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Economic Implications of Extreme Heat Effects on Rice Yield and Milling Quality in Arkansas

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ABSTRACT

Future increases in global surface temperature threaten those worldwide who depend on rice production for their livelihoods and food security. Past analyses of extreme heat effects on rice production have focused on paddy yield and have not accounted for the detrimental impact of extreme heat on milling quality outcomes which ultimately determine edible (marketable) rice yield and value. Using rice yield and milling quality data on six popular rice cultivars from Arkansas, USA, combined with on-site, half-hourly and daily temperature observations, this study finds a nonlinear effect of extreme heat exposure on yield and milling quality. A 1 °C increase in average growing season temperature reduces paddy yield and producer revenue by 8.2%; total edible rice yield by 9 to 9.9%; high-quality edible rice yield (kg ha-1) by 10.4 to 15.6%; and total milling revenue by 11.1 to 38.7% across genotypes. Utilization of the significant annual and locational temperature variability in the dataset allows examination of further mean growing season temperature increases of 2 and 4 °C. Results show that failure to account for changes in milling quality leads to significant understatement of the impacts of extreme heat on rice production outcomes.

This thesis is approved for recommendation
to the Graduate Council.

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I also owe many thanks to my brilliant spouse, Danielle, and fantastic pets – Cleo, Lincoln, and Sierra.

Finally, I must express my deep gratitude to my loving parents, Anne Meszko and Mark Lyman, who have always supported my academic endeavors.

DEDICATION

To my smoking-hot wife, Danielle

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LIST OF ABBREVIATIONS

Abbreviation	Definition
RRY	Rough rice yield
MRY	Milled rice yield
HRY	Head rice yield
BKN	Broken rice yield
CHK	Chalk content
Tmin	Average daily minimum temperature
Tmax	Average daily maximum temperature
Tavg	Average daily temperature
VPD	Vapor pressure deficit
TD33	Thermal days above 33 C
TN22	Thermal nights above 22 C
TDN	Total thermal exposure above critical levels (TD33 + TN22)
W1	Window 1
W2	Window 2
W3	Window 3

I. INTRODUCTION

Current climate change models project mean global temperature increases between 1.8 °C and 4 °C by the end of the century (IPCC 2007). Increases of even the lower magnitude could result in current notions of extreme temperatures becoming the norm, and future extreme temperatures becoming catastrophic to rice production. Climate change therefore threatens roughly one billion people who depend on rice cultivation as their primary source of income, and the food security of roughly 3.5 billion people who depend on rice for more than 20 percent of their daily caloric intake (IRRI 2012). Impacts of climate change on rice production could devastate rural Asian economies where average farm size ranges from less than half a hectare in China, Indonesia, and Vietnam, to over two hectares in Thailand, Myanmar, the Punjab in India, and Cambodia (Toriyama, Heong, and Hardy 2005). Rice provides nearly 50 percent of daily caloric intake in South East Asia, 30 percent in South Asia, and over 25 percent in East Asia. In contrast, rice production plays a relatively small role in U.S. food security with rice consumption accounting for less than three percent of daily caloric intake (IRRI 2012).

Despite being the world's 10th largest rice producer by volume and area (FAO 2012), the relatively low domestic demand for rice allows the U.S. to export around half of domestic production, making it the fourth largest rice exporter (USDA-ERS 2012). Thus, the United States plays a substantial role in a very thin international market where global trade of milled rice accounts for roughly 6.8 percent of worldwide consumption and less than five percent of worldwide production (USDA-FAS 2012). The thin nature of the international rice market means that shocks to U.S. rice production from extreme heat can dramatically impact international price levels, sending ripples through the Asian rice markets where stable supply is critical to meet daily demand.

The economic value of rice production is determined at the field, mill, and market stages. Production shocks in any given stage affect value creation in later stages. Producer welfare depends on the sale of rough (unprocessed) rice to millers and miller welfare depends on sale of milled rice to domestic and international markets. Extreme heat, defined as the cumulative exposure to day and night temperatures above critical thresholds, can decrease rough rice yield and milling quality. The affected milling quality outcomes most important to economic and nutritional outcomes of rice producers and consumers are milled rice yield (MRY) – the mass ratio of milled kernels to initial rough rice kernels; and head rice yield (HRY) – the mass ratio of milled kernels ≥ three-quarters the length of an unbroken (whole) milled kernel to initial rough rice kernels; and broken rice yield (BKY) – the mass ratio of milled kernels < three-quarters the length of an unbroken (whole) milled kernel to initial rough rice kernels; and chalk content (CHK) – defined experimentally as the ratio of total chalky to non-chalky area of 100 brown rice kernels or in the market as the ratio of chalky to non-chalky kernels in a sample of milled rice, where chalky kernels are one-half or more chalky.

Broken kernels sell for roughly 60-70 percent of the value of whole kernels in the United States, depending on broken kernel dimension (USDA-ERS Rice Yearbook). Other milling quality aspects affected by extreme heat include premature (green) kernels, kernel dimension, amylose content and amalyopectin chain length. Chalk reduces HRY and can decrease the market value of head rice by up to 25 percent (Lisle et al. 2000). Recent research at the field and mill levels has shown modest increases in daily maximum and minimum temperatures can decrease rough rice yields by as much as 10 percent (Peng et al. 2004), dramatically alter the distribution of head and broken rice, and greatly increase the proportions of chalky kernels (Ambardekar et al. 2011; Lanning et al. 2011; Fitzgerald and Resurreccion 2009).

Despite the substantial amount of agronomic and physiological literature correlating extreme heat effects to reduced rice yield and quality outcomes at the plant and field levels (Wassmann 2009), very few studies have estimated heat effects in a predictive framework that quantify reductions in paddy yield quality given increases in temperature (Peng et al. 2004; Welch et al. 2010), and no such model exists for milling quality. Thus, the popular estimate of a 10 percent reduction in rough rice yield given a 1°C increase in mean growing season minimum temperature does not account for likely decreases in MRY and HRY and increase in chalk content that further reduce the yield and value of milled, edible rice (Peng et al. 2004).

To begin filling this gap in the literature, this study estimates effects of extreme heat on rough rice yield and the major determinants of milling quality using field-level experimental data from Arkansas, USA. Rough rice yield is estimated using a linear fixed effects model accounting for growth-stage specific, diurnal-temperature effects. Growth stage-specific effects of extreme heat on milling yield and chalk content are estimated using a system-of-equations model. Milling quality and chalk estimates are cultivar-specific, but data availability prohibits varietal specific estimation of the rough rice model. Data on varieties included in the milling model are pooled to estimate the rough rice model. Varietal-specific fixed-effects are estimated in the rough rice model. Together these models provide comprehensive, practical estimates of reductions in paddy and milling yield and quality attributable to growth stage specific, diurnal extreme heat events. Changes in mean paddy yield, milled yield, and chalk content are estimated given 1, 2, and 4 °C warming and economic implications are discussed. Expected future warming and the global economic importance of rice production necessitate this discussion.

II. LITERATURE REVIEW

Explaining the relationship between extreme heat and rough rice yield and milling quality outcomes requires identification of growth stages sensitive to extreme heat exposure, the definition of "extreme," and how these differ across rice cultivars. Sensitive stages and the definition of extreme differ among yield and quality attributes across cultivars and existing literature often focuses on a specific element for a specific cultivar. The following analysis of this vast, disjointed body of literature focuses seperately on the documented relationships between extreme heat and rough rice yield and milling quality.

A. ROUGH RICE YIELD

Paddy yield responses to temperature differ among developmental stages and depend on the magnitude and diurnal distribution of heat. Physiological processes affected by extreme temperatures can be divided into three broad developmental stages: vegetative, reproductive, and ripening (Wassman et al. 2009; Welch et al. 2010). Extreme day temperatures during the vegetative stage have been shown to reduce plant height, tiller quantity and dry weight (Yoshida et al. 1981). Reproductive processes surrounding anthesis are sensitive to day temperatures above 33 °C (Satake and Yoshida 1978). Daytime temperatures above 33 °C have been linked to decreased paddy yield by reducing spikelet sterility (Prasad et al. 2006). Jagadish et al. (2010) found varietal differences in response to extreme temperatures (38 °C) at anthesis with spikelet fertility varying between 18 and 71 percent. Baker (2004) reported constant growing season temperatures of 36 °C resulted in zero grain yield for three U.S. cultivars.

Night temperatures have also been shown to negatively affect reproductive processes and reduce yield. Night temperatures above 29 °C during anthesis increase susceptibility to sterility and sterility inhibits seed-set and reduces yield (Satake and Yoshida 1978; Ziska et al.

1996). Mohammed and Tarpley (2009) exposed rice to extreme night temperatures (32 °C) from 20 days after emergence to harvest and reported decreased crop growth duration, percent pollen germination and spikelet fertility. Nagarajan et al. (2010) identified 22-23 °C as the critical night temperature threshold and attributed significant reductions in grain yield to 1-2 °C increases in night temperatures above the threshold during the flowering and grain filling period. It is unclear whether vegetative temperature variability is controlled for in Nagarajan et al. (2010)'s analysis of night temperatures during the flowering and grain filling stage. Kanno and Makino (2010) observed night temperatures of 27 °C lead to a decline in grain yield relative to night temperatures of 22 °C. They attributed this decline to a reduction in grain weight and ratio of filled spikelets. Vegetative stage temperatures were held constant in their experiment and they reported no difference in number of panicles or spikelets. Recent econometric analysis of farmer and experimental field data correlate increases in average daily minimum temperatures (Tmin) during the vegetative stage with decreases in rough rice yield (Welch et al. 2010; Peng et al. 2004).

Recent econometric analyses of extreme temperature effects on rough rice yields estimate the marginal effects of diurnal temperature variability. Peng et al. (2004) use experimental field data and find a significant inverse relationship between T_{min} and rough rice yield, and conclude a 1 °C increase in minimum temperature is associated with a 10 percent reduction in paddy yield. Peng et al. (2004) is a benchmark study of the relationship between rice yields and extreme heat because it presents the link between nighttime temperatures and rough rice yield, and uses field-level data to establish the link. Welch et al. (2010) find a similar link between nighttime temperatures and paddy yield using a field level dataset. The study expands on Peng et al. (2004) by looking at the effects of temperatures and solar radiation in three growth periods: vegetative, reproductive, and ripening; and, by estimating the effects using more sophisticated multiple regression models. Dixon et al. (1994) use a similar approach to estimate climatic effects on maize yields in the central United States. Welch et al. (2010) conclude minimum temperatures decrease yield during the vegetative and ripening stages; maximum temperatures increase yield during the vegetative stage; and, solar radiation decreases and increases yield during the vegetative and ripening stages, respectively. Dixon et al. (1994) find a similar negative effect of solar radiation on maize yields during the vegetative growth stage. Similar approaches are used to estimate the effects of temperature variability on wheat, soybeans, corn, and cotton (Lobell et al. 2011; Schlenker and Roberts 2009).

B. MILLING QUALITY

Milling quality refers to the many aspects of milled rice affecting cooking quality, visual appearance, and value. Often reported quality aspects include chalk content, grain dimensions, immature kernel content, amylose content, and/or amylopectin chain lengths. Temperature variability during the reproductive and ripening stages affects all of these qualities to some degree, but chalk content has been a primary focus of experimental research because it is easily detected visually and consequent reduction of the market value of milled rice (Asaoka et al. 1985; Patindol and Wang 2003; Naranjan et al. 2010; Hayashi et al. 2011). Chalk manifests as an opaque or milky white region in part or all of the endosperm resulting from air spaces between loosely packed and poorly-developed starch granules (Tashiro and Wardlaw 1991). Extreme temperatures at various stages of endosperm development are thought to be responsible for the various types of chalk; hot temperatures during early endosperm development (grain filling) cause milky-white and white-core chalk development at the center of the endosperm; hot temperatures during later grain filling can cause white-back and basal white chalk development on the outer portions of the endosperm (Tashiro and Wardlaw 1991; Tsukaguchi and Ida 2008).

Recent research suggests the irregularly packed starch granules responsible for chalk formation result from curtailed substrate (nutrient) availability during grain filling in hot temperatures. The decreased nutrient availability is especially detrimental to grain development among inferior spikelets. Inferior spikelets begin grain development up to seven days later than spikelets on the primary panicle branch, leading these spikelets to fill in nutrient-sparse conditions if temperatures have shortened the substrate availability window (Fitzgerald and Resurreccion 2009). This research suggests spikelets located on inferior branches, even on the main stem panicle, will have relatively high chalk contents and thus decreased grain weight.

Elevated temperatures decrease kernel dry weight during the grain filling stage and extreme heat during early grain filling can interfere with the development of a fertilized endosperm and lead to abortion of kernel development (Tashiro and Wardlaw 1991). High day and night temperatures increase the rate of grain dry weight accumulation, final grain weight decreases due to reduced endosperm size (Morita et al. 2005). Elevated day and night temperatures also decrease grain length, width, and thickness (Yamakawa et al. 2007).

A substantial body of literature focuses on the inverse relationship between HRY and elevated night temperatures. Counce et al. (2005) find elevated night temperatures during late grain filling reduce HRY, but do not control for nor test effects of elevated day temperatures. The study suggests elevated night temperature inhibit the production/function of enzymes responsible for starch synthesis and is supported by Cheng et al. (2005). Using a historical data set from Arkansas, USA, Cooper et al. (2006) correlate mean daily minimum and maximum temperatures occurring during reproductive growth stages (using methodology developed in

Counce et al. (2000)) to HRY and find high night temperatures during the R8 stage – defined as one grain on the main stem panicle having developed a brown hull – explain 26 percent of the variability in HRY for two long-grain cultivars grown in Arkansas over a 17 year period and increased minimum temperatures throughout the latter two-thirds of grain filling explain 50 percent of HRY variability. A follow-up, phytotron study by Cooper et al. (2008) using controlled night temperatures of 18, 22, 26, and 30°C from midnight to 5 a.m. found that HRYs of both pure-line and hybrid cultivars are negatively related, with the exception of two cultivars generally known for their stable milling quality. Neither Counce et al. (2005), Cheng et al. (2005), Cooper et al. (2006), nor Cooper et al. (2008) hold day temperatures constant during their analyses of night temperature effects, nor do they use statistical methods (e.g. multiple regression) capable of ceteris parabus analyses.

Ambardekar et al. (2011) evaluate night temperature effects on six pure-line and hybrid cultivars grown across various locations from northern to southern Arkansas. The study reports that the 95th percentile of night temperature observations for a given variety/location/year is significantly correlated to HRY and chalk. Increased NT95 results in decreased HRY and increased chalk for the majority of cultivars. Lanning et al. (2011), using field trials on the same varieties used in Ambardekar et al. (2011), confirms the detrimental impact of elevated night temperatures. Addition of the historically high temperatures observed in 2010 reveals that even the varieties with previously stable HRY and CHK (Ambardekar et al. 2011) exhibit a positive correlation of CHK and a negative correlation of HRY when exposed to extreme temperatures during grain-filling.

III. METHODOLOGY

Understanding the economic impacts of increasing temperatures on rice production at the farm and mill level requires modeling the relationship between high temperature events, rough rice yield, milling quality, and rice prices. At the farm level, producer revenue per unit area harvested depends on rough rice yield and rough rice price, where rough rice price is a function of both milling quality and exogenous market forces. Mill revenue from a unit area of harvested rough rice delivered to the mill is a function of the mass quantities of milled rice and byproducts obtained from the initial quantity of rough rice and the associated prices of milled rice and byproducts.

Cost functions associated with revenue at the farm and mill levels include variables that are functions of the temperature parameters, such as flood depth and/or duration (Hayashi et al. 2011), crop nutrient application (Fitzgerald and Resurreccion 2009), and other production decisions that influence temperature related outcomes. To maximize profits given these costs functions would thus require balancing input costs and expected returns. Due to data limitations, mitigation of the detrimental effect of high temperatures is not a subject of this article so the discussion of economic implications is limited to changes in revenue at the farm and mill levels given changes in temperature parameters, holding constant any heat damage mitigation responses. Furthermore, data is not available on the relationship between expected rough rice yield quality and rough rice prices so in this analysis rough rice prices will be assumed constant given changes in growing season temperature conditions.

Despite lacking data to estimate high temperature mitigation response functions and resulting profit implications, the interrelated nature of rough rice yield and milling quality given the mill's reliance on rough rice input and the dependence of rough rice price on milling quality necessitates modeling the implications of increasing growing season temperatures on both rough rice yield and milling quality.

A. ANALYTICAL FRAMEWORK

This analysis models the effects of extreme heat events on RRY, MRY, HRY, and CHK to examine implications of increases in mean growing season air temperatures on rice producer and miller returns. Assume that rough rice output is given by $Y_R(H)$, where H denotes a general term representing growing season temperatures with producer decisions affecting Y_R held constant. Let P_R denote the price of rough rice. The farm revenue maximization problem is:

(1) $$\max \mathrm{TR}_{\mathrm{Farm}} = P_R RRY(H).$$

As mass percentages, MRY and HRY serve as useful experimental and market measures of the quality of a sample of rough or milled rice, but alone they do not provide enough information to estimate mill revenue implications of a change in H. Given $Y_R(H)$, $MRY(H)$, and $HRY\big(H, CHK(H)\big)$ the mass quantities of milled head rice (Y_{HR}) and broken rice (Y_{BK}) can be approximated as $Y_R HRY$ and $Y_R(MRY - HRY)$, respectively. Chalky head rice is discounted by separating Y_{HR} into chalky (Y_{CHR}) and non-chalky (Y_{NCHR}) head rice given by $Y_{HR}CHK$ and $Y_{HR}(1 - CHK)$, respectively. Let $P_1$and P_2 denote the prices of high quality (non-chalky head) and low quality (chalky head and broken) rice, respectively. Mill revenue per acre of harvested rice is:

(2) $$\max \quad {}_{\mathrm{Mill}} = P_1 Y_{NCHR} + P_2(Y_{CHR} + Y_{BK}).$$

Changes in equations (1) and (2) given changes in *H* provide the primary results of this analysis. Holding constant P_R, the implications of a change in *H* on total farm revenue are straightforward:

$$\frac{d \quad {}_{\text{Farm}}}{dH} = P_R \frac{dY_R(H)}{dH}. \tag{3}$$

Implications of a change in *H* on mill revenue are less straightforward because Y_{NCHR}, Y_{CHR}, and Y_{BK} are functions of the endogenous variables Y_R, MRY, HRY, and CHK. As a result, changes in *H* have less clear effects on mill revenue than on farm revenue. Breaking Y_{NCHR}, Y_{CHR}, and Y_{BK} into their component functions, a change in *H* has the following effects on milling revenue:

$$\frac{d\text{TR}_{\text{Mill}}}{dH} = P_1 \frac{dY_{NCHR}}{dH} + P_2 \left(\frac{dY_{CHR}}{dH} + \frac{dY_{BK}}{dH} \right), \tag{4}$$

where changes in $\quad_{NCHR}, Y_{CHR}$, and Y_{BK} are given by:

$$\begin{aligned} \frac{d\text{Y}_{NCHR}}{dH} &= \frac{dY_R(H)HRY\big(H, CHK(H)\big)\big(1 - CHK(H)\big)}{dH} \\ &= \frac{dY_R}{dH} HRY(1 - CHK) + Y_R \left[\frac{dHRY}{dH} + \frac{dHRY}{dCHK} \frac{dCHK}{dH} \right] (1 - CHK) \\ &\quad - Y_R HRY \frac{dCHK}{dH}, \end{aligned} \tag{5}$$

$$\begin{aligned} \frac{d\text{Y}_{CHR}}{dH} &= \frac{dY_R(H)HRY\big(H, CHK(H)\big)CHK(H)}{dH} \\ &= HRY \frac{dY_R}{dH} CHK + Y_R \left[\frac{dHRY}{dH} + \frac{dHRY}{dCHK} \frac{dCHK}{dH} \right] CHK + Y_R HRY \frac{dCHK}{dH}, \end{aligned} \tag{6}$$

and,

$$
\begin{aligned}
\frac{dY_{BK}}{dH} &= \frac{dY_R(H)\big[MRY(H) - HRY\big(H, CHK(H)\big)\big]}{dH} \\
&= \frac{dY_R}{dH}[MRY - HRY] + Y_R\left[\frac{dMRY}{dH} - \frac{dHRY}{dH} - \frac{dHRY}{dCHK}\frac{dCHK}{dH}\right].
\end{aligned} \tag{7}
$$

Equations (5), (6), and (7) describe the cumulative change in both quantity and distribution of mill outputs given a change in growing season temperature conditions (*H*) in terms of changes in rough rice yield and milling quality.

An ideal empirical model of the economic implications of a change growing season temperature conditions would specify rough rice and milling quality as a system of equations; however, in this study data limitations prevent such a specification and rough rice yield must be modeled separately from the milling quality system. As a result, equations (5), (6), and (7) are calculated using outcomes from the separate rough rice yield and milling quality models described below.

B. ROUGH RICE YIELD

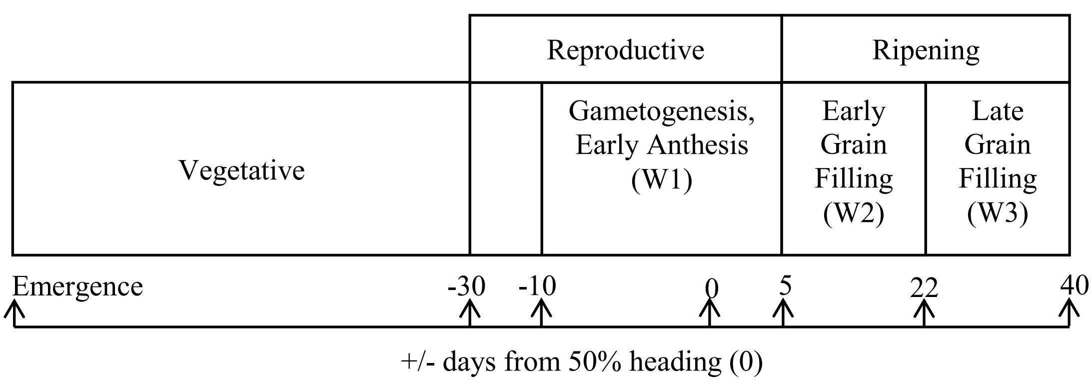
Rough rice yield is estimated using a fixed-effects OLS multiple regression model of the form:

$$
\ln Y_{R,isj} = \boldsymbol{a}\boldsymbol{X}_{R,isj} + \boldsymbol{b}_s + \boldsymbol{c}_j + \varepsilon_{isj}, \tag{8}
$$

where $\ln(Y)_{R,isj}$ is the natural logarithm of rough rice yield (kg ha^{-1}) for trial *i* at station *s* and variety *j*; $\boldsymbol{X}_{R,isj}$ is a vector of weather variables for that trial-location-variety combination; $\boldsymbol{a}$ is a vector of weather coefficients; $\boldsymbol{b}_s$ is a vector of station intercepts to control for spatially invariant unobserved effects such as soil type; $\boldsymbol{c}_j$ is a vector of variety intercepts to capture genetic yield differences across varieties; and ε_{isj} is a vector of error terms. Under this specification $\boldsymbol{a}\boldsymbol{X}_{R,isj}$ represents the growing season conditions (*H*) for a given observation.

Previous literature agrees neither on the appropriate set of weather variables to include in $\boldsymbol{X}_R$ – suppressing trial, location and variety subscripts – nor on the best method of aggregating weather data. Appropriate weather variable aggregation method and variable selection has been shown to depend on weather data availability, frequency, variability and correlations (Peng et al. 2004; Sheehy et al. 2006; Welch et al. 2010; and Lobell and Monasterio 2007, 2011). Considering these factors, this study estimates equation (8) using three methods of weather data aggregation to define variables in$\boldsymbol{X}_R$ (denoted $\boldsymbol{X}_{R1}, \boldsymbol{X}_{R2}$, and $\boldsymbol{X}_{R3}$), and for each aggregation method multiple combinations of weather variables are included. Weather data is aggregated in $\boldsymbol{X}_{R1}$ across the entire growing season following Peng et al. (2004); in $\boldsymbol{X}_{R2}$ across the vegetative, reproductive, and ripening growth stages (Figure 1) following Welch et al. (2010); and in $\boldsymbol{X}_{R3}$ combining the growth stage with a novel approach using narrower windows (Figure 1) for especially sensitive growth periods. Sets of weather variables are selected for each aggregation method following the previous modeling literature.

Figure 1. Rice (*Oryza sativa L.*) developmental stages



Vegetative, reproductive and ripening growth stages are defined relative to the observed 50 % heading and emergence dates at each station. The vegetative, reproductive, and ripening stages are defined as the intervals [emergence, H – 30), [H – 30, H + 5], (H + 5, harvest], respectively, where H denotes 50 % heading. The ripening stage is divided into early and late grain filling denoted by W2 and W3 to account for the differential effects of temperature on the physiological processes occurring during these periods.

Harvest dates are not available for the rough rice yield data so harvest is approximated as 40 days after 50% heading. Harvest dates are available for the milled rice yield and quality data, but some plots were not harvested at maturity to allow harvest moisture content (HMC) to decrease. To avoid inclusion of temperatures beyond maturity, min {H + 40, harvest} is used as the harvest date for milling quality trials.

Correlations among weather variables are especially important when selecting the proper model because collinearity can confound statistical estimates of day versus night temperatures on crop yields and omission of correlated weather factors may produce biased parameter estimates (Sheehy et al. 2006; Lobell and Monasterio 2007; Welch et al. 2010). Multiple regression analysis can sort out partial marginal effects of mutually correlated independent random variables, but high correlations among two or more independent variables can lead to near perfect multicollinearity and result in highly unreliable parameter estimates characterized by inflated standard errors and unexpected signs and/or magnitudes (Verbeek 2008, 43). Correlations among weather variables in each model are examined and colliniarity diagnostics are preformed to identify potentially misleading parameter estimates and/or standard error inflation.

Specification of yield as a function of growing-season (emergence to harvest) weather variables precludes observation of growth stage specific weather effects, but eliminates uncertainty associated with stage definition and requires only one-third of the parameters of a stage specific model and thus reduces the potential parameter instability associated with multicollinearity. Weather data aggregated over the entire season may provide a parsimonious specification of the yield equation, but it does not allow a sophisticated physiological explanation for extreme heat impacts on yield. Furthermore, the predictive power of season aggregated variables depends on the distribution of growing season temperatures in future years. Future extreme temperature observations may occur at times when plant growth is not susceptible to heat (or cold) damage, but annual weather variables could appear no different from in-sample observations of yield reduction, thus leading to incorrect prediction of out of sample observations. Stage-specific definitions of weather variables reduce this likelihood because they are capable of capturing the various harmful effects of extreme temperatures discussed above. Growth stage specific estimates as in Welch et al. (2010) can provide more interesting or insightful results, but often come at the cost of multicollinearity (Sheehy et al. 2006; Lobell and Monasterio 2007). For both season and growth stage aggregation methods eight definitions of $\boldsymbol{X}_R$ are used to estimate equation (8). The eight definitions are described in Table 1.

Table 1. Specifications of $\boldsymbol{X}_{R,isj}$ and definition of weather variables

Specification	$\boldsymbol{X}_{R,isj} = \{\ \}$
1	Mean daily minimum temperature (Tmin)
2	Tmin, Solar radiation (SR)
3	Mean daily maximum temperature (Tmax)
4	Tmax, SR
5	Tmin, Tmax, SR
6	Mean daily average temperature (Tavg)
7	Tavg, SR
8	Vapor Pressure Deficit (VPD)

The third aggregation method utilizes the high frequency (30-minute interval relative to daily) temperature data available during sensitive growth periods (W1, W2, and W3 in Figure 1). To utilize the higher-frequency data, a thermal time approach is used to capture the extreme heat accumulation during growth stages similar to thermal accumulation methodologies implemented in previous studies (Jagadish et al. 2009; Lobel et al. 2011; Lobell et al. 2012). Unlike previous studies these variables are generated separately for day and night temperature observations allowing a diurnal approach shown important in Welch et al. (2010).

Harmful thermal day and night thermal time variables are defined for the following windows (W): W1, the early-flowering stage from 10 days before 50-percent heading to 5 days after 50-percent heading; W2, the early-grain filling window from 6 days after 50-percent heading to 22 days after 50-percent heading; and, W3, the late grain-filling stage from 23 days after 50-percent heading to the earlier of 40 days after 50-percent heading or harvest. W3 is capped at the earlier of 40 days after 50-percent heading or harvest to avoid inclusion of weather observations during periods shown non-responsive to weather fluctuation (Figure 1). Harmful day and night thermal time are defined using 33°C and 22 °C as the day and night temperature thresholds. Daytime exposure above 33 °C is defined as:

(9)
$$TD_k = \sum_{T \in D_k} T_{idst},$$

for k = W1, W2, and W3, where T_{idst} is the temperature at time i on day d at station s in year t, and $D_k = \{T_{idst} : T_{idst} > 33\ ,\ sunrise_{dst} < i < sunset_{dst}, d_{\underline{k}} < d \leq d_{\overline{k}}\}$, where $d_{\underline{k}}$ and $d_{\overline{k}}$ start and end day of k, respectively.

The variable describing thermal nighttime above 22 °C is defined as:

(10)
$$TN_k = \sum_{T \in N_k} T_{idst},$$

for k = W1, W2, and W3, where T_{idst} is the temperature at time τ at station s in year t, and $N_k = \{T_{idst} : T_{idst} > 22\ ,\ sunset_{dst} < i < sunrise_{dst}, d_{\underline{k}} < d \leq d_{\overline{k}}\}$, where $d_{\underline{k}}$ and $d_{\overline{k}}$ start and end day of k, respectively. Daily sunrise and sunset estimates were calculated for each day/station/year combination using the National Oceanic and Atmospheric Administration's (NOAA) solar calculator (www.srrb.noaa.gov/highlights/sunrise/sunrise.html).

C. MILLING QUALITY

No predictive models of the relationship between extreme temperatures and milling quality currently exist. Previous experimental correlations of the relationships between extreme heat and milling quality guide the specification of a model capable of isolating diurnal and stage specific temperature effects. Following previous literature, this study focuses on extreme heat effects during the early (W2) and late (W3) grain filling periods (Counce et al. 2005; Ambardekar et al. 2010; Lanning et al. 2010). Controlling for harvest moisture content (HMC) is important as HMC proxies for immature and fissured kernels for which data is unavailable in this study; rice harvested at high HMC is prone to immature kernels and rice harvested at low HMC is highly susceptible to fissured kernels (Siebenmorgen et al. 2007).

Effects of extreme heat on milling quality are estimated using a system of linear-fixed effects equations:

$$CHK_{is} = \boldsymbol{\alpha}_1 \boldsymbol{W}_{is} + \boldsymbol{b_s} + u_{1is}, \tag{11}$$

$$HRY_{is} = \gamma CHK_{is} + \boldsymbol{\alpha}_2 \boldsymbol{W}_{is} + \beta_{21} HMC_{is} + \beta_{22} HMC_{is}^2 + \boldsymbol{b_s} + u_{2,is}, \tag{12}$$

$$MRY_{is} = \boldsymbol{\alpha}_3 \boldsymbol{W}_{is} + \beta_{31} HMC_{is} + \boldsymbol{b_s} + u_{3,is}, \tag{13}$$

where CHK_{is}, HRY_{is}, and MRY_{is} denote to chalk, head rice yield, and milled rice yield, respectively, for trial i at station s; $\boldsymbol{W}_{is}$ is the vector of the same weather variables in equations (11), (12), and (13); and $\boldsymbol{\alpha}_1$, $\boldsymbol{\alpha}_2$, and $\boldsymbol{\alpha}_3$ are the vectors of coefficients associated with the weather variables in $\boldsymbol{W}_{is}$. CHK_{is} appears on the right hand side (RHS) of equation (12) as an endogenous explanatory variable; γ is the slope parameter for CHK_{is} in equation (12); HMC_{is}

represents harvest moisture content (HMC) in equations (12) and (13); β_{21}, β_{22} and β_{31} are the slope parameters associated with HMC and HMC^2 in equations (12) and (13); $\boldsymbol{b_s}$ is a vector of station intercepts; and, $u_{1,is}$, $u_{2,is}$, and $u_{3,is}$ are error terms for each observation. Weather variables in $\boldsymbol{W}_{is}$ include TDN_{W2} and TDN_{W3} to capture temperature effects during early (W2) and late (W3) grain filling (Figure 1). HMC is included on the RHS of equations (12) and (13) to control for reductions in HRY due to fissured and immature kernels and to disentangle reductions in HRY and MRY attributable to extreme heat from those due to early or late harvest (Siebenmorgen, Bautista, and Counce 2007).

Both direct and indirect effects of extreme heat on HRY are estimated by including CHK_{is} and $\boldsymbol{W}_{is}$ on the RHS of equation (12), calculating the vector of indirect effects of extreme heat on HRY as $\boldsymbol{\alpha}_1\gamma$, the product of the effect of extreme heat on chalk and the effect of chalk on HRY. The vector of direct effects of extreme heat is $\boldsymbol{\alpha}_2$, thus the vector of total effects of extreme heat on HRY is calculated as $\boldsymbol{\alpha}_1\gamma + \boldsymbol{\alpha}_2$. Including CHK_{is} on the RHS of (12) makes the system recursive. Because $\boldsymbol{W}_{is}$ is included on the RHS of (13) with CHK_{is}, unbiased estimation of RHS parameters in (12) requires the error term of (12) be pairwise uncorrelated with the error term in equation (11). If ov$(u_{1,is}, u_{2,is}) \neq 0$, equation (12) includes an explanatory variable correlated with the error term and ordinary least squares (OLS) estimates will be biased (Wooldridge 2010). Omitting chalk content from equation (12) and regressing HRY_{is} and MRY_{is} on the weather and control variables would only provide unbiased estimates of the temperature coefficients if chalk content formation depended only on temperature conditions. Experimental research suggests at least some component of chalk formation is genetic (Fitzgerald and Resurreccion 2009), so CHK_{is} should be included on the right hand side of equation (12) to control for variation in HRY. Thus, it is necessary to test the null hypothesis

$_0$: ov$\left(u_{1,is}, u_{2,is}\right) = 0$ to determine whether an instrumental variables approach should be used to estimate equations (11) – (13).

Testing the endogeneity hypothesis requires additional exogenous variables correlated with chalk content, but uncorrelated with the error term of the HRY equation. For each observation, lagged mean daily minimum and maximum W2 and W3 temperatures are used as instruments to test the null hypothesis that CHK_{is} is endogenous in equation (12). This hypothesis is tested using a two stage procedure known as the Durbin-Wu-Hausman test (Wooldridge 2010). In the first stage of the test, a stepwise procedure was used to select the strongest instruments for inclusion in equation (12). Instrument strength was determined by F-tests of the joint significance of the coefficients associated with the included instruments where F-statistics greater than 10 signify a strong set of instruments (Verbeek 2008, 157). The first stage residuals are then included in the HRY equation as an explanatory variable. A t-test of the null hypothesis that the estimated coefficient of the residuals equals zero determines whether or not inclusion of CHK_{is} on the RHS of equation (12) requires an estimator that is consistent in the presence of an endogenous explanatory variable.

IV. DATA

Experimental data on six rice cultivars came from six University of Arkansas experiment stations in Arkansas over a four year period (2007 – 2010). Three long-grain (Wells, LaGrue and Cypress), two medium-grain (Bengal and Jupiter) and one long grain-hybrid (XL723) cultivar were grown in each location-year combination. However, data were not available from each location throughout the four year period. Table 2 describes data availability by location and model. Three randomized plots of each cultivar were planted in each location-year combination and cultivated for under conditions for "near optimal" yields and grain quality (Ambardekar et al. 2011).

Table 2. Characteristics of study sites

				Observations	
Station	Abbreviation	Latitude/longitude	Years	Rough	Milled
Corning	COR	36.4 °N / 90.6 °W	2007 - 2008	34	133
Kieser	KSR	35.7 °N / 90.1 °W	2009 - 2010	29	36
Newport	NPT	35.6 °N / 91.3 °W	2007 , 2010	43	75
Pine Tree	PT	35.1 °N / 90.9 °W	2008 - 2010	44	93
Rohwer	RWR	33.8 °N / 91.3 °W	2007 - 2010	62	157
Stuttgart	STGT	34.5 °N / 91.4 °W	2007 - 2010	76	215
Totals	--	--	--	288	709

In 2007, 2008 and 2009 the cultivars were harvested over a range of harvest moisture contents (HMC) and milled in duplicate. In 2010, the cultivars were harvested at targeted moisture contents based on optimal harvest moisture content levels defined in Siebenmorgen et al. (2007) and milled in duplicate. The change in harvest procedure resulted in fewer observations for each cultivar in 2010 than in 2007, 2008 and 2009. In each year, HMC and chalk were recorded for each harvest repetition and MRY and HRY was recorded for each milling repetition. Therefore, given two milling repetitions for each harvest repetition, there exist two unique HRY observations for each harvest repetition and associated chalk and HMC observations. Only the MRY and HRY observations associated with the measured chalk content were used in the current analysis.

MRY is calculated as the mass percentage polished head and broken kernels remaining after the milling of a 150 gram sample of rough rice:

$$MRY = \left(\frac{head\ rice + broken\ rice\ (g)}{rough\ rice\ (g)}\right) * 100. \tag{14}$$

HRY is calculated as the mass percentage polished whole kernels remaining after milling a 150 gram sample of rough rice and separation of broken kernels using a double-tray sizing device (Seedburo Equipment Co., Chicago, IL):

$$HRY = \left(\frac{head\ rice\ (g)}{rough\ rice\ (g)}\right) * 100. \tag{15}$$

Chalk content represents the percentage chalky area of a 100 kernel sample:

$$CHK = \left(\frac{chalky\ area}{total\ area}\right) * 100. \tag{16}$$

This experimental definition of chalk content differs from the common market definition. Marketers define chalk content as the ratio of chalky to non-chalky kernels in a sample and a chalky kernel is defined as consisting of 50 percent or more chalk (USDA Grain Standards, 2009). Experimental definitions of chalk content are usually defined as the ratio of chalky to non-chalky area of a sample of kernels. The inconsistent nature of definitions makes difficult the task of extrapolating experimental data to the market level because, for example, an experimental measurement of 25 percent chalk content does not necessarily mean that 25 percent of a sample of rice kernels has at least 50 percent chalky content.

Ambient air temperature and relative humidity recordings were collected at each location in 30-minute intervals using two temperature sensors (HOBO Pro/Temp Data Logger, Onset

Computer Co., Bourne, MA). The sensors were placed amid the 18-plot block of rice cultivars grown at each station. Given the randomized block design of cultivar location within each field, this study uses the set of means of each pair of 30-mintue temperature observations as the set of temperatures associated with a given year-location combination. Vapor pressure deficit (VPD) (kPa) was calculated using these data following Howell and Dusek (1995):

(17) $$VPD = 0.611e^{\left(\frac{17.27*T_i}{T_i+237.3}\right)}\left(1-\frac{RH_i}{100}\right).$$

Half-hourly weather data were not available prior to 50 percent heading at any experiment stations because the researchers were concerned only with high temperatures during grain filling. So other sources were used for temperature data during the early reproductive and vegetative growth stages. Daily mean minimum and maximum temperatures (°C) from nearby weather stations were used in place of these measurements. These data were obtained from National Oceanic and Atmospheric Administration (NOAA) weather stations within 50 km, but usually much closer to each experiment station. Daily averaged insolation on horizontal surface (mJ m^{-2}) (solar radiation) data for 2007-2010 and daily minimum and maximum air temperatures at two meters for 2006 data were obtained from the NASA Climatology Resource for Agroclimatology (NASA 2012).

Arkansas rice price, acreage, and export data used for economic analysis were obtained from USDA-ERS (2012) and USDA-FAS (2012). National averages of rough long- and medium-grain rice prices were used because Arkansas rough rice prices are not available. International production estimates were obtained from FAO (2012).

V. RESULTS

A. ROUGH RICE YIELD

Estimates of the regressions of RRY on weather variables are grouped by method of weather data aggregation: growing season, growth-stage, and stage-window combination.

1. GROWING SEASON SPECIFICATION

Aggregation of weather data across growing seasons serves as a logical starting point given the trajectory of existing literature relating weather events to rough rice yield. Peng et al. (2004) provided the landmark estimate of a 10 percent decline in rough rice yield given a one degree increase in season average minimum temperature. Sheehy et al. (2006) critiqued this approach arguing the researchers had not controlled for solar radiation and minimum temperature in a multiple regression framework and thus overestimated the impact of an increase in minimum (night) temperatures. Sheehy et al. argued their estimate of a five to six percent decline in rough rice yield given a one degree increase in season average minimum temperature served as a more robust estimate.

Data used to follow the approach of Peng et al. (2004) and Sheehy et al. (2006) are described in Table 3. These statistics are representative of the pooled cultivar-rough rice yield and weather data. Pooling the high yielding hybrid (XL723) and medium grain (Jupiter) with lower yielding medium and long grain conventional varieties explains the large standard deviation of yield. These cultivar-specific differences are accounted for with cultivar fixed-effects (not shown in following results but available in Appendix A.

Table 3. Descriptive statistics for rough rice yield and weather variables aggregated by season

	Yield kg ha^{-1}	Tmin °C	Tmax °C	Tavg °C	SR mJ m^{-2}	VPD kPa
Mean	9,478	19.9	31.5	25.7	22.8	0.7
Std. Dev.	1,932	1.1	1.1	1.0	1.7	0.1
Min	5,569	18.1	29.0	23.8	20.6	0.5
Max	15,353	22.1	33.6	27.7	28.8	1.1

Results from the regressions of yield on the sets of weather variables listed in Table 1 are presented in Table 4. Tmin is negative and statistically significant ($p < 0.01$) in specifications (1) and (2) suggesting a one degree increase in average daily minimum temperature is associated with a four percent decrease in rough rice yield, ceteris paribus (Table 4). In specification (2), SR is positive and marginally significant ($p < 0.10$). In specifications (3) and (4), Tmax and SR follow the direction and statistical significance of Tmin and SR in specifications (1) and (2), but the marginal effect of Tmax is roughly half the magnitude of the effect of Tmin. Including Tmin, Tmax, and SR in specification (5) (Table 4), Tmin remains negative and statistically significant ($p < 0.05$), Tmax becomes statistically insignificant, and SR remains positive and statistically significant at the 0.10 level. In this specification, the marginal effect of Tmin increases by roughly one percentage point.

Table 4 (1/2). Marginal effects (p-values) of weather variables aggregated across growing season on rough rice yield*

Variable	Specification (1)		(2)		(3)		(4)	
Tmin	-0.035	(0.000)	-0.037	(0.000)	--	--	--	--
SR	--	--	0.009	(0.075)	--	--	0.010	(0.071)
Tmax	--	--	--	--	-0.021	(0.005)	-0.022	(0.003)
Tavg	--	--	--	--	--	--	--	--
VPD	--	--	--	--	--	--	--	--
Adjusted R^2	0.554		0.558		0.547		0.551	
F-statistic	33.4		31.2		32.5		30.3	

*Harvest moisture content (HMC) and cultivar and station fixed-effects estimates have been excluded but are available in Appendix A. P-values calculated using heteroskedasticity robust standard errors are in parentheses.

Table 4 (2/2). Marginal effects (p-values) of weather variables aggregated across growing season on rough rice yield*

Variable	Specification (5)		(6)		(7)		(8)	
Tmin	-0.047	(0.034)	--	--	--	--	--	--
SR	0.009	(0.085)	--	--	0.010	(0.069)	--	--
Tmax	0.008	(0.597)	--	--	--	--	--	--
Tavg	--	--	-0.028	(0.001)	-0.029	(0.001)	--	--
VPD	--	--	--	--	--	--	0.297	(0.002)
Adjusted R^2	0.557		0.551		0.555		0.550	
F-statistic	28.7		33.0		30.8		32.9	

*Harvest moisture content (HMC) and cultivar and station fixed-effects estimates have been excluded but are available in Appendix A. P-values calculated using heteroskedasticity robust standard errors are in parentheses.

Marginal effects of Tavg in specifications (6) and (7) are positive, statistically significant, and slightly larger than the marginal effects of Tmax in specifications (3) and (4), indicating that a one degree increase in average daily temperature is associated with a nearly three percent decline in rough rice yield. Specification (8) includes VPD, describing the relationship between rough rice yield and the interaction of temperature and relative humidity, which previous studies have ignored (Peng et al. 2004; Sheehy et al. 2006; Welch et al. 2010). The positive, statistically significant ($p < 0.01$) sign is expected (Jagadish et al. 2010) suggesting a one (kilopascal) change is associated with a 30 percent change in rough rice yield, ceteris paribus. It is important to note that given the very small variance (1.2) and range (0.6) of VPD (Table 3) makes it much more likely to observe smaller changes in this variable.

2. GROWTH STAGE SPECIFICATION

Variables used for estimating growth stage-specific impacts are summarized in Table 5.

Table 5. Means (standard deviations) of weather variables aggregated by growth stage

	Tmin °C	Tmax °C	Tavg °C	SR mJ m^{-2}	VPD kPa
Vegetative	19.3	30.3	24.8	22.9	0.8
	(1.8)	(1.5)	(1.6)	(1.5)	(0.1)
Reproductive	21.1	32.1	26.6	22.0	0.6
	(1.4)	(1.4)	(1.4)	(1.5)	(0.2)
Ripening	19.7	32.6	26.2	20.3	0.7
	(2.7)	(3.1)	(2.8)	(3.0)	(0.3)

The stage-specific specifications presented in Table 6 marginally better fit the rough rice yield data than to the season specifications presented in Table 4. Adjusted R-squared values from these regressions indicate that around five percent more of the variability in rough rice yield than the season specifications. Across specifications within the stage-specific group in Table 6 there is little variation in adjusted R-squared as values range from 0.58 (8) to 0.65 (5). Coefficient directions and statistical significances across stages are similar to the season specifications, but the individual coefficients become less stable across specifications.

Tmin has a statistically significant, negative effect on rough rice yield in at least one growth stage, but the coefficient magnitudes change dramatically as additional regressors are included. Similarly, in specifications (3) and (4) vegetative and reproductive stage Tmax is negative and statistically significant ($p < 0.01$ and $p < 0.10$, respectively), but for both stages Tmax becomes statistically insignificant ($p > 0.1$) upon inclusion of Tmin in specification (5). In specifications (6) and (7), Tavg has a negative, statistically significant effect on rough rice yield during the vegetative stage, but only in specification (6), before the addition of SR does Tavg have a statistically significant, negative effect during the reproductive stage.

Table 6 (1/3). Marginal effects (p-values) of growth stage weather variables on rough rice yield*

		Specification					
Growth Stage	Variable	(1)		(2)		(3)	
Vegetative	T_{min}	-0.056	(0.000)	-0.044	(0.002)	--	--
	T_{max}	--	--	--	--	-0.035	(0.000)
	SR	--	--	0.018	(0.062)	--	--
	T_{avg}	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
Reproductive	T_{min}	-0.003	(0.747)	-0.049	(0.000)	--	--
	T_{max}	--	--	--	--	-0.015	(0.084)
	SR	--	--	0.040	(0.006)	--	--
	T_{avg}	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
Ripening	T_{min}	-0.005	(0.487)	-0.025	(0.014)	--	--
	T_{max}	--	--	--	--	0.010	(0.008)
	SR	--	--	0.028	(0.000)	--	--
	T_{avg}	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
	Adjusted R^2	0.614		0.648		0.608	
	F-statistic	36.1		34.0		35.3	

*Harvest moisture content (HMC) and cultivar and station fixed-effects estimates have been excluded but are available in Appendix A. P-values calculated using heteroskedasticity robust standard errors are in parentheses.

Table 6 (2/3). Marginal effects (p-values) of growth stage weather variables on rough rice yield*

Growth Stage	Variable	Specification (4)		(5)		(6)	
Vegetative	T_{min}	--	--	-0.055	(0.003)	--	--
	T_{max}	-0.031	(0.009)	-0.001	(0.929)	--	--
	SR	0.019	(0.054)	0.023	(0.033)	--	--
	T_{avg}	--	--	--	--	-0.042	(0.000)
	VPD	--	--	--	--	--	--
Reproductive	T_{min}	--	--	-0.080	(0.015)	--	--
	T_{max}	-0.029	(0.079)	0.045	(0.141)	--	--
	SR	0.008	(0.670)	0.025	(0.179)	--	--
	T_{avg}	--	--	--	--	-0.014	(0.158)
	VPD	--	--	--	--	--	--
Ripening	T_{min}	--	--	-0.028	(0.093)	--	--
	T_{max}	0.012	(0.131)	-0.004	(0.796)	--	--
	SR	0.000	(0.997)	0.037	(0.034)	--	--
	T_{avg}	--	--	--	--	0.007	(0.199)
	VPD	--	--	--	--	--	--
	Adjusted R^2	0.617		0.649		0.613	
	F-statistic	29.9		29.0		36.0	

*Harvest moisture content (HMC) and cultivar and station fixed-effects estimates have been excluded but are available in Appendix A. P-values calculated using heteroskedasticity robust standard errors are in parentheses.

Table 6 (3/3). Marginal effects (p-values) of growth stage weather variables on rough rice yield*

		Specification			
Growth Stage	Variable	(7)		(8)	
Vegetative	Tmin	--	--	--	--
	Tmax	--	--	--	--
	SR	0.020	(0.044)	--	--
	Tavg	-0.028	(0.022)	--	--
	VPD	--	--	0.215	(0.106)
Reproductive	Tmin	--	--	--	--
	Tmax	--	--	--	--
	SR	0.018	(0.281)	--	--
	Tavg	-0.043	(0.006)	--	--
	VPD	--	--	-0.304	(0.006)
Ripening	Tmin	--	--	--	--
	Tmax	--	--	--	--
	SR	0.015	(0.051)	--	--
	Tavg	-0.002	(0.853)	--	--
	VPD	--	--	0.311	(0.000)
	Adjusted R^2	0.630		0.579	
	F-statistic	31.5		31.4	

*Harvest moisture content (HMC) and cultivar and station fixed-effects estimates have been excluded but are available in Appendix A. P-values calculated using heteroskedasticity robust standard errors are in parentheses.

Unlike season specification (8) (Table 4), the only statistically significant effect of VPD in Table 6 is negative, not positive (specification (8)). The lack of variation in relative humidity, one of two components of the VPD function, across trial/site/years can explain this nonsensical result. The instability of Tmax and Tmin coefficient estimates in Table 6 is likely due to multicollinearity caused by high correlations among weather variables within and across stages. Correlations between Tmin, Tmax, and SR greater than 0.8 (Table 7) are cause for concern and may explain some of the parameter instability exhibited in Table 6.

Table 7. Pairwise correlations of growth stage-specific weather variables

		Vegetative					Reproductive					Ripening				
		Tmin	Tmax	SR	Tavg	VPD	Tmin	Tmax	SR	Tavg	VPD	Tmin	Tmax	SR	Tavg	VPD
Vegetative	Tmin	1														
	Tmax	0.83	1													
	SR	0.52	0.39	1												
	Tavg	0.97	0.95	0.48	1											
	VPD	-0.18	0.08	-0.27	-0.07	1										
Reproductive	Tmin	0.21	0.21	0.43	0.22	-0.35	1									
	Tmax	0.21	0.33	0.26	0.27	-0.09	0.85	1								
	SR	0.04	-0.01	0.28	0.02	-0.26	0.69	0.61	1							
	Tavg	0.22	0.28	0.36	0.26	-0.23	0.96	0.96	0.68	1						
	VPD	-0.03	-0.20	0.50	-0.11	-0.35	0.70	0.60	0.74	0.68	1					
Ripening	Tmin	-0.52	-0.45	-0.10	-0.51	-0.07	0.55	0.43	0.63	0.51	0.52	1				
	Tmax	-0.61	-0.41	-0.29	-0.54	0.15	0.38	0.37	0.41	0.39	0.39	0.86	1			
	SR	-0.69	-0.58	-0.32	-0.67	0.01	0.37	0.25	0.38	0.32	0.43	0.80	0.92	1		
	Tavg	-0.59	-0.44	-0.21	-0.55	0.05	0.47	0.41	0.53	0.46	0.46	0.96	0.97	0.90	1	
	VPD	-0.45	-0.43	0.19	-0.46	-0.09	0.48	0.38	0.57	0.45	0.76	0.77	0.81	0.80	0.82	1

Note: dotted lines separate growth stages. All correlations greater than 0.01 are statistically significant at the 0.05 level.

Variance inflation factors associated with weather parameters in specifications (1) – (8) (Appendix A) support the hypothesis that multicollinearity has affected the estimates in Table 6. Only in specifications (3), (6), and (8) are all weather parameter VIFs less than 10. In specification (5), VIFs associated with temperature parameters reach 86, implying essentially all of the variation in those parameters can be explained by variation in other regressors. Multicolliniarity of this degree inhibits meaningful analysis of the individual parameter estimates produced by the stage-specific estimation.

Inclusion of Tmin and Tmax in the above specifications has resulted in a multicolliniarity problem due to the lack of diurnal variability in this data. Replacing Tmin and/or Tmax with Tavg lessens the multicollinearity problem, but does not add to the ongoing discussion in the literature of whether increasing day or night temperatures have the greater effect on rough rice yield. Additionally, Tavg serves as a crude measure of temperature given intraday weather fluctuations and the possible nonlinear relationship between extremity of temperature and rough rice yield response. These questions require a more advanced aggregation of weather data.

3. STAGE & WINDOW SPECIFICATION

Results from the regression of rough rice yield on harmful thermal accumulation are presented in Table 8. Vegetative stage Tavg is included in all three specifications to account for the effect of high temperature on rough rice yield documented above in Table 6 and found previously Welch et al. (2010). Specification (1) includes only thermal time and solar radiation variables in addition to vegetative stage Tavg, (2) includes window-specific average VPD in place of thermal time and (3) includes both VPD and thermal time variables.

Table 8. Effects of harmful thermal accumulation* on rough rice yield

	Specification					
Variable	(1)		(2)		(3)	
V. Tavg	-0.025	(0.101)	-0.056	(0.000)	-0.033	(0.069)
V. SR	0.032	(0.005)	0.006	(0.671)	-0.024	(0.188)
TDN_{W1}	-0.003	(0.000)	--	--	-0.001	(0.118)
TDN_{W2}	-0.001	(0.474)	--	--	-0.001	(0.641)
TDN_{W3}	0.000	(0.884)	--	--	0.000	(0.987)
VPD_{W1}	--	--	0.012	(0.927)	0.211	(0.132)
VPD_{W2}	--	--	-0.045	(0.737)	-0.118	(0.480)
VPD_{W3}	--	--	0.161	(0.087)	0.305	(0.088)
SR_{W123}	0.034	(0.001)	--	--	--	--
Adjusted-R^2	0.642		0.627		0.642	
F-statistic	33.2		33.2		29.6	

*Harvest moisture content (HMC) and cultivar and station fixed-effects estimates have been excluded but are available in Appendix A. P-values calculated using heteroskedasticity robust standard errors are in parentheses.

In specification (1), Tavg is statistically insignificant, but negative and TDN_{W1} is statistically significant ($p < 0.01$) and negative. W1 corresponds with early flowering and late panicle development, a time period found extremely sensitive to extreme heat events in the experimental literature (Wasserman 2009). TDN_{W2} and TDN_{W2} are highly insignificant, but inspection of the VIF associated with these parameters reveals that nearly all of the variation in these regressors can be explained by variation in other regressors in the equation (Appendix A). This is unexpected given the pairwise correlation coefficient for these variables is 0.57, much smaller than the coefficients for pairs responsible for multicollinearity in the stage-specific model. Multicollinearity, unsurprisingly becomes a significant problem in specification (3) given the inclusion of window specific VPD and TDN variables.

The benefit of specifications (1) and (3) in Table 8 relative to alternative specifications discussed in the season and growth stage-specific sections is that thermal accumulation measures allow nonlinear responses to temperature increases without having to add additional terms (quadratic, cubic, etc.). Addition of such terms would likely increase multicollinearity and require additional assumptions about the functional form of the general relationship between temperatures and rough rice yield. For these reasons and for consistency with the milling quality specifications discussed below and later used to estimate economic implications of changes in average growing season temperature, specification (1) in Table 8 will be used to estimate the changes in rough rice yield that will serve as a baseline for the economic analysis.

B. MILLING QUALITY

Results from the system of equations estimation of CHK, HRY, and MRY by Generalized Method of Moments (GMM) are presented in this section. GMM estimation was selected for its ability to account for potential problems caused by the endogeneity of CHK in the HRY response function and unknown forms of heteroskedasticity in the system (Wooldridge 2010). GMM also allows easy calculation of the indirect and direct effects characteristic of this recursive milling quality system of equations. Extreme heat effects on CHK, HRY, and MRY differ across growth windows, day and night, and varieties.

1. ENDOGENEITY TEST

Results from the two-stage DWH test described in the methods section are presented in Table 9. Results from the joint test of instrument strength are presented in the first two columns of data where $\widehat{\boldsymbol{\beta}}_z$ represents the vector of instrument coefficients in the first stage regression of CHK on all exogenous variables in the milling quality system. F-statistics greater than 10 suggest strong instruments. Strong instruments are thus available for Jupiter, LaGrue, and XL23 with Wells on the borderline (F = 8.88). Residuals from the first stage regression are saved and included in the second stage regression: HRY on all variables in equation (9) plus the saved first stage residuals. The coefficient estimate of the residuals serves as the test statistic where the null hypothesis is that the coefficient equals zero. T-tests performed on these residuals give the p-values in the rightmost column of Table 9, where rejection indicates that including CHK in the HRY equation will bias the estimator, that is, the residuals from equation (9) affect HRY, ceteris paribus.

Table 9. Two-stage test of $\boldsymbol{H_0: Cov(u_1, u_2) = 0}$

	First stage $H_0: \hat{\boldsymbol{\beta}}_z = 0$		Second stage $H_0: \hat{\tau}_{\hat{u}_1} = 0$	
	F-statistic	p-value	$\hat{\tau}_{\hat{u}_1}$	p-value
Bengal	5.07	(0.026)	0.88	(0.753)
Jupiter	13.7	(0.000)	2.26	(0.084)
Cypress	4.84	(0.010)	-0.21	(0.893)
LaGrue	19.6	(0.000)	-0.13	(0.827)
Wells	8.88	(0.003)	-0.08	(0.951)
XL723	22.0	(0.000)	-0.94	(0.068)

Only in Jupiter can the null be rejected at the 0.1 level and for no cultivar can the coefficient be rejected with more confidence. Given the very weak evidence of an endogeneity problem in only one of six cultivars, this study does not utilize additional instruments to estimate the milling quality system. GMM is utilized despite the lack of additional instruments to account for heteroskedasticity of unknown forms. Seemingly unrelated regression (SUR) was implemented but provided very small efficiency gains.

2. SYSTEM ESTIMATES

Recent attention to the effects of night temperatures on milling quality (Ambardekar et al. 2010; Lanning et al. 2010) warrants discussion of results from system estimation first using only day thermal accumulation variables, then only night, then day and night in the same model, and finally day and night combined. All four of these sets include only W2 and W3 thermal accumulation variables following previous literature on the relationship between high temperatures and milling quality development (Ambardekar et al. 2010; Lanning et al. 2010).

2.1 CHALK CONTENT

esults from the regression of K on day, night, and both day and night ("full" specification) thermal accumulation variables are presented in Table 10. Coefficients associated with the same temperature variable have been placed next to one another for ease of comparison across cultivars and varieties. Across all cultivars except Bengal, adjusted R-squared values are between 1.5 and 2.5 times larger in the night and full specifications than in the day specification. Similar results have led previous research to conclude that night temperatures drive chalk formation (Counce 2007; Ambardekar et al. 2011; Lanning et al. 2011); however, it is important to note that day temperatures alone are capable of explaining between 37 and 51 percent of the variability in CHK.

In the "day" and "night" specifications, the magnitude of the W3 variables are significantly larger than the magnitudes of the W2 variables. Effects of TD_{W2} and TN_{W2} in these models, respectively, are largest for XL723 and LaGrue. This agrees with the consensus that XL723, a hybrid variety, is susceptible to chalk formation given even modest increases in temperature during grain filling. The same is true of the magnitudes of the effects of TD_{W3} and TN_{W3}. Importantly, in the "day" and "night" specifications, all coefficient estimates, statistically significant or not, are positive. Negative, statistically significant coefficients on these variables would suggest that high day and/or night temperatures reduce chalk formation during the grain filling phase. Such a result would disagree with every experimental result presented above in the literature review and is in fact what happens in this study when both day and night thermal accumulation variables are included in the system of equations (Table 10).

Table 10. Coefficients (p-values) from regression of chalk on day, night, and day and night thermal accumulation variables

	TD_{W2}		TD_{W3}		TN_{W2}		TN_{W3}		Adjusted R^2		
	Day	Full	Day	Full	Night	Full	Night	Full	Day	Night	Full
Bengal	0.013	-0.052	0.045	0.061	0.011	0.028	0.016	-0.008	0.37	0.38	0.45
	(0.332)	(0.015)	(0.000)	(0.001)	(0.030)	(0.001)	(0.001)	(0.375)			
Jupiter	0.004	-0.079	0.138	0.039	0.018	0.043	0.078	0.059	0.37	0.82	0.84
	(0.859)	(0.019)	(0.000)	(0.085)	(0.001)	(0.000)	(0.000)	(0.000)			
Cypress	0.034	-0.089	0.104	0.113	0.032	0.060	0.055	-0.002	0.42	0.65	0.69
	(0.011)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.909)			
LaGrue	0.108	-0.239	0.253	0.344	0.085	0.164	0.130	-0.009	0.51	0.80	0.85
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.717)			
Wells	0.064	-0.211	0.172	0.146	0.060	0.123	0.127	0.046	0.43	0.72	0.76
	(0.038)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)			
XL723	0.165	-0.115	0.247	0.107	0.088	0.121	0.141	0.098	0.42	0.79	0.80
	(0.000)	(0.080)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)			

Note: only daytime thermal accumulation variables were included in the "day" specification, only nighttime thermal accumulation variables were included in the "night" specification, and both were included in the "full" specification.

Including both TD and TN in the CHK equation leads to nonsensical, statistically significant parameter estimates similar to those in the rough rice yield model encountered above in Tables 5 and 7 and only marginally increases the goodness of fit relative to the specification only including TN (Table 10). Unexpected, nonsensical coefficients in Table 10 are those which are statistically significant and negative. That is to say that more time spent at temperatures above the optimal decreases chalk content, increasing milling quality, ceteris paribus. For TD_{W2}, this occurs in Wells, LaGrue, Cypress, Bengal, and Jupiter with significance at the 0.05 level and in XL723 at the 0.1 level (Table 10). This estimated reduction in CHK given larger values of TD_{W2}, the early grain filling stage, is in direct contradiction to Fitzgerald and Ressureccion (2009) who found that under controlled growing conditions, hot temperatures during early grain filling have the largest impact on chalk formation due to increased assimilate demand and a shortened window of assimilate supply. The combination of multicollinearity and over fitting appears to cause these nonsensical estimates.

The nonsensical estimates in the full model and the relatively small improvement in goodness of fit between the full and TN specifications compared to the full and TD specification might lead one to drop the day temperature variables and proceed with only night variables. Ambardekar et al. 2011 and Lanning et al. 2011 follow this approach, despite their complete lack of attention to day temperatures. An alternative is adding the TD and TN variables is to create a measure of total daily exposure to hot temperatures, diurnally defining "hot." Table 11 presents the results of this specification.

Table 11. Marginal effects (p-values) of TDN_{W2} and TDN_{W3} on CHK

	Bengal	Jupiter	Cypress	LaGrue	Wells	XL723
TDN_{W2}	0.007	0.014	0.022	0.063	0.043	0.068
	(0.049)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
TDN_{W3}	0.015	0.057	0.039	0.096	0.081	0.105
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.412	0.620	0.769	0.787	0.676	0.772

This specification provides stable parameter estimates across all six cultivars and goodness of fit statistics nearly if not as high as those in the night and full specifications provided in Table 10. Across all cultivars the estimated effects of high temperatures are largest for the late grain filling temperature variables (TDN_{W3}). Similar to the day and night specifications, XL723 appears most susceptible to chalk formation given high temperature exposure while Bengal and Cypress are least susceptible, ceteris paribus. Both the order of magnitudes across cultivars and the larger impact of high temperatures during late grain filling supports the results of Ambardekar et al. 2011 and Lanning et al. 2011, who found the strongest pairwise correlation between 95th percentile temperature and CHK during late grain filling, labeled “ 8” in their study following the growth staging procedure of oun ce et al. (2000).

2.2 HEAD RICE YIELD

Correct specification of the CHK equation is particularly important because of its impact on HRY. In their studies of the relationship between high night temperatures and milling quality, Ambardekar et al. (2011) and Lanning et al. (2011) correlated 95th percentile to HRY, but in doing so did not control for the detrimental effect of CHK on HRY (Bautista and Siebenmorgen 2007). In this study, HRY has been specified as a function of CHK in addition to weather variables to separate the indirect and direct effects of high temperatures on HRY; the indirect effects being those which occur as a result of the change in CHK associated with a change in HRY and the direct being the impact of high temperatures on HRY through other, unobserved processes. Including CHK in the HRY model worsens the parameter stability problem discussed above in the chalk section because temperature variation can explain so much of the variation in CHK. Use of the TDN variables instead of both day and night allows stable estimation of indirect and direct effects of temperature on HRY. Results from the day, night and full specifications are in Appendix B**.**

Estimated marginal effects of TDNW2, TDNW3, and CHK on HRY are presented in Table 12. The effects of TDN_{W2} are negative and statistically significant across all cultivars. The effects of TDN_{W3} on HRY are statistically insignificant ($p > 0.1$) for Bengal, Jupiter, LaGrue, and Wells, but are significant at the 0.05 and 0.10 levels for Cypress and XL723, respectively, ceteris paribus. Unexpectedly, the estimated effect on Cypress is positive but this may be explained by strong correlation between TDN_{W3} and CHK discussed above (Table 11). TDN_{W2} and TDN_{W3} explain nearly 80 percent of the variation in CHK for Cypress and this combined with ypress' inherent resistance to chalk formation likely lead to both the statistical insignificance of the CHK coefficient for Cypress in Table 12 and the misleading direction of TDN_{W3}.

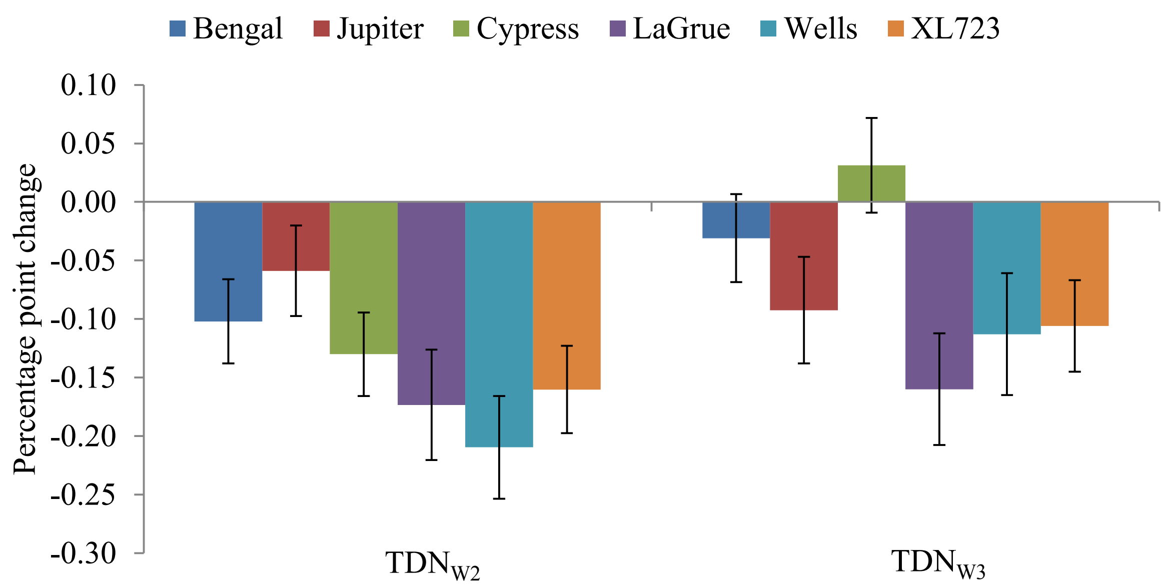
Table 12. Marginal effects (p-values) of extreme heat and CHK on HRY

	Bengal	Jupiter	Cypress	LaGrue	Wells	XL723
TDN_{W2}	-0.096	-0.043	-0.137	-0.155	-0.101	-0.133
	(0.000)	(0.065)	(0.000)	(0.000)	(0.000)	(0.000)
TDN_{W3}	-0.039	-0.025	0.079	0.041	0.020	-0.048
	(0.078)	(0.429)	(0.039)	(0.398)	(0.418)	(0.064)
CHK	-0.045	-1.177	-0.314	-1.140	-1.859	-0.478
	(0.921)	(0.019)	(0.508)	(0.000)	(0.000)	(0.021)
Adjusted R^2	0.451	0.450	0.521	0.779	0.788	0.693

Other than the TDN_{W3} coefficient for Cypress, all statistically significant coefficients follow expected direction. Surprisingly given the susceptibility of XL723 to CHK formation, the estimated effect of CHK on HRY is smaller than the statistically significant CHK coefficients for other cultivars. For XL723, a one percentage point increase in CHK is associated with a 0.48 percentage point reduction in HRY, ceteris paribus, where similar increases in CHK for Jupiter, LaGrue, and Wells are associated with 1.2, 1.1, and 1.9 percentage point declines in HRY, respectively, ceteris paribus.

Total effects of TDN_{W2} and TDN_{W3} on HRY are a function of their effects on CHK and HRY and the effect of CHK on HRY. For i = TDN_{W2} and TDN_{W3}, let α_i and β_i be the effects of i on CHK and HRY and let γ be the effect of CHK on HRY. The sum of indirect $\alpha_i\gamma$ and direct β_i effects yields the total effect $\alpha_i\gamma + \beta_i$ of a one unit change in i on HRY, ceteris paribus. Figure 2 presents these total effects. Total effects presented in Figure 2. are later used to calculate the impact of changes in growing season temperatures on HRY.

Figure 2. Total effects of TDN_{W2} and TDN_{W3} on HRY*



*Error bars represent 95% confidence intervals calculated using the Delta Method.

2.3. MILLED RICE YIELD

Table 13 presents the effects of extreme heat during W2 and W3 on MRY. Across cultivars, the TDN_{W2} coefficients are statistically significant ($p < 0.01$), negative, and larger (in absolute value) than the corresponding TDN_{W3} coefficients. Furthermore, only Wells and XL723 have statistically significant ($p < 0.05$) TDN_{W3} coefficients and they are approximately one half and one quarter the magnitude of the corresponding TDN_{W2} coefficients, respectively.

Table 13. Marginal effects (p-values) of extreme heat on MRY

	Bengal	Jupiter	Cypress	LaGrue	Wells	XL723
TDN_{W2}	-0.039	-0.052	-0.054	-0.062	-0.049	-0.068
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TDN_{W3}	-0.008	-0.004	0.014	-0.007	-0.021	-0.021
	(0.266)	(0.586)	(0.166)	(0.458)	(0.000)	(0.011)
Adjusted R^2	0.593	0.724	0.606	0.690	0.591	0.555

Estimated declines in MRY given increases in temperature suggest the total mass percentage of milled rice obtained from milling a sample of rough rice decreases as temperatures increase. This implies that the increased quantity of broken kernels obtained under a high temperature scenario will not entirely compensate for the mass quantity of head rice lost, ceteris paribus. Without data on the breakdown of other byproducts – hulls and bran – obtained during milling, it is difficult to say what happens to the total quantity of marketable milling outcomes given increased temperatures.

C. ECONOMIC IMPACTS

Economic impacts of changes in milling quality depend on the impacts of temperature at the rough rice yield level. Total milled output depends on the amount of rough rice available for milling and its milling quality. Because temperatures affect rough rice production, using previously published cultivar yields to estimate the economic impacts of temperature effects on milling quality would likely underestimate the total impacts of extreme heat on milled rice quantity. Sample means of rough rice yield and milling quality variables presented in Table 14 serve as baselines for the economic analysis.

Table 14. Sample means (standard deviations) of rough rice yield and milling quality variables

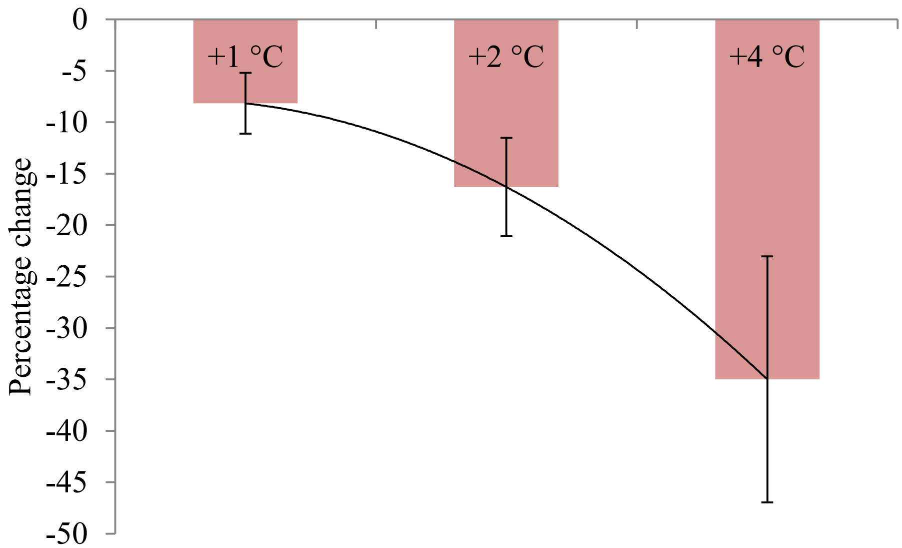
	Rough Rice Yield		Milling Quality (%)				
Cultivar	t ha^{-1}	Obs.	MRY	HRY	BKR	CHK	Obs.
Bengal	9.0	60	72.0	66.6	5.4	3.5	118
	(1.6)		(2.2)	(5.0)	(3.6)	(1.0)	
Jupiter	9.9	78	71.3	66.0	5.3	2.3	112
	(1.8)		(2.8)	(5.2)	(4.0)	(1.8)	
Cypress*	8.0	22	69.9	64.9	5.1	3.3	117
	(1.3)		(2.5)	(5.9)	(3.9)	(1.7)	
LaGrue	9.0	45	68.7	58.5	10.2	4.9	100
	(1.7)		(2.6)	(9.4)	(7.4)	(4.3)	
Wells	8.9	58	71.3	58.9	12.3	4.5	137
	(1.6)		(2.5)	(9.6)	(8.4)	(3.2)	
XL723	10.6	47	70.4	61.9	8.5	7.6	125
	(2.5)		(2.8)	(6.8)	(5.0)	(4.2)	

*Rough rice yield data for Cypress was not available for this analysis, so the latest available Arkansas Rice Performance Trial data (2004) experimental yield observations provided the baseline for reductions in mass quantities of milled rice outcomes given changes in milling quality.

Changes in baseline mean rough rice yield milling quality estimates (Table 14) given 1, 2 and 4°C increases in growing season (emergence to harvest) temperatures are estimated using specification (1) of the rough rice yield model presented in Table 8 and the milling quality model in Tables 12, 13, and 14. Total effects of the temperature changes are calculated for rough rice yield and milling quality estimates. To estimate these changes, 1, 2 and 4 °C are added to each observed temperature datum. TDN_{W1} (only included in the rough rice yield model), TDN_{W2} and TDN_{W3} are then recalculated for each hypothetical scenario. Finally, the hypothetical sample means of each of these variables are recalculated and used to predict changes in Y_R, HRY, (MRY – HRY = BKN), and CHK.

Rough rice yield mean responses to 1, 2, and 4 °C increases in growing season temperature are illustrated in Figure 3. These estimates represent the total effects of increased TDN during W1, W2, and W3, and corresponding increases to vegetative stage Tavg. Coefficients associated with these variables are listed in Table 8.

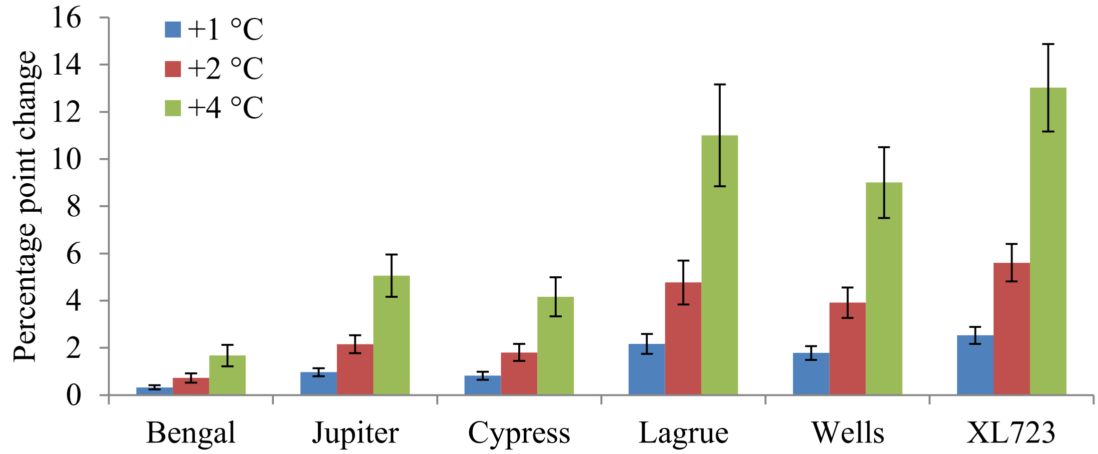
Figure 3. Rough rice yield response to 1, 2, and 4 degree increases in growing season temperature*



*Second order polynomial trend included to highlight nonlinearity of rough rice yield response to increased growing season temperature. Error bars represent 95% confidence intervals calculated using heteroskedasticity robust standard errors.

Milling quality responses to increased temperatures are estimated based on the TDN system estimates presented in Tables 12, 13, and 14. Estimates of BKN are presented because there is no obvious valuation of MRY – it represents the sum of HRY and BKN. Figure 4 illustrates the estimated changes in CHK given 1, 2, and 4 °C increases in mean growing season temperature. Despite XL723 having a relatively large baseline mean CHK content (Table 14), it's response to increased temperatures is very similar to that of LaGrue and Wells, cultivars with relatively small baseline mean CHK.

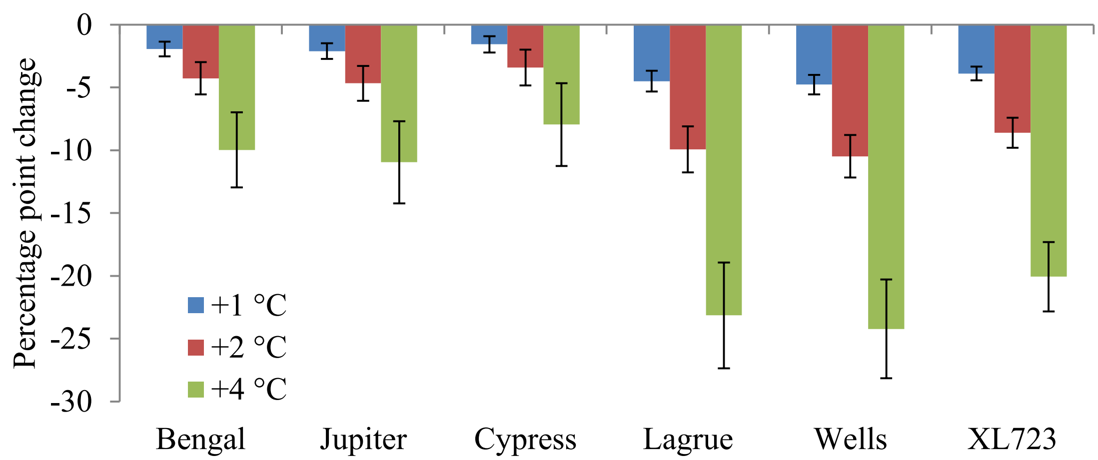
Figure 4. Chalk content (CHK) response to 1, 2, and 4 °C increases in mean growing season temperature*



*Error bars represent 95% confidence intervals calculated using heteroskedasticity robust standard errors.

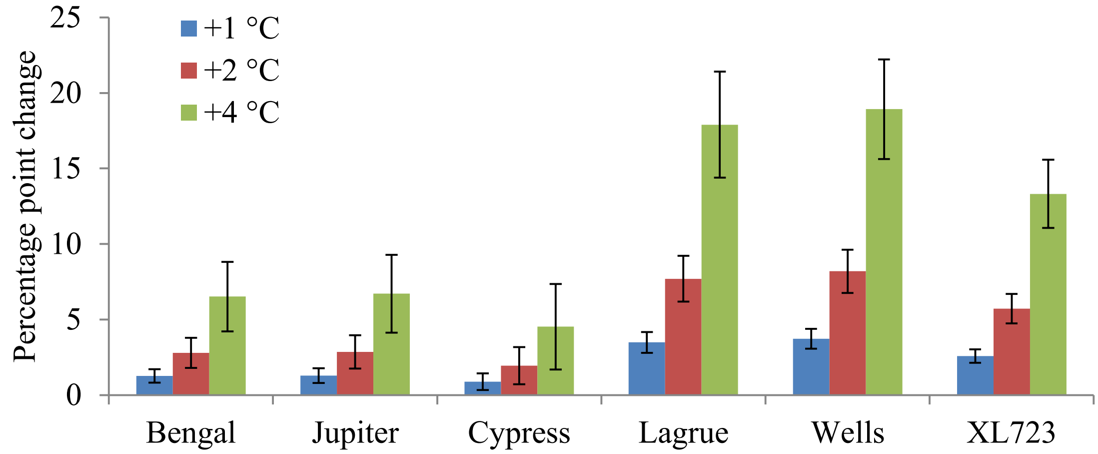
HRY and BKR responses to increased growing season temperatures are presented in Figures 5 and 6.

Figure 5. Head rice yield (HRY) responses to 1, 2, and 4 °C increases in mean growing season temperature*



*Error bars represent 95% confidence intervals calculated using heteroskedasticity robust standard errors.

Figure 6. Broken rice yield (BKR) response to 1, 2, and 4 °C increases in mean growing season temperature*



*Error bars represent 95% confidence intervals calculated using heteroskedasticity robust standard errors.

Estimated changes in RRY, CHK, HRY, and BKR presented in Figures 3, 4, 5, and 6 are used to estimate changes in mean rough rice yield (Y_R) and mass milled rice outputs (t ha^{-1}). Milled rice outputs include non-chalky (high quality) milled head rice (Y_{NCHR}), chalky head rice (Y_{CHR}) and broken rice (Y_{BK}) as described and defined in equations (5), (6), and (7) of the methodology section. Again, let Y_{HR} refer to the total mass quantity (t) of head rice expected from one hectare of harvested rough rice.

Cultivar specific changes in chalky and non-chalky head rice and broken rice (t ha^{-1}) across temperature increases are presented in Figure 7. The blue sections represent non-chalky head rice (Y_{NCHR}), the red sections represent chalky head rice (Y_{CHR}) and the green sections represent broken rice (Y_{BK}). Figure 7 illustrates XL723's susceptibility to chalky kernel formation while maintaining high non-chalky head rice potential per hectare due to its high yield and its resistance to breaking during the milling process. Cypress, the relatively low-yielding, high quality long-grain variety (Table 14) compares very well in non-chalky head rice production despite having a baseline yield disadvantage.

Figure 7. Effects of increased growing season temperatures on long-grain cultivar milling outcomes

The baseline estimate of XL723's non-chalky milled head rice is higher than ypress' because of XL723's 31 percent rough rice yield advantage over Cypress (Table 14). The relative proportions of non-chalky and chalky head rice, and broken rice change as average growing season temperature increases from the baseline level by 1, 2 and 4 °C. Given an increase of 4 °C, Cypress is estimated to produce over 0.7 t ha^{-1} more non-chalky head rice than XL723 and roughly 1.2 t ha^{-1} more than LaGrue or Wells.

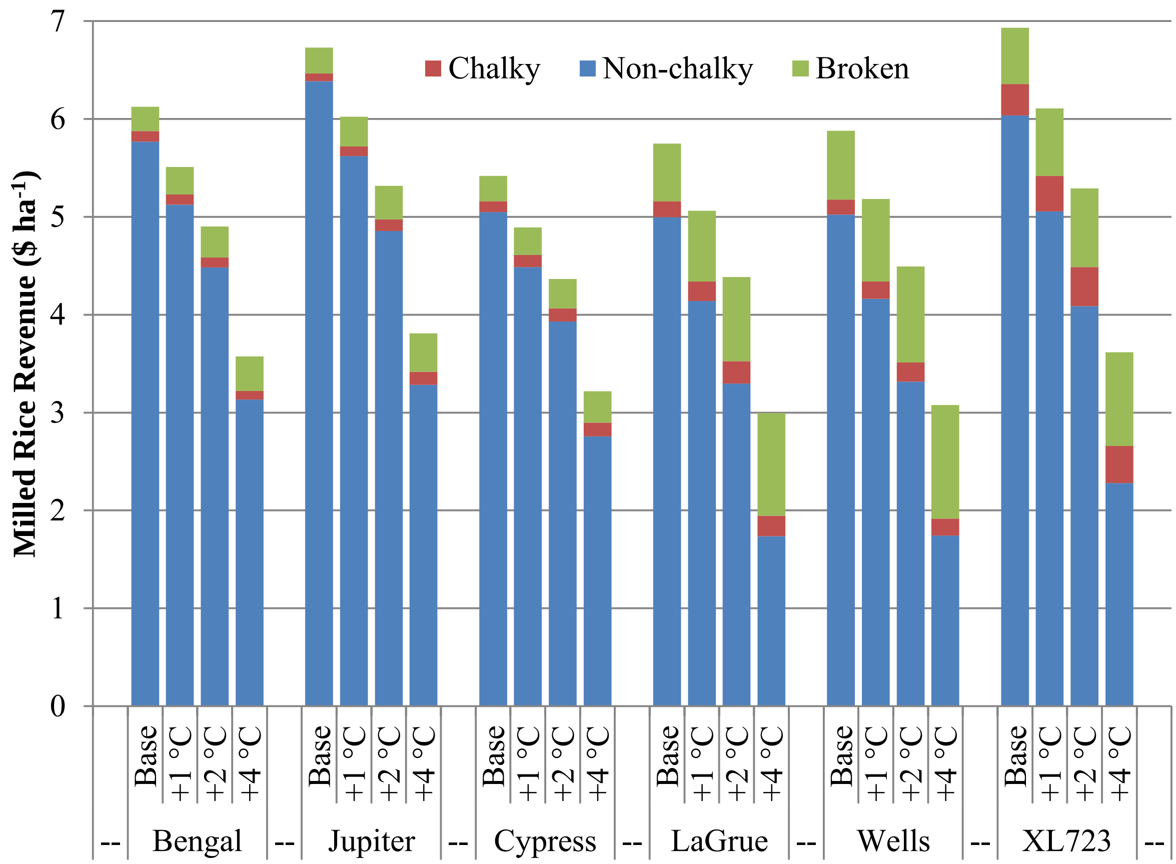
Among medium grains, yields a greater quantity of milled chalky and non-chalky head rice and broken rice per hectare than Bengal due to its relatively high paddy yield. Despite its relative susceptibility to chalk, the higher rough rice yield potential of Jupiter enables production of more non-chalky head rice per hectare than Bengal across all three-temperature increases. As temperatures increase, it becomes less clear which cultivar a mill would rather producers plant if the goal is maximization of quantity delivered per hectare, all else held constant, across both long- and medium-grain cultivars.

Total milling revenues across cultivars do not follow the same pattern as milled rice quantity because the quantities of broken and chalky kernels are valued less than the quantities of non-chalky kernels. Normalizing the price milled non-chalky head rice to 1 \$ t^{-1} and setting the price of broken and chalky kernels to the market price ratio of broken to whole kernels allows comparison across long- and medium-grains. Average monthly broken-to-whole kernel price ratios over the August 2007 – February 2012 period are 0.51 (s.d. = 0.11) and 0.64 (s.d. = 0.12) for medium- and long-grain cultivars, respectively, where lower ratio for medium grains reflects the higher value of milled medium grain rice and the price of milled brewers rice serves as the price of broken rice (USDA-ERS 2012). Normalized mill revenue (\$ ha^{-1}) for all six cultivars is presented in Figure 8.

Medium-grain cultivars follow the same patterns as they did in Figure 7 because of their relatively stable milling quality. Jupiter maintains the revenue per hectare advantage given its high yield potential relative to Bengal, despite Bengal's narrow quality advantage. Long-grain cultivars, however, experience changes in relative appeal from a mill standpoint because of dramatic variations in milling quality across cultivars which leads to substantial differences in revenue because of the discounted chalky and broken kernels.

As temperatures increase, revenue per hectare from Cypress overtakes that of LaGrue and Wells because of ypress' resistance to breaking (Figure 8). Broken rice revenue from LaGrue and Wells is larger than that of any other cultivar, including XL723, but XL723 generates the largest proportion of revenue from chalky head rice.

Figure 8. Normalized milling revenue by quality



The scale of Figure 8 makes difficult the observation of changes in relative total revenue across long-grain cultivars, especially between Cypress, LaGrue, and Wells. Figure 9 graphically represents these changes for each temperature scenario. LaGrue and Wells have less than 10% revenue advantages over Cypress in the base scenario and that advantage shrinks and becomes a disadvantage (+4 °C) of up to 5% for LaGrue.

Figure 9. Milled long-grain total revenue relative to Cypress

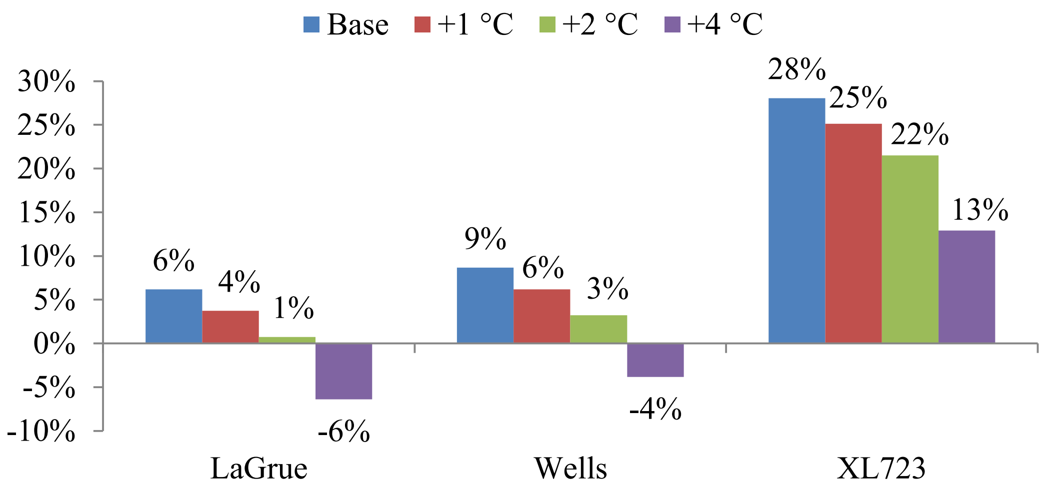
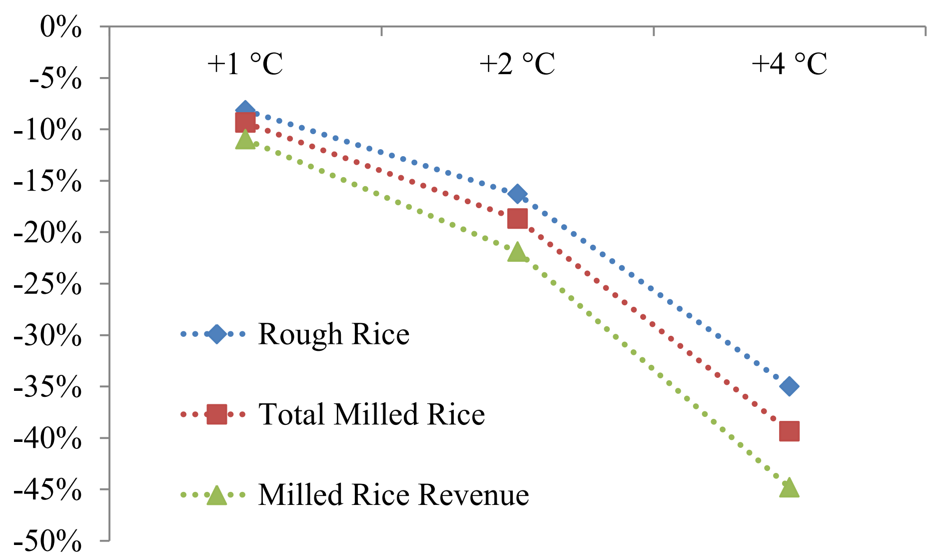


Figure 9 illustrates indirectly the tradeoff between yield and quality. The 11-12% RRY advantage of LaGrue and Wells in the base scenario (Table 14) shrinks to 6-9% total revenue advantages. Any increase in average growing season temperatures further shrinks these advantages to negligible and likely statistically insignificant figures.

VI. CONCLUSIONS

Climate change necessitates the development of cultivar-specific models capable of simultaneously estimating the relationship between extreme temperatures and rice yield and milling quality. Omission of rough rice yield or milling quality inevitably leads to underestimation of the true extent of extreme heat effects on rice production. Figure 10 illustrates the average impacts of increased temperatures on rough rice yield, total milled rice quantity, and total mill revenue. Effects of increased growing season temperatures are neither linear nor constant across rough rice yield, milling quality, and milled revenue potential. Producer (farm) revenue has been excluded from this analysis due to lack of quantitative data on the relationship between price and milling quality, but since mills set rough rice prices based on expected quality one would expect understated implications of extreme heat on producer revenue beyond yield loss. For these reasons, changes in rough rice yield depicted in Figure 10 are equivalent to reductions in producer revenue.

Figure 10. Average impact of increased temperatures across cultivars



Understanding cultivar-specific responses to extreme heat is critical to assessing the best course forward as climate change threatens the status quo of rice production in the United States and the world. Medium and long grain cultivars exhibit variable milling quality responses to extreme temperatures and variation exists within grain length among cultivars. Among medium grains, Jupiter's high yield potential gives it a higher revenue potential than Bengal, despite larger quantities of chalky and broken rice per hectare. Cypress has the lowest yield potential of all cultivars, including medium grains, but under hot conditions will deliver more high quality, non-chalky head rice per hectare than any of the other long grain cultivars.

XL723 offers a long grain with high yield potential and low-susceptibility to breaking relative to LaGrue and Wells, but loses value due to high chalk content. Despite high chalk content, XL723 delivers more non-chalky head rice than LaGrue or Wells because the relative rough rice yield advantage outweighs the higher percentage of chalky kernels. Currently stable yields of non-chalky, conventional cultivars such as LaGrue and Wells offer mills easy avoidance of the problem of color sorting, but this will likely not be the case as temperatures increase. Mills will likely either turn to lower-yielding, high-quality varieties such as Cypress or invest in infrastructure capable of separating the high- and low-quality milled rice for sale to disaggregate markets. Yet even the conclusions of this study only tell part of the story.

The robustness of rough rice models estimated in this study rely on pooling cultivars to accurately estimate effects of extreme heat on paddy yield. As a result, the only source of variability among cultivars throughout the temperature scenarios is the baseline, cultivar-specific yields. Cultivar-specific rough rice yield models would eliminate the need for the likely naive assumption that susceptibility to rough rice yield loss under hot growing season conditions is the same across all cultivar types. Furthermore, the efficiency and accuracy of season- and stage-specific coefficient estimates could be further improved using one dataset for both rough rice yield and milling quality. And finally, multicollinearity makes difficult the accurate separation of diurnal and stage-specific extreme heat effects.

Despite these weaknesses, this study provides insight where previous experimental and econometric analyses of rice production outcomes have not – first, rough rice yield and milling quality models are simultaneously examined, if not estimated; second, extensive treatment of collinearity issues among explanatory weather variables in econometric models; and third, the economic motivation of these innovations. Continued observation the effects of increasingly variable temperature conditions on rice production outcomes will allow refinement and enhancement of this modeling approach to hopefully provide plant breeders, agricultural policy makers, and private enterprise important direction for rice production in an increasingly hot future.

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VI. APPENDIX

A. ROUGH RICE YIELD

Table A1 (1/2). Regression results:* weather data aggregated over growing season

	Specification														
Variable	(1)			(2)			(3)			(4)			(5)		
Tmin	-0.035	(0.000)	*3.1*	-0.037	(0.000)	*3.4*	--	--	--	--	--	--	-0.047	(0.034)	*12.5*
SR	--	--	--	0.009	(0.075)	*2.0*	--	--	--	0.010	(0.071)	*2.0*	0.009	(0.085)	*2.0*
Tmax	--	--	--	--	--	--	-0.021	(0.005)	*1.8*	-0.022	(0.003)	*1.9*	0.008	(0.597)	*6.5*
Tavg	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
VPD	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--
ln(HMC)	-0.108	(0.014)	*1.3*	-0.120	(0.007)	*1.4*	-0.184	(0.000)	*1.6*	-0.199	(0.000)	*1.6*	-0.096	(0.127)	*2.7*
XL723	0.183	(0.000)	*1.8*	0.181	(0.000)	*1.8*	0.167	(0.000)	*1.7*	0.164	(0.000)	*1.6*	0.185	(0.000)	*1.8*
Jupiter	0.117	(0.000)	*2.2*	0.114	(0.000)	*2.3*	0.117	(0.000)	*2.2*	0.115	(0.000)	*2.2*	0.113	(0.000)	*2.3*
Bengal	0.037	(0.156)	*1.9*	0.037	(0.164)	*1.9*	0.033	(0.219)	*1.8*	0.032	(0.230)	*1.8*	0.037	(0.158)	*2.0*
Wells	0.019	(0.484)	*2.0*	0.017	(0.523)	*1.9*	0.013	(0.633)	*1.9*	0.011	(0.679)	*1.8*	0.018	(0.502)	*1.9*
COR	0.240	(0.000)	*2.4*	0.259	(0.000)	*3.3*	0.280	(0.000)	*1.9*	0.300	(0.000)	*2.6*	0.247	(0.000)	*5.2*
KSR	0.160	(0.000)	*1.8*	0.159	(0.000)	*1.8*	0.160	(0.000)	*1.9*	0.159	(0.000)	*1.9*	0.161	(0.000)	*1.8*
NPT	0.330	(0.000)	*3.9*	0.343	(0.000)	*4.7*	0.379	(0.000)	*2.3*	0.395	(0.000)	*2.9*	0.329	(0.000)	*6.9*
PT	0.041	(0.138)	*2.8*	0.041	(0.142)	*2.8*	0.069	(0.009)	*2.2*	0.069	(0.009)	*2.3*	0.034	(0.275)	*3.7*
STGT	0.168	(0.000)	*2.2*	0.173	(0.000)	*2.7*	0.184	(0.000)	*2.5*	0.190	(0.000)	*3.1*	0.167	(0.000)	*3.8*
Intercept	9.902	(0.000)	--	9.742	(0.000)	--	10.02	(0.000)	--	9.882	(0.000)	--	9.635	(0.000)	--
Adjusted R^2	0.554			0.558			0.547			0.551			0.557		
F-statistic	33.4			31.2			32.5			30.3			28.7		

*Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed-effects.

Table A1 (2/2). Regression results:[*] weather data aggregated over growing season

Variable	(6)			(7)			(8)		
Tmin	--	--	--	--	--	--	--	--	--
SR	--	--	--	0.010	(0.069)	*2.0*	--	--	--
Tmax	--	--	--	--	--	--	--	--	--
Tavg	-0.028	(0.001)	*2.0*	-0.029	(0.001)	*2.1*	--	--	--
VPD	--	--	--	--	--	--	0.297	(0.002)	*3.1*
ln(HMC)	-0.154	(0.000)	*1.4*	-0.168	(0.000)	*1.4*	-0.197	(0.000)	*1.8*
XL723	0.174	(0.000)	*1.8*	0.171	(0.000)	*1.7*	0.146	(0.000)	*1.6*
Jupiter	0.117	(0.000)	*2.2*	0.115	(0.000)	*2.3*	0.099	(0.000)	*1.9*
Bengal	0.035	(0.186)	*1.8*	0.034	(0.195)	*1.9*	0.016	(0.553)	*1.7*
Wells	0.015	(0.559)	*2.0*	0.014	(0.601)	*1.9*	-0.003	(0.905)	*1.6*
COR	0.264	(0.000)	*2.0*	0.284	(0.000)	*2.7*	0.260	(0.000)	*2.0*
KSR	0.159	(0.000)	*1.9*	0.158	(0.000)	*1.9*	0.204	(0.000)	*1.9*
NPT	0.359	(0.000)	*2.8*	0.374	(0.000)	*3.5*	0.371	(0.000)	*2.1*
PT	0.058	(0.032)	*2.4*	0.057	(0.032)	*2.4*	0.118	(0.000)	*3.2*
STGT	0.178	(0.000)	*2.4*	0.184	(0.000)	*2.9*	0.166	(0.000)	*2.3*
Intercept	10.02	(0.000)	--	9.869	(0.000)	--	9.214	(0.000)	--
Adjusted R^2	0.551			0.555			0.55		
F-statistic	33.0			30.8			32.9		

Specification columns: (6), (7), (8).

[*]Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed effects.

Table A2 (1/4). Regression results:[*] weather data aggregated over vegetative, reproductive, and ripening growth stages

		Specification					
Growth stage	Variable	(1)			(2)		
Vegetative	Tmin	-0.056	(0.000)	*17.2*	-0.044	(0.002)	*20.0*
	Tmax	--	--	--	--	--	--
	SR	--	--	--	0.018	(0.062)	*4.7*
	Tavg	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
Reproductive	Tmin	-0.003	(0.747)	*3.9*	-0.049	(0.000)	*8.7*
	Tmax	--	--	--	--	--	--
	SR	--	--	--	0.040	(0.006)	*12.1*
	Tavg	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
Ripening	Tmin	-0.005	(0.487)	*8.1*	-0.025	(0.014)	*21.0*
	Tmax	--	--	--	--	--	--
	SR	--	--	--	0.028	(0.000)	*12.9*
	Tavg	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
	ln(HMC)	-0.085	(0.040)	*1.3*	-0.117	(0.007)	*1.7*
	XL723	0.181	(0.000)	*2.1*	0.153	(0.000)	*2.2*
	Jupiter	0.098	(0.000)	*2.4*	0.089	(0.000)	*2.5*
	Bengal	0.025	(0.323)	*2.3*	0.008	(0.738)	*2.8*
	Wells	0.019	(0.434)	*2.1*	0.015	(0.532)	*2.0*
	COR	0.144	(0.000)	*3.4*	0.015	(0.803)	*9.6*
	KSR	0.266	(0.000)	*3.1*	0.195	(0.000)	*5.6*
	NPT	0.226	(0.000)	*7.8*	0.199	(0.000)	*11.1*
	PT	0.065	(0.025)	*3.0*	0.021	(0.462)	*3.8*
	STGT	0.130	(0.000)	*2.6*	0.103	(0.000)	*3.0*
	Intercept	10.43	(0.000)	--	9.845	(0.000)	--
	Adjusted R^2	0.614			0.648		
	F-statistic	36.1			34.0		

[*]Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed effects.

Table A2 (2/4). Regression results:[*] weather data aggregated over vegetative, reproductive, and ripening growth stages

		Specification					
Growth stage	Variable	(3)			(4)		
Vegetative	Tmin	--	--	--	--	--	--
	Tmax	-0.035	(0.000)	*5.2*	-0.031	(0.009)	*4.6*
	SR	--	--	--	0.019	(0.054)	*9.2*
	Tavg	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
Reproductive	Tmin	--	--	--	--	--	--
	Tmax	-0.015	(0.084)	*2.6*	-0.029	(0.079)	*15.2*
	SR	--	--	--	0.008	(0.670)	*10.0*
	Tavg	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
Ripening	Tmin	--	--	--	--	--	--
	Tmax	0.010	(0.008)	*3.7*	0.012	(0.131)	*17.8*
	SR	--	--	--	0.000	(0.997)	*18.5*
	Tavg	--	--	--	--	--	--
	VPD	--	--	--	--	--	--
	ln(HMC)	-0.198	(0.000)	*1.4*	-0.247	(0.000)	*2.5*
	XL723	0.154	(0.000)	*2.1*	0.144	(0.000)	*2.2*
	Jupiter	0.102	(0.000)	*2.2*	0.100	(0.000)	*2.3*
	Bengal	0.022	(0.357)	*2.2*	0.018	(0.436)	*2.5*
	Wells	0.013	(0.583)	*1.9*	0.009	(0.711)	*1.9*
	COR	0.185	(0.000)	*2.9*	0.201	(0.000)	*6.7*
	KSR	0.242	(0.000)	*2.4*	0.250	(0.000)	*5.5*
	NPT	0.302	(0.000)	*5.1*	0.353	(0.000)	*7.4*
	PT	0.119	(0.000)	*2.6*	0.115	(0.000)	*3.0*
	STGT	0.158	(0.000)	*2.8*	0.167	(0.000)	*3.2*
	Intercept	10.66	(0.000)	--	10.44	(0.000)	--
	Adjusted R^2	0.608			0.617		
	F-statistic	35.3			29.9		

[*]Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed effects.

Table A2 (3/4). Regression results:[*] weather data aggregated over vegetative, reproductive, and ripening growth stages

		Specification					
Growth stage	Variable	(5)			(6)		
Vegetative	Tmin	-0.055	(0.003)	*33.6*	--	--	--
	Tmax	-0.001	(0.929)	*5.7*	--	--	--
	SR	0.023	(0.033)	*16.2*	--	--	--
	Tavg	--	--	--	-0.042	(0.000)	*9.3*
	VPD	--	--	--	--	--	--
Reproductive	Tmin	-0.080	(0.015)	*51.0*	--	--	--
	Tmax	0.045	(0.141)	*20.7*	--	--	--
	SR	0.025	(0.179)	*40.9*	--	--	--
	Tavg	--	--	--	-0.014	(0.158)	*3.3*
	VPD	--	--	--	--	--	--
Ripening	Tmin	-0.028	(0.093)	*56.9*	--	--	--
	Tmax	-0.004	(0.796)	*84.7*	--	--	--
	SR	0.037	(0.034)	*85.3*	--	--	--
	Tavg	--	--	--	0.007	(0.199)	*5.1*
	VPD	--	--	--	--	--	--
	ln(HMC)	-0.035	(0.588)	*4.3*	-0.157	(0.000)	*1.2*
	XL723	0.162	(0.000)	*2.1*	0.165	(0.000)	*2.1*
	Jupiter	0.080	(0.001)	*2.9*	0.100	(0.000)	*2.3*
	Bengal	0.006	(0.776)	*2.8*	0.022	(0.361)	*2.3*
	Wells	0.018	(0.465)	*2.0*	0.016	(0.508)	*2.0*
	COR	0.002	(0.976)	*11.1*	0.170	(0.000)	*3.0*
	KSR	0.214	(0.000)	*5.5*	0.251	(0.000)	*2.7*
	NPT	0.113	(0.086)	*18.2*	0.276	(0.000)	*6.0*
	PT	0.012	(0.713)	*5.0*	0.104	(0.000)	*2.5*
	STGT	0.076	(0.011)	*4.7*	0.148	(0.000)	*2.7*
	Intercept	9.32	(0.000)	--	10.59	(0.000)	--
	Adjusted R^2	0.649			0.613		
	F-statistic	29.0			36.0		

[*]Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed effects.

Table A2 (4/4). Regression results:* weather data aggregated over vegetative, reproductive, and ripening growth stages

		Specification					
Growth Stage	Variable	(7)			(8)		
Vegetative	Tmin	--	--	--	--	--	--
	Tmax	--	--	--	--	--	--
	SR	0.020	(0.044)	*20.0*	--	--	--
	Tavg	-0.028	(0.022)	*4.7*	--	--	--
	VPD	--	--	--	0.215	(0.106)	*4.4*
Reproductive	Tmin	--	--	--	--	--	--
	Tmax	--	--	--	--	--	--
	SR	0.018	(0.281)	*8.7*	--	--	--
	Tavg	-0.043	(0.006)	*12.1*	--	--	--
	VPD	--	--	--	-0.304	(0.006)	*4.6*
Ripening	Tmin	--	--	--	--	--	--
	Tmax	--	--	--	--	--	--
	SR	0.015	(0.051)	*21.0*	--	--	--
	Tavg	-0.002	(0.853)	*12.9*	--	--	--
	VPD	--	--	--	0.311	(0.000)	*6.4*
	ln(HMC)	-0.211	(0.000)	*1.7*	-0.054	(0.408)	*3.3*
	XL723	0.143	(0.000)	*2.2*	0.173	(0.000)	*2.0*
	JUP	0.097	(0.000)	*2.5*	0.098	(0.000)	*2.1*
	BENG	0.014	(0.559)	*2.8*	0.022	(0.358)	*2.0*
	WELLS	0.011	(0.652)	*2.0*	0.007	(0.784)	*1.7*
	COR	0.143	(0.012)	*9.6*	0.223	(0.000)	*2.9*
	KSR	0.232	(0.000)	*5.6*	0.250	(0.000)	*2.3*
	NPT	0.320	(0.000)	*11.1*	0.382	(0.000)	*2.9*
	PT	0.086	(0.002)	*3.8*	0.131	(0.000)	*3.7*
	STGT	0.150	(0.000)	*3.0*	0.166	(0.000)	*2.4*
	Intercept	10.20	(0.000)	--	8.862	(0.000)	--
	Adjusted R^2	0.630			0.579		
	F-statistic	31.5			31.4		

*Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed effects.

Table A3. Regression results:[*] weather data aggregated over vegetative stage[†] and windows 1, 2, and 3

	Specification								
Variable	(1)			(2)			(3)		
Veg. Tavg	-0.025	(0.101)	*15.3*	-0.056	(0.000)	*7.1*	-0.033	(0.069)	*22.0*
Veg. SR	0.032	(0.005)	*6.0*	0.006	(0.671)	*8.1*	-0.024	(0.188)	*18.1*
TDN_{W1}	-0.003	(0.000)	*6.2*	--	--	--	-0.001	(0.118)	*7.6*
TDN_{W2}	-0.001	(0.474)	*41.6*	--	--	--	-0.001	(0.641)	*91.5*
TDN_{W3}	0.000	(0.884)	*47.5*	--	--	--	0.000	(0.987)	*130.9*
VPD_{W1}	--	--	--	0.012	(0.927)	*17.3*	0.211	(0.132)	*23.6*
VPD_{W2}	--	--	--	-0.045	(0.737)	*28.5*	-0.118	(0.480)	*51.4*
VPD_{W3}	--	--	--	0.161	(0.087)	*12.3*	0.305	(0.088)	*48.1*
SR_{W4}	0.034	(0.001)	*20.1*	--	--	--	--	--	--
ln(HMC)	-0.124	(0.003)	*1.6*	-0.136	(0.005)	*2.2*	-0.119	(0.022)	*2.6*
XL723	0.143	(0.000)	*2.0*	0.159	(0.000)	*2.0*	0.165	(0.000)	*1.9*
Jupiter	0.089	(0.000)	*2.5*	0.089	(0.000)	*2.2*	0.099	(0.000)	*2.5*
Bengal	0.009	(0.671)	*2.6*	0.013	(0.580)	*2.3*	0.023	(0.316)	*2.7*
Wells	0.016	(0.499)	*2.0*	0.009	(0.714)	*2.0*	0.017	(0.487)	*2.1*
COR	0.145	(0.000)	*3.7*	0.149	(0.000)	*4.9*	0.114	(0.010)	*5.8*
KSR	0.292	(0.000)	*2.9*	0.277	(0.000)	*3.2*	0.249	(0.000)	*4.1*
NPT	0.302	(0.000)	*8.0*	0.236	(0.000)	*10.6*	0.188	(0.002)	*18.7*
PT	0.102	(0.000)	*2.7*	0.085	(0.001)	*2.8*	0.107	(0.000)	*3.3*
STGT	0.159	(0.000)	*3.7*	0.127	(0.000)	*3.7*	0.132	(0.000)	*5.4*
Intercept	8.43	(0.000)	--	10.21	(0.000)	--	10.31	(0.000)	--
	0.642			0.627			0.642		
	33.2			33.2			29.6		

[*]Marginal effects, p-values (parentheses) and VIFs (italics) are included for each variable and cultivar and station fixed effects.

[†]Vegetative stage variables include average daily temperature (Tavg) and average daily solar radiation (SR) because high frequency (half-hourly) data is not available for this period as it is for windows 1, 2, and 3.

B. MILLING QUALITY

Table B1 (1/3). GMM system estimation results: full (TD, TN) specification

Eq. 1: CHK	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	2.768	(0.000)	0.241	(0.078)	1.720	(0.000)	0.340	(0.186)	0.956	(0.000)	2.392	(0.000)
TD_{W2}	-0.052	(0.015)	-0.079	(0.019)	-0.089	(0.001)	-0.239	(0.000)	-0.211	(0.000)	-0.115	(0.080)
TD_{W3}	0.061	(0.001)	0.039	(0.085)	0.113	(0.000)	0.344	(0.000)	0.146	(0.000)	0.107	(0.002)
TN_{W2}	0.028	(0.001)	0.043	(0.000)	0.060	(0.000)	0.164	(0.000)	0.123	(0.000)	0.121	(0.000)
TN_{W3}	-0.008	(0.375)	0.059	(0.000)	-0.002	(0.909)	-0.009	(0.717)	0.046	(0.019)	0.098	(0.000)
COR	0.080	(0.696)	0.273	(0.111)	-0.553	(0.068)	0.844	(0.257)	-0.526	(0.120)	-0.278	(0.580)
KSR	0.887	(0.037)	0.340	(0.177)	-0.459	(0.091)	0.023	(0.954)	0.365	(0.200)	0.846	(0.242)
RWR	0.521	(0.010)	-0.037	(0.851)	1.152	(0.000)	1.561	(0.000)	0.386	(0.163)	0.479	(0.236)
PT	0.067	(0.782)	0.442	(0.006)	-0.248	(0.457)	-0.494	(0.288)	-0.282	(0.422)	0.561	(0.245)
NPT	-1.245	(0.000)	-1.020	(0.000)	-2.125	(0.000)	-5.699	(0.000)	-2.775	(0.000)	-1.014	(0.082)
Adjusted R^2	0.448		0.837		0.690		0.854		0.756		0.799	

Note: p-values are in parentheses.

Table B1 (2/3). GMM system estimation results: full (TD, TN) specification

Eq. 2: HRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	44.561	(0.000)	55.749	(0.000)	52.145	(0.000)	39.846	(0.000)	-4.141	(0.760)	53.203	(0.000)
TD_{W2}	0.251	(0.000)	0.101	(0.508)	-0.014	(0.820)	0.144	(0.130)	0.396	(0.006)	-0.186	(0.098)
TD_{W3}	0.004	(0.963)	0.091	(0.332)	0.593	(0.000)	0.304	(0.021)	-0.068	(0.572)	0.194	(0.000)
TN_{W2}	-0.202	(0.000)	-0.101	(0.023)	-0.191	(0.000)	-0.337	(0.000)	-0.372	(0.000)	-0.144	(0.000)
TN_{W3}	-0.050	(0.101)	-0.152	(0.001)	-0.257	(0.000)	-0.238	(0.000)	-0.147	(0.041)	-0.227	(0.000)
HMC	2.399	(0.010)	1.316	(0.053)	2.044	(0.015)	3.353	(0.002)	7.283	(0.000)	1.905	(0.035)
HMC^2	-0.053	(0.014)	-0.029	(0.059)	-0.052	(0.010)	-0.087	(0.001)	-0.168	(0.000)	-0.049	(0.031)
COR	2.517	(0.000)	1.709	(0.044)	0.597	(0.401)	-3.809	(0.044)	-2.796	(0.020)	-0.672	(0.496)
KSR	-6.923	(0.000)	-7.540	(0.000)	-6.901	(0.000)	-10.938	(0.000)	-12.534	(0.000)	-8.062	(0.000)
RWR	-0.250	(0.776)	0.918	(0.313)	-0.440	(0.588)	-3.291	(0.000)	-2.658	(0.050)	-1.134	(0.107)
PT	2.141	(0.002)	1.731	(0.026)	3.048	(0.000)	1.439	(0.095)	0.430	(0.751)	0.708	(0.385)
NPT	1.518	(0.469)	0.399	(0.845)	-6.077	(0.000)	-4.395	(0.124)	-0.752	(0.714)	-1.466	(0.187)
Adjusted R^2	0.576		0.499		0.769		0.883		0.771		0.738	

Table B1 (3/3). GMM system estimation results: full (TD, TN) specification

Eq. 3: MRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	76.164	(0.000)	78.229	(0.000)	73.486	(0.000)	74.124	(0.000)	76.090	(0.000)	76.494	(0.000)
TD_{W2}	0.151	(0.000)	0.163	(0.000)	0.032	(0.218)	0.055	(0.093)	0.140	(0.000)	-0.013	(0.749)
TD_{W3}	-0.008	(0.687)	-0.009	(0.780)	0.139	(0.000)	0.014	(0.731)	0.002	(0.951)	0.132	(0.000)
TN_{W2}	-0.098	(0.000)	-0.121	(0.000)	-0.081	(0.000)	-0.096	(0.000)	-0.109	(0.000)	-0.076	(0.000)
TN_{W3}	-0.002	(0.850)	0.010	(0.519)	-0.063	(0.001)	-0.021	(0.242)	-0.037	(0.033)	-0.087	(0.000)
HMC	-0.140	(0.000)	-0.239	(0.000)	-0.089	(0.010)	-0.176	(0.000)	-0.148	(0.000)	-0.169	(0.000)
COR	2.077	(0.000)	1.386	(0.000)	1.327	(0.000)	1.521	(0.003)	2.094	(0.000)	1.342	(0.000)
KSR	-3.549	(0.015)	-5.949	(0.000)	-3.420	(0.030)	-2.140	(0.019)	-3.003	(0.002)	-2.887	(0.073)
RWR	0.198	(0.528)	-0.379	(0.270)	0.445	(0.087)	-0.057	(0.876)	0.246	(0.396)	-0.806	(0.033)
PT	1.389	(0.000)	1.173	(0.000)	2.314	(0.000)	1.715	(0.000)	2.014	(0.000)	0.880	(0.001)
NPT	0.895	(0.066)	0.135	(0.813)	-0.572	(0.394)	0.227	(0.771)	0.688	(0.168)	0.292	(0.486)
Adjusted R^2	0.733		0.827		0.765		0.782		0.736		0.702	

Note: p-values are in parentheses.

Table B2 (1/2). GMM system estimation results: day (TD) specification

Eq. 1: CHK	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	3.03	(0.000)	1.38	(0.000)	2.25	(0.000)	2.15	(0.000)	2.60	(0.000)	4.82	(0.000)
TD_{W2}	0.013	(0.332)	0.004	(0.859)	0.034	(0.011)	0.108	(0.000)	0.064	(0.038)	0.165	(0.000)
TD_{W3}	0.045	(0.000)	0.138	(0.000)	0.104	(0.000)	0.253	(0.000)	0.172	(0.000)	0.247	(0.000)
COR	0.145	(0.489)	0.631	(0.009)	0.041	(0.895)	2.957	(0.002)	0.894	(0.054)	1.022	(0.107)
KSR	0.977	(0.009)	0.492	(0.379)	-0.112	(0.798)	0.460	(0.383)	0.092	(0.844)	1.132	(0.442)
RWR	0.697	(0.003)	0.731	(0.182)	1.680	(0.001)	2.428	(0.029)	1.506	(0.137)	1.562	(0.079)
PT	0.140	(0.569)	0.344	(0.187)	0.011	(0.964)	-0.194	(0.476)	-0.025	(0.930)	0.682	(0.254)
NPT	-1.089	(0.000)	-1.394	(0.000)	-1.655	(0.000)	-3.546	(0.000)	-1.968	(0.005)	-0.247	(0.696)
Adjusted R^2	0.374		0.366		0.418		0.514		0.430		0.423	

Eq. 2: HRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	63.03	(0.000)	54.30	(0.000)	87.32	(0.000)	84.94	(0.000)	32.20	(0.011)	74.32	(0.000)
TD_{W2}	-0.159	(0.053)	-0.093	(0.332)	-0.273	(0.000)	-0.302	(0.001)	-0.255	(0.000)	-0.361	(0.000)
TD_{W3}	0.059	(0.407)	0.104	(0.088)	0.501	(0.000)	0.557	(0.000)	0.199	(0.000)	0.161	(0.002)
CHK	-1.678	(0.008)	-1.947	(0.000)	-2.174	(0.000)	-2.136	(0.000)	-2.423	(0.000)	-1.249	(0.000)
HMC	0.890	(0.425)	1.536	(0.015)	-1.360	(0.235)	-1.348	(0.294)	4.049	(0.002)	0.134	(0.892)
HMC^2	-0.020	(0.445)	-0.036	(0.011)	0.027	(0.335)	0.027	(0.403)	-0.097	(0.002)	-0.012	(0.642)
COR	1.664	(0.056)	1.946	(0.026)	-0.554	(0.614)	-4.795	(0.015)	-4.981	(0.000)	-1.417	(0.179)
KSR	-4.873	(0.066)	-7.114	(0.000)	-7.355	(0.001)	-9.985	(0.000)	-10.613	(0.000)	-5.349	(0.003)
RWR	-0.523	(0.631)	0.287	(0.787)	1.362	(0.242)	0.489	(0.725)	-1.930	(0.120)	-0.847	(0.335)
PT	2.476	(0.002)	2.543	(0.003)	3.827	(0.000)	1.482	(0.224)	-0.049	(0.967)	2.647	(0.004)
NPT	0.053	(0.983)	-1.392	(0.501)	-7.942	(0.000)	-11.336	(0.000)	-6.197	(0.001)	-2.231	(0.134)
Adjusted R^2	0.255		0.437		0.484		0.776		0.776		0.661	

Note: p-values are in parentheses.

Table B2 (2/2). GMM system estimation results: day (TD) specification

Eq. 3: MRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	77.18	(0.000)	79.11	(0.000)	75.66	(0.000)	75.11	(0.000)	78.41	(0.000)	79.38	(0.000)
TD_{W2}	-0.065	(0.093)	-0.103	(0.002)	-0.099	(0.001)	-0.095	(0.001)	-0.065	(0.006)	-0.126	(0.001)
TD_{W3}	0.031	(0.187)	0.133	(0.000)	0.150	(0.000)	0.146	(0.000)	0.072	(0.000)	0.121	(0.000)
CHK	-0.431	(0.109)	-0.812	(0.000)	-0.817	(0.000)	-0.493	(0.000)	-0.566	(0.000)	-0.488	(0.000)
HMC	-0.189	(0.000)	-0.291	(0.000)	-0.178	(0.000)	-0.239	(0.000)	-0.263	(0.000)	-0.296	(0.000)
COR	1.667	(0.000)	1.419	(0.000)	0.563	(0.194)	1.349	(0.010)	1.375	(0.000)	0.963	(0.013)
KSR	-3.249	(0.079)	-6.216	(0.000)	-3.616	(0.053)	-1.853	(0.117)	-2.525	(0.034)	-1.962	(0.269)
RWR	-0.234	(0.586)	-0.985	(0.012)	1.022	(0.009)	0.659	(0.142)	0.118	(0.731)	-0.760	(0.133)
PT	1.358	(0.000)	1.177	(0.002)	2.265	(0.000)	1.562	(0.000)	1.777	(0.000)	1.460	(0.001)
NPT	0.144	(0.828)	-1.341	(0.058)	-2.096	(0.007)	-2.434	(0.001)	-0.941	(0.087)	-0.253	(0.687)
Adjusted R^2	0.420		0.735		0.520		0.671		0.602		0.510	

Table B3 (1/2). GMM system estimation results: night (TN) specification

	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	2.723	(0.000)	0.238	(0.106)	1.239	(0.000)	-0.499	(0.238)	0.154	(0.678)	2.283	(0.000)
TN_{W2}	0.011	(0.030)	0.018	(0.001)	0.032	(0.000)	0.085	(0.000)	0.060	(0.000)	0.088	(0.000)
TN_{W3}	0.016	(0.001)	0.078	(0.000)	0.055	(0.000)	0.130	(0.000)	0.127	(0.000)	0.141	(0.000)
COR	0.120	(0.559)	0.367	(0.061)	0.075	(0.801)	1.847	(0.048)	0.093	(0.819)	-0.264	(0.622)
KSR	0.908	(0.032)	0.440	(0.136)	-0.119	(0.646)	1.152	(0.009)	1.157	(0.002)	1.028	(0.183)
RWR	0.738	(0.001)	0.158	(0.513)	1.480	(0.000)	2.251	(0.000)	1.667	(0.000)	0.654	(0.160)
PT	0.160	(0.493)	0.587	(0.003)	0.158	(0.635)	0.454	(0.397)	0.555	(0.202)	0.793	(0.142)
NPT	-0.617	(0.007)	-0.646	(0.001)	-0.766	(0.016)	-1.143	(0.052)	-0.962	(0.028)	-0.672	(0.268)
Adjusted R^2	0.380		0.824		0.647		0.805		0.720		0.788	

HRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	41.279	(0.000)	53.586	(0.000)	56.435	(0.000)	59.781	(0.000)	19.911	(0.113)	53.541	(0.000)
TN_{W2}	-0.132	(0.000)	-0.068	(0.018)	-0.226	(0.000)	-0.278	(0.000)	-0.162	(0.000)	-0.191	(0.000)
TN_{W3}	-0.070	(0.007)	-0.098	(0.033)	-0.007	(0.895)	-0.084	(0.098)	-0.033	(0.423)	-0.137	(0.000)
CHK	0.146	(0.771)	-0.455	(0.414)	0.893	(0.036)	-0.320	(0.151)	-1.442	(0.000)	-0.085	(0.712)
HMC	2.645	(0.005)	1.570	(0.016)	1.084	(0.238)	1.256	(0.237)	5.152	(0.000)	1.898	(0.037)
HMC^2	-0.058	(0.011)	-0.036	(0.016)	-0.024	(0.285)	-0.036	(0.169)	-0.121	(0.000)	-0.050	(0.032)
COR	2.338	(0.001)	1.748	(0.041)	1.574	(0.109)	-4.246	(0.023)	-4.156	(0.000)	-0.654	(0.507)
KSR	-7.326	(0.000)	-7.663	(0.000)	-7.046	(0.000)	-10.946	(0.000)	-11.595	(0.000)	-7.586	(0.000)
RWR	-0.548	(0.526)	0.705	(0.477)	-2.394	(0.013)	-2.082	(0.079)	-1.682	(0.137)	-0.767	(0.349)
PT	1.649	(0.030)	1.621	(0.055)	3.397	(0.000)	1.468	(0.084)	-0.107	(0.915)	1.188	(0.166)
NPT	1.270	(0.519)	0.450	(0.827)	-0.390	(0.842)	-1.526	(0.430)	-3.292	(0.047)	-0.941	(0.402)
Adjusted R^2	0.531		0.482		0.609		0.837		0.798		0.723	

Table B3 (2/2). GMM system estimation results: night (TN) specification

MRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	74.129	(0.000)	78.857	(0.000)	71.564	(0.000)	74.432	(0.000)	77.091	(0.000)	75.384	(0.000)
TN_{W2}	-0.058	(0.000)	-0.068	(0.000)	-0.084	(0.000)	-0.079	(0.000)	-0.060	(0.000)	-0.102	(0.000)
TN_{W3}	-0.023	(0.012)	0.017	(0.283)	-0.013	(0.409)	-0.012	(0.356)	-0.027	(0.028)	-0.073	(0.000)
CHK	0.374	(0.022)	-0.301	(0.071)	0.339	(0.011)	-0.034	(0.588)	-0.126	(0.127)	0.230	(0.016)
HMC	-0.092	(0.002)	-0.266	(0.000)	-0.030	(0.479)	-0.192	(0.000)	-0.187	(0.000)	-0.142	(0.001)
COR	1.972	(0.000)	1.311	(0.000)	1.327	(0.000)	1.312	(0.006)	1.554	(0.000)	1.229	(0.001)
KSR	-4.068	(0.003)	-6.067	(0.000)	-3.564	(0.022)	-2.199	(0.022)	-3.179	(0.003)	-3.243	(0.060)
RWR	-0.220	(0.521)	-0.739	(0.042)	-0.391	(0.276)	0.019	(0.965)	0.039	(0.903)	-1.016	(0.023)
PT	1.045	(0.001)	0.971	(0.015)	2.190	(0.000)	1.615	(0.000)	1.556	(0.000)	0.579	(0.074)
NPT	0.799	(0.084)	-0.347	(0.569)	0.567	(0.329)	0.139	(0.735)	0.108	(0.825)	0.440	(0.246)
Adjusted R^2	0.672		0.780		0.689		0.763		0.680		0.650	

Table B4 (1/2). GMM system estimation results: TDN specification

Eq. 1: CHK	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	2.745	(0.000)	0.371	(0.027)	1.400	(0.000)	-0.133	(0.761)	0.636	(0.097)	2.510	(0.000)
TDN_{W2}	0.007	(0.049)	0.014	(0.004)	0.022	(0.000)	0.063	(0.000)	0.043	(0.000)	0.068	(0.000)
TDN_{W3}	0.015	(0.000)	0.057	(0.000)	0.039	(0.000)	0.096	(0.000)	0.081	(0.000)	0.105	(0.000)
COR	0.073	(0.727)	0.393	(0.040)	0.089	(0.767)	2.002	(0.021)	0.442	(0.284)	-0.015	(0.977)
KSR	0.953	(0.021)	0.481	(0.134)	-0.037	(0.898)	1.180	(0.004)	1.017	(0.005)	1.182	(0.161)
RWR	0.655	(0.002)	0.234	(0.402)	1.616	(0.000)	2.153	(0.000)	1.503	(0.007)	0.847	(0.079)
PT	0.197	(0.402)	0.629	(0.001)	0.218	(0.476)	0.466	(0.344)	0.586	(0.127)	1.005	(0.054)
NPT	-0.823	(0.000)	-0.980	(0.000)	-1.073	(0.003)	-2.101	(0.002)	-1.350	(0.009)	-0.474	(0.434)
Adjusted R^2	0.412		0.769		0.620		0.787		0.676		0.772	

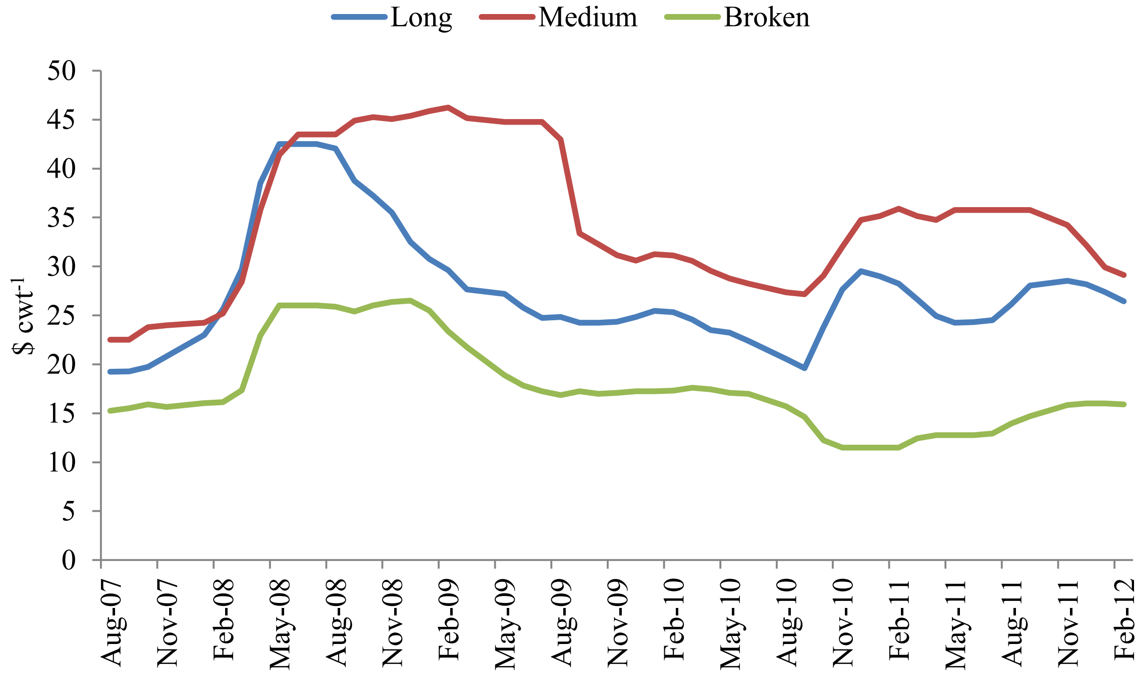
Eq. 2: HRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	44.526	(0.000)	55.053	(0.000)	69.842	(0.000)	65.206	(0.000)	5.818	(0.662)	61.281	(0.000)
TDN_{W2}	-0.096	(0.000)	-0.058	(0.004)	-0.144	(0.000)	-0.229	(0.000)	-0.187	(0.000)	-0.162	(0.000)
TDN_{W3}	-0.040	(0.097)	-0.092	(0.000)	0.068	(0.028)	-0.063	(0.134)	-0.115	(0.000)	-0.096	(0.000)
HMC	2.308	(0.021)	1.382	(0.032)	-0.165	(0.871)	0.535	(0.652)	6.230	(0.000)	1.002	(0.299)
HMC^2	-0.050	(0.035)	-0.032	(0.031)	0.005	(0.852)	-0.017	(0.573)	-0.142	(0.000)	-0.027	(0.270)
COR	2.056	(0.006)	1.428	(0.116)	0.502	(0.634)	-6.843	(0.005)	-5.531	(0.000)	-1.259	(0.256)
KSR	-7.041	(0.000)	-7.848	(0.000)	-7.207	(0.000)	-11.696	(0.000)	-13.483	(0.000)	-7.578	(0.000)
RWR	-0.690	(0.461)	0.310	(0.771)	-1.802	(0.115)	-3.182	(0.024)	-4.475	(0.005)	-1.491	(0.076)
PT	1.707	(0.028)	1.314	(0.125)	3.626	(0.000)	1.324	(0.183)	-1.244	(0.311)	1.098	(0.194)
NPT	1.388	(0.530)	1.199	(0.576)	-2.749	(0.166)	-1.670	(0.496)	-2.615	(0.161)	-1.272	(0.256)
Adjusted R^2	0.456		0.416		0.523		0.726		0.684		0.679	

Table B4 (2/2). GMM system estimation results: TDN specification

Eq. 3: MRY	Bengal		Jupiter		Cypress		LaGrue		Wells		XL723	
Intercept	75.617	(0.000)	78.654	(0.000)	72.491	(0.000)	74.216	(0.000)	76.228	(0.000)	76.932	(0.000)
TDN_{W2}	-0.039	(0.000)	-0.052	(0.000)	-0.054	(0.000)	-0.062	(0.000)	-0.049	(0.000)	-0.068	(0.000)
TDN_{W3}	-0.008	(0.266)	-0.004	(0.586)	0.014	(0.166)	-0.007	(0.458)	-0.021	(0.000)	-0.021	(0.011)
HMC	-0.129	(0.000)	-0.270	(0.000)	-0.066	(0.099)	-0.191	(0.000)	-0.161	(0.000)	-0.210	(0.000)
COR	1.856	(0.000)	1.105	(0.000)	0.932	(0.012)	0.808	(0.154)	1.204	(0.001)	0.947	(0.018)
KSR	-3.652	(0.018)	-6.303	(0.000)	-3.613	(0.029)	-2.307	(0.024)	-3.281	(0.002)	-2.703	(0.117)
RWR	-0.077	(0.821)	-1.009	(0.013)	-0.167	(0.649)	-0.151	(0.720)	-0.338	(0.435)	-1.111	(0.020)
PT	1.124	(0.000)	0.735	(0.064)	2.188	(0.000)	1.559	(0.000)	1.453	(0.000)	0.876	(0.013)
NPT	0.622	(0.260)	-0.194	(0.763)	-0.289	(0.665)	-0.044	(0.936)	0.063	(0.904)	0.074	(0.872)
Adjusted R^2	0.593		0.724		0.606		0.690		0.591		0.555	

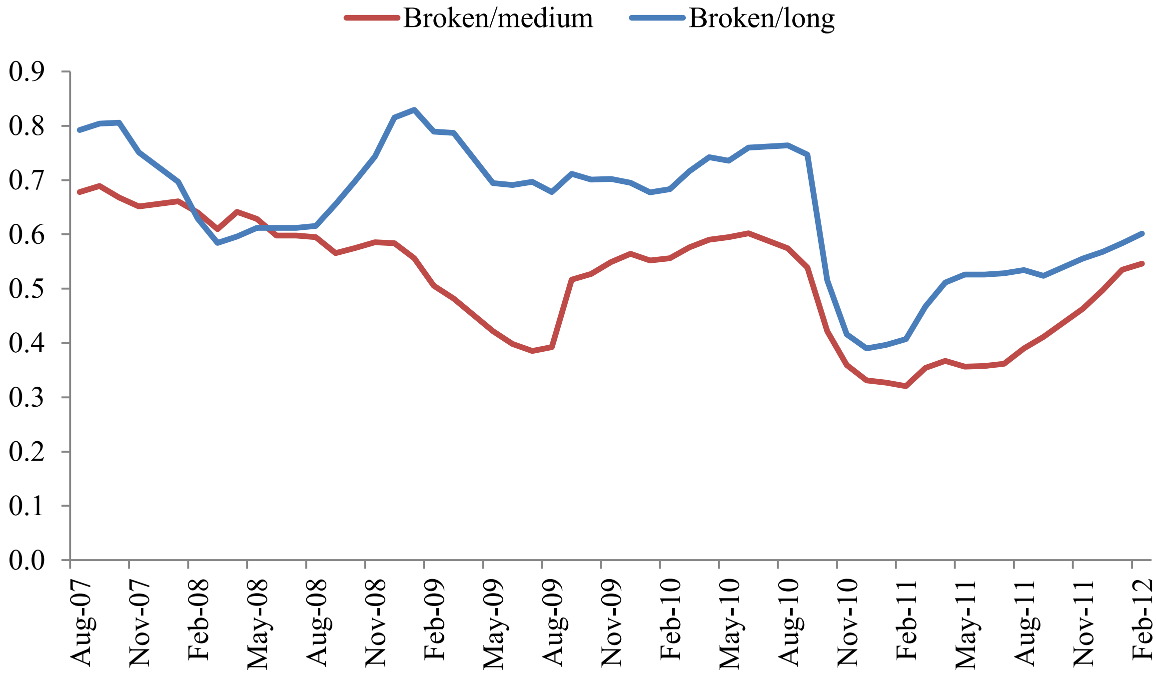
C. RICE PRICES

Figure C1. Milled long- and medium-grain and broken* rice monthly prices



Source: Stuttgart, Arkansas milled rice prices, f.o.b. (USDA-ERS)
*Arkansas milled brewers rice used as the price of broken kernels.

Figure C2. Ratio of broken* to medium- and long-grain milled rice monthly prices



Source**:** Stuttgart, Arkansas milled rice prices, f.o.b. (USDA-ERS)
*Arkansas milled brewers rice used as the price of broken kernels.