Did Grain Futures Prices Overreact to the Russia-Ukraine War?

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Abstract

We study the impact of the 2022 Russian invasion of Ukraine on corn, wheat, and soybean futures prices. The war provides a natural experiment to evaluate whether futures markets are driven by investor herding. Using event study methods, we find that wheat futures prices rose by 30 percent above the counterfactual immediately after the invasion, more than corn futures prices, which were up by 10 percent. This relative price response cannot be explained by herding behavior. Instead, we argue the larger move in wheat was due to fundamental concerns over the possibility of a complete disruption of Black Sea grain exports, including exports from Russia, the world's largest wheat exporter. Soybean prices did not respond to the war, contradicting herding. There is no statistical evidence of abnormal speculative pressure in the market around the time of the invasion, and we conclude the markets put a fair price on the wartime risk of Black Sea grain shipment disruptions.

Keywords: Russia-Ukraine war, war premium, event study, behavioral finance, herding

JEL codes: G13, G14, Q02

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"The worries about shortages may have been overstated in the first place…Global wheat stocks were extremely high…which told us either that the relationship between stocks and prices had broken down or…that speculation had got ahead of itself." Charles Robertson, Renaissance Capital, Economist (August 22, 2022)

1. Introduction

The Russian invasion of Ukraine in February 2022 created a significant response in the commodity futures markets, with considerable swings in the prices of energy and agricultural commodities. The war also stoked the most significant food security concerns since the 2007-2008 commodity price boom (World Bank Outlook 2022; The Economist 2022). The above quote from the chief economist of Renaissance Capital refers to the reaction of grain futures markets to the Russian invasion. Wheat futures prices rose by about 30 percent in March 2022, a monthly percent price jump almost unprecedented, being only eclipsed by price increases during the 1930s dust bowl and the Russian grain robbery in 1972 (Cowley, Rodziewicz and Cook 2022). The Renaissance Capital economist quoted above is responding to the stylized fact that by the end of July 2022, grain futures prices had come back down to the same price level as before the February start of the war.

Given that commodity futures prices came back down five months later does not mean the market overreacted in the first place. Whether or not "speculation got ahead of itself" following the Russian invasion of Ukraine is a testable hypothesis and the focus of this paper. The Russian invasion of Ukraine provides a natural experiment to allow us to test the behavioral finance theory that herding behavior drives commodity futures prices. We study the corn, wheat, and soybean markets—the grains complex. If herding behavior did take over the market in Feb-Mar 2022, then corn, wheat, and soybeans prices should have all risen beyond counterfactual prices. Speculators move in a herd by buying into rising markets and selling into falling markets (Steen and Gjolberg 2013). Using a new way to measure herding in commodities, an event study approach that relies on credible counterfactuals, we find that soybeans did not respond at all to the war. Furthermore, with herding, we might expect that corn prices would have moved more than wheat and soybean prices in the grain complex, because of Ukraine's importance as a corn exporter, but that did not happen either. Wheat prices rose more (percentage-wise) than corn prices, which only fundamentals and not herding behavior can explain. In the worst-case scenario, grain exports shipped across the Black Sea and through the Bosphorus Strait (connecting the Mediterranean and the Black Sea) could be halted due to the war, cutting off 27% (17%) of global wheat (corn) exports from Russia and Ukraine combined.

When traders follow one another and make buy/sell decisions based on the collective actions of the market, herding arises. This may be particularly acute when the market is subjected to a large shock and is stressed (Pindyck and Rotemberg 1990; Hwang and Salmon 2004), as it was in Feb-Mar 2022. The herding theory incorporates findings from psychology and sociology and postulates that markets are inefficient due to psychological biases of investors, such as overconfidence, emotions, or wishful thinking. Herding leads to overshooting of financial markets, and once herding takes over, prices can move from their fundamentals in an irrational way, accompanied by excess volatility.

The impact of the rising presence of noncommercial players (e.g., pension and hedge funds) in commodity futures markets has been dubbed the *financialization of commodity markets*, and this financialization became controversial during the 2007/08 commodity boom and global food crisis (Kang, Tang and Wang 2023). The total value of various commodity index-related instruments purchased by institutional investors increased from an estimated \$15bn in 2003 to about \$450bn in 2011 (Adams, Collot and Kartsakli 2020). Cheng and Xiong (2014) argue that more work is needed to measure whether financialization has affected commodity markets. The work of Natoli (2021) and Adams, Collot and Kartsakli (2020) supports this conclusion. The literature suggests that commodity market financialization was partly driven by herd behavior (Demirer, Lee and Lien 2015). Following the 2007/08 commodity boom, Robles, Torero and Von Braun (2009) and Henderson, Pearson and Wang (2015) argued that excessive speculation influences commodity prices, implying herd behavior. But the evidence is far from conclusive; for example see Schmidt (2017), Boyd, Harris and Li (2018), and Júnior et al. (2020).

Despite unanswered questions surrounding the financialization of commodity markets and the rise of commodity-index investing, there has been relatively little behavioral finance research on commodity futures markets (especially for agricultural products), unlike the voluminous research on stock markets, see Júnior et al. (2020); Youssef (2022). Exceptions in the commodity markets include Steen and Gjolberg (2013), Babalos, Stavroyiannis and Gupta (2015), Demirer, Lee and Lien (2015), Schmidt (2017), and Júnior et al. (2020). These studies looked for herding behavior in commodities and found little or no evidence of herding.

There have been generally two approaches used to study herding in commodity futures. One approach builds on Pindyck and Rotemberg (1990), who attributed excess price co-movements among commodities to herding. The second has developed from Chang, Cheng and Khorana (2000) and looks for similar trends in asset returns relative to market returns, the *beta* approach.

Steen and Gjolberg (2013) follow Pindyck and Rotemberg (1990) to estimate co-movements among commodity returns in conjunction with principal component analysis. They find little or no support for herd behavior. Following the Chang, Cheng and Khorana (2000) method, Demirer, Lee and Lien (2015) find some evidence of herd behavior in grains but not for other commodities. Babalos, Stavroyiannis and Gupta (2015) use a similar method and also end up with inconclusive findings. Júnior et al. (2020) investigate the presence of herding in the energy, metals, and agricultural commodities markets. They estimate each commodity's beta vis-à-vis the Standard & Poor's Goldman Sachs Commodity Index, measuring returns to individual commodities relative to price movements in the overall commodity market, following the method developed by Chang, Cheng and Khorana (2000). They then test for "beta" herding, a convergence of individual commodity betas. They find some evidence of herding toward the market portfolio.

To summarize, previous studies have failed to find much evidence of herding except in a few particular cases during certain periods. Part of the problem lies with the inability of the two most popular methods of measuring herding to control for fundamental supply and demand factors in the market. The Pindyck and Rotemberg (1990) and Chang, Cheng and Khorana (2000) methods only offer an indirect test for herding, and both methods are somewhat imprecise. In this paper, we introduce a new approach to test for herding—an event study approach based on credible counterfactuals to measure herding in commodity markets.

The Chicago corn, wheat, and soybean futures and options markets are at the center of price discovery in the global grain market. They represent some of the largest volume agricultural futures contracts traded globally. The literature has generally found that these Chicago markets are informationally efficient (Kristoufek and Vosvrda 2014; Lehecka 2014; Main et al. 2018; Kuruppuarachchi, Lin and Premachandra 2019), which means that prices tend to react quickly and rationally to changes in supply and demand information, with price behavior approximately following a martingale process (Samuelson 1965). The arrival of new information causes imperfection, but it is assumed that every such imperfection is promptly arbitraged away; see, for example, Mandelbrot (1971), Haase, Zimmermann and Zimmermann (2016), and Simmer et al. (2021). The conclusion that commodity futures markets are informationally efficient contradicts the herd behavior argument. Market efficiency is underscored by the observation that most hedge funds investing in commodities using momentum strategies and banking on market inefficiencies, have experienced relatively low returns over the past ten years.[1]

In this paper, we study the grain futures market response to the Russian invasion of Ukraine. First, we conduct an event study analysis relying on credible counterfactuals to measure the market's response to the event. Then, we use the price response in each market to evaluate claims the market overreacted. If the market expected that both Russia and Ukraine exports would be disrupted, we hypothesize wheat prices would have responded more than corn prices, which is precisely what happened. This outcome would be unlikely under herding behavior, which would have caused both corn and wheat prices to rise but not result in wheat overtaking corn. The fact that soybean prices did not respond to the invasion supports our conclusion that there is no behavioral finance story here. Normally corn and soybean prices are linked (Avalos 2014) as they are substitutes in animal feed rations or as planted acreage, and also complements in managed futures portfolios.

The wheat and corn futures price response to the invasion began to subside when the European Union (EU) established the *Solidarity Lanes* to facilitate grain exports from Ukraine through alternative routes in May 2022. The Solidarity Lanes were established on the border between Ukraine and the EU and allowed for Ukraine grain exports via road, rail, and the Danube ports up river to other parts of Europe, and down river onto the Black Sea. The Solidarity Lanes pre-dated the July *Black Sea Grain Initiative* brokered by the United Nations and Turkey, allowing Ukraine to

[1] For instance, a $10,000 investment ten years ago in the Invesco DB Commodity Index Tracking Fund would be worth less than $10,000 today (https://www.invesco.com/us/financial-products/etfs).

export grain directly by the Black Sea ports.

Grain exports from Ukraine started to recover sharply after the Solidarity Lanes were implemented. Our results indicate that the futures market reacted more strongly to the opening of the Solidarity Lanes than it did to the Grain Deal. While the corn futures price was about 16 percent above the counterfactual until the EU Solidarity Lanes were announced, the wheat futures price increase was almost double the corn futures prices, reaching 35 percent during the same period. In addition, using Commodity Futures Trading Commission (CFTC) *Commitments of Traders* data on the ratio of non-commercial longs to the sum of non-commercial longs and non-commercial shorts, we construct a measure of speculative pressure in the wheat, corn, and soybean futures markets. Our event study analysis finds no statistically significant evidence that speculative pressure was abnormally high in the futures market following the Russian invasion of Ukraine.

2. Background

The Russian Empire previously ruled Ukraine from the time of Catherine the Great (1729-1796). Ukraine tried to break free from Russia after the empire's collapse in 1917, but that was unsuccessful, and most Ukrainian lands were incorporated into the Soviet Union as a colony. Following the Ukrainian War of Independence (1917-1921), the tragic Soviet famine of 1930-33, known as the *Holodomor*, left millions dead in the Soviet Union, mainly Ukrainians. This has been described as an artificial famine, as Joseph Stalin allowed about 4 million Ukrainians to starve. The famine touched Russia far less than Ukraine, with overall excess deaths of 3 percent of the population in Russia, against about 15 percent in Ukraine (Applebaum 2018). Stalin used the Holodomor to suppress Ukrainian resistance to the forced Soviet state farming system. Before the Holodomor, Ukraine accounted for about 37 percent of the entire Soviet Union grain collection, and most of this grain was shipped out to Moscow, and some of it was exported out of the USSR (Applebaum 2018). Ukraine finally became independent in 1991, and Crimea remained part of Ukraine. However, Russia then illegally annexed Crimea in 2014 through military force.

After a period of post-Soviet economic stagnation, Russia evolved to become the largest single wheat exporter. Today Russia accounts for roughly 20 percent of world wheat exports. Egypt, Turkey, and Iran are large buyers of Russian wheat. However, Russia is not a major player in the world corn market as it only supplies about 2 percent of its corn exports. Alternatively, Ukraine is not a major player in the world wheat market but is very important in corn. Ukraine provides 9 percent of the world's wheat and 14 percent of its corn and ranks as the third largest corn exporter, behind the United States and Argentina. Following the 2022 invasion, Russia boosted its wheat exports to a record 45.5 MMT in the marketing year 2022/2023, partially backfilling Ukraine's lost wheat exports.

As with other exporters, grain exports from Ukraine are typically seasonal, with increased exports following the wheat harvest in July and the corn harvest in September. In February 2022, corn and wheat futures prices increased sharply due to fears that the war would disrupt the 2022 harvest and 2022/23 exports. In addition, sown areas to spring crops in Ukraine declined by about 20 percent, and input supply chains were disrupted. Ukraine's Black Sea export routes were blocked after the invasion, and Ukraine exporters resorted to more costly modes of transportation, such as truck, rail, and barge, through the Solidarity Lanes. However, these alternative export channels needed to be improved to move the harvest, as Ukraine had amassed large grain stocks.

Figure 1 shows Ukraine's corn and wheat exports in the top two panels versus global exports in the bottom two. Referring to Ukrainian corn exports in panel (a), the blue line shows the average calendar year exports over the 2019/2021 period, and the red line shows the 2022 exports. Exports dropped to near zero from March to June 2022 and did not recover to the previous level until the last few months of 2022. Ukraine corn exports from February to July 2022 were below average (based on monthly statistics), and then they started to pick up in July 2022 after the Grain Deal. For wheat, the post-invasion Ukraine export volume never reached average monthly levels until the end of calendar year 2022. Panels (c) and (d) of Figure 1 report the importance of Russian and Ukraine in the global corn and wheat markets before the war. These panels show that the war had minimal impact of the volume of global trade in wheat and corn.

The *Black Sea Grain Initiative*–BSGI (which took effect on August 1, 2022) allowed exports from three Ukraine Black Sea ports that had been blocked: Odesa, Chornomorsk, and Yuzhny.[2] After

[2] https://www.un.org/en/black-sea-grain-initiative.

the deal was reached, the *Wall Street Journal* reported that wheat prices tumbled and "the trade is just unwinding all of the premia from the concerns around the Russia-Ukraine invasion."[3] However, we find that prices declined before the BSGI was announced.[4]

Our primary data series are summarized in Figure 2. The left panels (a) and (d) plot the nearby corn and wheat weekly futures prices, with vertical dashed lines marking the invasion, the Solidarity Lanes, and the BSGI. After the attack, corn prices moved from around \$6.50 to \$8 per bushel. Once the Solidarity Lanes were established, corn futures prices started to fall, and by the time the BSGI was in place, corn prices were back to pre-invasion levels. Wheat futures prices–panel (d) in Figure 2–show a very similar pattern to corn prices during this period, although wheat prices moved more percentage-wise than corn, from around \$8 to over \$12 per bushel after the invasion. Like in corn, wheat futures prices retraced the invasion run-up starting when the Solidarity Lanes were set up. When the BSGI was signed, wheat prices were back at \$8 per bushel.

Panels (b) and (e) display implied volatility in the CME's corn and wheat options markets. Wheat volatility increased much more than corn volatility around the time of the invasion. Wheat volatility almost tripled from just over 20 percent to 60 percent. At the same time, corn volatility went from 20 percent to 30 percent. This means wheat options became much more expensive than corn options at the time of the invasion. Volatility in both markets fell with the introduction of the Solidarity Lanes and by the end of calendar 2022 the implied volatility was at its pre-war levels.

Finally, panels (c) and (d) in Figure 2 show a measure of speculative pressure in the wheat and corn futures markets. Speculative pressure is measured by the index Z = (non-commercial longs) / (non-

[3] Kirk Maltais, *Wheat Prices Fall After Russia-Ukraine Deal*, Wall Street Journal, July 22, 2022.

[4] Unfortunately, Russia backed out of the BSGI in July 2023 and corn and wheat prices both responded. This event is beyond the scope of this paper because there are insufficient data since it happened to allow us to conduct a full event study. In any case, the relative responses in the wheat and corn markets were similar to what happened in February 2022. After the July 2023 BSGI shock, wheat prices increased by 15% and corn prices by 10%, although prices reversed in less than two weeks. Implied volatility rose more for wheat compared to corn. This is not surprising because if the war were to jeopardize all the grain shipments on the Black Sea, the wheat market would be hit harder than corn because the volume of wheat shipments on the Black Sea were about 1.7 times corn shipments prior to the war. Furthermore, being primarily a food grain, the short run export import elasticity is about -0.4 (-1.0) for wheat (corn) (see Reimer, Zheng and Gehlhar (2012)).

commercial longs + non-commercial shorts) sourced from Commodity Futures Trading Commission, Commitment of Traders (COT) weekly reports. When Z = 0.5, speculators are neither long nor short on the net. When Z > 0.5, speculators are net long, and when Z < 0.5, speculators are net short. The patterns in panels (c) and (d) mimic the price behavior in panels (a) and (e). Speculative pressure initially increased at the time of the invasion, then started to subside with the Solidarity Lanes, and then fell sharply before the Grain Deal.

Figure 3 reports selected monthly percent price moves for corn and wheat going back to 1900. As noted by Cowley, Rodziewicz and Cook (2022), the jump in wheat prices following the invasion of Ukraine was historically very significant. The wheat price increase in March 2022 was one of the largest price moves since the USDA records began. Price advances of this magnitude had not occurred since the Russian great grain robbery in the 1970s or the Dust Bowl of the 1930s. In August 1973, wheat prices increased by over 80 percent during the Russian grain robbery. During the 1930s dust bowl, there were five different months when wheat prices increased from 30 to 48 percent.

We find a handful of studies in the literature that have measured the price impact of a supply or demand shock similar to the Russian invasion of its neighbor.[5] These studies provide insight into the potential price impacts resulting from a loss of grain exports from Ukraine and possibly Russia. For instance, Miranda, Glauber and Romero-Aguilar (2014) employed a stochastic, spatial-temporal equilibrium model to study the market impact of China's growing role as a major grain importer. They modeled China and the "Rest of the World" (ROW) and solved a spatial equilibrium model through trade and assuming competitive storage in the ROW. Their results show that a 20 MMT (about 2.7 percent of rest-of-world corn production) increase in China's import demand for corn would raise the world's corn price by 10 percent. Hausman, Auffhammer and Berck (2012) estimated a structural variance autoregression model of U.S. cropland allocation. They found that removing land from food production for purposes of making corn ethanol raised corn prices in 2007 by about 10 percent. Roberts and Schlenker (2013) estimate the elasticities of world supply

[5] We note that a leftward shift in world grain supply due to the war would likely have a larger percentage price impact on price than an equivalent demand shift.

and demand for calories from agricultural commodities and create a calorie-weighted index of prices and quantities using instrumental-variables techniques. Based on their model, the increased ethanol demand caused grain prices to increase by 20 percent. Carter, Rausser and Smith (2017) determined that corn prices increased 30 percent when the U.S. revised its biofuels policy from the initial 2007 Renewable Fuel Standard (RFS) to the 2010 RFS2, which shifted corn demand by 33 MMT. They used a partially identified structural vector autoregression model. Mustafa (2022) estimated the war in Ukraine raised international food and feed prices by 8 to 22 percent.

3. Empirical Strategy and Data

We utilize event study methods to assess the response of grain futures markets to the Russian invasion of Ukraine. Event studies have been commonly used for assessing the ex-post treatment effects of an external shock (see, for a review, Freyaldenhoven et al. 2021; Roth et al. 2023). The approach allows us to incorporate leads and lags relative to the event of interest within a dynamic model specification that captures pre-trends and enables us to evaluate the post-event treatment dynamics (Freyaldenhoven, Hansen and Shapiro 2019). We employ a log-linear regression model to estimate the impact of the market uncertainty caused by the Russia-Ukraine conflict on the futures price, options implied volatility, and speculative pressure for corn, wheat, and soybeans:

$$y_{ct} = \nu_{cd} + \phi_{cw} + \psi_{cy} + \sum_{r \neq 0} \mathbb{1}\left\{R_{ct} = r\right\} \beta_r + \eta_{ct} \, , \tag{1}$$

where c represents the commodity and t the day. The outcome of interest is denoted by y_{ct} and maps into the futures price, options implied volatility, and speculative pressure. We assume that all latent confounders are captured by the high-dimensional fixed effects that are defined at the commodity-event-day (ν_{cd}), commodity-event-week (ϕ_{cw}), and commodity-event-year (ψ_{cy}) levels. This regression specification addresses (unobserved) market shifts through the commodity-event-year fixed effects and accounts for seasonality in the outcome of interest with commodity-event-week fixed effects. The central identifying assumption is that the treatment timing is independent of the error conditional on the high-dimensional fixed effects. We define the time relative to treatment as $R_{ct} = t - G_c + 1$, where the summation is run over all possible realizations of $R_{c,t}$ except for zero. We follow common practice in the event study literature and use a symmetric event window of 21 weeks around G_c (Roth 2021). The event study is centered around the week when the Russian invasion of Ukraine commenced (week 8 of 2022). The additive error term is denoted by ϵ_{ct} and adjusted for heteroskedasticity following standard practice (Cameron and Miller 2015).

A causal identification of the treatment effects depends on a reliable comparison group with similar trends in the pre-treatment period (parallel trends assumption) (Marcus and Sant'Anna 2021). At the same time, this comparison group needs to be unaffected by (or exogenous to) the market uncertainty caused by the Russia-Ukraine war. We cannot use futures price series for other commodities during the same period as a control group as they are likely affected by the same market uncertainty and may exhibit different pre-trends (Rambachan and Roth 2021). Instead, we rely on grain futures outcomes from previous years as the comparison group. Previous studies have used a similar research design to investigate the trade implications of the Covid-19 pandemic, maritime shipping disruptions, and Russia-Ukraine war (see, e.g., Arita et al. 2022; Carter, Steinbach and Zhuang 2022; Steinbach 2022; Ahn, Kim and Steinbach 2023; Steinbach 2023). Futures price data from earlier years have the benefit of exhibiting similar seasonality patterns as the outcomes of interest. The difficulty lies in selecting a comparison group unaffected by the market uncertainty caused by the Russia-Ukraine war that exhibits the same trends in the pre-treatment period (Marcus and Sant'Anna 2021). Since we have daily data available for all outcomes going back to 2005, there are n potential tuples that could be used to construct the comparison group. To identify the tuple that best replicates the treatment group in the pre-event period, we conduct an F test for the null hypothesis that the pre-event coefficients are jointly equal to zero (Griffiths et al. 1985). By selecting the tuple with the lowest F statistic, we can identify the comparison group that reflects the treatment group best in the pre-treatment period.[6] This approach resembles the synthetic difference-in-differences methods, which aims to match pre-event trends to weaken the reliance on parallel trend assumptions (Arkhangelsky et al. 2021).

We follow common practice in the related empirical literature and rely on a log-linear regression

[6] We require each tuple to include at least seven event years to make the analysis computationally feasible. By applying this constraint, we end up with 50,653 tuples per outcome, which includes event years between 2005 and 2021. We estimate each model and conduct an F test for the null hypothesis that the pre-event coefficients are jointly equal to zero.

specification to identify the relationship of interest (Kristoufek and Vosvrda 2014; Lehecka 2014; Main et al. 2018; Kuruppuarachchi, Lin and Premachandra 2019). The main outcomes of interest are the futures price, implied volatility, and speculative pressure for corn, wheat, and soybeans. Our dataset consists of daily observations of Chicago futures contracts from January 2005 to January 2023, sourced from Barchart (2023). Each futures contract with a specific delivery month over this study period was included in our data. CBOT corn and wheat (SRW) wheat futures have five delivery months (March, May, July, September, and December). Soybean futures have seven delivery months (January, March, May, July, August, September, and November).

We rely on options implied volatility to measure the heightened market uncertainty caused by the Russian invasion of Ukraine, obtained from IVolatility (2023). The 30-day implied volatility is computed using the Black-Scholes option pricing model (Black and Scholes 1973). In contrast to historical volatility, a measure of past futures price changes, the implied volatility measure reflects expectations regarding the market's future volatility. Lastly, we rely on the weekly Commitment of Traders reports from the Commodity Futures Trading Commission (2023) to construct a measure of speculative pressure in the corn and wheat futures markets. The measure is defined as $Z =$ (non-commercial longs) / (non-commercial longs − non-commercial shorts). Table A.1 provides descriptive statistics, comparing the outcomes 21 weeks before and after the Russian invasion of Ukraine. The simple comparison shows that corn futures prices were about 25 percent higher after the conflict started, while those for wheat and soybeans were 34 percent and 23 percent higher.[7]

4. Main Results

Figure 4 presents event study estimates for the corn and wheat futures price response to the Russian invasion of Ukraine. Each subfigure displays the dynamic treatment parameters, 95-percent confidence intervals, and uniform sup-t bands for the event-time of the outcome following Montiel Olea and Plagborg-Møller (2019) and Freyaldenhoven et al. (2021). The estimates for a static regression

[7] An issue with this simple comparison is trending in the outcomes. As shown in Figure 2, particularly corn futures prices were upward trending before market uncertainty started to increase considerably due to the Russia-Ukraine war. Therefore, a simple comparison can be misleading regarding the true nature of the treatment effect, justifying the use of a dynamic treatment model for causal inference.

model are overlaid, with test statistics for pre-trends, leveling-off treatment effects, and the static effect p-value reported in the figure notes. We find no evidence of statistically significant pre-trends for the futures prices and speculative pressure, indicating that the Russian invasion of Ukraine is exogenous to those outcomes (Freyaldenhoven, Hansen and Shapiro 2019; Sun and Abraham 2021; Roth 2022). Conditional on the high-dimensional fixed effects, the treatment group exhibits similar trends in the pre-treatment period to the control groups, validating the research design.[8] At the same time, there is limited evidence for leveling-off treatment effects for corn and wheat futures prices and speculative pressure.

The event study estimates reveal important patterns in the response of futures prices to the Russian invasion of Ukraine. First, futures prices for corn and wheat increased sharply with the start of the hostilities between Russia and Ukraine, as the markets were concerned over the ability of Ukraine and Russia to ship grain to foreign markets via the Black Sea route. These treatment effects are immediate but differential for corn and wheat.[9] While the corn futures price was about 16 percent above the counterfactual until the EU Solidarity Lanes were announced, the wheat futures price increase was almost double the corn futures prices, reaching 35 percent during the same period. This finding supports our hypothesis that the markets expected that both Russia and Ukraine exports could be disrupted since wheat futures prices responded more than corn prices. If the war were to jeopardize all the grain shipments on the Black Sea, the wheat market would be hit harder because wheat shipments on the Black Sear were about 1.7 times corn shipments, measured by metric tons.

In May 2022, the Solidarity Lanes were established on the border between Ukraine and the EU and allowed for Ukraine grain exports via road, rail, and the Danube river ports. The Solidarity Lanes pre-dated the Back Sea Grain Deal brokered by the UN and Turkey in July 2022. The war premium

[8] We find that corn options implied volatility had been below the counterfactual 12 weeks before the Russian invasion of Ukraine. A similar pattern is observable for wheat options implied volatility. Although this pattern speaks to long-term differences in implied volatility between the treatment and control groups, these differences are neither upward- nor downward-sloping in the pre-treatment period. Therefore, we can conclude that the treatment is also exogenous to the corn and wheat options implied volatility (Freyaldenhoven et al. 2021).

[9] The average post-event treatment effect for the corn futures price is about 10 percent, while it is almost three times larger for the wheat futures price.

subsided once the EU Solidarity Lanes were operational, implying that the markets put a fair price on the wartime risk of Black Sea grain shipments being completely disrupted. In addition, contrary to the common narrative, our event study approach that relies on credible counterfactuals for causal inference finds limited statistically significant evidence that speculative pressure was abnormally high in the corn and wheat futures market following the Russian invasion of Ukraine. The post-event treatment effects are indifferent from zero at conventional levels of statistical significance for corn and slightly elevated for wheat futures up to the establishment of the EU Solidarity Lanes. This pattern implies that speculation did not get ahead of itself, and commodity traders put a fair price on the wartime risk.

5. Robustness Checks

Placebo Treatment — A potential concern regarding our identification strategy relates to the control group choice. We rely on grain futures outcomes from previous years as the control group, as futures price series from earlier years benefit from similar seasonality patterns as the outcomes of interest. In contrast, we cannot use futures price series for other commodities during the same period as a control group as they are likely affected by the Russia-Ukraine war. At the same time, we would expect futures prices from previous years and unrelated commodities to be unaffected by the event. Therefore, an insightful falsification analysis is to use these alternative outcomes in a placebo treatment model. Figure A.1 replicates the main results using 2017 as the treatment year. The average post-event treatment effect for the corn futures price is about -3 percent, while that for wheat is less than 1 percent. Both estimates are insignificant at conventional levels of statistical significance. A similar pattern is observable for the second placebo test. For this purpose, we use soybeans as the main outcome, as the combined share of Russia and Ukraine in the global soybean market is less than 2 percent. Figure A.2 provides no evidence for statistically significant post-event treatment effects for all outcomes. This pattern implies that the Russia-Ukraine had no impact on soybean markets, and traders acted rationally by pricing in the expectation that both Russian and Ukrainian wheat exports could be halted due to the war.

Comparison Group Choice — A causal interpretation of the treatment effects depends on a comparison group that exhibits similar trends in the pre-treatment period to the treatment group (parallel trends assumption). At the same time, this comparison group needs to be unaffected by the economic turmoil caused by the Russia-Ukraine war. Therefore, our identification strategy relies on grain futures outcomes from previous years as this comparison group. We selected this comparison group based on all potential combinations (tuples) of event years between 2006 and 2021. The choice of this control group is determined by how well the selected model fits the pre-event paths of the treatment group. To understand better how robust our main results are to this choice, we reestimate Equation 1 under the alternative assumption that the comparison group is randomly drawn from the potential set of alternative tuples. This approach resembles a cross-validation design where a surrogate model is estimated to validate the model choice (see, e.g., Sobester, Forrester and Keane 2008; Angione, Silverman and Yaneske 2022). Table A.2 compares the main results to three surrogate models, for which we randomly selected the comparison group based on the ranked F tests for parallel trends. Focusing on the average post-event treatment effects for corn and wheat futures prices, we find evidence of statistically insignificant differences in the estimated treatment effects. Across the range of surrogate models, the corn futures price is 9 to 11 percent above the counterfactual level during the post-event period, while the wheat futures price is between 25 and 33 percent higher. Because the wheat futures price was more affected than the corn futures price, the market anticipated that Black Sea grain exports would be completely halted when the Russian invasion of Ukraine started.

Linear Pre-Trend Adjusted Post-Event Treatment Paths — The potential for significant pre-trends before the treatment month requires us to be cautious about the causal interpretation of the post-event treatment effects (Freyaldenhoven, Hansen and Shapiro 2019; Marcus and Sant'Anna 2021). Although the dynamic treatment specification avoids downward bias from averaging over the periods before the treatment month, it also assumes that treated units would have continued on the same growth path as non-treated units after February 2022. To account for the potential impact of pre-trends, we reestimate Equation 1 under the alternative assumption that the linear pre -trends of targeted units would have continued on their pre-treatment paths following the approach outlined by Dobkin et al. (2018) and Freyaldenhoven et al. (2021). There are two notable differences from the baseline specification. First, only the treatment response relative to the post-event period is estimated. Second, we include a linear trend that takes the value of the monthly difference relative to the treatment month and is set to zero during the post-event period. This specification identifies the adjusted treatment effects as the deviation between the estimated treatment effect after the event and the extrapolated pre-trend. We overlay the estimated linear pre-trends in Figure A.3 and show the treatment paths with subtracted linear pre-trends in Figure A.4. The estimated linear pre-trends are statistically insignificant for futures prices and speculative pressure but statistically significant for implied volatility. After subtracting the linear pre-trends from the post-event treatment estimates, we find similar treatment patterns than observed for our main results. First, we find that futures prices for corn and wheat increased sharply after the Russian invasion of Ukraine. The markets likely expected an inability of exporters to ship grain to foreign markets via the Black Sea route. These treatment effects are statistically indifferent to the main results for corn and wheat futures prices. While the corn futures price was about 17 percent above the counterfactual until the Solidarity Lanes were announced, the wheat futures price increase was more than double the corn futures prices, reaching 34 percent in the post-event period after controlling for linear pre-trends.

Devil's Advocate Model — A failure to reject the null hypothesis of no pre-event trends does not imply that there is no confounding variable that could threaten the identification of the 'true' treatment effects of the Russia-Ukraine war (Roth 2021). To test for the presence of a confounding variable, we estimated a devil's advocate model, which assumes that the 'true' value of the treatment effect is zero. We identified the least "wiggly" event-time path, which is, among polynomial confounds consistent with the estimated event-time path, the least "wiggly" path with the lowest polynomial order (Rambachan and Roth 2021). Figure A.5 shows estimates of the devil's advocate model. The event-time paths for the futures price and implied volatility are both "wiggly", implying that it is unlikely that a confounding variable exists that threatens the identification of the treatment effects of the Russia-Ukraine war.

Alternative Volatility and Speculation Measures — Our empirical analyses partially relies on options implied volatility and the Z speculative pressure index to assess the impact of the Russia-Ukraine war. Although these measures are frequently used to evaluate volatility and speculative pressure in futures markets, there are alternative measures used in the literature (Haase, Zimmermann and Zimmermann 2016; Algieri and Leccadito 2019; Chen and Mu 2021). Figure A.6 compares estimates for the impact of the Russia-Ukraine war on corn and wheat historical volatility and the Holbrook Working speculative T index. Historical volatility is a statistical measure of return dispersion for the corn and wheat futures markets. We use a 30-day rolling window to calculate the historical volatility. The event studies for corn and wheat historical volatility in panels (a) and (c) reveal a similar picture as those presented in Figure 4. The treatment effects are more persistent than with implied volatility due to the nature of the historical volatility measure because it is defined as a rolling average over a 30-day window.

An alternative to the Z index is the T index by (Working 1960). The T index measures speculation in futures markets as the net of hedging demand, which estimates excessive speculation as those positions that are more than the hedging needs (Haase, Zimmermann and Zimmermann 2016). To understand how robust our main results are to the choice of the speculation measure, we estimate the model using the T index, as presented in panels (b) and (d). Notably, the event study estimates for corn speculative pressure are similar to the main results above for the Z measure. Furthermore, there is no evidence of increased speculation in the wheat futures markets in response to the Russia-Ukraine war using the alternative T measure of speculative pressure.

Alternative Distributional Assumption — The applied economics literature relies on log-linear regression specification to estimate the impact of exogenous shocks on commodity futures price movement (see, e.g., Sockin and Xiong 2015; Ouyang, Wei and Wu 2019; Crosby and Frau 2022). The log transformation has the advantage of addressing heteroskedasticity, ensuring a symmetric residual distribution, and providing a unit-free elasticity interpretation (Wooldridge 2010). In contrast, a growing literature has advocated for modeling the relationship between the outcome and treatment directly using an exponential regression model under the Poisson distribution (Gourieroux, Monfort and Trognon 1984; Cameron and Trivedi 2013). The Poisson distribution has previously been used to study price formation in commodity markets (see, e.g., Hilliard and Reis 1999; Li et al. 2017). To understand better how robust our main results are to the distributional assumption, we reestimate Equation 1 under the alternative assumption that the data-generating process follows the Poisson distribution. The estimates of this analysis are presented in Figure A.7. They indicate that the average post-event treatment effects for the corn and wheat futures prices are indifferent from the main results at conventional levels of statistical significance. The corn futures price is 10 percent above the counterfactual level during the post-event period, while the wheat futures price is 35 percent higher. Similar patterns are observable for the implied volatility and speculative pressure of corn and wheat futures.

Choice of Fixed Effects — The central identifying assumption is that the treatment timing is independent of the error term (Wooldridge 2010; Roth et al. 2023). We assume that the baseline specification absorbs all unobserved factors potentially correlated with the outcome and treatment by including high-dimensional fixed effects at the commodity-event-day, commodity-event-week, and commodity-event-year levels. Among others, such unobserved factors are uncorrelated market shifts and seasonality patterns. To understand better how robust our main results are to including the high-dimensional commodity fixed effects at the event-day, event-week, and event-year levels, we estimate Equation 1 under the alternative assumption of unobserved correlation at the calendar week and year levels. The event study results for this analysis are presented in Figure A.8. The average post-event treatment effect for the corn futures price is the same as for our main results.[10] In contrast, the estimated average treatment effect for the wheat futures price is slightly larger (32 percent versus 30 percent). However, both estimates are statistically indifferent from one other at conventional levels. Therefore, the choice of fixed does not affect our main results.

6. Conclusion

Russia's invasion of Ukraine raised concerns over growing food security issues in the developing world. The war compounded food security issues related to Covid-19 and supply chain disruptions that arose during the pandemic. Some view the war as creating an ongoing significant food crisis causing famine in Africa and elsewhere. Indeed the U.S. envoy to the United Nations recently said that the worst food crisis since World War II would only end if the Russian Federation pulled out of Ukraine. We find that the initial grain futures market reaction to the Russian invasion was in line with an expectation that Russian and Ukrainian grain exports via the Black Sea could be halted

[10] Note that this alternative regression specification results in a discontinuity in the pre-treatment period due to the overlap of the calendar year and event window, explaining the jump in the alternative event study estimates and our preference for including high-dimensional fixed effects at the commodity-event-day, commodity-event-week, and commodity-event-year levels.

during the war. The impact on the wheat futures price was more pronounced than the reaction in the corn futures price because Russia is the world's largest wheat exporter, underscoring the market's apparent anticipation that Black Sea grain exports from both Russia and Ukraine were at risk when the war broke out. Overall, there is more wheat than corn exported by way of the Black Sea. However, the war premium dissipated as EU Security Lanes and the Black Sea Grain Initiative allowed grain exports from Ukraine to resume. According to our findings, the EU Security Lane initiative was a significant positive policy development. Open markets and world trade mitigated the worse of the grain market disruptions caused by the Russian invasion of Ukraine.

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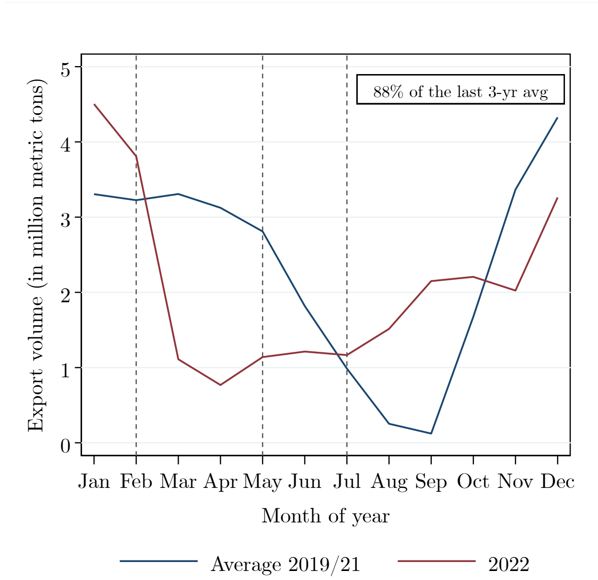
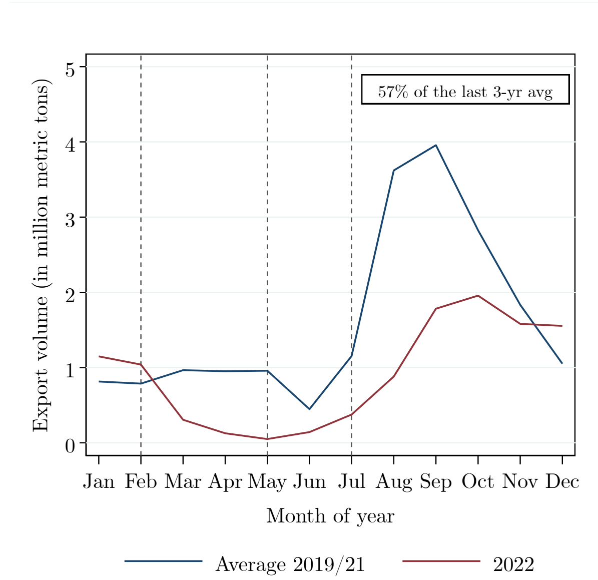
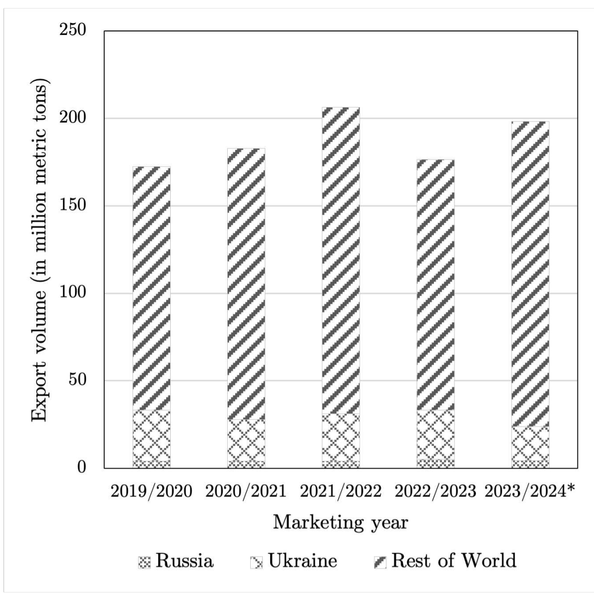
Figures and Tables



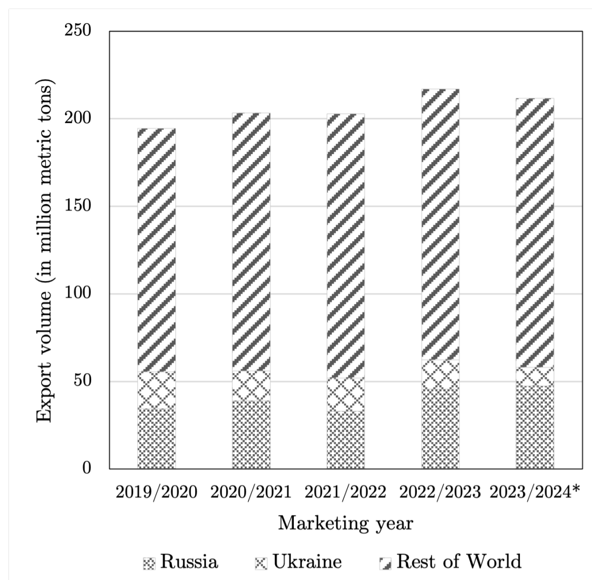
(a) Ukrainian Corn Export Volume.



(b) Ukrainian Wheat Export Volume.



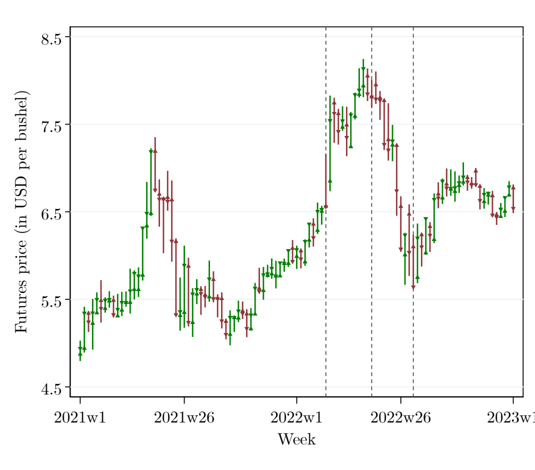
(c) Global Corn Market.



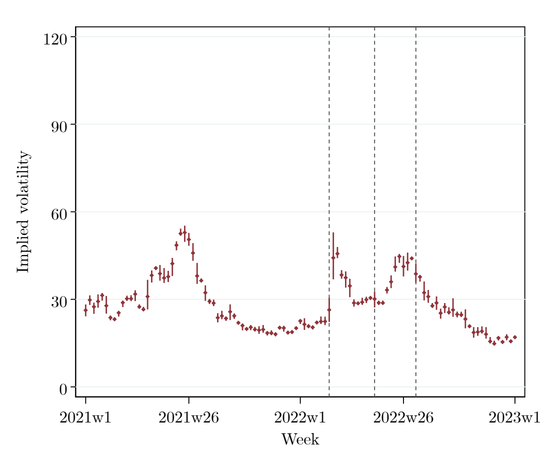
(d) Global Wheat Market.

Figure 1: Black Sea Grain Exports.

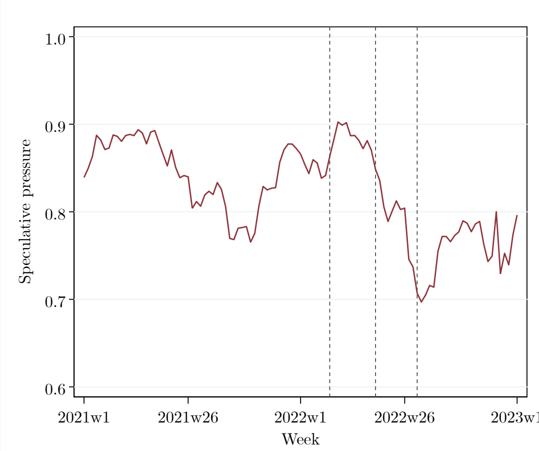
Note. The figure shows the evolution of black sea grain exports. Subfigures (a) and (b) compare the average 2019/21 Ukrainian corn and wheat exports with those from 2022. Export volumes are from the Trade Data Monitor (2023). Subfigures (c) and (d) show the share of Russia and Ukraine in global corn and wheat market shares. Data for this analysis come from the Grain: World Markets and Trade Report (USDA 2023).



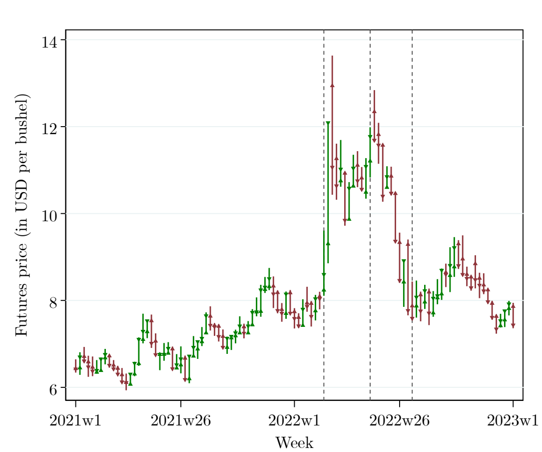
(a) Corn Futures Price.



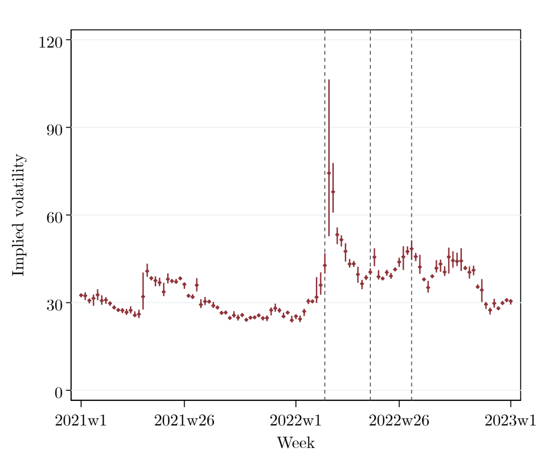
(b) Corn Options Implied Volatility.



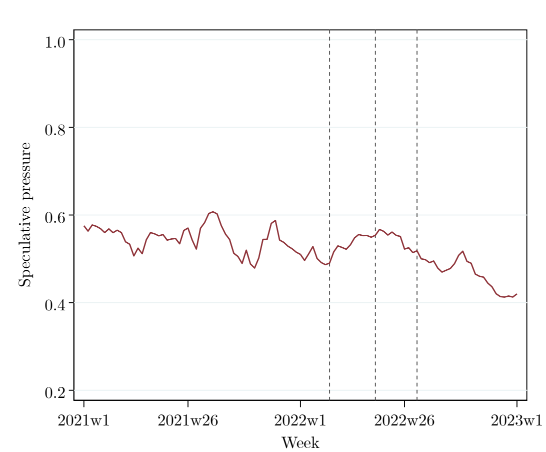
(c) Corn Futures Speculative Pressure.



(d) Wheat Futures Price.



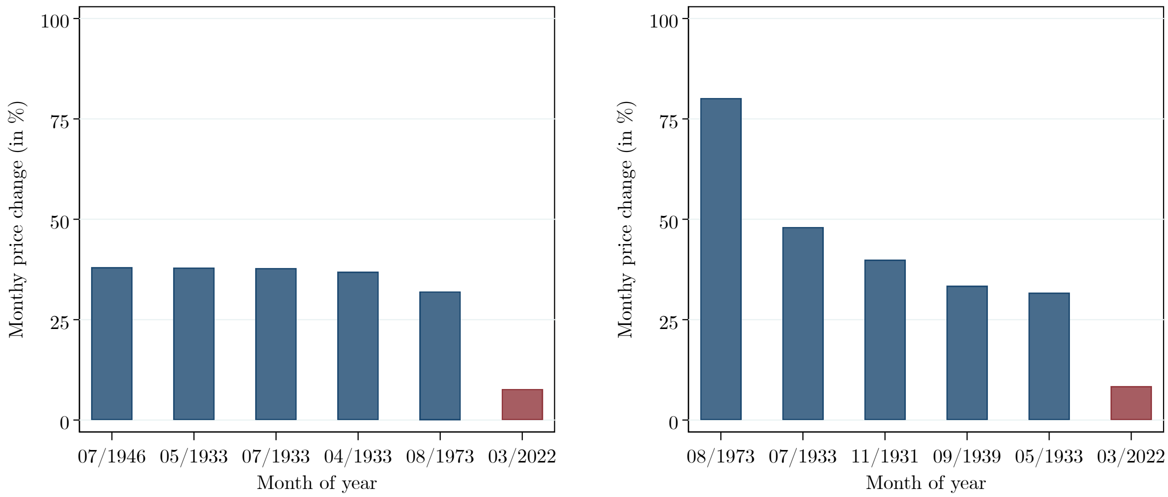
(e) Wheat Options Implied Volatility.



(d) Wheat Futures Speculative Pressure.

Figure 2: Grain Futures Price, Options Implied Volatility, and Speculative Pressure.

Note. The figure shows corn and wheat futures prices, implied volatility, and speculative pressure in 2021 and 2022. Corn and wheat futures prices are based on the last day of the calendar week, the implied volatility on the rolling 30-day annualized standard deviation of the end-day futures prices, and the speculative pressure is defined as the CFTC's COT non-commercial longs / (non-commercial longs - non-commercial shorts).

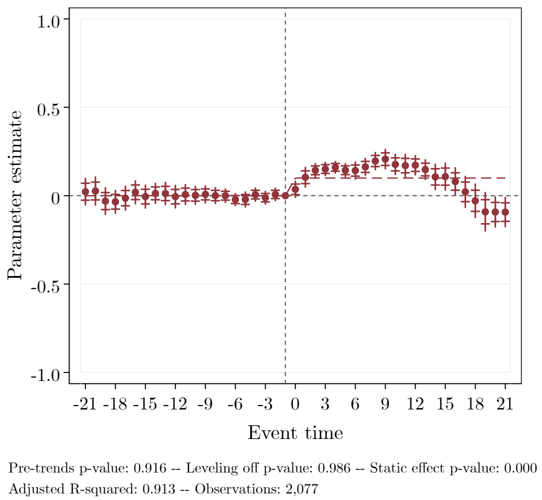


(a) Corn Prices.

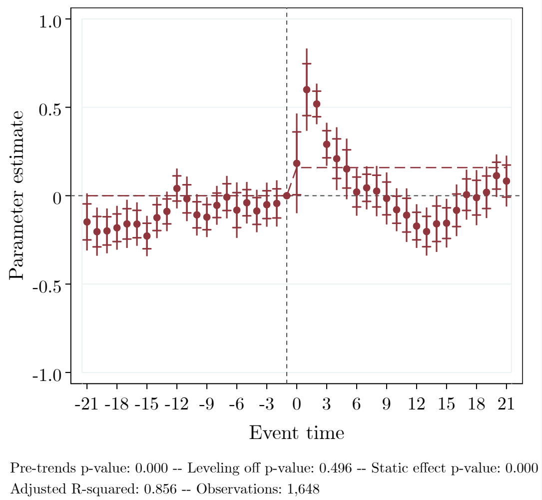
(b) Wheat Prices.

Figure 3: U.S. Historical Grain Price Movements.

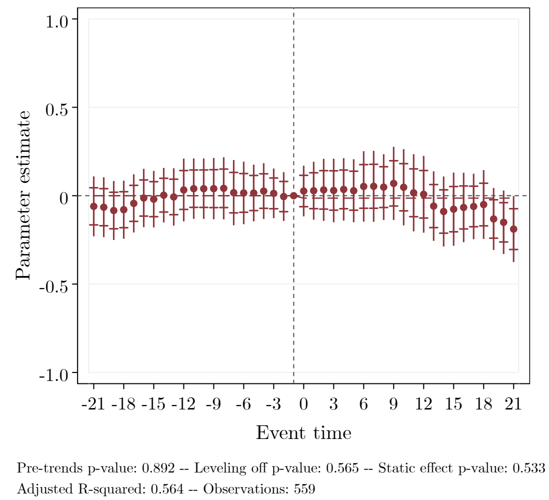
Note. The figure shows the monthly movement in the average national price received for corn and wheat in the United States. Data for this analysis come from the National Agricultural Statistics Service (United States Department of Agriculture 2023). The price movement was calculated as the monthly change, and the top 5 price movements between 1990 and 2022 are shown. In addition, the price movement from February to March 2022 is presented in the figure.



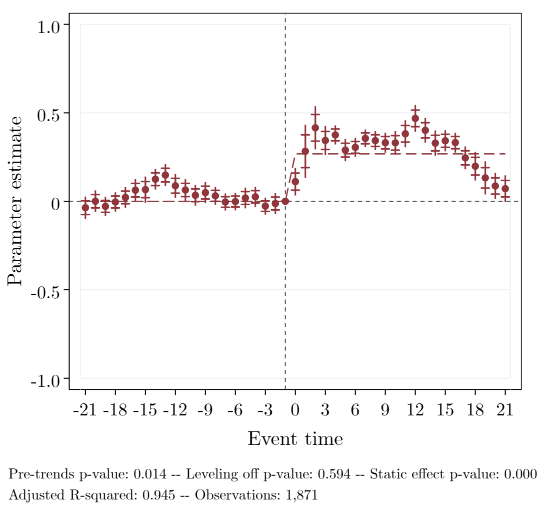
(a) Corn Futures Price.



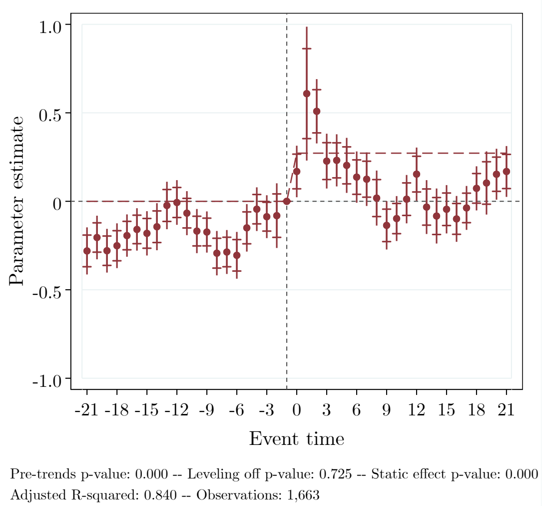
(b) Corn Options Implied Volatility.



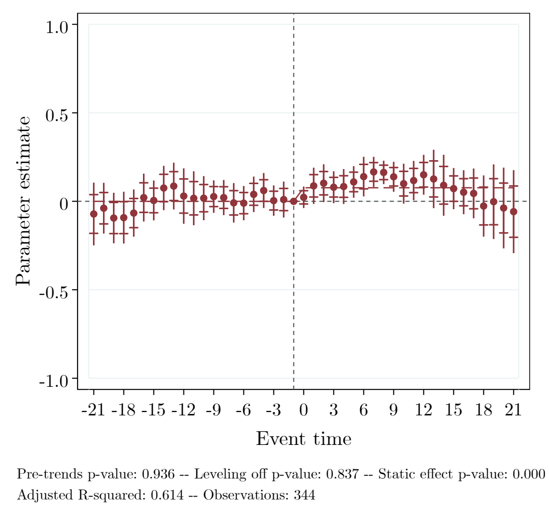
(c) Corn Futures Speculative Pressure.



(d) Wheat Futures Price.



(e) Wheat Options Implied Volatility.



(f) Wheat Futures Speculative Pressure.

Figure 4: Event Studies.

Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report several Wald tests and regression statistics in the figure notes. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.

Appendix Tables and Figures

Table A.1: Descriptive Statistics.

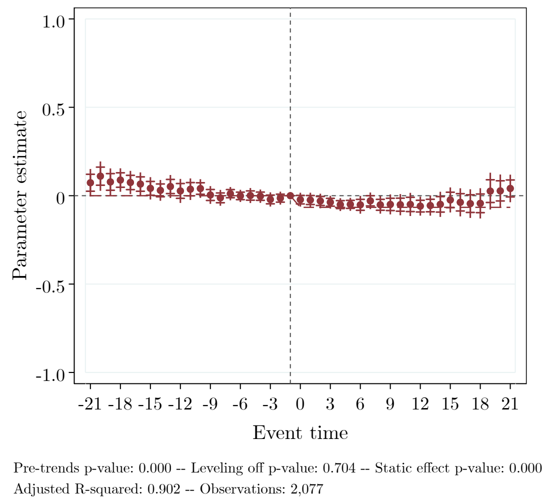
	Sum	Mean	Median	SD	Min.	Max.	Obs.
Panel (a): Before the Event							
Corn Futures Price	60,184	584.31	586.00	35.79	512.25	655.25	103
Wheat Futures Price	80,135	778.01	777.00	33.37	706.50	867.50	103
Soybeans Futures Price	136,986	1,329.96	1,274.25	117.73	1,188.50	1,603.50	103
Corn Options Implied Volatility	2,087	20.26	20.15	1.52	17.36	24.13	103
Wheat Options Implied Volatility	2,765	26.85	25.63	3.23	23.25	40.37	103
Soybeans Options Implied Volatility	1,805	17.52	16.58	2.95	13.77	25.12	103
Corn Speculative Pressure	1,753	83.49	84.14	3.48	76.54	87.75	21
Wheat Speculative Pressure	1,434	68.28	68.79	1.76	65.16	71.88	21
Soybeans Speculative Pressure	1,477	70.32	65.63	10.02	56.26	85.34	21
Panel (b): After the Event							
Corn Futures Price	76,406	727.68	748.25	67.14	564.25	813.50	105
Wheat Futures Price	109,155	1,039.57	1,072.50	123.51	759.00	1,294.00	105
Soybeans Futures Price	167,464	1,594.89	1,647.00	121.84	1,301.50	1,732.25	105
Corn Options Implied Volatility	3,738	35.60	35.42	6.64	22.26	52.95	105
Wheat Options Implied Volatility	4,830	46.00	42.87	10.55	34.60	106.40	105
Soybeans Options Implied Volatility	2,545	24.24	23.58	3.56	18.53	31.04	105
Corn Speculative Pressure	1,842	83.71	85.58	5.74	70.70	90.26	22
Wheat Speculative Pressure	1,581	71.87	72.94	5.75	56.12	78.22	22
Soybeans Speculative Pressure	1,806	82.09	83.09	3.50	73.76	85.21	22

Note. The table shows the descriptive statistics for the main outcomes. The statistics are calculated for the pre-event and post-event window of 21 weeks. We calculated the sum, mean, median, standard deviation (SD), minimum (Min.), maximum (Max.), and observation numbers (Obs.) for the three outcomes and agricultural commodities. The post-period has two additional days since the invasion started on Thursday, February 24, 2022.

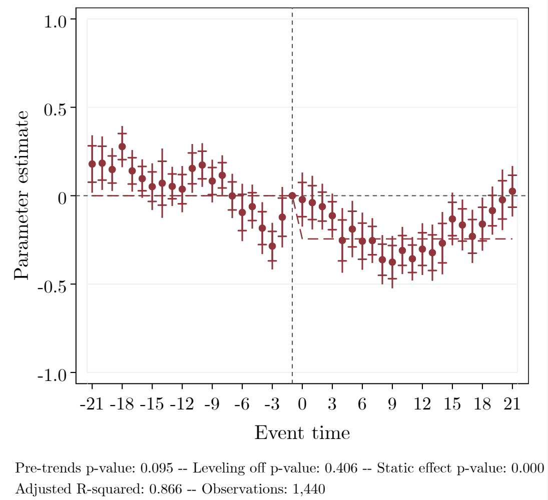
Table A.2: Robustness to Comparison Group Choice.

	Corn			Wheat		
	Futures Price	Implied Volatility	Speculative Pressure	Futures Price	Implied Volatility	Speculative Pressure
Panel (a): Main Results						
Post-event average	-0.001	-0.103***	-0.003	-0.012	-0.169***	0.015
	(0.009)	(0.029)	(0.038)	(0.016)	(0.038)	(0.032)
Post-event average	0.097***	0.058*	-0.044	0.262***	0.107***	0.025
	(0.010)	(0.030)	(0.038)	(0.016)	(0.039)	(0.032)
Adjusted R-squared	0.913	0.856	0.401	0.888	0.840	0.678
Observations	2,077	1,648	387	1,663	1,663	473
Panel (b): Random Control Group 1						
Post-event average	0.002	-0.171***	0.000	0.004	-0.168***	0.014
	(0.009)	(0.029)	(0.032)	(0.010)	(0.034)	(0.032)
Post-event average	0.090***	0.137***	-0.042	0.218***	0.186***	0.038
	(0.009)	(0.029)	(0.033)	(0.010)	(0.035)	(0.032)
Adjusted R-squared	0.928	0.870	0.602	0.944	0.802	0.561
Observations	2,076	1,647	344	1,659	1,663	387
Panel (c): Random Control Group 2						
Post-event average	0.001	-0.160***	0.000	0.015	-0.192***	-0.004
	(0.011)	(0.030)	(0.046)	(0.014)	(0.035)	(0.037)
Post-event average	0.090***	0.103***	0.019	0.282***	0.153***	0.030
	(0.011)	(0.030)	(0.047)	(0.015)	(0.036)	(0.037)
Adjusted R-squared	0.853	0.824	0.512	0.915	0.862	0.618
Observations	1,871	1,646	387	1,871	1,664	387
Panel (d): Random Control Group 3						
Post-event average	0.002	-0.169***	0.002	0.012	-0.227***	-0.003
	(0.009)	(0.029)	(0.035)	(0.012)	(0.039)	(0.031)
Post-event average	0.102***	0.094***	0.050	0.275***	0.085**	0.032
	(0.010)	(0.030)	(0.035)	(0.012)	(0.040)	(0.031)
Adjusted R-squared	0.910	0.815	0.630	0.933	0.823	0.627
Observations	2,078	1,648	473	2,284	1,872	430

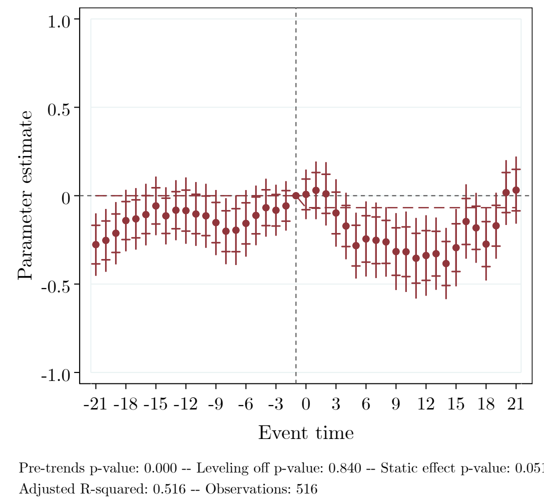
Note. The table shows average pre-event and post-event treatment effects for the futures price, implied volatility, and speculative pressure of corn and wheat. The alternative comparison groups were selected from the potential comparison group tuples using a uniformly distributed integer ranked by the F-tests for parallel trends. All regressions include commodity-event-day, commodity-event-week, and commodity-event-year fixed effects. Heteroskedasticity-robust standard errors are reported in parenthesis. ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent confidence levels, respectively.



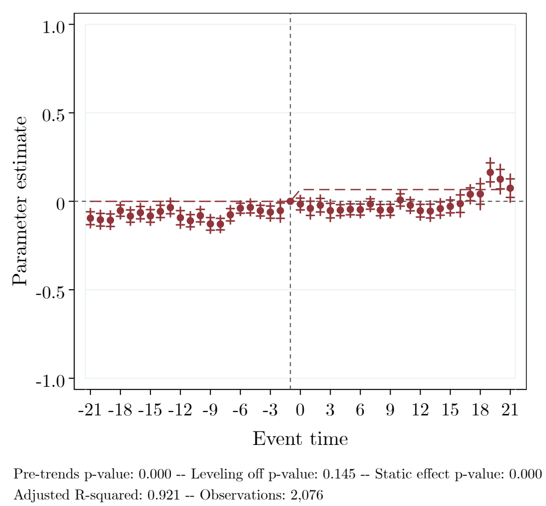
(a) Corn Futures Price.



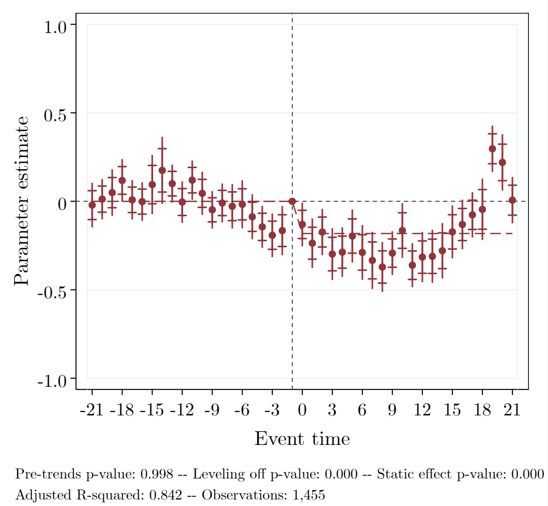
(b) Corn Options Implied Volatility.



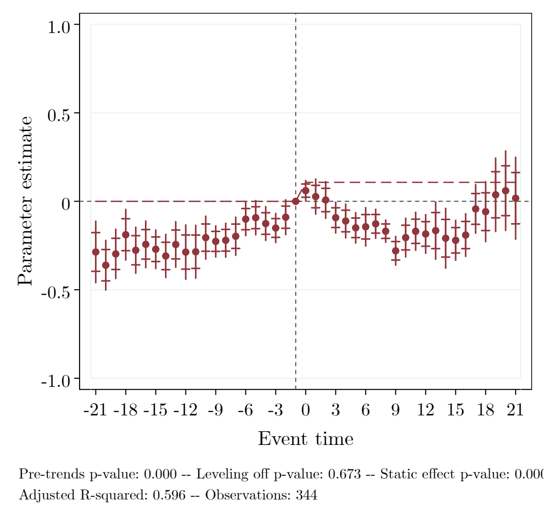
(c) Corn Futures Speculative Pressure.



(d) Wheat Futures Price.



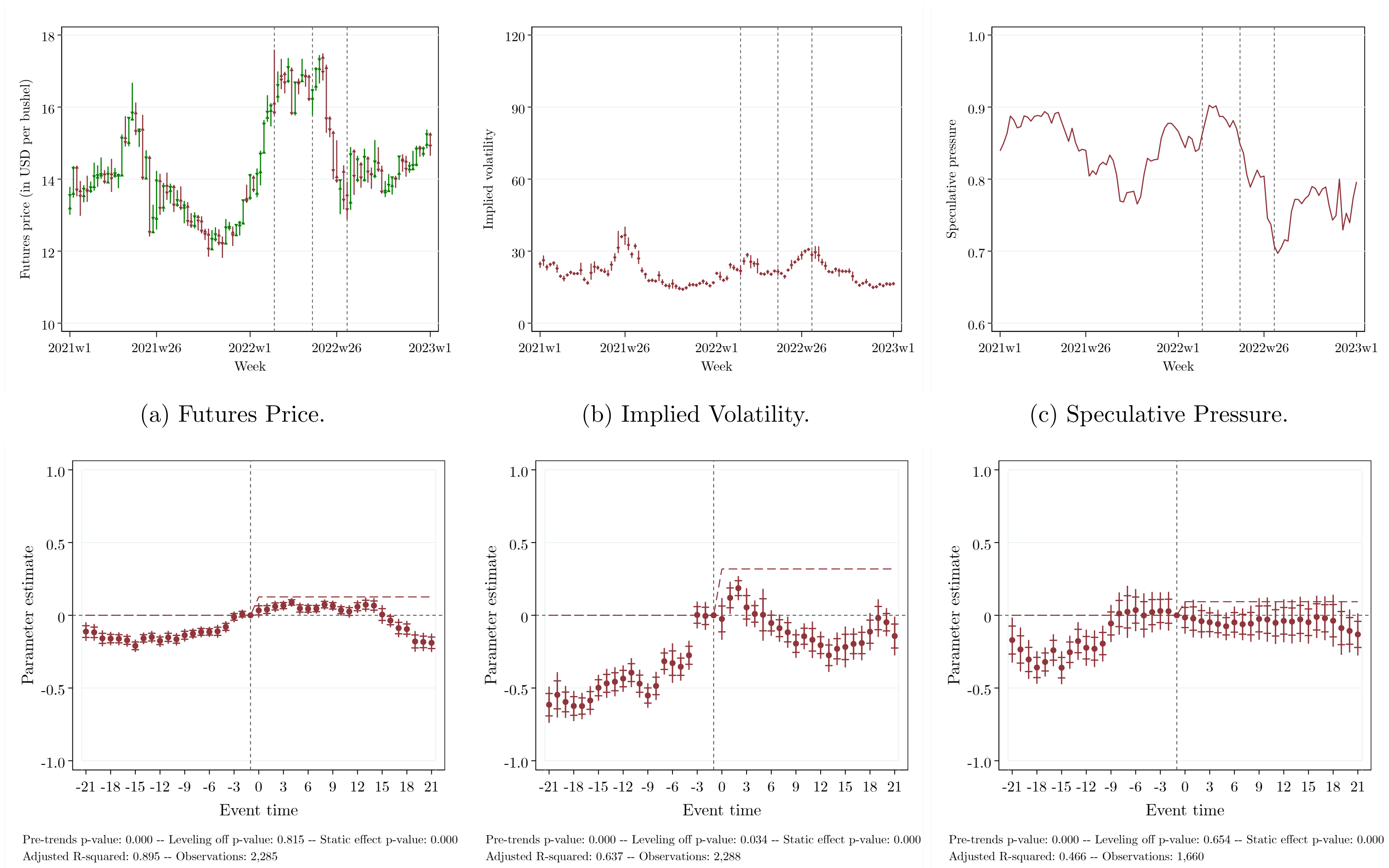
(e) Wheat Options Implied Volatility.



(f) Wheat Futures Speculative Pressure.

Figure A.1: Falsificiation Test for 2017.

Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report several Wald tests and regression statistics in the figure notes. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.

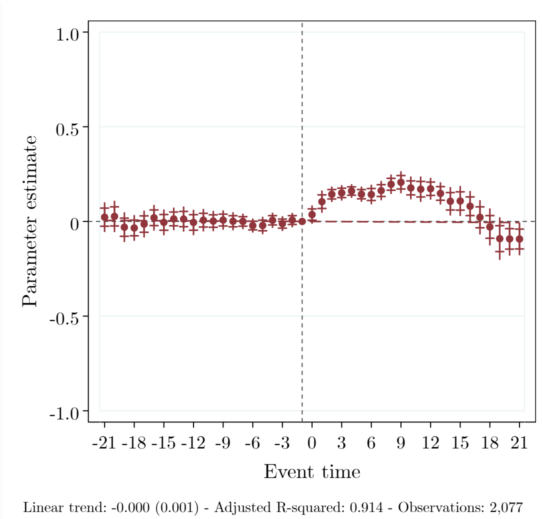


(a) Futures Price. (b) Implied Volatility. (c) Speculative Pressure.

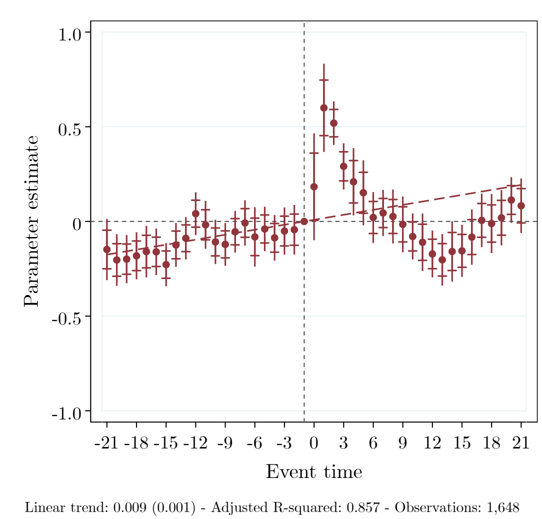
(d) Futures Price Event Study. (e) Implied Volatility Event Study. (f) Speculative Pressure Event Study.

Figure A.2: Event Studies for Soybeans.

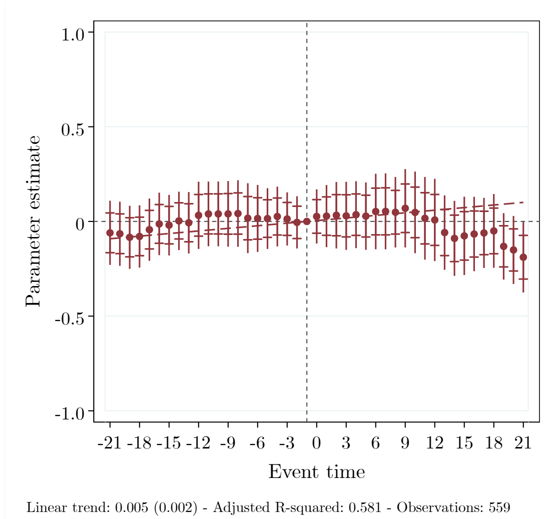
Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report several Wald tests and regression statistics in the figure notes. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.



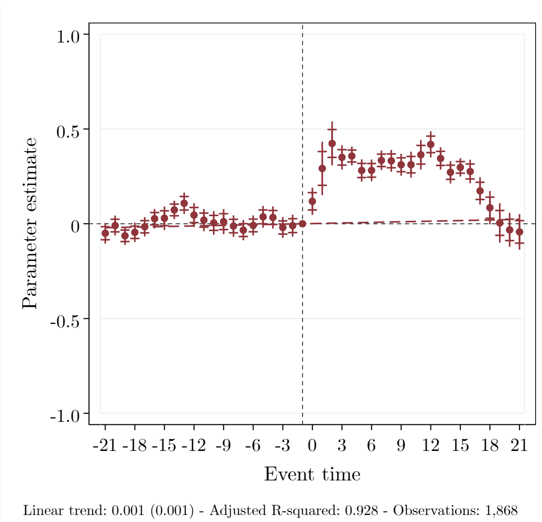
(a) Corn Futures Price.



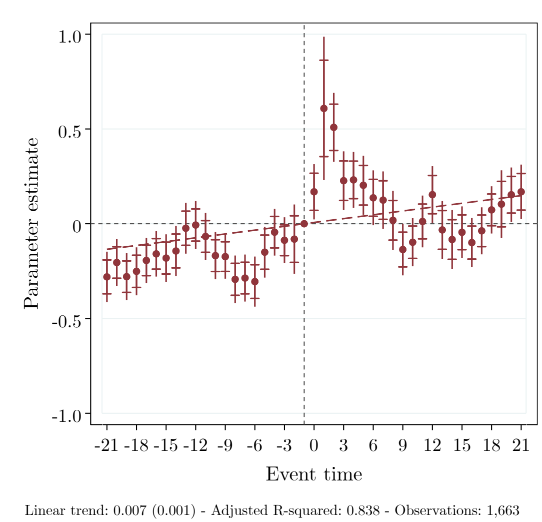
(b) Corn Options Implied Volatility.



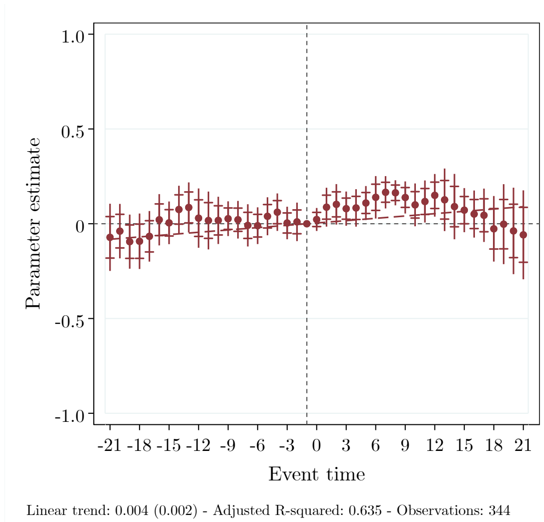
(c) Corn Futures Speculative Pressure.



(d) Wheat Futures Price.



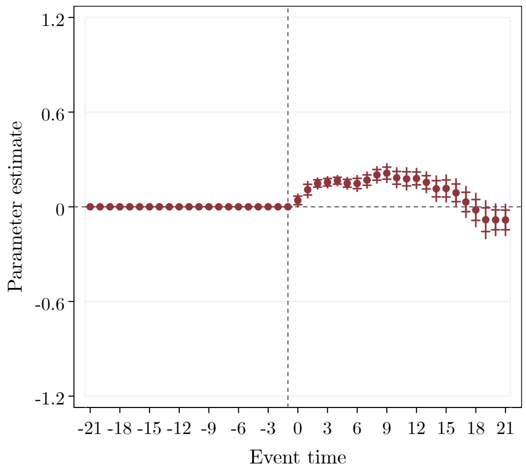
(e) Wheat Options Implied Volatility.



(f) Wheat Futures Speculative Pressure.

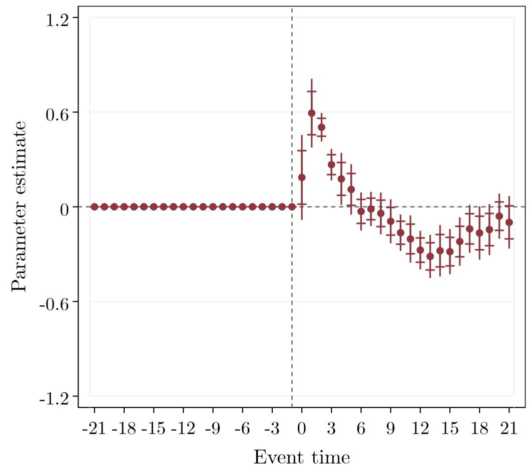
Figure A.3: Overlaid Linear Pre-Trends.

Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report the slope and standard error of the overlaid linear pre-trend and several regression statistics in the figure notes. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.



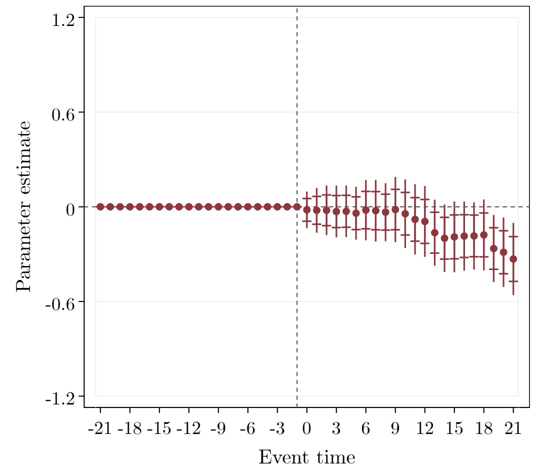
Linear trend: -0.000 (0.001) - Adjusted R-squared: 0.914 - Observations: 2,077

(a) Corn Futures Price.



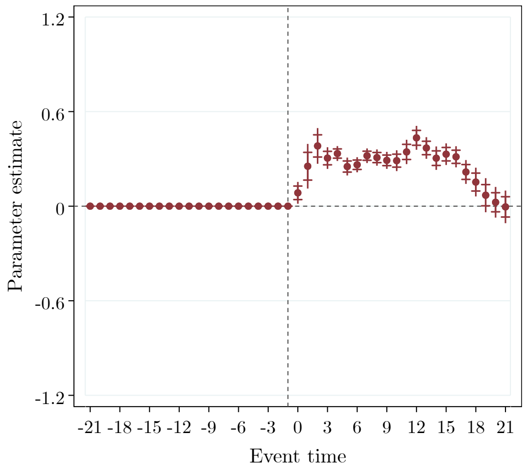
Linear trend: 0.009 (0.001) - Adjusted R-squared: 0.857 - Observations: 1,648

(b) Corn Options Implied Volatility.



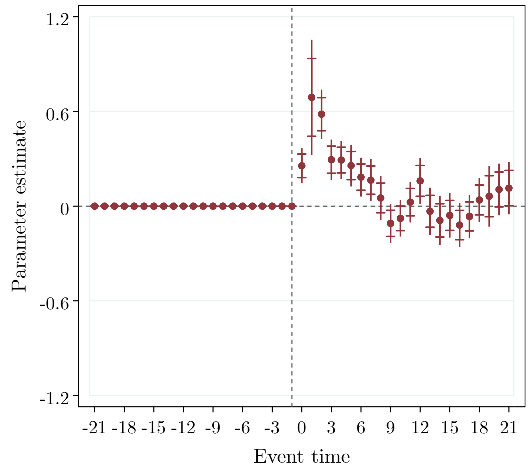
Linear trend: 0.005 (0.002) - Adjusted R-squared: 0.581 - Observations: 559

(c) Corn Futures Speculative Pressure.



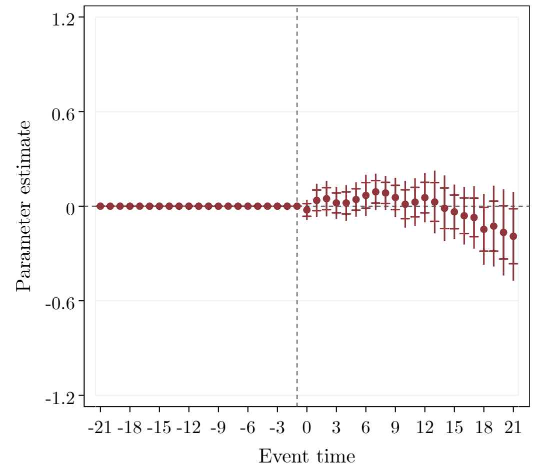
Linear trend: -0.000 (0.001) - Adjusted R-squared: 0.934 - Observations: 2,286

(d) Wheat Futures Price.



Linear trend: 0.007 (0.001) - Adjusted R-squared: 0.838 - Observations: 1,663

(e) Wheat Options Implied Volatility.

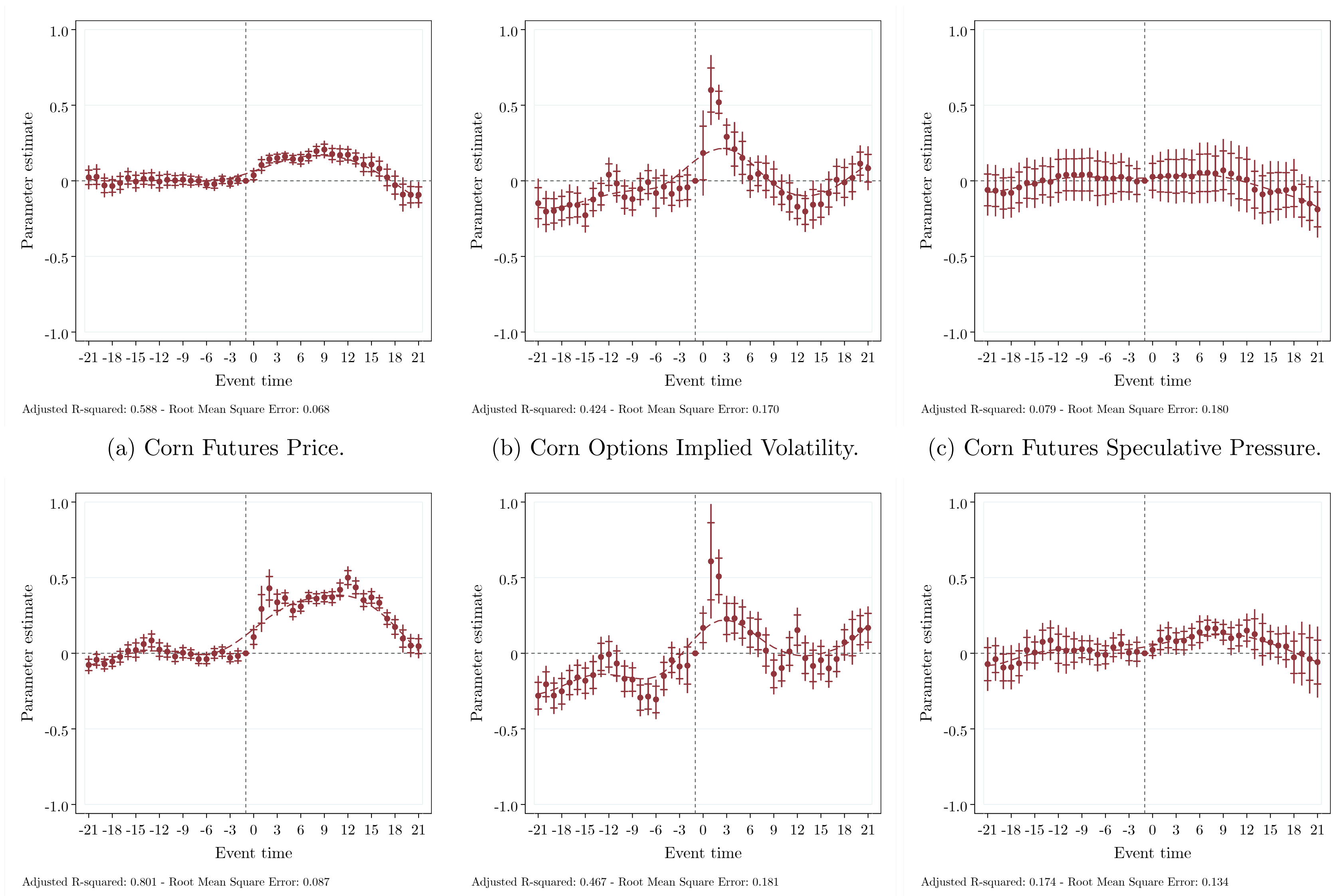


Linear trend: 0.004 (0.002) - Adjusted R-squared: 0.635 - Observations: 344

(f) Wheat Futures Speculative Pressure.

Figure A.4: Subtracted Linear Pre-Trends.

Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report the slope and standard error of the overlaid linear pre-trend and several regression statistics in the figure notes. The post-event treatment coefficients are adjusted for linear pre-trends. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.

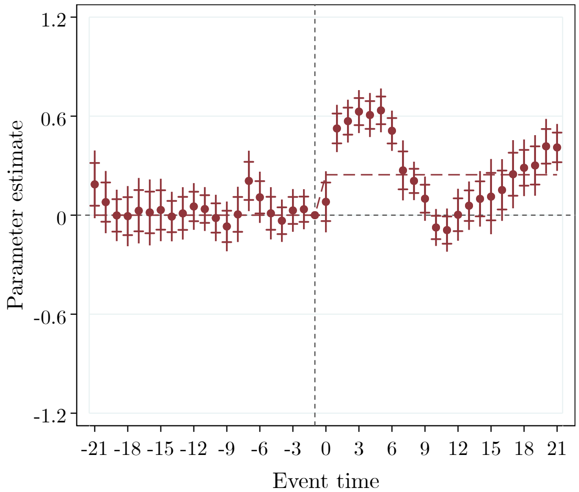


(a) Corn Futures Price. (b) Corn Options Implied Volatility. (c) Corn Futures Speculative Pressure.

(d) Wheat Futures Price. (e) Wheat Options Implied Volatility. (f) Wheat Futures Speculative Pressure.

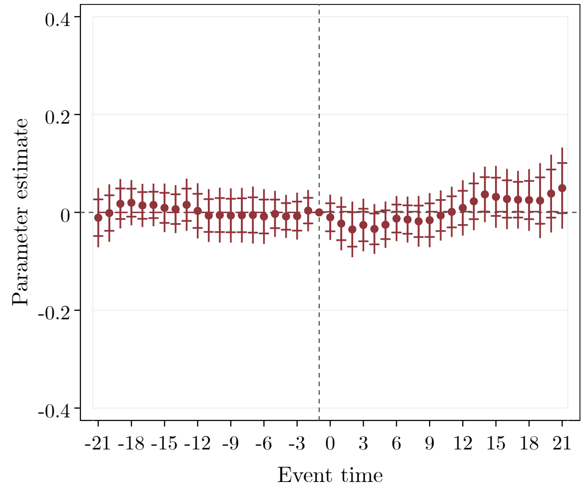
Figure A.5: Devil's Advocate Model.

Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We display the path of the smoothest line through the sup-t confidence interval with the dashed line and report several polynomial fit statistics in the figure notes. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.



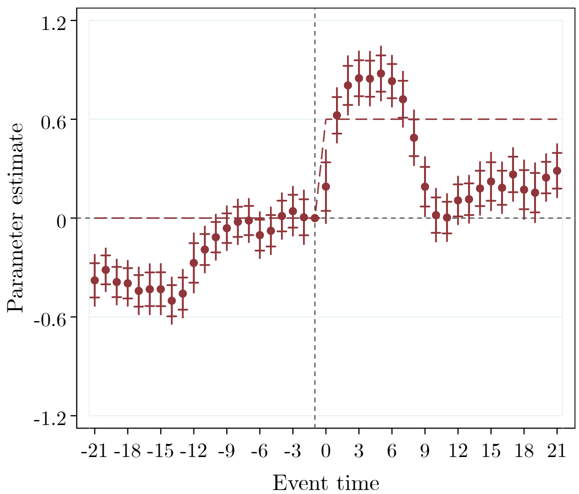
Pre-trends p-value: 0.293 - Leveling off p-value: 0.901 - Static effect p-value: 0.000
Adjusted R-squared: 0.631 - Observations: 1,662

(a) Corn Futures Historical Volatility.



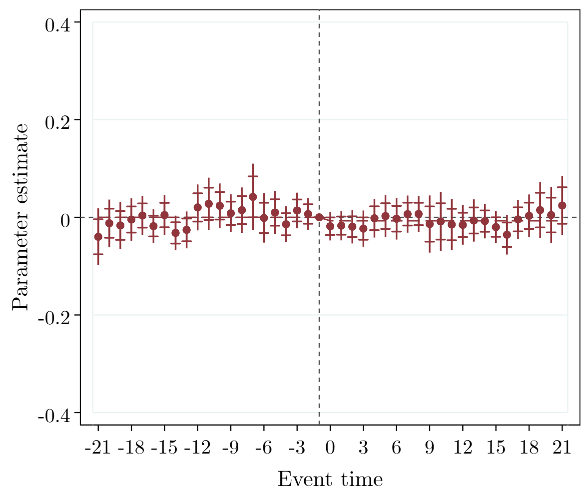
Pre-trends p-value: 0.860 -- Leveling off p-value: 0.740 -- Static effect p-value: 0.827
Adjusted R-squared: 0.605 -- Observations: 516

(b) Corn T Index Speculative Pressure.



Pre-trends p-value: 0.000 - Leveling off p-value: 0.387 - Static effect p-value: 0.000
Adjusted R-squared: 0.741 - Observations: 1,662

(c) Wheat Futures Historical Volatility.

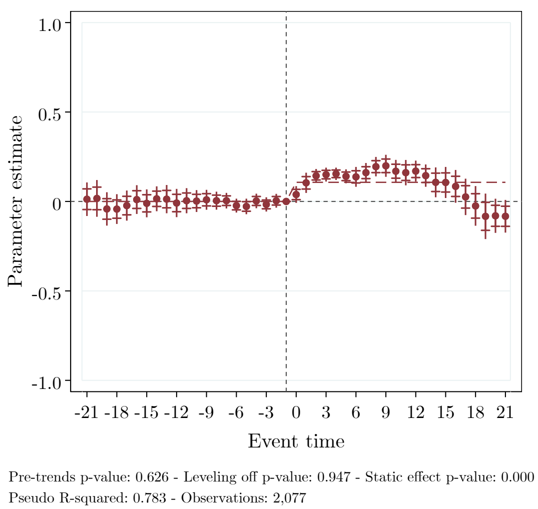


Pre-trends p-value: 0.946 -- Leveling off p-value: 0.424 -- Static effect p-value: 0.234
Adjusted R-squared: 0.850 -- Observations: 344

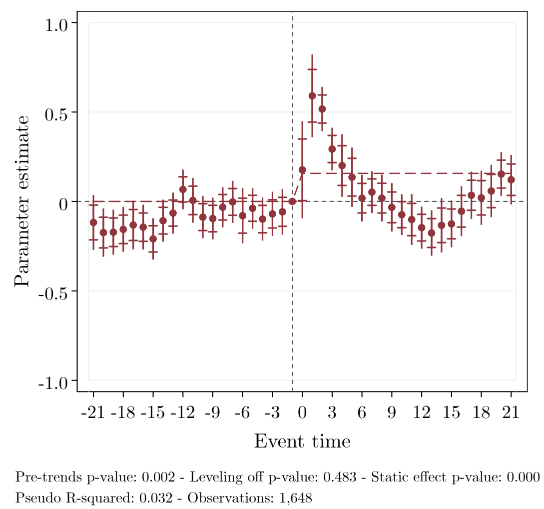
(d) Wheat T Index Speculative Pressure.

Figure A.6: Event Studies for Alternative Corn and Wheat Futures Volatility and Speculative Pressure Measures.

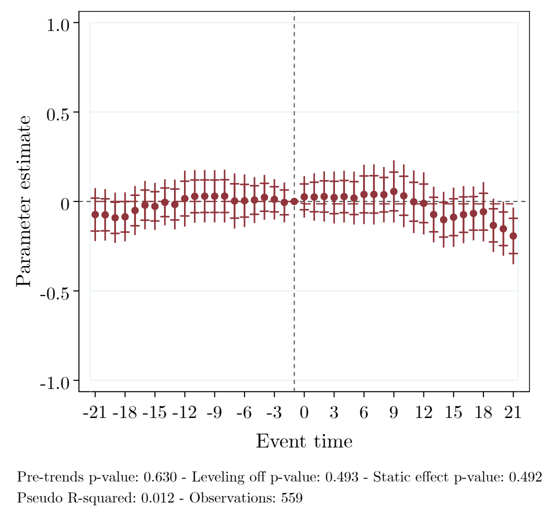
Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report several Wald tests and regression statistics in the figure notes. We used a log-linear regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.



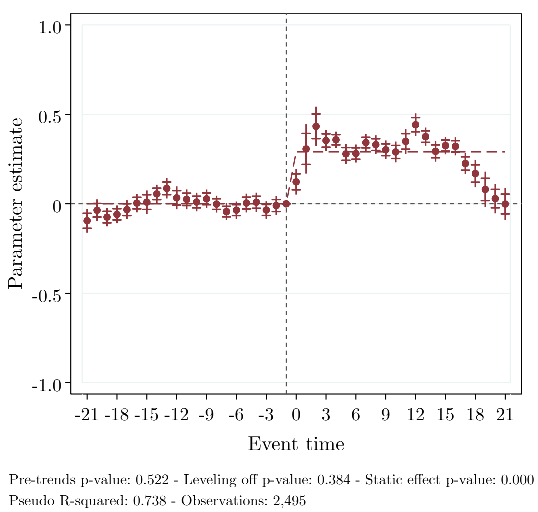
(a) Corn Futures Price.



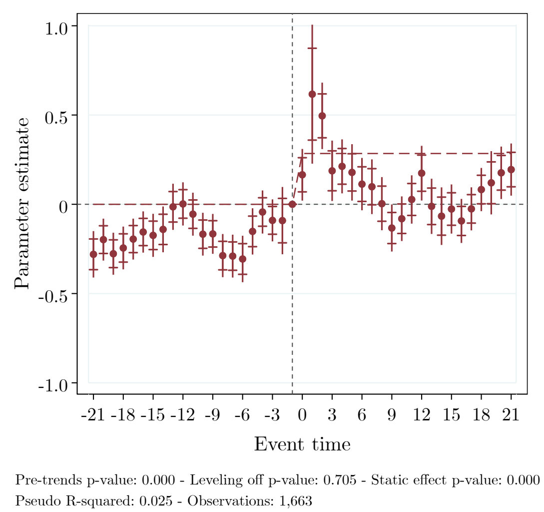
(b) Corn Options Implied Volatility.



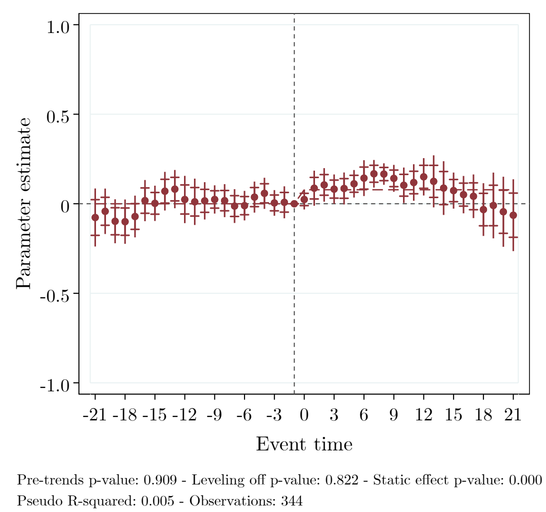
(c) Corn Futures Speculative Pressure.



(d) Wheat Futures Price.



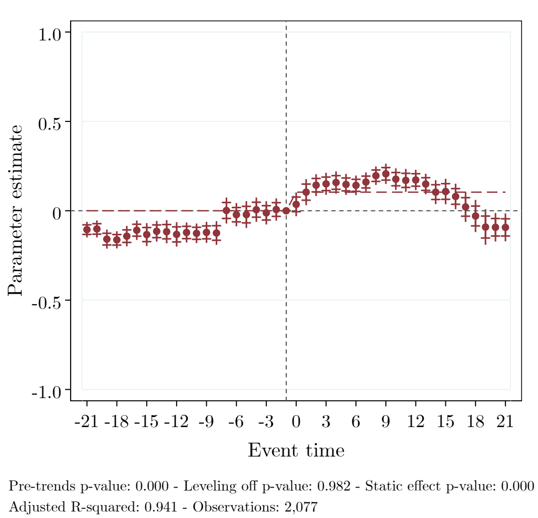
(e) Wheat Options Implied Volatility.



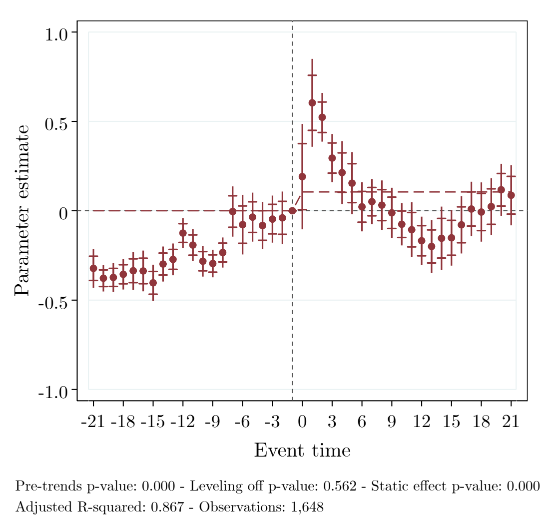
(f) Wheat Futures Speculative Pressure.

Figure A.7: Event Studies under the Alternative Distributional Assumption.

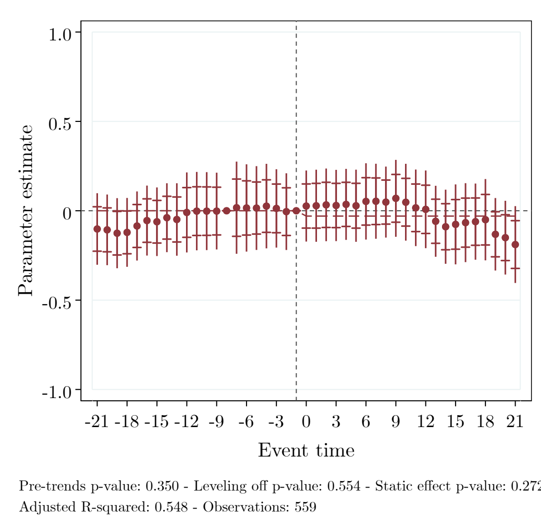
Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report several Wald tests and regression statistics in the figure notes. We used an exponential regression specification and included commodity-event-day, commodity-event-week, and commodity-event-year fixed effects in the regressions.



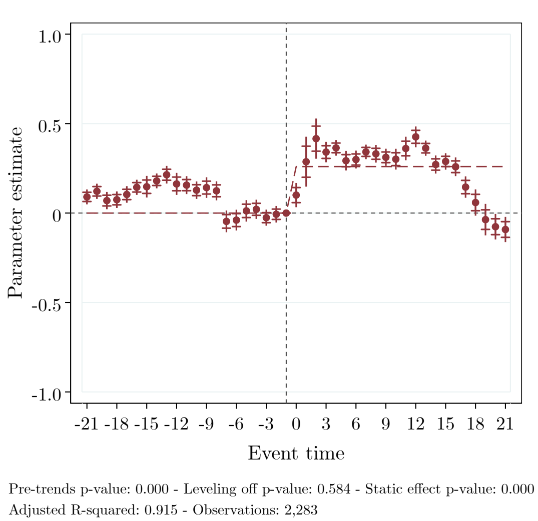
(a) Corn Futures Price.



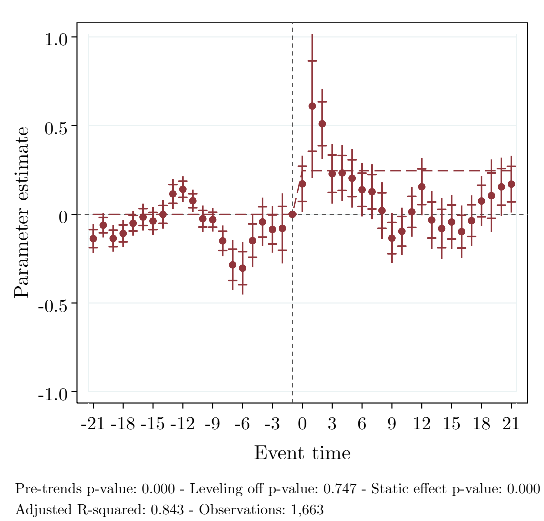
(b) Corn Options Implied Volatility.



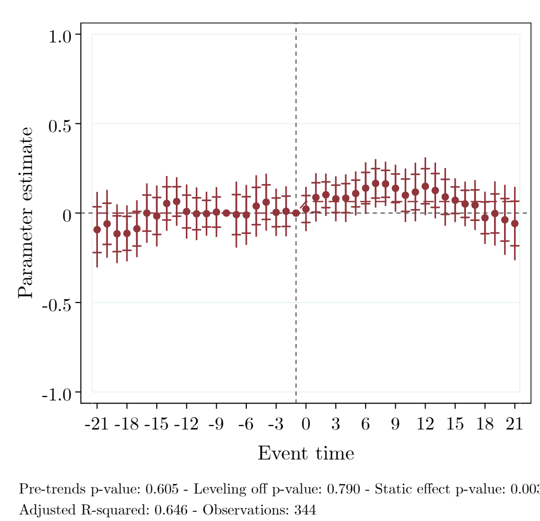
(c) Corn Futures Speculative Pressure.



(d) Wheat Futures Price.



(e) Wheat Options Implied Volatility.



(f) Wheat Futures Speculative Pressure.

Figure A.8: Robustness Checks with Alternative Fixed Effects.

Note. The figure shows the dynamic treatment parameters, 95 percent confidence intervals, and uniform sup-t bands for the event-time coefficients. We report several Wald tests and regression statistics in the figure notes. We used a log-linear regression specification and included commodity-calendar-day, commodity-calendar-week, and commodity-calendar-year fixed effects in the regressions.