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An *Ex Ante* Analysis of the Effects of Climate on Agricultural Production Risk

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We investigate the dynamic and spatial determinants of the distribution of agricultural productivity around the world, with a focus on the effects of climate on production risk. We treat weather shocks as part of the error term and proceed evaluating the probability distribution of agricultural productivity conditional on climate. The adverse effects of higher temperature are found to be more severe in countries exhibiting low agricultural productivity. The negative codependence across countries means that spatial diversification tends to reduce food insecurity at the world level. This effect contributes to dimming the adverse effects of rising temperatures on world food insecurity.

Key words: food security, productivity, quantile

Introduction

Climate and weather affect agricultural production: They both influence the ability of agroecological systems to produce food. Distinguishing between climate and weather effects is important: Climate reflects long-term meteorological patterns (e.g., 30-year temperature or precipitation) in a region; in contrast, weather reflects the fluctuating outcomes of climate in a given place and time (e.g., frost, heatwave, drought, flood). While climatic factors can vary a lot across regions, they change slowly over time. In contrast, weather effects can fluctuate a lot over time (e.g., a drought or a heat wave) and are difficult to predict, thus exposing agricultural production to significant risk (e.g., Just and Pope, 2002).

The effects of climate and weather on agricultural production and food security have been the subject of much research (e.g., Mendelsohn, Nordhaus, and Shaw, 1994; Deschênes and Greenstone, 2007; Groom et al., 2008; Ray et al., 2012; Wheeler and Von Braun, 2013; Lobell et al., 2014; Nelson et al., 2014; Gammans, Mérel, and Ortiz-Bobea, 2017; Mendelsohn and Massetti, 2017; Liang et al., 2017; Ortiz-Bobea, Knippenberg, and Chambers, 2018; Ortiz-Bobea et al., 2021; Arora et al., 2020; Anderson et al., 2023). This research has typically focused on *ex post* analyses evaluating how specific weather conditions during the growing season affect agricultural production. But the complexities of weather effects make *ex post* analyses of weather shocks difficult for at least four reasons: (i) weather shocks are often location specific and can vary over time in unpredictable ways; (ii) there are many weather shocks (e.g., drought, heat wave), making it difficult to estimate their separate effects; (iii) the effects of weather shocks vary depending on their timing and severity, on soil conditions, and on the crops grown (e.g., Adamopoulos and Restuccia, 2022); and (iv) the impacts of weather shocks can be mitigated through management (e.g., using irrigation or planting drought-resistant crops can reduce the effects of a drought).

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This article takes a different approach: It presents an *ex ante* analysis of the effects of climate on agricultural productivity. While an *ex post* analysis treats weather shocks as explanatory variables, an *ex ante* approach treats them as unobserved shocks that generate production risk (as they affect the distribution of agricultural production). An *ex ante* approach amounts to putting ourselves in the situation of a farmer or policy maker at the beginning of a growing season: At planting time, one knows the climate but does not know what weather conditions will develop during the growing season. As such, an *ex ante* analysis of the effects of climate on agricultural productivity treats weather shocks as production risk and proceeds by evaluating the probability distribution of agricultural productivity conditional on climate. In our risk assessment, we are also interested in evaluating the evolving prospects of facing extreme events (e.g., the case of crop failure). This indicates a need to go beyond simple mean-variance analysis and to assess risk exposure based on the whole distribution of agricultural outputs. This is the *ex ante* approach used in this article: Treating weather shocks as random variables, we evaluate the probability distribution of agricultural productivity under alternative agroclimatic conditions.

How can we measure agricultural productivity under risk? Two measures have been commonly used: crop yield (e.g., Lobell et al., 2014; Asseng et al., 2015; Powell and Reinhard, 2016; Gammans, Mérel, and Ortiz-Bobea, 2017; Alidoost, Su, and Stein, 2019; Ramsey, 2020; Chavas et al., 2022; Schmitt et al., 2022; Anderson et al., 2023) and total factor productivity (TFP) (e.g., Ortiz-Bobea, Knippenberg, and Chambers, 2018; Ortiz-Bobea et al., 2021). Both measures can capture the effects of production uncertainty (including weather shocks) on agricultural outputs. But we see crop yield (measuring production per hectare for a given crop) as a deficient measure: It is a partial productivity measure that focuses on land productivity and neglects the role of adaptation.[1] Our analysis relies instead on TFP measures, which do not suffer from these limitations. First, applied to a multi-input, multi-output production process, TFP measures the effectiveness of inputs used in the production of multiple outputs (e.g., Ball et al., 1997). It means that TFP can capture the role of management and adaptation (e.g., as farmers choose different output mix under different agroclimatic conditions). Second, as TFP captures the effects of production risk (e.g., TFP declines when adverse weather conditions have negative impacts on farm production). Third, TFP captures the role of technological progress in agriculture (e.g., Ball et al., 1997; Fuglie, 2015, 2018; Ortiz-Bobea et al., 2021). To the extent that the adoption of technology is a slow process, this stresses the need to present our analysis of productivity in a dynamic context.

This article presents a dynamic spatial analysis of the probability distribution of agricultural productivity, with a focus on the effects of climate on production risk. Using data from Fuglie (2015, 2018), the standard deviation of agricultural TFP across countries is reported in Figure 1, showing much variability in agricultural TFP across countries. This article explores how climate affects risk exposure in agriculture around the world. This includes addressing the following key questions: What are the effects of higher average temperatures on agricultural production risk? How do these effects vary across countries? And how does the spatial distribution of production risk affect world food security?

The article makes two main contributions. Its first contribution is methodological: We develop a general econometric approach to specify and estimate the evolving distribution of productivity both over time and across countries. The analysis involves a two-step approach: First, specify and estimate a quantile autoregression (QAR) model representing the determinants and dynamics of the probability distribution of productivity; second, rely on a copula to evaluate the spatial distribution of productivity across countries. Note that these methods are not new: The QAR analysis builds on the

[1] Note that this argument is not new. The inability of crop yield to capture the role of farmers' adaptation across outputs has been used to motivate the "Ricardian approach" in the analysis of climate change effects on agriculture (e.g., Mendelsohn, Nordhaus, and Shaw, 1994; Mendelsohn and Massetti, 2017). This argument gains relevance as previous literature has stressed the importance of agricultural adaptations to climate change Groom et al. (e.g., 2008); Reidsma et al. (e.g., 2010); Kaminski, Kan, and Fleischer (e.g., 2013); Sesmero, Ricker-Gilbert, and Cook (e.g., 2018); Adamopoulos and Restuccia (e.g., 2022); Bareille and Chakir (e.g., 2024).

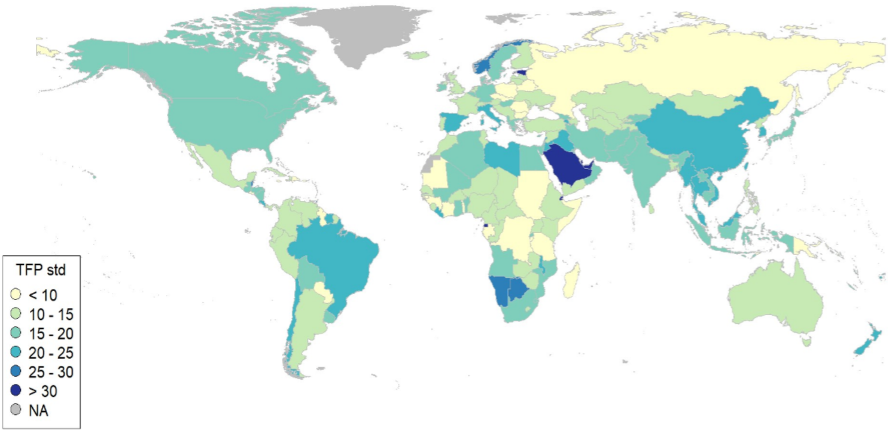

Figure 1. Standard Deviation of TFP Across Countries, 1961–2016

Notes: Total factor productivity (TFP) indexes across countries are from Fuglie (2015, 2018).

seminal work by Koenker (2005) and Koenker and Xiao (2006), and the copula approach has been developed to support a flexible investigation of joint probability distributions (Sklar, 1959; Nelsen, 2006; Joe, 2014). These methods have been used before in the investigation of climate change and agricultural risk. For example, Conradt, Finger, and Bokusheva (2015) have used quantile regression to evaluate risk exposure in agricultural production. Alidoost, Su, and Stein (2019) have used a copula to assess the effects of climate extreme in potato production. Chavas (2021) and Goodwin et al. (2024) have relied on copula to estimate the nature of price risk in agricultural markets. And Chavas et al. (2022) have used a joint quantile-copula approach to estimate the spatial distribution of production risk in Italian agriculture. To identify the contributions made by this article, note that our analysis goes beyond Chavas et al. (2022) in three important ways. First, the TFP measures used in this article are arguably better than the yield approach used in Chavas et al. (2022). Second, this article examines agricultural productivity around the world, much broader than the Italian focus in Chavas et al. (2022). Third, this article proposes a different modeling of the copula in the second stage of the analysis. Our copula modeling of codependent risk across countries appears to be new. It supports the specification and estimation of spatial effects of production risk across countries and of the role of climate in agricultural production.

The second contribution of the article is empirical: We apply our approach to investigate the evolution of the probability distribution of agricultural productivity in the world, with an application to TFP covering 160 countries over the period 1961–2016. Our empirical analysis documents how agricultural productivity has changed over time and across countries. It provides useful information on the linkages between climate and farm production risk and on the evolving nature of world food security.

Our *ex ante* approach treats weather shocks as random variables affecting agricultural productivity and investigates how climate (measured by long-term averages of temperature and precipitation) affects the evolving probability distribution of productivity. Our approach has several attractive features. First, it relies on TFP measures, which have the advantage of capturing the role of management and adaptation as farmers change inputs and farm outputs in response to changes in agroclimatic and economic conditions. Second, our analysis relies on a reduced-form specification of the determinants of agricultural productivity. Our reduced-form approach avoids endogeneity issues related to the joint determination of agricultural productivity and management. Third, our analysis makes use of the large variations in climate across countries to estimate how climate affects the evolving distribution of agricultural productivity. Our reduced-form analysis provides a valid framework to evaluate the effects of climate (as measured by long-term temperature and precipitation) on productivity. Finally, our investigation provides some new and useful information on the dynamic effects of climate on the probability distribution of agricultural productivity and on production risk.

Our analysis shows that dynamic productivity adjustments are sluggish, reflecting the slow process of adopting new technology and adaptation in agriculture. Our evidence shows that higher temperatures have moderate impacts on the mean or median of agricultural productivity, but that their dominant effects are to contribute to large increases in production risk in agriculture, including tail risk (i.e., the risk of facing rare events located in the tail of the productivity distribution). The adverse effects of higher temperatures are also found to be more severe in countries exhibiting low agricultural productivity. Our analysis shows that the spatial transmission of production risk differs between latitude and longitude: Spatial codependence is stronger for positive shocks across longitude, and it is stronger for negative shocks across latitude. In the presence of negative codependence across countries, spatial diversification helps reduce exposure to production risk at the world level. We find that the adverse effects of higher temperatures on world food security are muted for two reasons: (i) spatial diversification generates risk-reducing benefits, and (ii) countries that are less sensitive to the adverse effects of temperature tend to account for a large share of world food production.

Model

Consider an agricultural production system in location i at time t, where inputs $\boldsymbol{I}_{it} = (I_{it,1}, I_{it,2}, \ldots)$ are used to produce food as an output O_{it}.[2] The production technology is represented by the production frontier $O_{it} = G_{it}(\boldsymbol{I}_{it}, \boldsymbol{v}_{it})$, where $\boldsymbol{v}_{it}$ are random variables representing the effects of production uncertainty. For a given $\boldsymbol{I}_{it}$ and $\boldsymbol{v}_{it}$, $G_{it}(\boldsymbol{I}_{it}, \boldsymbol{v}_{it})$ is the largest amount of food that can be produced in location i at time t. Besides capturing the effects of inputs $\boldsymbol{I}_{it}$, the production frontier $G_{it}(\boldsymbol{I}_{it}, \boldsymbol{v}_{it})$ reflects the role of agroclimatic conditions specific to the ith location, of technological change taking place over time t, and of weather shocks $\boldsymbol{v}_{it}$ affecting agricultural outputs during the growing season. For a small change in t (with $dt = t_1 - t_0 > 0$) and assuming that $O_{it} = G_{it}(\boldsymbol{I}_{it}, \boldsymbol{v}_{it}) > 0$, the differentiation of $\log[G_{it}(\boldsymbol{I}_{it}, \boldsymbol{v}_{it})]$ with respect to t gives $\frac{d\log(O_{it})}{dt} = \sum_k \frac{\partial \log(G_{it})}{\partial I_{it,k}} \frac{dI_{it,k}}{dt} + y_{it}$, where $y_{it} \equiv \frac{\partial \log(G_{it})}{\partial t} + \frac{\partial \log(G_{it})}{dv_{it}} \frac{dv_{it}}{dt}$. It follows that

$$y_{it} = \frac{d\log(O_{it})}{dt} - \sum_k \frac{\partial \log(G_{it})}{\partial I_{it,k}} \frac{dI_{it,k}}{dt}, \tag{1}$$

where y_{it} is the proportional change in output $\frac{d\log(O_{it})}{dt}$ *not* due to changes in input use (as captured by $\sum_k \frac{\partial \log(G_{it})}{\partial I_{it,k}} \frac{dI_{it,k}}{dt}$). Note that y_{it} can be alternatively written as $y_{it} = \log(TFP_{it})$, where TFP_{it} is a total factor productivity index defined as $TFP_{it} \equiv \frac{OQ_{it}}{IQ_{it}}$, $OQ_{it} \equiv \exp(\frac{d\log(O_{it})}{dt})$ being an output quantity index, and $IQ_{it} \equiv \exp(\sum_k \frac{\partial \log(G_{it})}{\partial I_{it,k}} \frac{dI_{it,k}}{dt})$ being an input quantity index. In the absence of production risk, y_{it} in equation (1) reduces to a standard total factor productivity (TFP) measure reflecting the rate of technological progress between time t_0 and t_1 (e.g., Ball et al., 1997). In the presence of production risk, the TFP measure y_{it} in equation (1) is a random variable capturing two effects: the effects of technological change and the effects of production risk. As noted in the introduction, y_{it} in equation (1) has the advantage of evaluating agricultural productivity while controlling for the effects of all input/output decisions.

Let n be the number of locations around the world, with $N = \{1, \ldots, n\}$. Food production can be added across all locations to obtain world food production $O_t = \sum_{i \in N} O_{it}$. Noting that $\frac{d\log(O_t)}{dt} =$

[2] Extending the analysis to a multiple output technology can be done by treating $\boldsymbol{O}_{it}$ as an output quantity index capturing the effects of changing output mix on agricultural productivity.

$\sum_{i \in N} \frac{O_{it}}{O_i} \frac{d \log(O_{it})}{dt}$, define aggregate agricultural productivity as

(2) $$y_t \equiv \sum_{i \in N} w_i y_{it},$$

where $w_i = \frac{O_{it}}{O_t}$ is the share of food production coming from the ith location, $i \in N$. Equations (1) and (2) make it clear that the analysis of agricultural productivity and risk can be applied at any level of aggregation, going from farm level to national level to the world level. Our empirical analysis will rely on national level data, with y_{it} being an index of agricultural productivity in country $i \in N = \{1, \ldots, n\}$ at time $t \in T = \{1, \ldots, \tau\}$, where n is the number of countries and τ is the number of time periods. In this context, y_t in equation (2) has two interpretations: (i) y_t is a TFP measure of world agricultural productivity; and (ii) under production risk, y_t is a random variable with distribution reflecting the effects of production risk on world food production at time t. We use this second interpretation below to evaluate the extent of world food insecurity.

Equation (1) defines y_{it} as a static measure of agricultural productivity in location i at time t. But there are several reasons why y_{it} would exhibit dynamics. First, when technology changes, the adoption of a new technology is typically slow. Second, producers are often slow adapting to changes in their agroecological and environmental conditions, leading to technical inefficiency that can evolve over time. Third, under production risk, the term y_{it} is expected to exhibit stochastic dynamics. Fourth, the process of agricultural productivity growth is complex and involves many factors (e.g., soil fertility) that change over time. Thus, we expect agricultural productivity to exhibit significant dynamics.

We start with a general representation of the evolution of agricultural productivity both over time and across space. In the presence of dynamics, assume that agricultural productivity is determined by the mth order stochastic difference equation:

(3) $$y_{it} = f_i\left(y_{i,t-1}, \ldots, y_{i,t-m}, \boldsymbol{x}_{it}, \boldsymbol{e}_{it}\right),$$

where $\boldsymbol{x}_{it}$ is a vector of explanatory variables and $\boldsymbol{e}_{it}$ is a vector of random variables (including production risk) affecting productivity in country $i \in N$ at time $t \in T$. As discussed in the introduction, a key issue in equation equation (3) is the distinction between weather and climate. Our *ex ante* analysis proceeds as if we were at the beginning of the growing season: We know the climate but do not know weather conditions during the growing season. As a result, we include in $\boldsymbol{x}_{it}$ climatic variables reflecting country-specific agroclimatic conditions (including average temperature and precipitation in location $i \in N$), thus providing a basis to evaluate the effects of climate on agricultural productivity. And we treat weather shocks as random variables that are included in the error term $\boldsymbol{e}_{it}$ in equation (3). Treating weather shocks as random variable is consistent with the fact that weather conditions (including temperature and precipitation) are not fully predictable at the beginning of each growing season. This has two implications: (i) it avoids the difficult issue of assessing interactions between weather effects and management, and (ii) it stresses the need to expand the analysis to examine the probability distribution of agricultural productivity. In this context, we interpret the error term $\boldsymbol{e}_{it}$ in equation (3) as capturing all uncertainties (including weather shocks) affecting agricultural productivity.

Equation (3) provides a general reduced form representation of agricultural productivity in country i at time t. This reduced form has an associated structural model in which agricultural productivity is jointly determined with agroecological system dynamics, management, and technology change. As noted in Zellner and Palm (1974, p. 22), the reduced-form representation given in equation (3) is consistent with such a structural model. This reduced-form approach allows us to evaluate the dynamics of agricultural productivity without an explicit modeling of processes associated with the functioning of agroecological systems, their management and technology adoption, with an understanding that the effects of such processes are all captured implicitly in equation (3). This has four significant advantages: (i) the reduced form model in equation (3) avoids endogeneity issues related to the joint determination of agricultural productivity and management, (ii) it reduces the data requirements for our empirical analysis, (iii) it provides a valid representation of the spatial and dynamic determinants of agricultural productivity under general conditions, and (iv) climate effects can be captured by the exogenous variables $\boldsymbol{x}_{it}$ while the effects of climate change (e.g., due to GHG accumulation in the atmosphere) are captured through the dynamics in equation (3). This last point is as attractive feature of our approach given that climates change slowly over time. For example, the average temperature on earth has increased from 14°C in the 1960s to 14.7°C in the 2010s (an increase of only 0.7°C), which contrasts with average temperatures across countries covering a range exceeding 30°C (at least 40 times greater). This means that, as far as climate is concerned, observing average temperature is a lot more informative across countries than over time.

Finally, as discussed in Zellner and Palm (1974), any variable (besides y_{it}) exhibiting dynamics has been implicitly substituted away in the reduced-form specification (3). When applied to unobserved variables, it means that the error terms $\boldsymbol{e}_t = (\boldsymbol{e}_{1t}, \ldots, \boldsymbol{e}_{nt})$ can be assumed to exhibit no dynamics. On that basis, we assume that $\boldsymbol{e}_t = (\boldsymbol{e}_{1t}, \ldots, \boldsymbol{e}_{nt})$ are serially independent across time periods $t \in T$, with $\boldsymbol{e}_t$ having a given joint distribution. However, we allow the error terms $\boldsymbol{e}_{it}$ to be spatially dependent, with $\boldsymbol{e}_{it}$ being correlated across countries, $i \in N$. In this context, we will investigate below the spatial dependence in the stochastic determination of agricultural productivity across countries.

Equation (3) is a dynamic model applied to panel data. It is consistent with panel data models commonly found in the econometric literature (e.g., Arellano and Bonhomme, 2017; Baltagi, 2021). Standard panel data models typically focus on the regression estimation of the conditional mean in equation (3): $E_{it}[f_i(y_{i,t-1}, \ldots, y_{i,t-m}, \boldsymbol{x}_{it}, \boldsymbol{e}_{it})]$, where E_{it} is the expectation operator based on the information set available at time $t, i \in N, t \in T$. But a conditional mean is typically not a sufficient statistic for the distribution. As noted above, we are interested in estimating the evolution of the probability distribution of agricultural productivity.

Assuming that $\boldsymbol{e}_t = (\boldsymbol{e}_{it}, \ldots, \boldsymbol{e}_{nt})$ are serially independent in equation (3), our analysis will examine the joint probability distribution function:

$$F(\boldsymbol{y}_t \mid \boldsymbol{z}_t) \equiv \mathrm{Prob}\left\{f_i\left(y_{i,t-1}, \ldots, y_{i,t-m}, \boldsymbol{x}_{it}, \boldsymbol{e}_{it}\right) \leq y_{it}, i \in N\right\}, \tag{4}$$

where $\boldsymbol{y}_t = (y_{it}, \ldots, y_{nt})$ and $\boldsymbol{z}_t = \{y_{i,t-1}, \ldots, y_{i,t-m}, \boldsymbol{x}_{it} : i \in N\}$, $t \in T$. Below, we will assume that $F(\boldsymbol{y}_t \mid \cdot)$ is absolutely continuous. Applied to one country at a time, consider the marginal distribution of y_{it} for the ith country:

$$F_i(y_{it} \mid z_{it}) \equiv \mathrm{Prob}\left\{f_i\left(y_{i,t-1}, \ldots, y_{i,t-m}, \boldsymbol{x}_{it}, \boldsymbol{e}_{it}\right) \leq y_{it}\right\}, \tag{5}$$

where $z_{it} = \{y_{i,t-1}, \ldots, y_{i,t-m}, \boldsymbol{x}_{it}\}$, $i \in N$, $t \in T$. The associated quantile function $Q_i(q_i \mid z_{it})$ is

$$Q_i\left(q_i \mid z_{it}\right) \equiv \inf_{y_{it}}\left\{y_{it} : q_i \leq F_i\left(y_{it} \mid z_{it}\right)\right\}, i \in N, t \in T, \tag{6}$$

where $q_i \in [0,1]$ is the ith quantile for y_{it}, $i \in N$. From Sklar's theorem (1959), the following relationship exists between joint and marginal distributions:

$$F\left(y_{it}, \ldots, y_{nt} \mid \boldsymbol{z}_t\right) = C\left[F_1\left(y_{1t} \mid z_{1t}\right), \ldots, F_n\left(y_{nt} \mid z_{nt}\right)\right], \tag{7}$$

where $C(F_1, \ldots, F_n)$ is a copula (Sklar, 1959; Nelsen, 2006; Joe, 2014).[3] The copula function $C : [0,1]^n \to [0,1]$ is nondecreasing and satisfies $C(1, \ldots, 1, F_j, 1, \ldots, 1) = F_j$, $j \in N$. When $F(\boldsymbol{y}_t \mid \cdot)$ is absolutely continuous, the copula function is unique and can be written as $C(q_1, \ldots, q_n) = F[Q_1(q_1 \mid z_{it}), \ldots, Q_n(q_n \mid z_{nt})]$, where $Q_i(q_i \mid z_{it})$ is the quantile function defined in equation (6).

[3] Note that, conditional on $\boldsymbol{z}_t$, equation (7) implicitly assumes that the copula $C(F_1, \ldots, F_n)$ is the same for all time periods $t \in T$.

Equation (6)–(7) provide all the information needed to evaluate the joint probability distribution of agricultural productivity $F(y_{it}, \dots, y_{nt} \mid z_t)$ and to assess production risk.

Below, we propose a two-step econometric approach to estimate this joint distribution. As suggested in equations (6)–(7), the two steps are, first, to specify and estimate the quantile function $Q_i(q_i \mid z_{it})$ in equation (6), and, second, to specify and estimate the copula $C(F_1, \dots, F_n)$ in (7). As noted in the introduction, Chavas et al. (2022) used a similar two-step approach, with three important differences: (i) TFP is a better measure of agricultural productivity than is yield, as used in Chavas et al. (2022); (ii) our analysis of agricultural productivity around the world is much broader than the focus on Italy in Chavas et al. (2022); (iii) we propose a different modeling of the copula in the second stage of the analysis. Our copula modeling in stage two appears to be new and provides a flexible representation codependent risk across countries.

Our two-step approach proceeds as follows. In the first step, consider the specification for the quantile function $Q_i(q_i \mid z_{it})$ in equation (6):

$$Q_i\,(q \mid z_{it}) = a(q) + \sum_{j=1}^{m} b_j(q) y_{i,t-j} + c(q)\boldsymbol{x}_{it} + d(q)\boldsymbol{x}_{it} y_{i,t-1}\,, \tag{8}$$

where $\{a,b_j,c,d\}$ are parameters conditional on quantile $q \in [0,1]$, $i \in N$, $t \in T$.[4] Equation (8) is a quantile autoregression (QAR) model (Koenker, 2005; Koenker and Xiao, 2006). The lagged variables in equation (8) reflect the process of technology adoption as well as the evolution of agroecological systems as they adjust to environmental and economic changes. Equation (8) provides a flexible representation of the probability distribution of agricultural productivity. Indeed, the term $[c(q)\boldsymbol{x}_{it}]$ allows productivity to vary across countries. And equation (8) allows the variables $\boldsymbol{x}_{it}$ to affect both productivity level (when $c(q) \neq 0$) and productivity growth (when $d(q) \neq 0$). Of special interest is the case where the vector $\boldsymbol{x}_{it}$ includes agroclimatic conditions in country $i \in N$. It follows that $[c(q)\boldsymbol{x}_{it}]$ in equation (8) captures the spatial effects of agroclimatic conditions on the distribution of agricultural productivity, while $[d(q)x_{it}y_{i,t-1}]$ measures the spatial effects of agroclimatic conditions on the dynamics of this distribution. As these measures can vary across quantiles q, they provide useful information on the spatial and temporal patterns in the probability distribution of agricultural productivity. This illustrates how the QAR model in equation (8) provides a good basis to evaluate the spatial and temporal impacts of climate on agricultural productivity and on production risk around the world.

Importantly, note that equation (8) goes beyond simple mean regression: It represents the whole distribution of agricultural productivity, y_{it}. For example, allowing $a(q)$ to vary across quantiles can capture the shape of this distribution (including its variance, skewness and kurtosis). And it can capture the evolution of the productivity distribution both over time and across countries, as $(b_j(q),c(q),d(q))$ can vary across quantiles. These are attractive features to the extent that production risk is important in agriculture (Just and Pope, 2002), and there is much interest in understanding better how exposure to agricultural risk varies over time and across countries (e.g., Chavas et al., 2022).

Assuming that the variables $\boldsymbol{x}$ are exogenous, the QAR model in equation (8) can be estimated using quantile regression (Koenker, 2005; Koenker and Xiao, 2006), yielding consistent estimate of the parameters as $\tau \to \infty$. But specification (8) raises an important question: Applied to panel data, can it capture the effects of country-specific factors affecting agricultural productivity (Canay, 2011; Galvao, 2011)?[5] The answer to this question depends in part on the specification of the variables $\boldsymbol{x}_{it}$ in equation (8). The variables $\boldsymbol{x}_{it}$ act as intercept shifters (as captured by the parameters $c(q)$) and

[4] Equation (8) assumes that the parameters $\{a, b_j, c, d\}$ are time invariant. It also implicitly assumes that all country-specific effects are captured by the variables z_{it}; this assumption is further discussed below.

[5] In the presence of fixed effects, the standard econometric estimation of equation (8) yields inconsistent parameter estimates as $n \to \infty$ (e.g., Nickell, 1981). As discussed below, this argument would not apply to model (8) when the variables $\boldsymbol{x}_{it}$ capture all relevant country-specific effects.

as growth shifters (as captured by the parameters $d(q)$). We include in $\boldsymbol{x}_{it}$ country-specific climatic variables (average temperature and average precipitation) and technological change (captured by time trends).

Note that, while the QAR estimates of the parameters in equation (8) are τ-consistent under general conditions, their asymptotic distribution depends on the stationarity (or nonstationarity) of the model (Koenker and Xiao, 2004, 2006). Indeed, under nonstationarity (e.g., under "unit root"), the standard central limit theorem does not apply: The normality of the asymptotic distribution of the QAR estimates no longer holds, thus affecting hypothesis testing (Koenker and Xiao, 2004, 2006). Our hypothesis testing relies on bootstrapping, using "pair bootstrapping" with resampling from the sample data (Efron and Tibshirani, 1993; Hahn, 1995).

In the second step, we explore the joint distribution $F(y_{it},\ldots,y_{nt} \mid z_t)$ through the copula $C(F_1,\ldots,F_n)$ given in equation (7). The analysis of spatial codependence becomes more complex when n is large. A convenient way for us to proceed is to conduct the spatial analysis based on bivariate copulas. For some $j \in N$ and $i \in N - j$, consider the bivariate copula

$$C_{ij}\left(q_i,q_j\right) = C\left[\delta_{1ij}\left(q_i,q_j\right), \ldots, \delta_{nij}\left(q_i,q_j\right)\right], \tag{9}$$

where

$$\delta_{kij}(q_i,q_j) \equiv \begin{Bmatrix} q_i \\ q_j \\ 1 \end{Bmatrix} \text{ if } \begin{Bmatrix} k=i \\ k=j \\ k \in N-i-j \end{Bmatrix}, \; k \in N.$$

The function $C_{ij} : [0,1]^2 \to [0,1]$ is a bivariate copula that satisfies $F_{ij}(y_{it},y_{jt} \mid z_{it},z_{jt}) = C_{ij}[F_i(y_{it} \mid z_{it}),F_j(y_{jt} \mid z_{jt})]$, where $F_{ij}(y_{it},y_{jt} \mid z_{it},z_{jt}) = \text{Prob}[f_i(z_{it},\boldsymbol{e}_{it}) \leq y_{it}, f_j(z_{jt},\boldsymbol{e}_{jt}) \leq y_{jt}]$. The bivariate copula $C_{ij}(q_i,q_j)$ in equation (9) summarizes all the relevant information about the spatial codependence between y_i and y_j. The nature of this codependence can be measured as

$$R_{ij}\left(q_i,q_j\right) = C_{ij}\left(q_i,q_j\right) - q_i q_j. \tag{10}$$

Indeed, y_i and y_j being independently distributed corresponds to $R_{ij}(q_i,q_j) = 0$ for all $(q_i,q_j) \in [0,1]^2$. And $R_{ij}(q_i,q_j) > 0 (< 0)$ when y_i and y_j exhibit positive (negative) codependence at quantiles (q_i,q_j).

Define the conditional distribution associated with the copula $C_{ij}(q_i,q_j)$ as

$$C_{i|j}\left(q_i,q_j\right) \equiv \text{Prob}\left[U_i \leq q_i : U_j = q_j\right] = \lim_{\delta \to 0} \frac{c_{ij}\left(q_i,q_j+\delta\right) - C_{ij}\left(q_i,q_j\right)}{\delta} = \frac{\partial C_{ij}\left(q_i,q_j\right)}{\partial q_j} \tag{11a}$$

where $U_k \sim U[0,1]$, $k \in N$ (Nelsen, 2006, p. 41), implying that

$$C_{ij}\left(q_i,q_j\right) = \int_0^{q_j} C_{i|j}\left(q_i,\bar{q}_j\right) d\bar{q}_j. \tag{11b}$$

To make the analysis of equation (11a)–(11b) empirically tractable, we consider the specification

$$C_{i|j}\left(q_i,q_j\right) = \alpha\left(q_i\right) + \sum_{k \in K} \beta_k\left(q_i\right) D_{kij} q_j, \tag{12}$$

where $\{D_{kij} : k \in K\}$ are measures of distance between countries i and j, with $D_{kii} = 0$ and $D_{kij} \geq 0$. As discussed below, the distance measures D_{kij} can distinguish between latitude and longitude. For $j \in N$ and $i \in N - j$, equation (12) provides a basis to evaluate the spatial codependence in agricultural productivity between any two countries. The situation in which y_i and y_j are independently distributed is obtained as a special case when $\alpha(q_i) = q_i$ and $\beta_k(q_i) = 0$ for all

$q_i \in [0,1]$ and all $k \in K$. Alternatively, having $\beta_k(q_i) > 0$ (< 0) corresponds to a situation in which D_{kij} contributes to a positive (negative) codependence between y_i and y_j.

Equation (12) is a quantile regression model. It has two attractive features: (i) it is flexible, as it allows the parameters $(\alpha(q_i), \beta(q_i))$ to vary across quantiles;[6] and (ii) it can support an empirical analysis of the nature of spatial codependence in agricultural productivity across countries. Let q_{it}^e denote an estimate of q_{it} that solves $y_{it} = Q_i^e(q_{it} \mid z_{it})$, where $Q_i^e(q \mid z_{it})$ is consistent estimate of the quantile function obtained from the first-stage estimation of the QAR model in equation (8), $i \in N$, $t \in T$. Using the variables q_{it}^e obtained in the first stage and under the absolute continuity of $F(\boldsymbol{y}_i \mid \cdot)$, the second-stage quantile estimation of $C_{i|j}(\cdot)$ in equation (12) generates consistent estimates of the parameters $\{\alpha(q_i); \beta_k(q_i), k \in K\}$ in equation (12) (Chernozhukov, Fernández-Val, and Melly, 2013). But relying on the first-stage estimates q_{it}^e affects the distribution of the second-stage estimator in equation (12) (Murphy and Topel, 1985). On that basis, we will rely on bootstrapping over both stages to conduct hypothesis testing about the parameters in equation (12).

Finally, combining the QAR model in equation (8) with the conditional copula in equation (12) provides all the information needed to evaluate world food production risk as represented by the random variable y_t in equation (2). This can be done using the following four steps:

1. Let $\tilde{q}_i \sim U[0,1]$ denote *i.i.d.* random variables uniformly distributed in the interval $[0,1], i \in N$.
2. For some $j \in N$, obtain $\tilde{C}_{i|j} = C_{i|j}^e(\tilde{q}_i, \tilde{q}_j)$, where $C_{i|j}^e(q_i, q_j)$ is a consistent estimate of $C_{i|j}(\cdot)$ in equation (12), $i \in N - j$.
3. Obtain $\tilde{y}_{jt} = Q_j^e(\tilde{q}_j \mid z_{jt})$ and $\tilde{y}_{it} = Q_i^e(\tilde{C}_{i|j} \mid z_{jt})$, $i \in N - j$, where $Q_i^e(q \mid z_{it})$ is a consistent estimate of the QAR model in equation (8).
4. Using equation (2), obtain the random variable $\tilde{y}_t = \sum_{i \in N} w_i \tilde{y}_{it}$.

Food production risk at the world level is represented by the distribution of $\tilde{y}_t$, which can be used to evaluate world food security (as discussed below).

Application to Agricultural Productivity

This section presents an application of the model presented previously to the evolution of agricultural productivity, y_{it}, its probability distribution, and its dynamics, with a focus on linkages between climate and production risk.

Data

Our analysis of agricultural productivity relies on data over the period 1961–2016 and covering 160 countries around the world. The productivity data are TFP indexes developed by Fuglie (2015). The climatic data include long-term annual average temperature and precipitation for each country and were obtained from Ortiz-Bobea et al. (2021).[7] Table 1 presents summary statistics of the sample data. Importantly, the TFP indexes are calculated for each country and each year assuming a multi-input, multi-output production technology (Ball et al., 1997; Fuglie, 2015).[8] It means that the productivity measures reflect the role of management and adaptation as farmers change inputs and farm outputs in response to changes in agroclimatic and economic conditions across countries and over time.

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[6] As such, our quantile/copula approach is semiparametric and more flexible than the parametric copula approach used in Goodwin et al. (2024).

[7] No attempt was made to measure climate using sub-year season-specific data. The reason is that temperature or precipitation measurements during sub-year periods (e.g., April–May–June) are not meaningful when comparing countries across latitudes (e.g., in the Northern Hemisphere vs. equatorial region vs. the Southern Hemisphere).

[8] See Fuglie (2018) for a good discussion of the evolution of agricultural productivity across countries and over time.

Table 1. Summary Statistics

Variables	Mean	Median	Min.	Max.
Agricultural TFP index (= 100 in 2015)	91.03	91.93	17.07	254.77
Average temperature (°C)	19.02	22.29	−6.51	28.89
Average precipitation (100 mm)	12.88	11.38	0.21	42.37
Latitude (degree)	18.64	17.85	−40.90	64.96
Longitude (degree)	21.68	24.24	−106.34	179.41

Notes: The dataset covers the period 1961–2016 and 160 countries.

The econometric approach proposed previously is now used to evaluate the evolution of agricultural productivity and production risk around the world. Letting $y_{it} = \log(TFP_{it})$, $i \in N$, $t \in T$,[9] we proceed investigating the distribution of y_{it} and its determinants.

Evaluating the Determinants of Agricultural Productivity

In a first step, we analyze agricultural productivity by specifying and estimating the QAR model in equation (8). The specification of equation (8) involved two issues: (i) selecting the number of lags m and (ii) choosing the specification for the explanatory variables $\boldsymbol{x}_{it}$. Both issues were evaluated using the Bayesian information criterion (BIC) to help identify which specification provided the best fit to the data (Schwarz, 1978). Using BIC, the preferred model involved three lags ($m = 3$) and $\boldsymbol{x}_{it}$, including the effects of both technology and climate on agricultural productivity.[10] The technology effects are captured by time trends specified as linear spline functions: $t0$ = time trend starting at 0 in the first sample year; $t1$ = time trend starting at 0 in 1983, and $t2$ = time trend starting at 0 in 2000. The climate effects are captured by country-specific average temperature and average precipitation both as linear terms (*temp* and *prec*) and quadratic terms (*temp*2 and *prec*2, each measured as squared deviations from sample median). Finally, consistent with equation (8), the variables $\boldsymbol{x} = (temp, temp2, prec, prec2, t0, t1, t2)$ are introduced as interaction effects with $y_{i,t-1}$, thus allowing climate and technology to affect productivity growth. To determine whether the variables $\boldsymbol{x}_{it}$, $(y_{i,t-1}, y_{i,t-2}, y_{i,t-3})$ and $\boldsymbol{x}_{it} y_{i,t-1})$ provide a good representation of country-specific factors affecting agricultural technology, we add country-specific dummy variables to the model. Using BIC, we find that adding country-specific dummy variables did not improve the fit. We also investigate the statistical significance of the coefficients of these additional variables. We test the significance of country-specific dummy variables: The p-value for the test is 0.18 for dummies treated as intercept shifters, and the p-value is 0.08 for dummies introduced as slope shifters for the coefficient of $y_{i,t-1}$. Thus, we find that the country-specific dummy variables do not have statistically significant effects on agricultural productivity at the 5% significant level. These results indicate that there was no strong evidence that country-specific fixed effects need to be included in our analysis. In other words, we conclude that the variables $\boldsymbol{x}_{it}, (y_{i,t-1}, y_{i,t-2}, y_{i,t-3})$, and $(\boldsymbol{x}_{it} y_{i,t-1})$ in equation (8) capture all the relevant country-specific effects in equation (8).

Based on this specification, the QAR estimates of equation (8) are reported in Table 2 for selected quantiles, with statistical significance obtained from bootstrapping. Table 2 shows that many of the QAR parameters in equation (8) are statistically significant. This includes the lagged productivity effects of $(y_{i,t-1}, y_{i,t-2}, y_{i,t-3})$ either in linear form or in interactions $(y_{i,t-1}\boldsymbol{x}_{it})$. These lagged effects reveal slow adjustments in agricultural productivity over time, reflecting agroecosystem dynamics (e.g., the dynamics of soil nutrients or pest population), the slow process of developing new technology (as innovations contribute to reducing the evolving patterns of resource scarcity), and/or the slow adoption of new technology. While documenting the importance of dynamics in the determinants of agricultural productivity, these results stress the need to distinguish between

[9] It follows that $\exp(y)$ can be interpreted as a TFP index in our discussion below.

[10] We also explored introducing latitude and longitude as well as interaction effects ($temp \times prec$) in $\boldsymbol{x}$. Using BIC, we found that doing so did not improve the fit of the QAR model (8).

Table 2. Parameter Estimates for Selected Quantiles

	Quantile				
Parameter	$q = 0.1$	$q = 0.3$	$q = 0.5$	$q = 0.7$	$q = 0.9$
Intercept	0.2946	0.3115***	0.4336***	0.5838***	0.5750***
$TFP1$	0.6817***	0.7069***	0.6986***	0.6721***	0.6371***
$TFP1 * t0$	−0.0003	−0.0003	0.0002	−0.00001	−0.0003
$TFP1 * t1$	−0.0107***	−0.0074***	−0.0074***	−0.0065***	−0.0062**
$TFP1 * t2$	0.0257***	0.0213***	0.0195***	0.0169***	0.0194***
$TFP2$	0.2160***	0.1999***	0.1702***	0.1920***	0.1732***
$TFP3$	0.0148	0.0164	0.0342***	0.0122	0.0785***
$t0$	0.0006	0.0016	−0.0011	0.0003	0.0016
$t1$	0.0511***	0.0356***	0.0351***	0.0307***	0.0300**
$t2$	−0.1186***	−0.0992***	−0.0907***	−0.0785***	−0.0903***
$temp$	−0.0063	−0.0057	−0.0072*	−0.0102**	−0.0063
$temp2$	−0.0006*	−0.0006***	−0.0006***	−0.0008***	−0.0005
$prec$	0.0004	−0.0022	−0.0060**	−0.0097***	−0.0136***
$prec2$	0.00002	0.0001	0.0002*	0.0004***	0.0005**
$TFP1 * temp$	0.0013	0.0012	0.0016*	0.0022**	0.0016
$TFP1 * temp2$	0.0001*	0.0001***	0.0001***	0.0002***	0.0001
$TFP1 * prec$	0.0005	0.0007	0.0013**	0.0020***	0.0024**
$TFP1 * prec2$	−0.00005	−0.00004	−0.00006**	−0.00009***	−0.0001

Notes: Hypothesis testing was conducted using bootstrapping with resampling from the sample data. Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively.

short- and long-run effects of these determinants (as further discussed below). Finally, the interaction effects of $(y_{i,t-1}\boldsymbol{x}_{it})$ indicate that productivity dynamics can vary significantly across countries (as further evaluated below).

Table 2 also reports how the time trend variables ($t0$, $t1$, $t2$) affect productivity. Interestingly, while $t0$ does not have statistically significant effects, $t1$ shows strong positive linear effects across all quantiles, reflecting rapid agricultural productivity growth during the period 1983–2000. Yet the effects of $(t1y_{i,t-1})$ are all negative, indicating some slowdown in productivity growth during this period among countries exhibiting high productivity. Finally, in Table 2, the effects of $t2$ tends to be opposite those of $t1$: $t2$ has strong negative linear effects across all quantiles, reflecting a decline in agricultural productivity growth after 2000 (possibly due to the adverse effects of climate change on agriculture), but the effects of $(t2y_{i,t-1})$ are all positive, indicating that the post-2000 slowdown in productivity growth is muted among countries exhibiting high productivity. These results document the presence of heterogeneity in agriculture productivity growth both over time and across countries.

Table 2 also shows how the climate variables ($temp$, $temp2$, $prec$, $prec2$) affect the probability distribution of productivity. The variables ($temp$, $temp2$) have negative and statistically significant effects on agricultural productivity across many quantiles. Table 2 shows that higher average temperature has adverse impacts on agriculture production and that these adverse effects are nonlinear (e.g., they become stronger as temperature rises). These results are largely consistent with previous research documenting the effects of climate and climate change on agriculture (e.g., Ray et al., 2012; Lobell et al., 2014; Gammans, Mérel, and Ortiz-Bobea, 2017; Mendelsohn and Massetti, 2017; Arora et al., 2020; Ortiz-Bobea et al., 2021). Table 2 also reports that the interaction effects between ($temp$, $temp2$) and $y_{i,t-1}$ tend to be positive, indicating that the adverse effects of higher temperature tend to be muted in countries exhibiting high productivity growth. Implications of this result for world food security are further discussed below.

Finally, Table 2 shows that the effects of precipitation are complex. The variable $prec$ tends to have negative effects on productivity, while $prec$ 2 has positive effects, especially in the upper tail of the distribution. But the interactions effects of precipitation with $y_{i,t-1}$ are opposite: $(prec\,y_{i,t-1})$

tends to have positive effects on productivity, while $(prec2y_{i,t-1})$ has negative effects. In addition, these effects are weaker in the lower tail of the variable *prec* tends to have negative effects on productivity, while *prec*2 has positive effects, especially in the upper tail of the distribution. But the interactions effects of precipitation with $y_{i,t-1}$ are opposite: $(prec\, y_{i,t-1})$ tends to have positive effects on productivity, while $(prec2\ y_{i,t-1})$ has negative effects. In addition, these effects are weaker in the lower tail of the distribution.

Next, we explore the implications of the QAR estimates reported in Table 2 for the distribution of agricultural productivity across countries and over time. Noting that the QAR model provides a flexible representation of the productivity distribution, this raises a question about the shape of this distribution? To examine this issue, let $Q_i^e(q \mid z_{it})$ be the predicted quantile function obtained from the QAR estimation of equation (8), $i \in N$, $t \in T$. Under the absolute continuity of $F_i(y_{it} \mid \cdot)$, the equation $Q_i^e(q_{it} \mid z_{it}) = y_{it}$ can be solved for q_{it}, giving an estimate of q_{it}^e and providing information about the distribution function, $q_{it} = F_i(y_{it} \mid z_{it})$. We test the null hypothesis of a normal distribution using two tests: the Shapiro–Wilk (SW) test (Shapiro and Wilk, 1965) and the Jarque–Bera (JB) test (Jarque and Bera, 1980). Applied to each country and each year, both tests uncover strong evidence against a normal distribution. Using a 5% significance level, the SW test rejects normality for 98.1% of the observations, and the JB test rejects normality for 99.4% of the observations. This strong JB rejection of normality reflects that the distributions of productivity exhibit significant skewness and kurtosis.[11] This stresses the need to go beyond a mean-variance analysis and to examine the evolving patterns of skewness and kurtosis in the distribution of agricultural productivity both over time and across countries (as further discussed below).

For illustration purpose, Figure 2 reports the estimated distributions of the productivity index $\exp(y_{it})$ for six countries: Brazil, China, France, Greece, Togo, and the United States. Figure 2 shows that Brazil, China, France, and the United States exhibited large rightward shifts in productivity distribution over time, reflecting rapid productivity growth especially after 1996. In contrast, in Figure 2e, Togo exhibited a leftward shift in its productivity distribution over time, signifying productivity regress during the sample period. The situation in Greece was somewhere in between: Figure 2d shows only moderate productivity growth in Greek agriculture, especially after 1996. These results illustrate the presence of much heterogeneity in agricultural productivity growth both over time and across countries. Figure 2 also shows temporal changes in the spread of the distribution. For example, the distribution spread for Brazil (Figure 2a) increases over time, but the change in spread is less pronounced for Togo (Figure 2e).

These changes are further illustrated in Figure 3, which reports the temporal evolution of three quantiles (0.05, 0.5, representing the median; and 0.95) of the distribution of the productivity index $\exp(y_{it})$ for Brazil, China, France, Greece, Togo, and the United States. In general, the spread between the 0.05 and 0.95 quantiles reflects the magnitude of production uncertainty in agriculture. Figures 3a and 3b show that, for Brazil and China, this spread has increased sharply over the last few decades, reflecting a large rise in production uncertainty. This contrasts with Togo, where Figure 3e shows little change in the spread, indicating that Togo did not see much change in production uncertainty. Again, these results reflect important differences in agricultural production uncertainty both over time and across countries.

While Table 2 documents the presence of productivity dynamics, it also raises questions about the nature of these dynamics: How slow (or fast) are the dynamic adjustments? To answer these questions, note that the QAR model in equation (8) involves nonlinear dynamics in two ways: (i) the lagged variables $y_{i,t-1}$ interact with $\boldsymbol{x}_{it}$, and (ii) the parameters of the lagged variables vary across quantiles $q \in [0,1]$. In this context, under differentiability, a first-order Taylor series approximation of equation (8) with respect to $(y_{i,t-1}, y_{i,t-2}, y_{i,t-3})$ provides a local approximation to productivity dynamics in the neighborhood of point $(\boldsymbol{x}, q)$. As a linear difference equation, this approximation has a dominant root with modulus $\rho_D(\boldsymbol{x}, q)$. This modulus provides useful information about the nature

[11] Skewness reflects asymmetry while kurtosis measures "fat tail" in the probability function. As they are both 0 under a normal distribution, nonzero skewness or kurtosis reflects departures from normality.

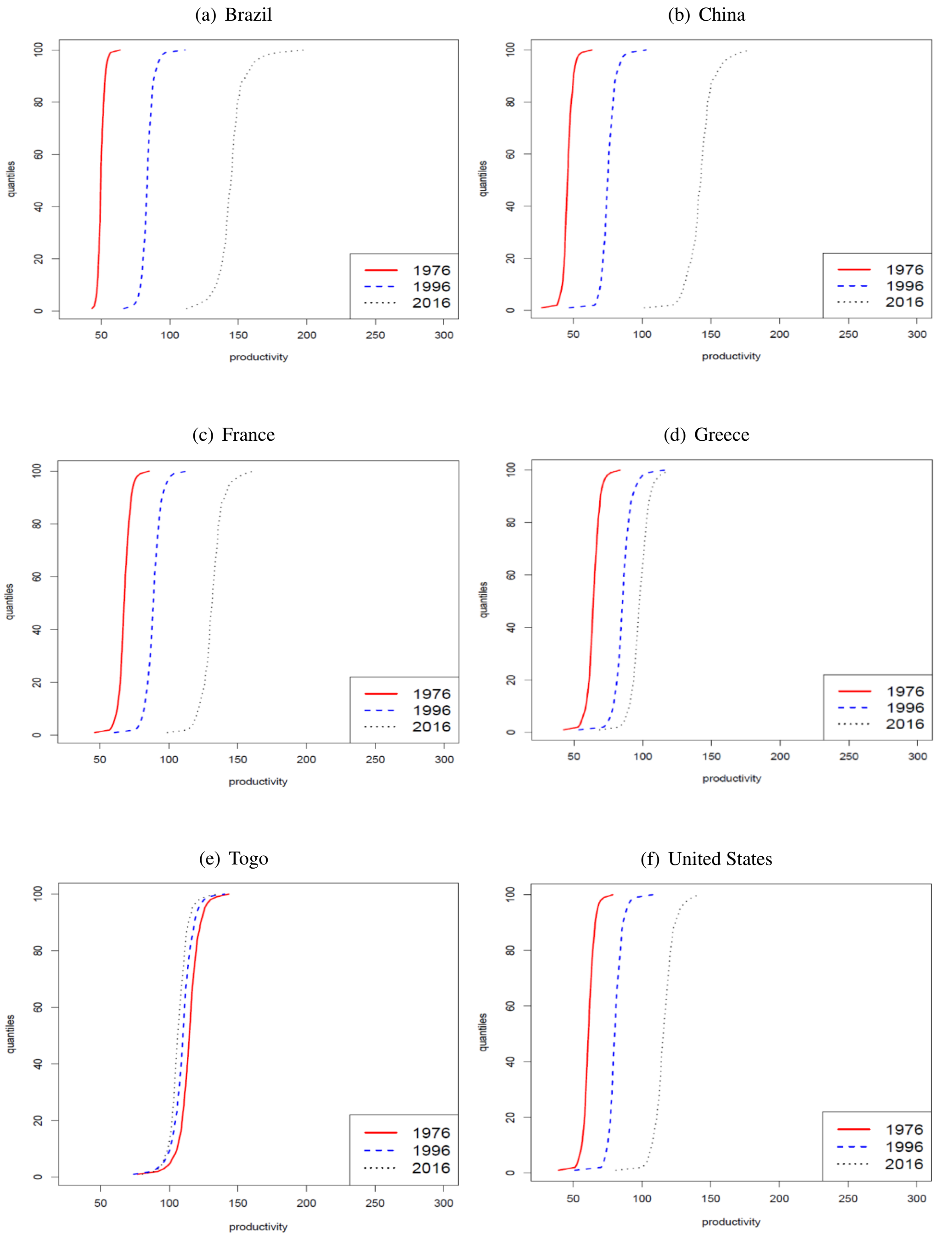

Figure 2. Distributions of Agricultural Productivity Index, Selected Countries

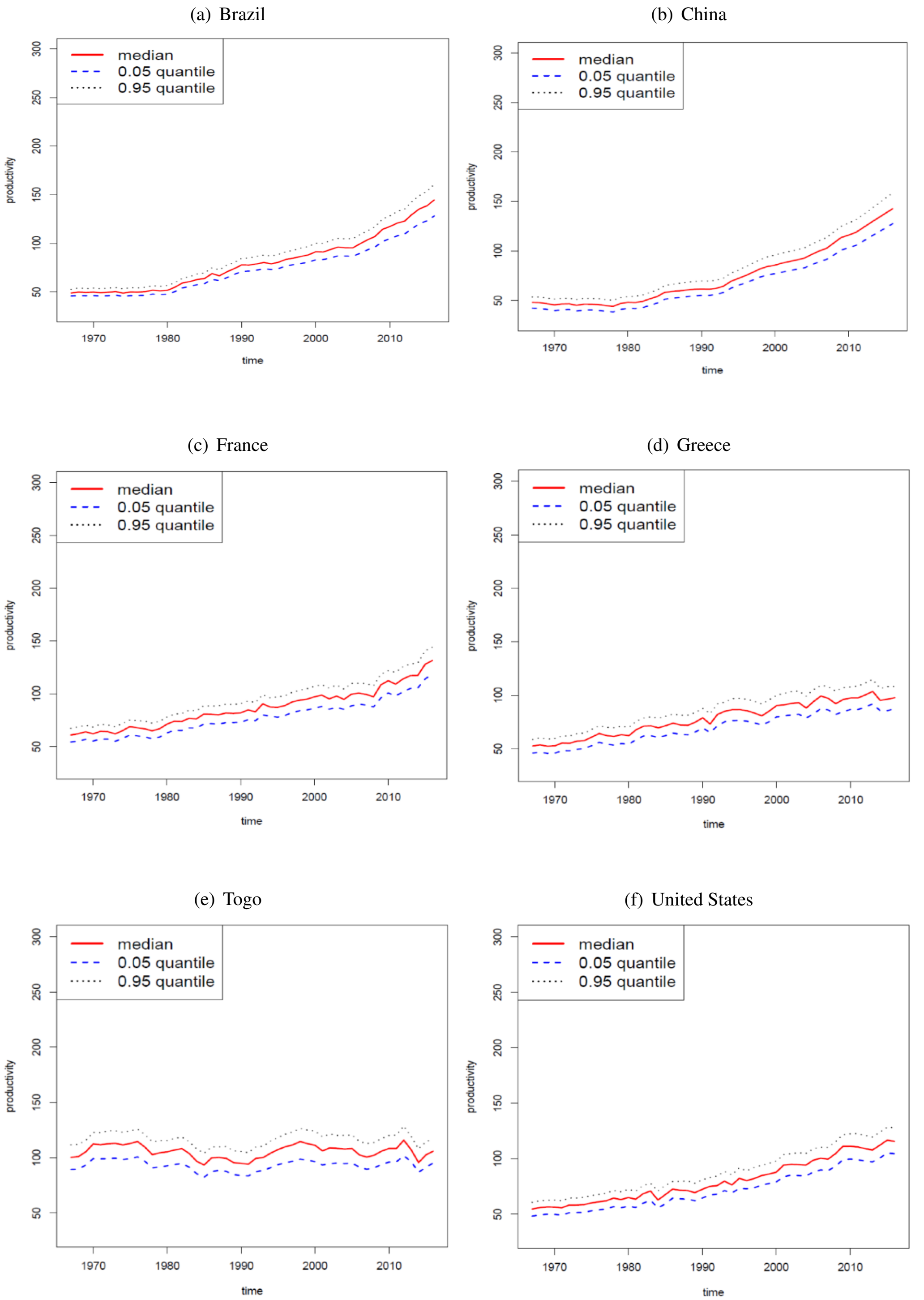

Figure 3. Evolution of Agricultural Productivity Index, Selected Countries

Table 3. Modulus of the Dominant Root, $\rho(\boldsymbol{x},q)$, Under Selected Scenarios

	Quantile								
	$q = 0.1$			$q = 0.5$			$q = 0.9$		
Year	**1970**	**1990**	**2010**	**1970**	**1990**	**2010**	**1970**	**1990**	**2010**
Low temp, low precip	0.965	0.902	0.930	0.959	0.923	0.963	0.947	0.911	0.954
Med temp, med precip	0.958	0.895	0.923	0.964	0.927	0.967	0.965	0.927	0.972
High temp, high precip	0.966	0.903	0.931	0.978	0.941	0.982	0.985	0.947	0.993

Notes: Hypothesis testing for a unit root was conducted using bootstrapping with resampling from the sample data. All reported roots were found to be less than 1 at the 5% significance level.

of dynamics (Hasselblatt and Katok, 2003): (i) The dominant root being in the unit circle (with $\rho_D(\boldsymbol{x},q) < 1$) corresponds to stable dynamics of y_{it} in the neighborhood of $(\boldsymbol{x},q)$ and (ii) $\rho_D(\boldsymbol{x},q)$ measures the speed of dynamic adjustments of y_{it} around point $(\boldsymbol{x},q)$. In the special case where ρ_D is constant, these reduce to standard properties of linear time-series models (e.g., Hamilton, 1994; Enders, 2010). But the QAR model in equation (8) permits the nature of dynamics to vary with the exogenous variables $\boldsymbol{x}$ and with the quantile q. This allows us to investigate whether productivity dynamics varies with climate (through the climatic variables in $\boldsymbol{x}$) or with the weather shocks (as reflected by the quantile q).

Using the QAR estimates of equation (8), Table 3 reports the modulus of the dominant root $\rho_D(\boldsymbol{x},q)$ under selected scenarios representing different climatic variables (average temperature and precipitation), years, and quantiles. Table 3 shows that $\rho_D(\boldsymbol{x},q)$ varies across scenarios between 0.902 and 0.993 . Using bootstrapping, we test for local instability (corresponding to the null hypothesis $\rho_D(\boldsymbol{x},q) \geq 1$). We reject this null hypothesis at the 5% significance level in each scenario. Thus, we find strong evidence of stability in the dynamics of agricultural productivity dynamics. In addition, finding that the dominant roots do not change much across scenarios means that productivity dynamics is not driven by either climate (as average temperature or precipitation have only small effects on $\rho_D(\boldsymbol{x},q)$) or production shocks (as $\rho_D(\boldsymbol{x},q)$ does not change much across quantiles). We interpret this result as indirect evidence that productivity dynamics are likely driven by the slow process of creation and adoption of new technology.

Evaluating the Spatial Codependence of Agricultural Productivity

We now examine the codependence in agricultural productivity, reflecting how production shocks get transmitted across countries. As discussed previously, following the first-stage estimation of the QAR model in equation (8), the analysis relies on a spatial copula. Our second-stage empirical analysis of spatial codependence is based on equations (10)–(12), with equation (12) capturing how spatial codependence can vary with distances D_{kij} as well as across quantiles. In equation (12), we use four measures of distance D_{kij}: $D_{lat,ij}$ = the difference in latitude between country i and country j; $D_{lon,ij}$ = the difference in longitude between country i and country j; $D_{lat2,ij}$ = the squared difference in latitude between country i and country j; and $D_{lon2,ij}$ = the squared difference in longitude between country i and country j. This specification allows us to distinguish between latitude and longitude effects in the evaluation of spatial codependence. And the inclusion of the terms $D_{lat2,ij}$ and $D_{lon2,ij}$ allow for spatial effects to be nonlinear. Finally, we estimate equation (12), choosing France as the jth reference country,[12] with $i \in N - j$. The quantile estimates of the parameters in equation (12) are reported in Table 4 for selected quantiles, with hypothesis testing conducted

[12] The choice of France as the reference country in equation (12) was based on two arguments: (i) France has good data on agricultural productivity; and (ii) France has many "close neighbors," making it easier to evaluate neighborhood effects. Conducting the analysis using a different base country gave different estimates but similar qualitative results.

Table 4. Spatial Conditional Copula $C_{i|j}(q_i,q_j)$

	Quartile				
Parameter	$q_i = 0.1$	$q_i = 0.3$	$q_i = 0.5$	$q_i = 0.7$	$q_i = 0.9$
Intercept	0.088***	0.273***	0.458***	0.663***	0.879***
$D_{lat} * q_j$	1.219*	12.516**	1.557	−0.275	0.003
$D_{lat2} * q_j$	−17.767*	−37.457**	−27.219*	1.811	−0.046
$D_{lon} * q_j$	−0.038	0.664	2.353***	2.748***	1.166***
$D_{lon2} * q_j$	0.676	−3.277	−13.954**	−18.137***	−8.513**

Notes: The spatial conditional copula $C_{i|j}(q_i, q_j)$ is given in equation (12). The jth country is France, taken as a reference point in the evaluation of spatial codependence. Hypothesis testing was conducted using bootstrapping with resampling from the sample data. Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively.

using bootstrapping applied to both stages of the approach.[13] Table 4 shows that many of the distance parameters are statistically significant. This provides strong statistical evidence of spatial dependence. Table 4 also shows differences between latitude effects and longitude effects. For example, the latitude effects are statistically significant in the lower tail (at $q_i = 0.1$ or 0.3), but the corresponding longitude effects are not. In contrast, the longitude effects are statistically significant in the upper tail (at $q_i = 0.7$ or 0.9), but the corresponding latitude effects are not. Thus, spatial codependence is stronger for negative shocks across latitude; and it is stronger for positive shocks across longitude. In addition, Table 4 reports that both latitude and longitude effects are nonlinear: When significant, the coefficients associated with D_{lat} and D_{lon} are positive, while the coefficients associated with D_{lat2} and D_{lon2} are negative. This indicates a general inverted U-shaped relationship between distance and codependence. This nonlinear relationship means that spatial codependence can be positive or negative depending on the evaluation point.

Next, we evaluate the nature of spatial codependence based on equations (10)–(12). Using the estimates of equation (12) along with equations (11a)–(11b), Table 5 reports selected codependence measures $R_{ij}(q_i,q_j)$ given in equation (10). When evaluated at quantiles (q_i,q_j), recall that $R_{ij}(q_i,q_j) = 0$ corresponds to no codependence between y_i and y_j, while $R_{ij}(q_i,q_j) > 0$ (< 0) corresponds to positive (negative) codependence. Table 5 indicates that the spatial transmission of production shocks is complex: Codependence can be positive or negative depending on the scenario considered. For example, Table 5 shows evidence of positive codependence when $q_i = 0.9$ and $q_j = 0.1$ but of negative codependence when $q_i = 0.5$ and $q_j = 0.5$. As further discussed below, a negative spatial codependence means that spatial diversification contributes to reducing world food insecurity. Finally, Table 5 shows that the $R_{ij}(q_i,q_j)$ estimates are not statistically significant when $q_i = 0.1$ or when distance measures become large. This last result is important: Large productivity shocks are not likely to be transmitted over long distances. It is consistent with the intuition that codependence is likely to be nonzero only when distance is relatively small.

Implications

This section explores the implications of our econometric analysis for the evolution of the distribution of agricultural productivity, including linkages between climate and production risk. This is done by simulating forward the productivity distribution of the QAR model in equation (8) under alternative scenarios reflecting climate effects at different time periods. The climate scenarios involve low, medium, and high levels for average precipitation and temperature, where "medium" means an evaluation at sample median, while low (high) means a 20% decrease (increase) from the sample median (corresponding to a change of ±4.51°C for temperature and ±228 mm for precipitation). The time scenarios involve three evaluation points: 1970, 1990, and 2010. Given

[13] We also explored whether spatial codependence varied over time. We introduced a time trend in equation (12), but we found that its coefficient was not statistically significant.

Table 5. Spatial Codependence 1,000 × $R(q_i,q_j)$, Selected Scenarios

Quantiles	Scenarios	$q_i = 0.1$	$q_i = 0.5$	$q_i = 0.9$
	low D_{lat}	−0.18	0.566*	6.72***
	med D_{lat}	−0.45	0.018	6.71
	high D_{lat}	−1.74	−2.08	6.71
$q_j = 0.1$				
	low D_{lon}	−0.27	0.68***	6.81***
	med D_{lon}	−0.25	1.00***	6.92**
	high D_{lon}	−0.18	0.30	6.36
	low D_{lat}	−2.82	−13.59	−1.56
	med D_{lat}	−9.24	−26.28*	−1.59
	high D_{lat}	−33.04	−74.96*	−1.67
$q_j = 0.5$				
	low D_{lon}	−4.94	−11.22**	0.75***
	med D_{lon}	−4.62	−3.45***	3.01***
	high D_{lon}	−3.40	−14.13	−5.97
	low D_{lat}	−2.87	−24.68	−9.85
	med D_{lat}	−23.35	−65.54*	−9.92*
	high D_{lat}	−69.04	−221.76*	−5.17
$q_j = 0.9$				
	low D_{lon}	−9.69	−17.06*	−2.40**
	med D_{lon}	−8.65	7.88***	4.86***
	high D_{lon}	−4.75	−26.41	−24.01

Notes: Using equations (10)–(12), the codependence measure is $R(q_i, q_j) = \inf_0^{q_j} c_{i|j}(q_i, \bar{q}_j)d\bar{q}_j - q_i q_j$. Hypothesis testing about codependence was conducted using bootstrapping with resampling from the sample data. Single, double, and triple asterisks (*,**,***) indicate significance at the 10%, 5%, and 1% level, respectively.

the importance of dynamics, we focus our attention on long-term effects: Under each scenario, we evaluate the productivity distribution obtained after 50 years of forward simulation. Table 6 summarizes the results, including the mean, median, standard deviation, skewness, and kurtosis of the simulated distributions of the productivity index $\exp(y_{it})$ obtained under the selected scenarios.

Table 6 illustrates how climate and evolving technology affect agricultural productivity. Under medium precipitation, Table 6 reports the simulated impacts of rising temperatures on productivity. Table 6 shows that higher temperatures have modest effects on median productivity: Under "med precip" and going from "low temp" to "high temp," 1970 median productivity declines slightly from 80.48 to 79.49 (−1.2%), while 2010 median productivity increases from 109.87 to 118.02 (+7.4%). Table 6 reports that the main impacts of higher temperatures are to contribute to large increases in the standard deviation, skewness, and kurtosis of agricultural productivity. Under medium precipitation, going from "low temp" to "high temp" increases the standard deviation from 16.07 to 22.79 (+41.2%) in 1970, from 13.69 to 17.39 (+27%) in 1990, and from 21.83 to 35.82 (+64.1%) in 2010, and it increases the kurtosis from 0.21 to 1.05 (+400%) in 1970, from 0.26 to 0.62 (+138.5%) in 1990, and from 0.66 to 2.36 (+257.6%) in 2010. These are our key findings:

i. The impacts of higher temperatures are mostly their contribution to a large increase in production risk in agriculture.
ii. These impacts also include a large increase in kurtosis (i.e., an increased exposure to rare events located in the tails of the probability function, including catastrophic risk).
iii. These effects have become stronger in the last few decades.

Table 6. Simulated Agricultural Productivity Index, Selected Scenarios

Scenarios		Year	Mean	Median	Std. Dev.	Skewness	Kurtosis
		1970	82.8	80.48	16.07	0.57	0.21
	Low temp	1990	95.13	94.09	13.69	0.46	0.26
		2010	114.43	109.87	21.83	0.82	0.66
		1970	82.89	80.38	18.18	0.69	0.42
Med precip	Med temp	1990	95.66	94.24	15.07	0.57	0.42
		2010	117.28	111.45	25.81	0.99	1.09
		1970	82.81	79.49	22.79	0.89	1.05
	High temp	1990	96.94	94.23	17.39	0.71	0.62
		2010	125.9	118.02	35.82	1.31	2.36
		1970	82.52	79.73	19.60	0.65	0.37
	Low precip	1990	95.23	93.76	16.08	0.56	0.42
		2010	115.08	94.73	26.37	0.94	0.97
		1970	82.89	80.38	18.18	0.69	0.42
Med temp	Med precip	1990	95.66	94.24	15.07	0.57	0.42
		2010	117.28	111.45	25.81	0.99	1.09
		1970	83.41	80.88	17.17	0.73	0.49
	High precip	1990	96.18	94.32	14.26	0.59	0.43
		2010	118.48	113.74	25.47	1.03	1.20

Notes: The medium scenarios are evaluated at sample medians: 11.38 cm for precipitation and 22.29°C for temperature. The low (high) scenarios correspond to a 20% decrease (increase) compared to sample medians, thus simulating a change of ±4.51°C for temperature and ±228 mm for precipitation.

These findings document how rising temperatures present a threat to food security around the world. They stress the importance of developing risk management schemes that can deal with the increased exposure of agriculture to production risk.

Under medium temperature, Table 6 also reports the simulated impacts of changing precipitations on productivity. It reveals the complex effects of rainfall: Higher precipitation has positive impacts on median productivity, negative impacts on standard deviation, and positive impacts on kurtosis. These effects are found to be relatively small, likely reflecting the fact that farmers adjust their production practices (e.g., by switching to drought-resistant crops under a drier climate).

Table 6 documents the evolving role of agricultural technology. For example, under medium temperature and precipitation, Table 6 reports that median productivity increases from 80.38 in 1970 to 94.24 in 1990, and to 111.45 in 2010. These large rises reflect rapid technological progress made in agriculture over the last few decades (e.g., Fuglie, 2018). Interestingly, the simulation results indicate that the patterns of rising agricultural productivity continue to hold in the early part of the twentieth century.

Finally, we evaluate the implications of our analysis for the distribution of world agricultural production. We rely on equation (2) to obtain y_t, a measure of world food productivity under risk, with weight w_i given by the proportion of the total value of agricultural production generated by each obtained from the Food and Agriculture Organization of the United Nations (2023). Using our QAR and conditional copula estimates, we simulate the distribution function of the production index $\exp(y_t)$. Figure 4 reports the estimate distribution evaluated under 2010 conditions. Figure 4 shows that the distribution is asymmetric and exhibits significant exposure to risk. This provides a basis to assess the extent of food insecurity in the world. For example, Figure 4 indicates that, in 2010, there was a 6.8% chance of seeing a 10% drop in world food production (compared to the median);

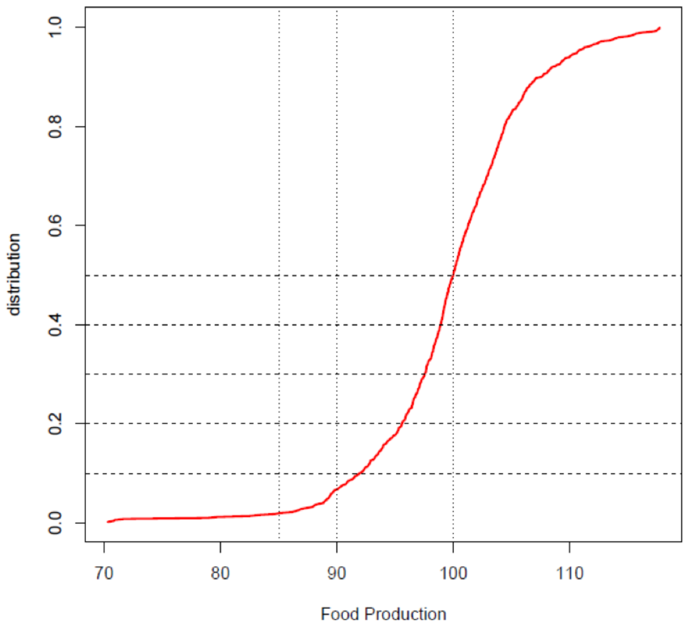

Figure 4. Assessing World Food Security: Estimated Distribution Function of World Agricultural Production in 2010

Notes: World food production is an index normalized so that its median is 100.

Table 7. Moments of Simulated World Agricultural Production Index in 2010, Selected Scenarios

Scenarios		Mean	Median	Std. Dev.	Skewness	Excess Kurtosis
Spatial codependence	Base temp and precip	111.83	111.94	7.44	−0.56	2.59
	Higher temp, base precip	111.75	111.9	7.88	−0.53	2.57
	Higher precip, base temp	111.95	112.02	6.91	−0.51	2.25
	Higher temp and precip	111.87	111.99	7.34	−0.49	2.29
Spatial independence	Base temp and precip	112.48	112.47	7.91	−0.20	2.95

Notes: In the base scenario, the distribution of world agricultural production is evaluated based on conditions present in 2010. The scenarios representing higher temperature (or precipitation) correspond to an increase in mean temperature (or mean precipitation) equal to 20% of the sample medians (i.e., a rise of 4.51°C for temperature and 228 mm for precipitation).

it also shows a 2% chance of seeing a 15% drop in world food production, and a 1.3% chance of seeing a 20% drop in world food production. These estimates document the presence of significant production risk in world agriculture.

We also evaluate the effects of climate on world food insecurity. Using y_t in equation (2), we simulate the distribution of world agricultural production under selected scenarios. The moments of the world production index $exp(y_t)$ are reported in Table 7. Under a base scenario, we obtain the distribution of world agricultural production under conditions present in 2010. In other scenarios, we consider situations of rising temperature and/or precipitation, where each country faces an increase in temperature and/or precipitation equal to 20% of the corresponding sample medians (i.e., a change of +4.51°C for temperature and +228 mm for precipitation). Table 7 shows that the impacts of a changing climate (as reflected by average temperature or precipitation) on world food insecurity tend to be small. For example, a higher temperature induces a very small decrease in the median of world food production, from 111.94 to 111.90. Table 7 reports that a rising temperature increases the standard deviation of world agricultural production, from 7.44 to 7.88 (or +5.9%). While positive, this effect is smaller than that reported in Table 6 (+64.1% in 2010). Also, the effects of higher temperature on tail risk exposure (as measured by kurtosis) differ between Tables 6 and 7. Indeed, Table 7 shows that a rising temperature induces a small decrease in the kurtosis of world agricultural production, from 2.59 to 2.57.

These results indicate that the adverse effects of a rising temperature on world food security are muted when one moves from a country focus to the world level. Why? These findings come from two sources: (i) spatial diversification generates risk-reducing benefits; and (ii) countries that are less sensitive to the adverse effects of rising temperature tend to produce a large share of world food production. The first explanation is documented in Table 7 by comparing the moments of world food production under spatial codependence versus a scenario that assumes spatial independence. Table 7 shows that negative codependences across countries contribute to reducing risk exposure at the world level in 2010: The standard deviation of world production declines from 7.91 under independence to 7.44 under codependence (or −5.9%); and its kurtosis declines from 2.95 under independence to 2.59 under codependence (or −12.2%). These results indicate that spatial diversification helps reduce the adverse impact of increased temperature on world food security: The increased variability in agricultural productivity documented in Table 6 is muted when negative shocks in a country are (at least partially) counteracted by positive shocks in other countries. The second explanation follows from our finding that climate has heterogeneous effects across countries: The adverse effects of higher temperatures are smaller in countries with high agricultural productivity. When such countries contribute a large share of world food production, this tends to reduce the adverse impacts of climate change on food security at the world level. These findings illustrate the usefulness of our analysis, showing how a quantile/copula approach can be applied to assess the risk facing agriculture production in countries around the world and its implications for world food security.

Conclusion

This article has studied the evolution of the probability distribution of agricultural productivity over time and across countries, with a focus on the effects of climate on production risk. Distinguishing between climate and weather, the analysis is based on an *ex ante* approach based on information available at the beginning of the growing season (when one knows long-term climate but not weather conditions during the growing season). As a result, we treat weather shocks as part of the error term and proceed evaluating the probability distribution of agricultural productivity (as measured by TFP) conditional on climate (as measured by long-term temperature and precipitation). In this context, the article relies on a two-step econometric approach: (i) specify and estimate a quantile autoregression (QAR) model representing the dynamic effects of climate and technology on the distribution of agricultural productivity and (ii) estimate a copula capturing the spatial distribution of productivity across countries. Applied to data covering 160 countries over the period 1961–2016, the analysis provides new and useful information about the spatial and temporal determinants of agricultural productivity and the linkages between climate and production risk. First, it documents the slow process determining productivity growth, stressing the importance of dynamics in the evaluation of agricultural productivity. Second, we estimate the effects of higher temperatures on the distribution of agricultural TFP. We find that higher temperatures have positive and large impacts on production risk (as measured by standard deviation and kurtosis), documenting that climate change contributes to significant increases in production risk in agriculture. Third, our analysis documents the presence of much heterogeneity in the patterns of agricultural productivity and productivity growth, indicating that the capacity to produce food and the ability to respond to shocks vary a lot across countries. We also evaluate the adverse effects of rising temperatures on world food security. We find that such effects are muted for two reasons: (i) spatial diversification generates risk-reducing benefits and (ii) countries that are less sensitive to the adverse effects of rising temperature tend to produce a large share of world food production.

Finding muted effects of climate change on world food security is somewhat reassuring. To some extent, these results reflect that spatial and temporal adaptations to climate change can help reduce the adverse effects of climate change on production risk in agriculture. But reducing threats to world food security remains a significant challenge. First, capturing the risk-reducing benefits of spatial diversification requires free trade and food aid that can support moving food toward the countries facing significant food shortages. Second, improved risk management remains an important way to deal with the adverse effects of evolving climatic conditions. This includes improved farm management (e.g., planting risk-tolerant crops adapted to local agroclimatic conditions). This also includes institutions and government policies that can help manage resources in the face of significant shocks to agricultural production (e.g., effective insurance schemes, buffer stock policies that can smooth out the spatial and temporal effects of risk, and climate policies that limit greenhouse gases and their effects on agriculture). Third, while technological innovations have been effective in increasing agricultural productivity and reducing world food insecurity over the last few decades, it remains unclear whether technological developments will be fast enough and effective enough to reduce the adverse effects of rapid climate change over the next few decades. Significant investments in private and public R&D will be required to help develop technological solutions dealing with the future effects of climate change on agriculture.

While this article presents new insights into the economics of agricultural productivity, the analysis could be extended in a number of directions. While our reduced-form approach applies under general conditions, it would be useful to complement our analysis using a structural approach to the investigation of productivity and risk (e.g., Kaminski, Kan, and Fleischer, 2013; Yang and Shumway, 2016; Sesmero, Ricker-Gilbert, and Cook, 2018; Bareille and Chakir, 2024). Additional research is also needed to explore the implications of climate change for economic policy and the prospects for future agricultural productivity growth in countries around the world. Finally, while this article focuses on risk and agricultural productivity, our quantile/copula approach could also be applied to the investigation of the spatial/temporal attributes of many economic and policy issues arising around the world. Addressing these questions appears to be good topics for future research.

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