Distributional and Temporal Heterogeneity in the Climate Change Effects on U.S. Agriculture*

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Abstract

Existing studies on climate change effects on crop yields mainly focus on the *average* climate–yield relationship that is typically assumed to be time-invariant. We apply a flexible panel-data quantile regression with time-varying coefficients to examine distributional heterogeneity and temporal variation in this relationship. We find that U.S. corn and soybean yields have gradually become less sensitive to temperature and precipitation over 1948–2010, which is especially the case for upper yield quantiles. Consequently, the negative impacts of future climate change are of larger magnitudes at the lower yield quantiles. Failure to accommodate temporal changes in the climate–yield relationship leads to significantly overestimated responsiveness of crop yields to weather variation and, therefore, overestimated negative impacts of future climate change. On many occasions, the corn yield decline projections from such time-invariant specifications are about twice as large as (and sometimes triple) the predictions from our time-varying-coefficient model.

Keywords: Adaptation, Agriculture, Climate Change, Crop Yields, Heterogeneity, Quantile Regression

JEL Classification: Q16, Q54

For an extended version of the paper, see the Supplementary Online Appendix.

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1 Introduction

Since Mendelsohn et al.'s (1994) seminal work, numerous studies have applied regression analyses to examine climate change effects on agriculture (e.g., Schlenker et al., 2005; Deschênes & Greenstone, 2007; Schlenker & Roberts, 2009; Burke & Emerick, 2016; Chen et al., 2016; Miao et al., 2016; Zhang et al., 2017). However, prior studies have mainly focused on the *average* climate–agriculture relationship, which inhibits our understanding of potential distributional heterogeneity in climate change effects. Although knowing how climate may affect mean agricultural outcomes are important, it is no less critical to examine potentially differential impacts of climate on lower and upper tails of the outcome distribution, particularly as agricultural outcomes are highly heterogeneous. Moreover, the existing literature also largely assumes time-invariance of the climate–agriculture relationship, which neglects the evolution of climate impacts on agriculture over time, even though studies have shown that the advances in management practices and agricultural technology such as plant breeding and agro-chemicals may considerably assist farmers in adapting to the changing climate (e.g., Howden et al., 2007; Ceccarelli et al., 2010).

The present study examines the reduced-form relationship between climate and crop yields by addressing the aforementioned research gaps. The analysis is based on the annual county-level data for weather variables as well as corn and soybean yields over 1948–2010 in the rainfed region of the United States (east to the 100th Meridian). Crop yields are chosen because they are a simple and direct measure of agricultural production with detailed historical data for many decades. We estimate a flexible, yet parsimonious, time-varying-coefficient panel-data quantile regression model which explicitly allows for (i) distributional heterogeneity in the effects of climate on yields at various quantiles, (ii) temporal variation in the dependence of crop yields on weather, and (iii) unobservable county-level confounders.

Unlike traditional regression models that focus on the first moment, quantile regression provides a complete description of the relationship between the distribution of outcome variable and its regressors. Since agricultural outcomes are highly heterogeneous across space, there remains much untapped benefit of examining the link between climate and agriculture via quantile analysis. Thus, contrary to previous studies, exemplified by Schlenker & Roberts (2009) who utilize fixed-effects panel data models to estimate climate change effects on the *average* crop yields via conditional-mean models, we focus on conditional *quantiles* of the yield distribution that enable us to examine potential heterogeneity in the climate-yield relationship.

Borrowing from Baltagi & Griffin (1988), we allow parameters of the conditional quantile to vary with time, which enables us to investigate the evolution of sensitivity of crop yields to weather variation. This evolution reflects farmers' technological adaptability to the changing climate. Most existing studies of the climate-yield relationship estimate models with time-invariant coefficients, implicitly assuming that the relationship is fixed. Although Burke & Emerick (2016) investigate the potential of adaptation to climate change by utilizing an innovative long-difference approach, they still implicitly assume that the climate change impact on crop yields does not vary over time. In other words, they impose that the responsiveness of crop yield to climate is constant over time. Few exceptions include Mendelsohn et al. (2001), Lobell et al. (2014), and Barreca et al. (2016) who quantify changes in the sensitivity of agriculture or mortality to climate by comparing coefficients estimated using data from different time periods. Although convenient, such a sample-splitting approach suffers from reduced degrees of freedom and is more likely to yield noisier estimates as a result of giving up valuable information embedded in a panel structure of the data with a longer time series. Some other studies interact time trend with weather variables (e.g., Yu & Babcock, 2010), which effectively requires an *a priori* assumption about the smoothness and a functional form of the dependence of marginal impacts on time. In contrast, we employ flexible non-neutral time indices à la Baltagi & Griffin (1988) to let the coefficients vary with time arbitrarily thereby capturing changes in responsiveness of crop yield to weather variation. These time indices are advantageous over simple time trends (including quadratic) in modeling temporal changes because they provide richer variation in the measurement of technological change and much closer approximation to observed temporal changes (Baltagi & Griffin, 1988).

We control for unobservable cross-county heterogeneity via fixed effects which absorb time-invariant confounding variation. Failing to control for fixed effects will cause omitted variable bias because the unobservable confounders (e.g., soil quality) may correlate with weather variables. However, the direct estimation of quantile regressions with fixed effects using routine estimators is not trivial due to nonlinearity of the quantile operator which makes it impossible to purge fixed effects from the regression via any transformation (e.g., see Koenker, 2004). We tackle this problem by adapting the recently developed approach by Machado & Santos Silva (2019) that allows an easy-to-implement indirect estimation of the quantile parameters via moments and is more fitting for nonlinear specifications. We now discuss the econometric strategy. As we proceed, note that an extended version of the article is available as an online supplementary material that elaborates on all aspects of the paper and includes additional results such as those for soybeans and robustness checks.

2 Econometric Strategy

We model the reduced-form relationship between the county-level climate and crop yield at different conditional quantiles of the latter. Let $\log y_{it}$ be the log-yield in county $i = 1, \dots, n$ in year $t = 1, \dots, T$, μ_i be the county fixed effect, and $\mathbf{x}_{it}$ be the vector of strictly exogenous weather variables and, possibly, their higher-order polynomial terms. Now, consider the following location-scale regression à la Koenker & Bassett (1982) with fixed effects and time-varying coefficients:

$$\log y_{it} = \mu_i + \beta_0 + \mathrm{B}(t) + \mathbf{x}_{it}'\big[\boldsymbol{\beta}_1 + \boldsymbol{\varphi}_1 \mathrm{B}(t)\big] + u_{it}, \quad u_{it} = \big(\gamma_0 + \Gamma(t) + \mathbf{x}_{it}'\boldsymbol{\gamma}_1\big)\varepsilon_{it}, \qquad (2.1)$$

where β_0, $\boldsymbol{\beta}_1$, $\boldsymbol{\varphi}_1$, γ_0 and $\boldsymbol{\gamma}_1$ are unknown fixed coefficients and, to allow for temporal variability in the relationship, we follow Baltagi & Griffin (1988) and introduce two scalar time indices $\mathrm{B}(t)$ and $\Gamma(t)$. Both time indices are unobservable and one may view them as the unknown functions of time. Furthermore, index $\mathrm{B}(t)$ enters the location function *non*-neutrally, shifting not only the intercept $\beta_0 + \mathrm{B}(t)$ but also the slopes $\boldsymbol{\beta}_1 + \boldsymbol{\varphi}_1 \mathrm{B}(t)$, thereby allowing for flexible locational shifts over time.[1] Scale changes over time are also allowed by means of $\Gamma(t)$ but, for computational ease, we assume additive separability of $\Gamma(t)$ from other variables in the scale function.

By following Machado & Santos Silva (2019), we assume that ***(i)*** ε_{it} is *i.i.d.* across i and t with some cdf F_ε; ***(ii)*** $\varepsilon_{it} \perp \mathbf{x}_{it}$ with the normalizations that $\mathbb{E}[\varepsilon_{it}] = 0$ and $\mathbb{E}[|\varepsilon_{it}|] = 1$; and ***(iii)*** $\Pr[\gamma_0 + \Gamma(t) + \mathbf{x}_{it}'\boldsymbol{\gamma}_1 > 0] = 1$. Then, for any given quantile index $\tau \in (0,1)$, from (2.1) it follows that the τth conditional quantile of the log-yield is

$$\mathbb{Q}_\tau[\log y_{it}|\mathbf{x}_{it}] = \mu_i + \underbrace{\Big[\beta_0 + \gamma_0 q_\tau + \mathrm{B}(t) + \Gamma(t)q_\tau\Big]}_{\text{time-varying quantile interecept}} + \mathbf{x}_{it}'\underbrace{\Big[\boldsymbol{\beta}_1 + \boldsymbol{\gamma}_1 q_\tau + \boldsymbol{\varphi}_1\mathrm{B}(t)\Big]}_{\text{time-varying quantile slopes}}, \qquad (2.2)$$

where $q_\tau = F_\varepsilon^{-1}(\tau)$ is the (unknown) τth quantile of ε_{it}, and both the intercept and slope coefficients in the conditional quantile regression vary with the quantile of log-yield and time. Furthermore, the presence of $\Gamma(t)$ in the intercept coefficient provides additional flexibility by which the intercept can vary over time in a manner different from that of the quantile slope coefficients.

Motivated by the presence of unobserved fixed effects in the model, we utilize the location-scale model to derive the conditional quantile function in (2.2) instead of postulating a quantile regression *prima facie*. We adopt the approach recently proposed by Machado & Santos Silva (2019) that estimates all quantile parameters based on the moments implied by the location-scale model in (2.1). Basically, we first estimate parameters of the location function and then, separately, those of the scale function. Based on these estimates, we then estimate the unknown quantiles and recover the time-varying quantile coefficients in (2.2).

To operationalize the estimator, following Baltagi & Griffin's (1988) we model unobservable $\mathrm{B}(t)$ and $\Gamma(t)$ via discretization using a series of time dummies, which is akin to a nonparametric local-constant estimation of these unknown functions of time using zero bandwidth. Though it might appear that, when $\mathrm{B}(t)$ estimated in this manner, we obtain the time-varying slopes on $\mathbf{x}_{it}$ by merely interacting the latter with time dummies, this is

[1] Unless $\boldsymbol{\varphi}_1$ is equal to 1 for all $\mathbf{x}_{it}$ regressors, the intercept and the slope parameters of the location function do not vary over time in the same manner.

not quite the case because time dummies are restricted to have the same parameters $\{\eta_k\}$ both when entering additively and when interacting with $\mathbf{x}_{it}$. Thus, the location function is not a "fully saturated" specification but a parsimonious nonlinear function with fewer coefficients. By avoiding a fully saturated specification that is equivalent to sample-splitting into cross-sections, we accommodate county fixed effects.

For hypothesis testing we rely on Efron's (1982) bias-corrected bootstrap percentile confidence intervals. To approximate the sampling distribution of the parameter estimators and secondary functions thereof, we use a wild residual block-bootstrap, which we adapt to allow for potential spatial cluster dependence in residuals across counties. Specifically, in addition to clustering of each county over time owing to the panel structure of the data, we also allow for clustering across counties that belong to the same climate division. The details of the estimation procedure and hypothesis testing are provided in the extended version of the paper, which also discusses the model specification tests against the specifications with time-invariant fixed-coefficients and additive time trends.

3 Data

Data related to the county-level corn yields are obtained from the National Agricultural Statistics Service of the U.S. Department of Agriculture. Our historical climate data (1948-2010) contain eight daily variables: maximum temperature, minimum temperature, precipitation, wind speed, humidity, long-wave radiation, short-wave radiation, and surface pressure, which are obtained from the Terrestrial Hydrology Research Group at Princeton University.

Following Schlenker & Roberts (2009), we define the growing season as March to August and obtain growing degree days (GDD) based on the data for the daily maximum and minimum temperature. Following the same study, we set the upper threshold of the GDD calculation at 29°C, with the lower threshold at 8°C. We label the GDD between this range as $\text{GDD}_{8-29^\circ\text{C}}$. We also include GDD above 29°C, denoted by $\text{GDD}_{29^\circ\text{C}+}$, to reflect the impact of overheat on corn yields. The precipitation variable is the accumulated precipitation over the growing season for each year. The remaining weather variables are measured as simple averages of daily values over the growing season. To capture potential nonlinearities in the effects of $\text{GDD}_{8-29^\circ\text{C}}$ and precipitation, we include their quadratic terms. Following Schlenker et al. (2006), the overheat measure $\text{GDD}_{29^\circ\text{C}+}$ is included after taking the square root.

Climate data used for projecting future climate change effects on crop yields, obtained from the Multivariate Adaptive Constructed Analogs (MACA) dataset, are generated by global climate models HadGEM2-ES365 and NorESM1-M. For each of the two models, we obtain the predicted climate data under warming scenarios RCP4.5 and RCP8.5.[2] We use data for the 2040–2059 and 2080–2099 periods to respectively represent the medium- and long-term future climate conditions.

4 Empirical Results

We estimate our model for the 0.25^{th}, 0.50^{th}, 0.75^{th}, and the 0.90^{th} conditional yield quantile based on the model in (2.1)–(2.2). To empirically assess how the adoption of a more restrictive fixed-coefficient modeling of the climate–yield relationship may affect the estimates and, subsequently, the conclusions about the climate change effects on the crop yields, we also estimate the quantile model that *a priori* assumes all slope coefficients are constant over time but includes additive linear time trends to allow for neutral temporal shifts in the climate-yield relationship.[3]

4.1 Climate Effects across Quantiles

Table 1 reports time-varying coefficient estimates which are measured in % of yield per unit in the corresponding regressor. Because we have 63 years of data and the coefficients are time-varying, we have 63 year-specific point estimates of the time-varying coefficient for each variable, whose minimum, maximum, and the first three quartile values are reported. The

[2]Data under RCP2.6 or RCP6.0 are unavailable in the MACA dataset.

[3]The extended version of the paper also includes the results of a fixed-coefficient specification with additive quadratic time trends. The two alternative specifications yield similar results.

column labeled "$\neq 0$ (%)" reports the share of the 63 year-specific point estimates for each time-varying slope coefficient that are statistically significant. We find that the coefficients of the linear $\mathrm{GDD}_{8-29^\circ\mathrm{C}}$ term are largely positive whereas the sign of its quadratic term coefficients is negative. This suggests an inverse-U-shaped relationship between the log-yield and $\mathrm{GDD}_{8-29^\circ\mathrm{C}}$ across all considered quantiles.

Figure 1 plots the marginal-effect functions of $\mathrm{GDD}_{8-29^\circ\mathrm{C}}$ for the corn yield by quantiles and by decades, where each dashed black line stands for a year-specific marginal effect function. The solid pink lines in Figures 1 correspond to the marginal effect estimate from the fixed-coefficient model that assumes time-invariant slopes. Figure 1 shows that, moving from the 0.25^{th} to the 0.90^{th} quantile, the bundles of dashed black lines shift closer to the zero line, especially in the later three decades of the sample period. This suggests that the marginal effect of $\mathrm{GDD}_{8-29^\circ\mathrm{C}}$ is smaller and less varying in absolute value for higher corn yield quantiles.[4]

Table 1 also shows that the time-varying coefficients of $\mathrm{GDD}_{29^\circ\mathrm{C}+}$ are all expectedly negative, with the share of statistically significant estimates being 100% for all yield quantiles. Figure 2 depicts the marginal effects of $\mathrm{GDD}_{29^\circ\mathrm{C}+}$ (evaluated at the sample median) on corn yields over 1948–2010 across different yield quantiles. As moving from lower to upper yield quantiles, the time-varying-coefficient estimates approach the zero line from below, indicating less negative marginal effects.

4.2 Sensitivity to Climate Variation across Decades

Because our model accommodates temporal changes in the climate–yield relationship, we can examine how marginal effects of weather variables on corn yields have evolved over time. Consider the sensitivity of corn yield to $\mathrm{GDD}_{8-29^\circ\mathrm{C}}$. Figure 1 shows that, for each of the four estimated corn yield quantiles, the plotted dashed black lines (year-specific marginal-effect functions) have become flatter with time, especially in later decades. This suggests that, with time, perhaps technology advances technology have made corn yields less sensitive to

[4]Marginal effect functions of precipitation display a similar pattern (see the extended version of the article).

total $\text{GDD}_{8-29°\text{C}}$ within the county, *ceteris paribus*. These advances, however, do not seem to have benefited low-yielding areas much.

Figure 2 shows that the negative marginal effects of $\text{GDD}_{29°\text{C}+}$ have displayed a clear upward trend, indicating that the magnitude of the negative marginal effect has been decreasing across all considered yield quantiles. The fixed-coefficient model is, however, unable to detect such a decline in the recent decades. It therefore tends to overestimate the negative impact of overheat GDD on corn yields in 1990–2010, with overestimation being particularly large (more than 100%) for lower yield quantiles.

4.3 Projections of Future Climate Change Impacts

We predict future crop yield quantiles using climatic forecast data and the estimated climate–yield relationship described above. We then compare to the crop yields predicted using historic average climate data from the most recent ten years (i.e., 2001–2010) in our sample. To avoid unnecessarily excessive extrapolation into the future, when predicting future crop yields we fix time-varying coefficients at their 2001–2010 average levels representative of the most recently available technology, effectively assuming no technology-driven improvements in the crop productivity in the future. Therefore, our estimates are likely to be conservative. The county-level yield projections are then aggregated via acreage-weighted averages.

Figure 3 summarizes these results based on the estimates of time-varying coefficients.[5] It shows that the estimated average decline in corn yields due to the future climate change can be up to about 50%, depending on the time horizon, global climate projections, and yield quantiles. Overall, the negative impacts of future climate change on corn yields are of larger magnitudes for lower quantiles, potentially making corn yields even more negatively skewed. For instance, under HadGEM2-ES365 long-term (2080–2099) RCP8.5 scenario, corn yield reductions are about 50% for the 0.25^{th} yield quantile but only about 20% for the 0.90^{th} quantiles. The figure also presents contrasting projections for corn yield decline attributed to climate change based on the time-varying-coefficient model to those based

[5]We only discuss results based on climatic forecasts from global climate model HadGEM2-ES365 due to space limitation. See the extended version of the paper for an analogous discussion and figure based on climatic forecasts from global climate model NorESM1-M.

on the fixed-coefficient conditional quantile model. Obviously, the predictions based on the fixed-coefficient model (dashed pink lines) lie well below their counterparts from the time-varying-coefficient model (solid lines with markers) thereby generating over-estimated climate-change-driven yield declines. On many occasions, corn yield reduction projections from the fixed-coefficient model are more than twice as large as (sometimes about triple) the predictions from the time-varying-coefficient model.

Figure 4 further presents contrasting projections for corn yield decline based on our time-varying-coefficient model and those based on a fixed-coefficient conditional *mean* model. We present this comparison because the latter model is widely used in the existing studies to examine the impact of climate change on agriculture. From the figure we can see that, depending on the future warming scenario and time horizon, the projections based on the fixed-coefficient conditional mean model range between -30% and -70%, a range close to the findings in Schlenker & Roberts (2009). However, these projections are well below the projections based on our time-varying coefficients conditional quantile model, which underscores the importance of accounting for the distributional and temporal heterogeneity in examining the climate-agriculture relationship.

4.4 Robustness

So far, we have employed GDD as the temperature variable. An alternative approach to GDD, proposed by Schlenker & Roberts (2009), is to measure exposure time within a certain temperature range during the growing season. We calculate such a time exposure within each 5°C interval and then use the result as a measure of temperature to re-estimate our model and future climate change impacts. As another robustness check, we weight our regressions by corn harvested acreage to facilitate a more representative acre-based interpretation of our results. The results are robust to these changes and we refer readers to the extended version of the paper for details.

5 Conclusions

Applying a panel-data quantile regression with time-varying coefficients, we find that the sensitivity of U.S. corn yields to $\text{GDD}_{8-29^\circ\text{C}}$, $\text{GDD}_{29^\circ\text{C}+}$, and precipitation exhibits a clear distributional heterogeneity and that the yields have gradually become less responsive to these weather variables over the past six decades. Based on future climate data generated by some widely-used global climate models, we show that the negative impacts of future climate on corn yields are of much larger magnitudes for yields at lower quantiles. This finding sheds light on the distributional heterogeneity of climate change effects on agriculture: crop yields in less productive regions (e.g., developing countries) may be hit by future climate change the most, whereas yields in more productive regions may suffer less.

When compared with the time-varying coefficient model, we find that the fixed-coefficient model tends to significantly overestimate the responsiveness of crop yields to climate variation and, therefore, overestimates the negative impact of future climate on crop yields by up to three times. Therefore, establishing damage functions for the integrated policy assessment models based on fixed-coefficient estimates should proceed with caution.

Future research along the line in this article may benefit from the increasing availability of sub-county-level or even field-level data to further explore the distributional heterogeneity of climate change effects. Moreover, since the present study is focused on quantifying the climate effect heterogeneity instead of exploring the sources of this heterogeneity, it does not shed much insight into the drivers of the heterogeneity. Future research is needed to identify these drivers and to quantify their roles in determining adaptation to climate change in agriculture.

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Table 1. Time-Varying Quantile Slope Coefficient Estimates for the Corn Yield

	All Estimates						*All Estimates*					
Variable	Min	1st Qu.	Median	3rd Qu.	Max	$\neq 0$ (%)	Min	1st Qu.	Median	3rd Qu.	Max	$\neq 0$ (%)
	The 0.25th Yield Quantile						**The 0.50th Yield Quantile**					
Total $GDD_{8-29°C}$	0.0433	0.0986	0.1402	0.203	0.2931	98.4	0.0255	0.0808	0.1223	0.1852	0.2753	96.8
Total $GDD_{8-29°C}$ sq. ($\times 10^{-3}$)	–0.0564	–0.0364	–0.0224	–0.0132	–0.0009	84.1	–0.0521	–0.0321	–0.0181	–0.0088	0.0035	69.8
Total $GDD_{29°C+}$ (square root)	–13.2564	–10.8901	–9.2392	–8.1473	–6.6947	100	–11.9087	–9.5424	–7.8915	–6.7996	–5.347	100
Total Precipitation	0.0913	0.1256	0.1514	0.1903	0.2461	100	0.0612	0.0954	0.1212	0.1601	0.2159	100
Total Precipitation sq. ($\times 10^{-3}$)	–0.2177	–0.1575	–0.1154	–0.0876	–0.0506	100	–0.1958	–0.1355	–0.0935	–0.0657	–0.0287	98.4
Average Wind Speed	–6.5986	–5.9685	–5.5289	–5.2381	–4.8513	81	–6.2351	–5.605	–5.1654	–4.8746	–4.4879	74.6
Average Humidity ($\times 10^{3}$)	–4.9245	–4.0543	–3.4471	–3.0455	–2.5113	93.7	–4.836	–3.9658	–3.3586	–2.957	–2.4228	88.9
Average Long-Wave Radiation	0.1447	0.2062	0.2524	0.3224	0.4226	55.6	0.0439	0.1054	0.1516	0.2215	0.3217	19
Average Short-Wave Radiation	–1.394	–0.7852	–0.3605	–0.0795	0.2942	73	–1.325	–0.7162	–0.2914	–0.0105	0.3633	71.4
Average Surface Pressure	3.0819	3.6667	4.1063	4.7709	5.7235	100	2.6499	3.2347	3.6743	4.3389	5.2915	100
	The 0.75th Yield Quantile						**The 0.90th Yield Quantile**					
Total $GDD_{8-29°C}$	0.0105	0.0658	0.1074	0.1703	0.2603	87.3	–0.0013	0.054	0.0956	0.1584	0.2485	84.1
Total $GDD_{8-29°C}$ sq. ($\times 10^{-3}$)	–0.0485	–0.0284	–0.0145	–0.0052	0.0071	57.1	–0.0456	–0.0256	–0.0116	–0.0024	0.0099	52.4
Total $GDD_{29°C+}$ (square root)	–10.7813	–8.415	–6.7641	–5.6722	–4.2196	100	–9.8896	–7.5233	–5.8724	–4.7804	–3.3279	100
Total Precipitation	0.0359	0.0702	0.096	0.1349	0.1907	98.4	0.016	0.0502	0.076	0.1149	0.1707	90.5
Total Precipitation sq. ($\times 10^{-3}$)	–0.1774	–0.1171	–0.0751	–0.0473	–0.0103	93.7	–0.1629	–0.1026	–0.0606	–0.0328	0.0042	84.1
Average Wind Speed	–5.931	–5.3009	–4.8614	–4.5706	–4.1838	49.2	–5.6905	–5.0604	–4.6209	–4.3301	–3.9433	39.7
Average Humidity ($\times 10^{3}$)	–4.762	–3.8917	–3.2846	–2.883	–2.3487	87.3	–4.7034	–3.8332	–3.226	–2.8244	–2.2902	87.3
Average Long-Wave Radiation	–0.0405	0.021	0.0673	0.1372	0.2374	0	–0.1072	–0.0457	0.0006	0.0705	0.1707	0
Average Short-Wave Radiation	–1.2672	–0.6584	–0.2337	0.0473	0.421	69.8	–1.2215	–0.6127	–0.188	0.093	0.4667	73
Average Surface Pressure	2.2886	2.8733	3.3129	3.9775	4.9301	100	2.0027	2.5875	3.0271	3.6917	4.6443	100

Notes: This table summarizes the point estimates of the time-varying slope coefficients of the 0.25^{th}, 0.50^{th}, 0.75^{th}, and the 0.90^{th} conditional yield quantiles based on the model in (2.1)–(2.2). Specifically, for each conditional yield quantile regression, the table presents the minimum, 1^{st} quartile, median, 3^{rd} quartile, and the maximum of the year-specific slope estimates, along with the share of sample period for which the time-varying slope coefficients are statistically significant. See the columns of 'Min', '1st Qu.', 'Median', '3rd Qu.', 'Max', and '$\neq 0$ (%)', respectively. Statistical significance is assessed using two-sided 95% bias-corrected percentile confidence intervals. To ease exposition of the table, we re-scale 'Total $GDD_{8-29°C}$ sq.' and 'Total Precipitation sq.' by a factor of 10^{-3} and re-scale 'Average Humidity' by a factor of 10^{3} so that their coefficient estimates are in similar range with other coefficient estimates.

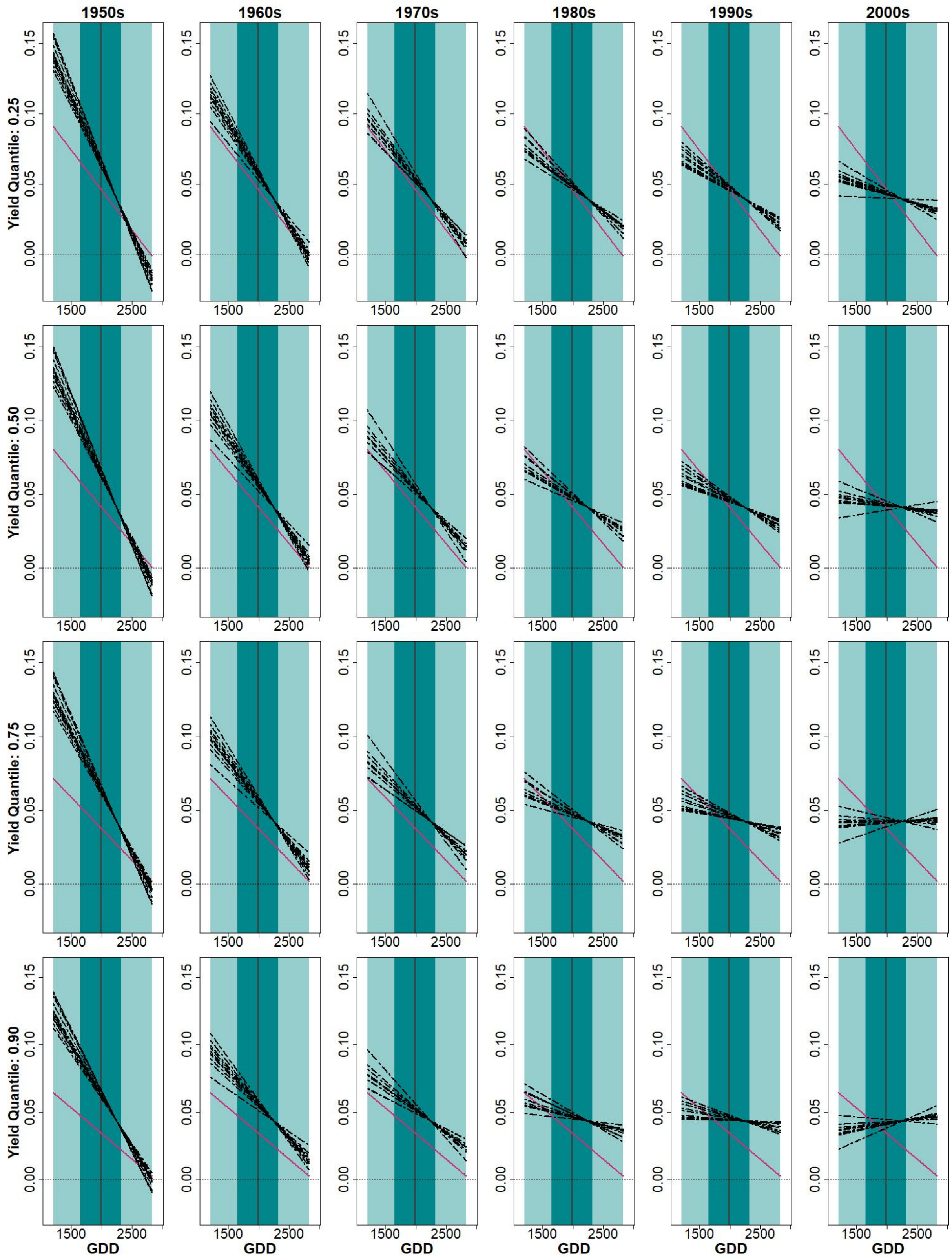

Figure 1. Marginal-Effect Function Estimates of Total $GDD_{8-29^\circ C}$ for the Corn Yield (in %)
Notes: This figure plots the marginal effect of total $GDD_{8-29^\circ C}$ in each year over the six decades in our sample. These marginal effects are linear functions of $GDD_{8-29^\circ C}$ because the estimated quantile function assumes a quadratic relationship between crop yield and $GDD_{8-29^\circ C}$. Each dashed black line corresponds to the estimates from our time-varying coefficient model in a specific year. A solid pink line corresponds to the estimates from a fixed-coefficient conditional yield quantile model. Dark (respectively, light) shaded areas illustrate the inter-quartile (respectively, middle 95%) ranges of total $GDD_{8-29^\circ C}$ in each decade.

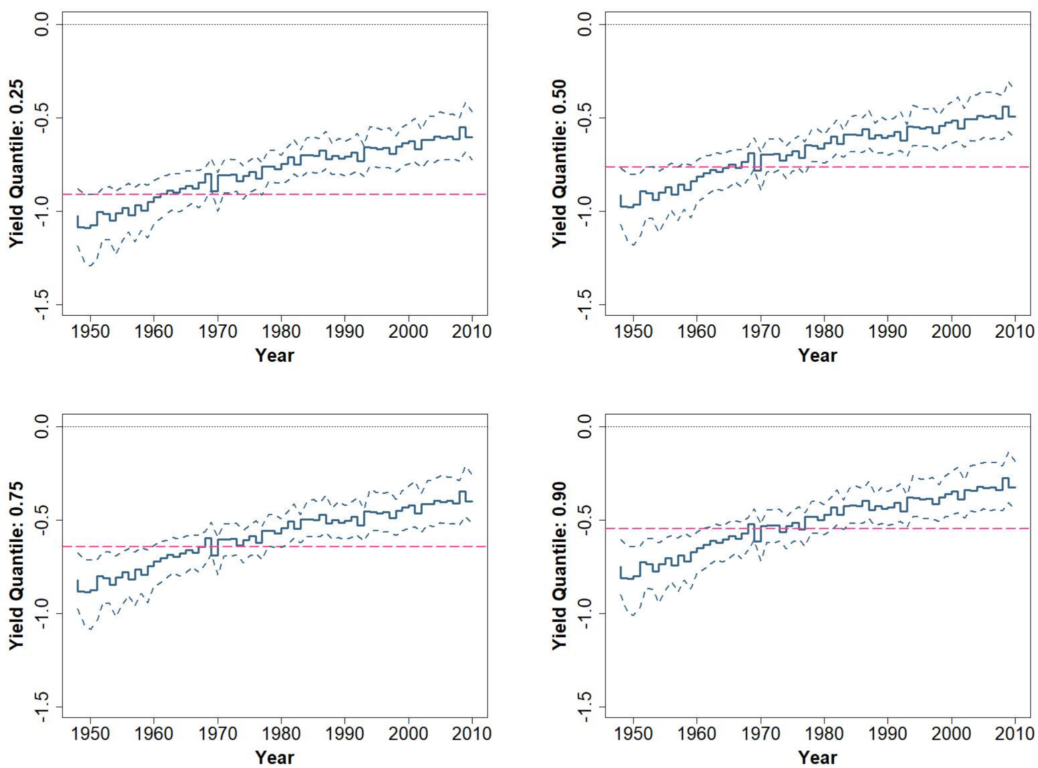

Figure 2. Marginal Effect Estimates of Total $GDD_{29^\circ C+}$ for the Corn Yield with Two-Sided 95% Confidence Intervals (in % per GDD)

Notes: This figure depicts the marginal effect estimates of total $GDD_{29^\circ C+}$ in each year of the sample. The marginal effect depends on the value of total $GDD_{29^\circ C+}$ because the variable enters regression in its square root value. The estimates presented in the figure are evaluated at the median $GDD_{29^\circ C+}$ in a year across the counties in the sample. Horizontal dashed pink lines correspond to the same estimates but from a fixed-coefficient model.

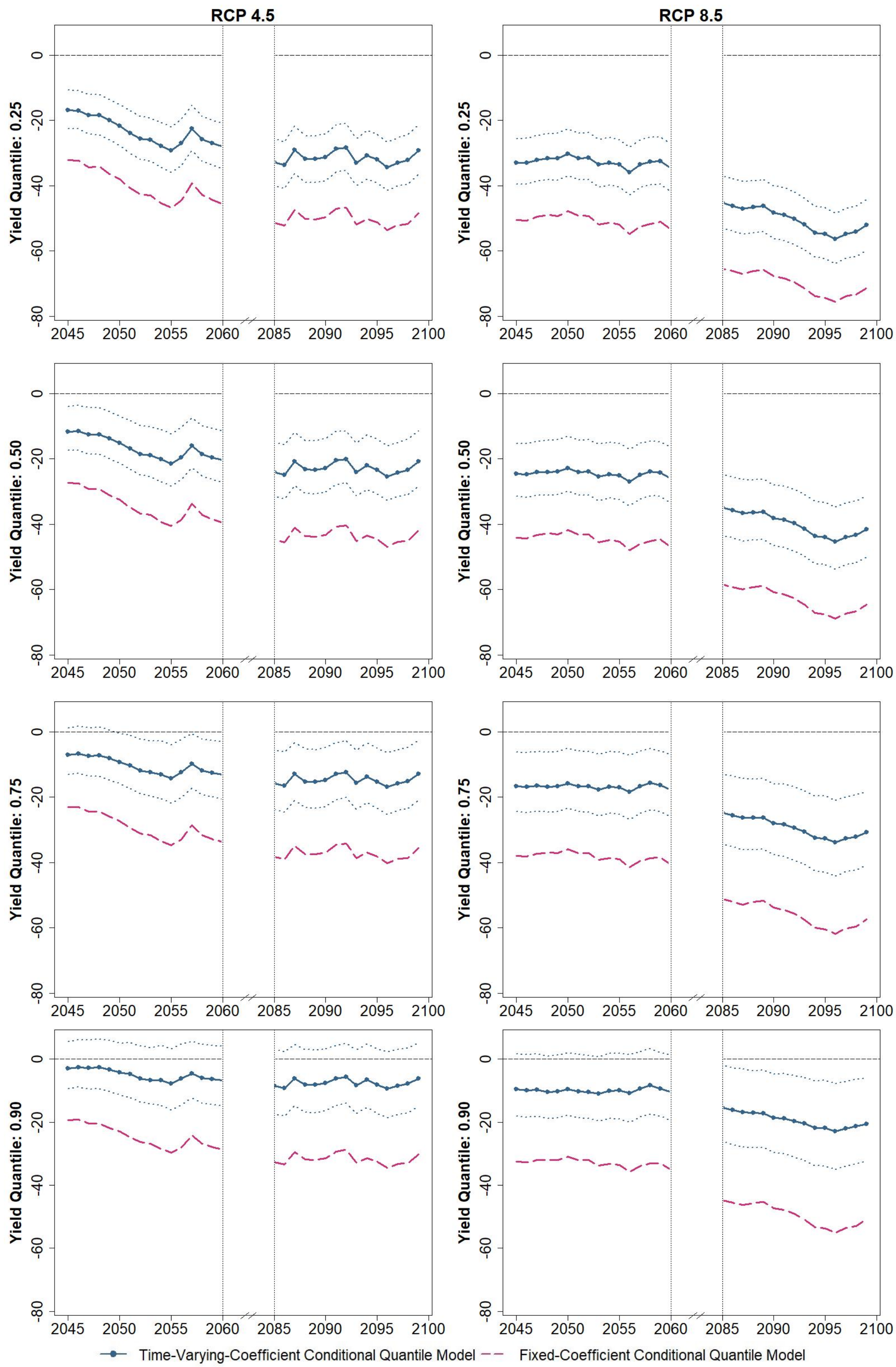

Figure 3. Projections for Corn Yield Decline under Future Climate (in %)

Notes: This figure plots projections of corn yield decline due to future climate change. To smooth out the annual variation of future weather, we present six-year rolling-window average of the projected yield decline. Solid blue lines correspond to the estimates from our time-varying coefficient model. The dotted blue lines depict the 95% confidence intervals. Dashed pink lines correspond to the estimates from a fixed-coefficient conditional quantile model. Future climate data are generated by global climate model HadGEM2-ES365 under RCP4.5 and RCP8.5, respectively.

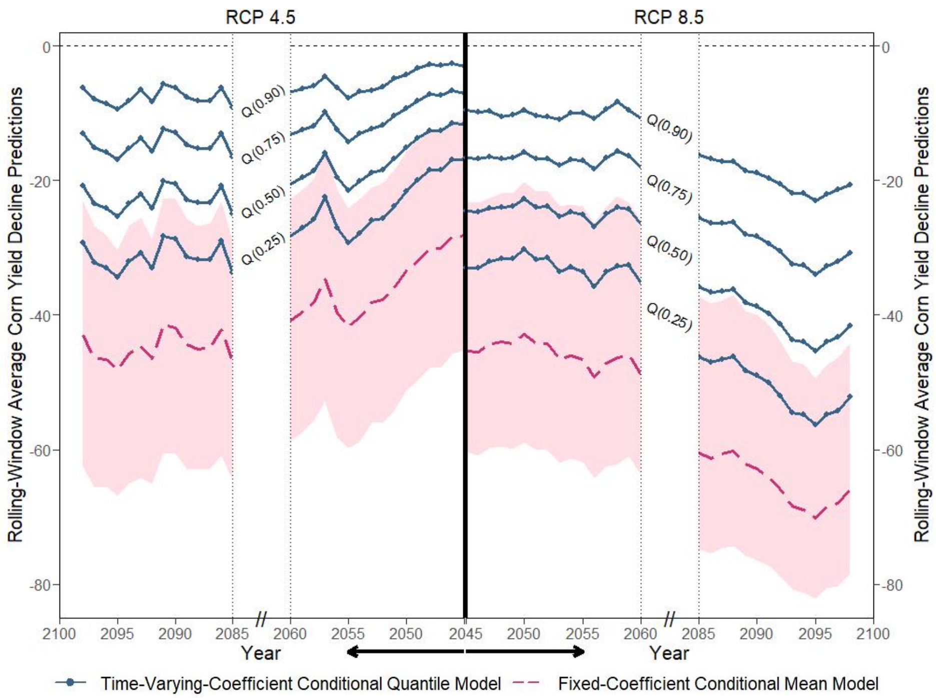

Figure 4. Projections for Future Corn Yield Decline: Time-Varying-Coefficient Conditional Quantile Model vs. Fixed-Coefficient Conditional Mean Model (in %)

Notes: This figure depicts projections of corn yield decline under future climate. The left half of the figure shows projections under RCP4.5 (a moderate warming scenario) and the right half shows projections under RCP8.5 (a severe warming scenario). Solid blue lines correspond to the estimates from our time-varying-coefficient conditional *quantile* model. From top to bottom, the solid blue lines are projections for the 0.90^{th}, 0.75^{th}, 0.50^{th}, and the 0.25^{th} conditional yield quantile. Dashed pink lines show the projections based on a fixed-coefficient conditional *mean* model, with the shaded areas illustrating their corresponding 95% confidence intervals. To smooth out the annual variation of future weather, we present six-year rolling-window average of the projected yield decline. Future climate data are generated by global climate model HadGEM2-ES365 under future warming scenarios RCP4.5 and RCP8.5, respectively.