Despite these efforts, the program's efficacy in GHG mitigation raises interesting questions: What is the scope of the CRP's carbon benefits, including GHG mitigation and carbon sequestration? How might farmers' CRP enrollment decisions be influenced by the program's incentives and carbon credit markets? Additionally, how can the CRP enrollment process be optimized to yield greater carbon benefits?

This study attempts to address these questions by performing economic analysis to inform and enhance the CRP's role in climate change mitigation. When evaluating the CRP, it is important to not only measure its environmental benefits but also farmers’ willingness to participate in it. As a voluntary conservation program, the CRP pays farmers annual rental payments in exchange for retiring land under conservation practices. With an average annual rental payment rate at $83/acre, the program's outlay is currently about $1.7 billion per year (FSA 2021d).

The development of carbon credits that offer payments for carbon benefits provides opportunities for farmers to earn additional revenues from their CRP land and for the CRP to reduce its program outlays (Bruner and Brokish 2021). For instance, if farmers are allowed to obtain and sell carbon credits from their CRP land by sequestering CO_2 or reducing GHG emissions, then CRP managers may have some freedom to reduce program rental payment rates while still keeping the enrollment acreage unchanged. Because carbon credit payments and CRP rental payments differ in risk and sources, farmers may have preference for one type of payment over the other. However, little is known about farmers' preferences regarding these two types of payments as well as any trade-offs between them. A potential caveat of the later versions of this research project will implement results a farmer survey to study farmers' willingness to enroll their land into the CRP under various payments schemes considering the potential interaction between carbon credit payments and CRP rental payments. Knowledge in this aspect will deepen our understanding about farmers' incentives to enroll their land into the CRP and will assist CRP program managers in harnessing the opportunities offered by emerging carbon credit markets to strengthen the CRP.

Since its establishment, the CRP has constantly evolved to meet the need from changing market conditions and environmental concerns over time (Hellerstein 2017; USDA, 2020). In its early stage (1985-1989), the CRP was designed to reduce soil erosion, with an enrollment mechanism that maximized total enrolled acreage (Reichelderfer and Boggess 1988; Ribaudo 1989). Starting in 1990, multiple environmental factors were introduced, and the concept of the Environmental Benefits Index (EBI) was used in order to balance environmental gains with program costs. During an enrollment period, each CRP offer is assigned an EBI value by the FSA and offers with EBI values larger than a national EBI cut-off value will be enrolled in the CRP.[2] As the crux of the CRP enrollment mechanism, the EBI has been changed a few times to adapt to technological and institutional constraints as well as environmental benefit targeting (Hamilton 2010, ch. 2; Hellerstein 2017; Jacobs 2010). Particularly, starting in 2003 (signup #26), carbon sequestration benefits of CRP land were included in the EBI to reflect the increasing interest in agricultural carbon sequestration during that time. However, since its inclusion, carbon sequestration benefits have only accounted for up to 10 EBI points among the maximum total 395 non-cost EBI points, about 2.5% (Jacobs 2010; FSA 2021a).

As Cattaneo et al. (2006, pp. 45) pointed out, the design of the EBI allowed program managers to adjust the maximum EBI points (the weights) assigned to a specific environmental benefit to reflect changed relative values of environmental benefits to society. Given the urgency of climate change mitigation, it is reasonable to consider increasing the maximum EBI points assigned to carbon sequestration benefits in the current design of EBI. However, because the CRP is a multi-objective program that balances various environmental benefits such as wildlife habitat cover, water quality, erosion reduction, and air quality (Cattaneo et al. 2006), an increase in the weight of one environmental benefit factor may affect other types of environmental benefits realized in program outcomes (Cattaneo et al. 2006). Moreover, due to the complexity and the national nature of the CRP, a change in enrollment mechanism can produce different environmental and economic implications across geographical regions.

2 There are two major types of enrollments in the CRP: General enrollment and continuous enrollment. The former allows farmers to enroll their land during specified sign-up periods to compete for acceptance whereas the latter is non-competitive and allows farmers to enroll their environmentally sensitive land in CRP at any time (Stubbs, 2014). As of May 2021, the CRP consisted of 11.3 million acres of general enrollment and 6.3 million acres of continuous enrollment (FSA, 2020). In this proposal we focus on general enrollment because it covers the majority of CRP land.

The way that CRP rental payments requested by farmers enter the EBI has also evolved since 1990. For the general signups over 1991-1995, the EBI design used rental payments to calculate benefit-cost ratios for program enrollment (Osborn 1993; Ribaudo et al. 2001; Jacobs et al. 2014). Commencing with the Federal Agriculture Improvement and Reform Act of 1996, the EBI underwent significant changes, and this benefit-cost ratio approach was discontinued. Instead, CRP rental payments were added to environmental components after a linear transformation, with larger rental payments implying lower EBI values. This additive approach remained to date and had been criticized for resulting in low cost-efficiency of the CRP (Miao et al. 2016). Moreover, how the potential carbon credit payments might be incorporated into the EBI will affect the environmental and geographical configurations of CRP enrollment. Therefore, a careful examination of the CRP enrollment mechanism (EBI) considering both the environmental benefit factors and cost factors is in order.

Since the enactment of the Food Security Act of 1985, the Conservation Reserve Program (CRP) has played a pivotal role in environmental conservation by withdrawing environmentally sensitive land from agricultural use and promoting the cultivation of plant species that enhance environmental health and quality. The program incentivizes farmers through annual rental payments—averaging $83 per acre as of 2021, amounting to approximately $1.7 billion in total disbursements annually (FSA, 2021d)—to adopt conservation practices. These practices not only reduce greenhouse gas (GHG) emissions associated with conventional farming (Robertson et al., 2000; Gelfand et al., 2011) but also enhance soil carbon sequestration (De et al., 2020).
In the quest to harmonize CRP objectives with the recently introduced carbon credit markets, it is vital to quantify the CRP's impact on carbon savings and soil organic carbon (SOC) sequestration. By providing financial incentives for carbon benefits, carbon credit markets offer a

two main advantages, they enable farmers to gain additional income from their CRP lands and potentially allow the CRP to curtail its overall expenses (Bruner and Brokish 2021). If farmers can monetize carbon credits from CO2 sequestration or GHG emission reductions on their CRP land, the program could gain flexibility to adjust rental rates without altering the enrolled acreage.

Over the years, the CRP has evolved to align with shifting market dynamics and ecological imperatives (Hellerstein, 2017; USDA, 2020). In 1990, the program integrated a range of environmental factors into its framework, utilizing the Environmental Benefits Index (EBI) to equalize ecological gains with fiscal expenditures. The EBI scores, determined by the FSA during enrollment periods, dictate land eligibility based on a national cut-off value. The EBI, a cornerstone of the CRP's enrollment mechanism, has undergone several revisions to reflect technological progress and priority shifts in environmental benefit targeting (Hamilton 2012, ch. 2; Hellerstein, 2017; Jacobs, 2010). Notably, in 2003 (signup #26), the EBI began incorporating the carbon sequestration benefits of CRP land, marking a growing interest in agricultural carbon capture. Despite this, carbon sequestration has historically represented a meager fraction of the total EBI score, a mere 2.5% (Jacobs, 2010; FSA, 2021a), which suggests an opportunity to enhance this aspect in light of the urgency surrounding climate change mitigation. The intricate nature of the CRP means that alterations to its enrollment mechanism can have diverse environmental and economic consequences across regions. Initially, the EBI employed a benefit-cost ratio for enrollment decisions (Osborn, 1993; Ribaudo et al., 2001; Jacobs et al., 2014). However, following the Federal Agriculture Improvement and Reform Act of 1996, significant reforms to the EBI were enacted. The benefit-cost ratio methodology was supplanted by a linear transformation model that inversely correlates rental payments with EBI values, a system that has faced criticism for compromising the CRP's cost-efficiency (Miao et al., 2016).

The integration of carbon credit payments into the EBI is poised to reshape the environmental and geographical landscape of CRP enrollment. Thus, a meticulous evaluation of the EBI, considering both ecological and financial elements, is paramount. This paper delves into the ramifications of various proposed redesigns of the CRP enrollment mechanism, focusing on outcomes like carbon sequestration, environmental benefits, and acreage change. We explore the effects of amplifying the weight of carbon benefits within the EBI and analyze the combined influence of CRP rental and carbon credit payments on enrollment outcomes. Our objective is to deduce optimal strategies for leveraging the CRP to maximize GHG mitigation and assess its cost-effectiveness under diverse enrollment scenarios in the era of carbon credit markets.

2. Background of CRP enrollment mechanism

The enrollment of land into the Conservation Reserve Program (CRP) typically occurs through a competitive bidding process during specified general signup periods. Since the program's inception in 1985, its land enrollment efficiency and the subsequent environmental and economic repercussions have been a focal point of analysis. Reichelderfer and Boggess (1988), as well as Ribaudo (1989), critiqued the initial nine signup periods' design, which prioritized maximizing acreage over environmental benefits. Subsequent studies, such as those by Babcock et al. (1996, 1997), examined alternative enrollment designs under fiscal constraints, demonstrating that the efficiency loss of suboptimal designs was contingent on the correlation and variability between CRP offers' environmental benefits and the requested rental payments. Wu, Zilberman, and Babcock (2001) expanded on this by evaluating how different stakeholder groups favored the various designs.

Despite these insightful contributions, a gap remains regarding the cost-effectiveness of the current Environmental Benefits Index (EBI) design. Studies like Hellerstein et al. (2015) and Cramton et al. (2021) primarily focused on the implications of maximum CRP payment rates on cost-effectiveness using auction theory and economic experiments. Meanwhile, Cattaneo et al. (2006) deduced that minor adjustments to EBI weights minimally impact CRP outcomes. They did, however, acknowledge that significant alterations in these weights could reshape the program's outcomes if shifts in environmental improvement preferences occur.

However, the weight assigned to carbon benefits within the EBI was not the focus of these studies, casting uncertainty on their applicability to the primary focus of this research. The current EBI design's ability to accommodate more cost-effective structures remains untested, a question this study aims to explore. Miao et al. (2016) postulated that while the existing EBI design seeks to calibrate environmental gains with rental costs, it falls short on cost-effectiveness, instead appearing to optimize the net benefit per acre. The proposition for a cost-effective criterion involves a benefit-cost ratio aimed at maximizing environmental benefit per dollar. Utilizing data from Signup #26 and #41, their simulations indicated that an EBI design that integrates crop insurance premium subsidies could expand CRP acreage and environmental benefits without increasing governmental expenditure.

Our paper extends this inquiry by focusing on the potential interplay between the CRP and carbon credit markets. We investigate the influence of modifying EBI weights for carbon sequestration and analyze the enrollment outcomes across various EBI designs. Historically, the CRP has been directed by dual objectives: curtailing soil erosion and reducing agricultural surplus. This focus led to a rapid increase in enrollment strategy during its early signups. With legislative evolutions such as the Food, Agriculture, Conservation, and Trade Act of 1990, the

EBI was refined to a benefit-cost ratio design, enhancing enrollment efficiency by maximizing environmental gains for each dollar spent. The subsequent Federal Agriculture Improvement and Reform Act of 1996 saw the EBI evolve into its current form, where environmental benefits are linearly aggregated, and rental payments are adjusted post-linear transformation.

The current EBI encompasses a spectrum of environmental benefits, with erosion reduction, water quality, and wildlife benefits each assigned up to 100 points, while enduring benefits and air quality (which includes carbon sequestration) are valued at 50 and 45 points respectively. Carbon sequestration benefits are capped at 10 points within the air quality category. Under the prevailing CRP framework, an offer's EBI value is calculated using a linear equation that incorporates rental rates and environmental benefits. Offers surpassing a predetermined EBI threshold are accepted into the program. Increasing the weight given to carbon sequestration within the EBI could potentially prioritize land with greater carbon storage potential, underscoring the importance of CRP's role in climate change mitigation. This study will evaluate how such adjustments to the EBI could enhance the efficacy and environmental contributions of the CRP in the context of an evolving climate policy landscape.

The environmental benefits included in the current EBI are wildlife benefits, water quality benefits, erosion reduction, enduring benefits, and air quality benefits, where the former three types of benefits are assigned the same weights (maximum 100 points each), and the latter two are assigned a smaller weight (maximum 50 and 45 points, respectively). Carbon sequestration benefits are included in the air quality benefits and only account for up to 10 points[3]. Let EEBI denote the EBI points for environmental benefits of an offer and r denote the

[3] (see FSA (2021c) for details about the EBI factors and their points used in the most recent signup period).

rent per acre requested in this offer. The EBI points of this offer under the current CRP specification can be written as:

$$EBI = EEBI + f(r) + c \tag{1}$$

where $f(r) = a \times (1 - r / b)$ is a linear function which transforms rental rate, *r*; parameters *a* and *b* are determined by the program administrator based on actual offer data in a signup period, indicating that they are unknown to farmers when CRP enrollment offers are made; and finally, *c* is the extra bonus points that are a relatively small numbers reflecting how much the requested rental rate is below the maximum payments that FSA is willing to offer. For each CRP offer, by using equation (1), the FSA assigns an EBI value to the offer based on the offer's environmental benefit factor and rental payment requested by the farmer. Then all offers are ranked according to their EBI values and offers with EBI values no less than the cut-off EBI value will be enrolled into the CRP. Intuitively, suppose the weight assigned to carbon sequestration benefits is increased in the EBI design. In that case, CRP offers with larger carbon sequestration capacity will be more likely to be enrolled in the CRP.

3. Empirical Approach

We aim to investigate to what extent an increase in the weight will enhance the capacity of the CRP to sequester carbon and the economic and environmental implications of such an increase under various EBI designs.

To investigate how to utilize the CRP to better mitigate GHG emissions we first define the EBI design in equation (1) as the benchmark EBI (denoted as EBI_0. That is, we have:

$$EBI_0 = EEBI + f(r) + c. \tag{1}$$

where $EEBI^{'}$ denotes the new EEBI after the weight of carbon benefits is modified and p denote carbon credit payment rate ($/acre/year). Then, deviating from the benchmark EBI design, we consider the following four alternative of EBI designs:

$$EBI_1 = EEBI^{'} + f(r) + c, \quad (2)$$

$$EBI_2 = EEBI^{'} + f(r-p) + c, \quad (3)$$

$$EBI_3 = (EEBI^{'} + c) / r, \quad (4)$$

$$EBI_4 = (EEBI^{'} + c) / (r-p), \quad (5)$$

Note that EBI_1 in equation (2) is the same as the benchmark EBI_0 except that the weight for carbon benefits is increased to a new level. Both EBI_0 and EBI_1 ignore the potential carbon credit payments in the EBI design (i.e., carbon credit payment rate, *p*, is missing in equations (1) and (2)). Different from EBI_1, EBI_2 in equation (3) considers the carbon credit payments that a CRP land tract may receive and deducts them from CRP rental payments. In other words, under EBI_2, CRP rental payment rate is max [0,r-p]. Unlike EBI_1 and EBI_2 that combine the CRP rent with environmental benefits after a linear transformation of the rent, EBI_3 and EBI_4 are simply obtaining benefit-to-cost ratios. The difference between EBI_3 and EBI_4 is that under EBI_3 the carbon credit payments are ignored whereas under EBI_4 the CRP rental payment rate is adjusted based on the amount of carbon credit payments.

Miao et al. (2016) shows that EBI_1 and EBI_2 are consistent with maximizing environmental benefits with a linear adjustment of program costs subject to an acreage constraint, whereas EBI_3 and EBI_4 are consistent with maximizing environmental benefits subject to a budget constraint.

The numerical simulation under will be based on equations (1) to (5) and CRP contract-level data in a specific general signup (e.g., signup #54 occurred in 2021, under which farmers made 56,788 offers). The dataset includes each CRP offer's detailed EBI points under each environmental benefit factor and EBI points associated with costs, as well as the rental rate requested by farmers. It also the acceptance status which indicates whether or not the FSA accepted an offer for a particular land parcel.

We use EBI_1 in equation (2) as an example to describe the procedure of obtaining enrollment outcomes under a new EBI design. First, based on the contract-level data, we calculate EEBI' for each offer under the new weight assigned to the carbon benefit factor. Then we insert EEBI' into equation (2) and obtain EBI_1 under this specific new weight for carbon benefits for each CRP offer. We then rank all offers in this signup according to their values of EBI_1. Offers with larger values will be enrolled into the CRP until the total enrolled acreage equals the enrolled acreage under that signup. We then calculate the environmental benefits and total program payments associated with the accepted offers under EBI_1 and compare them with enrollment outcomes under EBI_0 to quantify the impact of changes in EBI.

Similar procedures can be used to study the impact of adopting EBI_2, EBI_3, or EBI_4 on CRP enrollment outcomes. The carbon credit payment rate, p, will be calculated based on a carbon price of \$15/Mg and on the carbon benefits for each CRP offer based on the simulation results. To , each offer's potential carbon payment is calculated based on the carbon sequestration score (N5d) of the land, adjusted by a set base payment rate (\$15/Mg), and then scaled down by a factor of 2. The reason for scaling by 2 is due to the fact that 2 is the minimum N5d value that is larger than 0. This means that no score for carbon sequestration (N5d) will be less than 2, other than a score of 0 which indicates no carbon sequestration potential. Therefore, dividing by 2 scales the payment to a reasonable range, and ensures that for every unit increase in the N5d score, the payment increases by half the base rate. This is important because it prevents the payment from escalating too quickly for small increases in N5d and keeps the additional carbon payments proportional to the sequestration potential of the land. So, this scaling method serves a way to normalize the payment across various offers, ensuring that it remains proportionate to the N5d score while not allowing the payment to exceed a certain limit or to maintain it within a reasonable range relative to other CRP payments. We consider different weights for carbon benefits N5d, starting from 10 (the status quo) up to 100.

The scenarios that we analyze in the main text of the paper are described as follows:

Baseline scenario,(EBI_0), represents the current state of the EBI without considering potential carbon credit payments.

Scenario 1, ($EBI_{1)}$ same as EBI_0 in structure but increases the emphasis on carbon sequestration. We inflate N5d (carbon sequestration), by 10 times to bring its range from "3 to 10" to "30 to 100." This adjustment is made because other environmental factors (like N1, N2, N3) are scaled at 100.

Scenario 2, (EBI_2) the presence of f(r−p) implies that the carbon credit payment is seen as a cost-saving factor for the CRP. This could incentivize landowners to engage in carbon sequestration practices by effectively lowering their rental payment obligations in the eyes of the CRP and potentially improving their EBI score.

Scenario 3, (EBI_3) is a benefit-cost ratio, no carbon credit payments, or adjustments to carbon sequestration points. It divides the environmental benefits by the cost of rental payments to prioritize offers that provide the highest environmental benefits for the lowest cost.

Scenario 4, (EBI_4) Here, the EBI considers a benefit-to-cost design and deducting the carbon payment from the rent. The carbon payment deduction from the rent effectively lowers the rental cost from the perspective of the program, while significantly increasing the weighting of the carbon sequestration benefit in the overall EBI score.

4. CRP Enrollment Data

Our analysis hinges on a comprehensive dataset obtained from the USDA Economic Research Service (USDA/ERS) that detail county-level enrollment statistics for the Conservation Reserve Program (CRP) for signup 54 which took place in 2021. A breakdown of variable statistics and interpretation of factors is presented in Table 1. The contract-level data affords us a unique look into the particulars of CRP participation, including the acreage committed, proposed rental payment bids, actual acceptance into the program, and the Environmental Benefits Index (EBI) scores correlated with each environmental goal. In the landscape of signup 54, we have at our disposal 56,788 individual records at the county level. An examination of these records discloses an average enrollment of approximately 67.6 acres per county. Landowners entered bids with an average CRP rental payment of $94.81 per acre. The EBI, which indicates a parcel of land's environmental benefit potential, held an average score of 273 points across submissions.

We analyze the dataset further by looking at the data in terms of overall participation vs the actual accepted offers. Table 2 reveals that in terms of total offers made vs actual accepted offers there were 56,788 offers made and 51,610 accepted, the acceptance rate under signup 54 is relatively high close to 91%. This suggests that a large proportion of the offers met the necessary EBI threshold, implying that most lands offered for enrollment aligned well with the CRP's environmental goals. In terms of acreage, total acres offered were 3,839,488, and 3,418,597 of these acres were accepted into the program.

The average CRP rental payment bid was $94.8 per acre, while the average payment for accepted offers was slightly higher at $95.2 per acre. This implies that higher rental payments are associated with offers that have higher environmental benefits and were thus accepted into the program. In terms of EBI scores there was difference of around 8.13 points in the average EBI score between parcels offered (273.89) and accepted (282.02) parcels of land while the average EEBI shows a smaller difference between offered (193.23) and accepted (201.33) bids, once again indicating CRP's preference for parcels with higher environmental benefits.

The data provides a solid foundation for analyzing the effectiveness of the CRP and the potential for integrating carbon credit markets. With a high acceptance rate and the average EBI score for accepted offers being higher than that for all offers, it is clear that the CRP is selective towards offers that promise a higher return in terms of environmental benefits. With the addition of carbon credit payments and the refinement of carbon sequestration as a factor in the EBI calculation there may be potential to further refine the program's impact on climate change mitigation.

5. Results

CRP outcomes under scenario simulations

Table 3 and 4 explain and illustrates the differential outcomes of the Conservation Reserve Program (CRP) under various simulation scenarios, each imposing different constraints, and adjustments to the program's enrollment criteria, specifically within the context of acreage and budget constraints. In Table 4, 50% acreage constraint represents enrolled CRP acreage in the county with a 50% acreage constraint imposed (under Status quo (baseline), Scenario 1, and Scenario 2). The baseline represents the current status quo of the CRP without any modifications. The program under the acreage constraint has 1.9 million acres enrolled, with a total payment for these acres amounting to $112.7 million and total EEBI acreage weighted points of 403 million. Under scenario 1 there was a modest increase in total payment (2.27%) suggesting a slight improvement in the program's cost without a notable change in acreage. There’s a negligible decrease in EEBI points (-0.046%), which implies a very minimal trade-off between cost and environmental benefits. Scenario 2 shows a further increase in total payment (3.01%) compared to the baseline. Similar to Scenario 1, there’s a minimal decrease in EEBI points (-0.00228%), an even smaller trade-off compared to Scenario 1.

For the 50% Budget Constraint, scenario 3 acts as a reference point for budget-constrained scenarios (scenario 3 represents the alternative status quo or alternative baseline), where 3.1 million acres are enrolled, and the total payment for these acres is $102.5 million, with EEBI points at 498 million. Scenario 3 shows a decrease in acres enrolled (-0.593%) compared to the alternative baseline, indicating that under this scenario slightly fewer acres are enrolled for the same budget, potentially reflecting a tighter selection based on the adjusted criteria. There is also a minor decrease in EEBI points (-0.00117%), suggesting a marginal reduction in environmental benefits. Scenario 4 shows a larger decrease in total acres enrolled (-0.858%) compared to alternative baseline, again showing that the criteria applied under this scenario are more selective. However, there's a slight increase in EEBI points (0.00467%), suggesting an improvement in environmental benefit scores per acre enrolled under this budget constraint.

Overall, the numeric differences in the table may seem marginal, but spatially, these impacts can vary significantly. Different areas have varying environmental and soil characteristics which can affect the efficiency of carbon sequestration and the overall environmental benefits. A small increase in EEBI points in a region with high carbon sequestration potential could lead to substantial environmental improvements. The changes in enrolled acres might be concentrated in specific regions where the land is more conducive to achieving the CRP's objectives. Therefore, the environmental impact could be significant in these areas even if the overall acreage change is small. Additionally, even slight shifts in payment rates can have meaningful economic consequences for the regions that depend heavily on agriculture. This could mean that the economic ripple effects in rural communities may be more pronounced than the percentage changes suggest. Moreover, benefits like erosion control, water quality improvement, or wildlife habitat enhancement could be more significant in certain areas, meaning that even small changes in the CRP could lead to greater benefits in those particular environmental aspects.

While the table estimates provide a useful overview, a spatial analysis is essential to fully grasp and understand the impact of these scenarios. It will shed light on where the CRP is most effective and where there might be room for improvement in terms of program design to meet both economic and environmental goals more efficiently.

Spatial analysis of CRP outcomes under scenarios

Figure 1 represents the spatial implications of changes made to the CRP under various scenario analyses. The top map represents baseline enrollment depicting the geographic distribution of acreage enrolled under the current CRP baseline scenario with a 50% acreage constraint. The shades of green illustrate the intensity of enrolled acres across the United States, with darker greens indicating higher acreage enrollments. This provides us with a reference for understanding the spatial impact of the CRP as it currently operates.

The second map displays the differences in acreage enrollment between Scenario 1 and the Baseline scenario. The color scale ranges from green to red, where green areas signify counties where Scenario 1 resulted in more acres being enrolled compared to the Baseline, and red areas indicate fewer acres enrolled under Scenario 1. This highlights the regions where modifications under Scenario 1 lead to an increase or decrease in terms of CRP participation, reflecting the scenario's focus on a benefit-minus-cost analysis that may favor areas where conservation provides greater environmental returns per dollar spent.

The third map compares the Baseline scenario with Scenario 2. Under Scenario 2 the spatial distribution shows how financial incentives could alter landowner participation in the CRP. Regions that see an increase in green are possibly those where landowners find the new carbon-related payments more attractive, while areas in red may not find these changes as advantageous, possibly due to existing land use value or lower carbon sequestration potential.

Figure 2 represents the spatial implications of changes made to the CRP under the alternative baseline, scenario 3, and scenario 4. For acreage under the alternative baseline this map shows the acreage enrolled under the alternative baseline across the United States with a 50% budget constraint in place. The green areas represent higher enrollment under the budget-constrained scenario and set a baseline for understanding how a fixed budget influences CRP enrollment across different regions.

The second map illustrates the difference in acreage enrollment between Scenario 3 and the alternative baseline. Since Scenario 3 emphasizes the weight of carbon sequestration by inflating the N5d component, regions with increased green may represent a shift in enrollment to areas with high carbon-capturing potential.

The bottom map compares the changes in acreage enrollment under Scenario 4 to the alternative baseline. The areas with an increase in enrollment reflect the combination of cost adjustments and increased emphasis on carbon sequestration. This might redistribute enrollment to areas where the economic and environmental incentives of the CRP are maximized.

Overall, the spatial distribution in the maps reveals the heterogeneity of policy impacts across different regions. These maps illustrate that policy changes do not affect all areas uniformly; instead, they can have varied effects depending on regional characteristics such as agricultural productivity, land value, and potential for carbon sequestration. Ultimately, adjusting policy to emphasize carbon sequestration benefits could incentivize more CRP enrollment in areas with higher potential for carbon capture. Additionally, accounting for carbon credit payments could make CRP participation more appealing in some regions but less so in others, potentially due to varying economic returns from agriculture versus carbon credits. While some areas may see a significant impact, others might experience minimal or no change.

Environmental Benefit Change

Figures 3 and 4 showcase the percent change in total Environmental Benefits Index (EEBI) points for our scenarios under a 50% acreage constraint. Figure 3 shows the change between the baseline scenario and scenario 1 for environmental factors, with scenario 1 amplifying the weight of carbon sequestration by inflating the N5d component tenfold. Figure 4 shows the change between the baseline scenario and scenario 2 where scenario 2 reflects inflating the N5d component tenfold and $15/Mg carbon payment subtracted from the rental payment. Each graph represents a different environmental component of the EBI, and the x-axis shows the percentage of total offered acreage. The y-axis reflects the percentage change in total EEBI points under the scenario.

From Figure 3 we see the effects of varying responses across different environmental benefit categories to the recalibrated weighting of carbon sequestration in scenario 1. Environmental components, such as those related to wildlife and soil erosion for instance, display some trade-off effects of increased carbon sequestration points. This suggests a trade-off when increasing emphasis on carbon capture and that bolstering the weight given to carbon sequestration could potentially divert focus from these other conservation priorities. For example, Changing land use to maximize carbon sequestration could involve converting areas that were previously diverse ecosystems into monoculture forests or grasslands, which might not provide the diverse habitat that various wildlife species require. Similarly, intensive afforestation can disrupt existing wildlife habitats that certain species depend on. Additionally, some carbon-focused practices may not always align with soil conservation. For instance, the choice of vegetation for carbon sequestration might not be optimal for soil health in all contexts. Certain fast-growing tree species used in afforestation might deplete soil nutrients more rapidly than native vegetation or might lead to increased soil acidification.

Conversely though factors such as surface and ground water quality and enduring benefits see a significant increase, signaling that this adjustment aligns with the aim of enhancing long-term environmental benefits, possibly through sustained carbon storage. This result seems to imply that Scenario 1 effectively promotes practices with enduring impacts, which could have significant positive effects on long-term sustainability and climate change mitigation. Carbon sequestration often involves practices such as afforestation or reforestation, cover cropping, and improved soil management. These practices can reduce runoff and erosion, which in turn helps in improving surface water quality by decreasing sediment and pollutant loads entering water bodies. Moreover, carbon sequestration practices that involve long-term changes to land use or management (such as establishing permanent forests or grasslands) inherently contribute to enduring environmental benefits. These practices not only capture carbon but also provide long-term habitat stability, improve soil structure, and increase biodiversity, which are recognized under the enduring benefits factor. Figures 4 reveals a similar effect on environmental impacts from Scenario 2. Similarly Figures 5 and 6, reflecting the scenarios under the budget constraint yield similar results.

Table 5 presents a correlation matrix of the environmental factors. The correlation matrix illustrates the relationships between various EEBI factors within the CRP. These correlation estimates can help us understand how different environmental components might influence each other when they are considered together in the program's evaluation process. In terms of the N5d (carbon sequestration) factor we observe a strong positive correlation of 0.78 with N4 (enduring benefits factor). This suggests that increasing the emphasis on carbon sequestration strongly aligns with long-term environmental benefits. The high correlation indicates that areas prioritized for carbon sequestration are also areas that contribute significantly to enduring benefits. The results also show moderate positive correlation (0.22 and 0.12) with N2b (Groundwater Quality) and N2c (Surface Water Quality). This indicates that there is some alignment between carbon sequestration efforts and groundwater quality improvements, suggesting that these environmental aspects may be complementary. Initiatives aimed at increasing carbon storage might also positively influence surface water quality, although the link is not as strong as with groundwater.

We observe a moderate negative correlation of N5d with N5a (Wind Erosion Impacts), N5b (Wind Erosion Soils), and N5c (Air Quality Zones). This negative correlation suggests that focusing more on carbon sequestration could potentially lead to less emphasis on controlling environmental aspects such as wind erosion, and that increasing carbon sequestration might detract from focusing on air quality zones, potentially impacting efforts to improve air pollution control.

Overall, the shifts in EEBI points across the various environmental factors suggest that inflating the carbon sequestration factor influences the CRP’s environmental priorities. While it bolsters the program's contribution to carbon storage, it has potential to also impact other environmental benefits. This intricate balance underscores the need for a careful, multifaceted approach in CRP policy adjustments to ensure that enhancements in carbon sequestration do not undermine other critical environmental benefits. The effectiveness and environmental impact of carbon sequestration practices depend heavily on how they are implemented. Variations in management practices, the ecological suitability of chosen methods for specific regions, and the balance between different conservation goals can all influence whether the outcomes are beneficial or detrimental to particular environmental factors.

6. Conclusion and Policy Implications

Our research presents a nuanced analysis of the Conservation Reserve Program's enrollment outcomes under various simulated scenarios, each offering its unique recalibration of the Environmental Benefits Index to integrate carbon sequestration more resolutely into the program's framework. The findings indicate that emphasizing carbon capture, while pivotal for climate change mitigation, introduces some trade-offs across other conservation priorities within the CRP. Our spatial analyses further unravel the heterogeneous impact of these policy adjustments across the United States, highlighting that the effects of CRP modifications are not universally felt but vary significantly based on a variety of regional attributes. These variations underscore the importance of a targeted approach and regional analysis in policy design that accommodates the diverse environmental and economic landscapes across different counties and states.

Moreover, our analysis of CRP enrollment data and subsequent simulations illustrate that high acceptance rates and EBI scores indicate a program well-aligned with environmental goals. However, integrating greater prioritized carbon sequestration into this equation requires careful consideration of how best to maintain a balance between all facets of environmental stewardship. While it is feasible for policymakers to adjust the weight of N5d to increase the carbon sequestration component of the CRP, such changes must be implemented thoughtfully and strategically, considering both the potential benefits and the complexities involved. The goal should be to enhance the program's effectiveness in climate change mitigation without compromising its capacity to meet other essential environmental conservation objectives.

This study advances our understanding of how conservation programs can evolve in response to climate change needs, particularly within the context of emerging carbon markets. It recommends a balanced approach that does not disproportionately prioritize carbon sequestration at the expense of other environmental benefits. Policymakers must recognize the intrinsic value of a multifaceted environmental agenda that sustains biodiversity, soil integrity, water quality, and air quality alongside carbon capture initiatives.

As the demand for environmentally conscious policies grows, so does the imperative need to evaluate and iterate our conservation strategies. Our research suggests that while pursuing carbon sequestration is vital, it should be within the broad spectrum of ecological benefits that conservation programs are uniquely positioned to deliver. The future of environmental policy, particularly within the framework of the CRP, lies in its adaptability and capacity to balance our ecosystems' diverse needs with the overarching goal of mitigating climate change.

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Table 1. Signup 54 Descriptive Statistics

Variable	Description	Average
n1	Wildlife habitat benefits (10 to 100 Points)	60.80
n2	Water quality benefits (0 to 100 Points)	55.02
n3	Erosion Factor (0 to 100 Points)	52.74
n4	Enduring Benefits (0 to 50 Points)	8.26
n5	Air Quality Benefits (3 to 45 Points)	16.41
n6	Cost	80.66
n1a	Wildlife Habitat Cover Benefits (10 to 50 points)	41.63
n1b	Wildlife Enhancement (0, 5 or 20 points)	6.69
n1c	Wildlife Priority Zones (0 or 30 points)	12.48
n2a	Location (0 or 30 points)	15.32
n2b	Groundwater quality (0 to 25 points)	8.84
n2c	Surface water quality (0 to 45 points)	30.86
n5a	Wind Erosion Impacts (0 to 25 points)	11.80
n5b	Wind Erosion Soils List (0 or 5 points)	0.16
n5c	Air Quality Zones (0 or 5 points)	0.31
n5d	Carbon Sequestration (3 to 10 points)	4.14
n5d10	Carbon Sequestration (30 to 100 points)	41.37
n6a	Cost (point value determined after end of enrollment)	75.62
n6b	Offer Less Than Maximum Payment Rate (0 to 25 points)	5.04
crpacre	number of acres enrolled	67.61
SRR	maximum county soil rental rate	98.29
offer	rental payment requested by landowner	94.81
ebitot	Total EBI points	273.89
total obs.	Total county enrollments under CRP Signup 54	56788

Table 2: Summary Statistics for Conservation Reserve Program: Signup 54 (2021)

Signup 54 (2021)	Offered	Accepted
Total number of offers	56,788	51,610
Total acres (acres)	3,839,488	3,418,597
Average CRP rental payment ($/acre)	94.8	95.2
Average WASRR ($/acre)	98.3	98.7
Average EBI	273.89	282.02
Average EEBI	193.23	201.33

Table 3: Interpretation of EBI change under each Scenario

Status Quo	**Scenario 1**	**Scenario 2**
Baseline (EBI_0)	carbon sequestration points increased 10 times (EBI1)	carbon sequestration points increased 10 times; $15/mg carbon credit payment included (EBI2)
Alternative Status Quo	**Scenario 3**	**Scenario 4**
Baseline (EBI_3)	carbon sequestration points increased 10 times (EBI3)	carbon sequestration points increased 10 times; $15/mg carbon credit payment included (EBI4)

Table 4: Comparisons of Budgetary and Environmental Outcomes of CRP

(50% acreage constraint)	**% Change from Status Quo**		
Signup 54	**Status Quo (Abs Value)**	**Scenario 1**	**Scenario 2**
Total acres enrolled (million acres)	1.9	-	-
Total payment acres enrolled (million $)	112.7	2.27%	3.01%
Total EEBI acreage weighted points (millions)	403	-0.046%	-0.228%
(50% budget constraint)	**% Change from Alt. Status Quo**		
Signup 54	**Alt. Status Quo (Abs Value)**	**Scenario 3**	**Scenario 4**
Total acres enrolled (million acres)	3.1	-0.593%	-0.858%
Total payment acres enrolled (million $)	102.5	-	-
Total EEBI acreage weighted points (millions)	498	-0.117%	-0.465%

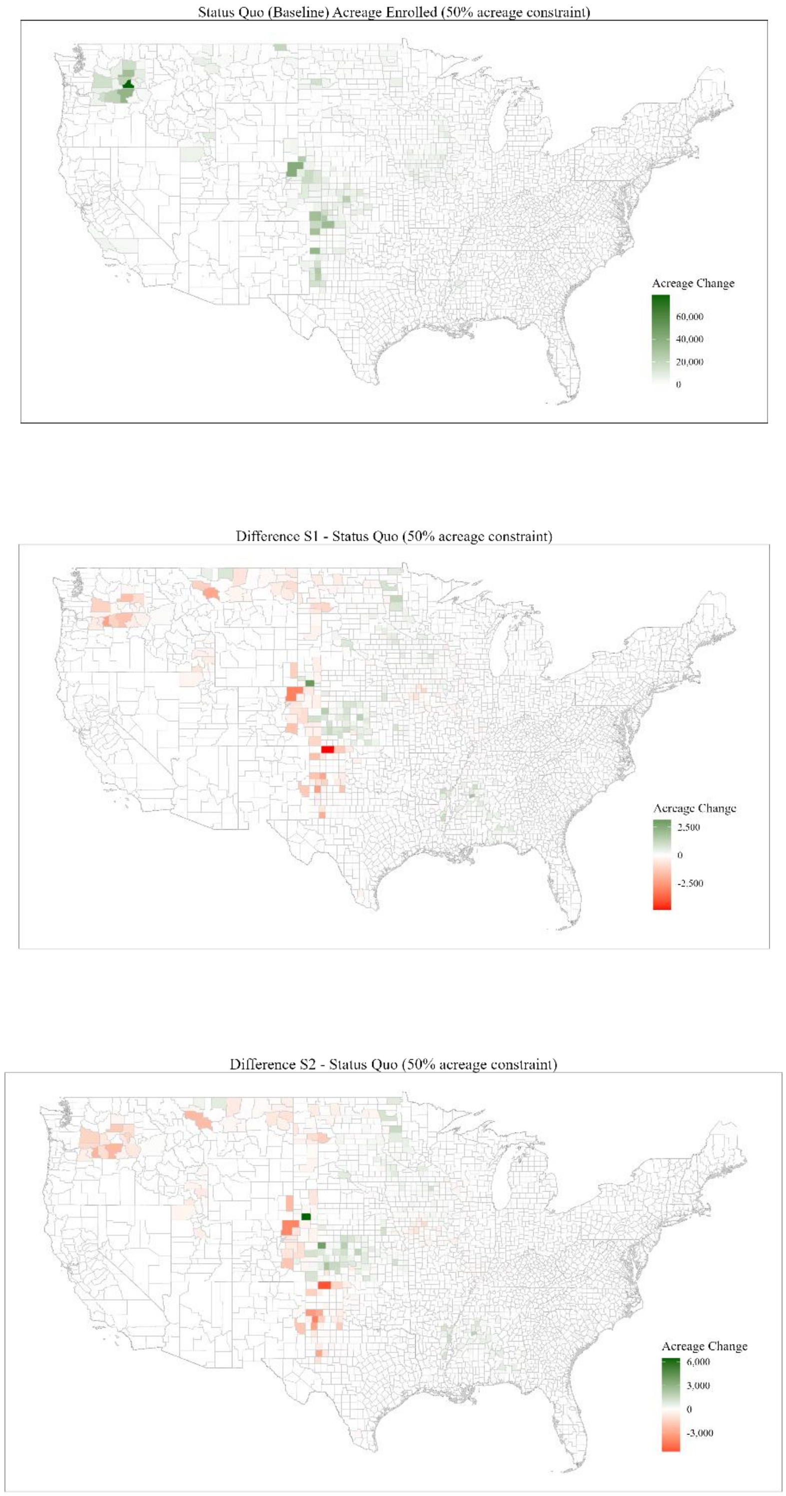

Figure 1 Acres Enrolled into CRP under Status Quo (Baseline) and Scenario Comparisons

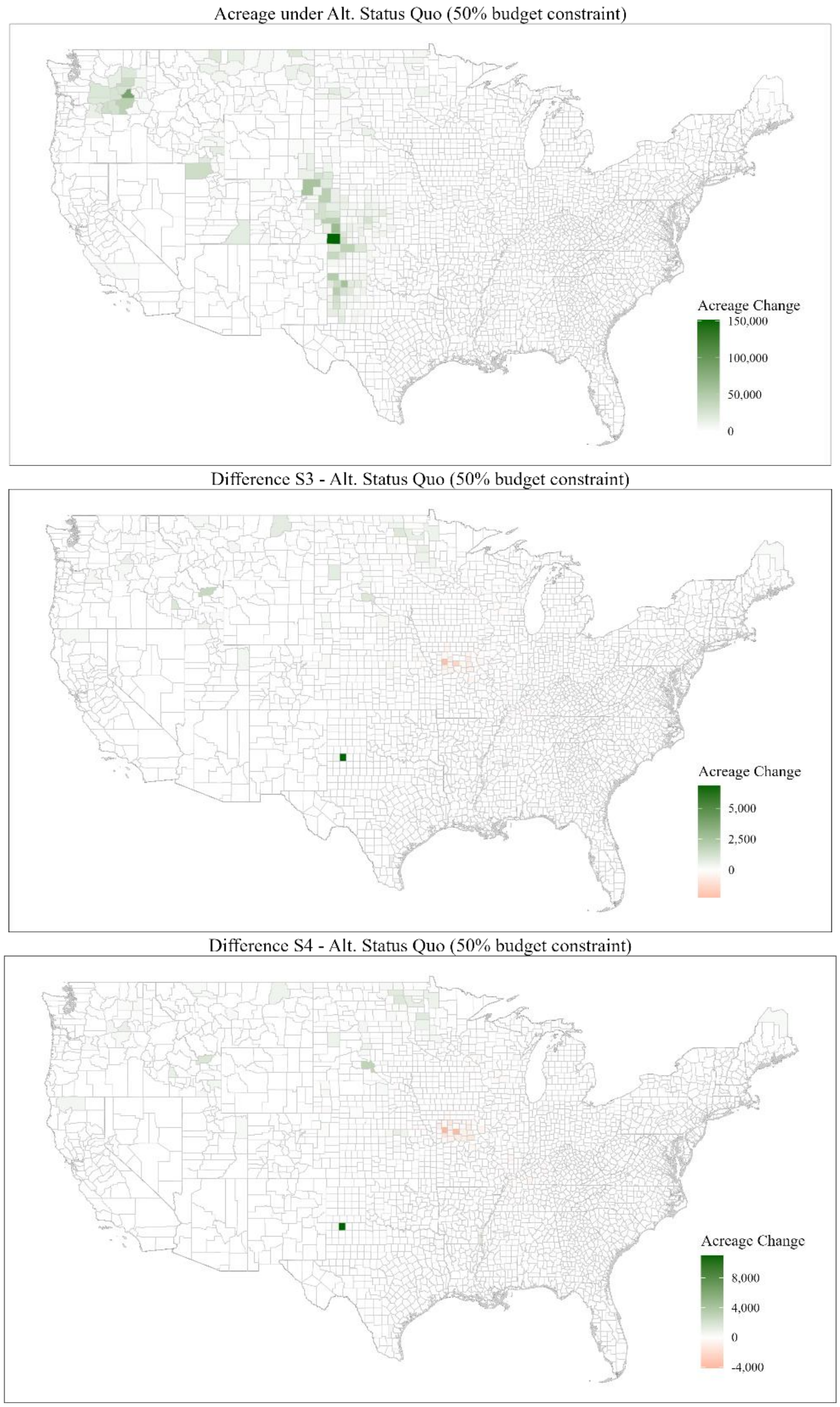

Figure 2 Acres Enrolled into CRP under Alternative Status Quo and Scenario Comparisons

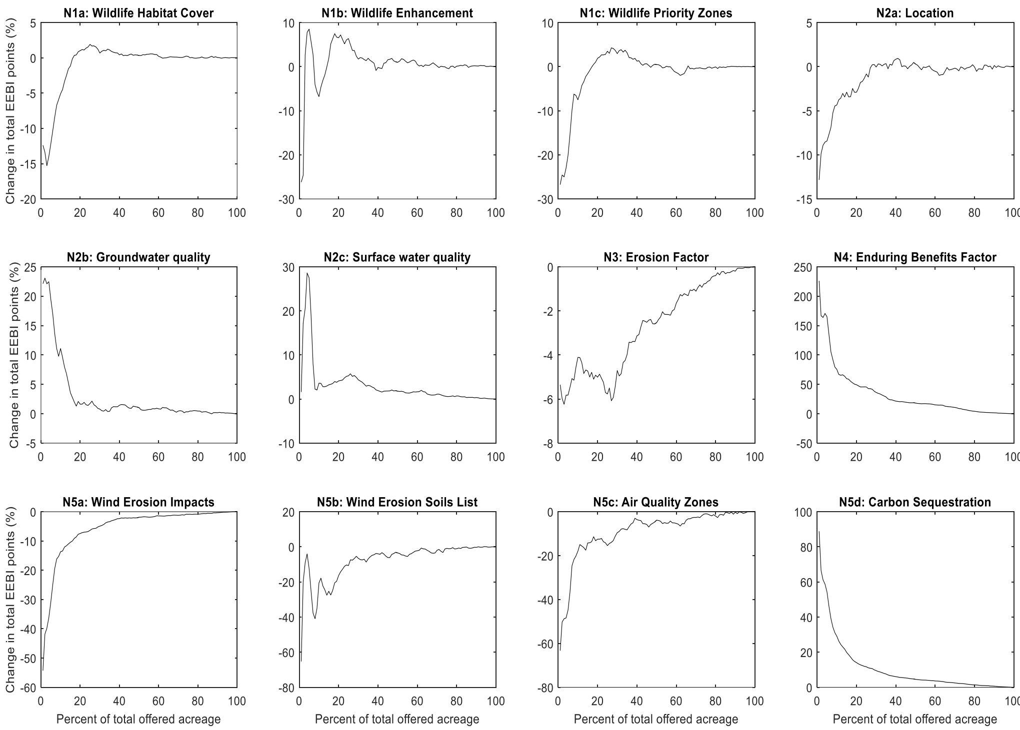

Figure 3: Percent change in Total EEBI Points under 50% acreage constraint
Note: Comparisons between Status Quo (baseline) and scenario 1 (10 times of N5d)

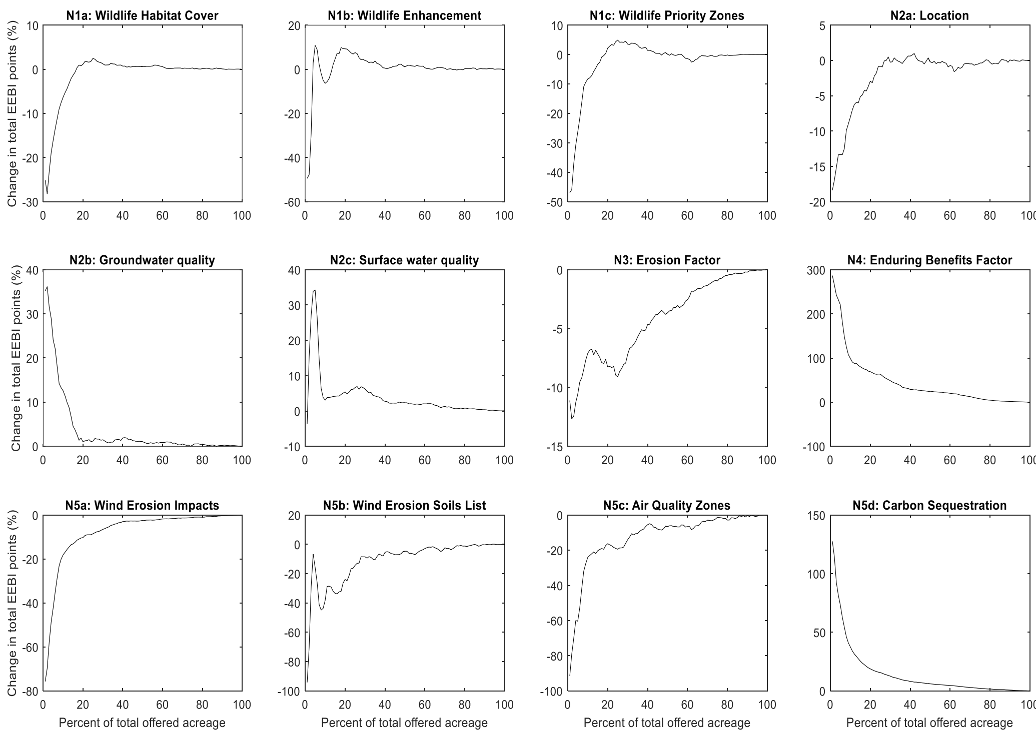

Figure 4: Percent change in Total EEBI Points under 50% acreage constraint

Note: Comparison between Status Quo (baseline) and scenario 2 (10 times of N5d) and carbon payment subtracted from rent.

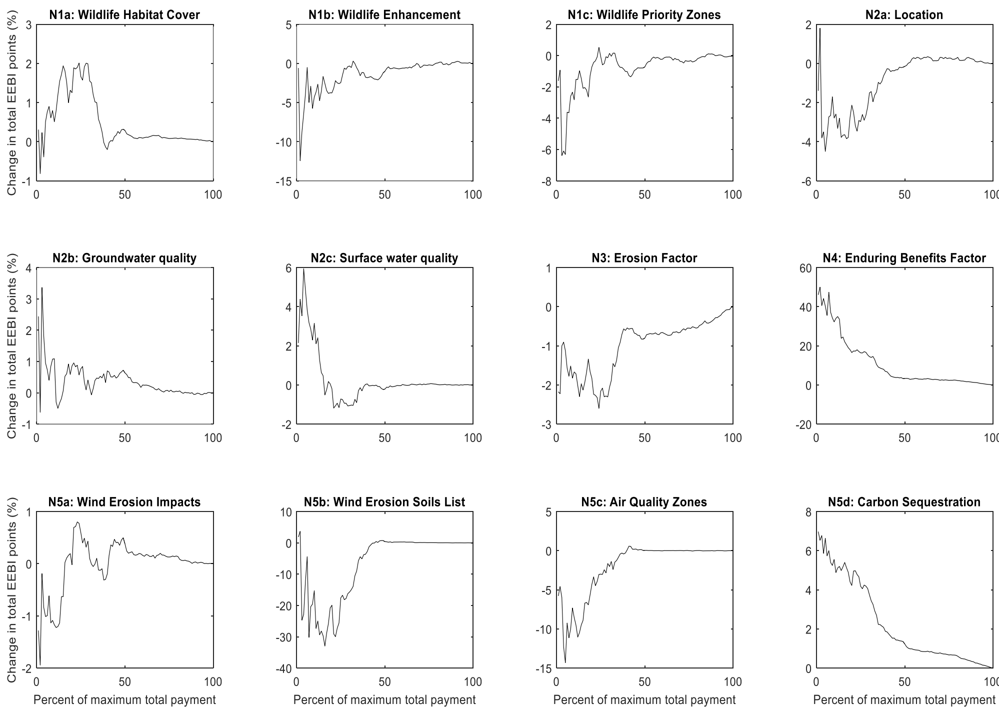

Figure 5: Percent change in Total EEBI Points under 50% budget constraint
Note: Comparison between Alternative Status Quo and scenario 3 B/C with 10 times inflated N5d vs. B/C without inflated N5d.

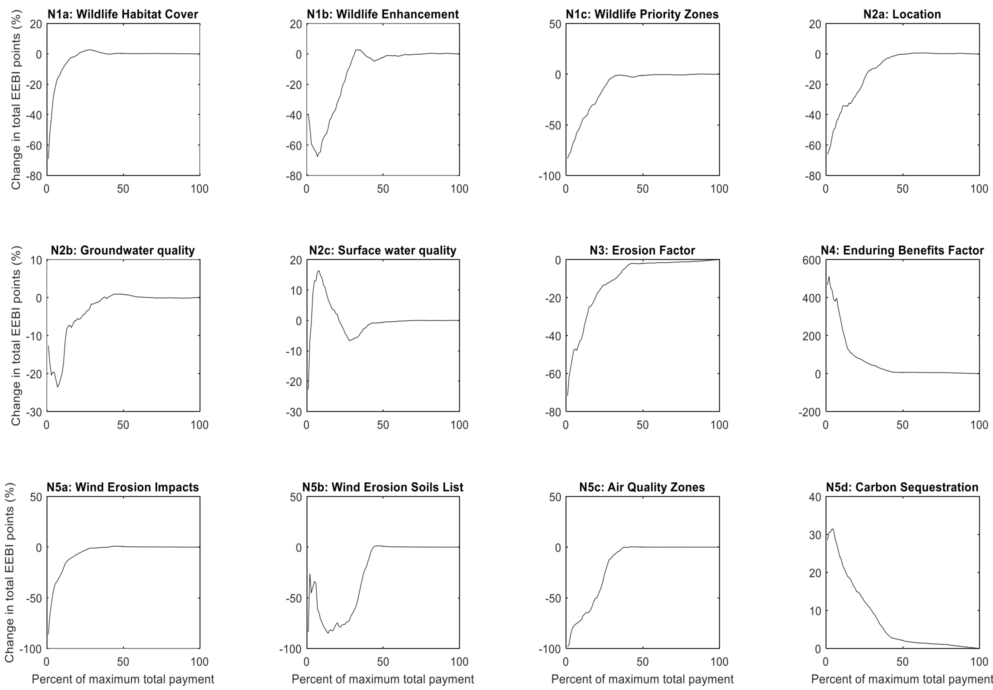

Figure 6: Percent change in Total EEBI Points under 50% budget constraint
Note: Comparison between Alternative Status Quo and scenario 4 10 times of N5d and carbon payment subtracted from rent.

Table 5: Correlation Matrix of EEBI Factors

	N1a	N1b	N1c	N2a	N2b	N2c	N3	N4	N5a	N5b	N5c	N5d
N1a	1											
N1b	0.30	1										
N1c	0.36	0.18	1									
N2a	0.01	0.03	0.73	1								
N2b	-0.08	0.03	-0.03	0.04	1							
N2c	0.11	0.24	-0.01	-0.04	0.31	1						
N3	-0.26	-0.08	-0.36	-0.30	0.18	0.26	1					
N4	0.21	0.18	0.07	0.03	0.11	0.20	-0.16	1				
N5a	0.09	-0.10	-0.01	0.00	-0.22	-0.31	-0.01	-0.17	1			
N5b	-0.11	-0.10	-0.08	0.04	0.04	-0.01	0.01	-0.11	0.09	1		
N5c	-0.10	-0.14	0.00	0.20	-0.02	-0.33	-0.01	-0.18	0.29	0.24	1	
N5d	-0.04	-0.01	0.02	0.05	0.22	0.12	-0.11	0.78	-0.35	-0.09	-0.15	1