Global Agricultural Supply Response to Persistent Price Shocks

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1 Introduction

Traditional supply analysis estimates acreage and yield response using the variation in prices from year-to-year (e.g., Nerlove 1958; Roberts and Schlenker 2013; Hendricks, Smith, and Sumner 2014). Such price variation is mostly due to transitory shocks—the price change does not persist over an extended period of time. The supply response to these transitory price shocks is likely to be different than the response to persistent changes in prices. The usual approach in the literature to account for long-run response to price due to adjustment costs is to include a lagged dependent variable. However, including a lagged dependent variable to account for partial adjustment may not give the true long-run response because the coefficient on the lag may simply reflect heterogeneity in price response rather than true adjustment behavior (Hendricks, Smith, and Sumner 2014). Our paper takes a new approach to estimating supply response to persistent price shocks by exploiting changes in price incentives across countries due to changes in government distortions.

We develop a conceptual model that describes supply as a function of the long-run average price and the expected short-run deviation of price from the long-run average. Supply response to these two types of price shocks are not the same due to adjustment costs. Estimating the impact of persistent changes in international prices is difficult for two reasons. First, it is difficult to determine which changes in prices are transitory versus persistent. Second, it is difficult to separately identify the impact of persistent shocks to international prices from other global factors. Instead, we argue that changes in average policy distortions over time represent a persistent shock to incentives that we can exploit to estimate the supply response to persistent price shocks.

Our econometric model regresses different measures of production (i.e., production, inputs, or total factor productivity) on a measure of the policy distortions that is smoothed over time. Policy distortions change dramatically from year-to-year but we seek only to exploit long-run changes in distortions over time in different countries. Our model includes country and year fixed effects along with other controls to reduce concerns about omitted variable bias. Intuitively, our model estimates how changes in distortions in a particular country affect production relative to other countries that changed distortions in a different direction or different magnitude.

Governments distort incentives to producers using various policy instruments. Our estimation strategy is feasible because of a unique dataset from the World Bank that quantifies these distortions across 82 countries and 75 agricultural products since 1955 (Anderson and Nelgen 2013). They construct the Nominal Rate of Assistance (NRA) which measures the relative difference between domestic prices that producers receive (p_{it}^D) in the presence of distortions and the price at the border that would exist under free trade (p_t^B) minus one ($NRA = \frac{p_{it}^D}{p_t^B} - 1$). In this paper, we use the Nominal Assistance Coefficient (NAC) which simply adds one to the NRA ($NAC = \frac{p_{it}^D}{p_t^B}$).

Our empirical analysis seeks to test the pioneering ideas of T.W. Schultz. Schultz (1978, 1980) argued that agricultural distortions that undervalued agricultural production in low-income countries were a key determinant of the lack of productivity in these countries. He argued that these policies reduced productivity by reducing the incentive to research productive technologies and reducing the incentive to adopt superior technologies and inputs. Schultz (1978) also argued that the primary impact of countries overvaluing production is an overproduction in these countries. We separately estimate our econometric model for countries with an anti-agricultural bias and those with a pro-agricultural bias.

Our work is related to previous literature that estimates the impact of price distortions on productivity (Fulginiti and Perrin 1993; Hu and Antle 1993; Block 1995; Fulginiti and Perrin 1998; Nin Pratt and Yu 2008; Headey et al. 2010; Rada, Buccola, and Fuglie 2011; Rakotoarisoa 2011; Block 2013; Fuglie and Rada 2013). All of these studies find some evidence of a positive impact of removing negative distortions on agricultural productivity. However, Headey et al. (2010) is the only study that includes country fixed effects. So a concern with these studies is that there may be unobserved factors about a country that affect productivity that may also be related to the level of policy distortions.

Headey et al. (2010) estimates a differenced cross-section regression of 48 countries. The dependent variable is the change in TFP growth rate from the period 1970–1985 to the period 1986–2001 regressed on the change in average relative rate of assistance between these periods. They finds a positive impact of changes in the relative rate of assistance on the change in the growth rate of Total Factor Productivity (TFP). Lin (1992) estimate the contribution of different factors—including the increase in the state procurement price for commodities—to the incredible increase in agricultural output in China from 1978 to 1984. Lin (1992) includes province level fixed effects in his model but is not able to estimate the impact of price distortions separately from year fixed effects.

Another recent paper that is relevant to our work is Magrini et al. (2017). Magrini et al. (2017) estimate how distortions to agricultural incentives affect food security, but do not directly estimate the impact of distortions on production. They find that an increase in assistance increases food availability up to a certain point and then further increases in assistance decrease food availability. Importantly, the main results of Magrini et al. (2017) rely on an assumption that after matching on the observed political economic variables that the variation remaining in the NAC is as good as randomly assigned. Less restrictive assumptions are required in a model with country and year fixed effects. Magrini et al. (2017) compare a fixed effects model with and without an instrumental variable and do not reject exogeneity. However, their preferred specification does not include country and year fixed effects and they do not test if the fixed effects can be reasonably omitted.

2 Model

2.1 Conceptual Framework

We assume that production in the current year depends on the long-run expected price ($\overline{p}_{it}^{D}$) as well as the expected deviation from long-run price in the current year ($ln(E_t p_{it}^{D}) - ln(\overline{p}_{it}^{D})$). Producer decisions depend on the long-run price when making long-run investment decisions and short-run deviations from the long-run price affect variable input decisions. We assume a constant-elasticity supply equation written as

$$(1) \quad ln(q_{it}) = \beta ln(\overline{p}_{it}^D) + \gamma(ln(E_t p_{it}^D) - ln(\overline{p}_{it}^D)) + \eta_{it},$$

where the subscript i denotes the country and t denotes the year.

Consider two types of price shocks: persistent versus transitory. Persistent price shocks are expected to persist for a long period of time—for example, due to changes in policies that distort incentives for producers. Transitory price shocks are price shocks that are only expected to last a short period—for example, due to a drought in a previous period. Supply response due to a persistent price shock is β and supply response due to a transitory price shock is γ.

The NAC is domestic price including distortions relative to the border price with no distortions. We assume that the border price is roughly constant across countries so that we can write $NAC_{it} = \frac{p_{it}^D}{p_t^B}$, where p_t^B is the border price that does not vary across countries. Substituting $p_{it}^D = NAC_{it} p_t^B$ into equation (1) and rearranging gives

$$\begin{aligned}(2) \quad ln(q_{it}) = &\beta ln(\overline{NAC}_{it}) + \gamma(ln(E_t NAC_{it}) - ln(\overline{NAC}_{it})) + \beta ln(\overline{p}_t^B) \\ &+ \gamma ln(E_t p_t^B - \overline{p}_t^B) + \eta_{it}.\end{aligned}$$

The first term $(\beta ln(\overline{NAC}_{it}))$ represents the response to persistent changes in incentives due to anticipated changes in policy distortions. The second term $(\gamma(ln(E_t NAC_{it}) - ln(\overline{NAC}_{it})))$ represents the response to transitory changes in policy distortions in the current year. A key driver of changes in distortions from year to year are international prices. For most countries with a pro-agricultural bias, NAC is larger (i.e., more distorting) when international prices are low in order to support producer incomes. For most countries with an anti-agricultural bias, NAC is also larger (i.e., less distorting) when international prices are low because the price for consumers is already low. The last two terms $(\beta ln(\overline{p}_t^B) + \gamma ln(E_t p_t^B - \overline{p}_t^B))$ represent the response to persistent and transitory changes in the international border prices.

We measure $ln(\overline{NAC}_{it})$ by exploiting trends in NAC_{it} over time. NAC has evolved differently in different countries. For example, some countries reduced export taxation at different rates, some countries reduced subsidies at different rates, and some countries increased subsidies. We assume that the evolution in NAC was anticipated by producers. We measure the expected NAC by smoothing the raw NAC using country-specific regressions of NAC on a restricted cubic spline of time with 5 spline knots, a quadratic in precipitation, and temperature. We then calculate the predicted NAC setting the precipitation and temperature equal to their long-run averages. This measure of a smoothed NAC is our measure of the expected NAC.

Measuring E_tNAC_{it} represents a substantial challenge. This would require an understanding of how producers expect NAC_{it} to respond to changes in prices for each specific country and a measure of the expected market price at the time input decisions are made. One option is that we could estimate country-specific regessions where we regress NAC_{it} on the international price and use the regression results to adjust expected prices. However, we expect such estimates to be measured with error and difficult to distinguish separately from year fixed effects that capture the effect of international prices. Therefore, we omit the term $ln(E_tNAC_{it}) - ln(\overline{NAC}_{it})$ from our regressions. We discuss the implications of this below.

We seek to understand the impact on supply through three margins of adjustment: (i) the intensive margin, (ii) the extensive margin, and (iii) the productivity margin. The intensive margin represents a change in production due to a change in input use but holding constant land use. The extensive margin represents the effect of changes in land area used for production. The productivity margin represents changes in production per unit of total input. We estimate the different margins of adjustment by using different dependent variables to represent each margin of adjustment.

2.2 Econometric Model

Based on the conceptual framework developed above, we estimate econometric models of the form

$$(3) \quad ln(y_{it}) = \beta ln(\overline{NAC}_{it}) + \mathbf{X}_{it}\boldsymbol{\theta} + \alpha_i + \lambda_t + \varepsilon_{it},$$

where y_{it} is the dependent variable of interest for country i in year t (e.g., production, input use, or productivity), $\overline{NAC}_{it}$ is the nominal assistance coefficient that has been smoothed (as described above), $\mathbf{X}_{it}$ is a vector of other control variables, α_i represents country fixed effects, and λ_t represents year fixed effects. In our main specification, our controls ($\mathbf{X}_{it}$) include a quadratic function of GDP per capita, an indicator of democratic institutions, a quadratic of precipitation, and temperature. When we estimate regressions with pro-agricultural countries, we also include measures of factor (labor, capital, and land) abundance. Standard errors are clustered by country.

Our coefficient on $ln(\overline{NAC}_{it})$ reflects the supply response due to a change in the long-run expected price. Note that our model in equation (3) differs from traditional supply response literature because we include year fixed effects. The year fixed effects in our econometric model capture the impact of changes in international prices on supply ($E_t p_t^B$ and $\overline{p}_t^B$). Year fixed effects also capture the short-run change in NAC for a given year ($ln(E_t NAC_{it}) - ln(\overline{NAC}_{it})$) that are common across countries. Therefore, the impact of transitory price shocks that most of previous literature estimates are absorbed into the year fixed effects.

We estimate the regression model separately for countries with an anti-agricultural bias and those with a pro-agricultural bias. As mentioned in the introduction, Schultz (1978) suggested that an anti-agricultural bias could reduce productivity and a pro-agricultural bias could result in overproduction. Several papers account for the differential impact by either estimating separate regressions by type of policies or including nonlinear functions of distortions (e.g., Hu and Antle 1993; Headey et al. 2010; Magrini et al. 2017).

2.3 *Identification Concerns*

A key challenge in estimating the impact of policy distortions on production is the potential for endogeneity bias. In this section we describe the key sources of endogeneity and our empirical approach alleviate each endogeneity concern.

Countries that have relatively better production conditions for agriculture might have systematically different agricultural policies. Therefore, we think it is critical to include country fixed effects in the model. In years with low global agricultural production, prices will be high and the NAC tends to decrease. Therefore, it is also critical to include year fixed effects.

Another concern is that domestic prices may not change exactly the same as international prices so that some domestic price movements are not captured by the year fixed effects. We address this concern in two ways. First, we include controls for precipitation and temperature to account for shocks in production due to weather. Second, we use smoothed NAC values in the regression rather than actual NAC values. If a particular country has a negative shock to production, then prices in that country increase (and perhaps more than the effect on international prices) and the government decreases NAC. Therefore, using actual NAC data rather than smoothed NAC data results in upward bias.

A related concern is that we omit $(ln(E_tNAC_{it}) - ln(\overline{NAC}_{it}))$ from our econometric model. This only induces bias in our estimate of β if the short-run deviation in NAC is correlated the long-run average NAC. Conditional on country and year fixed effects and weather, we think this is unlikely to induce substantial bias.

Another reason to use smoothed NAC values is that we want to measure changes in expected NACs that would affect long-run investment decisions. Changes in NACs from year to year can be large and not reflect the long-run anticipated change. This creates a form of measurement error using the actual NAC values that could bias estimates with actual NAC data towards zero. Given the discussion in the previous paragraph, using actual NAC data rather than smoothed NAC data could result in upward or downward bias depending on the relative magnitude of the different forms of bias.

It is well established in the literature that GDP per capita has a strong relationship with agricultural distortions (e.g., Swinnen 2010; Anderson, Rausser, and Swinnen 2013). Usually the relationship between NAC and GDP per capita is a concave function with increases in GDP per capita increasing NAC at a diminishing rate. An endogeneity concern arises if increases in GDP per capita are also related with greater production. For example, greater incomes in other sectors of the economy could draw people out of the agricultural labor force. Alston (2018) suggests there could be a rapid increase in productivity when an economy transitions from agrarian to industrial. Greater incomes in other sectors of the economy may also be associated with a more highly educated agricultural producers and greater access to advanced technologies.

Changes in political institutions can also have an impact on the NAC (Olper, Falkowski, and Swinnen 2013). But these changes in political institutions may directly affect agricultural production. For example, better institutions may improve the protection of property rights and reduce uncertainty that affects investment. To account for changes in institutions we include a control for whether or not the country is considered democratic.

As a country loses comparative advantage in agriculture over time, it may increase assistance to protect the agricultural industry. This creates a negative correlation between production and NAC. We account for this potential bias by including measures of factor abundance to account for changes in comparative advantage over time based loosely on a Heckscher-Ohlin argument. Factor abundance for the whole economy—not just agriculture—is calculated as the share of the country's global input use divided by the country's share of global GDP. A country that becomes more abundant in capital, arguably loses comparative advantage in agriculture. We only include measures of factor abundance in our regressions of countries with a pro-agricultural bias since we do not expect changes in comparative advantage as a major explanation of changes in policies in countries with an anti-agricultural bias.

3 Data

3.1 Data Sources

We use several different dependent variables in the analysis. The agricultural output index, production of specific products, and crop yields are obtained from the FAOSTAT database maintained by the Food and Agriculture Organization (FAO). Measures of total factor productivity and input use indices are from the Economic Research Service (ERS), USDA database on International Agricultural Productivity assembled by Keith Fuglie. The Fuglie data are sourced mostly for FAOSTAT but sometimes supplemented with national statistics. FAOSTAT and international productivity data are available beginning in 1961.

Alston (2018) cites several concerns with the international productivity data. In particular, the international data do not indicate a slow-down in productivity in the United States in recent years while other productivity data assembled by ERS and InSTePP (International Science and Technology Practice and Policy) do indicate a recent slow down. The alternative ERS and InSTePP productivity measures use a more complete set of data on inputs that are not available for the international productivity data. Therefore, there is evidence that measures of Total Factor Productivity (TFP) and input indices from the international productivity data could have measurement error. Since this measurement error is on the left-hand side of our regressions, it only induces bias if it is correlated with changes in the NAC.

A critical source of data for our paper is the unique dataset "Estimates of Distortions to Agricultural Incentives, 1955-2011" from the World Bank (Anderson and Nelgen 2013). The agricultural distortions data include a measure of the distortions due to a wide range of price distorting policies including trade distortions, domestic subsidies or taxes, distortions to exchange rates, and distortions to the price of inputs. The Nominal Rate of Assistance

(NRA) measures the relative difference between domestic prices that producers receive in the presence of distortions and the price that would exist under free trade—under the assumption that world prices are not affected by trade liberalization—minus 1. We use the Nominal Assistance Coefficient (NAC=NRA+1) in this paper. An NAC less than 1 indicates an anti-agricultural bias and an NAC greater than 1 indicates a pro-agricultural bias. In addition to reporting product-specific NRAs, the database also reports an average NRA across all products for each country. The agricultural distortions database covers 82 countries and 75 products from 1955 to 2011. However, the distortions data are an unbalanced panel with data not available for all products in all countries and data on distortions starting much later for some countries.

Data on GDP per capita are from the World Bank's World Development Indicators adjusted to US dollars in 2000. Data on political institutions are obtained from Integrated Network for Societal Conflict Research (INSCR). INSCR includes a variable called the Polity score of governments that ranges between -10 and 10. Scores closer to -10 indicate a more autocratic government and closer to 10 indicate more democratic. We create a binary variable equal to 1 if the polity score is greater than 0 to indicate a democratic government as used by Olper, Falkowski, and Swinnen (2013).

Data on effective labor and effective capital are from the Penn World Tables. Effective input use refers to an adjustment for input quality. We calculate effective labor as the number of people in the workforce times the human capital index. Effective capital is the capital stock adjusted for Purchasing Power parity in 2011 US dollars. Data on effective land are from the international productivity database where land area used for pasture, rainfed cropland, and irrigated cropland are given different weights. Factor abundance is calculated as

$$\frac{factor_{it}/\sum_i factor_{it}}{TotalGDP_{it}/\sum_i TotalGDP_{it}} \tag{4}$$

where $factor_{it}$ is the amount of effective inputs of the particular factor and $TotalGDP_{it}$ is the total GDP of the country. If a country's share of global effective labor is greater than its share of global GDP, then a country is considered to be abundant in labor.

Historical data on weather are obtained from the Climate Research Unit (CRU), University of East Anglia. The CRU data are monthly data in a gridded format. We aggregate the gridded data for each product in each country over the area within the country classified as a growing area for the specific product using global maps of production by Monfreda, Ramankutty, and Foley (2008). For animal products, we aggregate weather over the growing area of grassland. When we estimate regressions with an aggregate measure of production—rather than product-specific—we use annual average values of precipitation and temperature averaged across products.[1] When we estimate regressions with a measure of product-specific production, we use average values of precipitation and temperature between the months of planting and harvest. Data on planting and harvest dates are from Sacks, Deryng, and Foley (2010).

3.2 Data Visualization

Figures 1–5 illustrate NAC values by country over time. The blue line in each graph shows the actual NAC values and the red line shows the smoothed NAC values that we use in our econometric model. Each figure shows countries from different regions of the world. The x-axis in every plot ranges from 1961 to 2011 to show the range of data available for each country. The range of values on the y-axis in each plot differs in order to better illustrate the trends over time in each country.

A couple important observations from figures 1–5. First, there are clear differential trends in NACs across countries. Some countries increased NACs in early years and then began to decrease. Other countries decreased NACs and then increased in later years. And many trends in NAC are not unimodal. We exploit these differential trends in our econometric

[1] Precipitation and temperature differ across commodities within a given country and year because they are aggregated over different areas of the country.

model that includes country and year fixed effects. Second, the NACs in any particular year can deviate largely from the smooth NAC trend. Much of the volatility in NACs is due to changes in international prices.

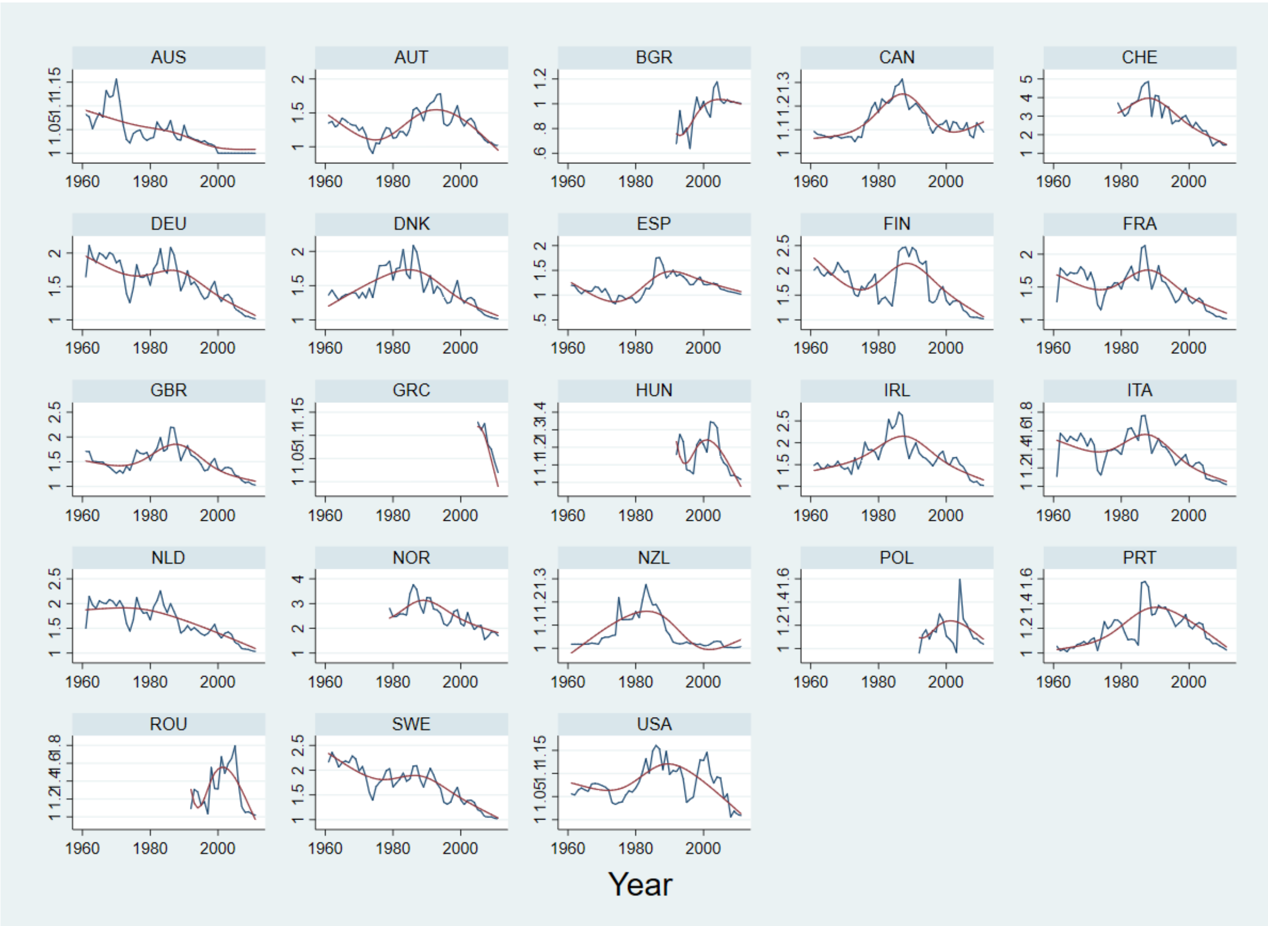

Figure 1: Predicted Distortions by Country in North America, Europe, and Oceania

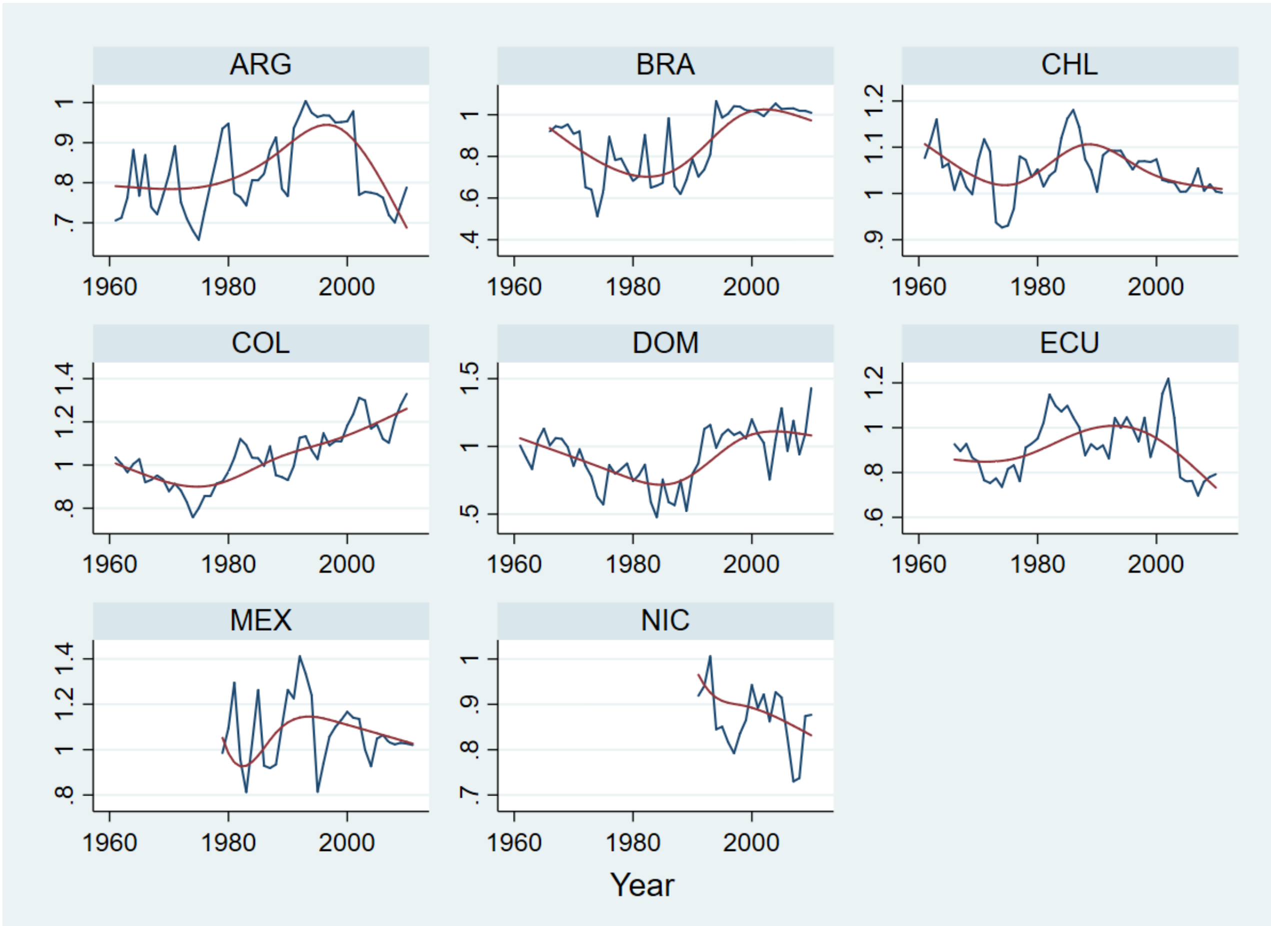

Figure 2: Predicted Distortions by Country in Latin America

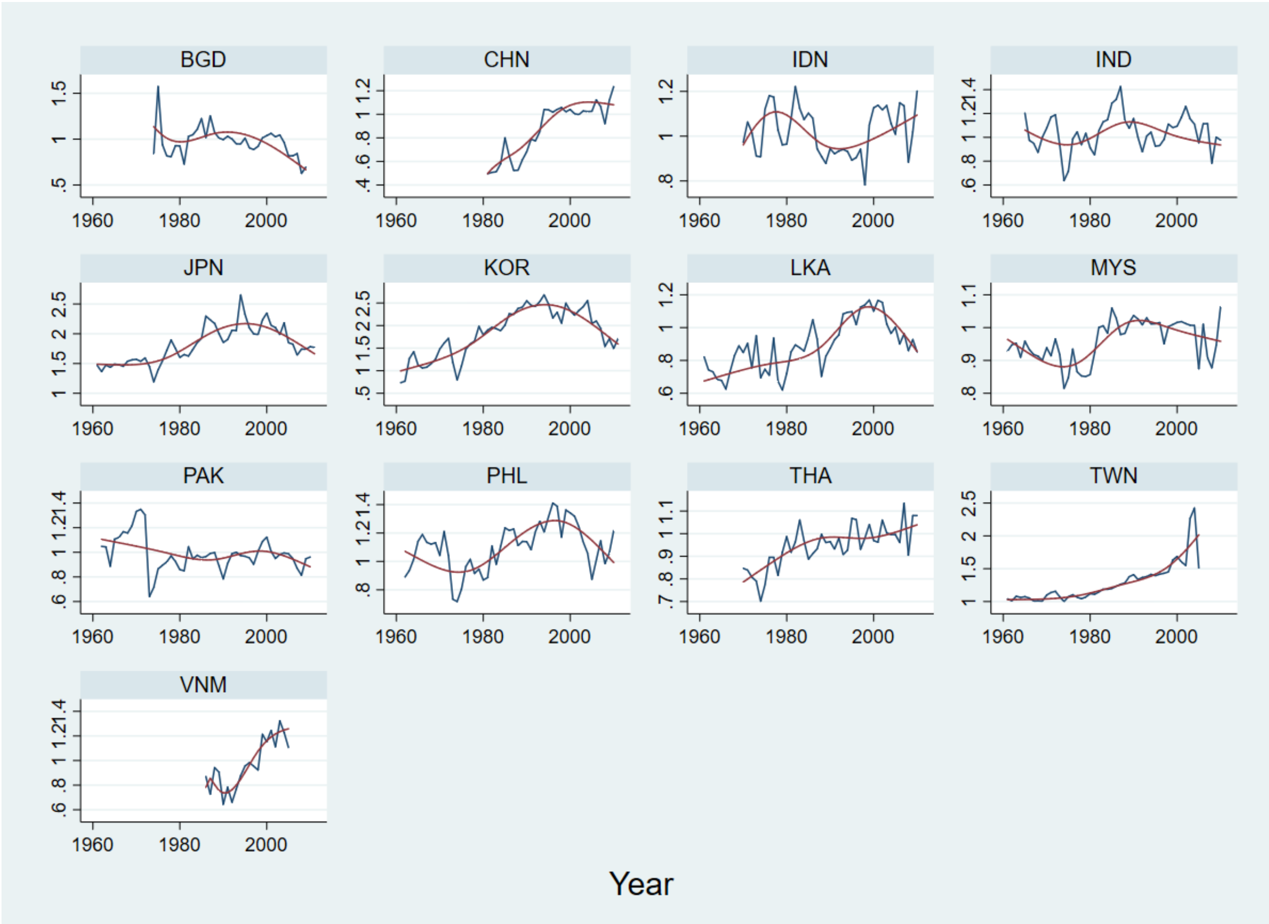

Figure 3: Predicted Distortions by Country in Asia

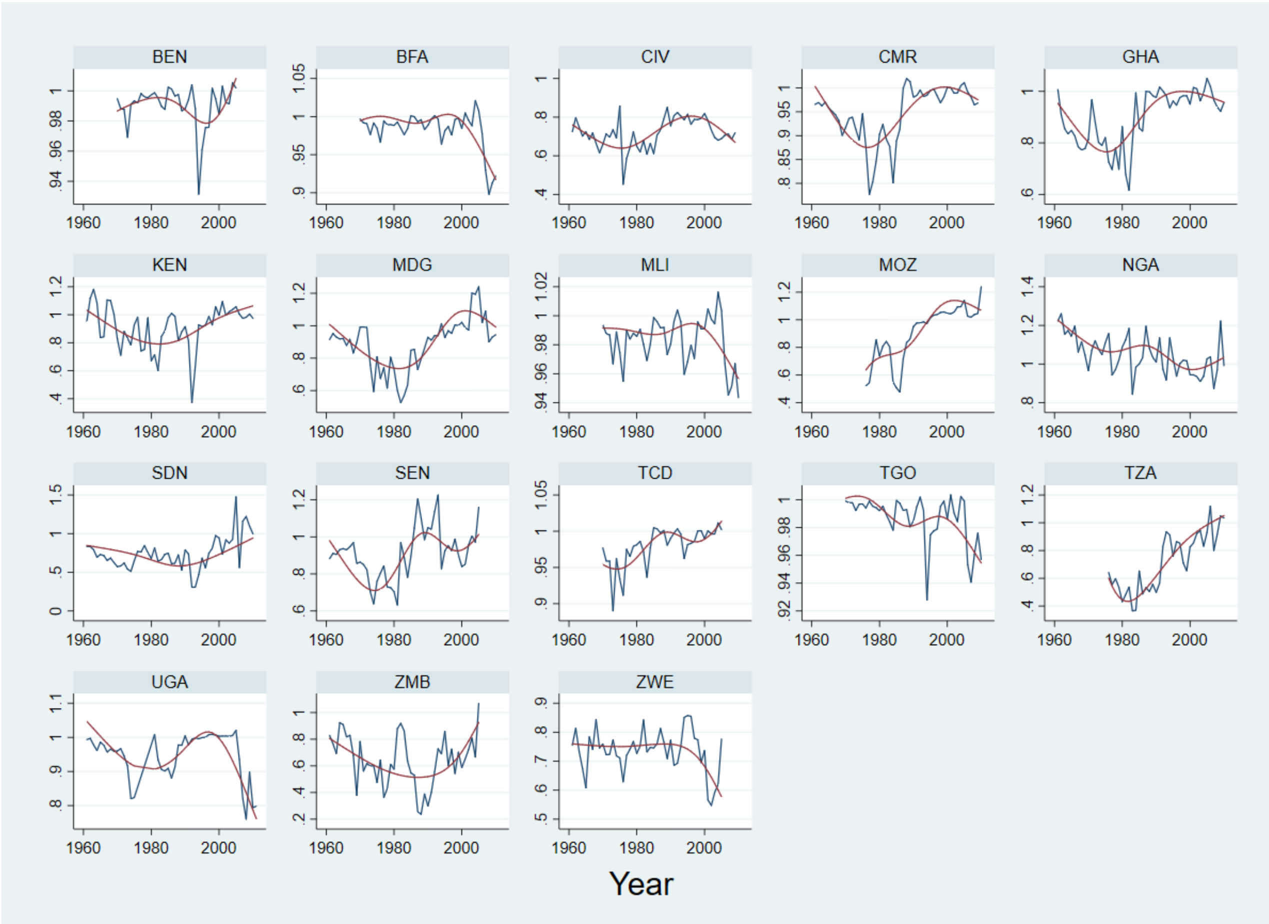

Figure 4: Predicted Distortions by Country in Sub-Saharan Africa

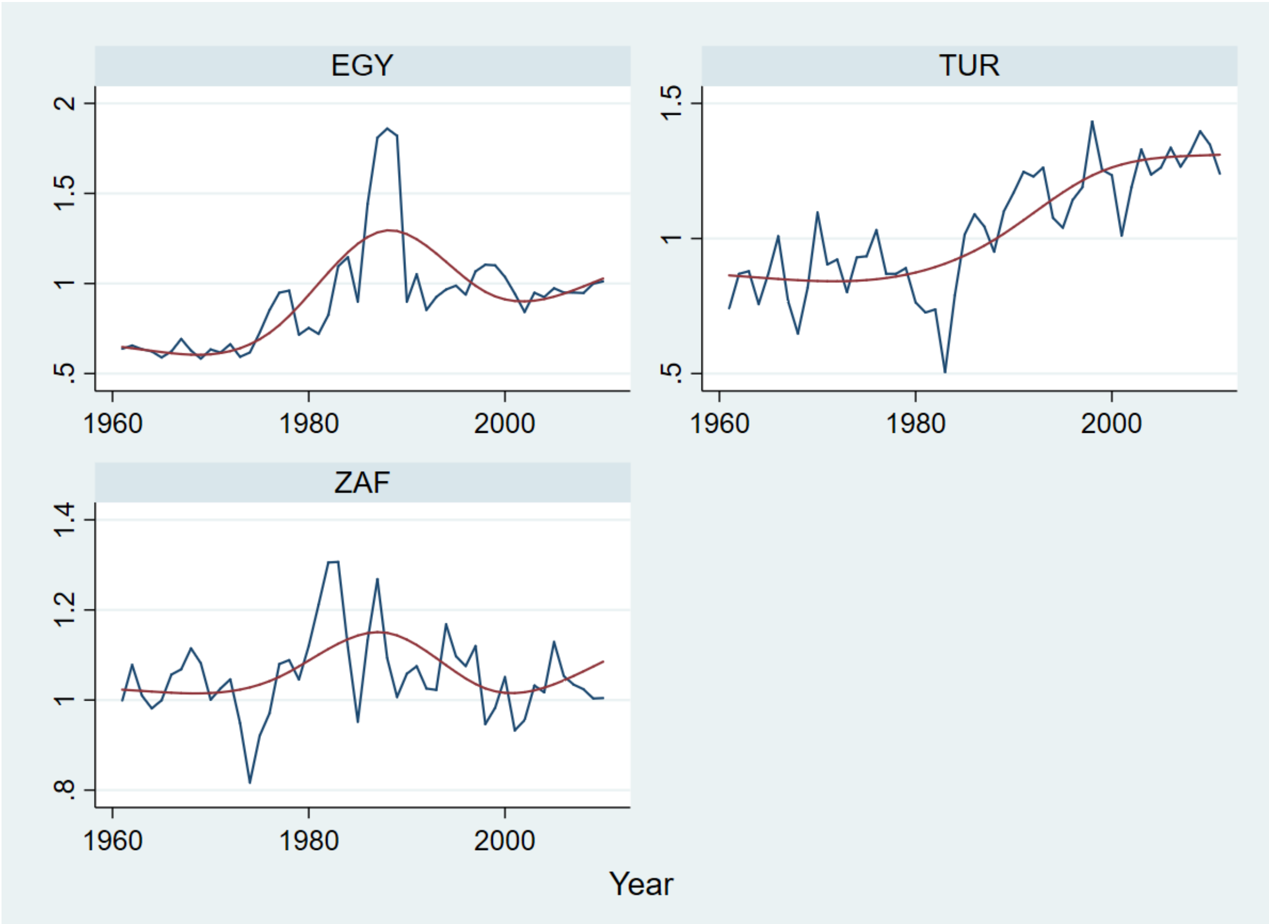

Figure 5: Predicted Distortions by Country in Rest of Africa and Middle East

Figure 6 shows the NAC by commodity group averaged across countries with a pro-agricultural bias. We only average the NAC values if there are 10 or more countries with NAC data. The largest changes in NAC occurred for milk and sugar. Cereals and oil crops had changes in distortions over time as well but these changes are not substantially larger than for meat and eggs.

Figure 7 shows NAC values for countries with an anti-agricultural bias. Note that figure 7 does not contain data on meat, milk, and eggs because there is little data for these products in countries with an anti-agricultural bias. The bias against cereals has decreased since the mid-1970s but cereals by no means face the largest negative distortions. Stimulant crops like cocoa, coffee, and tea faced the largest negative distortions followed by fibre and oil crops. Stimulant crops have seen the greatest reduction in anti-agricultural bias. Sugar has generally been positively supported, even in countries with an overall anti-agricultural bias.

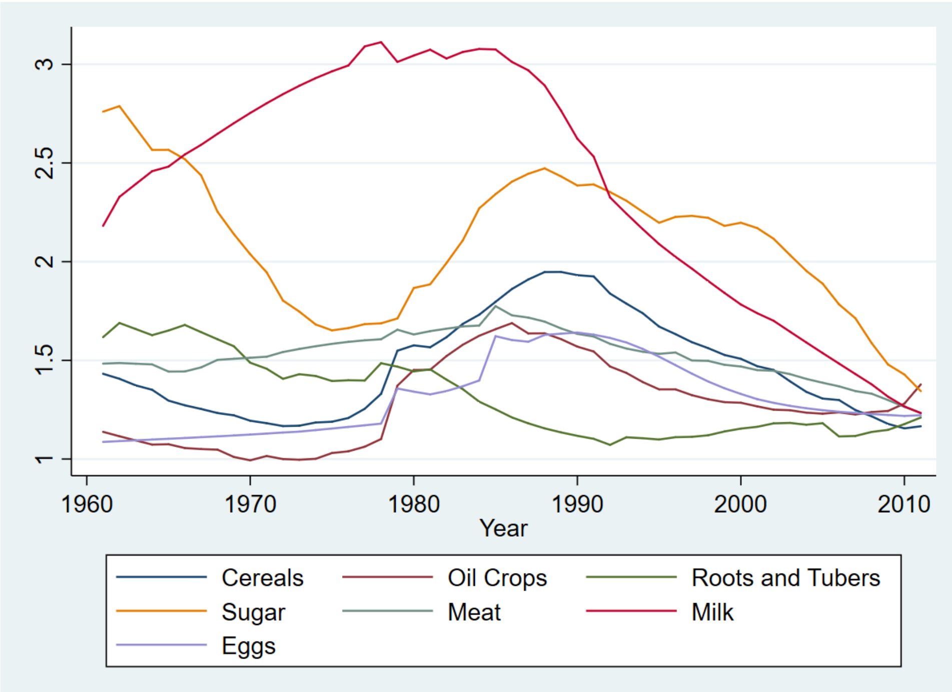

Figure 6: Average Distortions by Product Category across all Countries with a Pro-Agricultural Bias

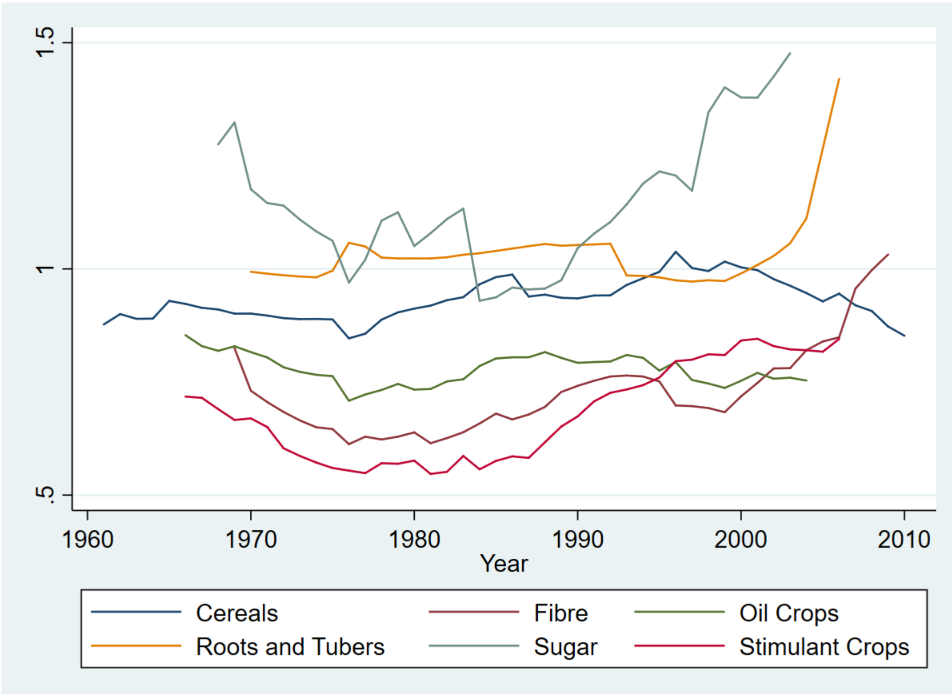

Figure 7: Average Distortions by Product Category across all Countries with an Anti-Agricultural Bias

4 Results

4.1 Anti-Agricultural Bias

Table 1 shows results from our econometric model for aggregate measures of agriculture but only includes observations (i.e., country-year pairs) with an anti-agricultural bias in the regressions. An observation is considered an anti-agricultural bias if $\overline{NAC}_{it}$ is less than 1 and we only include observations from countries that had an anti-agricultural bias for at least 10 years. An NAC less than 1 means the price farmers receive is lower than the world price. The dependent variable is indicated by the column heading in table 1.

Table 1 shows that an increase in NAC is associated with an increase in the annual growth rate of TFP. A 10% increase in price from a persistent price shock increases the productivity growth rate in countries with an anti-agricultural bias by 0.2 percentage points. The growth in TFP appears to come from a decrease in input use, rather than an increase in outputs.

Table 2 is the same as table 1 except that the dependent variable represents the different input categories. Increases in NAC are associated with a decrease in area used for agriculture and fertilizer use. The effect on agricultural area is unexpected. The negative effect on fertilizer use could be because some structural adjustment required countries in Sub-Saharan Africa to decrease fertilizer subsidies in addition to the reduction in export taxes (Nin Pratt and Yu 2008). However, the NAC includes measures of distortions to inputs in addition to distortions to outputs. Disentangling the impacts of output and input distortions is an important area for future research.

We find a significant concave relationship of GDP per capita with overall input use (table 1), and primarily with labor (table 2). Reductions in labor as incomes become especially large is intuitive as high incomes incentivize migration out of agriculture and into other sectors of the economy. Transitions to a democratic government are not associated with changes in production or TFP growth. The coefficients on the weather variables in the production equation have the expected signs and are statistically significant (table 1). Weather does not have a significant impact on overall inputs as expected (table 1) with mixed signs on input categories (table 2).

We further explore the impact of NAC on productivity by estimating crop-specific regressions reported in table 3. The dependent variable is the log of yield for the crop indicated in the column heading. We focus on crops since there are little distortions for animal products in countries with an anti-agricultural bias. Note that the NAC in each regression is the NAC for that particular commodity and the regression sample is restricted to observations with a bias against that particular product.

Results in table 3 indicate a positive and significant impact of NAC on cocoa, soybean, and wheat yields. For cocoa, we find that a 10% increase in price due to a persistent shock increases yield by 3.19%. Many of the coefficients on NAC are statistically insignificant.

Table 1: Impacts on Overall Indicators of Agriculture for Countries with an Anti-Agricultural Policy Bias

	(1)	(2)	(3)
	ln(Production)	TFP Growth	ln(Inputs)
ln(NAC)	-0.128	0.022*	-0.288***
	(0.139)	(0.013)	(0.102)
ln(GDP)	0.283	-0.052	1.149***
	(0.507)	(0.034)	(0.257)
ln(GDP)^2	-0.007	0.003	-0.088***
	(0.039)	(0.003)	(0.019)
Democratic	0.008	-0.000	0.001
	(0.039)	(0.003)	(0.026)
Precipitation	0.005**	-0.001***	0.001
	(0.002)	(0.000)	(0.001)
Precipitation^2	-0.000**	0.000***	-0.000
	(0.000)	(0.000)	(0.000)
Temperature	-0.036*	0.002	-0.013
	(0.020)	(0.002)	(0.014)
N	1142	1133	1142
Country Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 2: Impacts on Input Categories for Countries with an Anti-Agricultural Policy Bias

	(1) ln(Area)	(2) ln(Labor)	(3) ln(Machinery)	(4) ln(Fertilizer)
ln(NAC)	-0.315**	-0.101	-1.126	-0.911**
	(0.140)	(0.110)	(0.731)	(0.372)
ln(GDP)	0.387	1.916***	3.013	-1.244
	(0.404)	(0.239)	(2.057)	(1.099)
$\ln(\text{GDP})^2$	-0.028	-0.164***	-0.149	0.144*
	(0.031)	(0.018)	(0.149)	(0.080)
Democratic	0.019	-0.043	-0.051	0.129
	(0.033)	(0.027)	(0.143)	(0.084)
Precipitation	0.002**	-0.001	-0.005*	0.000
	(0.001)	(0.001)	(0.003)	(0.002)
Precipitation^2	-0.000**	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.001	0.029**	-0.092	-0.213***
	(0.026)	(0.013)	(0.083)	(0.068)
N	1142	1142	1142	1142
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 3: Impacts on Log Crop Yields for Countries with an Anti-Agricultural Policy Bias

	(1) Cocoa	(2) Coffee	(3) Cotton	(4) Groundnut	(5) Maize	(6) Rice	(7) Sorghum	(8) Soybean	(9) Sugar	(10) Wheat
ln(NAC)	0.319*	-0.126	0.027	-0.010	-0.054	-0.015	-0.025	0.179***	-0.026	0.214**
	(0.076)	(0.223)	(0.885)	(0.913)	(0.427)	(0.446)	(0.856)	(0.000)	(0.861)	(0.039)
ln(GDP)	-1.974	-1.215	0.057	-9.469**	-0.454	0.655*	-0.931	-0.466	2.684	-0.041
	(0.171)	(0.378)	(0.949)	(0.027)	(0.265)	(0.062)	(0.288)	(0.125)	(0.222)	(0.950)
ln(GDP)^2	0.107	0.108	0.015	0.834**	0.050	-0.050**	0.073	0.038*	-0.182	-0.002
	(0.252)	(0.316)	(0.825)	(0.026)	(0.111)	(0.029)	(0.205)	(0.082)	(0.256)	(0.967)
Democratic	0.094	-0.067	0.156	0.081	0.127	-0.070*	-0.046	0.047	-0.057	0.001
	(0.245)	(0.541)	(0.160)	(0.333)	(0.158)	(0.068)	(0.518)	(0.287)	(0.619)	(0.977)
Precipitation	-0.002	0.004**	0.003	0.008	0.011***	0.004**	0.004	0.006***	-0.000	0.005
	(0.178)	(0.030)	(0.359)	(0.159)	(0.002)	(0.011)	(0.168)	(0.009)	(0.991)	(0.111)
Precipitation^2	0.000	-0.000*	-0.000	-0.000	-0.000**	-0.000**	-0.000	-0.000**	0.000	-0.000
	(0.802)	(0.053)	(0.534)	(0.272)	(0.016)	(0.015)	(0.218)	(0.010)	(0.864)	(0.163)
Temperature	-0.136	-0.052	-0.009	-0.127***	-0.069*	0.071**	-0.105**	-0.044*	0.009	-0.047*
	(0.352)	(0.425)	(0.861)	(0.001)	(0.055)	(0.029)	(0.014)	(0.088)	(0.875)	(0.082)
N	296	432	726	287	536	510	318	293	289	370
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

p-values in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

4.2 Pro-Agricultural Bias

Table 4 shows the regression results for agriculture as a whole for countries with a pro-agricultural bias. We define a pro-agricultural bias as an observation that did not have an anti-agricultural bias. An increase in NAC is strongly associated with an increase in production and inputs with no significant impact on TFP growth. Results indicate that a 10% increase in price due to a persistent price shock increases production by 4.0%. Surprisingly, we do not find a significant impact of the NAC on each specific input category even though we find a significant impact on total inputs (table 5).

Table 4 also indicates a significant concave relationship between production and GDP per capita. This significant concave relationship holds with each of the specific input categories in table 5. But there is no significant relationship between GDP per capita and TFP growth, counter to the results found by Alston (2018).

There is also evidence that factor abundance affects production, TFP growth, and inputs in table 4. An increase in capital abundance typically indicates a loss in comparative advantage for agriculture and appears to be associated with decreases in production and inputs. However, the loss in comparative advantage for agriculture may also lead to greater incentive to increase productivity and we find a positive impact of capital abundance on TFP growth. However, we interpret the coefficient of capital abundance on TFP growth with some caution as the international productivity measures are particularly poor at measuring capital inputs in agriculture. So it could be that capital abundance is associated with an increase in TFP growth simply due to measurement error in TFP.

We explore the impact of pro-agricultural policies on production further by estimating the impact of NAC on the production of different groups of commodities (table 6). The dependent variable in each column is the log of the total production index of the product group indicated in the column heading. The NAC is the average NAC for products with NAC data within the specific product group. The sample is restricted to observations with

Table 4: Impacts on Overall Indicators of Agriculture for Countries with a Pro-Agricultural Policy Bias

	(1) ln(Production)	(2) TFP Growth	(3) ln(Inputs)
ln(NAC)	0.398***	0.004	0.248**
	(0.112)	(0.008)	(0.114)
ln(GDP)	2.107***	-0.018	2.220***
	(0.269)	(0.014)	(0.211)
ln(GDP)^2	-0.121***	0.000	-0.134***
	(0.015)	(0.001)	(0.015)
Democratic	0.020	0.005	0.093***
	(0.049)	(0.004)	(0.027)
Labor Abundance	-0.016	-0.001	0.021
	(0.035)	(0.003)	(0.036)
Capital Abundance	-0.156**	0.019***	-0.136*
	(0.074)	(0.006)	(0.072)
Land Abundance	0.040*	0.002	0.025
	(0.022)	(0.002)	(0.020)
Precipitation	0.000	-0.000	-0.000
	(0.001)	(0.000)	(0.001)
Precipitation^2	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Temperature	-0.018**	0.004***	-0.018**
	(0.008)	(0.001)	(0.009)
N	1514	1490	1514
Country Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Impacts on Input Categories for Countries with a Pro-Agricultural Policy Bias

	(1) ln(Area)	(2) ln(Labor)	(3) ln(Machinery)	(4) ln(Fertilizer)
ln(NAC)	0.016	0.199	1.026	0.340
	(0.094)	(0.201)	(0.681)	(0.319)
ln(GDP)	0.916***	3.311***	7.556***	5.960***
	(0.263)	(0.394)	(1.511)	(0.672)
ln(GDP)^2	-0.067***	-0.221***	-0.363***	-0.364***
	(0.014)	(0.024)	(0.080)	(0.048)
Democratic	0.039	0.077	0.062	0.120
	(0.026)	(0.047)	(0.190)	(0.106)
Labor Abundance	-0.093***	0.136**	-0.381*	0.111
	(0.033)	(0.055)	(0.209)	(0.123)
Capital Abundance	-0.142**	-0.343***	0.095	-0.418**
	(0.057)	(0.111)	(0.268)	(0.186)
Land Abundance	0.088***	-0.055*	0.320**	0.037
	(0.021)	(0.033)	(0.139)	(0.068)
Precipitation	0.000	-0.001	-0.001	-0.001
	(0.000)	(0.001)	(0.003)	(0.002)
Precipitation^2	0.000	0.000**	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	0.010	-0.035*	0.005	-0.044*
	(0.007)	(0.019)	(0.025)	(0.023)
N	1514	1514	1514	1514
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

a pro-agricultural bias for that specific product group. We omit result for fibre and fruits due to few observations in the regression—in particular, limited NAC data.

We find a large and statistically significant positive impact of NAC on milk and egg production. The impact on milk production is not surprising given the very large decreases in NAC for milk since the mid-1980s (figure 6). Eggs also saw a large increase in NAC from the late 1970s until 1990 and then a reduction in NAC. The significant negative impact of NAC on cereal production is the opposite of expected. One explanation of the negative sign is that our coefficient could be biased due to not perfectly capturing the effect of losses in comparative advantage. That is, countries that lost comparative advantage in cereals may have increased NAC to support the industry from import competition. For cereals, this could have been especially large in Japan, South Korea, and Taiwan where assistance for rice has increased dramatically.

Table 6: Impacts on Production by Product Category for Countries with a Pro-Agricultural Policy Bias

	(1) Cereals	(2) Oil Crops	(3) Meat	(4) Milk	(5) Eggs
ln(NAC)	-0.194**	-0.071	0.014	0.155**	0.407**
	(0.023)	(0.853)	(0.924)	(0.030)	(0.012)
ln(GDP)	1.791***	0.549	2.464***	3.678***	5.020***
	(0.000)	(0.725)	(0.000)	(0.000)	(0.002)
ln(GDP)^2	-0.120***	-0.042	-0.114***	-0.167***	-0.252***
	(0.000)	(0.671)	(0.000)	(0.002)	(0.004)
Democratic	0.101*	-0.271	0.258***	0.133*	0.093
	(0.052)	(0.213)	(0.000)	(0.088)	(0.436)
Labor Abundance	-0.008	0.312	-0.217	-0.225	0.074
	(0.864)	(0.341)	(0.230)	(0.447)	(0.807)
Capital Abundance	-0.062	0.310	0.005	0.134	-0.234
	(0.561)	(0.518)	(0.954)	(0.155)	(0.273)
Land Abundance	0.038*	-0.146	0.210	0.258**	0.044
	(0.095)	(0.304)	(0.399)	(0.043)	(0.880)
Precipitation	0.006***	0.007	-0.001	-0.002	0.001
	(0.002)	(0.151)	(0.349)	(0.104)	(0.426)
Precipitation^2	-0.000***	-0.000	0.000	0.000**	-0.000
	(0.002)	(0.205)	(0.201)	(0.014)	(0.543)
Temperature	-0.015	-0.024	-0.027*	-0.034**	-0.013
	(0.232)	(0.654)	(0.062)	(0.011)	(0.323)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	1790	841	1397	1326	826

p-values in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

5 Conclusion

We estimate how anticipated changes in policy distortions affect agricultural supply. These changes in distortions represent persistent shocks to agricultural prices and thus we capture a different type of supply response than is traditionally estimated in the supply response literature that exploits transitory price shocks. Our econometric model includes country and year fixed effects along with other controls to reduce concerns about omitted variable bias.

We find some support for the Schultz (1978, 1980) argument that anti-agricultural policies reduce productivity and pro-agricultural policies lead to overproduction. We find that increases in the NAC for countries with an anti-agricultural bias results in an increase in TFP. However, this appears to occur through reductions in inputs rather than an increase in output which is counter to what we expect. For countries with a pro-agricultural bias, we find increases in NAC results in a significant increase in production. We find the strongest impact in milk and egg production, which had substantial changes in distortions since 1960.

Our results are still preliminary. Future work will attempt to disentangle the impact of output distortions from input distortions. We will also further investigate if there is any remaining endogeneity issues and identify strategies to alleviate those endogeneity concerns.

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