Effect of Weather Disturbances on Spring and Winter Wheat Price Spread

Presented in Partial Fulfillment of
the Requirements for the Degree of

Master of Science

with a Major in

Applied Economics

in the

College of Graduate Studies

University of Idaho

by

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May 2023

Abstract

We study the impact of weather disturbances on the price relationship between spring and winter wheat in the United States. Using the USDA crop progress and condition report as a proxy for extreme weather events, we show that weather events significantly affect the price differences between spring and winter wheat. Estimation results support that a lower percentage of spring wheat in good/excellent conditions leads to a higher price spread between spring and winter wheat. The 2021 drought alone raised the price of spring wheat by 8% above winter wheat. Further, the impact of weather disturbances differs by the inventory level, with the impact increasing at higher levels of ending stocks-to-use ratios. And, quantile estimation shows that the impact of spring crop conditions on price spread is greatest when the price spread between spring and winter wheat is low. Overall, our results show how weather disturbances affect commodity markets beyond production.

Acknowledgements

I would like to express my deepest gratitude to my major professor, Dr. Xiaoli Etienne, and my co-major professor, Dr. Andres Trujillo-Barrera for their unwavering support and guidance throughout my graduate studies. Their mentorship and dedication to my success have been instrumental in shaping my academic journey. I am deeply grateful for the time and effort they invested in my growth as a researcher.

I would also like to extend my thanks to my committee member, Dr. Randall Fortenbery, for his valuable feedback and insights, which have greatly contributed to the development and refinement of my research.

Furthermore, I would like to express my gratitude towards Dr. Garth Taylor and Dr. Liang Lu who have played a significant role in my academic and personal growth. Their knowledge, expertise, and valuable suggestions have been truly beneficial. Additionally, I would like to thank the entire faculty and staff of the Department of Agricultural Economics and Rural Sociology for fostering an environment that is both conducive to success and supportive in building academic careers.

Finally, I would like to convey my gratitude to my friends and parents, with a special mention to Shristi Gautam for being there with me with her constant support and love throughout the journey of graduate studies. I am also grateful to Saroj Adhikari, Kiran Adhikari, Srijan Budhathoki, Birochan Acharya, and Rabindra Khanal for their encouragement and steadfast support. Their understanding and compassion have aided me during some of the more difficult phases of my graduate studies.

Thank you all for being a part of my journey and for helping me achieve my goals.

Dedication

Dedicated to my beloved parents.

Table of Contents

List of Tables

List of Figures

CHAPTER 1

Introduction

Agricultural production is susceptible to weather disturbances. With changing climate, extreme weather events such as droughts, floods, and heat waves are predicted to increase in frequency and intensity in the future (IPCC, 2014). Ortiz-Bobea *et al.* (2021) document that anthropogenic climate change has reduced global agricultural total factor productivity by as much as 21% since 1961. Projected warmer weather is expected to significantly reduce crop yield and increase yield uncertainty if the current temperature trend continues (Wang *et al.*, 2020).

Although the relationship between crop yield and climate change has been well established in the literature, few studies have examined how weather disturbances are linked to crop prices. Financial theory suggests that asset prices can be viewed as a function of public information and order flows, with the latter driven by both public/private information and investor shocks (Fleming *et al.*, 2006). Given the public nature of weather information, it is expected that market participants would actively incorporate such information into their trading strategies provided the information is valuable. Heterogeneous interpretation of public information, as well as the arrival of private weather information and forecasts, could change order flows, leading to additional price volatility.

The present paper aims to examine how weather disturbances affect the pricing relationship between different classes of wheat in the United States. Wheat is one of the most important staple crops in the world and plays a critical role in global food security. Despite the increase of wheat productivity due to improved management and higher-yielding crop varieties, climate stress (heatwaves and droughts in particular) reduced global wheat production by 5.5% in 1980-2008 (Lobell *et al.*, 2015; Zampieri *et al.*, 2017). The US is a major wheat producer and has been historically among one of the top wheat exporters. Meanwhile, wheat futures trading in the US plays a dominant role in global wheat price discovery (Janzen and Adjemian, 2017). Understanding the impact of weather disturbances on wheat prices in the US is important in helping market participants, both in the US and globally, to prepare for and mitigate the negative effects associated with those events.

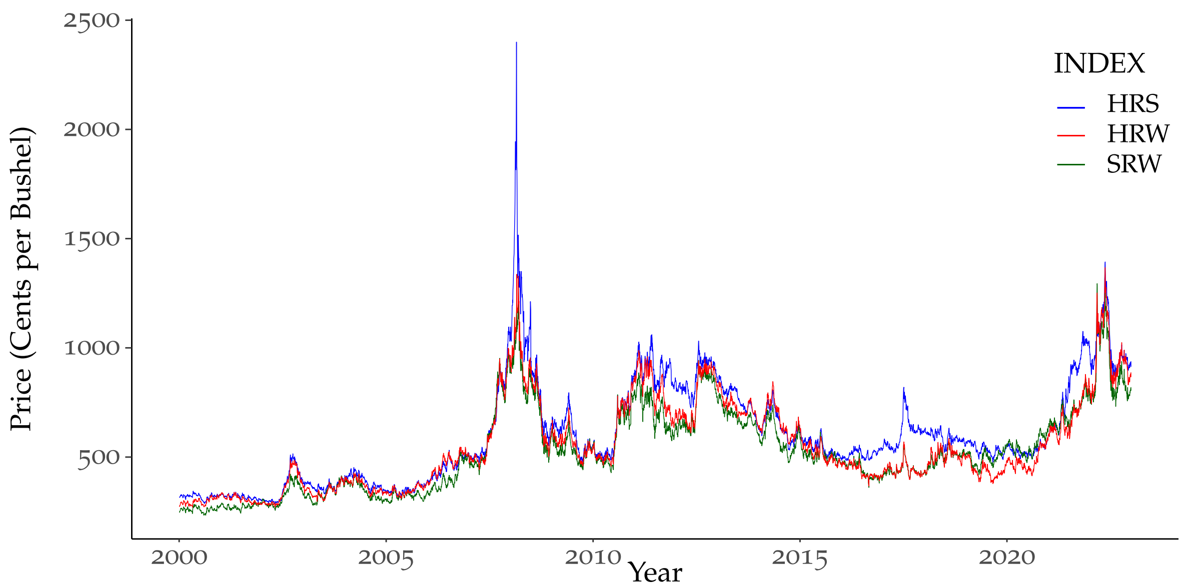
Five major wheat classes are produced in the US, including hard red spring (HRS), hard red winter (HRW), soft red winter (SRW), white wheat, and durum wheat (ERS, 2022). Out of these, HRS, HRW, and SRW are actively traded on futures markets. Although not perfectly substitutable, different wheat classes are often blended to achieve the desired protein level.[1] The production timeline differs between spring and winter wheat, with the former planted in the fall and harvested in the summer the following year, while the latter is sowed in spring and harvested in late summer or fall in the same year. HRW, grown primarily in the Great Plains, accounts for about 40% of total US wheat production. Meanwhile, HRS (mainly in the Northern Plains) and SRW (mainly in states along the Mississippi River and in eastern States), account for 25% and 15% of the US production, respectively (ERS, 2022). Given the differences in the production timeline and geographical distribution, the three major classes of wheat are subject to different weather shocks.

Understanding the relative prices between different classes is key for millers who wish to blend different classes of wheat to get the desired protein levels in their product. Spring wheat, which has a higher protein content, is ideal for products like bread, while winter wheat, which has lower protein content, is suitable for products like pastries and cake. With the knowledge of relative prices, millers can obtain the desired blend by blending different classes of wheat based on available protein content and prices, allowing them to make an informed decision and capitalize on the opportunities presented by each class. Furthermore, knowledge of the price spread is also pivotal for exporters and traders who are involved in spread trading. Instead of focusing on the single price alone, understanding the relative prices can enable traders to potentially profit from the price spread between different classes of wheat. This can also help traders to manage their risk more effectively, as they are not solely reliant on the performance of one asset.

[1] The protein level of HRS wheat typically ranges between 12% and 15% protein. HRW wheat has a protein level of 10% to 13% and SRW's protein content ranges from 8.5% to 10.5%.

As shown in Figure 1.1, the prices of HRS, HRW, and SRW wheat show a high correlation and tend to move together most of the time. However, extreme weather events, particularly droughts, have significantly impacted these relationships. For instance, when the U.S. northern plains[2] was hit by a severe drought in 2021, HRS wheat prices rose from less than $6/bushel at the beginning of 2021 to over $9/bushel in July 2021. The increases in HRW wheat and SRW wheat prices, by comparison, were much milder. Nearby HRW wheat futures prices only increased from around $6 to $6.5/bushel, and SRW wheat futures prices increased from around $6.5 to $7/bushel during the same period.

Figure 1.1: Hard red spring (HRS), hard red winter (HRW) and soft red winter (SRW) wheat prices (cents/bushel), 2000-2022



Similar extreme weather events have coincided with spikes and troughs in the price differences between different classes of wheat (e.g., the 2012 and 2017 drought episodes). Yet, very few studies have empirically examined such linkages. When other market fundamentals are constant, wheat price differences are determined by their average protein contents. For example, HRS wheat is often priced higher

[2]The US northern plains includes regions of the western Dakotas, Montana east of the Rocky Mountains, northeast Wyoming, and a small section of northern Nebraska, where most of the US HRS wheat is grown.

than HRW and SRW due to a higher protein content (Espinosa and Goodwin, 1991). Bekkerman (2021) notes that the spread between HRS and HRW is indicative of the market demand for higher-protein wheat relative to the baseline winter wheat. Size of the crop, carry-in stocks, domestic use, and export of the wheat is noted as other fundamental factors driving the price differentials between different classes of wheat (Wilson, 1983; McNew, 1991; Yang and Leatham, 1999). Bekkerman *et al*. (2016) noted that transportation costs, availability of wheat in different regions, differences between end-users, and supply and demand factors unique to the wheat classes may also significantly affect the spread.

We hypothesize that in addition to those commonly examined variables, weather disturbances significantly change the relative relationship between spring and winter wheat prices in the U.S. While weather shocks can impact wheat price movements in a number of ways, the main channel of its effect is by changing the expected yield and supply at harvest. Since wheat is a storable commodity, changes in expected supply are likely to further affect the projected ending stocks-to-use ratio, a key variable in determining commodity price levels and volatility (Wright and Williams, 1982). Meanwhile, precipitation, temperature, and heat during the growing season affect the protein content of wheat, incurring protein premiums or discounts. Pepe and Heiner (1975) note there is a strong inverse relation between protein content and yield in spring wheat, while Bekkerman (2021) found that the trade-off between protein level and yield for wheat produced in the southern U.S. is minimal. Given the substitutability between different classes of wheat, the expected yield and protein changes may affect the relative demand of the three main classes of wheat, which further impacts their pricing relationships. Finally, since all weather-related variables contain measurement errors (Fleming *et al*., 2006), market participants may hold heterogeneous views about the weather shock, and their trading strategies (which often directly affect prices) can differ substantially.

The paper contributes to the literature on the economic cost of weather shocks. As noted earlier, most of the existing studies evaluate the relationship between agricultural production and climate change/weather shocks (e.g., Kuwayama *et al*., 2019; Lobell *et al*., 2015; Ortiz-Bobea *et al*., 2021; Sternberg, 2011). Still, a few studies have attempted to explain how weather shocks affect commodity prices. Using structural vector autoregression (SVAR) models, Schaub and Finger (2020) show that regional and national droughts caused substantial increases in hay prices (up to +15%) but did not affect feed grain prices. Maystadt and Ecker (2014) note that drought caused livestock price changes, which fueled violent conflicts in Somalia. Ubilava (2017, 2018) show that El Nino Southern Oscillation (ENSO), a much-discussed climate anomaly, strongly affects commodity price dynamics. Quiggin (2007) estimated that food prices in Australia increased by 4.4% in 2002-2003 and by 12% in 2005-2007 due to drought and other severe weather events.

Previous studies on the impact of weather shocks mostly use meteorological variables (e.g., rainfall, temperature deviations, Standard Precipitation Index, US Drought Monitor, and ENSO), which do not necessarily depict the real scenario of the field. In fact, Proctor *et al*. (2022) find that how a weather variable is measured significantly affects the estimate of its yield impact. A similar conclusion likely applies to the impact of weather shocks on crop prices. In the present paper, we instead use crop ratings from the USDA Crop Progress and Condition report as a proxy for weather shocks. The report has been used to anticipate positive or negative anomalies in production and forecast yield as it captures weather shocks more aligned with field conditions. (e.g., Beguería and Maneta, 2020; Irwin *et al*., 2009a; Kruse and Smith, 1994; Fackler and Norwood, 1999).

Our work is also linked to the strand of literature that investigates how market participants respond to the arrival of news. In the crop market, USDA reports, such as the World Agricultural Supply and Demand Estimates (WASDE), are closely monitored by market participants. Various studies have shown that market prices significantly react to USDA reports, and they lead to better resource allocation decisions by realigning market participants' expectations (Adjemian, 2012). Lehecka (2014) investigated the informational value of USDA Crop Progress and Condition report by analyzing reactions in corn and soybean futures markets, noting that market prices react rapidly and rationally to newly available crop condition information. Bethlem *et al*. (2022) further found that a 1% increase in good and excellent condition rating from the Crop Progress and Condition report would reduce the soybean futures contract prices by 0.45% the day following the report release.

The present study links the two strands of the literature, to explore how weather disturbances in the United States have changed the price relationship between spring and winter wheat. Our empirical analysis relies on regression models comparing spring and winter wheat prices, using crop data from the USDA Crop Progress and Condition report as the main indicator of weather disturbances. Estimation results show that crop conditions significantly affect the spread between spring and winter wheat prices, with the 2021 drought raising the price of spring wheat by almost 8% over winter wheat. Further, the impact of weather disturbances differs by the level of inventory, with the magnitude of the impact increasing at higher levels of ending stocks-to-use ratios. Quantile estimation shows that the impact of spring crop conditions on the price spread is greatest when the price spread between spring and winter wheat is low. Our results show how weather disturbances affect commodity markets beyond production. Such information would be useful for commercial traders, spread traders, and hedgers in designing their portfolios and trading outcomes. Millers, exporters, and grain merchandisers can make informed decisions about sourcing different classes of wheat ahead of time based on the price spreads between classes and achieve profitability.

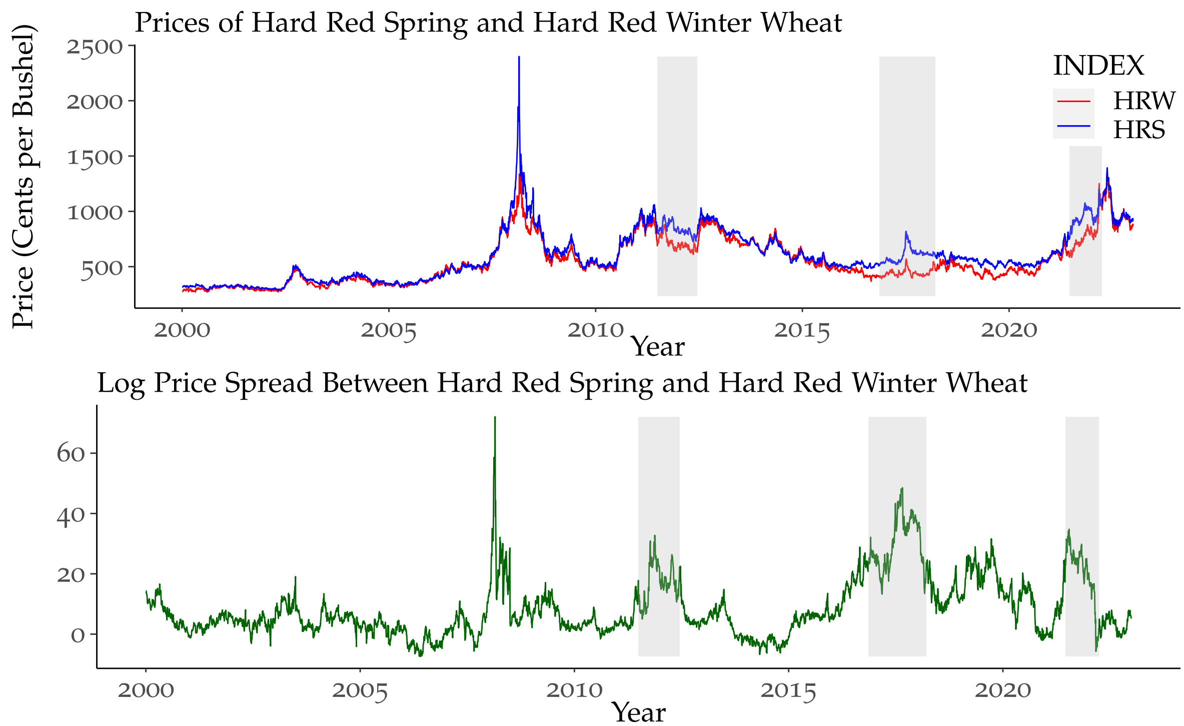
CHAPTER 2

Variables and Data

We consider futures prices of hard red spring (HRS), hard red winter (HRW), and soft red winter (SRW) wheat. HRS is traded on Minneapolis Grain Exchange (MGEX), with the main deliverables being HRS with a protein content of 13.5%. HRW and SRW are traded on the Kansas City Board of Trade (KCBT) and Chicago Board of Trade (CBOT), and the main deliverables are HRW with a minimum protein content of 11% and #2 SRW wheat (with a protein level of 8.5-10.5%), respectively. Premiums and discounts in the cash market are offered for different protein contents or grades of wheat. Espinosa and Goodwin (1991) estimated one additional protein percentage would increase the price premium by approximately 5 cents per bushel or about $1.83 per metric ton for HRW wheat. A similar assessment was done by Parcell and Stiegert (1998), estimating the marginal value of protein to be 8.5 cents per bushel for HRW wheat and 6 cents per bushel for dark northern spring (DNS) wheat.

The dataset consists of weekly nearby futures prices of the three wheat classes considered from 2000/01 to 2021/22, retrieved from the Bloomberg terminal. The expiring futures contract is rolled to the next-to-expire contract on the last day of the month prior to contract expiration. To match the release date of the Crop Progress and Condition report, which is released on Thursdays at 8:30 am Eastern time, we consider closing futures prices on Thursdays. Figure 2.1 top panel plots the prices of HRS vs. HRW wheat, while figure 2.2 top panel plots the trajectories of HRS vs. SRW wheat prices. Summary statistics are presented in table 2.1. Prices of all three classes of wheat tend to move in tandem, with the HRS wheat having the highest price, followed closely by HRW and SRW. On average, HRS is priced at a 56 cents/bushel, and 78 cents/bushel premium above HRW and SRW wheat, respectively. As noted earlier, a large portion of the price differences can be attributed to variations in protein levels. Other variables such as stocks, production, domestic use, and exports may also play a significant role in the price spreads (Wilson, 1983; Wilson and Chan, 1987; McNew, 1991).

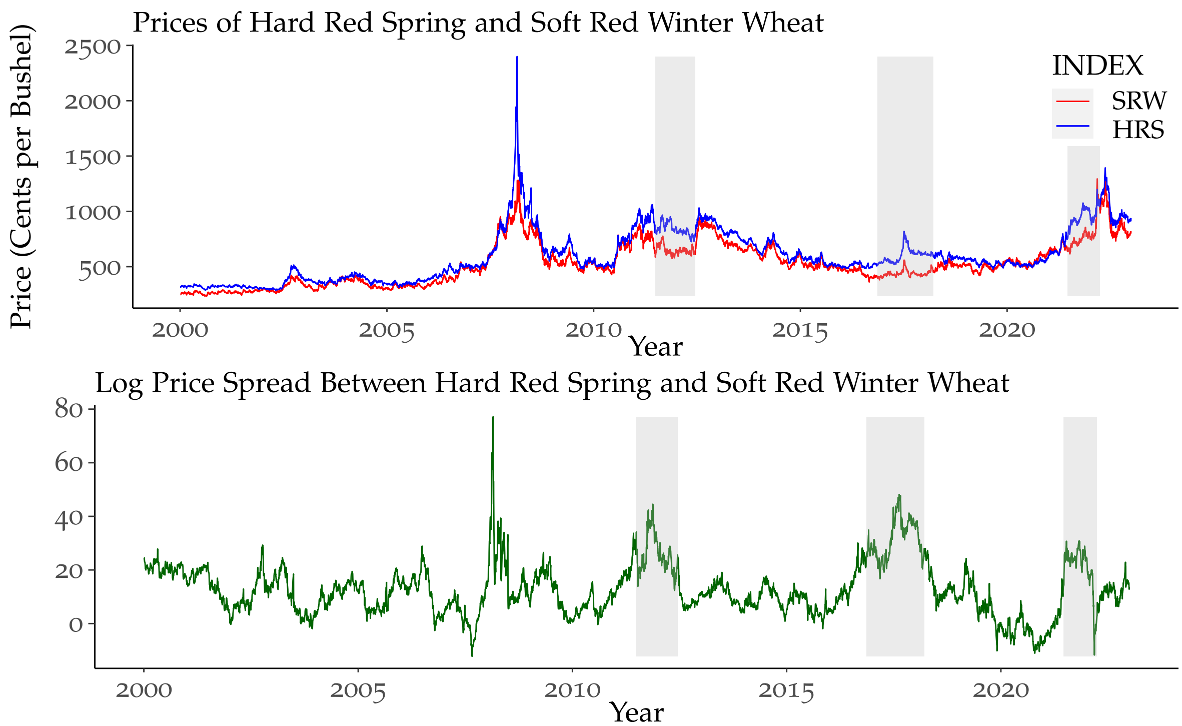
Figure 2.1: Hard red spring (HRS) and hard red winter (HRW) wheat prices and spread (cents/bushel), 2000-2022



The bottom panels of figures 2.1 and 2.2 show the spread between spring and winter wheat prices, computed as logarithmic price differences. The spread fluctuated around 9% and 13%, respectively, for HRS-HRW and HRS-SRW during the sample period. Nonetheless, there are several notable periods where spreads experienced significant surges and dips. In particular, the spread showed sharp increases in 2008, 2012, 2017, and 2021 in both plots.

In 2008, HRS wheat prices were almost 72% higher than HRW prices and about 77% higher than SRW prices. This period coincides with rapid fluctuations in commodity prices and the subsequent financial crisis (Etienne *et al.*, 2015). Although a myriad of factors may have played a role, late-spring freeze, and heavy rain at harvest in the U.S., along with poor weather in other major wheat-producing countries exacerbated the price increase. Janzen *et al.* (2014) indicate that the heightened price volatility around this time can largely be attributed to supply disruptions—supply

Figure 2.2: Hard red spring (HRS) and soft red winter (SRW) wheat prices and spread (cents/bushel), 2000-2022



shocks accounted for 40-62 % of the rise in wheat prices, while broad-based demand shocks only had a 9-12% price impact.

In 2012, 80% of the US agricultural land was under severe drought, during which the prices of spring wheat surged by roughly 30% compared to HRW and SRW wheat prices. Another spike in the price spread occurred in 2017 when extreme heat and drought took a toll on the spring wheat crop in the Northern US. The percentage of the crop in "good" to "excellent" conditions in North Dakota, South Dakota, and Montana fell to 36%, 10%, and 11%, respectively, leading to expectations of a lower HRS wheat supply. Early indications of below-average HRW protein levels compounded this effect, resulting in spring wheat prices rising above HRW and SRW wheat prices by almost 50%. The most recent spike occurred in 2021 when almost all the HRS wheat-growing regions in the Northern Plains experienced a drought. Due to the significantly lower spring wheat supply, HRW and SRW wheat prices were almost 35% below the HRS wheat prices during the summer of 2021.

Table 2.1: Summary statistics of variables considered in the paper, 2001-2022

Variables	Mean	SD	Min	Max
HRS Wheat Prices (cents/bu.)	618.3	220.67	286.25	1330.5
HRW Wheat Prices (cents/bu.)	561.9	201.12	275.0	1295.2
SRW Wheat Prices (cents/bu.)	540.2	183.89	242.80	1200.5
Spread: HRS-HRW (%)	9.36	9.38	-7.38	48.12
Spread: HRS-HRW (cents/bushel)	56.41	61.70	-42.75	350.25
Spread: HRS-SRW (%)	12.96	8.87	-7.89	48.18
Spread: HRS-SRW (cents/bushel)	78.16	65.93	-41.5	420.0
Spring Wheat Crop Condition (G+E %)	62.71	16.57	9	86.0
Winter Wheat Crop Condition (G+E %)	45.66	11.40	27	71.0
HRS Stocks-to-Use (%)	34.87	11.19	10.64	66.20
HRW Stocks-to-Use (%)	37.39	15.78	9.31	69.22
SRW Stocks-to-Use (%)	35.22	16.99	9.40	76.87
Speculative Pressure HRS (%)	19.56	39.41	-71.93	94.38
Speculative Pressure HRW (%)	17.69	22.62	-47.97	71.58
Speculative Pressure SRW (%)	-1.43	12.86	-35.70	46.70
Canadian Wheat Export (1000MT)	18988	3846.34	1500	27000
Argentine Wheat Export (1000MT)	9493	3175.06	1500	15000

While most of the spreads are positive, reflecting the protein premium between spring and winter wheat prices, it is interesting to note that negative spreads occurred rather frequently during the sample period. For instance, HRS wheat prices were at a discount relative to HRW wheat for most of 2014. Data from the USDA shows that the HRW crop production was low in 2013 compared to historical standards,[3] while HRS crop production had been high. Emslie (2014) notes that the large Canadian wheat production further contributed to the negative price spread. In December 2013, estimates showed that Canadian wheat yield would surpass the previous record by 21%. Since Canadian wheat is largely equivalent to the HRS wheat in the US and Canada is one of the world's largest wheat exporters, the HRS wheat prices in the US significantly dropped following the news on expected yield. Meanwhile, Argentina, which exports a significant amount of wheat to the global market, had a poor crop.

[3]Winter wheat usually enters dormancy in winter, using little water or soil nutrients. The warmer-than-usual winter in 2012 caused young winter wheat plants to grow, but the soil was too dry to support the growth due to the drought in the summer of 2012. See `https://www.reuters.com/article/usa-wheat-drought/warm-and-dry-a-devastating-combination-for-u-s-wheat-crop-idUSL1E8N3DLP20121204` for a detail discussion.

The additional demand for HRW wheat from Brazil strengthened the HRW wheat prices in the US, further contributing to the negative HRS and HRW spread.

Previous studies note that supply shocks play a role in the price spread between different classes of wheat (Wilson, 1983; Wilson and Chan, 1987; McNew, 1991). To examine the supply shock caused by weather disturbances, we use the data derived from the USDA Crop Progress and Condition report. Although weather or meteorological data are readily available, we prefer using the Crop Progress and Condition data because it depicts the real scenario in the field. The report provides information on the progress and qualitative condition ratings of important crops based on extensive surveys. NASS, USDA obtains this data by the non-probability crop progress and condition surveys, representing subjective assessments provided by the producers and other individuals such as county extension agents, and farm service agency staff. These individual assessments are aggregated based on the weights derived from historical NASS acreage estimates to form the report, expressing crop condition data as a percentage of crops in "excellent", "good", "fair", "poor", and "very poor" conditions. These estimates thus reflect the status of different variables on the crop, including drought, excessive moisture, frost, heat stress, insect infestation, and diseases. However, the impact of weather disturbances such as these can be significant and have a greater influence on changes in crop conditions, as opposed to the more localized and manageable impact of insects and diseases.

The winter wheat report is available starting from week 14 of a calendar year (April) and ends with the harvest season in week 27 (July).[4] For Spring wheat, the data is available from week 20 (May) and ends in week 33 (August). But, in some years, these reports available weeks can vary according to growing conditions. Since the report shows the state of a crop at the regional or national level, it has been used to anticipate positive or negative anomalies in production and forecast yield (e.g., Beguería and Maneta, 2020). Despite the widespread availability of weather information in real-time, the weekly Crop Progress and Condition reports continue to hold significant value as a primary source of information on crop growth and conditions. Lehecka (2014) posits that these reports are highly sought after and are

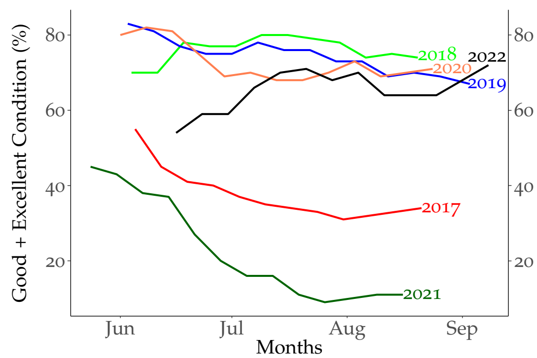
[4]The report does not distinguish between HRW and SRW wheat.

among the most frequently requested publications distributed by NASS in addition to the monthly Crop Production and World Agricultural Supply and Demand Estimates (WASDE) report.

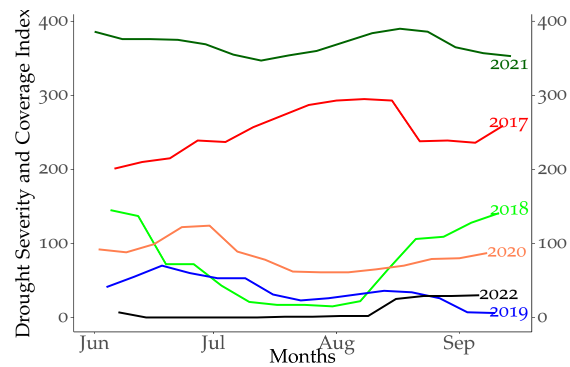
Following previous studies (e.g., Bekkerman, 2021), we combine the "good" and "excellent" ratings to indicate the proportion of wheat crops in higher quality groups and the remaining three ratings as lower quality groups. In general, the value of this variable is high for good crop years and low for years impacted by weather disturbances. Bekkerman (2021) argued that higher quality ratings (based on crop conditions) may be associated with either higher yield or higher protein. In the case of the former for spring wheat, this suggests that its supply should increase and prices should decrease relative to winter wheat. For the latter, spring wheat prices may increase, given the higher protein content. Bekkerman (2021) finds that a higher proportion of Montana wheat categorized as excellent or good by the USDA is associated with a lower probability that elevators would offer high protein premiums in the region.

As suggested by table 2.1, the average good plus excellent crop conditions in spring wheat is 62.71%, whereas for winter wheat it is 45.66%. However, spring wheat crop conditions show higher variability, with the lowest value reaching 9% and the highest reaching 86%. Figure 2.3a shows spring wheat crop conditions from 2017 to 2022. In the years with normal weather conditions, the good plus excellent percentage of spring wheat is in the range of 70-80% during the harvest, whereas in the years with significant weather disturbances (e.g., 2017 and 2021), the percentage of crops in higher-quality conditions drops to as low as 10%. Further, figure 2.3b shows the drought severity and coverage index developed by the US Drought Monitor for North Dakota in the same time frame of June to September for years from 2017 to 2022. This index converts 5 different drought levels given by the drought monitor (abnormally dry, moderate drought, severe drought, extreme drought, and exceptional drought) into a single value for the area, ranging from 0 (for abnormally dry) to 500 (for exceptional drought). North Dakota is the state with one of the highest production of HRS wheat in the US. In 2021 and 2017, the index has risen distinctly high above other normal crop years, showing the severity of drought in these years. This shows a strong correspondence between the crop condition and the severity of weather disturbances during the respective periods. In other words, the crop condition variable we constructed should at least partially reflect weather disturbances in the wheat market.

Figure 2.3: Spring crop condition and drought severity index



(a) Percentage of spring crop in good and excellent conditions in selected years



(b) Drought Severity and Coverage Index of North Dakota in selected years

In addition to weather disturbances, we consider several other explanatory variables. The first is the relative scarcity of each wheat class, proxied by the projected ending stocks-to-use ratio for the current marketing year constructed using the USDA WASDE report. Each month, the USDA WASDE report releases annual projections of supply and demand in the current and next marketing years for various crops, including the three classes of wheat. The ending stocks-to-use ratio measures carry-over stocks as a percentage of total use, showing the tightness of the current supply-demand relationship of the wheat market. The variable has been extensively used in previous studies to estimate the impact of market-specific shocks on the prices of storable commodities (e.g., Serra and Gil, 2013; Etienne *et al.*, 2018; Lawson *et al.*, 2021). In this study, we use monthly projections from WASDE report and interpolate it to four weeks to match the frequency of crop condition variable. The average stock-to-use ratios for the three different wheat classes considered here are quite similar, 34.87% for HRS, 37.39% for HRW, and 35.22% for SRW wheat.

Given the importance of international competition on US wheat prices, we also include monthly wheat export quantities from Argentina and Canada in our analysis.

As noted earlier, Canadian wheat is largely equivalent to the HRS wheat produced in the US. As Canada is a large exporter of spring wheat, the export of Canadian wheat changes the world supply of HRS wheat. Similarly, Argentine wheat is similar to winter wheat produced in the US. Given this, Argentine wheat exports can potentially alter the prices of winter wheat in the US market. The export data is retrieved from the Foreign Agriculture Service of the USDA. Here also, we interpolate the monthly export data to four weeks to match with other variable frequency. The average monthly export quantity of Canadian wheat is close to 19 million metric tons, whereas Argentine wheat export is around 9 million metric tons during the sample period. As a robustness check, we also consider exports from other major exporters (Russia, EU, Ukraine and Australia). These results are reported in the Appendix.

Speculative activity is often cited as one reason for volatile commodity prices, especially since the commodity market "financialization" started in the mid-2000s. While some studies find evidence that speculation affected commodity prices (e.g., Bohl *et al.*, 2018; Mayer, 2012; Obadi and Korecek, 2018), most of the existing literature rejects the premise that speculation moved prices away from fundamentals (Irwin *et al.*, 2009b; Sanders *et al.*, 2004; Buyuksahin and Harris, 2011). Following the literature (Sanders *et al.*, 2004; Lehecka, 2015), we use the percent net long positions held by non-commercials to measure speculative activities[5]:

$$SP = \frac{NCL - NCS}{NCL + NCS + 2 \times NCSP} \times 100$$

where NCL is non-commercial long, NCS is non-commercial short and NCSP is non-commercial spread. We calculate the speculative pressure variable for all classes of wheat using the Commitment of Traders (COT) report from the Commodity Futures Trading Commission (CFTC). The COT report is released each Friday, reflecting the position of each type of trader as of the Tuesday of each week. The average percent of net long positions held by non-commercials in the HRS and HRW wheat market is quite similar, 19.56% for HRS and 17.69% for HRW. By contrast, the speculative index is much lower for SRW wheat, averaging -1.43%.

[5]we consider alternative speculative measures, and the results are qualitatively consistent with the ones presented in the paper

CHAPTER 3

Empirical Approach

We estimate the following regression to understand the effect of weather disturbances on the price spread between spring and winter wheat:

$$Spread = \beta_0 + \beta_1 Crop_S + \beta_2 Crop_W + \beta_3 SU_S + \beta_4 SU_W + \mathbf{\Gamma X} \tag{3.1}$$

where, $Spread$ refers to the logarithmic price difference between HRS wheat relative to HRW or SRW wheat, $Crop_S$ and $Crop_W$, are the percentages of good plus excellent crop conditions for spring and winter wheat, respectively, and SU_S, SU_W denote the stock-to-use ratio of spring and winter wheat. $\mathbf{X}$ is a vector of control variables including wheat exports from Argentina and Canada expressed in natural logarithm and speculative activities in each of the wheat markets. $\beta's$ and $\mathbf{\Gamma}$ are regression coefficients. Since the projected ending stocks may contain weather information, we also consider models excluding the stocks-to-use ratio. To allow the crop condition reports to have differential effects on the dependent variable depending on the underlying inventory level, we further consider interaction terms between stocks-to-use ratios and crop ratings. Year-fixed effects are included to control for other variables that do not vary much during a given marketing years, such as the average protein content of each class of wheat and carry-in stocks from the previous marketing year. Also, week-fixed effects are included to control for the effects like seasonality in price spread. As noted earlier, weekly data from 2000 to 2022 is used for the analysis.

One issue with equation (3.1) is the potential endogeneity of speculative measures and ending stocks-to-use ratios. The CFTC COT data are released every Friday for positions held by different types of traders as of Tuesday. Since the dependent variable refers to price differences at market close on Thursdays, the endogeneity issue of the speculative measure may be minimal. For the stocks-to-use ratio, we match the WASDE release schedule so that the ratios are computed based on the report released prior to the date used to compute the dependent variable. This also minimizes the overlap between the information contained in the projected stocks-to-use ratio and the crop conditions.

Along with the mean regression, we further use quantile regressions to allow for possible non-linear relationships between weather disturbances and price spread. Quantile regression examines the relationship between independent variables and a conditional quantile of a dependent variable without making any assumptions about the conditional distribution. The approach allows us to uncover dependencies that exist in the conditional distribution's outer regions rather than just the mean. Specifically, the quantile regression for τth quantile is specified as:

$$\begin{aligned} Q_{Spread}(\tau) =& \beta_0(\tau) + \beta_1(\tau)Crop_S + \beta_2(\tau)Crop_W + \beta_3(\tau)SU_S, \\ &+ \beta_4(\tau)SU_W + \mathbf{\Gamma}(\boldsymbol{ø})\mathbf{X} \end{aligned} \tag{3.2}$$

where $Q_{(}.)$ is the quantile function. Compared to the conventional OLS regression, quantile regression has two main advantages. First, it does not assume any distributions for the target variable. Conventional OLS regression assumes that the target variable is normally distributed and can provide a false interpretation when the variables have non-normal distributions. For instance, the dependent variable may be skewed, have heavy tails, or have outliers. Quantile regression makes no distributional assumptions about the target variable. Instead, it estimates the relationship between the predictor variables and different quantiles of the target variable, allowing for a more flexible modeling of the target variable's distribution. Second, it is more robust to outliers. Conventional OLS regression is sensitive to outliers in the data, which can lead to biased estimates of the model parameters. In contrast, outliers in quantile regression only affect the estimates of the quantiles to which they belong and not the estimates of other quantiles. This means that outliers have less impact on the overall relationship between the predictor variables and the target variable, making quantile regression a more robust method for modeling data with outliers.

We estimate the models using two versions of the data. The first data set only includes dates when the Crop Progress and Condition reports are available. As a robustness check, we assume the same value of crop condition till the next season for weeks without the Crop Progress and Condition reports, since the crop condition remains the same after harvest.

CHAPTER 4

Results

In this section, we first discuss the results for the main variable of interest, weather disturbances proxied by crop condition data, and the impacts of other explanatory variables on the price spread from OLS regression. Subsequently, we discuss the results from the quantile regressions. All results are reported based on the dates when Crop Progress and Condition reports are available.

4.1 OLS ESTIMATION RESULTS

Table 4.1 shows the estimation results for equation (3.1). Models (1) and (2) report the results without considering stocks-to-use ratios, model (3) and (4) includes stocks-to-use ratios as well, and model (5) and (6) reports the interaction terms between crop conditions and stocks-to-use ratios. All models include year-fixed effects and week-fixed effects. Autocorrelation-consistent standard errors are used to account for potentially correlated errors.

Our main focus is the relationship between crop conditions and the spread between spring and wheat prices. Estimation results show that spring crop conditions negatively affect price spread. All else equal, when the portion of spring wheat in good or excellent condition decreases by one percentage point, the HRS-HRW spread on average increases by 0.1338%, and the HRS-SRW spread increases by 0.1327%. This translates to an increase in the spring wheat premium on average by approximately 0.75 cents/bushel (27 cents per metric ton) above HRW, and approximately 0.71 cents/bushel (26 cents per metric ton) above SRW at the sample mean.

The average portion of spring wheat in good or excellent condition during the sample period is around 60%, with the highest value reaching over 85% in favorable crop years. However, during the years impacted by severe weather disturbances, this ratio drops to between 10% and 30%. In 2021, the crop condition was 60 percentage points lower than that of 2020, a year when the crop did not experience

Table 4.1: Estimation results of equation (3.1), weekly data from 2001-2022

	Price Spread					
	HRS-HRW	HRS-SRW	HRS-HRW	HRS-SRW	HRS-HRW	HRS-SRW
	(1)	(2)	(3)	(4)	(5)	(6)
Spring Crop Condition	-0.1502^{***}	-0.1694^{***}	-0.1338^{***}	-0.1327^{**}	0.0231	-0.1662
	(0.0463)	(0.0601)	(0.0433)	(0.0544)	(0.0963)	(0.1275)
Winter Crop Condition	0.2552^{***}	-0.0924^{*}	0.3013^{***}	-0.0436	-0.1598^{*}	-0.3671^{***}
	(0.0488)	(0.0471)	(0.0518)	(0.0454)	(0.0919)	(0.0889)
HRS Stock to Use			-0.1189^{*}	-0.2854^{***}	0.2614	-0.4536
			(0.0629)	(0.0651)	(0.2249)	(0.3163)
HRW Stock to Use			-0.0847		-0.6909^{***}	
			(0.0598)		(0.1286)	
SRW Stock to Use				0.0338		-0.3603^{***}
				(0.0543)		(0.1279)
Spring crop condition* HRS stock to use					-0.0068^{**}	0.0018
					(0.0032)	(0.0046)
Winter crop condition* HRW stock to use					0.0129^{***}	
					(0.0025)	
Winter crop condition* SRW stock to use						0.0086^{***}
						(0.0024)
Speculation HRS	-0.0166	0.0317	-0.0265	0.0396^{**}	-0.0321^{*}	0.0363^{**}
	(0.0177)	(0.0207)	(0.0192)	(0.0188)	(0.0190)	(0.0176)
Speculation HRW	-0.0643^{**}		-0.0568^{**}		-0.0624^{**}	
	(0.0267)		(0.0285)		(0.0274)	
Speculation SRW		-0.1341^{**}		-0.1804^{***}		-0.1684^{***}
		(0.0564)		(0.0497)		(0.0491)
Canadian Export	-0.0972	2.3214^{**}	0.8539	3.6052^{***}	0.5528	3.4340^{***}
	(0.9184)	(1.1235)	(0.9912)	(1.0795)	(0.9256)	(1.0922)
Argentine Export	-3.5319^{**}	-1.6729	-3.1838^{**}	-1.5455	-2.9567^{*}	-1.9129
	(1.5082)	(1.5792)	(1.5392)	(1.8690)	(1.5389)	(1.9430)
Constant	34.9044^{**}	18.9134	26.7744^{*}	10.0340	41.3302^{**}	33.3652
	(15.1516)	(18.5540)	(15.8777)	(20.0399)	(18.3823)	(23.4274)
Observations	547	547	547	547	547	547

Note: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is the price spread between different classes of wheat. Models 1 and 2 are results excluding stocks-to-use ratios, and models 3 and 4 are the results with stocks-to-use ratios. Models 5 and 6 add interaction terms between crop condition and stock-to-use ratio in the regression. All models include year-fixed effects and week-fixed effects. Auto-correlation consistent standard errors are reported in parenthesis.

any significant weather disturbances. This 60-percentage point reduction in crop condition results in a price increase of HRS on average by approximately 8% above the price of HRW and SRW. In other words, the 2021 drought increased spring wheat prices by approximately 44 cents/bushel (around 16 dollars/ton) over winter wheat. For comparison, the average HRS-HRW spread was 17.4% (144.75 cents/bu) in 2021/22. Similarly, the average spread between HRS and SRW wheat was 18.18% (156.24 cents/bu), with a low of -11.7% (-142.5 cents/bu) and a high of 30.8% (284 cents/bu).

When a higher percentage of winter wheat is in good/excellent condition, the price of winter wheat is expected to decrease due to the likely good harvest. All else equal, this should widen the spread between spring and winter wheat prices. All else equal, when the portion of winter wheat in good or excellent condition decreases by one percentage point, the HRS-HRW spread on average decreases by 0.3013%. However, its effect is not statistically significant in the case of the spread between HRS and SRW. This result appears to be consistent with Bain and Fortenbery (2017), who found that, unlike corn and soybeans, crop condition report for winter wheat generally does not affect prices. Bain and Fortenbery (2017) note that one plausible explanation is that the crop conditions reports for winter wheat combine information from many classes of wheat, including hard red, soft red, soft white, and hard white, each of which has distinct qualities. As a result, expectations for average yield across all classes of wheat may conceal heterogeneity within a given class. However, the portion of Hard Red Winter (HRW) wheat grown in the US is larger than that of other winter wheats, the condition of the winter crop may more accurately reflect the condition of HRW wheat than Soft Red Winter (SRW) wheat. This could result in the winter wheat crop condition being more significant for HRW wheat spreads, but not necessarily for SRW wheat spreads. Similarly, even though spring crop condition also comprises different classes of wheat like HRS, durum and white wheat, the proportion of other spring wheat production compared to HRS is much smaller, which may have enhanced the capability of spring crop condition to represent HRS wheat.

A higher stock-to-use ratio implies greater supply in excess of demand and hence should suggest lower prices. This is the case with the ending stocks-to-use ratio of spring wheat, which negatively affects the price spread. A one percentage point increase in the stock-to-use ratio of HRS wheat results in a 0.12% decrease in the HRS-HRW price spread and a 0.28% decrease in the HRS-SRW spread. This result is in line with those found by previous studies (e.g., Algieri, 2014; Wilson, 1983; Wilson and Chan, 1987).Algieri (2014) found that 1% increase in the stocks-to-use ratio would trigger the real price of wheat to drop by 0.9%. Wilson (1983) found a negative relationship between the supply of HRS wheat and prices. Similarly, Wilson and Chan (1987) noted the importance of stocks of each class of wheat in explaining the price levels—they found HRS wheat stocks were overwhelmingly significant across all three wheat futures markets.

We further explore whether the impact of crop conditions varies by the levels of stocks-to-use ratios. Models (5) and (6) of table 4.1 present the estimation results when interaction terms between crop conditions and the stocks-to-use ratio of respective wheat classes are included. For spring crop conditions, the impact on the spread between HRS and HRW goes on increasing with the increasing stocks-to-use ratio of HRS wheat. On the other hand, the impact on the spread between HRS and SRW does not vary with the stocks-to-use ratio of HRS wheat. Similarly, for winter wheat crop conditions, the interaction term is positive with the coefficients of crop condition being negative. This also shows that the impact of winter crop conditions increases with increasing stocks-to-use ratios. However, the magnitude of the coefficients are small for the interaction term.

4.2 IMPACTS OF OTHER CONTROL VARIABLES

We also consider exports of major competitors and speculative activities as control variables in the estimation. Most of the wheat produced in Argentina is similar in protein levels to the hard red winter wheat produced in the US. An increased supply of winter wheat from Argentina would depress the price of winter wheat in the global market. On the other hand, most of the wheat produced in Canada closely resembles the HRS wheat in the US. Increased export of Canadian wheat leads to a decrease in the price of spring wheat in the USA. However, the estimation results are counter-intuitive as seen in table 4.1, with exports from Argentina having negative coefficients and exports from Canada having positive coefficients. Also, Canadian exports only affect the price spread between HRS and SRW. Meanwhile, Argentine exports only affect the price spread between HRS and HRW, this may be because the Argentine wheat resembles HRW wheat produced in the US. Other major wheat exporting countries like Australia, EU, Russia, and Ukraine export both spring and winter wheat and can also play a role in the price discovery of wheat traded in the US futures market. Results including these exporting countries are reported in the appendix.

Speculation is sometimes blamed to be responsible for increased volatility and price changes in commodity markets. There is a long going debate in the literature on whether speculative activity affects the prices of commodities in the futures market. Wimmer *et al*. (2021) suggests that the results found in previous studies differ with the type of commodity under examination, the sample period of the data, the measurement of the focus variables (return, volatility, or spread), and the inclusion of other control variables. Our estimation results show that speculative activity significantly impacts price spreads. All else equal, a one percentage point increase in the speculative pressure in the HRS market increases its price by 0.04% relative to SRW prices. The results on speculative activities hold across most of the specifications considered and are consistent with some previous studies on the speculative effect of wheat prices. For instance, Algieri (2014) found a positive relationship between speculation and wheat futures and cash prices, with a 1% increase of financial speculation increasing wheat prices by 0.7%. In a recent study, Li *et al*. (2022) found that commodity index traders, a group of speculators, exerted a more important role in the SRW wheat futures market than corn and soybeans, noting that the percentage of open interest attributed to commercial traders were significantly lower in wheat relative to the other markets.

4.3 QUANTILE REGRESSION RESULTS

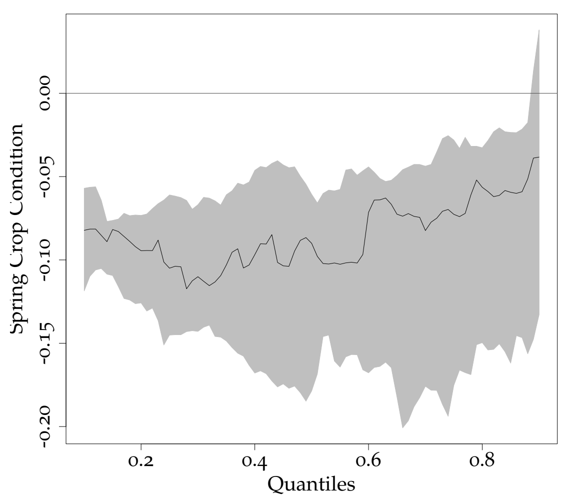
Figure 4.1 shows the results from quantile regressions as specified in equation 3.2 for various quantiles (τ) of price spreads. The coefficients of spring crop conditions in the HRS-HRW spread and HRS-SRW equation is presented in the top row of the figure, while the coefficients for winter crop conditions are plotted in the bottom row. Results overall are consistent with the OLS results in table 4.1—increase in good to excellent spring crop conditions negatively affect spread, while the impacts of winter crop conditions positively affect the spread with HRW and are mostly non-significant in the case of spread with SRW. However, considerable heterogeneity exists at different quantiles.

As can be seen in figure 4.1a, in the case of the spread between HRS and HRW, the magnitude of the effect for spring crop conditions declines as we move to higher quantiles. This suggests that when the spread between spring and winter wheat prices is narrower, the same magnitude of change in crop condition exerts a much larger impact than when the spread is wider (i.e., at higher quantiles). When the spread is narrow due to possibly high expected supply and consequently low spring wheat prices, a shock to weather conditions that further improves spring crop conditions may lead traders to overreact to the positive yield scenarios, further narrowing the spring and winter price spreads. It may also be possible that when the expected yield is high, the expectation of potentially lower protein content of spring wheat (Pepe and Heiner, 1975; Bekkerman, 2021, e.g.,) significantly decreases spring wheat prices relative to winter wheat. Similarly, the impact of spring crop condition in the spread between HRS and SRW also declines to become insignificant in the higher quantiles of price spread above 80%, as seen in figure 4.1b.

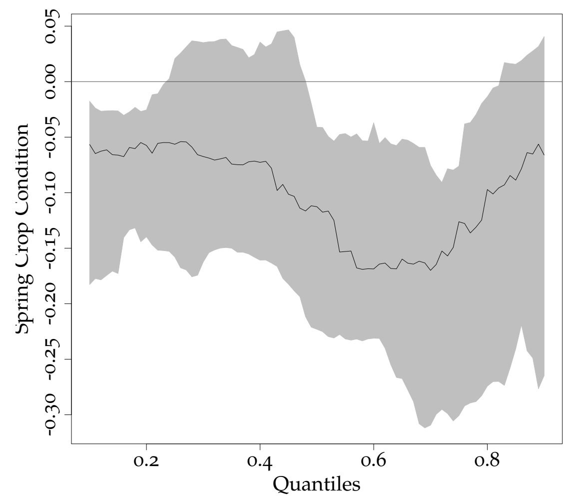
While the effect of winter crop conditions is mostly non-significant for the spread between HRS and SRW, it is positively significant for the spread between HRS and HRW. Also, the effect increases when the spread between HRS and HRW is in higher quantiles. That is, when the price spread between spring and winter wheat is large, an improvement in winter crop conditions will further widen the price spread. Veronesi (1999) shows that people tend to overreact to the bad news in good times and underreact to the good news in bad times. This can explain why the impact

Figure 4.1: Coefficients of crop conditions at different quantiles of price spread

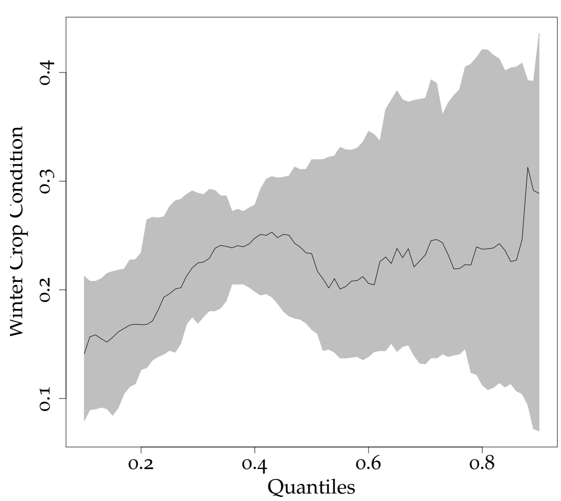
(a) Spring crop condition, HRS-HRW spread



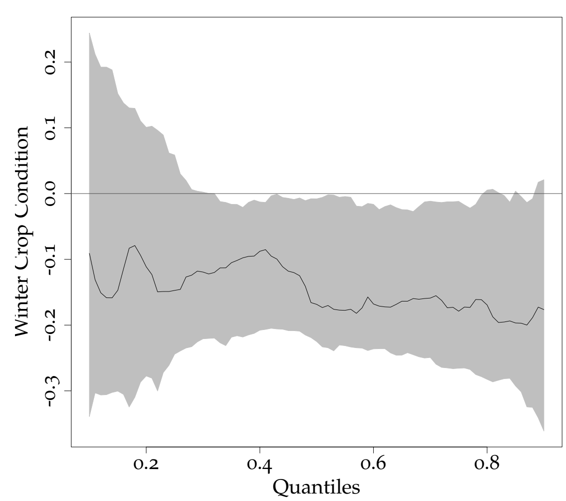
(b) Spring crop condition, HRS-SRW spread



(c) Winter crop condition, HRS-HRW spread



(d) Winter crop condition, HRS-SRW spread



Notes: for each subplot, shaded areas represent 95% confidence interval, dark black line represents quantile estimates.

of spring crop condition ratings is higher when the price spread is lower and the impact of winter crop condition ratings is higher when the price spread is higher. Overreaction in the financial market happens when traders respond excessively to the market news or events, causing the price of the asset to temporarily deviate from their underlying fundamental values. Borgards *et al*. (2021) confirms this hypothesis of overreaction in the futures market too. In the case of spring wheat, when the price spread is lower, the expectation of a good crop that leads to low prices can be perceived as bad news by traders, causing them to overreact and further decrease the prices of spring wheat, thus lowering the price spread even further. Similarly, in the case of winter wheat, when the price spread is higher, the expectation of a good winter crop leading to lower winter wheat prices can again be perceived as bad news by traders, causing them to overreact and further moving the prices down, thus widening the spread. Along with overreaction, other market phenomenons like herd mentality and momentum trading can also contribute in moving the prices further.

Overall, quantile regression results suggest that weather information as proxied by crop conditions has the greatest impact when the spring and winter wheat price spread is low, or when spring wheat prices are close to winter wheat prices. Examining the data, we find that the low price spread period between spring and winter wheat prices is typically associated with higher levels of supply of spring wheat relative to winter wheat. This surplus of spring wheat creates an expectation of lower protein content, which in turn reduces the protein premium received by spring wheat and contributes to a narrower price spread. Two notable examples of low price spread periods between spring and winter wheat prices occurred in 2006/07 and 2013/14. In 2006/07, a larger HRS wheat crop expectation put downward pressure on spring wheat prices, resulting in a narrower price spread. Similarly, in 2013/14, a higher world supply of spring wheat, driven in part by increased production of Canadian HRS wheat, contributed to a lower protein premium and narrower price spread between spring and winter wheat.

CHAPTER 5

Conclusions

Weather patterns play a significant role in crop production. Despite the abundant evidence on the negative impact of weather disruptions on global crop supply, empirical evidence on how these events affect crop prices remains scant. In this study, we examine how weather disturbances affect the price spread between spring and winter wheat in the United States. This spread is a critical factor for millers, traders, and exporters in determining their acquisition decisions for different wheat classes, either to blend or trade. To measure the impact of weather events, we use the percentage of crops in good to excellent condition from the USDA Crop Progress and Condition report as a proxy for weather events, as it provides the real field scenario of the crop and is continuously used to anticipate positive or negative anomalies in the crop production. Using these crop condition reports, we show that weather disturbances, especially those associated with spring wheat, significantly affect the price relationship between different classes of wheat.

Estimation results show that a lower percentage of spring wheat in good or excellent condition, suggesting negative weather disturbances, leads to a wider spread between spring and winter wheat prices. In 2021 when the drought decimated much of the spring wheat crops, the anticipated reduction in supply is estimated to have raised the price of spring wheat by 8% above winter wheat prices. On the other hand, weather disturbances in winter wheat appear to significantly alter the price spread between HRS and HRW but not between HRS and SRW. This may be due to the aggregated nature of the winter crop condition report that comprises many different classes of wheat with unique characteristics and uses. And, as HRW is the most widely grown type of winter wheat, the aggregated report may better reflect its condition compared to other types of winter wheat, such as SRW.

We further show that the impact of weather disturbances varies little with the level of inventory. The impact of crop conditions increases with the increasing levels of stock-to-use ratios. Through quantile regressions, we evaluate the heterogeneous effect of crop conditions on different quantiles of price spreads. The effect of the spring crop conditions variable is seen to be higher when the price spread between spring and winter wheat is narrow. Whereas, for the winter wheat crop condition, its effect grows to be higher when the price spread becomes wider.

Weather events have become increasingly volatile in recent years due to climate change, which poses a significant threat to the price stability in commodity markets. For the different classes of wheat which are closely related and often show co-movement in their prices, these weather disturbances can cause one class of wheat price to deviate, leading to higher variations in the price spread. Farmers, exporters, hedgers, commercial traders, millers, and spread traders are among the groups vulnerable to the disruptions caused by these events.

Our results provide information for policymakers to anticipate the possible damages caused by extreme weather events and the possible need for the policies in future to mitigate the loss. Further, despite the debate on the usefulness of crop progress and condition report, our results show that the report is still used by the market participants in anticipating the potential yield of the crop. For commodity traders, with increasing variation in the price spread, a better understanding of how weather events affect the relative price relationship between different classes of wheat can improve their portfolio design and trading outcomes. The relative prices can be particularly important for the traders involved in spread trading. Further, hedgers also can use this information to decide which futures contracts to buy or sell in order to effectively manage the price risk. Information from this study would also benefit the milling industry as the relative price ratio affects the use of different classes of wheat when blending for desired protein levels. As millers usually make their sourcing decisions months ahead of the actual delivery, understanding how weather events impact these ratios would enable millers to make informed decisions about sourcing and pricing strategies. Both the domestic and international millers can benefit from these findings. For exporters, relative prices can have an impact on deciding the destination of the exports. For example, some countries are rigid in their protein requirement in wheat, whereas others are very sensitive to the prices regardless of protein content. In this scenario, when the price spread is larger, exporters can direct the higher protein wheat with higher prices to the countries willing to pay higher prices for protein content. Meanwhile, they can direct the lower-priced wheat to countries sensitive to price changes. These results would benefit the overall grain merchandisers in deciding and maintaining the inventory levels in relation to the price changes.

It is essential to recognize that, there may be other factors in addition to the ones considered in this study that can potentially have an impact on the prices of different classes of wheat. Given that wheat is a globally traded commodity, different supply and demand factors around the globe can have an impact on the price spreads between spring and winter wheat. The impact of weather disturbances in other wheat-producing regions of the globe may also be felt in the wheat markets of the US. Additionally, the effect of COVID-19 and the Russia-Ukraine conflict on the global commodity market could be substantial which is not explicitly isolated in this study. Further, the interrelationship between different commodities in their end uses can also impact the demand for one or other commodities. For instance, a drought in the corn-producing belt could have an impact on wheat prices. As SRW wheat is often used as a substitute feed grain to corn, a rise in corn prices can shift the demand for SRW wheat leading to price changes in SRW wheat. These limitations of the current study can be extended in future works to explore the full range of factors that could impact the prices of different classes of wheat.

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APPENDIX A

Robustness Checks

Table a.1: Estimation results of equation (3.1) using the extended dataset, weekly data from 2001-2022

	Price Spread					
	HRS-HRW	HRS-SRW	HRS-HRW	HRS-SRW	HRS-HRW	HRS-SRW
	(1)	(2)	(3)	(4)	(5)	(6)
Spring Crop Condition	-0.1277^{***}	-0.1402^{***}	-0.1111^{***}	-0.1182^{***}	0.0165	-0.2376^{**}
	(0.0433)	(0.0513)	(0.0393)	(0.0445)	(0.0770)	(0.0939)
Winter Crop Condition	0.0773^{***}	-0.1077^{***}	0.1090^{***}	-0.0568^{**}	-0.2972^{***}	-0.2324^{***}
	(0.0225)	(0.0278)	(0.0238)	(0.0266)	(0.0575)	(0.0508)
HRS Stock to Use			-0.2145^{***}	-0.3254^{***}	0.0582	-0.6729^{***}
			(0.0444)	(0.0447)	(0.1713)	(0.2254)
HRW Stock to Use			0.0333		-0.6485^{***}	
			(0.0432)		(0.1063)	
SRW Stock to Use				-0.0046		-0.2548^{***}
				(0.0424)		(0.0816)
Spring crop condition* HRS stock to use					-0.0051^{**}	0.0050
					(0.0024)	(0.0032)
Winter crop condition* HRW stock to use					0.0136^{***}	
					(0.0019)	
Winter crop condition* SRW stock to use						0.0052^{***}
						(0.0015)
Speculation HRS	0.0088	0.0357^{***}	0.0058	0.0356^{***}	-0.0056	0.0348^{***}
	(0.0133)	(0.0133)	(0.0134)	(0.0120)	(0.0137)	(0.0120)
Speculation HRW	-0.1161^{***}		-0.1150^{***}		-0.0954^{***}	
	(0.0190)		(0.0191)		(0.0195)	
Speculation SRW		-0.1761^{***}		-0.2107^{***}		-0.2116^{***}
		(0.0294)		(0.0266)		(0.0254)
Canadian Export	-0.2958	1.0704	0.9327	3.3531^{***}	1.0561	3.6343^{***}
	(0.9580)	(1.4675)	(1.1109)	(1.0500)	(1.0278)	(1.0162)
Argentine Export	-0.4572	-0.7354	-0.3569	-0.2679	-1.4635^{*}	-0.9259
	(0.8282)	(0.9147)	(0.8513)	(1.0441)	(0.8639)	(1.0484)
Constant	14.2016	17.6756	4.8803	-1.5971	28.5515^{**}	19.0035
	(11.7611)	(18.0861)	(13.0564)	(14.6788)	(13.3802)	(15.7917)

Note: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is the price spread between different classes of wheat. Models 1 and 2 are results excluding stocks-to-use ratios, and models 3 and 4 are the results with stocks-to-use ratios. Models 5 and 6 add interaction terms between crop condition and stock-to-use ratio in the regression. All models include year-fixed effects and week-fixed effects. Auto-correlation consistent standard errors are reported in parenthesis.

Table a.2: Estimation results of equation (3.1) including other variables as a robustness check

	HRS-HRW (1)	HRS-SRW (2)	HRS-HRW (3)	HRS-SRW (4)	HRS-HRW (5)	HRS-SRW (6)
Spring crop condition (Poor + Very Poor)	0.0443	0.0563	−0.0054	0.2449		
	(0.0509)	(0.0600)	(0.1683)	(0.2330)		
Winter crop condition (Poor + Very Poor)	−0.2878***	0.0440	0.1118	0.3156***		
	(0.0464)	(0.0434)	(0.0798)	(0.0847)		
Spring crop condition (Good + Excellent)					−0.1410***	−0.1381**
					(0.0443)	(0.0562)
Winter crop condition (Good + Excellent)					0.3105***	−0.0920*
					(0.0584)	(0.0499)
HRS Stock to Use	−0.1017	−0.3035***	−0.1995**	−0.2330**	−0.1415**	−0.2903***
	(0.0624)	(0.0661)	(0.0898)	(0.1116)	(0.0691)	(0.0697)
HRW Stock to Use	−0.0871		0.1869**		−0.0786	
	(0.0593)		(0.0797)		(0.0649)	
SRW Stock to Use		0.0270		0.1837**		0.0233
		(0.0556)		(0.0829)		(0.0539)
Spring crop condition* HRS stock to use			0.0037	−0.0086		
			(0.0067)	(0.0094)		
Winter crop condition* HRW stock to use			−0.0113***			
			(0.0023)			
Winter crop condition* SRW stock to use				−0.0066***		
				(0.0023)		
Speculation HRS	−0.0174	0.0436**	−0.0263	0.0350*	−0.0155	0.0471***
	(0.0183)	(0.0188)	(0.0188)	(0.0182)	(0.0195)	(0.0174)
Speculation HRW	−0.0588**		−0.0592**		−0.0544*	
	(0.0278)		(0.0279)		(0.0314)	
Speculation SRW		−0.1843***		−0.1569***		−0.2309***
		(0.0504)		(0.0525)		(0.0571)
Canadian Export	1.1402	3.6694***	0.7663	3.1669***	5.3663	8.8262**
	(0.9693)	(1.1146)	(0.9657)	(1.1352)	(4.1202)	(4.4063)
Argentine Export	−2.6300	−1.6506	−2.8317*	−1.9212	−3.2910**	−1.2491
	(1.7456)	(1.9215)	(1.6724)	(1.8836)	(1.5179)	(1.9323)
Russian Export					−1.5365	0.2184
					(1.2583)	(1.2730)
Ukraine Export					1.3870	−0.0977
					(0.9454)	(1.1796)
EU Export					−4.6649	3.4184
					(3.6041)	(3.8810)
Australian Export					−4.9220	−5.8987
					(4.2342)	(4.5229)
Constant	29.0382	0.2785	26.9746	0.6870	75.0742*	−18.6038
	(17.9887)	(20.8353)	(17.4534)	(20.5796)	(40.3694)	(45.5509)

Note: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is the price spread between different classes of wheat. All models include year-fixed effects and week-fixed effects. Auto-correlation consistent standard errors are reported in parenthesis.