# A Globally Flexible Model for Crop Yields Under Weather Risk

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Joseph Cooper and Steven Wallander*[#]

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*Cooper and Wallander are economists with the Economic Research Service, USDA. The views expressed are the authors' and do not necessarily represent those of the Economic Research Service or the US Department of Agriculture.

[#]jcooper@ers.usda.gov and swallander@ers.usda.gov

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***Abstract***

The literature on climate change and crop yields now recognizes the need to allow for highly non-linear marginal effects. This study combines these two areas of the literature by using Flexible Fourier Transforms (FFT's) to ensure flexibility for both the time trend and the weather effects. This study also illustrates how FFT's can be combined with quantile regression (QR) to provide both robustness to outliers and information on the scale effects of time and weather variables. For U.S. county level data on corn, soybeans, and winter wheat, we estimate the relationship between yield and temperature and precipitation using a traditional parametric expected-yield estimator, our quantile-FFT regression evaluated at the median, and our QR-FFT regression that incorporates information on the tails of the distribution. We find that quadratic terms are not sufficient for capturing nonlinearities in the relationship between yield and the explanatory variables.


## INTRODUCTION

Flexible functional forms are important tools for modeling crop yield distributions. To evaluate crop insurance policies and to estimate the effects of climate change on crop yields, analysts must draw on data that is generated from complex, non-linear production functions and in most cases must correct that data for technical change. The literature on estimation of unconditional crop yield distributions has established the need to flexibly control for deterministic time trends (Goodwin and Ker 1998). The literature on climate change and crop yields recognizes the need to allow for highly non-linear marginal effects (Schlenker and Roberts 2006). This study combines these two areas of the literature by using Flexible Fourier Transforms (FFT's) to ensure flexibility for both the time trend and the weather effects. This study also illustrates how FFT's can be combined with quantile regression (QR) to provide both robustness to outliers and information on the scale effects of time and weather variables.

A basic question in climate change research is: how will changes in weather distributions influence crop yields? This question illustrates the need for flexible estimation methods that can capture the location and the scale effects of weather on crop yields. The costs of climate change to agricultural production may be driven more by environmental risks such as drought and flooding than by changes in average temperature and precipitation, particularly if climate change increases the frequency and intensity of extreme events (IPCC 2007). Such predictions have increased the need for estimates of higher-order moments of crop yield distributions conditional on weather (or climate) outcomes. Obtaining information on more than just the central tendencies of crop yield distributions generally requires data that is drawn from multiple decades to include at least several "major" yield shocks, usually either droughts or floods. Such data places a premium on estimation methods that are robust to potentially skewed distributions and misspecifications of functional form, particularly with respect to time trends that are used as a proxy for technical change.

Flexible Fourier Transforms (FFT) – a semi-nonparametric method – allow for non-linear responses of yield to both weather variables and to time-trends. FFTs provide a parsimonious representation of non-linear marginal effects and allow for much greater flexibility than higher-order polynomial functions and are more easily applied to multivariate estimations than kernel regressions. The Fourier functional form is one of the few functional forms known to have

Sobolev flexibility, which means that the difference between an estimated function $g(\mathbf{x},\theta)$ and the true function $f(\mathbf{x},\theta)$ can be made arbitrarily small for any value of $\mathbf{x}$ as the sample size becomes large (Gallant 1987).

However, the flexible properties of the FFT are asymptotic. To reduce the burden on the applied FFT analysis in converging on the true function, this study uses the FFT in conjunction with quantile regressions (QR). M-estimators – such as quantile regression – have been advocated in crop yield studies for both their robustness to outliers and their semi-parametric properties, i.e. their freedom from distributional assumptions (Harri *et al*. 2009, Finger 2010). The combined FFT-quantile estimator is semi-nonparametric, and is free of assumptions regarding the distribution of the regression error as well as the functional form of the yield relationship $g(.)$. The benefit of this approach over a nonparametic quantile (kernel) regression is that multiple explanatory variables can be easily included. In the context of weather-related risks, quantile regressions have an additional benefit that has not been fully exploited. Namely, the approach's ability to estimate quantiles in the tails of the crop yield distribution provides information on production risk that is largely absent from estimates of conditional mean yields. This flexibility allows for the sort of conditional heteroskedasticity that is typically captured through Just-Pope production functions (Chen *et al*. 2004).

The combination of FFTs and QRs is implemented for estimations of yield distributions for corn, soybeans, and wheat, in all U.S. counties where all three crops are grown and for which the National Agricultural Statistics Services reported data over 1975 to 2007. We demonstrate graphically the estimated relationship between yield and temperature and precipitation using a traditional parametric expected-yield estimator, our quantile-FFT regression evaluated at the median, and our quantile-FFT regression that incorporates information on the tails of the distribution.

This paper is organized into four sections. The first section presents a brief review of the literature on crop yield estimation method. The second section frames analysis of crop yields in the context of the farmer's maximization problem and presents the FFT and QR estimation methods. The third section summarizes the data used in the analysis. The fourth section presents the results of the model by graphically comparing the FFT-QR results to traditional parametric results.

## LITERATURE ON ESTIMATION OF CROP YIELD DISTRIBUTIONS

A large literature exists on methods for estimating crop yield distributions. Examples include conditional (e.g.: Schlenker and Roberts 2006) and unconditional (e.g.: Harri *et al*. 2009) crop yield distributions when (county-level) crop yield data includes time-dependent technical change (Moss and Shonkwiler 1993), influential outliers (often due to drought or flooding), potentially non-normal yield distributions, and non-linear response to weather shocks.

Agronomic simulation models provide an alternative method to estimate the impacts of climate change on expected crop yields (Adams *et al.* 1990, Park and Sinclair 1995). However, crop simulators may not adequately represent optimization at the farm level, which leads some analysts to prefer econometric models of conditional crop yields (Lobell *et al.* 2007, McCarl *et. al.* 2008, Huang and Khanna 2010). Some of these studies also examine change in production risk by examining conditional variance of yield (Chen *et al.* 2004). For the most part, these studies focus on specification of weather variables and rely on linear or quadratic time trends, There is evidence that crop yields may not be either difference-stationary or trend-stationary

(Pujala *et al.* 2010), although conditioning on weather variables may solve these problems (Chen *et al.* 2010).

Controlling for time trends is a more central topic in the estimation of unconditional crop yield distributions.  Potentially non-linear trends in technical adoption are difficult to estimate in the presence of non-normal distributions (Moss and Shonkwiler 1993).  Kernel-density estimation is a useful method for capturing non-linearities and may help reduce sensitivity to non-normality (Ker and Goodwin 2000, Ker and Coble 2003).

Skewness is a prevalent concern in crop yield distributions, although there are dramatic differences in skewness across regions and crops (Harri *et al.* 2009, Ramirez *et al.* 2010).  In general, skewed crop yield distributions generate outliers that make estimation of time trends sensitive to large yield shocks that occur toward the beginning or end of a data series.  Robust estimators, such as quantile regression, provide one means of controlling for these outliers (Finger 2010).  Skewness may also results from underlying skewness in weather variables even if the underlying conditional distribution is normal (Hennessey 2009), so conditioning on weather also provides a useful means of ensuring robustness in time trend estimation.

## OVERVIEW OF THE FARM MANAGEMENT AND ECONOMETRIC MODELS

### *Farm Management Model*

The stochastic nature of yields and prices ensures that agricultural producers do not know at planting time what their realized revenue will be. Consequently, with the likelihood that farmers are not risk neutral, a wide body of literature addresses the effect of risk on agricultural producer decisions (Just, 1974; Love and Buccola, 1991; Pope and Just, 1991; Saha, Shumway, and Talpaz 1994; Coyle, 1999; Sckokai and Moro, 2006; Serra *et al.*, 2006).  A critical component of this literature is the impact of risk on producer's acreage decisions (Just 1974, Chavas and Holt 1990, Coyle 1992, Lin and Dismukes 2005; Arnade and Cooper, 2010). Due to this link between production risk and adjustments on the extensive margin, models of conditional yield distributions that rely on observational data are best framed within the context of the literature on production decisions under risk, whether stemming from theoretical frameworks such as expected utility maximization, prospect theory, or other paradigms.

Production lags and the volatility of agricultural markets suggest that price and yield uncertainty may affect the producer's planting decisions. For example, Just (1974) estimated agricultural supply equations and showed that revenue variances can have a significant impact on producer's acreage decisions. Since then, expected utility models have been used to measure the impact of price risk on acreage decisions. Implicit in our analysis of yields is that farmers chose acreage and other inputs (e.g., fertilizer) to maximize a concave von Neumann Morgenstern utility function over wealth or some other measure of income. In such a case, yields will be a function of the farmer's input choices, soil and other agronomic characteristics of the land, and stochastic weather variables, all transformed by technology into yields. Taking first order conditions of expected utility function, input levels can be expressed as function of input and output prices. Hence, yields should be a function of prices, proxies for technology, land characteristics, and weather variables, which we denote as $Y = \mathrm{f}(\boldsymbol{x})$. In the following analysis we directly control for the ratio of input and output prices as well as weather variables. We proxy for technical change with a flexible function of time. For land characteristics, we rely upon regional fixed effects.

**Globally Flexible Model for Yields**

Expanding parameter space, or semi-nonparametric (SNP), methods, are halfway between parametric and nonparametric inference procedures. An advantage of SNP over nonparametric methods is that they allow the researcher to reduce the potential for misspecification bias associated with parametric techniques, while at the same time accounting for explanatory variables more easily than nonparametric methods.

The Fourier functional form we use for the SNP is the only functional form known to have Sobolev flexibility, which means that the difference between the model $Y^{SNP}(\boldsymbol{x},\theta)$ and the true function $f(\boldsymbol{x})$ can be made arbitrarily small for any value of $\boldsymbol{x}$ as the sample size becomes large (Gallant, 1987). The Fourier flexible functional form, which attaches linear and quadratic terms to the Fourier terms to help decrease the number of terms needed to model nonperiodic functions, is specified as (Gallant, 1982)

**(1)** $$Y_{it}^{SNP}(\boldsymbol{x},\theta_k)= U_0+\boldsymbol{b}'\boldsymbol{x}+0.5\boldsymbol{x}'D\boldsymbol{x}+2\sum_{\alpha=1}^{A}\left\{\sum_{j=1}^{J}\left(v_{j\alpha}\cos\left[j\boldsymbol{k}'_\alpha s(\boldsymbol{x})\right]-w_{j\alpha}\sin\left[j\boldsymbol{k}'_\alpha s(\boldsymbol{x})\right]\right)\right\}$$

where $(k\text{-}A\text{-}J)$ x 1 vectors $\boldsymbol{b}$ and $\boldsymbol{x}$ are the set of coefficients and variables, respectively,

$U_0 = u_0 + \sum_{\alpha=1}^{A}\{u_{0\alpha}\}$, and $D=\sum_{\alpha=1}^{A} u_{0\alpha}k_\alpha{}' k_\alpha$, $k$ is the dimension of $\theta$, $A$ (the length) and $J$ (the order) are positive integers, and $\boldsymbol{k}_\alpha$ are vectors of positive and negative integers that form indices in the conditioning variables, after shifting and scaling of $x$ by s($x$). The function s($x$) prevents periodicity in the model (Gallant, 1982; Mitchell and Onvural,1996).

As parametric function $Y$ = f($\boldsymbol{x}$) is nested in Equation (1), validity of the parametric specification can simply be assessed by statistically testing whether or not the parameters $u_{0\alpha} = \upsilon_{j\alpha} = w_{j\alpha} = 0$, $\forall\, j, \alpha$. If a variable has only three unique values, then only the $v$ or $w$

transformation may be performed. With two values, none of the transformations can be performed. A formal criterion for choosing $A$ and $J$ is not well established. Chalfant and Gallant (1985) suggest a rule of thumb that the dimension of $\theta = N^{2/3}$, but this may be high. Asymptotic theory calls for $\theta = N^{1/4}$, but Fenton and Gallant (1996) note that $\theta = N^{1/2}$ is likely to be more representative of actual practice. Appending an additive error term, Equation (1) can be estimated via least squares approaches and quantile approach.

Taken individually, Fourier coefficients do not have an economic interpretation, and there is little point reporting them, especially if the number of parameters is large. To give the Fourier regression results an economic interpretation, they must be re-expressed in terms of the base (i.e., untransformed) variables $\boldsymbol{x}$. One possible way to add economic content is to generate graphs of the relationship between acres and the explanatory values numerically. Another way is to evaluate $\partial Y_{it}^{SNP}(x,\theta)/\partial x$ and use this expression to form elasticities.

**Quantile Estimation**

The condtional mean of the yield function, equation 1, is a natural starting point. However, our interest extends beyond the condtional mean for two reasons. First, if the condtional distribution of $Y^{SNP}(\boldsymbol{x},\theta)$ is not symmetric, then robustness of coefficient estimates to outliers becomes a concern. Second, given the assumption of risk averse producers, there is an interest in higher order moments of the conditional distribution.

Both of these concerns can be addressed through the use of quantile regression (Koenker 2005). For each quantile of interest, the conditional quantile of yields is estimated. This returns a set of parameter estimates specific to that quantile.

## DATA

U.S. county-level data from the National Agricultural Statistics Service (NASS) of the USDA covering 1975 to 2007 were obtained for corn for grain, soybeans, and winter wheat. Note that before the mid-1970s, NASS did not have all continental U.S. States included in its coverage of county level data. These are placed in balanced data sets containing all counties for which NASS has reported planted acres in these crops in every year over the study period. Our strict requirement of no missing data means that some marginal counties – counties with too few planted acres to permit publishing of data without consequences for confidentiality – are left out the analysis.

Yields in each year are planted-acre yield, total production divided by planted acreage. This accounts for fluctuations in the total number of harvested acres. Since planted acreage for corn includes both silage and grain production, total planted acreage is corrected by subtracting out acreage that is harvested for silage.

Weather data is obtained from Oregon State's PRISM (Parameter-elevation Regressions on Independent Slopes Model) climate mapping system (PRISM 2009). Taking into account the interaction of topography and meterological processes, the PRISM data is a gridded interpolation of weather station data and includes monthly values of total precipitation, average daily maximum temperature and average daily minimum temperature. For this study, PRISM grid cells were averaged for temperature values and summed for precipitation values over all cells that fell with agricultural land within each county. Monthly values were averaged or summed into bimonthly values within the spring crop growing season. Minimum temperature and precipation during the winter are the combination of January, February, March and the previous year's December values.

The effect of input and input prices are proxied by the ratio of the effective output price $p_i$ to a fertilizer price $w$, thus imposing homogeneity of degree zero in input and output prices and contributing to parsimony in the explanatory variables. For the input price, we use the April ammonia price from the ERS fertilizer data, as April is reasonably close to planting dates for soy and corn. The output prices are the NASS cash price per bushel for the planting decision month for each crop, where this month is the same as that defined by the Risk Management Agency of the USDA for the pricing of various crop insurance products. The output price is truncated at the commodity loan rate, where the loan rate for each year is defined by Title I of the U.S. Farm Act covering that year. This truncation approach is an approximation to a more theoretically correct approach that would use futures prices in a framework of a truncated distribution. However, such an approach would require a series of prior year prices in order to calculate the conditional expectations. As we do not have futures prices prior to 1975, such an approach would result in a loss of degrees of freedom. As the correlation between cash prices and futures prices is quite high for storage commodities and as annual fertilizer use has changed little over our study period, the ratio as constructed should be sufficient for this paper where the focus is on weather shocks that should not be correlated with prices at planting time.

## RESULTS

We begin by evaluating the FFT model estimated by OLS. The combined FFT quantile regression model is discussed below. The FFT model includes quadratic terms for all weather variables and time trends, which means that the traditional parametric yield model including these quadratic terms is nested within the FFT. As noted above, this allows the FFT to be tested by examining the joint significant of the coefficients on the Fourier terms. For the corn, soybean and wheat models, the F-test values comparing the FFT model to the nested parametric model without the FFT terms are 40.07, 36.20 and 46.91, respectively, all of which are statistically significant at any reasonable (measurable) level of significance. Hence, the parametric models are rejected. F-tests comparing the FFT model with a parametric model including quadratic terms are also rejected at reasonable (measurable) level of significance.

The FFT and parametric models can be compared graphically as a function of the explanatory variables. Figure 1 shows the predicted yields from each model as a function of time, evaluating all other variables at their sample averages. The first column of results compares the parametric and FFT models. For corn the two models are quite different. The quadratic time trend shows consistently declining gains in corn yields over time. In contrast, the FFT model shows declining gains in yields in the late 1980's followed by increasing gains since 2000. The differences in expected yields between the two models is greatest in the 1990's. For soybeans, the differences in trend lines are much less pronounced and both a nearly linear. For winter wheat, the trend line in the parametric model is almost perfectly linear, whereas the trend line in the FFT model exhibits considerable periodicity and large declines between 2004 and 2007. The FFT model for wheat could be sensitive to both the nature of the sample and the terminal year of the sample. Since the sample includes only counties that grow corn, soybean and wheat, this does not represent the majority of wheat acreage. (The sample primarily represents growers of soft red winter wheat.) This sample is likely particular sensitive to the inclusion of 2007 as the final year of the sample since both corn and soybean prices had almost doubled whereas winter wheat harvested in 2007 had preceded any major increase in the price of wheat.

We extend the FFT model into estimation of quantile regression by estimating the 0.1, 0.5 (median) and 0.9 conditional quantiles. To provide a general sense of the sensitivity of yield to key variables, table 1 shows the elasticity of yield with respect to each variable. The maximum temperature in July and August has a negative impact on the yields of all three crops and has the largest magnitude of any elasticity with respect to the weather variables. Given the highly non-linear nature of the model, these elasticities clearly are not constant, as exemplified by the negative elasticity on the wheat time trend.

Figure 2 compares the time trends within each of these quantiles with the conditional mean time trend discussed above. For all three crops the conditional mean lies slightly below the conditional median, suggesting that, even after conditioning on weather, there may be some slight negative skew to the crop yield distribution although the difference is usually quite small and unlikely to be statistically significant. The 0.9 quantile for all three crops is generally increasing at a faster absolute rate than the 0.1 quantile, indicative of increase yield variance over time.

To illustrate the potential of the FFT model to capture non-linear responses of yield to weather variables, we examine the response of corn and soybean yields to average daily maximum temperatures. Given the high elasticity on maximum temperature in July and August, we examine that variable first. Higher maximum temperature are initially beneficial for both corn and soybeans. For corn, past an average daily maximum temperature of about 78 degrees yields decline at a roughly constant rate for all quantiles. There does not appear to be an increase in yield variance in response to temperature for corn, but there may be an initial increase in variance for soybeans.

The right hand side of figure 2 compares the effects of temperatures across different times of the growing season for the conditional median. The positive effects of water temperature are more pronounced in corn in the earlier months. Most significantly, this model shows that the marginal benefit of heat accumulation is not constant throughout the growing season, a result which contrasts with the assumptions embedded in most yield models that make use of growing degree days to specify the cumulative exposure of a crop to heat over the course of the growing season.

## CONCLUSION

The implementation of FFTs within a quantile regression framework provides a flexible way of examining the conditional distribution of crop yields. This study has illustrated the feasibility of combining these two techniques, which provides a bridge between efforts to robustly model unconditional crop yields and efforts to model the effects of weather on crop yields using traditional parametric models. Future research will use this model to examine the implications of model specification on federal crop insurance premiums and other commodity support calculations.

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Figure 1: Time Trend Estimates

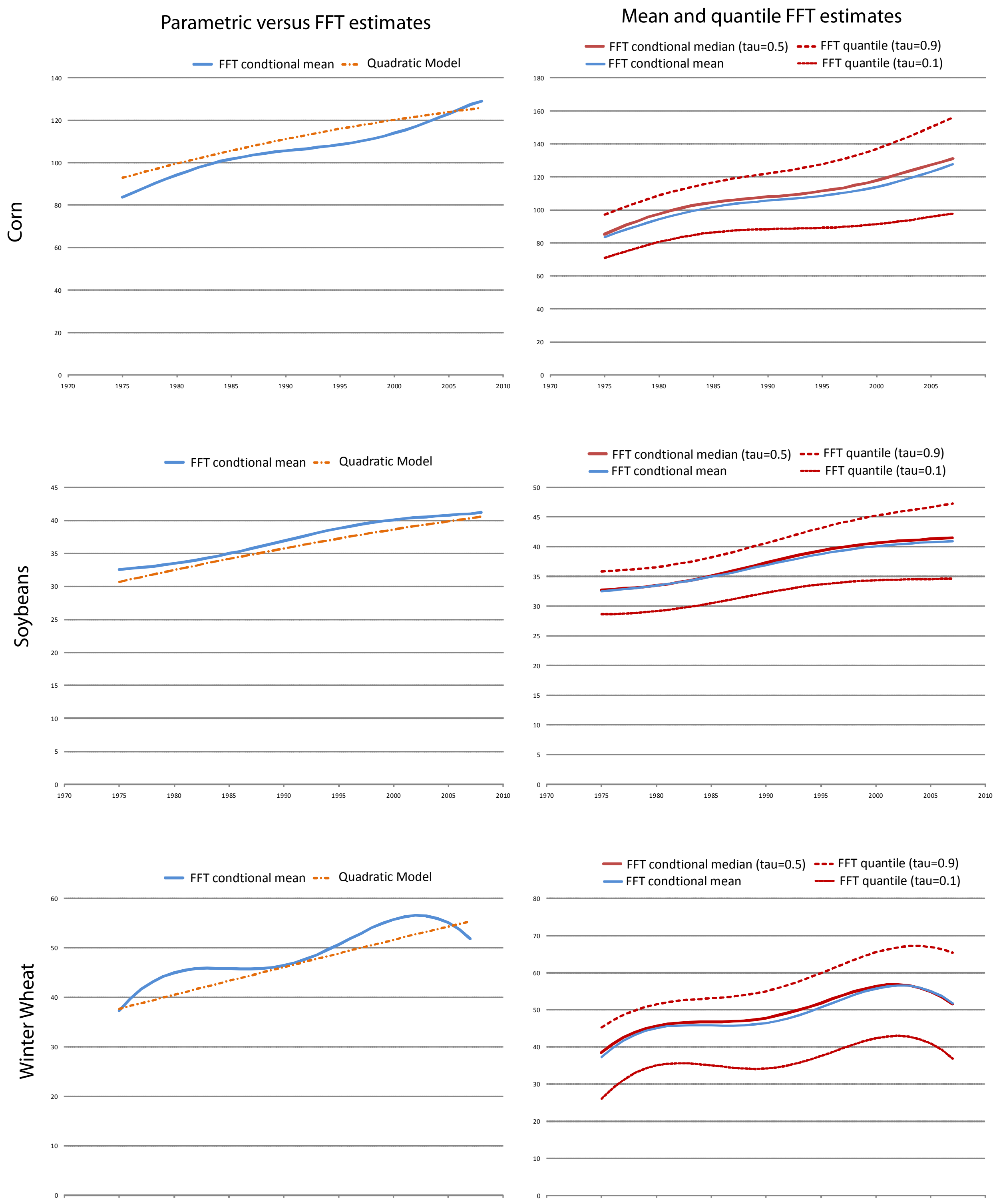

Figure 2: Average Maximum Daily Temperature Effects

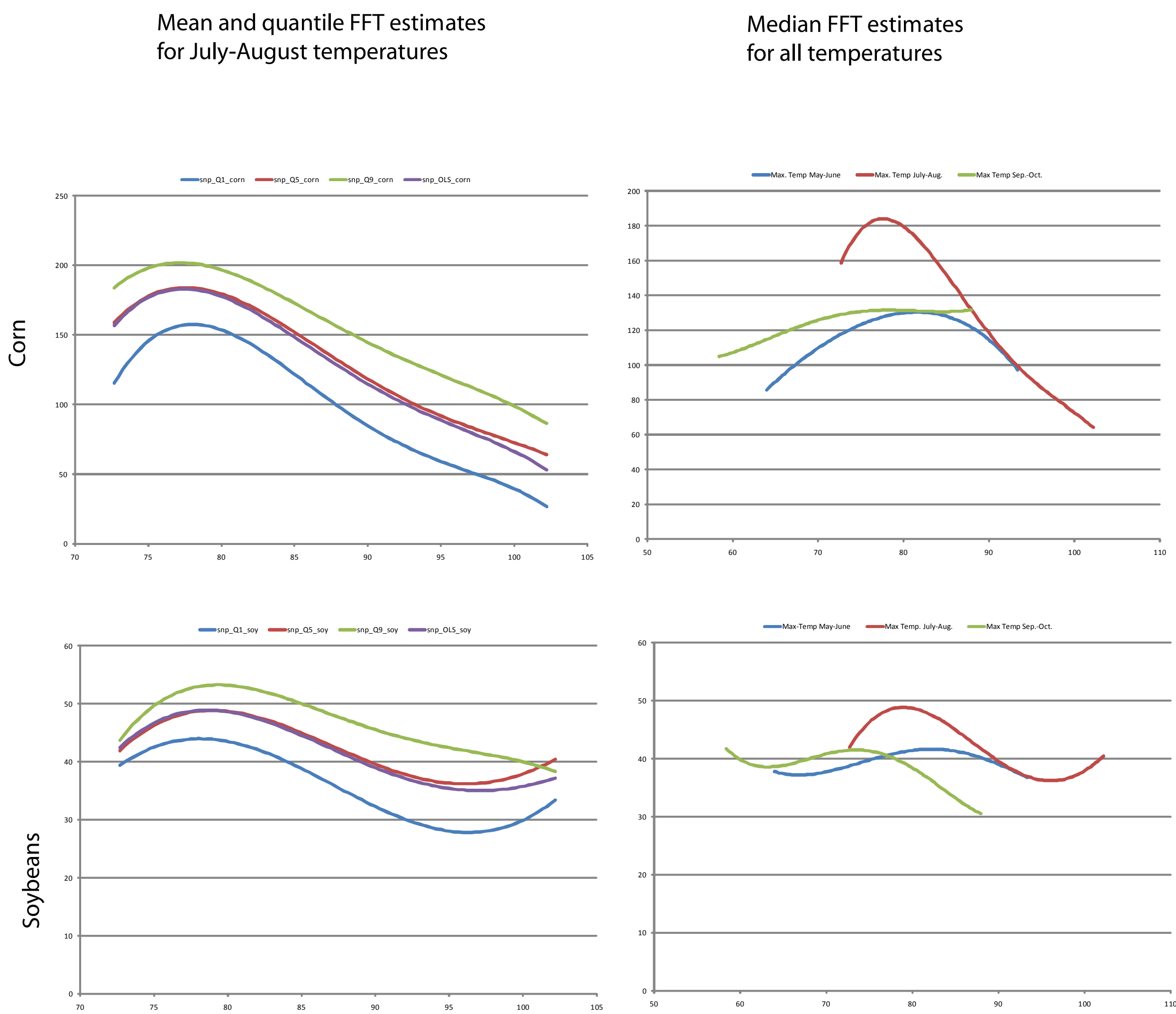

Table 1: Elasticities of Crop Yields in Median FFT Regressions

| Variable | Corn | Soybeans | Wheat |
|---|---|---|---|
| trend | 0.492 | 0.106 | -1.298 |
| P_"crop"_N | -0.188 | -0.245 | -0.214 |
| pcpMarApr | -0.030 | 0.006 | -0.052 |
| pcpMayJun | 0.034 | 0.014 | -0.036 |
| pcpJulAug | 0.066 | 0.172 | 0.037 |
| pcpSepOct | 0.007 | -0.027 | 0.015 |
| tmaxMayJun | 0.186 | 0.213 | 0.390 |
| tmaxJulAug | -3.097 | -1.681 | -0.847 |
| tmaxSepOct | 0.234 | -0.100 | 0.134 |
| tminWint | -0.033 | 0.017 | -0.039 |
| tminMarAug | 0.009 | 0.020 | -0.039 |
| tminMayJun | 0.110 | 0.083 | -0.532 |
| tminJulAug | 0.152 | 0.070 | 0.574 |
| tminSepOct | -0.104 | 0.086 | -0.163 |