Climate Change and Its Implications for Agricultural Productivity and Adaptation

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Abstract

Agricultural production is susceptible to changes in climate variability observed as increases in the frequency of extreme temperatures and precipitation. This study is intended to shed light on the impact of climate variability on agricultural total factor productivity (TFP) growth for crop and livestock production by province over 1949–2019. A stochastic frontier (SF) model is chosen to estimate TFP growth for both types of producers for several reasons. First, TFP growth can be decomposed into technical change (TC), technical efficiency change (TEC), and scale effects (SE). Second, the model accounts for endogeneity, recognizing that producers may mitigate the influence of climate variability through their choice of factor inputs. Third, the model allows estimates of TFP and TEC to be expressed as functions of climate variability. This implies that changes in TEC predicted by climate variability are interpreted as a measure of producers' capacity to adapt to climate change, a United Nations core climate change-related indicator of environmental-economic accounting.

Introduction

Agricultural productivity growth is a key driver of the standards of living for farmers and the ability of nations to ensure food security, moderate food prices, and alleviate poverty, especially in developing countries. Historically, the importance of agricultural productivity growth has been amplified by the need to meet the demands of an increasing global population and changing income dynamics. More recently, though, climate change has been cited as an imminent threat to agricultural production by the IPCC (Oppenheimer (2014)) due to the increased prevalence of pest species, drought and flooding, among other risks. Consequently, the need to understand how increasing climate variability affects agricultural productivity has never been more urgent.

Empirically, the links between climate change, and particularly climate variability, with agricultural productivity have been documented in recent studies. For example, Plastina et al. (2019) find that estimating TFP growth without accounting for climate variability leads to the contribution of non-weather contributors to agricultural productivity growth, such as R&D spending, to be significantly biased upward for the U.S. agricultural sector. Using one of the longest and most comprehensive datasets, Wang et al. (2017) show individual states' productivity is strongly affected by its state-specific characteristics such that even with similar patterns of climate variation and natural resources, productivity can differ significantly.

Changes in climate variability can have large impacts on both potential and actual agricultural output. For example, the benefit of longer growing seasons may be countered by damage from extreme weather events. Producers who successfully adapt to these changes will be better positioned to achieve potential output than producers who do not adapt. Changes in potential output over time are typically associated with changes in technology but may also be associated with climate change, especially in the

case of agricultural production. Producers' ability to achieve potential output is a measure of productive efficiency, reflecting their ability to respond to changes in the business and natural environment through adaptation..

Methodological Framework

The method used in this paper is based on the stochastic production frontier approach initially proposed by Aigner et al. (1977), and Meeusen and Van den Broeck (1977). The specification of a stochastic production frontier function can be generally written as

$$Y_{it} = f(X_{it}, t; \beta\ ) exp(v_{it} - u_{it}\ ) \qquad (1)$$

where Y_{it} denotes the output of province i at time t, X_{it} is a vector of input factors used in the production process, t is a time trend which captures the technical change, β is a kx1 vector of unknown parameters to be estimated, v_{it} is an i.i.d. symmetric random disturbance such that $v_{it} \sim N(0, \sigma_v^2)$, u_{it} is an i.i.d. nonnegative random variable representing technical inefficiency such that $u_{it} \sim N^+(0, \sigma_v^2)$.

In addition to the standard factor inputs, X , climate variability is expressly incorporated into the model. Climate variability is represented by the variation in precipitation and temperature as is found commonly in the literature (Bannor et al. (2021), Amare et al. (2018), Dercon and Christiansen (2011), and Alem et al. (2010)) expressed as

$$cv_{it}^{g} = \log\left(\frac{\bar{Z}_i^g - Z_{it}^g}{\sigma_Z^g}\right)$$

where $\bar{Z}_i^g$ represents the historical average for climate indicator g, precipitation or temperature, in province i at a time t, Z_{it}^g is the current climate indicator value, and σ_Z^g measures the indicator's standard deviation from its 70-year mean.

Empirical Strategy

Assuming a translog functional form and letting y_{it}=ln(Y_{it}) and x_{it}=ln(X_{it}), we can write (1) as:

$$y_{it} = \alpha_i + \sum_{j=1}^{J} \beta_j x_{jit} + \frac{1}{2}\sum_{j=1}^{J}\sum_{l=1}^{L} \beta_j x_{jit} x_{lit} + \gamma_1 t + \frac{1}{2}\gamma_2 t^2 + + \sum_{j=1}^{J} \beta_{tj}\, t x_{jit} +$$

$$\sum_{m=1}^{M} \delta_{mi} cv_{mit} + \sum_{m=1}^{M}\sum_{j=}^{J} \delta_{mj} cv_{mit} x_{jit} + v_{it} - u_{it}$$

where α_i represents provincial fixed effects.

To estimate the model, we assume that the noise, v_{it}, is homoscedastic. This assumption is, however, relaxed for time-varying ineffciency, u_{it}. These are distriuted as $v_{it} \sim N(0, \sigma_v^2) \geq 0$ and $u_{i,t} \sim N^+(0, \sigma_{ui,t}^2) \geq 0$ where $\sigma_{ui,t}^2 = \sigma_u^2 \exp(cv_{ui,t}, \gamma_u)$ and γ is random noise.

Here, $cv_{ui,t}$ denotes the vector of covariates for climate variability that determines the variance of the time-varying inefficiency. Because efficiency is equal to $exp(-u)$, its rate of change due to changes in cv variables are by definition the marginal effect and are given by $-du/dcv$. They can be approximated by $-dE_\tau/dcv$. Since the assumed distributions of inefficiencies are half-normal, the marginal effect is given by $-\sqrt{(2/\pi)}d\sigma_u^2/dcv$. Hence the determinants of the variance of inefficiency is also the determinant of inefficiency.

We follow Kumbhakar and Knox Lovell (2000) to decompose TFP changes into three components: TC, SE, and TEC.

$$\widehat{TC} = \hat{\gamma}_1 + \frac{1}{2}\hat{\gamma}_2 \mathrm{t} + \sum_{j=1}^{J} \hat{\beta}_{tj}\, x_{jit} + \sum_{m=1}^{M} \hat{\delta}_m D_{mit}$$

$$\widehat{SE} = (\hat{\varepsilon} - 1) \sum_{m=1}^{M} \left(\hat{\varepsilon}_j / \hat{\varepsilon}\right) \Delta x_{jit}$$

where $\hat{\varepsilon}_j = \hat{\beta}_j + \hat{\beta}_{ij} t + \sum_{l=1}^{L} \hat{\beta}_{lj} x_{lit} + \sum_{m=1}^{M} \delta_{mt} cv_{mit}, j = 1, \dots, J$, $\hat{\varepsilon} = \sum_{j=1}^{J} \hat{\varepsilon}_j$, and $\Delta x_{jit} = x_{jit} - x_{jit-1}$.

$$\Delta\widehat{TE} = \Delta exp(-u_{it})$$

$$\Delta\widehat{TFP} = \widehat{TC} + \widehat{SE} + \Delta\widehat{TE}$$

The outputs, Y, are the aggregate crops and livestock outputs deflated by the appropriate Farm Product Price Index (FPPI; 1997 = 100) to remove the price effect. Inputs are aggregated into the four main input categories: capital (K), including machinery and equipment, and livestock inventory; labour (L), including paid and unpaid labour; land and buildings (LB), including cropped land, pasture, summer fallow, and buildings; and materials (M), including fertilizer, seed, pesticides, feed, fuel, electricity, irrigation, and other miscellaneous expenses.

One Hundred Years of Data, 1921 to 2020

Data required for this project includes information for four basic inputs: labour (paid and unpaid labour), capital (machinery and equipment, and livestock inventory), materials (fertilizer, seed, pesticides, feed, fuel, electricity, irrigation and other miscellaneous expenses) and land and buildings (cropped land, pasture, summer fallow and buildings). There are also two aggregate outputs: crops and livestock. Data for prices are from the Farm Product Price Index.

Climate data to account for temperature and precipitation are publicly available from Environment and Climate Change Canada (ECCC) (Historical Climate Data - Climate - Environment and Climate Change Canada (weather.gc.ca).

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