Does Options Trading Matter for Risk Management? Insights from the 1936 Options Ban on U.S. Futures Markets

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Abstract

Commodity options enhance information flow and risk management in futures markets. This paper investigates the impact of options trading on price volatility and hedging effectiveness in grain futures markets by analyzing the 1936 ban on commodity options trading in the United States. Utilizing newly collected data for wheat and corn futures from Chicago and London (1934-1939), we employ a difference-in-differences approach to compare treated (Chicago) and control (London) markets. Our findings show that active options trading is associated with reduced price volatility and improved hedging effectiveness in futures markets. Following the 1936 ban, Chicago futures experienced a significant but temporary short-term increase in volatility and a decline in hedging effectiveness, highlighting the essential role of options trading in stabilizing futures markets and facilitating efficient information transmission. These results offer important insights for regulatory policies governing derivative markets.

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

JEL Classification: G13, G14, G18, N22

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1 Introduction

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. This regulatory action was primarily motivated by the perception that options were being excessively utilized for speculative activities, resulting in price manipulation and disrupting market dynamics instead of fulfilling their intended role in risk management. Although futures markets are designed to transfer risk from hedgers to speculators (Kaldor, 1939; Keynes, 1923), the speculative use of options was believed to overshadow their hedging benefits, prompting the need for regulatory intervention.

Even today speculation in standardized products like options and futures is often criticized for contributing to increased price volatility and market instability. This paper uses the 1936 options ban as a natural experiment to examine the role of options trading in risk management. By exploiting this regulatory intervention as a source of exogenous variation, we analyze the impact of options trading 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? Unlike futures contracts, options offer greater flexibility by allowing market participants to set prices within a range of outcomes rather than fixed prices, thereby enhancing risk management capabilities. For instance, put options enable farmers to set a minimum selling price for their crops, protecting against price drops while allowing benefits from potential price increases. Similarly, call options establish a maximum buying price, permitting the purchase of commodities at lower prices if available (Kenyon, 1984; Urcola & Irwin, 2011).

The absence of options has two primary implications for risk management: it directly removes a hedging instrument and indirectly reduces the efficiency of futures markets in incorporating new information. The Black-Scholes model (Black & Scholes, 1973) revolutionized options pricing by highlighting the importance of the underlying asset's volatility.[1] However, in incomplete markets, the relationship between an underlying asset and

[1] Chambers and Saleuddin (2020) argue that interwar traders may have intuitively priced options based on similar assumptions even before BSM model. See Mehl (1934) on short-dated wheat options

their derivatives is not unidirectional. Options trading facilitates the flow of information by attracting informed traders, which in turn could help integrate new information into futures prices (Easley, O'Hara, & Srinivas, 1998; Johnson & So, 2012; Pan & Poteshman, 2006; Roll, Schwartz, & Subrahmanyam, 2010). The prohibition of options is likely to disrupt this information flow, reducing the predictive power of futures prices over spot markets and weakening their effectiveness as hedging tools. Without informative signals from options, uncertainty may increase in futures markets, complicating risk management strategies.

Using a novel dataset comprised of weekly grain futures and spot prices traded at the Chicago Board of Trade (treated group) and London Exchange (control group) collected from *Statistical Bulletins*, *Annual Reports of CBoT* and contemporary newspapers (*The Times*), we test two main hypotheses:

1. **Options trading stabilizes market volatility:** The ban on options written on CBoT futures contracts is expected to increase the volatility of grain futures prices.

2. **Options trading enhances hedging effectiveness:** The absence of options trading is expected to reduce the effectiveness of futures contracts as hedging tools, due to less efficient information flow within the market.

This study contributes to the existing literature by examining the causal effects of the 1936 options trading ban on market volatility and hedging effectiveness. It integrates multiple research strands, including the role of volatility in derivative pricing (Ball & Torous, 1986; Black & Scholes, 1973; Brenner, Courtadon, & Subrahmanyam, 1985; Myers & Hanson, 1993; Ramaswamy & Sundaresan, 1985), the impact of options on information flow and market efficiency (Easley et al., 1998; Johnson & So, 2012; Pan & Poteshman, 2006; Roll et al., 2010), the use of options as tools for enhancing risk management and market completeness (Biais & Hillion, 1994; Frank, Irwin, Pfeiffer, & Curtis, 1989; Ross, 1976), the impact of speculative behavior on derivatives markets (Duvel & Hoffman, 1927; Iorgulescu & Pütz, 2024; Irwin, 1937; Kang, Rouwenhorst, & Tang, 2020; Kim,

at the CBoT (19261931) and Dew-Becker and Giglio (2023) on synthetic grain options (19061936) for foundational insights into pre-BSM pricing mechanisms.

2015; Manera, Nicolini, & Vignati, 2016), and the consequences of derivative market bans (Beber & Pagano, 2013; Brunnermeier & Oehmke, 2014).

To assess the causal effect of the options ban on the volatility of grain futures markets, we use a difference-in-differences (DiD) approach. We compare grain futures in Chicago, where the ban was implemented, to those in London, where no ban occurred, over the period from 1934 to 1939. This comparison allows us to identify changes in volatility that coincide with the ban. The options trading ban serves as a natural experiment, addressing the endogeneity issues commonly found in observational studies of options markets. By examining this exogenous shock, we can isolate the impact of options trading on futures market volatility. The DiD approach requires the standard parallel trend assumption (PTA), in the absence of the ban, the Chicago (treated group) and London (control group) markets would have followed similar volatility trends. We include commodity-fixed 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 of realized volatility. Our results reveal a nuanced impact of the options trading ban. In the short term, the volatility of grain futures prices in Chicago increases significantly post-ban. However, in the long-term, this volatility effect vanishes and becomes statistically insignificant.

Our second hypothesis posits that in the absence of options trading, the efficiency of information incorporation into futures prices declines. Options trading not only provides hedging opportunities but also plays a crucial role in pricing new information into futures contracts. As noted in prior research, option trading volumes reflect valuable information about future stock prices (Easley et al., 1998; Johnson & So, 2012; Pan & Poteshman, 2006; Roll et al., 2010). Without the ability to trade options, markets may process new information more slowly and less efficiently.

To analyze the impact on hedging effectiveness, we employ an event-study approach (Roth, 2022) and measure hedging effectiveness using the minimum variance hedge ratio, following the methodology of Ederington (1979) and Figlewski (1984). Our empirical analysis shows that while futures markets effectively hedge cash market positions, hedging effectiveness significantly decreases after the options ban. These results suggest that hedgers are less capable of managing price risk in futures markets without options, highlighting the importance of options trading in facilitating risk management and efficient information incorporation. Our findings provide evidence that, in the absence of options, the futures market struggled to adapt quickly to new information, thereby reducing the effectiveness of hedging strategies.

The remainder of the paper is organized as follows. In Section 2, we provide a historical overview of options trading and the ban in the United States. Section 3 describes the dataset. Section 4 outlines the empirical methods used to test our hypotheses. The results are presented in Section 5, and Section 6 offers a discussion along with a theoretical interpretation of our findings. Finally, Section 7 concludes the paper.

2 Historical Background

2.1 The Rise of Speculation and the Regulatory Response

The origins of options trading date back to 16th century Antwerp, where transferable contracts were first traded (Barbour, 1950; Gelderblom & Jonker, 2005).[2] Negative attitudes toward options stem from their association with market manipulation and speculation. In the 19th and early 20th centuries, limited regulation of commodity markets allowed corners and manipulations, reinforcing the view that derivatives destabilize markets. In the U.S., populist and agrarian movements criticized speculators for causing erratic price fluctuations and demanded federal regulatory intervention. Cowing (1895) noted that after the Civil War, the rise of futures contracts led to unprecedented levels of speculation, involving traders with no connection to physical commodities. Trading volumes exceeded annual production, leading farmers to blame speculators for volatile prices, especially around harvest times.

During this era, options contracts, often referred to as "privileges", were criticized for enabling speculation that increased commodity price volatility. From the late 1890s to the early 1920s, speculation in grains became a major national political issue in the

[2]See Poitras (2009) for a thorough history of exchange-traded derivative contracts.

United States. Congress regularly debated *anti-option* bills aimed at curbing *excessive* speculation and targeting organized commodity exchanges, such as the CBoT (Banner, 2017).[3] 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, liquidity and market efficiency (Duvel & Hoffman, 1927, 1928; U.S. Secretary of Agriculture, 1926, 1933).

In contrast, the development of options trading in the U.K., specifically London, followed a different trajectory. Dating back to the 18th century, options trading in London survived attempts to prohibit it, such as Bernards Act (1733) following the South Sea Bubble (Morgan, 1962). In 1820, a controversy over stock options almost led to a split in the London Stock Exchange, yet the ban was ultimately rejected because members recognized the value of options trading in enhancing market liquidity and profitability (Michie, 2001). Options trading has therefore largely remained legal in London continuously to the present day.

What led to the options trading ban in 1936? In the U.S., *anti-options* sentiment intensified after agricultural prices collapsed during the Great Depression. Speculators were blamed for worsening farmers' hardships, leading to renewed efforts to limit speculation. The 1933 attempted manipulation of the wheat market, where a group of traders caused wheat futures prices to plummet by over 25% in just two days, served as a catalyst for regulatory action (GFA, 1933). Investigations exposed increased speculative activity, and legislators responded with the Commodity Exchange Act of 1936[4], which banned all commodity options trading (CFTC, 2024). The ban remained in effect until 1981. As this paper will demonstrate, this measure, intended to protect hedgers and small speculators in grain futures markets, may have inadvertently harmed farmers by reducing hedging effectiveness. We argue that without options as a hedging tool, farmers and merchants

[3]For instance, the 1890 anti-options bill aimed to curb excessive speculation but ultimately failed to pass (Markham, 1987).

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

faced greater exposure to price volatility, diminishing futures markets' effectiveness in risk management.

2.2 Options Trading Before the 1936 Ban

In the years leading up to the 1936 ban, options trading in the U.S. operated under a system of "privileges," which were privately negotiated contracts distinct from modern standardized options. These privileges granted traders the right, but not the obligation, to buy (call privilege) or sell (put privilege) grain at a predetermined price within a short timeframe, typically ranging from one day to a few weeks (Mehl, 1934).

The pricing of privileges was closely tied to market sentiment and served as an early indicator of expected futures price movements. According to Mehl (1934), the distance between privilege bid and offer prices relative to futures prices reflected traders expectations of futures market volatility. When bids and offers for privileges were set further from the closing futures price, it signaled that traders anticipated increased volatility in the underlying market. Conversely, when privileges traded close to the futures price, it indicated a more stable outlook. This predictive nature of privilege prices made them a valuable tool for gauging market expectations, functioning similarly to how implied volatility in modern options markets provides insights into future price movements.

Trading privileges followed a structured processTransactions took place during specific hours, and prices were typically set relative to the futures market. Traders paid a fixed fee per contract for the right to exercise a privilege, with bids for one-day privileges often priced 1 to 2 cents below the closing futures price and offers set slightly above it. Each contract covered 5,000 bushels of grain, with members paying $5 per contract and non-members slightly more (Mehl, 1934).

While speculators were the primary users of privileges, leveraging them to bet on short-term price movements with minimal capital, some traders also employed privileges as a hedging tool to manage temporary price fluctuations. Nevertheless, regulators viewed these instruments as primarily speculative rather than risk management tools. This perception, combined with the lack of standardization and oversight, contributed to growing calls for stricter regulation. Rather than introducing reforms to address these concerns, such as standardized contracts or enhanced oversight, U.S. regulators opted for a complete prohibition of options trading with the Commodity Exchange Act of 1936. This decision fundamentally altered the landscape of U.S. commodity markets, removing a tool that some market participants relied on for risk management and price discovery.

3 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 1934 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 analyze 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, spot price observations are provided in ranges, and we take their averages for consistency.

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.[5] 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, corn futures in London were traded in all calendar months,

[5]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).

while wheat futures were traded in additional months such as January, August, October and November. 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.

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

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

where $log[F_i(t,T)]$ and $log[F_i(t-1,T)]$ represent the logarithmized prices of a futures contract expiring in trading month $T =$ 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. Observable 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 trading 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] Additionally, we construct continuous series for returns, ensuring that these are always derived from futures contracts with the same maturities.

Finally, we merge the Chicago futures and spot price data with the London futures data. The final dataset consists of 292 weekly observations for each computed series.

[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.

Summary statistics are presented in Table 1.

Table 1: Summary Statistics: Pre and Post Treatment

This table presents summary statistics for wheat and corn futures prices, returns, and volatility measures for both the treatment group (CBoT) and the control group (London Exchange), covering the periods before and after the treatment date (June 1936). Returns are calculated as $R_{i,t}^{T} = log[F_i(t,T)] - log[F_i(t-1,T)]$. Volatility is measured using both a rolling window approach (Rolling σ^2) with a five-week window and a GARCH(1,1) specification (GARCH σ^2).

Statistic	Mean		Median		St. Dev.		Min		Max	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
$R_{corn,Chicago}$	0.427	0.292	0.307	0.000	3.316	3.898	-8.141	-11.717	11.593	15.202
$R_{wheat,Chicago}$	0.044	-0.024	-0.135	0.030	3.332	3.293	-11.824	-8.270	11.359	10.225
$R_{corn,London}$	0.133	0.522	-0.122	0.325	3.389	3.006	-9.496	-8.377	10.801	11.533
$R_{wheat,London}$	0.098	-0.015	-0.277	0.000	3.157	3.747	-7.714	-9.289	10.248	16.508
$Rolling\ \sigma^2_{corn,Chicago}$	10.650	12.513	7.119	5.953	11.383	15.573	0.616	0.474	57.793	80.329
$Rolling\ \sigma^2_{wheat,Chicago}$	11.170	9.522	6.658	7.607	12.446	7.632	0.236	0.648	71.137	34.315
$Rolling\ \sigma^2_{corn,London}$	11.351	8.214	7.197	5.213	12.333	8.294	0.375	0.469	48.760	52.141
$Rolling\ \sigma^2_{wheat,London}$	9.392	11.986	5.432	8.531	9.860	10.989	0.218	0.384	40.594	69.522
$GARCH\ \sigma^2_{corn,Chicago}$	3.500	3.653	3.108	3.152	1.146	1.598	2.280	2.230	8.486	10.691
$GARCH\ \sigma^2_{wheat,Chicago}$	3.415	3.338	3.180	3.279	0.887	0.633	2.292	2.235	6.263	5.036
$GARCH\ \sigma^2_{corn,London}$	3.353	3.102	3.167	2.913	0.846	0.623	2.360	2.281	5.821	5.391
$GARCH\ \sigma^2_{wheat,London}$	3.347	3.579	3.047	3.558	0.790	0.722	2.311	2.391	5.435	7.272
N = 292 on each series										

4 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, the extent to which the prohibition of options trading has affected the effectiveness of hedging strategies, specifically the ability of futures markets to serve as hedges for spot markets. In the following subsections, we discuss the DiD approach and the event-study methodology used to test these hypotheses.

4.1 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. It 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:

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

where $\sigma_{i,t}^2$ 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 A.1 in the Appendix shows the volatility measures derived from the rolling window approach for the Chicago and London futures markets.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models 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 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., $\varepsilon_{i,t} \sim N(0, \sigma^2_{i,t})$.

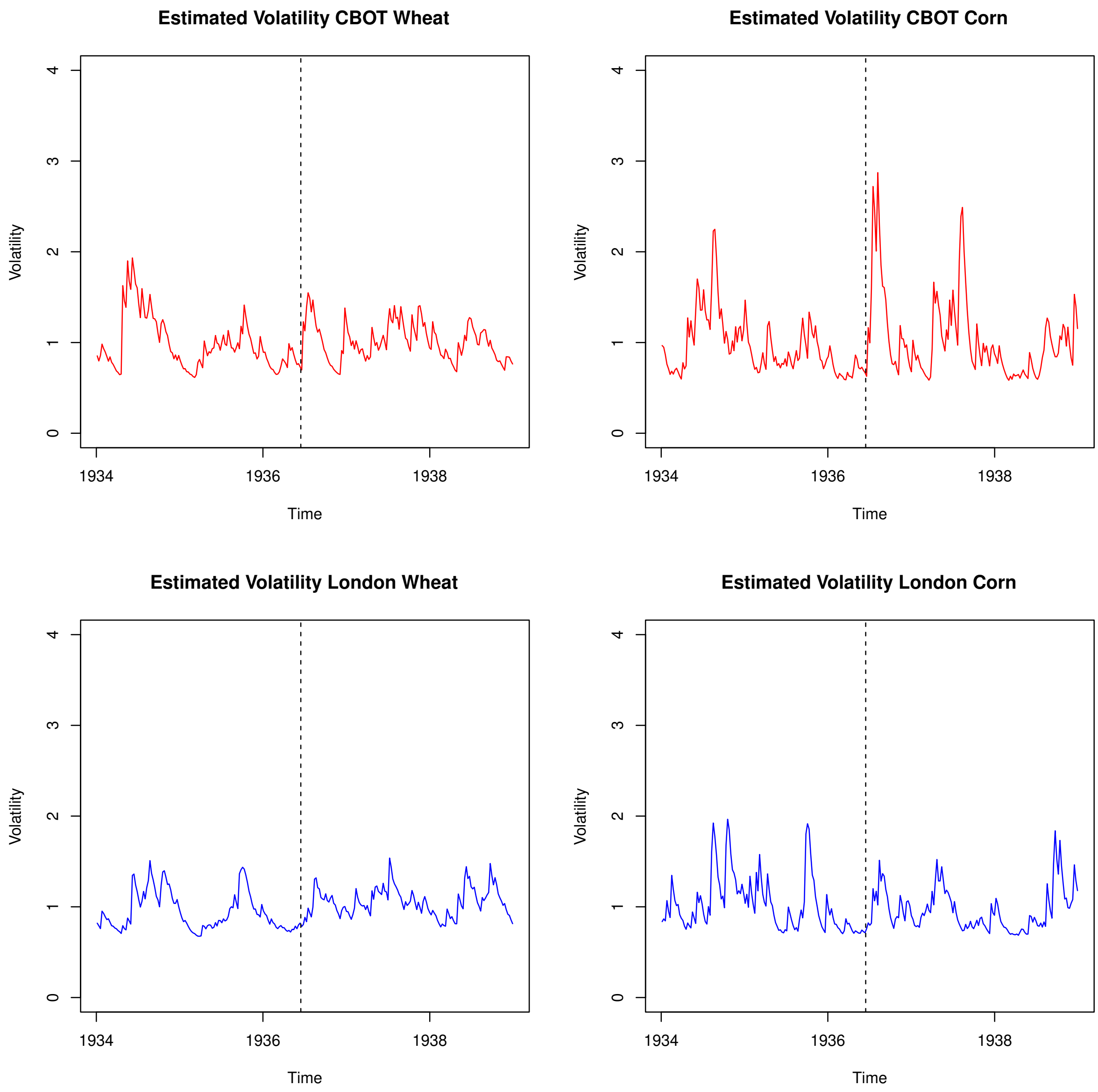
The GARCH volatility is measured by the conditional variance of $\varepsilon_{i,t}$ from Equation 3, as follows:

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

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 1.

[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 1: GARCH Volatility.
This figure illustrates the volatility of wheat and corn futures prices, as measured by an AR(1)-GARCH(1,1) model, for both the treatment group (CBoT) and the control group (London Exchange) from 1934 to 1939. The vertical dashed line denotes the treatment date (June 15, 1936). The volatility series are derived from the conditional variance equation of the GARCH model.



4.2 Differences-in-Differences

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. 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 versa. Consequently, estimates from a simple OLS regression 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. The 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.

Doing so, we assume that the volatility of grain futures markets in the non-treatment state, can be explained by the following additive model:

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

where $Volatility_{i,e,t}$ is the volatility of commodity i (corn or wheat) on exchange e at date t with options trading allowed (i.e., London Exchange). 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.

In this paper, we aim to determine whether option trading influences futures price volatility, either by increasing or reducing it. Using the additive model presented in equation 5, we can express observed market volatility as:

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

where Ban is a dummy variable that equals one for Chicago markets after the options trading ban and zero otherwise. The DiD estimator calculates the effect as follows: (the expected value of treated commodities post-treatment minus the expected value of treated commodities pre-treatment) minus (the expected value of control commodities post-treatment minus the expected value of control commodities pre-treatment). In our context, given Equation 6, this results in:

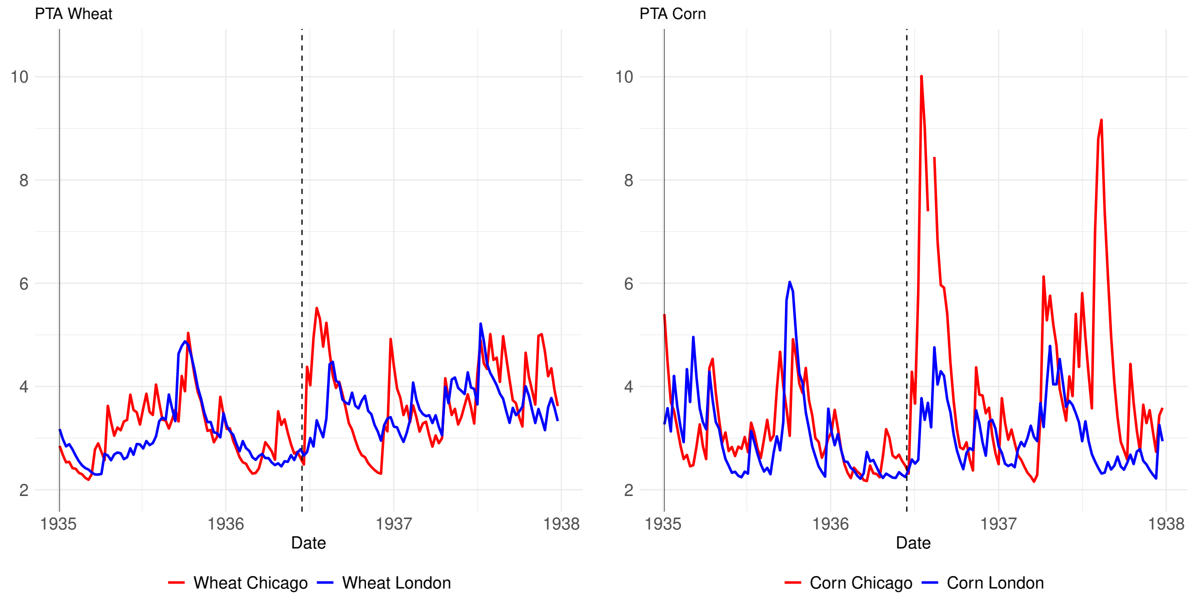
$$(\rho_e - \rho_e + \lambda_{t=\text{after}} - \lambda_{t=\text{before}} + \alpha_i - \alpha_i + z_{i,t=\text{after}} - z_{i,t=\text{before}} + \beta) \tag{7}$$
$$-\,(\rho_e - \rho_e + \lambda_{t=\text{after}} - \lambda_{t=\text{before}} + \alpha_j - \alpha_j + z_{j,t=\text{after}} - z_{j,t=\text{before}}) \tag{8}$$

where i accounts for treatment commodity and j indexes control commodity. Solving this reduces to:

$$\begin{aligned} &(z_{i,t=\text{after}} - z_{i,t=\text{before}} + \beta) \\ &\quad -\,(z_{j,t=\text{after}} - z_{j,t=\text{before}}) \end{aligned} \tag{9}$$

Equation 9 shows that a standard DiD regression will accurately capture the treatment effect of an option trading ban if the time-varying commodity-level shocks in the control group ($z_{j;t}$) match those in the treatment group ($z_{i;t}$). This requirement aligns with the traditional parallel trends assumption.

Figure 2: Parallel Trend Assumption.
This figure illustrates the parallel trend assumption by showing the volatility of wheat and corn futures prices for both the treatment group (CBoT) and the control group (London Exchange), before and after the treatment (options ban). The vertical dashed line denotes the treatment date (June 15, 1936). The similar pre-treatment trends and divergent post-treatment patterns provide visual evidence supporting the validity of the DiD approach used in the study.



Three key conditions must be satisfied in order to estimate a causal effect in a DiD framework: the *parallel trend* assumption (PTA), *no-anticipation of the treatment* assumption, and *no spillover effects* 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.[8] Figure 2 provides visual evidence consistent with the PTA. Before the ban (June 15, 1936), the volatilities of wheat and corn futures in Chicago and London followed similar trends. A clear divergence in volatility occurs after the ban, particularly for corn futures, indicating that the policy change is likely driving the observed effect rather than pre-existing trends.

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 treat-

[8]Accordingly, the control group is suitable to control for observable time trends in the treated group that might have occurred without treatment.

ment before it occurs, i.e., market participants did not adjust their behavior in anticipation of the ban. While there were ongoing debates about options speculation prior to 1936 in the US, these discussions had persisted for decades without immediate regulatory action. Thus, any anticipatory effects would have been gradual rather than concentrated just before the ban.

If traders had responded to the ban by shifting their trading activity from Chicago to London, the control group (London) would no longer serve as a valid counterfactual. However, given the high costs and logistical constraints of transatlantic trading in the 1930ssuch as information transmission via telegram or telephonesuch a shift was unlikely to be a profitable alternative. Therefore, we can reasonably assume that trading activity remained localized, ensuring that the treatment effect was not contaminated by cross-market spillovers.

With all three conditions satisfied, the DiD estimates can be interpreted as capturing the causal impact of the options trading ban on futures market volatility

4.3 Hedging Effectiveness

Our second hypothesis posits options trading enhances hedging effectiveness in US futures markets. More specifically, it tests whether the prohibition of options trading decreases the effectiveness of futures contracts as hedging tools. This suggests that, in the absence of options trading, information flow becomes less efficient, thereby reducing the utility and value of futures contracts for managing price risk.

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

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

given by:

$$E[r_p] = E[\Delta s_t] - h \cdot E[\Delta f_t] \tag{10}$$

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

$$\sigma_P^2 = \sigma_S^2 + h^2\sigma_F^2 - 2h\sigma_{SF} \tag{11}$$

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

$$h = \frac{cov(\Delta s_t, \Delta f_t)}{var(f_t)} \tag{12}$$

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.

We estimate hedging effectiveness using a OLS framework as follows (Ederington, 1979; Figlewski, 1984):

$$\Delta s_t = \alpha + h\Delta f_t + \epsilon_t \tag{13}$$

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:

$$\Delta s_t = \alpha + h_1 \times \Delta f_t + h_2 \times D_t + h_3 \times (D_t \times \Delta f_t) + \epsilon_t \tag{14}$$

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, $_2$ captures the shift in the mean of Δs_t due to the ban and $_3$ is the coefficient of interest, capturing the difference in hedging effectiveness prior and after the ban.

5 Results

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

5.1 Impact on Volatility

For the short term, we examine three windows in which we vary the observation window from 6 to 18 months: the year 1936 (covering six months before and after the ban), June 1936 to June 1937 (one year around the ban), and 1935–1937 (an 18-month period). The short-term regression results using the $GARCH$ σ^2 volatility measure as dependent variable are presented in Table 2. Results using the *Rolling* σ^2 are reported in Table A.1 in the Appendix.

In columns (2), (4) and (6) where we used time and commodity fixed effects, the coefficients on *Ban* (0.66, 0.52 and 0.54) are highly statistical significant at 1% level. This indicates that futures market volatility in Chicago, as compared to London, significantly increased in 6-month, 12-month and 18-month windows following the prohibition of options trading, supporting our first hypothesis that options trading stabilizes market volatility by facilitating efficient information flow.[10]. These findings remain consistent when employing a two-way fixed effects (TWFE) regression using Ordinary Least Squares (OLS) on the interaction term $Treated \times AfterTreatment$.[11]

Another interesting result emerges from this estimation. The constant term (ρ_e) which captures differences between trading environments at the Chicago and London exchanges

[10]Results are robust when using *Rolling* σ^2 as the dependent variable. See Table A.1 in the Appendix

[11]Estimated Equation:

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

and exchange-specific effects that might influence price volatility, is positive and highly significant across all three windows. This highlights the impact of distinct regulatory environments on volatility at each exchange.

Next, we investigate whether the increase in volatility observed immediately after the ban persisted over the long term. To achieve this, we extend our analysis to two broader windows: 1934–1939 and 1934–1938.[12] The empirical results presented in Table 3 indicate that the ban did not have a significant long-term effect on grain futures volatility. The coefficients on the *Ban* variable drop considerably compared to the short-term analysis, becoming low and statistically insignificant (0.04 and 0.10). This suggests that the initial increase in volatility following the ban was temporary and diminished over time as the Chicago market adjusted. These findings align with our theoretical expectations that, although the absence of options trading initially disrupts information flow and increases volatility, market mechanisms such as increased depth and reduced bid-ask spreads eventually restore some level of stability. The results remain consistent when employing a two-way fixed effects (TWFE) model.[13]

[12]Due to the onset of World War II, control group data from *The Times* became unavailable, limiting our analysis to 1939.

[13]Long-term results are robust when using *Rolling* σ^2 as the dependent variable. See Table A.2 in the Appendix. We also control for exchange rate effects and all results do not change.

Table 2: DiD Regression Results: short-term

This table presents short-term results from a difference-in-differences (DiD) regression of futures price volatilities before and after the options trading ban. The dependent variable is GARCH σ^2, the volatility estimated using an AR(1)-GARCH(1,1) model. Columns (1), (3), and (5) show results from the two-way fixed effects (TWFE) regression, while columns (2), (4), and (6) include time and commodity fixed effects. $Treated$ is a dummy variable for Chicago markets, $AfterTreatment$ indicates the post-ban period, and the interaction term (Ban) captures the causal effect of the options ban. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1936		**June 1935–June 1937**		**1935–1937**	
	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.14**		0.13		0.10	
	(0.06)		(0.09)		(0.08)	
$AfterTreatment$	0.75***		0.32***		0.31***	
	(0.08)		(0.09)		(0.08)	
$Treated \times AfterTreatment$	0.66***	0.66***	0.52***	0.52***	0.54***	0.54***
(Ban)	(0.25)	(0.21)	(0.15)	(0.12)	(0.14)	(0.12)
$Constant$	2.59***	3.07***	3.01***	3.26***	3.02***	3.23***
(ρ_e)	(0.04)	(0.07)	(0.08)	(0.04)	(0.06)	(0.04)
Time FE	NO	YES	NO	YES	NO	YES
Commodity FE	NO	YES	NO	YES	NO	YES
Observations	208	208	540	540	628	628
R^2	0.29	0.64	0.14	0.58	0.15	0.55

Table 3: DiD Regression Results: long-term

This table presents long-term results from a difference-in-differences (DiD) regression of futures price volatilities before and after the options trading ban. The dependent variable is GARCH σ^2, the volatility estimated using an AR(1)-GARCH(1,1) model. Columns (1) and (3) show results from the two-way fixed effects (TWFE) regression, while columns (2) and (4) include time and commodity fixed effects. *Treated* is a dummy variable for Chicago markets, *AfterTreatment* indicates the post-ban period, and the interaction term (*Ban*) captures the causal effect of the options ban. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1934–1939		**1934–1938**	
	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$
	(1)	(2)	(3)	(4)
$Treated$	0.27***		0.27***	
	(0.08)		(0.08)	
$AfterTreatment$	-0.01		0.09	
	(0.07)		(0.07)	
$Treated \times AfterTreatment$	0.04	0.04	0.10	0.10
(Ban)	(0.11)	(0.08)	(0.12)	(0.09)
$Constant$	3.23***	3.36***	3.23***	3.41***
(ρ_e)	(0.05)	(0.03)	(0.05)	(0.03)
Time FE	NO	YES	NO	YES
Commodity FE	NO	YES	NO	YES
Observations	1146	1146	1044	1044
R^2	0.02	0.57	0.03	0.55

5.2 Impact on Hedging Effectiveness

Our analysis of market volatility revealed that the 1936 options trading ban initially increased volatility in Chicago futures markets, contrary to regulatory intentions. This finding suggests that options trading contributes to market stability. This raises the question: how were hedgers affected by the ban, and to what extent did it impact their ability to manage risk effectively through hedging?

To investigate this, we test our second hypothesis: the absence of options trading reduces the efficiency of information incorporation into futures prices, thereby impairing hedging effectiveness. According to our theoretical framework, options facilitate the transmission of private information and enhance hedging strategies by providing additional channels for information flow and price discovery.

Table 4 presents the results from estimating our event-study model, where hedging effectiveness is measured in a static framework.[14] The event study analysis indicates that futures markets are generally effective hedges for spot markets, as evidenced by the positive and highly statistically significant coefficients on Δ_{ft}. However, the coefficients on the interaction term $D_t \times \Delta f_t$ are negative and highly significant (-0.175 and -0.180), suggesting that the prohibition of options trading reduced hedging effectiveness in Chicago markets. This decline implies that without options, the futures market became less efficient in incorporating new information, thereby diminishing its use as a risk management tool.

To ensure robustness, we further split our sample into pre-ban and post-ban periods, excluding the date of the ban, and present the results in Table 5. A simple OLS estimation with robust standard errors shows a significant decrease in hedging effectiveness from 0.436 to 0.179. A z-test confirms that the differences in hedging effectiveness pre- and post-ban are highly statistically significant, reinforcing our previous findings.

[14] We also analyze hedging effectiveness using dynamic frameworks (Baillie & Myers, 1991; Cecchetti, Cumby, & Figlewski, 1988), and the results remain consistent. See Figure A.2 in the Appendix.

Table 4: Event Study Regression Results

This table shows results from an event study regression examining hedging effectiveness in U.S. grain futures markets before and after the options trading ban (June 1936). The dependent variable Δs_t represents weekly changes in spot prices, while Δf_t represents changes in futures prices. D_t is a dummy variable equal to one for the post-ban period. The interaction term $D_t \times \Delta f_t$ captures the change in hedging effectiveness following the ban. Column (2) includes results with time and commodity fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	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

Table 5: Hedging Effectiveness Pre- and Post-Ban

This table presents results from an OLS regression on hedging effectiveness in U.S. grain futures markets, with the sample split before and after the options trading ban (June 1936). The dependent variable is the change in spot prices (Δs_t), and the independent variable is the change in futures prices (Δf_t). The coefficient on Δf_t represents the minimum variance hedge ratio. Columns (2) and (4) include time and commodity fixed effects. The t-test statistic tests the difference in hedging effectiveness between the pre-ban and post-ban periods. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	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
t-test statistic	118.501***			

6 Theoretical Explanations of the Options Ban

Our empirical findings highlight the important role options trading plays in the underlying markets, particularly in stabilizing futures prices and enhancing hedging effectiveness. The observed short-term volatility spike and decline in hedging effectiveness suggest that the absence of options disrupted established market mechanisms. But what underlying economic forces could drive these effects? In this section, we explore the theoretical mechanisms that could explain our results, drawing on the market microstructure framework of Easley et al. (1998).

In incomplete markets with asymmetric information, bid-ask spreads form around the prior expected value of an asset, and profits are transferred from uninformed to informed traders. This transfer occurs as market makers adjust their prices based on the likelihood of trading with an informed party. Informed traders, who possess private knowledge about future asset values, decide on their venue of trade (i.e. whether to trade in futures or options market) by weighing factors like the leverage and the liquidity in both the options and underlying futures markets.

According to Easley et al. (1998), options markets play a critical role in information transmission. The higher leverage offered by options attracts informed traders, who can amplify the impact of their information through options trading. Consequently, options trading volume becomes an early indicator of new information entering the market. In a functioning options market, informed traders can signal valuable insights about asset values, and the volume and types of option trades serve as informative signals for price-setting in the underlying futures markets.

When options trading is restricted, this signaling mechanism is disrupted. Consequently, futures become the sole venue for informed traders, but this could be less efficient. In line with Easley et al. (1998), three potential mechanisms might account for these inefficiencies:

1. Reduced leverage: Futures do not offer the same leverage as options, limiting the ability of informed traders to exploit their information fully. As a result, price movements in futures are less reflective of new information, and prices adjust more slowly.

2. Increased uncertainty for market makers: Without signals from options trading, market makers in the futures market face greater uncertainty in detecting informed trades. To mitigate potential losses from trading with informed parties, they widen bid-ask spreads, resulting in higher transaction costs for all traders. This wider spread reflects the added uncertainty and lack of precise information flow, making futures prices less efficient in reflecting true asset values.

3. Increased market noise: With the absence of options, all trading activity – including both informed and uninformed trades – is concentrated in the futures market. While this may seem to increase liquidity, it actually creates more noise in the market because uninformed (liquidity-motivated) trades are mixed with informed trades. This blending of noise with signals makes it harder for all market participants to identify true price signals, leading to less reliable futures prices. As a result, the futures market becomes more volatile and less effective as a tool for risk management.

These mechanisms explain why futures prices become noisier and more volatile in the absence of options, weakening their predictive power for the spot market. The reduced efficiency of information flow makes risk management more difficult, as futures prices less accurately represent anticipated spot prices.[15] Hence, the options ban indirectly hampers the hedging effectiveness of futures markets by impeding the transmission of informed insights into asset prices, a key element for effective risk management.

The theoretical model also predicts our long-run findings. Following the ban, market participants adjusted to the new conditions, leading to increased market depth in the futures market. The model predicts two effects of this increased depth:

1. Reduced bid-ask spreads: Assuming a constant probability of informed trading, greater market depth reduces bid-ask spreads, as a deeper market limits potential losses from trading with informed participants.

2. Attraction of informed traders: As market depth grows, the futures market becomes more attractive to informed traders, which may initially increase spreads. However, Easley et al. (1998) argue that the net effect of increased depth is a reduction in spreads over time.

This theoretical framework provides an explanation for our long-run results, where we observe that after an initial adjustment period, volatility in the futures market does not significantly differ from pre-ban levels. The market conditions gradually adjust as the shock of the ban vanishes, leading to a stabilization in volatility. Yet, hedging effectiveness remains lower than before the ban, indicating that the absence of options continues to impair the markets risk management capabilities.

[15] The relationship between the futures price (F_t) and the spot price (S_t) of a commodity is modeled using the cost-of-carry relationship: $F_t^T = S_t \cdot e^{(r+c-y)T}$ (Brennan, 1958; Kaldor, 1939; Telser, 1958; Working, 1948). The futures market often leads to price discovery.(Garbade & Silber, 1983; Yang, Bessler, & Leatham, 2001; Yang & Leatham, 1999; Zapata & Fortenbery, 1996). In the absence of option trading, the futures price might no longer be an unbiased predictor of future spot price.

7 Conclusion

This study explores the impact of the 1936 options trading ban on market volatility and hedging effectiveness within U.S. grain futures markets, specifically focusing on the Chicago Board of Trade (CBoT). Motivated by concerns over excessive speculation and market manipulation following the 1933 wheat market manipulation, the ban aimed to stabilize futures markets by restricting options trading. To empirically assess the causal effect of this regulatory intervention, we employed a Difference-in-Differences (DiD) approach, comparing grain futures in Chicago to those in London, where no such ban was implemented, using newly collected weekly data from 1934 to 1939.

We tested two primary hypotheses: first, that the ban would increase market volatility in Chicago by disrupting information flow and heightening uncertainty for market makers; and second, that the prohibition of options trading would reduce the effectiveness of hedging strategies, thereby impairing risk management for market participants. Our empirical analysis confirmed both hypotheses. In the short term, the ban led to a significant increase in futures market volatility in Chicago, supporting our first hypothesis and aligning with the theoretical framework (Easley et al., 1998) suggesting that options trading enhances information transmission and stabilizes markets by reducing uncertainty for market makers. The initial volatility spike indicates that the absence of options trading disrupted these mechanisms, leading to heightened price fluctuations.

However, the long-term analysis revealed that the increase in volatility was temporary, as volatility levels returned to pre-ban levels by 1939. This suggests that market participants and market makers adapted to the new trading environment, mitigating the initial impact over time. Nonetheless, the ban significantly impaired hedging effectiveness in Chicago, as indicated by the decline in the minimum variance hedge ratio. This finding supports our second hypothesis and highlights the essential role of options trading in facilitating efficient information flow and enhancing hedging effectiveness. The reduction in hedging effectiveness emphasizes that options trading is integral to the effective functioning of futures markets, enabling hedgers to manage price risk more accurately and efficiently.

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 the options trading ban destabilized the market and 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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A Appendix

A.1 Robustness Checks

Figure A.1: Rolling Volatility
This figure illustrates the volatility of wheat and corn futures prices, as measured by the rolling standard deviation with a five-week window, for both the treatment group (CBoT) and the control group (London Exchange). The vertical red line denotes the treatment date (June 15, 1936). This alternative volatility measure provides robustness to the main GARCH specification used in the paper.

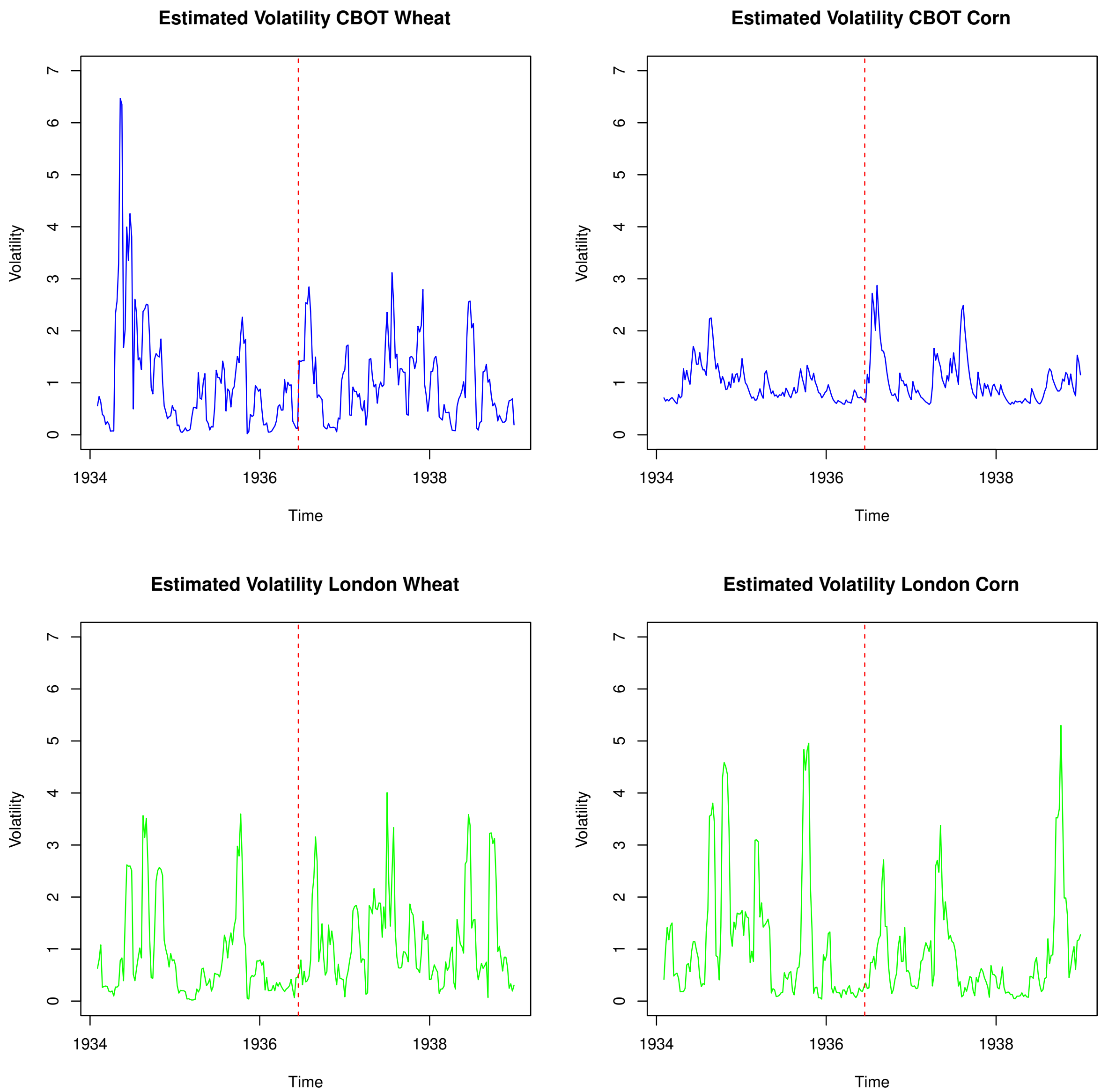

Table A.1: Regression Results: short-term, all measures

This table presents short-term difference-in-differences (DiD) regression results using both GARCH σ^2 and Rolling σ^2 as dependent variables. The sample periods are 1936 (columns 1-4), June 1935-June 1937 (columns 5-8), and 1935-1937 (columns 9-12). For each time window, results are shown with and without fixed effects for both volatility measures. $Treated$ is a dummy variable for Chicago markets, $AfterTreatment$ indicates the post-ban period, and the interaction term (Ban) captures the causal effect of the options ban. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1936				**1935.06-1937.06**				**1935 - 1937**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$Rolling\ \sigma^2$	$Rolling\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$Rolling\ \sigma^2$	$Rolling\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$Rolling\ \sigma^2$	$Rolling\ \sigma^2$
$Treated$	0.14**		0.70		0.13		-0.54		0.10		-1.05	
	(0.06)		(0.62)		(0.09)		(1.16)		(0.08)		(0.93)	
$AfterTreatment$	0.75***		6.43***		0.32***		2.90**		0.31***		2.76***	
	(0.08)		(1.07)		(0.09)		(1.20)		(0.08)		(1.03)	
$Treated \times AfterTreatment$	0.66***	0.66***	4.28*	4.28**	0.52***	0.52***	4.70***	4.70***	0.54***	0.54***	5.20***	5.20***
(Ban)	(0.25)	(0.21)	(2.33)	(1.93)	(0.15)	(0.12)	(1.77)	(1.40)	(0.14)	(0.12)	(1.63)	(1.38)
$Constant$	2.59***	3.07***	3.42***	7.23***	3.01***	3.26***	7.92***	9.39***	3.02***	3.23***	8.06***	8.96***
(ρ_e)	(0.04)	(0.07)	(0.41)	(0.66)	(0.08)	(0.04)	(1.02)	(0.49)	(0.06)	(0.04)	(0.81)	(0.42)
Time FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Commodity FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	208	208	208	208	540	540	540	540	628	628	628	628
R^2	0.29	0.64	0.22	0.60	0.14	0.58	0.07	0.53	0.15	0.55	0.08	0.50

Table A.2: Regression Results: long-term, all measures
This table presents long-term difference-in-differences (DiD) regression results using both GARCH σ^2 and Rolling σ^2 as dependent variables. The sample periods are 1934-1939 (columns 1-4) and 1934-1938 (columns 5-8). For each time window, results are shown with and without fixed effects for both volatility measures. $Treated$ is a dummy variable for Chicago markets, $AfterTreatment$ indicates the post-ban period, and the interaction term (Ban) captures the causal effect of the options ban. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1934–1939				**1934–1938**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$Rolling\ \sigma^2$	$Rolling\ \sigma^2$	$GARCH\ \sigma^2$	$GARCH\ \sigma^2$	$Rolling\ \sigma^2$	$Rolling\ \sigma^2$
$Treated$	0.27***		0.53		0.27***		0.53	
	(0.08)		(1.01)		(0.08)		(1.01)	
$AfterTreatment$	-0.01		-0.52		0.09		0.52	
	(0.07)		(0.86)		(0.07)		(0.90)	
$Treated \times AfterTreatment$	0.04	0.04	0.64	0.61	0.10	0.10	0.95	0.95
(Ban)	(0.11)	(0.08)	(1.32)	(1.04)	(0.12)	(0.09)	(1.40)	(1.13)
$Constant$	3.23***	3.36***	10.22***	10.21***	3.23***	3.41***	10.22***	10.75***
(ρ_e)	(0.05)	(0.03)	(0.69)	(0.37)	(0.05)	(0.03)	(0.69)	(0.38)
Time FE	NO	YES	NO	YES	NO	YES		
Commodity FE	NO	YES	NO	YES	NO	YES		
Observations	1146	1146	1146	1146	1044	1044	1044	1044
R^2	0.02	0.57	0.00	0.52	0.03	0.55	0.00	0.51

A.2 Methodology

As a further 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 13. 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:

$$h_1|\Omega_{t-1} = \frac{\sigma_{s,f}|\Omega_{t-1}}{\sigma_f^2|\Omega_{t-1}} \tag{15}$$

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

$$\begin{bmatrix} \Delta S_t \\ \Delta F_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \leftrightarrow \Delta Y_t = \mu + \epsilon_t \tag{16}$$

$$e_t|\Omega_{t-1} \sim N(0, H_t), H = \begin{bmatrix} H_{11,t} H_{12,t} \\ H_{21,t} H_{22,t} \end{bmatrix} \tag{17}$$

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.

Figure A.2: Estimated coefficients of treatment effect in the grain futures market This figure shows the time-varying hedging effectiveness for corn (top panel) and wheat (bottom panel) futures markets from 1934 to 1938. The hedging effectiveness is measured as the conditional minimum variance hedge ratio estimated from a bivariate GARCH model. The vertical red line indicates the options ban date (June 15, 1936). The figure illustrates how the effectiveness of futures market as a hedge against spot price fluctuation changed following the regulatory intervention.