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APPLIED COMMODITY PRICE ANALYSIS, FORECASTING, AND MARKET RISK MANAGEMENT

Drivers of Commodity Volatility in the Biofuel Era

Felipe G. Avileis

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Abstract

This paper investigates how the increased use of corn and soybean oil as motor fuel feedstock, driven by biofuel mandates, has affected price volatility. I model and study two different volatility drivers affected by the mandates: market integration and changes in the demand curve. Using the implementation of the Renewable Fuel Standard and the Renewable Diesel boom as key events, I measure the effects of these two drivers on implied volatilities using causal inference methods and a novel set of synthetic controls. Results indicate a 19% rise in corn volatility and a 18% increase in soybean oil volatility, on average, after the implementation and expansion of biofuel mandates. In the case of corn, the higher shares of corn used for fuel and a high volatility regime in energy markets are the drivers of volatility changes. For soybean oil, the increase is mostly driven by changes in marginal demand elasticity, as growing domestic demand led to the cessation of exports.

Keywords: biofuel policies, commodity volatility, renewable fuel standard, price risk, energy markets

JEL Codes: G13, Q11, Q42

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1 Introduction

Two of the most significant developments impacting agricultural markets in recent years have been the implementation of the Renewable Fuel Standard (RFS), passed as the RFS1 in 2005 and starting in 2006, and the Renewable Diesel boom (RD boom), in 2021. These events substantially increased the use of corn and soybean oil as inputs for motor fuel in the US. In the 2023/24 crop year, around 40% of corn and 50% of soybean oil produced in the US became fuel (USDA, 2024). This dramatic change in demand led to higher commodity prices (Carter, Rausser, and Smith (2017)), higher land allocated for grains and oilseeds (Hausman, Auffhammer, and Berck (2012)), increased market integration between agricultural and energy markets (Serra and Zilberman (2013), Trujillo-Barrera, Mallory, and Garcia (2012)), with questionable results regarding reduction in greenhouse gases emissions (Lark et al. (2022)).

But what are the impacts on commodity price volatility? While previous research has examined how geopolitical risks (Goyal, Mensah, and Steinbach (2024)) and export bans (Adjemian, Petroff, and Robe (2022)) affect commodity prices and volatilities, little is known about how biofuel mandates have affected the volatility of agricultural commodities prices. This paper addresses that gap.

A key measure of risk is implied volatility (IVols). IVols are forward looking volatilities priced in the market through options contracts (Egelkraut, Garcia, and Sherrick (2007)). In this paper, I answer two questions: By how much did biofuel mandates and the growing use of corn and soybean oil for motor fuel permanently affect implied volatility? And what are the mechanisms behind these changes? These questions are highly relevant because increased volatility leads to higher crop insurance premiums (Sherrick (2015)), higher operational costs due to higher trading margin requirements (Fishe et al. (1990)), complications to crop marketing, by increasing price risk, and a general decline in investment within the sector (Dixit and Pindyck (1994)).

I propose a simple stylized model to analyze demand-side factors after the implementation and expansion of biofuel mandates. The focus is on how changes in demand shock variance and the slope of the demand curve influence price risk. Two key events are central to this framework. First, the implementation of the Renewable Fuel Standard (RFS) in 2006 increased the linkage between agricultural and energy markets, amplifying the impact of energy market demand shocks on corn and soybean oil demand. Second, the renewable diesel (RD) "boom" in 2021 increased domestic demand for soybean oil, as RD production, in the US, increased by over 500% (EIA (2024)), reduced exports of soybean oil to zero and altered the marginal demand for the product. These events illustrate how higher volatility can arise through two mechanisms: market integration (by introducing additional demand shocks with higher variance from other markets, like energy) and international trade.

The data covers monthly short-dated at-the-money (ATM) European call options "implied volatility" recovered from the Black-Scholes model for corn, soybean oil, sugar, live cattle, coffee and WTI crude oil from 1996 to 2024. I divide these markets into 2 groups: biofuel commodities (corn and soybean oil) and other (exogenous) agricultural commodities (coffee, sugar and live cattle).

I estimate the effects of the Renewable Fuel Standard (RFS) implementation and the Renewable Diesel (RD) boom, marked by a sharp reduction in exports,on agricultural implied volatilities, drawing on the insights of Adjemian et al. (2017). To strengthen identification, I also employ a synthetic control approach following Abadie and Gardeazabal (2003), using exogenous agricultural commodities such as coffee, sugar, and live cattle as controls. This strategy provides a range of informative coefficient estimates. My analysis captures both the direct impact of biofuel policies and the role of shifting energy market volatility regimes before and after policy implementation. Conceptually, the effects operate through two distinct mechanisms: increased market integration following the RFS and trade reallocation pressures associated with the RD boom.

This work contributes to the literature in three ways. First, this is the first study to causally measure how these mandates affect agricultural price volatility. Documenting the effects of such policies on price volatility is of utmost relevance for policymakers.

Second, the methodology has two novel approaches. Previous research in agricultural commodity market volatility has focused on modeling historical volatility using GARCH and VECM models to capture volatility spillovers (Serra et al. (2010)). This purely time-series approach can yield inconclusive results regarding the impact of biofuel policies and often fails to offer meaningful economic insights into price behavior patterns (Abbott (2012); Headey and Fan (2008)). By using causal inference methods and synthetic controls, instead of GARCH and VECM, and implied volatility, instead of historical volatility, I offer a new angle to the literature.

Third, this approach allows me to decompose the effects of market integration and international trade on price volatility. I study how different energy market volatility regimes can affect agricultural markets. This is important because it allows policymakers, market agents, and traders to understand and consider the channels through which price volatility can change.

The results indicate that corn volatility increased by 19% following the implementation of the RFS. This increase was primarily driven by the increase in the share of corn allocated for fuel production after the RFS. Soybean oil volatility rose by 18%, mainly by the drastic reduction in exports post RD boom. The main mechanism driving this increase in soybean oil implied volatility was a change in the marginal demand, from exports to domestic markets, as exports dropped to zero, which led to the supply curve intersecting the demand curve on a steeper portion. These results follow the theoretical predictions that biofuel policies increase overall price volatility for agricultural inputs.

In addition, I find that agricultural commodities implied volatility sensitivity to energy market shocks increase by fourfold for corn and threefold for soybean oil post the implementation of the RFS. This implies that energy market volatility can both increase and dampen volatility in agricultural commodities. This is in line with the literature that finds increased spillovers from energy to agricultural markets. In combination, these results highlights the mechanisms through which agricultural commodities volatilities changed post implementation of biofuel mandates.

The remainder of this paper is organized as follows: Section 2 provides the institutional background on the biofuel policies and key events. Section 3 presents the stylized model. Section 4 outlines the data , while Section 5 details the empirical approach. Results are discussed in Section 6, and Section 7 concludes.

2 Institutional Background

In this section, I discuss the main events evaluated in this paper. The first event is the implementation of the Renewable Fuel Standard (RFS). The second event studied is the Renewable Diesel (RD) Boom.

2.1 Renewable Fuel Standard

The Renewable Fuel Standard (RFS) is a federal policy that aims at a reduction of green house gases (GHG) and mandates increased use of biofuels in the transportation sector in the US (U.S. Environmental Protection Agency (2024)). Implemented first in 2006, with a significant expansion in 2008 (RFS2), the policy requires minimum levels of biofuel blending in the diesel and gasoline pool. By setting yearly and increasing blending targets for ethanol and biodiesel, the program was the main driver behind the increased demand for these renewable fuels (CARB (2024)).

At the end of each year, the program requires fuel refineries and importers, called Obligated Parties, that produce or import gasoline and diesel to comply with the mandate by submitting Renewable Identification Numbers (RINs). These RINs are generated every time a biofuel gets blended with a fossil fuel. In other words, the mandate requires that the market buy and blend enough biofuels to generate sufficient credits for the policy.

The implementation of the RFS led to a significant increase in agricultural inputs usage for fuel production, as shown in Figure 1. Corn use for fuel purposes increased from 10.5 billion bushels in 2006/07, the policy implementation year, to 12.5 billion bushels by 2010/11, when corn-ethanol hit the "blend-wall".[1] Today, corn use for fuel purposes represents around 40% of total corn disappearance in the US.

Soybean oil represented a second agricultural input that was impacted, serving as feedstock for Fatty Acid Methyl Esters (FAME) biodiesel production during this period. However, the increase in demand occurred on a much smaller scale than other inputs. Throughout the same time from 2006/07 to 2010/11, soybean oil consumption for fuel purposes remained relatively stable at 2.7 billion pounds, accounting for approximately 15% of total US soybean oil consumption.

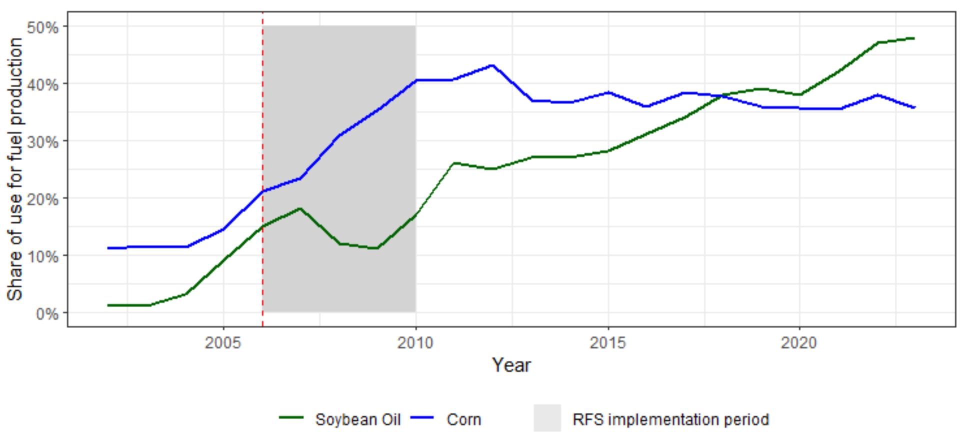

Figure 1: Changes in the share of corn and soybean oil use for fuel production
Source: WASDE/ USDA, 2025

Note: The figure shows the evolution of the shares of soybean oil and corn use for fuel production. The shaded area represents the RFS implementation period until it hit the ethanol "blend-wall". The vertical red line is the RFS implementation.

Overall, the effects of the RFS were significant for both agricultural inputs, corn and soybean oil. However, the share of corn for fuel production was significantly higher compared

[1] The 'blend wall' refers to the maximum percentage of ethanol that can be blended into conventional gasoline, which is set at 10% in the United States. By 2010/11, the mandated volume under the Renewable Fuel Standard (RFS) had reached this 10% blend threshold. Consequently, from this point forward, ethanol demand growth became directly tied to increases in overall gasoline consumption, since the blending ratio could not be increased further.

to soybean oil in the early period.

2.2 Renewable Diesel Boom and the Low Carbon Fuel Standard

California's clean fuel mandate, the Low Carbon Fuel Standard (LCFS), is one of the most ambitious in the world, aimed at reducing green house gas (GHG) emissions from fuels by 30% by 2030 (CARB (2025)). The central mechanism of the mandate is to generate a credit deficit every time an agent (i.e., refinery) sells a fuel (e.g., regular diesel) that is above the mandate GHG emission threshold in California. To be compliant, these agents need to acquire credits to offset their deficits, and they can do so by either purchasing cleaner fuels or by purchasing credits directly. Thus, agents in deficit will buy credits from clean energy producers.

The cleaner the fuel, the higher the number of credits it generates. In other words, cleaner fuels receive greater subsidies relative to "less clean" alternatives. For example, consider two identical biodiesel plants that use the same feedstock and chemical processes, with the only difference being their locations: one in Nebraska and one in Indiana. If both plants sell their product under California's Low Carbon Fuel Standard (LCFS), the biodiesel from Nebraska would have a lower carbon intensity (CI) and therefore generate more credits, since transportation emissions would be reduced due to the shorter shipping distance to California.

One of the cleanest fuels produced to supply California's market is renewable diesel (RD). The product is able to fully substitute for regular diesel (i.e., does not need blend) and can be produced using several different inputs (i.e., tallow, used cooking oil, vegetable oils). Due to the combination of high credit premiums, strong profitability, and ambitious program targets, renewable diesel (RD) production increased significantly. Production surged from 400 million gallons in 2018 to 1,200 million gallons in 2022 (EIA (2024)), as illustrated in Figure 2. This expansion resulted in renewable diesel and FAME biodiesel together capturing approximately 60% of California's diesel market by 2023, with the remaining 40% consisting of conventional

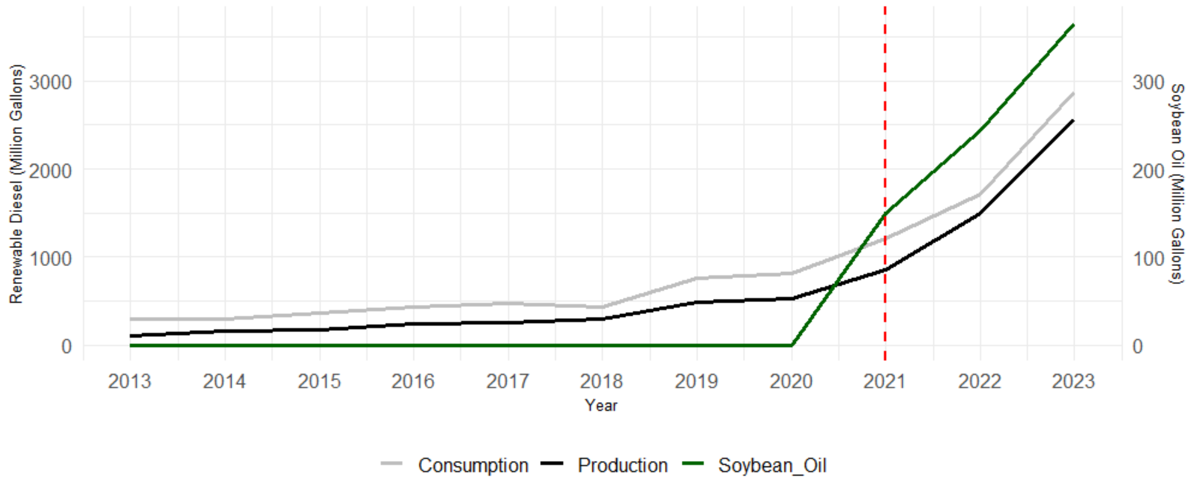

Figure 2: Renewable Diesel production and consumption and soybean oil use for RD production. Source: EIA and CARB, 2024.
Note: The left y-axis represents the annual US production and consumption of renewable diesel, while the right y-axis shows the volume of soybean oil used in RD production. The vertical red line marks the beginning of the RD boom. Note that soybean oil was not used in RD production prior to the boom in 2021.

non-renewable diesel. Within the renewable portion, renewable diesel accounts for roughly 85% of consumption, while FAME biodiesel represents the remaining 15%.[2]

Before the "boom" in 2021, soybean oil accounted for 0% of the feedstock used for RD production. After the "boom", soybean oil accounted for around 33% of feedstock used for RD production (CARB (2024)).

This is significant for two reasons. The technological improvement of RD, that created a perfect substitute, takes off the blend barrier for RD, unlike FAME biodiesel. Previously, fuels could only contain up to 5% of FAME Biodiesel, which not only limited the expansion of the biofuel, but also limited the use of soybean oil for fuel purposes.[3]

The second reason, and more important for this study, is that the boom led to a drop in US exports of soybean oil to almost zero, as noted in Figure 3. This happened for three main reasons: (i)RD producers opted to use more readily available domestic soybean oil to

[2]FAME biodiesel and renewable diesel represent alternative diesel sources with distinct production processes. FAME biodiesel production relies on transesterification of vegetable oils, which retains some residual oxygen content in the final product. In contrast, renewable diesel production involves hydrotreating and hydrogenation processes that eliminate residual oxygen entirely.

[3]In reality, even though the legal limitation was 5%, the most common blend was 2-3%.

keep up with increasing demand, (ii) Domestic food demand for soybean oil (i.e., cooking oil) is inelastic, and (iii) Global vegetable oil supply is inelastic in the short run. Therefore, the RD boom re-shaped the soybean oil demand system by increasing domestic demand to levels that significantly cut exports (GATS (2024)).

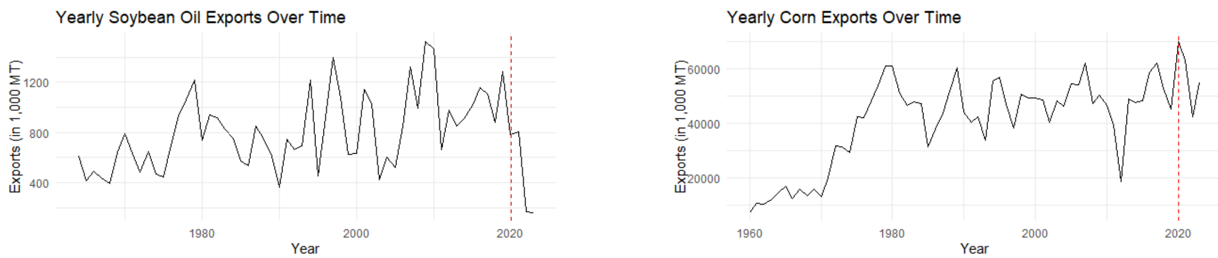

Figure 3: US Yearly exports of soybean oil and corn.
Source: Foreign Agricultural Service/ USDA, 2024.
Note: The red vertical line represents the RD boom. Note that soybean oil exports significantly drop after the boom, while corn remains unchanged.

2.3 Other uses for agricultural inputs

Feedstock for fuel is not the only use for the two agricultural inputs studied. The largest share of demand for these products, before the introduction of biofuel mandates, was for food and animal feed (USDA (2025)).

Corn is a staple food that serves as the base source of calories in many parts of the world. It also serves as animal feed, especially for pork and chicken. That makes the domestic demand for corn highly inelastic, stable at around 5.5 billion bushels a year over the past 24 years.

Soybean oil is mostly used as cooking oil in industries and in homes. While demand is also inelastic to price, as corn, the use of soybean oil grew exponentially in the US between 2000-2014 due to an increase in domestic crushing capacity. After that period, use has been mostly stable at around 14 billion lbs a year.

3 Conceptual Framework

A stylized way of thinking about supply and demand for agricultural products is by defining supply and demand functions subject to exogenous shocks (e.g., weather, geopolitical, and demand shocks). Following Baumeister and Peersman (2012), I define, for any agricultural product, demand and supply, respectively, as in Equations 1 and 2.

$$Q_t^D = -d_t \cdot P_t^* + \epsilon_t^d \tag{1}$$

$$Q_t^S = s_t \cdot P_t^* + \epsilon_t^s \tag{2}$$

Denote Q_t^D and Q_t^S as demand and supply for an agricultural commodity, respectively, and d_t and s_t are the slopes of the demand and supply curves at time t. These parameters are the supply and demand responses to price changes.

Supply and demand deviate from the steady state given exogenous and uncorrelated shocks ϵ_t^s and ϵ_t^d. These shocks follow a distribution such that $\mathbf{E}[\epsilon_t^s] = 0$, $\mathbf{E}[\epsilon_t^d] = 0$, and $var[\epsilon_t^s] = \sigma_{s,t}^2$ and $var[\epsilon_t^d] = \sigma_{d,t}^2$.

Solving equations 1 and 2 yields the equilibrium prices and quantity denoted in equations 3 and 4.

$$P_t^* = \frac{\epsilon_t^d - \epsilon_t^s}{s_t + d_t} \tag{3}$$

$$Q_t^* = \frac{s_t \epsilon_t^d + d_t \epsilon_t^s}{s_t + d_t} \tag{4}$$

Hence, combining the model above and the assumption of uncorrelated supply and demand shocks, I obtain the price and quantity variance for these markets, described in Equations 5 and 6.

$$Var[P_t] = \frac{\sigma_d^2 + \sigma_s^2}{(s_t + d_t)^2} \tag{5}$$

$$Var[Q_t] = \frac{s_t\sigma_d^2 + d_t\sigma_s^2}{(s_t + d_t)^2} \tag{6}$$

In the subsections to follow, I expand on the model proposed from Baumeister and Peersman for crude oil, adjusting it and decomposing its parameters for the agricultural sector. Using this model, I discuss each of the components of the variances for the corn and soybean oil markets and the potential sources of change in variance after the implementation of biofuel mandates. I start by discussing the variance of demand shocks (ϵ_t^d) and finish by discussing changes in the slopes of the supply and demand curves in these markets.

3.1 Demand Shocks in Agricultural Markets

As discussed in Section 2, the products studied in this research have two main uses: food/ feed and, especially after the implementation of the RFS and LCFS, fuel. The excess/ residual supply is either exported or held as inventory. Using the portfolio variance approach, I assume that the variance of the demand shocks depends on the share/ weights of the input use for each type of use (i.e., food, exports or fuel), the variance of the distribution of the demand shocks for each type of use, and the covariance of the portfolio, as in Equation 7, where w is the matrix of the share of that agricultural product uses.

$$\sigma_d^2 = w^T \Sigma w \tag{7}$$

Where,

$$
\mathbf{w} = \begin{bmatrix} w_{\text{food}} \\ w_{\text{fuel}} \\ w_{\text{exp}} \end{bmatrix} \quad \text{and} \quad \mathbf{\Sigma} = \begin{bmatrix} \sigma^2_{\text{food}} & \text{Cov}_{(\text{fuel, food})} & \text{Cov}_{(\text{food, exp})} \\ \text{Cov}_{(\text{fuel, food})} & \sigma^2_{\text{fuel}} & \text{Cov}_{(\text{food, exp})} \\ \text{Cov}_{(\text{food, exp})} & \text{Cov}_{(\text{fuel, food})} & \sigma^2_{\text{exp}} \end{bmatrix} \tag{8}
$$

Following from equations 5 and 6, after keeping all other parameters fixed, I find that a change in variance should affect the market as equation 9.

$$
\frac{\partial Var[P_t]}{\partial \sigma^2_d} > 0 \quad \text{and} \quad \frac{\partial Var[Q_t]}{\partial \sigma^2_d} > 0 \tag{9}
$$

First, I assume that $\sigma^2_{Fuel} > \sigma^2_{Food}$. I also assume that $w^{pre}_{fuel} \leq w^{post}_{fuel}$. In other words, I assume that energy demand shocks are more volatile than food demand shocks, following Wang, Wu, and Yang (2014), and that biofuel mandates did not reduce the share of any agricultural input for fuel production.

That is, the share of that agricultural product for fuel use is at least as big as before the mandate and demand shocks from energy markets have a higher variance than demand shocks from the food sector. These assumptions imply that demand variance changes depends on how big the changes in the shares w_{fuel} are and how volatile energy markets are σ^2_{fuel}.

Second, I assume that all covariances are negative. An intuitive way to think about it is that a positive fuel demand shock (i.e., a blending mandate) reduces demand in the other sectors. Thus, the negative covariances help dampen the effects of increased use for fuel.

As the policy is not aimed at minimizing the variance of this portfolio (i.e., achieve an optimal portfolio of demand components), the effects of the changes in weights (i.e., demand shares) are uncertain. I hypothesize that, because of increased weights for fuel use, after the implementation of mandates, summed with high volatility regimes in energy markets, total price variance increases. In short, this portfolio readjustment led to increase variance.

3.2 Slopes of Supply and Demand Curves in Agricultural Markets

The slopes and elasticities of agricultural supply and demand is a widely studied topic. Nerlove (1958) is the first author to discuss the response of acreage to unexpected supply shocks (e.g., weather). Roberts and Schlenker (2013)(RS) estimate short-run and long-run supply and demand elasticities for corn, rice, soybeans and wheat using instrumental variables and 3-stage least squares approach. Hendricks, Smith, and Sumner (2014)(HSS) use a county level panel dataset to estimate short-run and long-run corn and soybean supply elasticities in the US.

Both RS and HSS find that short-run supply elasticities are small and land use changes, in the US, are mostly attributed to changes in the intensive margin (i.e., crop rotation). HSS argue that the majority of the response happens in the short-run. RS finds even less elastic demand elasticities, approximately half of the elasticities in HSS.

The RS and HSS papers are set around the implementation of biofuel mandates. In fact, RS uses the supply and demand elasticities calculated to evaluate the impacts of the RFS. Nevertheless, the underlying assumption in both papers is that the implementation of biofuel mandates did not structurally changed supply elasticities and the slope of the supply curves. I maintain this assumption to argue that the slope of the supply curve is unchanged for both corn and soybean oil after the implementation of biofuel mandates.

3.3 Slope of the Demand Curve

Demand for agricultural products was mostly linked to food and feed consumption and exports before the biofuel mandates. Before the mandates, around 10% of corn and 3% of soybean oil were used for fuel production. Currently, this share is 36% for corn and 48% for soybean oil (USDA (2025)). In order to explain any changes in price variance and in quantity variance, given equations 5 and 6, I discuss the concept of marginal market elasticity of demand for agricultural products.

In general, the demand for agricultural products can be broken down in two segments:

domestic consumption, including inventories, and exports. If domestic supply is larger than domestic consumption, then the export market is the marginal user of the good. Otherwise, some sector of the domestic consumption is the marginal user.

As prices are set at the marginal unit of consumption, the slope of interest in this study (d_t) is the marginal demand slope. In other words, the price-setting mechanism depends exclusively on the slope of the marginal demand. Note that each market still has its own slope (e.g., food use, fuel use), but I argue that the price setting one is exclusively the marginal consumption market.

Let us use corn as an example. In 2023/24, the US produced around 15 billion bushels of corn, and domestic demand was around 14 billion bushels. That means the US had a surplus, which implies, that the marginal market was exports. In this case, the domestic demand is intra-marginal in terms of demand. Equilibrium prices, then, depend on how much product the export market can take, and that is defined by its market elasticity and slope.

Therefore, for this study, biofuel mandates can only change the slope of demand if they change marginal demand. For example, if exports drop to zero, as is the case of soybean oil, the marginal demand changes from exports to the domestic market. Overall, studies like Fontagne, Guimbard, and Orefice (2019) show that the exports demand is significantly more elastic (i.e., flatter slope) than domestic consumption. For corn, Fontagne, Guimbard, and Orefice (2019) measure that the free trade exports elasticity of corn is -3.13, compared to Ghanem and Smith (2022) domestic elasticity of demand of -0.051. Thus, I expect that either demand elasticity remains the same or becomes much less elastic. Following from Equation 5, if the marginal consumption changes, and the supply curve intersects with demand at a steeper part of the curve, the effects on price variance can be significant.

Another way of thinking about this is by approaching this problem as a change in the demand pool. Biofuel mandates are adding a new set of buyers (e.g. processing plants and fuel blenders) to the demand pool of corn and soybean oil. In theory, adding more buyers adds to the diversification of the pool and should reduce demand volatility.

However, under mandates, these new buyers have inelastic demand (i.e., they need to comply with the mandate). If demand increases driven by these inelastic buyers shifts demand outward sufficiently, to the point where other more elastic buyers are priced out (e.g., exports go to zero), demand becomes less elastic. Less elastic demand implies higher volatility, as in equation 5.

Therefore, despite adding more buyers to the demand pool, the shift in domestic soybean oil demand changed who the marginal buyer is, from a more elastic buyer to a less elastic one. Thus, I hypothesize that the RD boom increased price volatility in soybean oil.

3.4 Aggregate Effect

Now, I discuss how the aggregate effects can change price and demand variance. As discussed, I are assuming the supply side effects are unchanged by biofuel policies.

By assuming that energy market demand shocks increase overall demand shocks variance, as described in Equation 7, the overall price and demand variance would increase. Therefore, there are two possible scenarios: (i) Demand shock variance increase combined with no change in the slope of the demand curve, and (ii) Demand shock variance increase combined with a change in the slope of the demand curve.

In the first case, the effect is an increase in demand and price variance. From equation 6, the total effect on demand variance is the combination described in equation 10. As the slope of demand remains unchanged, there are no effects attributed to d_t. Thus, the demand variance increases only by the increase in demand shocks.

$$\text{If } d_t > s_t \implies \frac{\partial var(Q_t)}{\partial \sigma_d^2} = \frac{st}{(s_t + d_t)^2} > 0, \quad and, \quad \frac{\partial var(Q_t)}{\partial d_t} = -\frac{\sigma_s \cdot (d_t - s_t)}{(d_t + s_t)^3} > 0 \tag{10}$$

$$\text{If } d_t < s_t \implies \quad \frac{\partial var(Q_t)}{\partial \sigma_d^2} = \frac{st}{(s_t + d_t)^2} > 0, \quad and, \quad \frac{\partial var(Q_t)}{\partial d_t} = -\frac{\sigma_s \cdot (d_t - s_t)}{(d_t + s_t)^3} < 0 \tag{11}$$

The total effect in price variance is described in equation 12. Again, price variance increases exclusively because of increased demand shocks.

$$\frac{\partial var(P_t)}{\partial \sigma_d^2} = \frac{1}{(s_t + d_t)^2} > 0, \quad and, \quad \frac{\partial var(P_t)}{\partial d_t} = -\frac{2\sigma_s^2}{(d_t + s_t)^3} < 0 \tag{12}$$

In the second case, as d_t decreases when the marginal demand changes from exports to the domestic market (i.e., steeper), price variance increases, while demand variance becomes ambiguous. The direction of the effect depends if the demand curve is more or less steep than supply. If demand is more elastic (i.e., $d_t > s_t$), an increase in d_t implies higher demand variance as in 10. If not, then it decreases, as in Equation 11. Combining the elasticities found by HSS (around 0.4 for corn) with export elasticities found by Fontagne, Guimbard, and Orefice (2019) (around -5.66 for corn), and domestic demand elasticities in Ghanem and Smith (2022) (-0.051), I argue that if there was a change in marginal demand from exports to domestic consumption, the aggregate effect on demand variance is ambiguous (i.e., increases from a shock perspective, but decreases from an elasticity one). However, that effect is very positive for price variance.

In summary, the scenarios analyzed within this framework suggest an increase in price variance for both corn and soybean oil. For corn, I anticipate higher price variance following the implementation of the RFS, as it significantly increased the proportion of corn allocated to fuel production. However, I do not expect the RD boom to have any effect on corn price variance, as the marginal demand for corn remained unnafected during this period.

For soybean oil, I also expect price variance to increase as a result of the RFS. However, this effect is likely to be about half of that observed for corn, since the proportion of soybean oil used for fuel (approximately 20%) was about half of the corresponding share for corn (40%) over most of the sample period. In contrast, I anticipate substantial effects on soybean oil volatility following the RD boom. The surge in domestic demand during this period shifted the supply-demand intersection to a less elastic part of the demand curve, amplifying price variance.

4 Data and Methods

The dataset consists of monthly nearby contracts IVols for soybean oil, corn, soybeans, soybean meal, wheat, live cattle, sugar, and coffee from the Chicago Board Options Exchange (CBOE) and WTI Crude Oil from the NYMEX and the VIX from the Chicago Board Options Exchange (CBOE), from April 2004 to March 2025, extracted from Bloomberg. This series aggregates the daily closing prices considering the most traded option that day. Following Cui (2012), they represent at-the-money (ATM) options for that maturity.

The data are divided in three groups: biofuel commodities (corn and soybean oil), agricultural commodities susceptible to spillovers from biofuel mandates (soybeans, soybean meal and wheat) and exogenous agricultural commodities (sugar, coffee and live cattle). While the theoretical framework applies mainly to biofuel commodities, high linkages between agricultural products can lead to volatility spillovers across these markets (Serra and Zilberman (2013)). Thus, I study not only the direct effects of these changes on biofuel commodities, but also the potential spillovers to related commodity markets.

I model monthly IVols to study the effects of biofuel policies implementation and expansion on agricultural commodity volatility. I do this in two main ways. First, I estimate a model similar to Adjemian et al. (2017) and Adjemian, Petroff, and Robe (2022). Secondly, I estimate the same model, but using synthetic controls approach (Abadie (2021)) for robustness.

4.1 Synthetic Controls

Using exogenous agricultural commodities data, I construct synthetic controls, as conceptually introduced by Abadie and Gardeazabal (2003) and expanded by Abadie (2021). The synthetic control (denoted as $\hat{Y}^{nnls}$) estimates comprise all exogenous agricultural commodities mentioned above, excluding corn and soybean oil, which are the target variables in this study. I estimate it using non-negative least squares, as described in 13.

$$w^* = \arg\min_{\mathbf{w}} \|\mathbf{X}_1 - \mathbf{X}_0 \mathbf{w}\|_2^2 \quad \text{subject to} \quad \mathbf{w} \geq 0 \quad \text{and} \quad \mathbf{1}'\mathbf{w} = 1 \tag{13}$$

Where $\mathbf{X}_1$ is the implied volatility of the target products and $\mathbf{X}_0$ is the vector of "non-treated" (i.e., exogenous) commodities. The constraints restrict the weights to be positive and sum up to one. Thus, I have two distinct synthetic control estimates, $\hat{Y}^{nnls}$ and $\hat{Y}^{ew}$, from equation 14.

$$\hat{Y}_{0,i,t} = \sum_{j \neq i} w_j Y_{j,t} \tag{14}$$

I choose sugar, live cattle and coffee for controls as they are the exogenous in this analysis. Intuitively, these commodities are unlikely to have been affected by the implementation of biofuel policies (Adjemian, Petroff, and Robe (2022)). This is a key element of this analysis, as an unbiased estimator requires no spillover to controls.

4.2 Linear approximation under Black-Scholes

To address the linearity of synthetic controls relative to the non-linearity of the recovered implied volatilities from the Black-Scholes model. The model is described in 15, where $N(d_1)$ and $N(d_2)$ are CDFs of a standard normal evaluated at those points. A simple observation shows that the function is non-linear in standard deviation.

$$C = N(d_1)S_t - N(d_2)Ke^{-rt} \tag{15}$$
$$\text{where} \quad d_1 = \frac{\ln\left(\frac{S_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}$$
$$d_2 = d_1 - \sigma\sqrt{t}$$

As the weights in equation 13 are linearly estimated, this could lead to bias. I address this issue by choosing ATM options under short term expiration. Following Brenner and Subrahmanyan (1988), I know that for ATM calls $S = Ke^{-r(T-t)}$. This simplifies both d_1 and d_2, as in equation 16. Plugging back equation 16 and the ATM condition, I get equation 17.

$$d_1 = \frac{\sigma\sqrt{t}}{2} \quad d_2 = -\frac{\sigma\sqrt{t}}{2} \tag{16}$$

$$C(S,t) = \left[N\left(\frac{1}{2}\sigma\sqrt{T-t}\right) - N\left(-\frac{1}{2}\sigma\sqrt{T-t}\right)\right]S \tag{17}$$

Using Taylor's formula, for a small x, I get equation 18, in which $N'(0) = \frac{1}{\sqrt{2\pi}} \approx 0.4$. Then, for a small $\sigma\sqrt{T-t}$ I get equation 19.

$$N(x) = N(0) + N'(0)x + \frac{N''(0)}{2}x^2 + O(x^3) \tag{18}$$

$$C(S,t) \approx 0.4S\sigma\sqrt{(T-t)} \tag{19}$$

Therefore, under these conditions, recovering the implied volatility from the Black-Scholes formula is approximately linear.

4.3 Synthetic Controls Estimation

I estimate the controls using seven years of monthly data, from January 1996 to December 2002. The validation period is between January 2003 and December 2005.

Table 1 shows the weights for the four controls estimated for the biofuel variables - two for corn and two for soybean oil. Table 2 presents the summary statistics for the observed volatilities and synthetic controls.

Table 1: Synthetic Control Weights for Each Commodity

Commodity	*Corn*	*Soybean Oil*
Coffee	62%	48%
Sugar	22%	39%
Live Cattle	16%	13%

Note: The table reports synthetic control weights (estimated via Non-negative Least Squares) for Corn and Soybean Oil. Monthly implied volatility observations for the control commodities (Coffee, Sugar, and Live Cattle) from 1996–2002 were used to construct the synthetic controls, which were validated over the 2003–2005 period.

Figure 4 compares the synthetic controls with the observed implied volatilities (IVs). In the two bottom panels, I highlight the training period. The two vertical red lines represent the implementation of the RFS and the RD boom, respectively.

I proceed by calculating the differences between the actual values and controls and defining lowercase letters as the natural logarithm. Following [20], I define $iv_{ij,t}$ as the log excess implied volatility of commodity i relative to commodity j at time t.

Table 2: Selected Implied Volatility Summary Statistics

	Soybean Oil	*Corn*	*Synthetic Soy Oil*	*Synthetic Corn*
Full Sample - 1999 to 2024				
Observations	357	357	357	357
Min	3.39	6.63	6.07	7.15
Mean	24.44	27.13	22.81	26.95
Median	21.51	24.88	21.39	24.97
Max	188.01	183.50	135.41	183.09
St Dev	14.28	13.96	9.29	11.58
Pre-RFS - 1999 to 2005				
Observations	134	134	134	134
Min	3.39	11.75	14.11	17.02
Mean	21.66	23.53	21.34	25.20
Median	20.89	22.04	20.81	24.01
Max	39.25	43.31	34.02	42.96
St Dev	6.01	6.44	4.13	5.19
RFS Period - 2006 to 2020				
Observations	169	169	169	169
Min	7.43	6.63	6.06	7.15
Mean	22.56	28.06	22.81	27.05
Median	20.69	27.06	21.77	25.50
Max	97.29	101.13	44.93	68.19
St Dev	9.38	11.00	6.30	8.05
RD Boom - 2021-2024				
Observations	49	49	49	49
Min	19.32	16.44	13.95	16.38
Mean	30.98	26.82	25.99	30.50
Median	29.74	24.44	21.60	25.38
Max	51.73	47.88	135.41	183.09
St Dev	5.69	8.23	19.26	23.88

Source: Bloomberg (2024) and Author.
Note: This table provides summary statistics for implied volatilities of soybean oil, corn, and their respective synthetic controls. Statistics are reported by subsample for monthly observations and include the minimum, mean, median, maximum, and standard deviation.

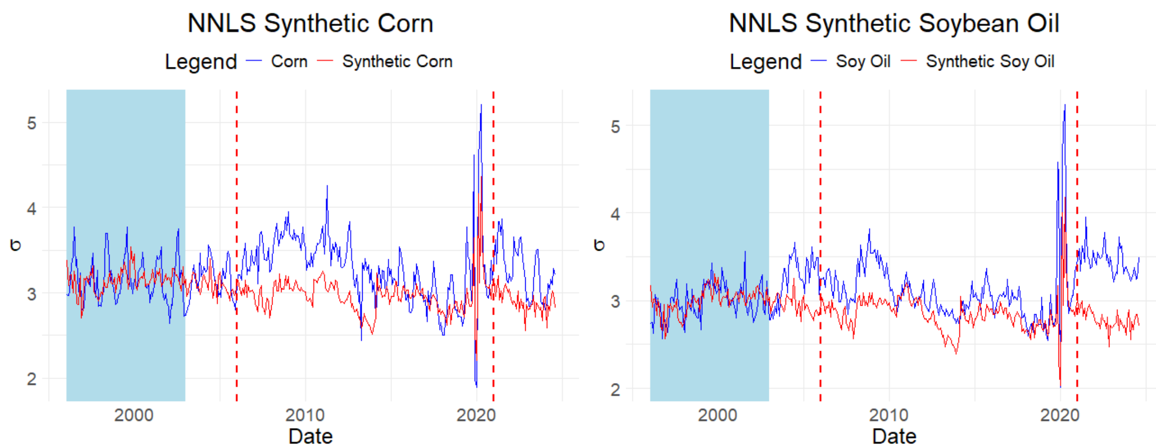

Figure 4: Comparison between target variables and synthetic controls

Note: This figure displays the actual implied volatilities (represented by the blue lines), the equally weighted control (black lines in the top row), and the estimated synthetic control (red line in the bottom row). The vertical red lines indicate the implementation of the RFS and the onset of the RD boom, respectively. The blue-shaded area on the bottom row charts highlights the training period for the synthetic control. The vertical axis represents the log excess implied volatility of the target variable relative to the control.

$$\sigma_{ij,t} = y - \hat{y} \tag{20}$$

4.4 Empirical Approach and Estimation

I estimate the models described in equations 21 and 22 by ordinary least squares (OLS). The vector ϕ_k captures the autorregressive parameters of the model. I define RFS_t as a dummy variable for the presence or not of the policy. I explicitly control for the blend-wall in the corn regression by adding the dummy BW_t. EXP_t is a regime changing variable that is equal to 1 when exports of at least one of the biofuel goods is zero. The variable $\bar{\sigma}_{wti_t}$ is the de-meaned log implied volatility calculated for WTI futures and X_t is a set of control variables, such as a specific controls for COVID, weather shocks and global financial crisis.

To evaluate the effects of the RFS, I observe coefficients β_1 and β_4. The first is the direct effect of the policy implementation, related to a change in expectations regarding biofuel demand, while the second is whether or not the relationship between the underlying product with energy markets changed after the implementation of the RFS. Coefficient β_3 is the effect of having no exports (i.e., moving to a steeper portion of the demand curve) on implied volatility.

$$\sigma_{i,t} = \beta_0 + \sum_{k=1}^{p} \phi_k \sigma_{i,t-k,l} + \beta_1 \, \mathrm{RFS}_t + \beta_2 \, \mathrm{BW}_t \mathbf{1}_{(i=corn)} + \beta_3 \, \mathrm{EXP}_t \mathbf{1}_{(exp_i \leq E)} \tag{21}$$
$$+ \beta_4 \left(\mathrm{RFS}_t \cdot \bar{\sigma}_{wti,t} \right) + \delta' X_t + \epsilon_t$$

$$\hat{\sigma}_{i,t} = \beta_0 + \sum_{k=1}^{p} \phi_k \hat{\sigma}_{i,t-k,l} + \beta_1 \, \mathrm{RFS}_t + \beta_2 \, \mathrm{BW}_t \mathbf{1}_{(i=corn)} + \beta_3 \, \mathrm{EXP}_t \mathbf{1}_{(exp_i \leq E)} \tag{22}$$
$$+ \beta_4 \left(\mathrm{RFS}_t \cdot \bar{\sigma}_{wti,t} \right) + \delta' X_t + \epsilon_t$$

The two periods studied are significant as they provide insights into two distinct mechanisms. I define the RFS period as the market integration phase, during which the use of agricultural inputs for biofuel production began to rise, particularly for corn. A key characteristic of this period is the increased connection between agricultural and energy markets, leading us to test whether this interaction varies for different agricultural fuel inputs.

Conversely, the RD boom refers to the period characterized by strong incentives for RD production, resulting in a surge in the use of soybean oil as a fuel input. This shift caused a notable decline in soybean oil exports and moved the intersection of supply and demand to a steeper portion of the demand curve. I leverage this period to evaluate the effects of changes in export regimes.

Given the theoretical framework presented in Section 2, I anticipate that corn markets will exhibit stronger responses to the RFS in both models, but both products are affected by the RFS implementation. In contrast, the RD boom is expected to primarily impact soybean oil markets, leading us to expect significant results for soybean oil but not for corn, whose exports regime remained unchanged.

5 Results

Table 3 presents the main results for corn, while table 4 presents the main results for soybean oil. The top row indicates the model and the specification. The lag specifications were determined using the Akaike Information Criterion (AIC).

5.1 Corn

Table 3: Impact of Biofuel Policies on Corn Volatility

CORN	*OLS*	*OLS + Ag Controls*	*Synthetic Control*
RFS	0.18**	0.17**	0.23**
	(0.04)	(0.03)	(0.05)
Blend-Wall	-0.22**	-0.13*	-0.12**
	(0.04)	(0.04)	(0.04)
RD Boom	–	–	–
	–	–	–
RFS × σ_{wti}	0.52**	0.43**	0.36**
	(0.15)	(0.14)	(0.12)
Other Ag Commodities	No	Yes	–
Weather Controls	Yes	Yes	Yes
Observations	340	340	340
F-stat	24.98	31.76	28.26
R-square	0.52	0.61	0.51

Note: The table presents regression results for target coefficients under different specifications. Synthetic control is the control estimated following Abadie and Gardeazabal (2003). Results represent a percent change in corn implied volatility. Robust standard errors are in parentheses. Significance levels: * $p < 0.05$, ** $p < 0.01$.

Results for corn, indicate that the implementation of the RFS increased price risk by around 19%, on average. This is in line with the theoretical approach. Corn usage for fuel significantly increased after the RFS implementation to more than 30% in the first two years of the policy. Drawing from equation 7, the implementation of the RFS translates to a big increase in w_{fuel}, which would lead to higher price variance.

The interaction term between the RFS implementation and WTI crude oil shocks reveals additional insights. Findings indicate that energy shocks become significantly more relevant after the RFS implementation, contributing to increases in corn volatility. In essence, periods of heightened volatility in the energy markets correspond to greater overall volatility in corn prices. Conversely, when energy market volatility is low, corn volatility tends to decrease. This observation aligns with equation 7, which posits that both the share of fuel use and the volatility of fuel markets play crucial roles in influencing agricultural price risk.

In summary, the RFS increased corn volatility because it increased the interaction with the energy market and energy markets volatility was high in the period. This is observed in periods like 2008 and recent years. However, I do not discard the possibility that under moments of low volatility, energy markets could dampen volatility in corn markets, following standard portfolio variance theory.

5.2 Soybean Oil

Table 4: Impact of Biofuel Policies on Soybean Oil Volatility

SOYBEAN OIL	*OLS*	*OLS + Ag Controls*	*Synthetic Control*
RFS	0.05*	0.00	0.00
	(0.22)	(0.02)	(0.03)
Blend-Wall	–	–	–
	–	–	–
RD Boom	0.18**	0.21**	0.16**
	(0.05)	(0.04)	(0.06)
RFS × σ_{wti}	0.34**	0.24**	0.34**
	(0.10)	(0.06)	(0.11)
Other Ag Commodities	No	Yes	–
Weather Controls	Yes	Yes	Yes
Observations	340	340	340
F-stat	44.08	61.61	39.65
R-square	0.62	0.72	0.61

Note: The table presents regression results for soybean oil implied volatility under different specifications. Synthetic control is defined following Abadie and Gardeazabal (2003). Results represent a percent change in volatility given a 1% change in the explanatory variables. Robust standard errors are in parentheses. Significance levels: * $p < 0.05$, ** $p < 0.01$.

The results for soybean oil indicate that the RFS had a minimal impact on price volatility. However, there are some indications in the interaction model that the relationship between energy markets and soybean oil volatility mirrors that of corn. I hypothesize that this reduced effect may be attributed to the slower adoption of soybean oil for fuel compared to corn, leading to less pronounced volatility impacts in the early RFS years. According to portfolio theory, the significance of energy markets on soybean oil variance is contingent upon the share of soybean oil utilized as fuel.

This is also predicted in the model. The increase in share of soybean oil used for fuel production due to the RFS was insufficient to induce drastic changes to price risk. In the same time-span that took corn usage for fuel to jump to 40%, soybean oil use for fuel production was lower than 20%. This reflects in a low enough w_{fuel} in equation 7 to generate significant effects. I hypothesize that these effects may begin to materialize given the recent uptick in soybean oil usage for fuel production.

On the other hand, the effects of the RD boom are notable. A consequence of the RD boom was that US soybean oil exports dropped to zero, as shown in figure 3. Thus, this event would have changed the marginal elasticity of demand for soybean oil. This move shifted demand to a less elastic portion of the demand curve, which would increase price volatility according to equation 12.

Results point that the effects of the RD boom, regardless of the approach used, are around 18%. That is, the change in exports regime caused by the increased use of soybean oil for fuel production resulted in a 18% increase in price volatility. These results highlight the importance of exports as a buffer to volatility. They also highlight a key factor for policymakers to take into account: overstretching domestic demand and foregoing participation in international markets.

6 Conclusion

Understanding the mechanisms that drive agricultural price volatility in the era of renewable fuels is fundamental for managing risk among farmers, merchandisers, users and processors. While the increased demand for agricultural products resulting from biofuel mandates has supported farmers with higher prices, it also introduced new market dynamics.

In this paper, I categorize these changes into two groups: increased integration with energy markets and changes in the slope of the demand curve. My analysis reveals heterogeneous effects across different commodities. I estimate that corn was significantly impacted by the market integration mechanism, experiencing a 19% increase in price volatility. In contrast, soybean oil was mainly affected by the slope of the demand curve mechanism, with an estimated increase in volatility of 18%.

Equally important, I find that different volatility regimes in energy markets play a crucial role in shaping the volatility of these agricultural commodities. After the introduction of the biofuel mandates, periods of high volatility in energy markets correspondingly increased the volatility of agricultural commodities. Conversely, periods of low volatility can dampen the volatility of corn and soybean oil.

These results are relevant for policymakers and underscore the importance of comprehending the mechanisms associated with the implementation and future expansions of biofuel mandates and other agricultural policies focused on increasing demand. For instance, I find that when domestic demand increases to the point of restraining exports, it can significantly elevate price volatility. The direct consequences of these changes affect option prices, increase trading margins, increase crop insurance costs, could increase price risk and heighten uncertainty in farmer revenue.

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