Does Options Trading Matter for Market Volatility and Hedging Effectiveness? Evidence from the 1936 Options Trading Ban on Futures Markets in the US.

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Abstract

Commodity options provide a useful tool for farmers to hedge against adverse price movements, but they can also be used as a tool for speculation, potentially increasing market volatility. This paper examines the effects of a 1936 ban on commodity options trading on both hedging effectiveness and price volatility, using newly collected data for Chicago and London futures markets and a difference-in-differences approach that exploits the fact that commodity options were banned in US but not in the UK. We find that in the short term, the volatility of grain futures prices in Chicago increased significantly post-ban. In the long term, our findings suggest that the ban decreased volatility by a significant margin, driven by the fact that there was no repeat of the severe manipulation of wheat markets that had occurred in 1933. However, this came at the cost of a reduction in hedging effectiveness in US grain futures markets.

Keywords: Market Volatility, Commodity Options, Hedging Effectiveness, Manipulation, Grain Futures Markets

1 Introduction and Motivation

On June 15, 1936, trading in options on grain futures contracts at the Chicago Board of Trade was banned and remained prohibited until October 1984 due to increasing allegations of price manipulation and abuse. The belief was that these options written on futures were distorting market prices as they were predominantly used as speculative instruments rather than for their intended purpose of risk management. The primary role of futures markets is the reallocation of risk from hedgers to speculators. However, concerns arose that the speculative nature of options trading was overshadowing their hedging benefits, leading to the regulatory intervention. This paper examines the consequences of this options ban, focusing on its impact on market volatility and the effectiveness of hedging strategies.

Options serve a dual purpose in financial markets: they function as both hedging tools and speculative instruments. But how are options beneficial for futures trading? Compared to futures contracts, options offer significant advantages. The main difference is that while futures contracts fix prices in advance, options allow farmers to set prices within a range of market outcomes. For instance, put options allow farmers to set a minimum selling price for their crops, ensuring protection against price drops while still allowing them to benefit from potential price increases. Similarly, call options establish a maximum buying price, yet still permit the owner to buy commodities at lower prices if available (Kenyon, 1984; Urcola & Irwin, 2011).

Ross (1976) argues that in uncertain markets, options improve hedging efficiency for risk-averse agents such as farmers. Biais and Hillion (1994) highlight that the introduction of options completes markets, reduces information asymmetry, and enhances risk sharing. Frank, Irwin, Pfeiffer, and Curtis (1989) investigate hedging strategies in soybeans markets and show that incorporating options strategies improves the risk efficiency of expected returns. Moreover, Ball and Torous (1986) suggest that the introduction of futures options enables the measurement of market participants' assessments of futures price volatility, thereby offering additional insights into the futures price process.

The 1936 ban on options trading in Chicago futures markets offers a unique historical context to explore the implications for market dynamics and efficiency of risk reallocation.

This paper contributes to the existing literature by investigating whether and to what extent the absence (rather than the introduction) of options affects market volatility and the hedging effectiveness in grain futures markets.

A key theoretical framework in this study is the Black-Scholes-Merton (BSM) model, which revolutionized options pricing by highlighting the importance of the underlying asset's volatility (Black & Scholes, 1973). Previous research has shown that futures price behaviour significantly affects the valuation of options written on futures contracts (Ball & Torous, 1986; Brenner, Courtadon, & Subrahmanyam, 1985; Ramaswamy & Sundaresan, 1985). However, the relationship is not unidirectional: while futures volatility influences options pricing, the trading volume of options can, in turn, affect futures volatility. Increased options trading creates opportunities for higher returns, attracting risk-seeking traders to the underlying market.

Although the BSM was introduced in the early 1970s, it is argued that interwar traders might have intuitively priced options according to similar assumptions (Chambers & Saleuddin, 2020).[1] While extensive literature exists on options pricing efficiency and the factors influencing option valuation, there remains a gap in understanding the broader economic and regulatory implications of prohibiting options on futures contracts as a risk management tool. This paper aims to address this gap by examining the effects of the 1936 options trading ban on market volatility and hedging effectiveness. Using a novel dataset comprised of weekly grain futures and spot prices traded at the Chicago Board of Trade (treated group) and London Grain Exchange (used as a control) collected from *Statistical Bulletins*, *Annual Reports of CBoT* and contemporary newspapers (*The Times*), we test two main hypotheses:

1. Impact on volatility: The ban on options written on CBoT futures contracts significantly affected the volatility of grain futures prices, potentially indicating that traders were able to manipulate futures prices through options trading.

[1]Previous studies of options pricing before the BSM model: Mehl (1934) analysed short-dated wheat options traded at the CBoT from 1926 to 1931; Dew-Becker and Giglio (2023) introduce synthetic options (implied volatility) on grains for the period 1906-1936.

2. Hedging effectiveness: Hedging effectiveness in futures markets decreased post-ban, suggesting that hedgers relied on options to manage risk more efficiently.

To test the causal effect of the options ban on the volatility of grains futures markets, we employ a difference-in-differences (DiD) approach (Angrist & Pischke, 2009), comparing grain futures in Chicago to those *same* futures contracts in London (where no ban was implemented) during the period from 1932 to 1939. This method helps identify any divergence in volatility between these markets coinciding with the ban. The DiD identification approach requires the standard parallel trend assumption (PTA), which means that the treated group would have evolved similarly to the control group if options had not been prohibited. We include individual and time-fixed effects in our DiD regressions to control for time-invariant commodity characteristics (e.g., storage costs) and time-varying shocks (e.g., seasonality). We model volatility according to a GARCH (1,1) specification and a standard rolling window approach. Our results suggest a nuanced impact of the options trading ban. In the short term, the volatility of grain futures prices in Chicago increased significantly post-ban, which contrasts with the long-term findings where the volatility effect vanishes and becomes insignificant. Additionally, we also provide findings which suggest that post-ban, the volatility of grain futures prices in Chicago, observed for three years before and three years after the ban, decreased. We argue that this decrease is totally driven by an outlier event: A heightened pre-ban volatility, caused by manipulation of the wheat market in 1933, which led to the political action to prohibit options trading.

Additionally, we use an event-study approach (Roth, 2022) to analyze hedging effectiveness, measured by the minimum variance hedge ratio. We take two approaches here and test this empirically in both static (Ederington, 1979; Figlewski, 1984) and dynamic frameworks (Baillie & Myers, 1991; Cecchetti, Cumby, & Figlewski, 1988). Interestingly, our findings indicate that as a result of the options ban, hedging effectiveness significantly decreased, implying that hedgers were unable to manage the price risk of their crops effectively without this risk management tool.

The remainder of this paper is organized as follows. Section 2 provides historical background on the options trading ban in the US. Section 3 discusses the theoretical motivations behind the study. Section 4 introduces the dataset. In Section 5, we outline the empirical methods used to test our hypotheses. The results are presented in Section 6. Finally, we discuss and conclude the findings in Section 7.

2 Historical Background

From the late 1890s to the early 1920s, speculation in grains became a major national political issue in the United States. Congress regularly debated bills, also known as *anti-option* bills, that primarily aimed to curb *excessive* speculation and targeted organized commodity exchanges, such as the CBoT (Banner, 2017). Political action for these measures was largely driven by farmers who accused speculators of manipulating crop prices and exacerbating volatility. During this period, the debate over the role of speculators in the market increased. While some argued that speculative practices harmed farmers, others defended speculation as an integral part of market operations, essential for price discovery and liquidity.

What led to the options trading ban in 1936? The ban was a direct response to market manipulation and political pressure. The catalyst was the attempted manipulation of the wheat market in July 1933. During this episode, wheat futures prices plummeted by over 25% within two days. Investigations by the Grain Futures Administration (GFA) revealed that ten traders, controlling fifteen accounts, were responsible for this sharp decline (GFA, 1933, p. 21). This incident, combined with the overall depressed prices resulting from the Great Depression prompted legislative action aimed at preventing market manipulation.

Throughout the interwar period, skepticism towards speculators grew among farmers and government officials. The debate centered on restricting large speculators, with the belief that prohibiting options trading would curb their perceived harmful impact. Based on thorough analyses of the GFA between 1924 and 1934[2], the federal government recognized the importance of small speculators in maintaining market liquidity and efficiency. However, the 1936 Commodity Exchange Act aimed to protect these small traders by

[2]GFA issued around 25 publications during this period, including Duvel and Hoffman (1927, 1928); U.S. Secretary of Agriculture (1926, 1933).

targeting large speculative practices through the prohibition of options trading.[3] Interestingly, this measure, intended to protect hedgers and small speculators in grain futures markets, may have unintentionally harmed farmers by reducing their hedging effectiveness, as this paper will demonstrate.

3 Theoretical Motivation

The theoretical motivation for our study is the BSM model for pricing options (Black & Scholes, 1973). According to this model, five factors determine the price of an option on futures: the futures price, time to maturity, the exercise price, the interest rate, and the volatility of the futures prices.

Options written on futures are securities that provide the right to buy or sell a futures contract under specific conditions within a given timeframe. An American call (put) option on a futures contract grants the holder the right to purchase (sell) a futures contract on or before a specified date at a specified futures price, known as the exercise price K. The option may expire at a date prior to the maturity of the underlying futures contract. Upon exercise at date s, the holder receives receives $F(s) - K$ in cash and opens a long position in the futures contract at the futures price $F(s)$. Conversely, the call-option writer provides $F(s) - K$ in cash and opens a short position in the futures contract at the futures price $F(s)$. Since the newly opened futures contract has zero value (Black, 1976), the portfolio's wealth is altered only by the cash inflow or outflow upon exercise, although the portfolio's future dynamics could be significantly affected by the new futures position (Ramaswamy & Sundaresan, 1985).

When the futures price for any given commodity at a specific maturity changes, it results in gains or losses for investors holding long and short positions in the corresponding futures contracts (Black, 1976). This price change affects the value of an option and the decision of an American trader to exercise their option if the underlying futures price significantly exceeds the exercise price, i.e., $F(s) > K$. In such cases, the option is

[3] For a comprehensive discussion of the events leading to the Commodity Exchange Act of 1936, see Saleuddin (2018).

typically exercised, and its value approximates the futures price minus the price of a pure discount bond maturing on the same date as the option, with a face value equal to the strike price of the option (Black & Scholes, 1973).

Research shows that accounting for time-varying changes in futures prices improves the estimation of options pricing on futures contracts (Myers & Hanson, 1993). Additionally, empirical studies highlight the significant role of the futures price and its volatility in the valuation of options on futures contracts (Ball & Torous, 1986; Brenner et al., 1985; Ramaswamy & Sundaresan, 1985). The pricing of futures options also provides insights into market participants' expectations regarding futures price volatility (Ball & Torous, 1986).

Despite the extensive theoretical and empirical research exploring the efficiency of options pricing and the factors influencing the pricing of an option, there remains a gap in understanding the implications of options trading on futures markets. Our study focuses on the reverse relationship between options and futures, asking: Is there a link or causal effect of options pricing on the volatility of futures prices? Were American traders able to "manipulate" futures price volatility through their early exercise privilege?

By addressing these questions, our research aims to shed light on the economic and regulatory consequences of the 1936 options trading ban on the underlying futures markets.

4 Data

For our empirical analysis, pre- and post-treatment data is needed as well as data on treated and control units. The data we utilize consist of weekly futures prices for wheat and corn from both Chicago and London, covering the period from 1932 to 1939. The Chicago futures data, which are the treated units in our sample, were sourced from the *Statistical Bulletins No. 54, 55, 72, 74* and were hand-collected. Futures prices represent closing traded prices on Fridays for contracts of varying maturities, including March, May, July, September, and December. As the closing quotations are provided in ranges, we take the average of the lower and upper bounds for analytical purposes. Futures prices are denoted in US cents per bushel.

Additionally, we digitize and include weekly spot prices for Chicago markets to measure and analyse hedging effectiveness before and after the ban. These spot prices for wheat and corn are sourced from the *Annual Reports of the Board of Trade of the City of Chicago, volumes 75-82*. Similar to the futures prices, the spot price observations are provided in ranges, and we take the average of these values as well.

For the London markets, which were unaffected by the regulatory change and serve as control groups in our empirical strategy, price data were transcribed from the *Home Commercial Markets* section of *The Times* newspaper. To the best of our knowledge, these data have not been previously used in other studies.[4] We collected all available closing traded Friday prices for the wheat and corn futures markets. If prices were not reported on Friday, for instance, due to bank holidays, we used the prices from the preceding trading day. Unlike Chicago, futures contracts for grains in London were traded in all calendar months. To match the maturities with the Chicago contracts, we retained only the 3, 5, 7, 9, and 12-month maturities, ensuring that we only compare contracts of the same maturities at any given point in time. Prices of these contracts are given in shillings and pence, representing prices per 480lbs of wheat and corn traded on the futures market. To match the prices per traded unit with those in Chicago, we divided the collected observations by 8 (for wheat) and 8.57 (for corn) to obtain the price per bushel in shillings. This transformation ensures that the futures prices are comparable between Chicago and London.[5]

Given the price observations, we compute week-to-week returns on each individual futures contract of maturity T as follows:

[4] Data on other commodities (copper, cotton, tin) from this source have been used to test options price efficiency (Chambers & Saleuddin, 2020) and to measure inflation expectations (Lennard, Meinecke, & Solomou, 2023).

[5] We chose not to adjust UK prices according to the pound-US exchange rate because our focus is on the variation of prices and their individual developments around the ban, rather than the direct relationship between the price series. Furthermore, Britain and the US left the gold standard at different times, which would complicate any exchange rate adjustments.

$$R_{i,t}^{T} = log[F_i(t,T)] - log[F_i(t-1,T)] \tag{1}$$

where $log[F_i(t,T)]$ and $log[F_i(t-1,T)]$ represent the logarithmized prices of a futures contract expiring in month $T = \{March,\ May,\ July,\ Sep,\ Dec\}$ for commodity $i = $ *Chicago corn, Chicago wheat, London corn, London wheat* for two consecutive weeks t and $t-1$, respectively.

To measure volatility and hedging effectiveness, further adjustments to the futures price observations are necessary. Prices for different futures contracts must be combined into continuous futures price series for each commodity and market. The literature suggests several rolling strategies to construct continuous series for futures prices (Carchano & Pardo, 2009). We use one of the most commonly employed and robust approaches: rolling on the first day of the delivery month. Specifically, for each commodity and market in our sample, we use the trading data of the nearest-to-expire contract in month M. On the first Friday of delivery month M, we switch to the next-to-expire contract.[6] The four constructed continuous futures price series (two for the treated units and two for the control units) are visualized in Figure 1. Additionally, we construct continuous series for returns, ensuring that these are always derived from futures contracts with the same maturities.

Finally, we merged the Chicago futures and spot price data with the London futures data and filtered the sample to cover the period from April 1933 to July 1939, ensuring that we include in our empirical analysis data from exactly three years before and three years after the ban. This results in a dataset of 326 weekly observations for each computed series. Summary statistics are presented in Table 4.

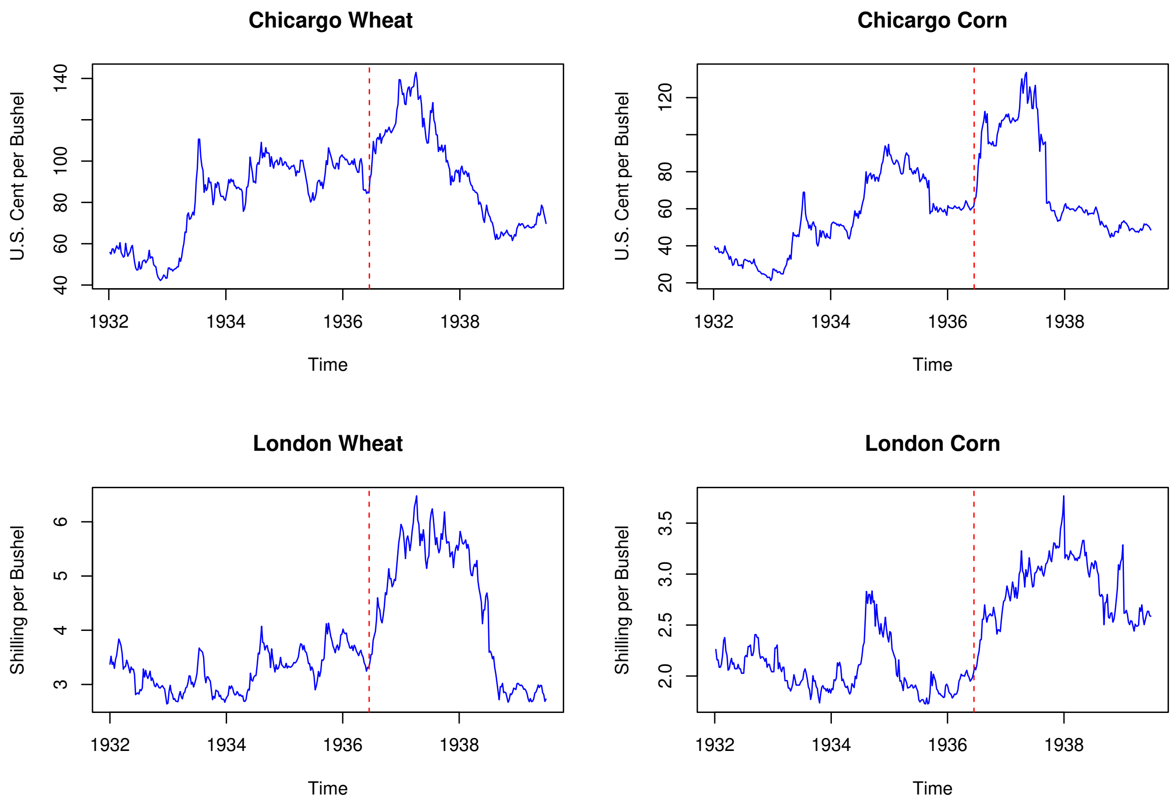
[6] We do not use trading price data up to the expiration day of contracts because, as Samuelson (1965) highlights, prices exhibit abnormal volatility in the final weeks of futures contracts.

Table 1: Summary Statistics: Pre and Post Treatment

Statistic	Mean		Median		St. Dev.		Min		Max	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
$P_{corn,Chiago}$	63.257	74.979	60.375	59.875	15.047	27.210	32.375	44.562	94.750	133.625
$P_{wheat,Chiago}$	92.053	94.800	94.562	94.188	9.565	24.251	57.562	61.500	110.625	142.938
$P_{corn,London}$	2.021	2.862	1.935	2.869	0.259	0.315	1.726	2.061	2.835	3.768
$P_{wheat,London}$	3.322	4.498	3.339	4.880	0.373	1.220	2.672	2.672	4.130	6.479
$R_{corn,Chicago}$	0.494	0.298	0.000	0.000	4.496	3.700	−19.860	−11.717	23.036	15.202
$R_{wheat,Chicago}$	0.200	−0.091	−0.127	−0.055	3.852	3.239	−11.824	−8.270	12.392	8.901
$R_{corn,London}$	0.076	0.535	0.000	0.338	3.213	2.874	−9.496	−8.377	10.801	8.198
$R_{wheat,London}$	0.032	0.007	−0.302	0.105	3.235	3.530	−10.173	−9.289	10.248	11.000
$Rolling\ \sigma^2_{corn,Chicago}$	19.810	11.937	9.696	5.827	29.989	15.403	0.616	0.474	161.894	80.329
$Rolling\ \sigma^2_{wheat,Chicago}$	14.037	9.803	9.559	7.961	13.770	7.721	0.236	0.648	71.137	34.315
$Rolling\ \sigma^2_{corn,London}$	10.102	7.981	5.958	5.182	11.237	8.202	0.375	0.469	48.760	52.141
$Rolling\ \sigma^2_{wheat,London}$	9.485	11.432	6.839	8.454	9.177	9.528	0.218	0.384	40.594	45.222
$GARCH\ \sigma^2_{corn,Chicago}$	4.219	3.634	3.546	3.109	2.134	1.663	2.141	2.110	14.789	10.876
$GARCH\ \sigma^2_{wheat,Chicago}$	3.786	3.351	3.398	3.304	1.180	0.697	2.197	2.123	7.107	5.173
$GARCH\ \sigma^2_{corn,London}$	3.151	3.006	2.890	2.779	0.898	0.704	2.157	2.159	6.181	5.780
$GARCH\ \sigma^2_{wheat,London}$	3.246	3.419	3.066	3.416	0.677	0.609	2.294	2.365	5.122	5.218

N = 326 on each series

Figure 1: Prices of Grain Futures Contracts in Chicago and London.



5 Methodology

The aim of this paper is to empirically analyze the impact of the 1936 options trading ban on market volatility and hedging effectiveness in US futures markets. Using the data discussed in the previous section, we test two main hypotheses: first, the causal effect of the ban on the volatility of grain futures prices in Chicago; and second, whether and to what extend the prohibition of options trading affected the effectiveness of hedging strategies of farmers. To address these hypotheses, we employ a comprehensive methodological approach, which is detailed in the following subsections.

5.1 Measures of Market Volatility

We begin by calculating the volatility of futures prices for our treated and control groups. For robustness purposes, we use two different approaches: standard rolling volatility and dynamic GARCH volatility.

The standard rolling volatility is a widely used method for measuring the volatility of financial time series. This approach calculates the rolling standard deviation of weekly returns, which captures temporal fluctuations in a market. By using a window of five weeks, we are able to smooth out short-term, within-month noise while still capturing significant changes in volatility. The rolling standard deviation is then squared to obtain the variance of the series, e.g., the standard rolling volatility measure:

$$\textit{Rolling } \sigma^2_{i,t} = \left(\sqrt{\frac{1}{s-1} \sum_{j=t-s+1}^{t} (R_{i,j} - \overline{R}_{i,t})^2} \right)^2 \tag{2}$$

where $\sigma^2_{i,t}$ is the rolling variance for futures price series i (e.g., *corn Chicago, wheat Chicago, corn London, wheat London*) at time t, $R_{i,j}$ represents the weekly return for series i at week j, s is the rolling window size and $\overline{R}_{i,t}$ is the mean of the weekly returns over the window ending at time t. Figure 2 shows the volatility measures derived from the rolling window approach for the Chicago and London futures markets.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are are widely used in financial time series analysis to capture the volatility clustering and persistence often observed in financial data. Introduced by Bollerslev (1986), this approach is based on the assumption of conditional heteroskedasticity, allowing the variance of the unobserved shocks in a regression model captured in the error term to vary over time. By including lagged values of squared errors, GARCH models effectively capture short term volatility dynamics.

In this study, we calculate the dynamic volatility of futures prices using an AR(1)-GARCH(1,1) model.[7] The mean equation for this model is given by:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

where the futures returns, $R_{i,t}$, are explained by an AR(1) term, i.e., previous week return. The serially uncorrelated errors, $\varepsilon_{i,t}$, are assumed to be normally distributed with mean zero and conditional variance $\sigma^2_{i,t}$, i.e., $\varepsilon_{i,t} \sim N(0, \sigma^2_{i,t})$.

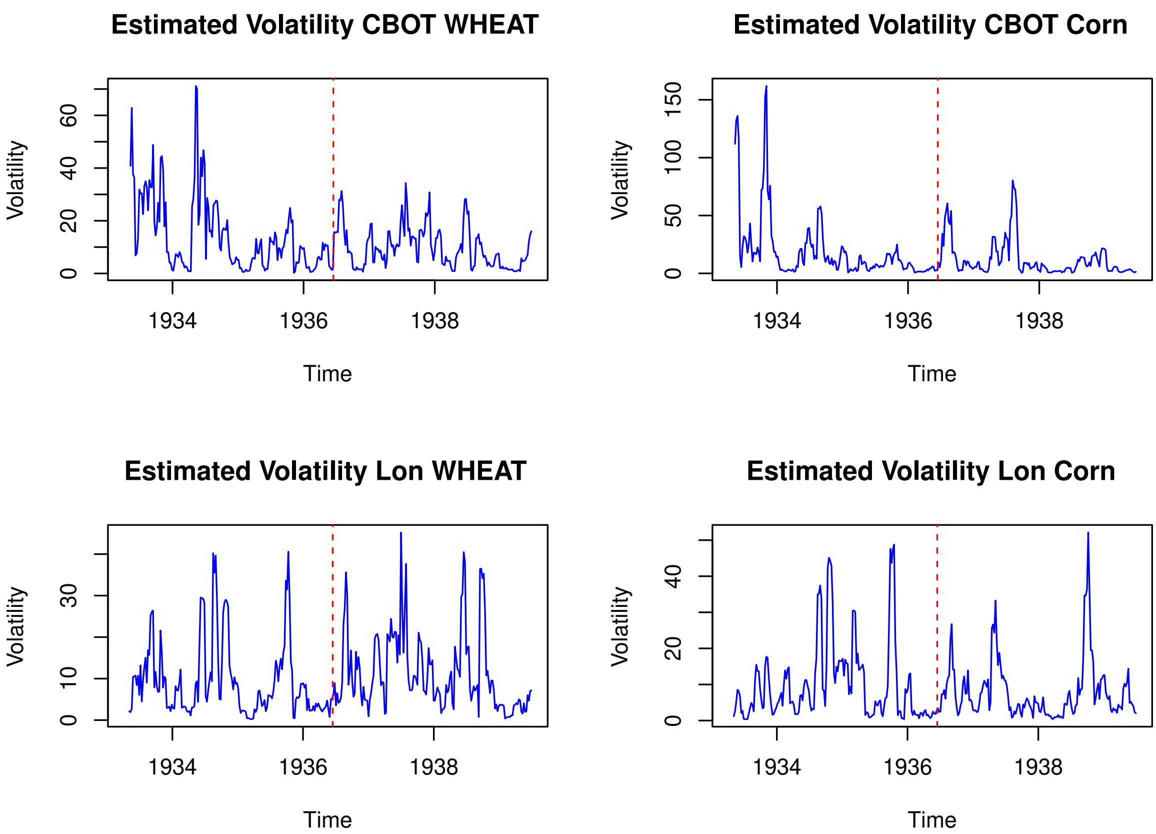
In the next step, GARCH volatility is measured by the conditional variance of $\varepsilon_{i,t}$ from Equation 3, as follows:

$$GARCH\ \sigma^2_{i,t} = \gamma_0 + \gamma_1 \varepsilon^2_{i,t-1} + \gamma_2 \sigma^2_{i,t-1} \tag{4}$$

where $\varepsilon^2_{i,t-1}$ are squared unobserved shocks lagged one period, e.g. one week, and $\sigma^2_{i,t-1}$ represents the one period lagged forecast error variance. Parameter γ_1 describes the ARCH effect indicating how strongly the conditional variance reacts to new information arriving in the futures market, whereas γ_2 denotes the GARCH effect, measuring the persistance of volatility shocks. Moreover, parameters γ_0, γ_1, and γ_2 are constrained to be positive, and that the sum of ARCH and GARCH effects $(\gamma_1 + \gamma_2)$ is less than one to ensure covariance stationarity and non-negative conditional variance. The GARCH volatilities for the four futures series in our sample are displayed in Figure 3.

[7] The finance literature suggests modeling financial asset returns using an AR(1)-GARCH(1,1) specification, as the time-varying second-order moments of the conditional variance are sufficient to capture the volatility clustering observed in financial time series. We estimate several AR(p)-GARCH(p, q) specifications where p and q vary from 0 to 2. Our empirical results do not change.

Figure 2: Rolling Volatility.

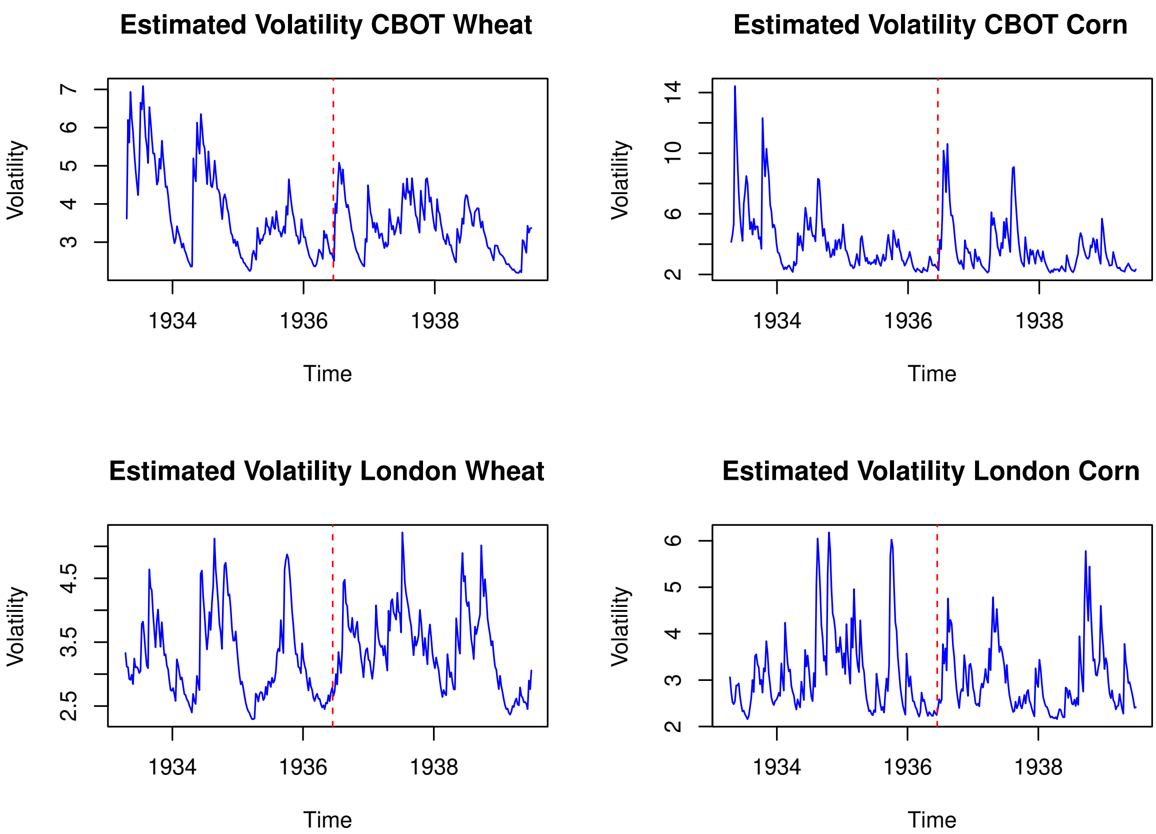


5.2 Differences-in-Differences

Now that we have computed measures of volatility, we can proceed to test the effect of the 1936 options trading ban on market volatility. The difference in difference approach (DiD) is a widely used econometric method for evaluating the causal effect of policy changes (Angrist & Pischke, 2009). It computes the difference in outcomes before and after a regulatory change between a treatment group - affected by the change - and a control group - unaffected by the policy change.

The challenge in identifying the causal effect of options trading on grain futures market characteristics, such as volatility, is that options trading is endogenous to commodity-specific characteristics. In other words, the trading activity in options written on futures might be influenced by the inherent characteristics of the grains themselves and vice

Figure 3: GARCH Volatility.



versa. Consequently, OLS regression estimates of the impact of options trading on market characteristics would be biased. We address this endogeneity problem by comparing changes over time (before and after the options ban, e.g., the "treatment") between grains with and without the ban, thereby isolating the causal effect of options trading.

To do this, we assume that the volatility of grain futures markets, measured, in turn, by $Rolling\ \sigma^2_{i,t}$ and $GARCH\ \sigma^2_{i,t}$, can be explained by the following model:

$$E[Volatility_{0,i,e,t}|i,e,t] = \rho_e + \lambda_t + \alpha_i + z_{i,t} \tag{5}$$

where $Volatility_{0,i,e,t}$ is the volatility of commodity i (corn or wheat) on exchange e at date t with options trading allowed (i.e., London Exchange) and $Volatility_{1,i,e,t}$ is the volatility of grain i on exchange e at date t with the prohibition of options trading (i.e. the "treated" markets in Chicago). ρ_e captures the differences between trading environments at the Chicago and London exchanges, λ_t are time-fixed effects, α_i are time-invariant commodity-fixed effects, and $z_{i,t}$ are time-varying commodity-specific unobserved shocks. Hence, the assumption modeled in Equation 5 indicates that the volatility of grain futures is determined by exchange-specific factors, overall market conditions, commodity specific characteristics, and time-varying shocks specific to each commodity.

The first hypothesis we test in our paper is the extent to which the options trading ban, effective as of June 15, 1936, affected the volatility of the underlying futures markets. Using the difference-in-differences (DiD) methodology and considering the assumption regarding volatility from Equation 5, we estimate the following model for the observed volatility:

$$Volatility_{i,e,t} = \rho_e + \lambda_t + \alpha_i + z_{i,t} + \beta \times Ban + \eta_{i,t} \tag{6}$$

where Ban is a dummy variable that equals one for Chicago markets after the options trading ban and zero otherwise. The coefficient of interest, β, is our DiD estimator, capturing the impact of the ban on futures market volatility in Chicago using futures market volatility in London as a control group.

This equation can also be expressed within an OLS regression framework with dummy variables and an interaction term as follows:

$$\begin{aligned} Volatility_{i,e,t} = \beta_0 + \underbrace{\beta_1 \times Treated}_{\text{commodity fixed effects}} + \underbrace{\beta_2 \times AfterTreatment}_{\text{time fixed effects}} + \\ + \underbrace{\beta_3 \times Treated \times AfterTreatment}_{\text{DiD estimator}} + \epsilon_{i,t} \end{aligned} \tag{7}$$

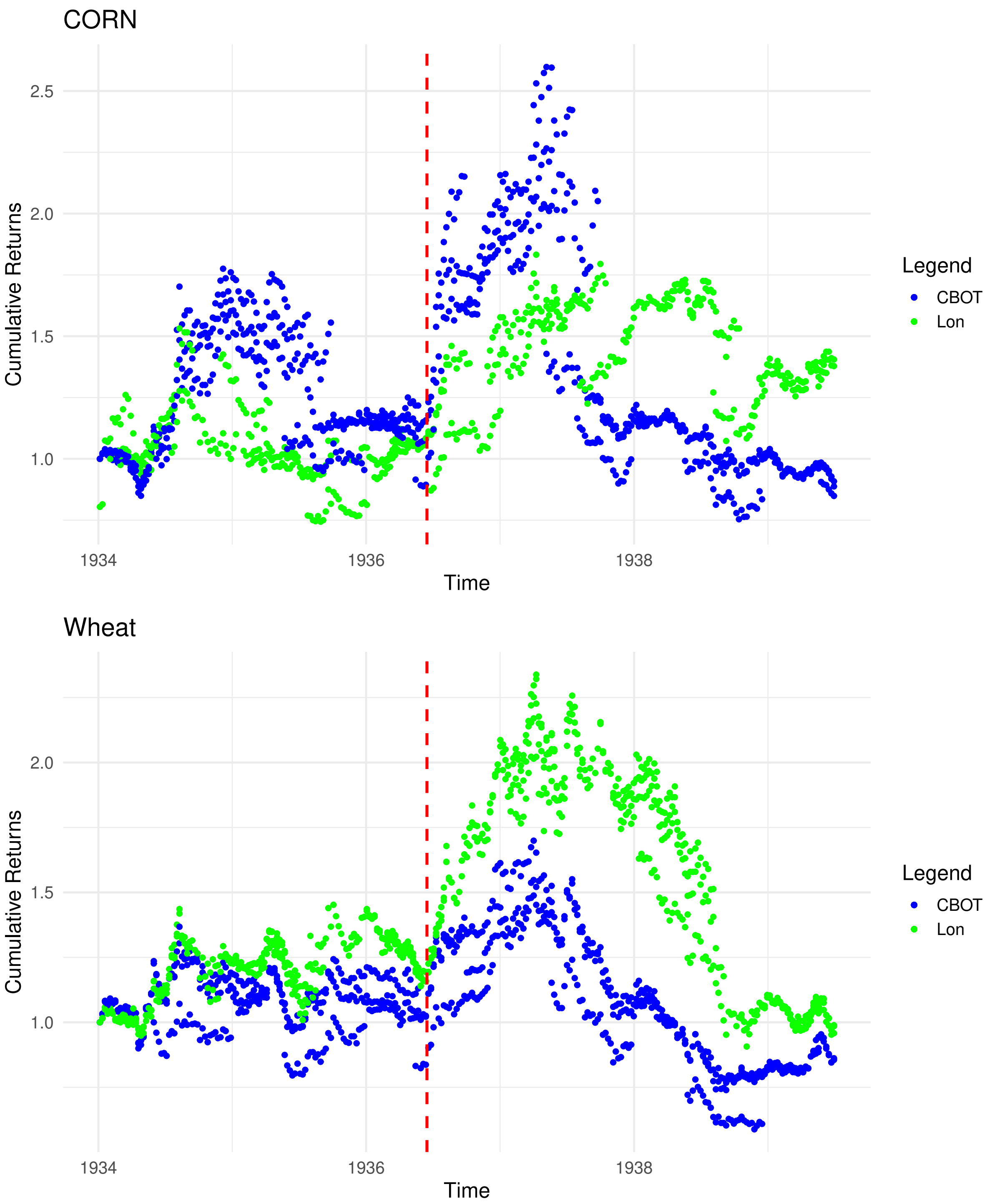
In this equation, $Treated$ is a dummy variable that equals one for the volatility of grain futures prices in Chicago, and $AfterTreatment$ is a dummy variable that equals one for the period after the ban was introduced. The interaction term $Treated \times AfterTreatment$ equals one if both hold true. equals one if both conditions hold true. Here, the coefficient of interest is β_3, the coefficient of the interaction term. which indicates whether there is a significant difference in the volatility of futures prices in Chicago (treated) compared to London (untreated) after the ban. We estimate this equation in addition to Equation 6 to empirically assess the time and individual fixed effects on the volatility of treated and untreated units.

Two key conditions must be met when estimating a DiD model: the parallel trend assumption (PTA) and "no-anticipation" assumption. The PTA ensures that in the absence of treatment (i.e. options trading ban), the difference in outcomes between the treated and control groups would have remained constant over time. Figure 4 provides visual evidence consistent with the PTA. It illustrates the cumulative returns of futures prices for all contracts in the treatment (CBoT) and control (London) groups, which represent the underlying data for our volatility measures.[8] The cumulative returns of futures prices behave similarly for both groups up to the ban. However, following the ban, a gap between returns is noticeable, indicating different trajectories. Specifically, in corn as well as wheat futures markets, the cumulative returns in Chicago and London show substantial divergence after the ban, with this trend persisting through 1938. In wheat markets, the difference continues to grow, while in corn markets, starting in 1938, returns in London start surpassing those in Chicago. Based on this graphical evidence, the PTA is fulfilled, demonstrating that our chosen control group is appropriate.

The second prerequisite for the DiD methodology is the "no-anticipation" assumption, which states that treated units do not change their behavior in anticipation of the treatment before it occurs. As discussed in Section 2, skepticism towards speculation was a recurring issue, and the debate over market manipulation had been ongoing since the inception of the CBoT in in the nineteenth century. This period, often characterized as an "anti-option era" in the US saw futures traders constantly anticipating stricter market regulations, particularly from 1921 onward with the introduction of federal regulation of exchanges. Due to this continuous expectation of regulatory intervention, any behavioral changes would have been gradual and spread over time, rather than concentrated immediately before the ban. Therefore, we can reasonably assume that short-term anticipation effects did not significantly influence market behavior in the treated group prior to the 1936 options trading ban.

[8] We include in this figure cumulative futures returns for all contracts in our sample to provide a comprehensive view of the overall market movements.

Figure 4: PTA.


CORN
2.5
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Cumulative Returns
1934
1936
1938
Time
Legend
CBOT
Lon
Wheat
2.0
1.5
1.0
Cumulative Returns
1934
1936
1938
Time
Legend
CBOT
Lon

5.3 Hedging Effectiveness

Our second hypothesis tests whether hedging effectiveness in US markets decreased after the ban, suggesting that hedgers relied on options trading to manage risk more effectively.

The most widely used approach to measure the hedge ratio[9] is by means of the *Minimum-Variance* (MV) hedge ratio. This approach minimizes portfolio risk, defined as the variance of changes in the value of the hedged portfolio. The intuition behind the MV hedge ratio is as follows: Theoretically, an investor constructs a portfolio consisting of a long position in the spot market and a short position in the futures market. The investor hedges the spot position at proportion h with a futures transaction, where $(1-h)$ represents the unhedged portion of the spot position. The expected return of this portfolio is given by:

$$E[r_p] = E[\Delta s_t] - h \cdot E[\Delta f_t] \tag{8}$$

The variance of the portfolio is given by the weighted variances of the spot and future returns, minus twice their covariance:

$$\sigma_P^2 = \sigma_S^2 + h^2\sigma_F^2 - 2h\sigma_{SF} \tag{9}$$

To minimize the portfolio risk, we take the first derivative with respect to h and set it to zero:

$$h = \frac{cov(\Delta s_t, \Delta f_t)}{var(f_t)} \tag{10}$$

For a given volatility of the futures returns, the hedge ratio and thus the hedging effectiveness are higher when the correlation between spot and futures returns is higher. This indicates that the primary role of futures markets—transferring risks associated with future price fluctuations from hedgers to speculators (Hicks, 1941; Keynes, 1923)—is fulfilled. The hedge ratio thus measures the level of correlation between spot and futures returns relative to the variance of the futures returns.

[9]Optimal Hedge Ratio refers to the proportion of the cash position that is covered by a contrary position in the futures market.

MV can be measured using static or dynamic approaches. For the static case, the literature suggests estimating hedging effectiveness via OLS as follows (Ederington, 1979; Figlewski, 1984):

$$\Delta s_t = \alpha + h\Delta f_t + \epsilon_t \tag{11}$$

Since we are interested in the effects of the options trading ban on hedging effectiveness, we employ an event study approach (Roth, 2022) and modify the above regression as follows:

$$\Delta s_t = \alpha + h_1 \times \Delta f_t + h_2 \times D_t + h_3 \times (D_t \times \Delta f_t) + \epsilon_t \tag{12}$$

where D_t is a dummy variable that equals one for the period after the introduction of the options trading ban (June 15, 1936), and zero otherwise. h_1 captures the hedging effectiveness before the ban, β_2 captures the shift in the mean of Δs_t due to the ban and β_3 is the coefficient of interest, capturing the difference in hedging effectiveness prior and after the ban.

In the second approach, we measure MV hedge ratio dynamically. The intuition behind this method is similar to the static case; however, instead of estimating h via a simple OLS regression, we estimate the Variance-Covariance Matrix dynamically. This involves calculating variances and covariances at each point in time, rather than once for the entire sample.

To allow the hedge ratio to change over time, we recalculate it based on the current (or conditional) information on the covariance $\sigma_{s,f}$ and the variance σ_f^2.

ARCH and GARCH models are employed to account for heteroscedastic errors in Equation 11. Rather than using the unconditional sample variance and covariance, the GARCH model's conditional variance and covariance are used to estimate the hedge ratio. Specifically, the DCC-GARCH model is utilized to study the interdependence in volatility between the futures and spot prices, allowing the hedge ratio to adjust dynamically during the hedging period.

Thus, the hedge ratio is calculated based on conditional information, $\sigma_{s,f}|\Omega_{t-1}$ and $\sigma_f^2|\Omega_{t-1}$ instead of unconditional information. The dynamic MV hedge ratio is given by:

$$h_1|\Omega_{t-1} = \frac{\sigma_{s,f}|\Omega_{t-1}}{\sigma_f^2|\Omega_{t-1}} \tag{13}$$

For estimation, we rely on a bivariate GARCH model (Baillie & Myers, 1991; Cecchetti et al., 1988):

$$\begin{bmatrix} \Delta S_t \\ \Delta F_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \leftrightarrow \Delta Y_t = \mu + \epsilon_t \tag{14}$$

$$e_t|\Omega_{t-1} \sim N(0, H_t), H = \begin{bmatrix} H_{11,t} H_{12,t} \\ H_{21,t} H_{22,t} \end{bmatrix} \tag{15}$$

Here, the conditional MV hedge ratio at time t is given by $h_{t|t-1} = H_{12,t}/H_{22,t}$. The hedge ratio changes over time, resulting in a series of hedge ratios over the entire horizon conditional on the available information.

6 Results

We begin by examining the causal impact of the 1936 options trading ban on the volatility of futures prices, utilizing the Difference-in-Differences (DiD) methodology. Next, we discuss the outcomes of the event study analysis, which explores the impact of the options ban on hedging effectiveness.

6.1 Impact on Volatility

6.1.1 Full sample

Regression results from estimating Equations 7 and 6 are presented in columns (1) & (3) and (2) & (4) of Table 2, respectively. We empirically analyse the impact of the ban on the two computed measures of volatility: $GARCH\ \sigma^2$ and *Rolling* σ^2, over the period from April 1933 to July 1939, ensuring a symmetric interval before and after the ban.

The London grain futures contracts are used as a control group to isolate the effect of the ban on the CBoT futures contracts.

In column (2) where we used time and commodity fixed effects, the coefficient of -0.52 on *Ban* is highly statistical significant at 1% level. This indicates that futures market volatility in Chicago, as compared to London, significantly decreased following the prohibition of options trading. Consistent results are obtained when estimating a two-way fixed effects (TWFE) regression via OLS on $Treated \times AfterTreatment$, further confirming our results. The significance and direction of the coefficient remain unchanged when using *Rolling* σ^2 as dependent variable, as shown in Columns (3) and (4). Although the magnitude of the coefficient differs, the interpretation remains consistent. It is important to highlight a critical consideration regarding these results. While the findings might support the prohibition of options trading, it is essential to account for the inclusion of the 1933 market manipulation in the sample period, which made the pre-ban period more volatile. Therefore, the observed decrease in volatility post-ban is not entirely surprising given this context.

Examining the coefficients when time and commodity fixed effects are not included (Columns (1) and (3)), we observe a further interesting result. The constant term (ρ_e) which captures differences between trading environments at the Chicago and London exchanges and exchange-specific effects that might influence price volatility, is positive and highly significant. This indicates that the regulatory environments significantly affect volatility between Chicago and London.

6.1.2 Further investigations

To gain a deeper understanding of the impact of the options ban on futures volatility, we conduct further investigations by excluding the 1933 market manipulation period to analyze a "more stable" market environment pre-ban. We repeat our analysis twice to explore both the short-term and long-term effects of the ban.

First, we assess the short-term effects of the ban, excluding the period influenced by the grain market manipulation. Specifically, this analysis covers the period from 1934 to 1937. The empirical results are presented in Table 3. Examining the estimated coefficient

Table 2: Regression Results 1933 - 1939

	(1)	(2)	(3)	(4)
	GARCH σ^2		*Rolling* σ^2	
$Treated$	0.80***		6.79***	
	(0.11)		(1.37)	
$AfterTreatment$	0.01		-0.09	
	(0.06)		(0.76)	
$Treated \times AfterTreatment$	-0.52***	-0.52***	-5.56***	-5.58***
(Ban)	(0.13)	(0.11)	(1.62)	(1.39)
Constant	3.20***	3.61***	9.79***	13.13***
(ρ_e)	(0.04)	(0.04)	(0.57)	(0.53)
Time FE (λ_t)	NO	YES	NO	YES
Commodity FE (α_i)	NO	YES	NO	YES
Observations	1282.00	1282.00	1282.00	1282.00
R-squared	0.07	0.53	0.04	0.47

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of interest (0.42 and 3.63), our DiD estimators (Ban), we observe that, in contrast to previous results, the coefficients are highly significant and positive, regardless of the volatility measure used. This indicates a significant increase in volatility in Chicago grain futures markets post-ban in the short-term. These results remain robust when we estimate our TWFE model.

Then, we examine the long-term effects of the ban, excluding any pre-ban market anomalies. This analysis spans the period from 1934 to 1939. The empirical results, shown in Table 4, reveal no significant long-term impact of the ban on grain futures volatility. The coefficients decrease substantially compared to the short-term analysis, becoming very low and insignificant (0.05 and 0.61). This indicates that the initial increase in volatility observed post-ban dissipates over time. Our findings remain robust when we estimate the TWFE model.

In sum, our empirical analysis reveals that the 1936 options trading ban had a significant short-term impact on futures market volatility in Chicago, as evidenced by the positive and highly significant coefficients in the immediate months following the ban. However, this effect diminishes over time, with long-term analysis indicating no significant impact on volatility. Including the period of market manipulation in 1933 revealed negative and significant results, highlighting that the difference between volatility in Chicago pre- and post-ban was due to the market anomaly pre-ban. Overall, these findings suggest that while the ban initially increased market volatility, its effects were not sustained in the longer term.

Table 3: Regression Results 1934 - 1937

	(1)	(2)	(3)	(4)
	$GARCH\ \sigma^2$		$Rolling\ \sigma^2$	
$Treated$	0.23***		0.53	
	(0.09)		(1.01)	
$AfterTreatment$	0.10		0.59	
	(0.07)		(0.94)	
$Treated \times AfterTreatment$	0.42***	0.42***	3.63**	3.63***
(Ban)	(0.15)	(0.13)	(1.67)	(1.39)
Constant	3.23***	3.38***	10.22***	10.72***
(ρ_e)	(0.05)	(0.03)	(0.69)	(0.38)
Time FE	NO	YES	NO	YES
Commodity FE	NO	YES	NO	YES
Observations	836.00	836.00	836.00	836.00
R-squared	0.06	0.56	0.02	0.54

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression Results 1934 - 1939

	(1)	(2)	(3)	(4)
	$GARCH\ \sigma^2$		$Rolling\ \sigma^2$	
$Treated$	0.23***		0.53	
	(0.09)		(1.01)	
$AfterTreatment$	-0.01		-0.52	
	(0.07)		(0.86)	
$Treated \times AfterTreatment$	0.06	0.05	0.64	0.61
(Ban)	(0.12)	(0.09)	(1.32)	(1.04)
Constant	3.23***	3.33***	10.22***	10.21***
(ρ_e)	(0.05)	(0.03)	(0.69)	(0.37)
Time FE	NO	YES	NO	YES
Commodity FE	NO	YES	NO	YES
Observations	1146.00	1146.00	1146.00	1146.00
R-squared	0.02	0.55	0.00	0.52

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2 Impact on Hedging Effectiveness

The results from our previous analysis on the impact of volatility suggest that the 1936 options trading ban may not have been necessary, as there were no significant long-term effects on volatility. In contrast, the short-term effects indicated increased volatility. This raises the question: how were hedgers affected by this ban? To what extent did the ban impact their ability to manage risk effectively through hedging? In this subsection, we present empirical results from testing our second hypothesis on hedging effectiveness.

Table 5 presents the results from estimating Equation 12 for measuring hedging effectiveness in static frameworks. Results for the dynamic framework are presented in Figure 5. Interestingly, the event study analysis reveals that hedging effectiveness decreased in the Chicago markets post-ban. The coefficients of interest on $D_t \times \Delta f_t$ are highly statistically significant and negative (-0.175 and -0.180).

For robustness, we repeat this analysis by splitting our sample into two periods: before the ban and after the ban, excluding the date of the ban. A simple OLS estimation with robust standard errors shows a marked decrease in hedging effectiveness. In the static case, hedging effectiveness decreases from 0.434 to 0.188 in the Chicago markets, while in the dynamic case it decreases from 0.436 to 0.179. A highly statistically significant z-test confirms that the differences in hedging effectiveness pre- and post-ban are significant, reinforcing our previous findings.

Taken together, our empirical analysis reveals that the 1936 options trading ban significantly impaired hedging effectiveness in the Chicago futures markets. Both static and dynamic frameworks show a significant decrease in hedging effectiveness, indicating that the prohibition of options written on futures reduced the ability of hedgers to manage risk. These results suggest that while the ban aimed to curb speculation and prevent market manipulation, it also weakened the futures market's essential function of risk management.

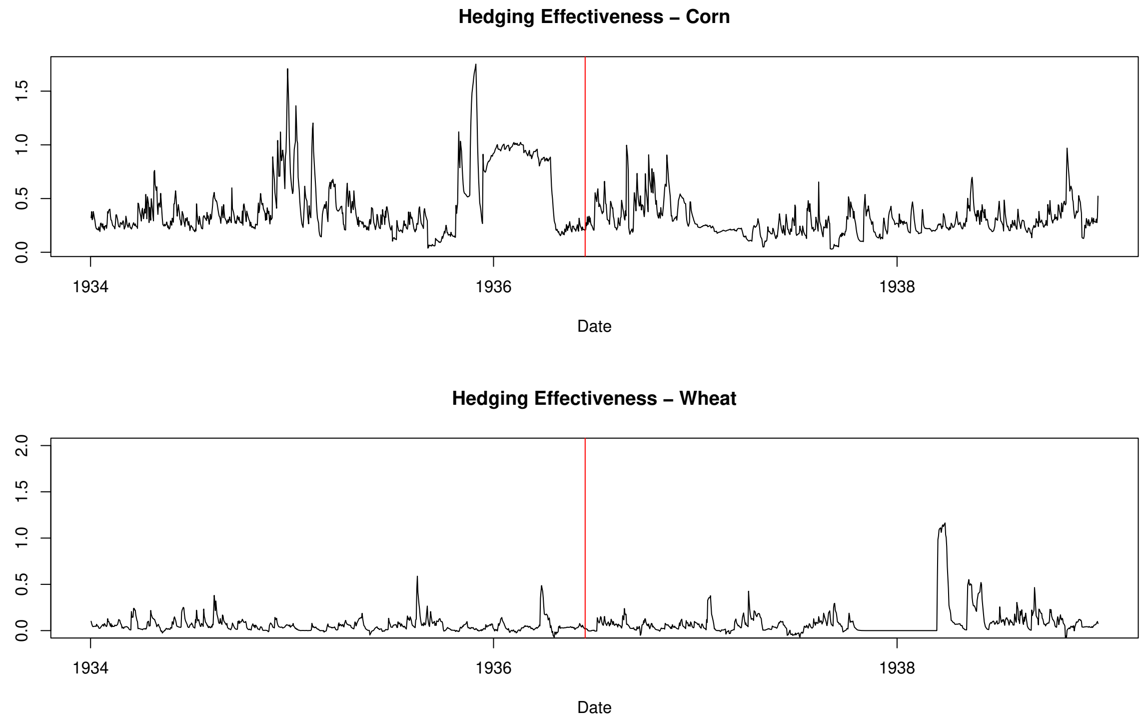
Table 5: Event Study - Fixed Effects Regression Results with Robust Standard Errors

	Δs_t	
	(1)	(2)
Δf_t	0.418^{***}	0.419^{***}
	(0.042)	(0.042)
D_t	-0.004^{***}	-0.004^{***}
	(0.001)	(0.001)
$D_t \times \Delta f_t$	-0.175^{**}	-0.180^{**}
	(0.082)	(0.081)
Constant	0.002^{***}	0.004^{**}
	(0.001)	(0.001)
Commodity FE	No	Yes
Monthly FE	No	Yes
Observations	3,756	3,756
R^2	0.097	0.112
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 6: Hedging Effectiveness Pre- and Post-Ban

	Pre Ban		Post Ban	
	(1)	(2)	(3)	(4)
Δf_t	0.434***	0.436***	0.188***	0.179***
	(0.043)	(0.044)	(0.064)	(0.061)
Individual FE	No	Yes	No	Yes
Monthly FE	No	Yes	No	Yes
Observations	1,648	1,648	1,504	1,504
R^2	0.148	0.160	0.030	0.069
Adjusted R^2	0.147	0.154	0.029	0.060
t-test statistic	118.501***			
Note:		*p<0.1; **p<0.05; ***p<0.01		

Figure 5: Estimated coefficients of treatment effect in the grain futures market.



7 Conclusion

The 1936 options trading ban was introduced in the US to address concerns about excessive speculation and market manipulation, particularly following the manipulation of the wheat market in 1933. This study examines the effects of this ban on the volatility and hedging effectiveness in the grain futures markets, focusing on the Chicago Board of Trade (CBoT). Using a newly collected dataset on futures and spot prices for grains in US and UK markets, we employed a difference-in-differences (DiD) approach, comparing grain futures in Chicago to those in London, where no ban was implemented, over the period from 1932 to 1939.

Our analysis reveals a significant impact of the ban on market volatility. Initial results over the entire sample period suggest a decrease in volatility post-ban compared to London. Although these results might be in favour of the ban, we argue that the observed decrease in volatility was not due to the ban itself but rather the inclusion of the 1933 market manipulation period pre-ban. Excluding market anomalies, our findings change significantly. In the short term, the volatility of grain futures prices in Chicago increased significantly post-ban. However, in the long term, the volatility effect dissipates and becomes insignificant, indicating that the ban's impact on market stability was not sustained over time. Our results also provide evidence for a causal relationship between options trading and futures volatility, at least in the short term.

In addition to analyzing volatility, we employed an event-study approach to evaluate hedging effectiveness, measured by the minimum variance hedge ratio. Our empirical findings indicate that the options ban significantly decreased hedging effectiveness in the Chicago markets. This decrease was observed in both static and dynamic frameworks, suggesting that hedgers were unable to manage the price risk of their crops effectively without the use of options. These results highlight the unintended consequences of the ban, which, while aimed at curbing speculation and preventing market manipulation, weakened one of the primary functions of futures markets: risk management for hedgers.

Overall, our study highlights the importance of considering both short-term and long-term effects when implementing regulatory measures in financial markets. The findings suggest that while the options trading ban may have temporarily stabilized the market, it ultimately disrupted the hedging strategies of market participants, reducing their ability to manage risk effectively. Policymakers should weigh the potential benefits of such regulations against their broader economic impacts, ensuring that measures designed to enhance market efficiency do not undermine its core functions.

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