Warming Temperatures and Potential Adaptation through Breeding: Evidence from U.S. Soft Winter Wheat

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Impact of warming on Quantity and Quality of Wheat Varieties in the US

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Abstract

This paper examines the impact of climate change on crop quality and quantity using annual wheat trial data. As much present research focuses on the relationship between grain yields and warming, we consider quality a critical component that must be stressed in climate studies since it can be associated with reduced protein content or size as well as production. Due to the importance of crop quality on nutrients, farmers' livelihoods and consumers' health, studies of the effects of temperature on agriculture disregard quality risk underestimating or overestimating the overall impact of warming (Ramsey et al., 2020). As a result, in this article, we quantify the quality by measuring wheat test weights as well as yield. Our results show that the extreme heat exposure is associated with the reduction in yield and test weight while moderate warm climate affects to them positively as in the existing literature. Another finding is that the quality reacts more stable on the climate changes and relatively more tolerant to high temperature compared to the quantity. However, quality reduced dramatically from 30 degree Celsius as well.

Keywords: Climate change, Agriculture, Crop yield, Crop quality

JEL Classification: L15, Q10, Q54

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1 Introduction

As a principal staple food for 35% of the world's population, the demand for wheat continues to rise as the population is projected to surge from its current level of 7.20 billion to 9.55 billion by 2050 (Curtis and Halford, 2014). Such a scenario could make food security difficult if demand levels cannot be met in the next century. The Intergovernmental Panel on Climate Change (IPCC, 2014) has reported that the three major cereal crops, i.e. wheat, rice, and maize, will decline in most farming areas due to a 2.4-6.4 degrees Celsius projected increase in air temperature within this century alone. Furthermore, this report is substantiated by many studies that have also examined the negative relationship between extreme temperatures and crop productivity (Schlenker and Roberts, 2009; Tack et al., 2017; Lobell and Asner, 2003; Lobell and Field, 2007). If climate change becomes a significant challenge in sustaining human life and the environment, it will be imperative to find effective adaptation and mitigation strategies.

One strategy is technological change through plant breeding and improved management practices which have enhanced farm productivity and increased agricultural output. There is a possibility that gains from improved management and new crop varieties could cancel out lower yields from warming. The literature on varietal improvement is well-established and focuses on attribution of changes in yields to different sources including plant breeding advancements (Nalley et al., 2008; Nolan and Santos, 2012; Wang et al., 2021). Studies have also recognized the important role of yield risk and empirical linkages between risk, changes in production technologies, and economic outcomes (Shi et al., 2013a). Given previous literature, this paper assesses the response of wheat to warming temperatures and also measures whether breeding efforts may mitigate temperature effects.

However, crop yield is not the only attribute of economic significance related to climate change and breeding-based crop improvement. Crop quality is also a crucial factor that should be stressed in breeding research as well as climate studies. Buyers purchase crops based on quality, and the price is determined accordingly. This price is closely related to farmers' livelihood. Voon and Edwards (1992) measures significant research benefits from quality improvements in wheat. Nogueira et al. (2015) find significant welfare impacts of yield improvement within different classes of wheat. Likewise, studies disregarding quality may risk underestimating or overestimating the overall impact of warming. Lyman et al. (2013) and Ramsey et al. (2020) reveal that when studies fail to account for changes in quality, it leads to an underestimation of the impacts of warming on outcomes, and the negative effect on market value would be even worse. On the contrary, Kawasaki and Uchida (2016) show that quantity and quality effects may operate in different directions. In any case, taking account of quality is critical for avoiding misleading economic results.

In this article, we quantify quality by measuring wheat test weight. Test weight is a density measurement that is used as an indicator of grain quality; its unit is pound per bushel (lbs/bushel), whereas grain yield is expressed in bushels per acre.[1] According to the USDA official standard of wheat, there are five grades depending on test weights.[2] In other words, the primary grade of wheat is determined by the test weight as it indicates how much flour can be extracted (NDSU Agriculture Communication, 2012). Although the test weight alone may not capture wheat quality, it is a widely accepted measure. [3]

In short, this paper has three-fold objectives: a) to investigate the nonlinear relationship between temperature and yield and quality, respectively; b) to simulate the impact of a one-degree Celsius temperature increase on wheat yield and test weight; and, c) to examine whether newer varieties of wheat are more or less susceptible to extreme temperatures. All three objectives are measured in terms of effects on wheat revenue: a combination of yield and quality.

[1] https://www.ag.ndsu.edu/news/newsreleases/2012/aug-20-2012/grain-yield-not-related-to-test-weight

[2] In case of soft wheat case, 1st grade is 60 lbs, 2nd grade is 58lbs, 3rd grade is 56lbs, 4th grade is 54lbs and 5th grade is under 51lbs. Other than test weights, the official grades include foreign materials, and damaged or shrunken kernels.

[3] Additional quality tests include moisture, protein, falling number but they are not part of the US grain standards.

2 Literature Reviews

Many studies have examined the relationship between weather and crop productivity, as climate change has become a serious challenge in sustaining human life and the environment. Align with a report from the IPCC in 2014, Schlenker and Roberts (2009) also evaluate the relationship between weather and yields for three major crops in the US: corn, soybeans, and cottons. They predict yield increases gradually up to a certain level but eventually decreases sharply for all three crops. Tack et al. (2017) shows that sorghum yields start to decline above 33 degrees Celsius. Lobell and Asner (2003) used corn and soybean data and found that yields decreased 17% with an increase of 1 degree Celsius. Lobell and Field (2007) found that prolonged maximum temperatures reduced rice yields. As a result, there is a possibility that the lower yields cancel out a substantial portion of the gains from management skills and technological improvements (Lobell et al., 2011). Even though the methodologies, study regions, periods, and crops vary to some extent, the common pattern of the literature is to simulate the impacts of weather in the future, which shows poor prospects in most cases. Same also suggest effective adaptation and mitigation strategies (Peng et al., 2004; Schlenker and Roberts, 2009).

However, climate change is not only affecting crop quantity; it is also expected to influence quality considerably (Wassmann et al., 2009). Relatively fewer, but a growing number of studies have analyzed the impact of warming on quality. Some focus on Japanese rice cases, showing that an elevated climate during the growing period dramatically degrades rice quality.() As a primary staple of Japan, data on rice in that region are systemically organized and open to the public. Hence, rice grading data are relatively accessible. However, in many other cases where grading data are unavailable, the most challenging part of studying crop quality is how to measure it and find alternative methods since crop quality is often multidimensional and there are few relevant data available (Ramsey et al., 2020).

To measure the quality, Lyman et al. (2013) calculated the portion of chalkiness and the broken kernel to measure the rice milling quality in Arkansas, and Ramsey et al. (2020)

used kernel size data as a proxy for peanut quality in Virginia, North Carolina, and South Carolina.

Meanwhile, the above two studies reveal that when an analysis fails to account for changes in quality, it leads to an underestimation of the impacts of warming on outcomes, and the negative effect on market value would be even worse. On the contrary, Kawasaki and Uchida (2016) demonstrated that, while the quantity effect rises due to increased high weather, the quality effect works oppositely. This implies that the directions and the magnitudes of the quantity and quality do not always work in the same way, so they should be deliberately compared to avoid misleading the results.

Along the same lines, our paper examines the weather effect on wheat considering both quantity and quality. To the best of our knowledge, there is little literature approaching this topic using US wheat data despite its leading role in agriculture. To measure wheat quality, we used test weight data, as it is considered the most common and easiest way to quantify wheat (Pomeranz, 1964).

3 Data

We use data from U.S. Uniform Southern Soft Winter Wheat Nursery Reports between 1962 and 2017. These reports contain the results of variety trials by conducted primarily by public institutions throughout the southern United States. The data contain just over 33,000 year-location-variety observations across over 928 cultivars and 116 locations. We have measurements of quantity (yield) as well as quality (test weight). The data form an unbalanced panel as locations and varieties enter and exit the nursery reports over time.

The unbalanced nature of the panel is particularly acute for variety. The nursery reports are the result of cooperative investigations in new wheat varieties undertaken by the USDA Agricultural Research Service and State Agricultural Experiment Stations. Cultivars are entered in the trials and then grown at all cooperating locations. The majority of cultivars in the trials are not commercially available and are planted for research purposes. These cultivars typically do not remain in the trials for an extended period of time. The nature of varietal development and experimentation requires yearly entry of new breeding lines and varieties.

Several check varieties are included in each year of the trials. These check varieties are usually commercialized varieties that remain in the trials for a number of years. They form an experimental control against which the research lines can be checked or compared. As an example, AGS2000, a variety developed at the University of Georgia, appeared as a check variety from 1999 to 2016. AGS2000 is the most common cultivar in the trials as it has a total of 434 location-year observations. The consistent inclusion of check varieties in the trials allows for more accurate estimates of variety-specific effects for some varieties.

Data from the trials are combined with weather data available from PRISM over a 2.5 by 2.5 mile grid of the contiguous United States. The trial data contain only approximate locations for the growing sites. The center of the town where the trials occurred was geocoded and matched to the corresponding PRISM grid cell. As we do not observe the precise location where the trials were conducted, measurement error may be introduced and could result in attenuation bias. As noted in a similar context by Miller et al. (2021), error in measurement of the weather variables will tend to cause downward bias in estimated climate impacts.

As in Schlenker and Roberts (2009), the daily minimum and maximum temperatures in the PRISM data are interpolated using a sinusoidal curve and then used to calculate the number of growing degree days across the growing season. Total precipitation is simply the sum of daily precipitation reported in the PRISM data. Miller et al. (2021) and Tack et al. (2015) indicate that the use of growing degree days is preferable to average temperature or order statistics which have a smoothing effect on measured weather variation.

4 Empirical Approaches

Before moving on to the model part, there are three methodological issues to be addressed in this research. First and foremost, the sample selection and attrition are problematic. As we mentioned earlier, there were frequent in-and-out among cultivars by year. To a lesser extent, but still, trial locations were not the same across the time, making it challenging to acquire a balanced panel. When sample selection or attrition occurs, there are three methodologies we can take: i) ignoring these issues and using the unbalanced panel. ii) removing the observations that have the issues and making the balanced subset. iii) setting up the model considering these issues Wooldridge (2015). In this paper, we choose the first option, but we need to add an assumption that weather variables are given randomly and exogenously. This assumption allows a consistent estimator and lets fixed effect terms control unobserved heterogeneity. In addition to that, we include only the locations and cultivars with a certain number of observations, as in Tack et al. (2017) and Shew et al. (2020).[4]

Second, we must consider positive trends between grain yields and time, which are caused by other than climate factors, such as technological advances (Shi et al., 2013b). Neglecting these factors would make bias in identifying the exact contribution of weather variables on yield and quality. To capture the technical improvement and other time-dependent trends, we include time trends variable with year and year squared in our preferred model instead of time fixed effect, following Schlenker and Roberts (2009).[5]

Third, Lobell et al. (2008) emphasize taking into account the different human activities by location, including management skills and adaptations, which may intensively affect crop growth as well. Moreover, Schlenker et al. (2005) argue that the highly irrigated regions cause bias since irrigation may correlate to climate. Since we could not find a proper measurements for human activities and irrigation, we added assumptions on best management practices and no irrigation in all regions.

[4]Locations should appear more than 5 trial years and cultivars should appear more than 2 trial years.
[5]Time fixed effect is considered in the alternative specification

4.1 Basic Model

We regress log wheat yield and log test weight on temperature, precipitation, and location, cultivar fixed effects. Specifically, we consider the following multiple regression model with fixed effects to estimate the weather effect on wheat quantity:

$$lny_{ijt} = \gamma_i + \tau_j + \alpha_1 t + \alpha_2 t^2 + f(X_{jt}; \beta) + \epsilon_{ijt}, \tag{1}$$

where lny_{ijt} denotes the log wheat yield for variety i at trial location j in year t; γ_i is a vector of cultivar intercepts to control; τ_j denotes a vector of location intercepts to control; $\alpha_1 t + \alpha_2 t^2$ captures the time trends, and $f(\cdot)$ represents the weather function while X_{ijt} is a vector of weather related variables and the β are the slope parameters for X_{jt}; ϵ_{ijt} is the error terms.

Precisely, we add intercepts γ_i to control for genetic differences in yield and τ_j to control for spatially-invariant unobserved effects such as soil quality. To avoid the potential omitted variable bias, these fixed effects are included to capture additive time-invariant influences. The time trend is included in this model as a quadratic form, as in Tack et al. (2017), to capture the genetic improvements at a diminishing rate over time. Since only elite lines are likely tested and developed in the trial area, this property needs to be reflected. Next, we cluster standard errors by location, which takes account of random correlation among unobservables within the the same regions.

This paper presumes the nonlinear relationship between temperature and quantity or quality rather than linearity as in Tack et al. (2017). In other words, we assume that when the climate is below or above a certain threshold, two dependent variables - quantity and quality - may decline dramatically. From this point of view, we use the function for capturing weather effects as follows:

$$f(X_{jt}; \beta) = \beta_1 low_{jt} + \beta_2 med_{jt} + \beta_3 high_{jt} + \beta_4 P_{jt} + \beta_5 P_{jt}^2 \tag{2}$$

where $\beta_1 low_{jt}$ measures degree days from 0 to the lower threshold, 14 Celsius degree, $\beta_2 med_{jt}$ measures degree days between 15 and the upper threshold, 31 Celsius degree, and $\beta_3 high_{jt}$ measures degree days above the upper threshold, 32 Celsius degree, $\beta_4 P_{jt}$ and $\beta_5 P_{jt}^2$ indicates a quadratic effect of precipitation during the growing season on wheat yield and test weight. The suggested numbers of degree days are referred from Tack et al. (2017)

Meanwhile, the weather effect on wheat quality is calculated in a similar way:

$$lnq_{ijt} = \gamma_i + \tau_j + \alpha_1 t + \alpha_2 t^2 + f(X_{jt};\beta) + \epsilon_{ijt}, \tag{3}$$

where lnq_{ijt} is the log wheat test weight for variety i in year t at trial location j.

5 Results

Table 1 illustrates the results from the equation (1) and (2), assessing the effect of different level of heat exposure on wheat yield (upper panel) and test weight (lower panel), respectively. The last part of the table gives brief information on alternative specifications. Here we consider five specifications. First column shows the estimates from our preferred model. In specification (2), we remove time trends and precipitation from the preferred model, so that we can see the response from weather effect directly. Specification (2) adds precipitation, so only the time trends are dropped. Specification (3) adds time fixed effects instead of time trends. Finally, in specification (4), we restrict our sample to only the top twenty locations, which appear more than 20 years. (In this case, our observations are reduced to 9,899)

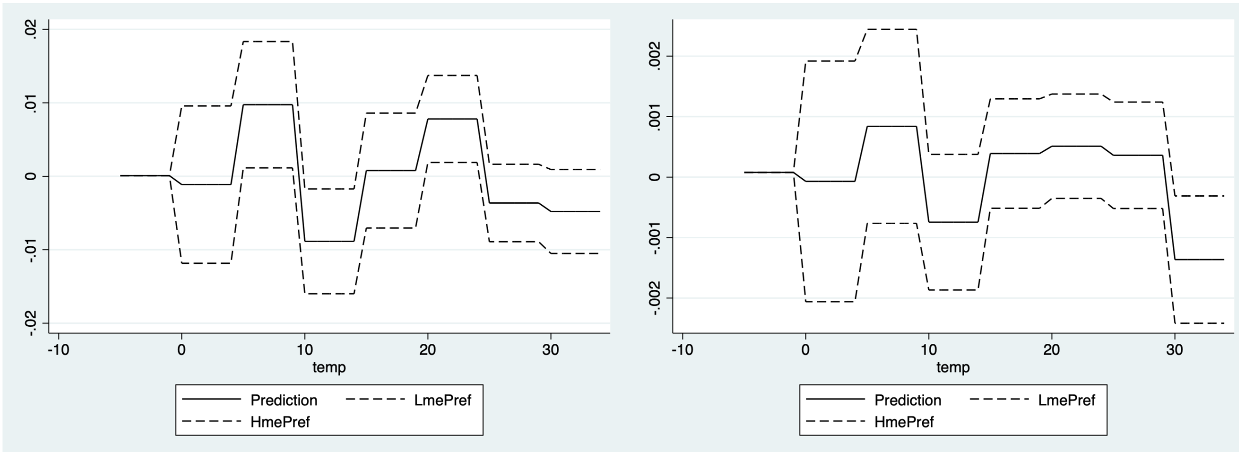
The noticeable results from our preferred model are the high level of heat exposures above 32 degree Celsius induce significant reductions on both wheat quantity and quality. That is, an additional twenty four hour of exposure over 32 degree Celsius during growing season is associated with approximately -0.79% and -0.16%, respectively. Also, the moderate range of heat exposure influence positively on wheat yield and test weight. The results show that the quality is more vulnerable to coldness compared to the quantity, although they are statistically insignificant in both cases. Additionally, they does not exhibit any strong sensitivity on precipitation as well.

Compared to the other specifications, the temperature effects on wheat from the specification (1), (2) represent the similar results even without the time trends and precipitation. When including the time fixed effect in our model, the coefficients on high and moderate temperature becomes statistically insignificant. We guess that this result comes from that the weather variables are correlated across locations over times. Meanwhile, when considering only the most appeared trial locations (more than 20 years) show weather effect less clearly compared to preferred model. Estimates are not significantly different in absolute value and have similar standard errors compared to the full-sample estimate, which implies

Table 1: Weather effect on Wheat Yields and Quality

	Preferred	Spec(1)	Spec(2)	Spec(3)	Spec(4)
			Wheat Quantity		
year	-0.2065			0	-0.2238
	(0.4403)			(.)	(0.6432)
year sq.	0			0	0.0001
	(0.0001)			(.)	(0.0002)
low temperature	0.0004	0.0005	0.0003	0.0011	0.0019
	(0.0006)	(0.0006)	(0.0006)	(0.0008)	(0.0013)
med tempertarue	0.0009***	0.0009***	0.0010***	0.0001	0.0010**
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
high temperature	-0.0079***	-0.0096***	-0.0083***	0.0035	-0.0034
	(0.0029)	(0.0029)	(0.0029)	(0.0043)	(0.0023)
preccipitation	-0.0003		-0.0003	0	0.0003
	(0.0005)		(0.0005)	(0.0005)	(0.0006)
precipitation sq.	0.0000		0.0000	0.0000	0.0000
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
_cons	216.7637	2.9469***	3.0973***	2.6478***	234.7498
	(440.1505)	(0.5820)	(0.5968)	(0.7916)	(642.6510)
r2	0.4101	0.408	0.4095	0.4863	0.3616
			Wheat Quality		
year	-0.0091			0	-0.0305
	(0.0659)			(.)	(0.0729)
year sq.	0			0	0
	(0.0000)			(.)	(0.0000)
low temperature	0.0000	0.0000	0.0000	0.0001	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
med tempertarue	0.0002***	0.0002***	0.0002***	0.0001**	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(-0.0001)	(0.0000)
high temperature	-0.0016***	-0.0024***	-0.0016***	0	-0.0018**
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0007)
preccipitation	0.0001		0.0001	0.0001	0.0001
	(0.0001)		(0.0001)	(0.0001)	(0.0001)
precipitation sq.	0.0000		0.0000	0.0000	0.0000
	(0.0000)		(0.0000)	(0.0000)	(0.0000)
_cons	13.7484	3.9484***	3.9529***	3.7683***	34.8916
	(65.6681)	(0.1014)	(0.1084)	(0.1310)	(72.7475)
r2	0.28	0.2732	0.2798	0.345	0.2816
Location FE	Y	Y	Y	Y	Y
Variety FE	Y	Y	Y	Y	Y
Time trend	Y	N	N	Y	Y
Time FE	N	N	N	Y	N
Top 20 Locations	N	N	N	N	Y

Figure 1: Marginal effect of temperature on quantity and quality



(a) Marginal effect of temp on yield

(b) Marginal effect of temp on quality

Note:

that the our preferred model does not cause severe noise with the low-appearing sites.

Figure 1 depicts the marginal effect of temperature on wheat yield and quality with each of 5 degree-Celsius interval. The up and down appear to be severe within the interval which corresponds to our low temperature variable(0-14 degree-Celsius), so that the aggregate effects from low degree days are hard to tell in both yield and test weight. Wheat quantity and quality rise in the range of moderate temperature (15-31 degree-Celsius) but drop radically in high temperature. Generally, even though yield and test weights response in the same direction, yield moves more dynamically depending on the temperatures and its threshold on extreme heat is less than test weight.

Overall, in case of wheat in the US, high temperatures lead to considerable loss both on yield and quality, while medium range of temperature increase both. The dominant effect between two would be discussed in the simulation part. Unlike the rice case, we could not find a significant negative effect from low temperature exposure (Kawasaki and Uchida, 2016). However, our findings are consistent with other previous studies (Tack et al., 2017; Ramsey et al., 2020).

5.1 Robustness checks

To check robustness, we apply following four other specification by i)changing the duration of growing season, ii)varying the thresholds value, iii)using average temperature and max/min temperature. Our preferred model assumes that the growing season is from early of May to early of October. We will adjust this duration from mid May to late October as in Shew et al. (2020) Several previous studies obtained meaningful results by using average temperature or max/min temperature (Kelly et al., 2005). Hence, we will replace the preferred piece-wise linear model with measures of average, maximum, minimum daily temperatures. In lieu of three thresholds used in Tack et al. (2017), Shew et al. (2020) set the various define high temperature from 30 Celsius degree to assess the South African wheat. Applying this approach to our own data yields the similar results that the extreme heat exposure is associated with the reduction in yield and test weight while moderate warm climate affects to them positively.(Table 2) Interestingly, the sign of the coefficients are changing in the range of low temperature, which indicates the total effect is hard to measure as in our preferred model.

6 Conclusion

In this article, we quantify the quality by measuring wheat test weights as well as yield. Our results show that the extreme heat exposure is associated with the reduction in yield and test weight while moderate warm climate affects to them positively as in the existing literature. Another finding is that the quality reacts more stable on the climate changes and relatively more tolerant to high temperature compared to the quantity. However, quality reduced dramatically from 30 degree Celsius as well.

There are several limitations to our model. First, we assume the growing season is fixed from May to October due to the lack of availability on planting date data. In this case, the climate impacts are regarded as constant across the periods, and the heterogeneous weather

Table 2: Robustness Check

	Quantity		Quality	
	preferred	robu1	preferred	robu1
year	-0.2065	-0.2364	-0.0091	-0.0156
	(0.4403)	(0.4422)	(0.0659)	(0.0657)
year2	0.0000	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	0.0000	0.0000
low	0.0004	0.0005	0.0000	-0.0001
	(0.0006)	(0.0009)	(0.0001)	(0.0001)
med	0.0009***	0.0009***	0.0002***	0.0002***
	(0.0003)	(0.0003)	0.0000	0.0000
high	-0.0079***	-0.0036**	-0.0016***	-0.0008***
	(0.0029)	(0.0015)	(0.0005)	(0.0002)
prec	-0.0003	-0.0003	0.0001	0.0001
	(0.0005)	(0.0004)	(0.0001)	(0.0001)
prec2	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0000	0.0000	0.0000
_cons	216.7637	246.6334	13.7484	20.2926
	(440.1505)	(441.9453)	(65.6681)	(65.5069)
r2	0.4101	0.4097	0.2800	0.2798
r2_a	0.3977	0.3973	0.2639	0.2636
F	4.8573	4.8928	9.9584	8.8677

effects on growth stages are difficult to understand, which may lead to bias (Kawasaki and Uchida, 2016). Second, as our study does not compare the quantity effect and quality effect in monetary terms, it is unclear which one is dominant. Third, our spatial data may be less accurate in interpolating the weather station and wheat sites. Forth, this study does not consider the interactive effects of temperature and precipitation as the combined effects may be synergistic to crop quantity and quality. (i.e.drought)

Reflecting these limitations, as a short-term goal, we would conduct the rest of the robustness checks and the simulation to provide more practical implications on policy-making, adaption, and breeding strategies for wheat. Long-termly, we would consider adding the factors such as the interaction of temperature and precipitation, wind speed, or radiation, avoiding the collinearity of these variables. More specified standards for wheat thresholds, interpolations, and growing periods should be developed as well. Additionally, as the Rsquare values from the model are not high enough, we would apply the Bayesian approach for comparison.

7 Supplementary Appendix

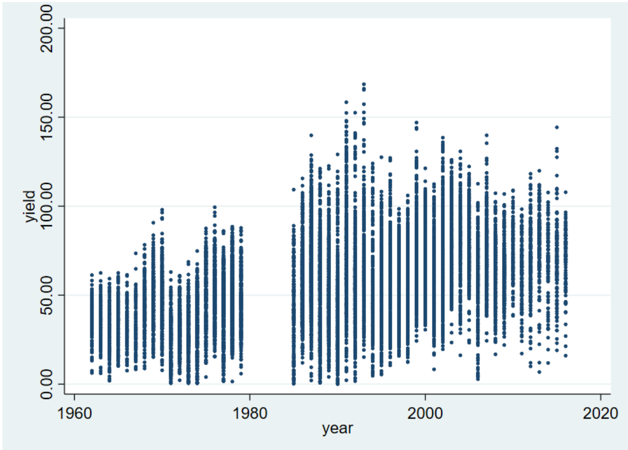
Table 3: S1. Summary Statistics

Variable	Obs	Mean	Std Dev	Min	Max
Yield (bushel/acre)	16,528	56.72914	23.66551	0.1	168.5
Testweight (lbs/bushel)	15,468	56.18637	3.891573	3.6	68.6
Location	16,712	31.03333	17.8796	1	62
Variety	16,712	133.2931	78.25539	1	271
Low Temperature (degree days)	16,597	1049.001	52.2227	744.7651	1103.956
Med Temperature (degree days)	16,597	569.0127	145.1504	106.9197	880.4106
High Temperature (degree days)	16,597	3.807941	4.763703	0	40.57397
Precipitation (cumulative)	16,597	318.4652	114.132	7.274976	792.7465

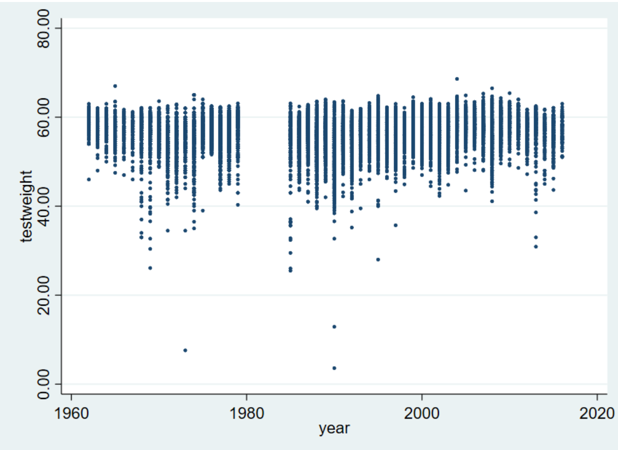
Table 4: S2. Number of Locations by States

State	locs (Total)	locs (Top 20)
Alabama	1	1
Arkansas	5	2
Delaware	1	
Florida	3	2
Georgia	5	4
Idaho	1	
Illinois	1	
Indiana	6	
Kansas	3	
Kentucky	5	1
Louisiana	3	1
Maryland	2	1
Mississippi	7	
Missouri	1	1
New Mexico	1	
North Carolina	4	2
Ohio	1	
Pennsylvania	1	
South Carolina	4	2
Tennessee	1	1
Texas	3	1
Virginia	2	1
Wisconsin	1	
24	62	20

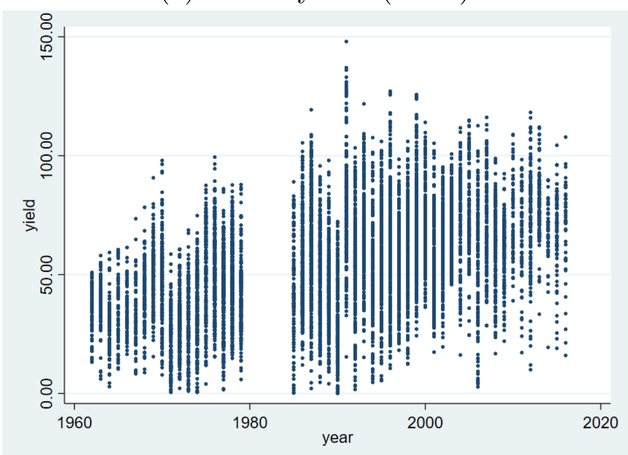
Figure 2: S1. Quantity and Quality by Year



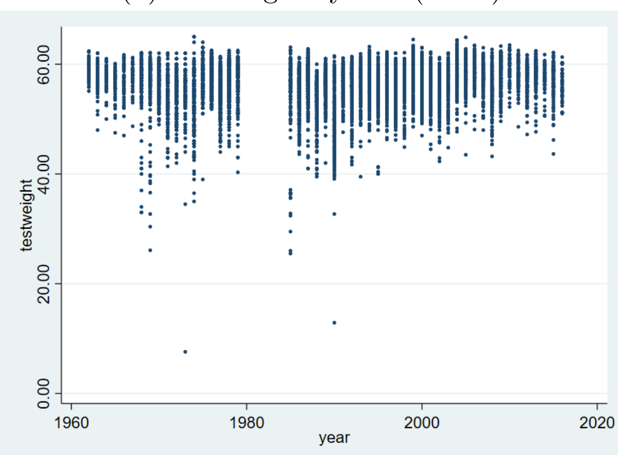
(a) Yield by Year(Total)



(b) Testweight by Year(Total)



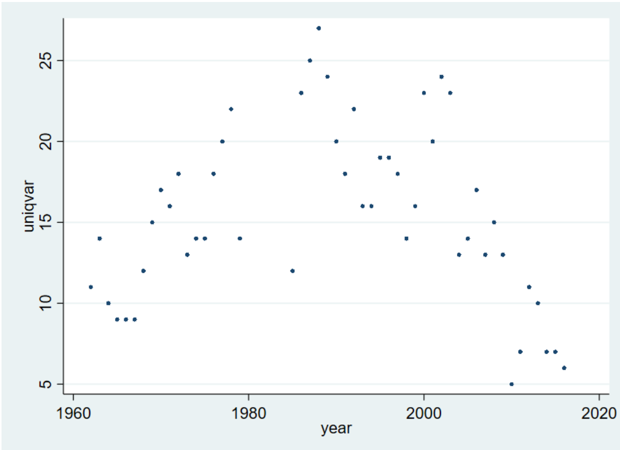
(c) Yield by Year(Top 20 locs)



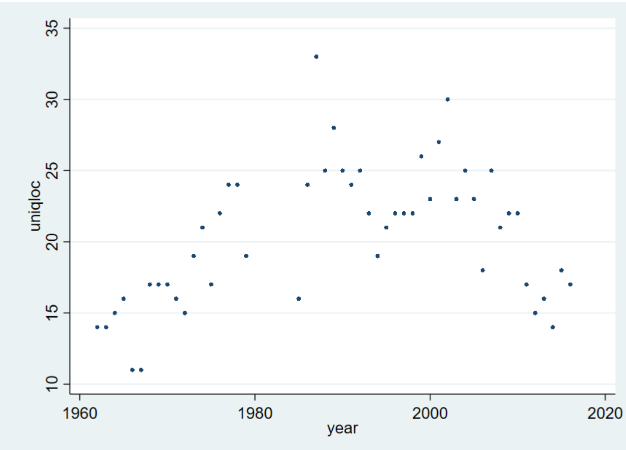
(d) Testweight by Year (Top 20 locs)

Note:The yield has an increasing trend over time but is slightly decreasing or similar after the 1990s. Test weight by year appears to be quite even across the time. The pattern is similar when only top 20 locations are considered.

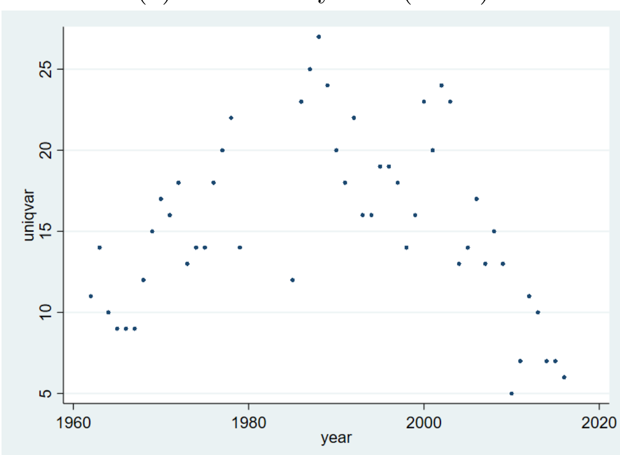
Figure 3: S2. Varieties and Locations by Year



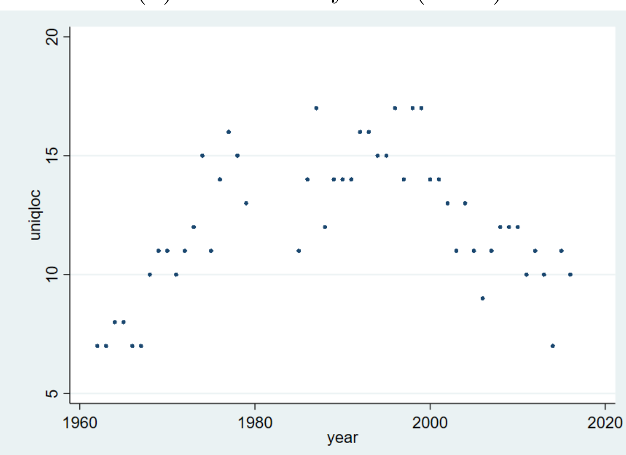
(a) Varieties by Year(Total)



(b) Locations by Year(Total)



(c) Varieties by Year(Top 20 locs)



(d) Locations by Year(Top 20 locs)

Note: The number of planted wheat varieties and locations have the inverted U-shapes in all cases.

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