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Importing Inputs for Climate Change Mitigation: The Case of Agricultural Productivity

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Importing Inputs for Climate Change Mitigation: The Case of Agricultural Productivity

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Abstract

This paper estimates agricutural total factor productivity (TFP) in 162 countries between 1991 and 2015 and aims to understand sources of cross-country variations in agricultural TFP levels and its growth rates. Two factors affecting agricultural TFP are analyzed in detail – imported intermediate inputs and climate. We first show that these two factors are independetly important in explaining agricultural TFP – imported inputs raise agricultural TFP; and higher temperatures and rainfall shortages impede TFP growth, particularly in low-income countries (LICs). We also provide a new evidence that, within LICs, those with a higher import component of intermediate inputs seem to be more shielded from the negative impacts of weather shocks.

JEL Classification Numbers: 013, 047, 054, 056.
Keywords: Agricultural Productivity, TFP, Imported Inputs, Weather Shocks, Climate Change Mitigation, LICs.

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Contents

I. Introduction

Agricultural productivity, as measured by total factor productivity (TFP), remains far below in low-income countries (LICs) compared to the levels registered in more advanced economies. Productivity in the agricultural sector is significantly lower than in the non-agricultural sector, and this difference is greater in LICs than in developed economies (Adamopoulos and Restuccia, 2018). It is thus not surprising that accelerations in agricultural TFP growth have often preceded episodes of aggregate economic growth (McArthur and McCord, 2017).

The goal of this paper is to understand the sources of cross-country variations in agricultural TFP and its growth rates by focusing on two key factors – imported intermediate inputs and weather shocks. These two variables are critical in explaining agricultural productivity. Trade in intermediate inputs covers 64 percent of world trade in 2014 according to the World Input-Output Table (Timmer et al., 2015 and Timmer et al., 2016) and a number of studies document economic benefits from expanding global value chains.[2] Guided by these, we aim to understand its implications in agricultural sectors. Moreover, climate change-related weather variations are an important ongoing issue (e.g., IMF, 2017) and agricultural productivity may suffer increasingly from a climate change-related deterioration in weather conditions. Therefore, it is important to understand their effects on agricultural productivity.

Using data from 162 countries during the period 1991-2015, we show that the two factors are independently important for countries' agricultural sectors. Imported intermediate inputs boost productivity because they tend to be higher quality while being less expensive than domestic equivalents. Furthermore, we show that weather shocks play a role because higher temperatures and rainfall shortages reduce agricultural TFP in LICs.

These findings are new to the literature because we focus on their effects on agricultural TFP and none of the previous studies has investigated the impacts of these variables on agricultural TFP using a panel dataset with a large cross-section of countries. However, our results may not be surprising because previous work finds comparable estimates in different contexts.

One of the most interesting results comes from interactions between the two key factors we focus. Within LICs where we find significant effects of weather shocks, stronger weather effects come from countries employing less imported inputs. Higher temperatures and rainfall shortages do not seem to have significant effects on countries employing greater imported inputs. These results imply that using imported intermediate inputs reduces negative effects of weather shocks.

There are three main reasons to believe imported inputs have such effects. First, imported inputs tend to be higher quality and embed better technologies. As a result, these work to reduce producers' sensitively to weather shocks. Second, a greater share of imported inputs to total

[2] For example, expanding global value chains induce countries in specializing in tasks in which they have comparative advantage (e.g., Timmer et al., 2014), leading to gains from specialization. Furthermore, new imported inputs raise firm productivity (e.g., Amiti and Konings, 2007) and help create new domestic varieties (e.g., Goldberg et al., 2010).

intermediate inputs makes the overall quality of inputs less sensitive to local weather shocks, because local climate has no effects on the quality of imported inputs.[3] Third, local final good producers are intermediate good suppliers because there are sectoral linkages. Local final good producers' productivity gains through imported inputs have positive effects on domestic intermediate goods. This contributes to make domestic input quality less climate sensitive, which in turn leads to more climate-robust agricultural sectors.

This paper contributes to two different strands of literature. First, it is related with the literature on productivity gains from imported intermediate inputs. It finds that imported inputs increase firms' productivity in manufacturing industries because those inputs tend to be higher quality and less expensive (e.g., Amiti and Konings, 2007; Topalova and Khandelwal, 2011).[4] To the best of our knowledge, all prior studies focuse on manufacturing industries, with a few exceptions, such as Chevassus-Lozza et al. (2013) focusing on the French food agriculture industry, and Olper et al. (2017) analyzing the data from the French and Italian food processing industry.[5] The current paper is the first to shed light on agricultural industry in general in the context of gains from imported inputs.[6]

Second, this paper contributes to the literature on the impacts of weather shocks on agricultural sectors. The previous work on this issue focuses on certain areas of the world (e.g., Deschenes and Greenstone, 2007, for the U.S., Aschenfelter and Storchmann, 2006, for Germany, and Wang et al., 2009, for China) and they are silent about cross-country differences in the effect of weather shocks. In contrast, by employing a large panel dataset we find that countries' income levels play a role in explaining countries' sensitivities to weather shocks. In particular, we find that only LICs are negatively impacted by higher temperatures and rainfall shortages. In this regard, this paper is attuned to recent studies finding significant effects of weather shocks in lower income countries (e.g., Dell et al., 2012, for GDP growth rate; and Cattaneo and Peri, 2016, for emigration from countries).

Our contribution is three-fold. First, our results imply that an increase in imported intermediate inputs, instrumented by tariff cuts and inward FDI, has a positive effect on agricultural TFP. A one percentage point increase in the share of imported inputs to total value of intermediate goods raises TFP by 3-4 percent. This result is robust to wide range of specifications and samples. This

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[3] For example, Caselli et al. (2015) show that diversified sources of imports and export destinations reduce a country's income volatility.

[4] Amiti and Konings (2007) analyze the firm-level data from Indonesia. Topalova and Khandelwal (2011) work with the data from India. See also Halpern et al. (2015) for evidence from Hungary and Kasahara and Rodrigue (2008) for evidence from Chile.

[5] The former study, Chevassus-Lozza et al. (2013), uses data from the French agricultural goods industry and finds that input tariff cuts led to the exit of the least productive firms and increased export sales of more productive firms. Olper et al. (2017) shows that a reduction of input tariffs increased French and Italian food processing firms' productivity.

[6] While the prior empirical studies employ firm-level microdata for a given country, this paper uses country-level macro data. We use a macro panel dataset instead of micro data because it is difficult to obtain micro data from the agricultural sector, particularly in lower income countries. In these countries, agricultural industries tend to rely on family-owned farms or individual workers instead of firms.

study is the first to show the positive effect of imported inputs on agricultural TFP using a large panel dataset.

Second, by exploiting plausibly exogenous year-to-year fluctuations in temperatures and rainfalls, we find that for LICs, higher temperatures have a negative impact on TFP and greater rainfalls have a positive one. This is consistent with prior articles arguing that agricultural production in developing countries are more sensitively affected by weather shocks because these countries tend to have lower capital-to-labor ratios and their technologies are more climate sensitive (Mendelsohn et al., 2001, 2006). We are the first to show this using a panel dataset on agricultural TFP, which makes it possible to overcome bias coming from time-invariant omitted variables as in recent studies such as Dell et al. (2012) and Cattaneo and Peri (2016).

Third, we go beyond the existing literature by finding interactions between imported inputs and climate effects in explaining agricultural TFP. While previous studies have found that income-levels explain countries' sensitivity to climate, we are the first to document that prevalence of imported inputs reduces countries' vulnerability to weather shocks.

The rest of the paper is organized as follows. The next section conducts a growth accounting exercise and estimates agricultural TFP. Section III presents summary of data and discusses our motivations. Section VI empirical assesses the effect of imported inputs and weather shocks on agricultural TFP. It also considers interactions between these two variables in explaining the impact of weather shocks. Section V conducts counterfactual exercises to understand economic magnitudes of the estimated impacts. Section VI concludes.

II. AGRICULTURAL TFP

A. The Method Estimating Agricultural TFP

We start from estimating agricultural TFP. Agricultural value-added is decomposed into TFP and of three inputs: capital stock, labor force, and land area in the agricultural industry. We first discuss the methodology, followed by a description of data sources, and then results are presented.

As in Herrendorf et al. (2015) and many others,[7] country *i*'s agricultural production function in year *t* is described by a Cobb-Douglas production function subject to constant returns to scale (CRS):[8]

$$Y_{it} = A_{it}(K_{it})^{\alpha_{it}^K}(L_{it})^{\alpha_{it}^L}(T_{it})^{\alpha_{it}^T} \text{ with } \alpha_{it}^K + \alpha_{it}^L + \alpha_{it}^T = 1, \tag{1}$$

[7] Herrendorf et al. (2015) examine structural transformation in the postwar United States by estimating Cobb-Douglas production functions for the agriculture industry. Other studies assuming a Cobb-Douglas production includes Macours and Swinnen (2000), Gollin and Rogerson (2014), and Craig et al. (1997).

[8] Previous articles employ various factors as inputs in addition to capital stock, employment, and land area. For example, Coelli and Rao (2005) include fertilizers and livestock as inputs in the agricultural production function. However, we do not include these as inputs because the data on fertilizers and livestock are not available for many countries, and we would need to drop many countries from the sample if we were to include these. In Section IV, we include fertilizers as a determinant of TFP following Craig et al. (1997).

where Y_{it}, A_{it}, K_{it}, L_{it} and T_{it} are value-added, TFP, capital stock, employment, and land area in the agricultural industry, respectively. α_{it}^K, α_{it}^L and α_{it}^T are the income shares of capital stock, labor, and land, respectively. Note that these income shares have country and year subscripts, meaning that these are different across countries and across time.

Data on agricultural value-added, agricultural capital stock, and agricultural land area are taken from FAO (2018) and data on agricultural employment come from the World Bank (2018a). We take the income share and the labor share data from the EORA database (Lenzen et al., 2012, 2013). It provides the data on payments to capital (consumption of fixed capital), payments to labor (compensation of labor), and value-added.[9] We compute the capital share as $\alpha_{it}^K = \frac{payments\ to\ capital_{it}}{value\text{-}added_{it}}$ and the labor share as $\alpha_{it}^L = \frac{payments\ to\ labor_{it}}{value\text{-}added_{it}}$. By the CRS assumption, the land share is $\alpha_{it}^T = 1 - \alpha_{it}^K - \alpha_{it}^L$.

TFP is then obtained as a residual: $A_{i,t} = Y_{i,t}/[(K_{it})^{\alpha_{it}^K}(L_{it})^{\alpha_{it}^L}(T_{it})^{\alpha_{it}^T}]$.[10] Annualized long-run growth rates of value added of country i from 1991 to 2015, $g_{i,1991-2015}^{VA} = 100 \times [\ln(VA_{i,2015}) - \ln(VA_{i,1991})]/24$, are decomposed into four components:

$$\text{TFP: } g_{i,1991-2015}^{TFP} = 100 \times [\ln(A_{i,2015}) - \ln(A_{i,1991})]/24,$$
$$\text{Capital stock: } g_{i,1991-2015}^{K} = 100 \times \alpha_{it}^K[\ln(K_{i,2015}) - \ln(K_{i,1991})]/24,$$
$$\text{Employment: } g_{i,1991-2015}^{L} = 100 \times \alpha_{it}^L[\ln(L_{i,2015}) - \ln(L_{i,1991})]/24,$$
$$\text{Land area: } g_{i,1991-2015}^{T} = 100 \times \alpha_{it}^T[\ln(T_{i,2015}) - \ln(T_{i,1991})]/24.$$

This decomposition exercise is conducted for each of the countries available.

Our sample includes 162 countries in the world. However, not all countries have complete data from 1991 to 2015. The growth accounting exercise focuses on countries where complete data from 1991 to 2015 are available. As a result, the sample size is restricted to 135 countries – 25 LICs, 35 lower-middle-income countries, 34 upper-middle-income countries, and 41 high-income countries.

We also provide alternative TFP estimate based on factor shares obtained by estimating a log-linearized Cobb-Douglas production function, which we call TFP$_b$. The productivity measure TFP$_b$ is based on a strong assumption that all countries have the same factor shares. However, this measure of TFP covers a slightly greater number of countries – 27 LICs, 37 lower-middle income countries, 38 upper-middle income countries, 42 high-income countries, totaling 144 countries. TFP$_b$ estimates are used for robustness checks of regression analyses.[11]

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[9] Consumption of fixed capital includes all tangible and intangible assets owned by producers and excludes non-produced assets such as land, mineral, coal, oil, or natural gas. Therefore, we employ this measure to find the capital share.

[10] See Appendix B for more details on data. See Appendix D.1 for calculated factor shares.

[11] See Appendix D.2 for more details on the productivity measure TFP$_b$.

B. Results from Growth Accounting

Table 1 presents results from the growth accounting exercise for four groups of countries. It shows simple averages of the growth rates of agricultural value-added and those of four decomposed components. TFP grew the most in lower-middle income countries – the annual average growth rate is 2.3 percent over the period 1991-2015. Upper-middle income countries (2.16%), high-income countries (1.93%), and LICs (1.87%) follow.

Agricultural value-added growth rate in LICs, 3.32 percent, is higher than that from richer countries. However, relatively higher input growth rate led to a small contribution of TFP. High-income countries have a lower value-added growth rate than other groups of countries, 1.08 percent. However, the TFP growth rate is estimated to be fairly high due to the fact that there is a decrease in inputs such as labor (-1.22%) and land (-0.02%).

Table *1*: Growth Accounting Results, Countries Grouped by Income Level, 1991-2015

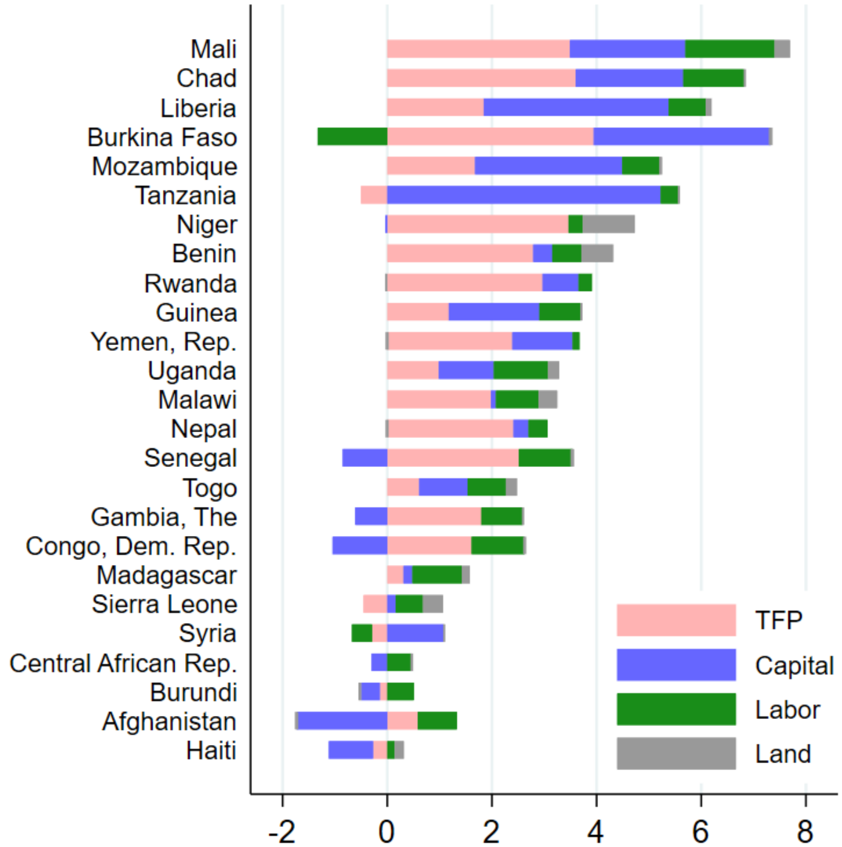
	Value-added	Decomposition			
		TFP	Capital stock	Labor	Land
Low-income countries	3.32	1.87	0.86	0.69	0.30
Lower-middle income countries	3.42	2.29	1.43	-0.03	0.26
Upper-middle income countries	3.01	2.16	1.49	-1.27	0.42
High-income countries	1.08	1.93	0.39	-1.22	-0.02

Notes: The table shows the decomposition of the annual average growth in agricultural value-added over 24 years, from 1991 to 2015. The growth accounting exercise is conducted at the country-level first and then the simple average of each country's growth rates are found. Countries' income levels are based on the World Bank's classification. See the main text for data sources.

Figure 1 summarizes results from each of LICs over the 24-year period 1991-2015.[12] Out of the 27 countries, Mali, Chad, and Liberia have the highest value-added growth rates: annual average growth rates of 7.7 percent, 6.8 percent, and 6.2 percent, respectively. TFP contributes the most in Mali and Chad: 3.5 percent and 3.6 percent, respectively. On the other hand, the growth in the capital stock explains the largest part of the agricultural value-added growth in Liberia, 3.5 percent. Among the LICs, Central African Republic, Burundi, and Haiti have the smallest value-added growth rate over the period: 0 percent, -0.14 percent, and -0.27 percent, respectively. All of these three countries have non-positive TFP growth rates and negative capital stock growth rates.

[12] We follow the World Bank's classification for income-level of countries. See Appendix C for results from individual countries from other groups of countries.

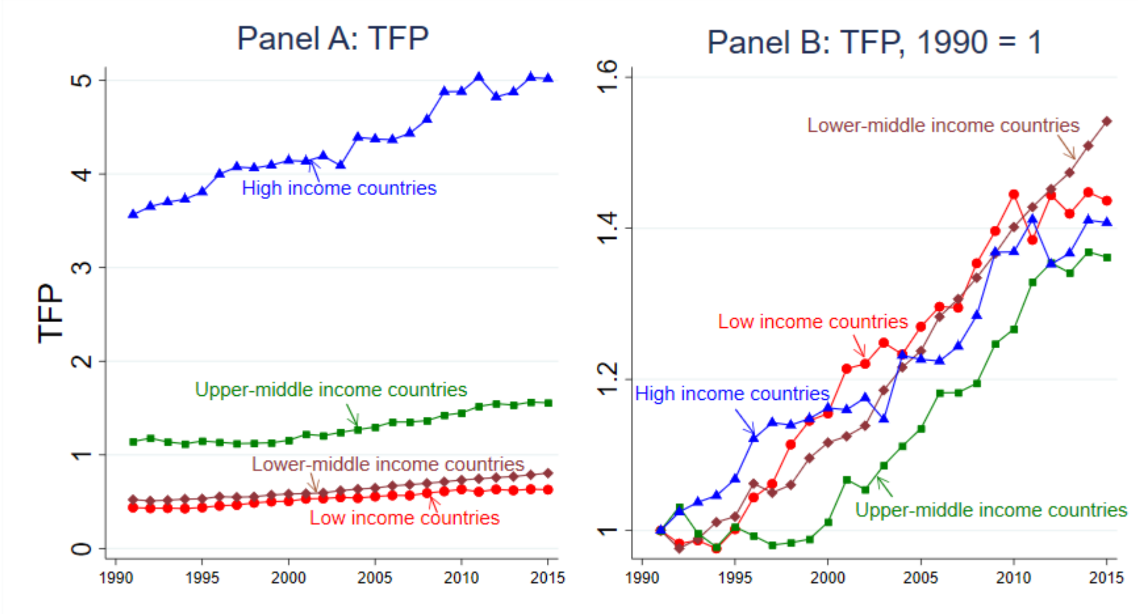
Figure *1*: Growth Accounting Results, LICs, 1991-2015



Notes: The figure shows annualized average growth rates of each component over 24 years, 1991-2015. See the main text for data sources. See Appendix C for a table for showing the growth rates of value-added and each component.

We are also interested in agricultural productivity *levels* and their gaps across countries. Figure 2 shows the average agricultural TFP for the four groups of countries. Panel A presents average TFP levels and shows that TFP levels have been increasing in all groups of countries over the period 1991-2015. Panel B displays the TFP levels normalized so as to make the TFP levels from 1991 to be one. It shows that among these four groups of countries, TFP levels increased almost at the same rate for all of the four groups of counties. We seek to disentangle the sources of this productivity gap.

Figure *2*: Agricultural TFP Levels by Income-Level of Countries, 1991-2015



Notes: The figure shows the simple average of agricultural TFP levels for the four groups of countries. Countries' income levels are based on the World Bank's classification. See the main text for the data sources.

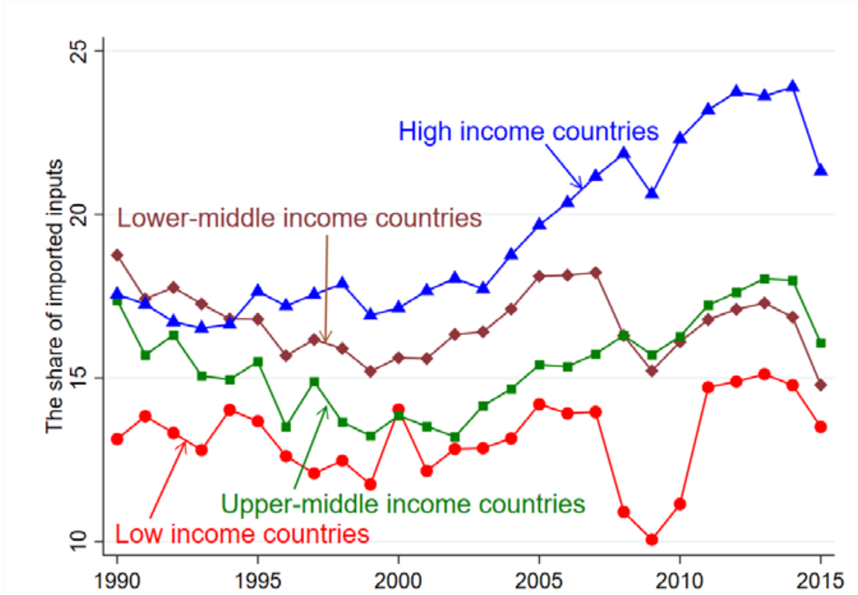
III. Stylized Facts on Imported Inputs, and Weather Shocks

We focus on two variables, imported inputs and weather shocks, to explain cross-country variations in agricultural TFP. This section presents empirical observations on these variables by showing their time-series variations by country income group.

Figure 3 shows the share of imported inputs to total purchase of intermediate goods in the agricultural sector. It indicates that high-income countries consistently have a higher share of imported inputs among the four groups of countries after 1995, and LICs always have the lowest share except for the year 2000. In terms of time-series variation, there is a slight declining trend of the share of imported inputs in the 1990s and it is increasing since early 2000s. There are sharp declines in the share of imported inputs during 2008-2010 due to the 2008-09 global financial crisis.

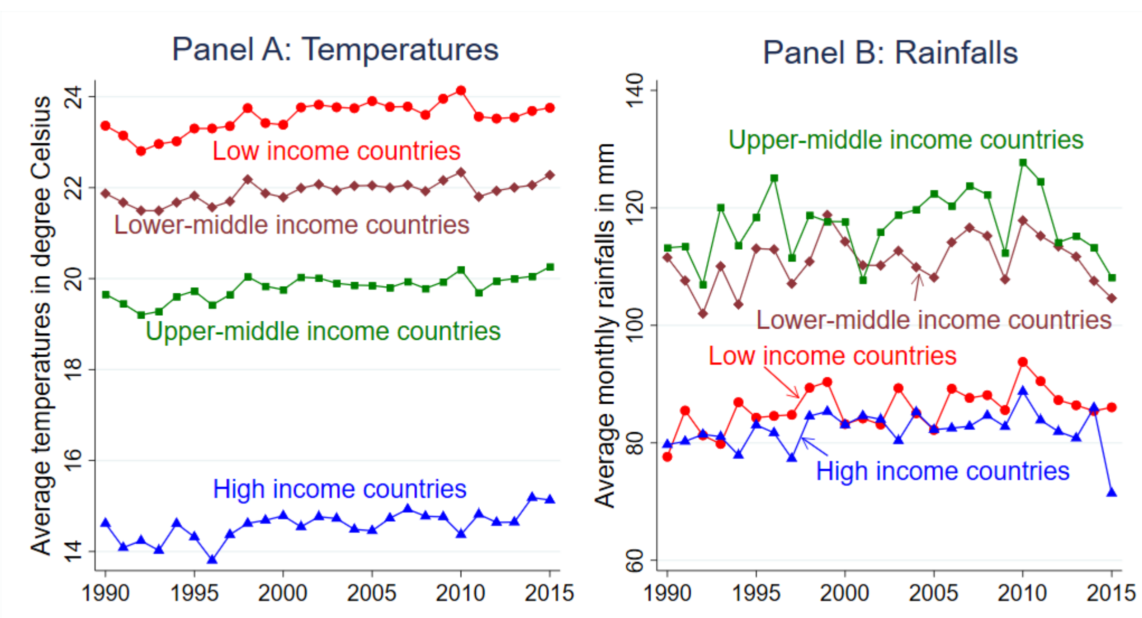
We display average temperatures and rainfalls across the four groups of countries in Figure 4. Panel A shows that lower income countries tend to have higher average temperatures. Average temperatures are rising over the period 1991-2015. Panel B indicates that middle-income countries have greater rainfalls on average. LICs and high-income countries have similar levels of rainfalls.

Figure *3*: The Share of Imported Inputs by Income-Level of Countries, 1990-2015



Notes: The figure shows simple averages of the share of imported inputs to total inputs for the four groups of countries. The authors' calculation based on the data from the EORA (Lenzen et al., 2012, 2013).

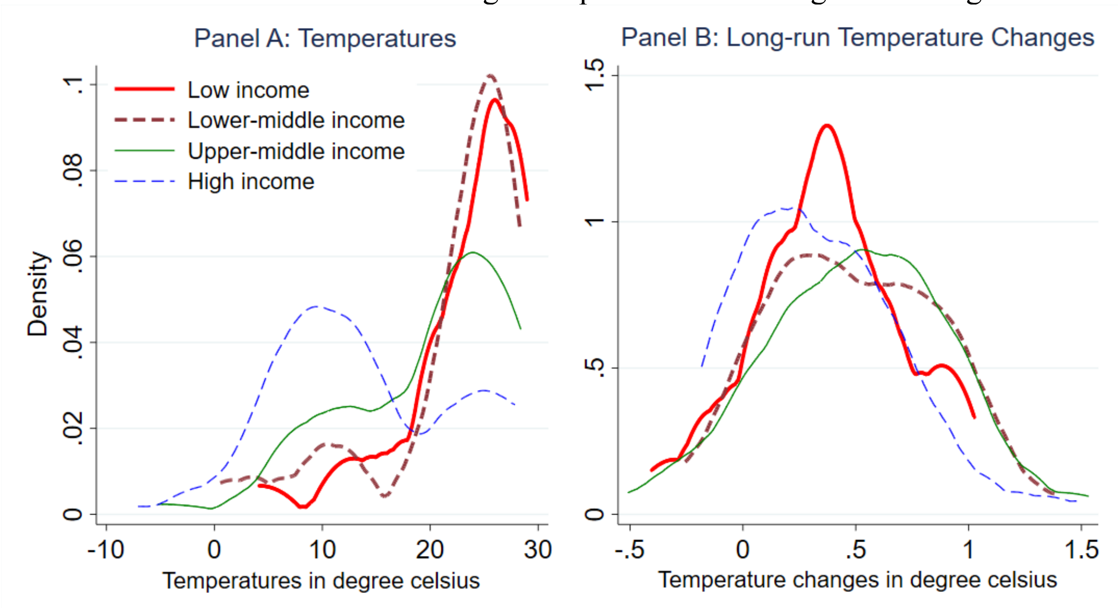
Figure *4*: Temperatures and Rainfalls by Income-Level of Countries, 1990-2015



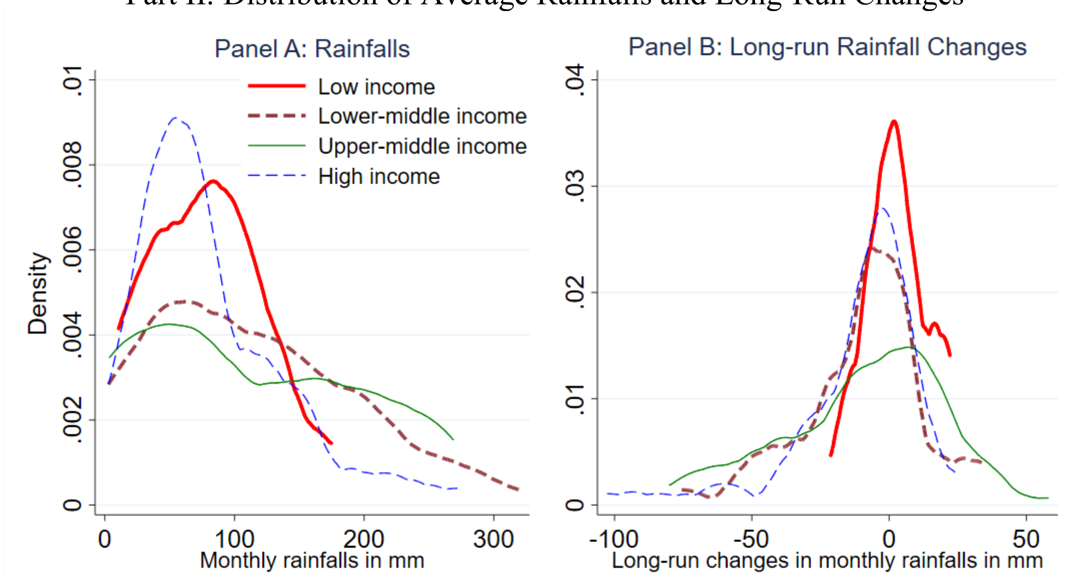
Notes: The figure shows the simple average of yearly average temperatures in degree Celsius and average monthly rainfalls in millimeters (mm) for the four groups of countries. The authors' calculation based on the data from World Bank (2018b).

Figure 5: Average Temperatures and Rainfalls in 2015 and their Long-Run Changes since 1990

Part I: Distribution of Average Temperatures and Long-Run Changes



Part II: Distribution of Average Rainfalls and Long-Run Changes



Notes: The authors' calculation based on the data from World Bank (2018b). The figures show kernel density estimates of average temperatures in degree Celsius and average monthly rainfalls in millimeters in Panel A of Part I and Part II, respectively. Long-run changes in temperatures and rainfalls between 1990 and 2015 are shown in Panel B of Part I and Part II, respectively. Countries' income levels are based on the World Bank's classification.

Figure 5 shows kernel density estimates of average of temperatures and rainfalls using the data from 2015. Panel A of Part I indicates that average temperatures are right-skewered in LICs and middle-income countries. The modes of the distributions are above 25 degrees Celsius. On the other hand, average temperatures for high-income countries is almost normally distributed and the mode is about 10 degrees Celsius. Panel B of Part I shows the long-run changes in average temperatures between 1990 and 2015. Strikingly, most countries experienced a rise in temperatures. The modes are above zero for all groups of countries. Panel A of Part II presents kernel density estimates of average monthly rainfalls and their long-run changes during 1990-2015 are presented in Panel B. Long-run changes in rainfalls are almost symmetrically distributed with mean zero.

IV. Regression Analysis

A. Imported Inputs and Agricultural TFP Level

This section examines the role of imported inputs in determining agricultural TFP. By closely following prior studies investigating determinants of TFP, we estimate the following regression model:[13] [14]

$$\ln\left(TFP_{i,t}\right) = \beta_i + \beta_1 ImInputs_{i,t} + \mathbb{X}_{i,t}\boldsymbol{\beta}_2 + e_{i,t}, \quad (2)$$

where $\ln\left(TFP_{i,t}\right)$ denotes natural log of TFP in country *i* in year *t*; β_i indicates country fixed effects; $ImInputs_{i,t} = 100 \times Imported\ Inputs_{i,t}/Total\ Inputs_{i,t}$ is the value of imported intermediate inputs divided by the value of total intermediate inputs times 100; $\mathbb{X}_{i,t}$ is a vector of control variables including the consumption of fertilizers and pesticides, the capital-to-labor ratio, the production taxes-to-value added ratio, the production subsidies-to-value added ratio, the political instability index, the expenditure share on research and development, and temperatures and rainfalls[15]; $e_{i,t}$ is an error term; β_1 and $\boldsymbol{\beta}_2$ are a scalar parameter and a vector of parameters to be estimated, respectively.

OLS estimates would lead to a bias because there is reverse causality from the level of TFP to countries' decisions to import. For example, productive countries may be more likely to import inputs from abroad because they have a greater incentive to remain competitive and increase

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[13] Previous studies estimating the impact of imported inputs on firm productivity employs either natural log of TFP (Olper et al el., 2017; Amiti and Konings, 2007) or TFP index (Topalova and Khandelwal, 2011) or natural log of firm sales (Halpern et al., 2015). All of these studies use firm-level data. Previous studies investigating determinants of TFP using country-level macro data include Craig et al. (1997) and Alene (2010). Craig et al. (1997) employ natural log of labor productivity as the dependent variable. Alene (2010) uses natural log of TFP as the dependent variable. See Appendix E for more details regarding the empirical specification.

[14] To address the potential existence of a trend in the growth rate of TFP, a Hariss-Tzavalis unit-root test for ln(TFP) was run for a strongly balanced panel dataset of 135 countries over 24 years (1991-2015). The test statistic obtained is 0.8429 with *p*-value of 0.000. Therefore, the null hypothesis that the panel variable contain unit roots is rejected at the 1 percent level. Furthermore, since we include country fixed effects, all variables are transformed to demeaned variables. As a result, we estimate the effect of changes in the share of imported inputs on changes in ln(TFP), which are percentage deviations from their country means.

[15] The unit of the variable for fertilizers and pesticides are tons per hectare. We normalize each of these variables, by calculating deviation from its mean and by divided by its standard deviation. Then the sum of these two variables are defined as the variable "Fertilizers and pesticides". The political instability index takes a discrete value between one and seven. A greater value implies that the observation is more politically unstable. It represents political factors relating with civil liberty. See Freedom House (2018) for more details. See Appendix B for summary statistics.

their global market share. Alternatively, less productive countries may be less likely to import because they often have a set of stringent industrial policy design setups biased towards domestically produced inputs. If the former story were true, β_1 would have an upward bias; on the other hand, β_1 would have a downward bias if the latter story were true.

In order to overcome this potential endogeneity, we employ tariffs applied by importing countries and inward FDI (as a share of agricultural value-added) as instruments. These variables are valid instruments because they satisfy the relevancy condition and the exclusion restriction. First, a decline in tariffs increases imported inputs but it does not affect agricultural TFP other than through changes in the value of imported inputs. Second, an increase in inward FDI to the agricultural sector increases imported inputs because these foreign-owned agricultural entities are more likely to use imports from abroad. An increase in inward FDI may increase agricultural TFP directly if there are some spillovers from foreign-owned entities. However, econometric tests suggest that our instruments satisfy the exclusion restriction.

The data come from various sources. Section II laid out the underlying sources of data used to calculate TFP. The data on imported inputs come from the EORA Input-Output tables (Lenzen et al. 2012; Lenzen et al., 2013). The share of imported intermediate goods to the total intermediate good used is computed for the agricultural sector for all EORA 189 countries and then the data on imported inputs are matched with our agricultural productivity dataset. The data on fertilizer consumption per area and R&D expenditures comes from the WDI. Pesticide consumptions per area are from FAO. We obtain the political instability index from the Freedon House. The data on the capital-to-labor ratio, production taxes, and production subsidies are from the EORA. Temperature and rainfall are taken from the World Bank Climate Change Knowledge Portal (World Bank, 2018b). See Appendix B for more details.

Table 2 reports regression results. The first two columns employ OLS – column (1) regresses log of TFP on imported inputs only and column (2) introduces other control variables. The results show that the imported inputs-to-total inputs ratio does not have a significant effect on TFP levels. These insignificant coefficients are presumably because there are endogeneity issues, leading to bias in both ways – negative and positive. As a result, we obtain zero point estimates.[16]

The last four columns in Table 2 show results from 2SLS. Column (3) employs the imported inputs-to-total inputs ratio as the only explanatory variables and shows that a one percentage point increase in the share of imported inputs raises TFP by 8.9 percent. Columns (4)-(6) introduce additional control variables. Column (4) includes the same set of regressors as for column (2). All of the additionally introduced variables have expected signs.[17] After controlling for these, the point estimate for the effect of imported inputs becomes 4.4. Column (4) is our preferred specification because the first-stage *F*-statistic is great enough and the Sargan test suggests that the exclusion restriction is satisfied.

[16] Indeed, results from the Hausman tests reported in IV columns, (3)-(6), show that the null hypothesis that there is no endogeneity is rejected at the 1 percent level.

[17] We expect positive signs from fertilizers and pesticides, the capital-labor ratio, and subsidies because these work to increase agricultural production, therefore TFP. On the other hand, we expect negative signs from taxes and the political instability index because these variables are anticipated to reduce agricultural production and TFP.

Table *2*: Determinants of TFP, Baseline Results
Dependent Variable = 100×ln(TFP)

	OLS		2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
Imported inputs/Total inputs×100	0.101	-0.048	8.863***	4.399***	4.023**	3.995***
	(0.246)	(0.371)	(1.093)	(1.290)	(1.677)	(1.114)
<u>*Controls*</u>						
Fertilizer & pesticides		0.465*		4.122***	4.590***	3.924***
		(0.274)		(1.304)	(1.344)	(1.281)
Capital-labor ratio		-0.020		0.344***	0.426***	0.368***
		(0.165)		(0.096)	(0.124)	(0.089)
Taxes		-0.420***		-1.606	-1.433	-1.717
		(0.038)		(1.241)	(1.182)	(1.209)
Subsidies		0.003***		0.475	0.421	0.600
		(0.000)		(0.593)	(0.581)	(0.581)
Political instability index		1.445		-7.596***	-4.011	-5.734**
		(2.821)		(2.520)	(2.495)	(2.569)
Research & development					2.237	
					(6.725)	
Temperatures						-1.752
						(1.738)
Rainfalls						0.023
						(0.051)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,914	1,511	2,654	455	371	424
Countries	162	111	161	61	54	56
Cragg-Donald Wald *F*- statistic			44.65	12.90	8.43	15.73
Sargan statistic			1.285	0.045	0.021	0.025
p -value of Sargan statistic			0.257	0.831	0.885	0.874
Hausman statistic			123.74	16.03	8.20	15.83
p -value of Hausman statistic			0.000	0.000	0.004	0.000

Notes: All regressions include country fixed effects. Standard errors are in parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% level, respectively. Instruments include weighted average tariffs on all products and the share of inward FDI to the agricultural sector to the agricultural value-added. See the main text for data sources.

Table 3: Determinants of TFP, Robustness Checks
Dependent Variable = 100×ln(TFP) or 100×ln(Value-Added), or 100×ln(TFP_b)

	Baseline specification & baseline sample		Excluding high income countries	Excluding oil producers	Excluding the period of commodity price hikes	Adding the effective exchange rate as an instrument
Dependent variable	Value-added	TFP_b	TFP			
	(1)	(2)	(3)	(4)	(5)	(6)
Imported inputs/Total inputs×100	5.408***	3.871***	4.178***	4.258***	4.006***	4.116**
	(1.334)	(1.115)	(1.447)	(1.330)	(1.526)	(1.627)
Controls						
Fertilizer & pesticides	4.587***	3.211***	3.652**	3.653***	5.625***	4.396**
	(1.348)	(1.127)	(1.693)	(1.352)	(2.125)	(2.070)
Capital-labor ratio	-0.012	-0.026	-1.819***	0.292***	0.534***	0.266**
	(0.099)	(0.083)	(0.693)	(0.096)	(0.154)	(0.105)
Taxes	-1.824	-1.204	-1.189	-1.565	-8.877	-14.75*
	(1.283)	(1.073)	(1.325)	(1.267)	(8.146)	(8.195)
Subsidies	0.388	-0.244	-1.064	0.777	0.198	2.18
	(0.613)	(0.513)	(1.576)	(0.659)	(0.738)	(1.335)
Political instability index	-6.801***	-4.538**	-7.026*	-9.151***	-6.284*	-8.046**
	(2.605)	(2.178)	(3.874)	(2.886)	(3.474)	(3.733)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	455	455	236	385	246	181
Countries	61	61	35	52	55	50
Cragg-Donald Wald *F*- statistic	7.45	11.40	7.78	5.95	12.90	12.90
Sargan statistic	0.073	0.009	0.008	3.997	0.142	0.007
p -value of Sargan statistic	0.787	0.924	0.930	0.136	0.707	0.936
Hausman statistic	17.65	15.07	9.72	6.19	29.19	14.82
p -value of Hausman statistic	0.000	0.000	0.002	0.013	0.000	0.000

Notes: The first two columns use the baseline specification presented in column (4) of Table 2. The definition of high-income countries follows the World Bank. Oil producers are countries where their oil rents as a share of GDP is greater than the 90th percentile of the sample in 1990 (16 percent). The period of commodity price hikes are defined as years when the food price index in December of that year is greater than 12 percent of the price index in December in the previous year. The excluded years as the period of commodity price hikes are 1991, 1994, 2002, 2005, 2006, 2009, and 2010. Instruments include weighted average tariffs on all products and the share of inward FDI to the agricultural sector to the agricultural value-added. In addition to these instruments, the real effective exchange rate is added as an instrument in column (6). All regressions include country fixed effects. Standard errors are in parentheses. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% level, respectively. See the main text for data sources.

Column (5) adds the expenditure on R&D. This is potentially an important variable in explaining agricultural TFP. However, this variable includes many missing observations, which reduces our sample size from 455 to 371. Moreover, the first-stage *F*-statistic becomes smaller. Column (6) introduces climate variables – the level of average temperature in degree Celsius and the level of average monthly rainfall – in order to control for climatic conditions. Temperature and rainfall are expected to have negative and positive signs, respectively, as document in the previous literature (e.g., Barrios et al., 2010; Dell et al., 2012). The result shows that we have expected signs but these are not statistically significant.[18] Overall, the results suggest that a one percentage point increase in the share of imported inputs raises agricultural TFP by about 4 percent.

Table 3 conducts several robustness checks to show that our baseline results are robust. Columns (1) and (2) employ natural log of agricultural value-added and natural log of TFP_b as the dependent variables, respectively, using our baseline specification, column (4) of Table 2.[19] We use these dependent variables in order to show that our baseline results do not come from particular assumptions we make to estimate TFP. Indeed, results remain qualitatively the same. A one percentage point increase in the share of imported inputs raises value-added by 5.4 percent and TFP_b by 3.9 percent.

Column (3) excludes observations from high-income countries because one may argue that these countries are different from other lower income countries in terms of the way they produce agricultural goods. However, excluding these countries does not change our results much. Column (4) drops oil producers.[20] However, again, the results are similar to those reported in Table 2. We drop periods of commodity price increases in column (5) because an exceptional increase in commodity prices may increase the value of agricultural output and therefore value-added and TFP. However, the result in column (5) is similar to those in other columns.

Lastly, one may claim that the real effective exchange rate can also be used as instruments because changes in real exchange rates alter the relative prices of imported inputs to domestic inputs, affecting countries' decitions to import intermediate inputs. Therefore, column (6) adds the real effective exchange rate as an additional instrument. However, results do not change qualitatively.

We compare our results with previous empirical findings. Halpern et al. (2015), Topalova and Khaldelwal (2011), and Amiti and Konings (2007) find that a 10 percent decrease in input tariffs raises TFP by 1.2-1.5 percent, 4.8 percent, and 12 percent, respectively. [21] In order to compare

[18] One reason why we have insignificant climate effects is that we do not allow different responses to weather shocks across countries, which will be addressed in the next section. These weather variables are added in the regression just to control for climatic conditions.

[19] As noted earlier, TFP_b denotes another TFP estimates based on equal values of the labor share, the capital share, and the land share across countries. See Appendix D.2 for details.

[20] Our measure of TFP is based on the data from the agricultural sector, which does not include mining and oils. Still, we concerned about the possibility that natural resource booms affect productivity of other industries, so-called a "Dutch disease" or a "Natural resource curse".

[21] Topalova and Khaldelwal (2011) show, using data from Indian manufacturing firms, that a 10-percentage point decrease in input tariffs increases TFP by 4.8 percent. Amiti and Konings (2007) show, using the data from Indonesian manufacturing firms, that a 10-percentage point decrease in input tariffs increase productivity by 12 percent. Halpern et al. (2015) show that, using the data from Hungarian manufacturing firms, a tariff cut from 40 percent to 30 percent increases productivity by 1.2 percent to 1.5 percent. Chevassus-Lozza et al. (2013) estimate the impact of lowering input tariffs on firms' decision to export using the firm-level data from the French agricultural

with these figures, we combine our first-stage and second-stage results. The first-stage regressions indicate that a 10 percentage point decline in tariffs increases the share of imported inputs to total inputs, $\frac{Imported\ inputs}{Total\ inputs}$, by 3 percentage points. The second-stage results show that a 1 percentage point increase in $\frac{Imported\ inputs}{Total\ inputs}$ raises TFP by 4 percent. Combining these implies that a 10 percentage point decrease in tariffs is associated with a 12 percent increase in the level of TFP. This number is almost the same as Amiti and Konings (2007)'s result.

B. Weather Shocks and Agricultural TFP Growth

The second key determinant of agricultural TFP is weather shocks, i.e., temperatures and rainfalls. Agricultural sectors are known to be more sensitively affected by weather shocks and climate change (Mendelsohn et al., 2001; and Mendelsohn et al., 2006). Moreover, previous studies find that countries' responses to weather shocks vary substantially depending upon income levels of countries (e.g., Dell et al., 2012; Cattaneo and Peri, 2016). Guided by these, this section seeks to understand if there are similar cross-country differences in the impacts of weather shocks on agricultural TFP.

We closely follow the literature to setup our regression model. Previous studies investigate the impact of weather shocks on the GDP growth rate by implicitely assuming that weather shocks affect the current level of GDP by changing its growth path from the previous year (Dell et al., 2012; Hsiang and Jina, 2014; Moore and Diaz, 2015; IMF, 2017).[22] We assume that a similar argument applies in the context of agricultyral TFP. Therefore, our baseline regression model is:[23]

$$\begin{aligned} g_{i,t}^{TFP} &= \gamma_0 + \gamma_1 d.Temp_{i,t} + \gamma_1^{Low}\left[d.Temp_{i,t}D_i^{Low}\right] + \gamma_1^{Middle}\left[d.Temp_{i,t}D_i^{Middle}\right] \\ &\quad + \gamma_2 d.Rain_{i,t} + \gamma_2^{Low}\left[d.Rain_{i,t}D_i^{Low}\right] + \gamma_2^{Middle}\left[d.Rain_{i,t}D_i^{Middle}\right] \\ &\quad + D_i^{Low}\theta_t + D_i^{Middle}\theta_t + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $g_{i,t}^{TFP} = 100 \times (TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$ denotes the annual growth rate of TFP of country *i* in year *t*; $d.Temp_{i,t} = Temp_{i,t} - Temp_{i,t-1}$ is the annual change in average temperatures in degree Celsius; $d.Rain_{i,t} = Rain_{i,t} - Rain_{i,t-1}$ is the annual change in average

food industry. They conduct a simulation analysis based on their regression results. They find that a 10 percent decrease in input tariffs applied to all sectors increases total export sales by 1.1 percent and employment by 0.1 percent. Olper et al. (2017) find that, using firm-level data from France and Italy, a 10 percent increase in the value of imported inputs raises TFP by 2.1 percent.

[22] Dell et al. (2014) provide a simple theoretical background. See Appendix E for more details.

[23] The model controls for country fixed effects because all variables are measured in changes (or percentage change) from previous years. Following Dell et al. (2012), two-way clustering standard errors by Cameron et al. (2011) are used to find robust standard errors where these are clustered in two ways, at the country-level and at the region-level.

monthly rainfalls in 100 mm[24]; D_i^{Low} and D_i^{Middle} are dummy variables taking unity if country i is a LIC and a middle-income country, respectively; θ_t and $\varepsilon_{i,t}$ denote year fixed effects and an error term, respectively; γ_0, γ_1^{Low}, γ_1^{Middle}, γ_2, γ_2^{Low}, and γ_2^{Middle} are coefficients to be estimated.

Climate variables, $d.Temp_{i,t}$ and $d.Rain_{i,t}$, are interacted with income-level dummies in order to capture heterogeneous responses to weather shocks across the three groups of countries – low-income countries, middle-income countries, and high-income countries. With these dummies and all observations from the world, coefficients γ_1 and γ_2 measure the impact of weather shocks on TFP in high-income countries. γ_1^{Low} and γ_1^{Middle} capture the difference in the impact of changes in temperatures, comparing with high-income countries, on TFP in LICs and middle-income countries, respectively. The overall impact of changes in temperatures on LICs, for example, is a linear combination of two coefficients: $\gamma_1 + \gamma_1^{Low}$.[25]

Table 4 summarizes results from estimating equation (2). Column (1) regresses TFP growth rate on *d.Temp* only, assuming that all countries respond to weather shocks in the same way. The estimated coefficient is negative, -0.6, as expected, but it is not statistically significant. This is because the model does not allow different responses to weather shocks across countries. As a result, positive responses and negative responses worked in difference directions, resulting in an insignificant coefficient.

Column (2) introduces interaction terms with income-level dummies. Linear combinations of coefficients reported in the bottom of the table show that a 1°C rise in temperatures reduces the TFP growth rate by 2.7 percent in LICs. Middle-income countries also have a negative coefficient, but the magnitude is small and statistically insignificant. These negative temperature effects in LICs are consistent with previous empirical results. For example, Dell et al. (2012) show that rising temperatures had reduced the GDP growth rate of LICs. Cattaneo and Peri (2016) find that an increase in temperatures increased emigration from middle-income countries, possibly because agriculture productivity declined due to higher temperatures, which led to a greater incentive to emigrate from the countries.

[24] One may concern about correlation between temperatures and rainfalls, leading to a multicollinearity. However, correlation between these two variables is quite low. Using a sample of all countries, we find that correlation coefficients between *d.Temp* and *d.Rainfall* are -0.0885 for the period 1990-2015. Even if we restrict our sample to LICs, the correlation coefficient is -0.0959 for the same period. See Appendix F for more details.

[25] Similarly, γ_2^{Low} and γ_2^{Middle} measure the difference in the impact of changes in rainfalls, comparing with high-income countries, on TFP in LICs and middle-income countries, respectively. In order to identify the different impacts of climate across countries, the model needs to introduce interaction terms between income-level dummies and year fixed effects: $D_i^{Low}\theta_t$ and $D_i^{Middle}\theta_t$.

Table *4*: The Impact of Weather Shocks, Baseline Results

Dependent Variable = 100 times Annual Agricultural TFP Growth Rate

	(1)	(2)	(3)	(4)	(5)
d.Temperature	-0.606	-0.215	-0.080	-0.290	-0.080
	(0.447)	(0.614)	(0.426)	(0.232)	(0.428)
Low-income country dummy × d.Temperature		-2.482**	-2.340**	-3.073***	-3.601***
		(1.121)	(0.967)	(1.107)	(0.970)
Middle-income country dummy × d.Temperature		-0.404	-0.451	-0.608	-0.650
		(0.296)	(0.390)	(0.790)	(0.543)
Hot country dummy × d.Temperature				1.619*	
				(0.848)	
Agricultural country dummy × d.Temperature					1.742
					(1.464)
d.Rainfalls			-2.069	2.051	-2.069
			(7.648)	(5.846)	(7.680)
Low-income country dummy × d.Rainfalls			7.919	9.074	8.494
			(9.131)	(9.602)	(9.156)
Middle-income country dummy × d.Rainfalls			3.324	6.163	3.390
			(7.957)	(9.483)	(7.988)
Hot country dummy × d.Rainfalls				-7.839*	
				(4.681)	
Agricultural country dummy × d.Rainfalls					-0.930
					(2.583)
Observations	3,266	3,266	3,242	3,242	3,242
Countries	141	141	141	141	141
R-squared	0.011	0.012	0.013	0.029	0.016
Linear combination of coefficients, Temperature effects					
Low-income countries		-2.697***	-2.419***	-3.363***	-3.680***
		(0.666)	(0.661)	(0.916)	(0.868)
Middle-income countries		-0.618	-0.530	-0.898	-0.730
		(0.633)	(0.651)	(0.693)	(0.771)
Linear combination of coefficients, Rainfall effects					
Low-income countries			5.850**	11.12**	6.425
			(3.385)	(5.077)	(5.327)
Middle-income countries			1.254	8.213	1.321
			(1.357)	(5.220)	(1.595)

Notes: All regressions include income-level dummies interacted with year fixed effects. Robust standard errors, clustered in two ways, at the country-level and the region-level, are in parentheses. Country classifications are based on the World Bank's classification. Hot countries are defined as countries having above median average temperature in 1990. Agricultural countries are defined as those having a share of agricultural value-added to GDP above the 75th percentile in 1990. Temperatures are in degrees Celsius and rainfalls are in units of 100 mm per month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. See the main text for data sources.

The significant weather effects are presumably because LICs employ agricultural technologies that are more sensitive to climatic conditions, in the sense that they use less machinery capital, fertilizers, and are less able to hedge against commodity price risk compared to richer countries. Mendelsohn et al. (2001) and Mendelsohn et al. (2006) argue that economic development reduces vulnerability of agricultural production to climatic changes. Another possible explanation is irrigation. Previous articles find that irrigated farms are less sensitive to weather shocks (e.g., Wang et al., 2009; Kurukulasuriya et al., 2006). LICs may have less irrigation, which possibly led to a sensitive reaction to weather shocks.

One may claim that higher temperatures negatively affect LICs just because they are located in hot areas such as Sub-Saharan Africa. In order to control for the level of temperatures, by following Dell et al. (2012), we introduce interaction terms between climate variables and a dummy variable taking unity if the country is a "hot country". Hot countries are defined as those having above median average temperature in the start year of the sample (1991). Column (4) indicates that adding the interaction terms does not change our baseline result qualitatively.

The next concern comes from the level of importance of agriculture in each country. The significant climate effects in LICs may be just because those countries are more agricultural-based than other countries. In order to examine if that is the case, we introduce interaction terms with a dummy variable taking unity if the share of value-added from the agricultural sector in GDP is greater than the 75th percentile of the sample in 1990.[26] The last column shows that adding the interaction terms does not change our baseline results much.

Next, we show that our results are robust to a wide range of different samples and specifications. Table 5 addresses various concerns that might affect our conclusion. The first two columns show results from estimating the baseline model by replacing the dependent variable with the agricultural value-added growth and the TFP_b growth rate as in the previous section. Although the coefficients change slightly, we obtain essentially the same results.

Column (3) reports a result from estimating the baseline model with excluding countries with greater share of oil production. Column (4) excludes all samples from commodity price hikes. Column (5) employs different income-level classification – the baseline specification uses the income-level classification from the World Bank while column (3) uses our own definitions based on income-level percentiles from 1995.[27] Column (6) adds explanatory variables from

[26] The reason for different cutoffs – the 50th percentile for the hot country dummy and the 75th percentile for the agriculture-based country – is that the distribution of the share of agricultural value-added is skewered and it takes small values for majority of countries. Therefore, we choose the 75th percentile for the cutoff to be defined as an agriculture-based economy.

[27] The reason for choosing 1995 as the base year is as follows. First, we define country groups based on one of the earliest years of the sample in order to avoid possible endogeneity issues arising from endogenous change in countries' income levels due to weather shocks. Second, however, choosing 1991 as the base year reduces our sample size because there are some missing observations on GDP per capita in 1991. Therefore, in order to cover as

Table 2 to control for other possible determinants of TFP.[28] Overall, Table 5 shows that our results are robust.

Table 5: The Impact of Weather Shocks, Robustness Checks

Dependent Variable = 100 times Annual Agricultural TFP Growth Rate or 100 times Annual Agricultural Value-Added Growth Rate

	Baseline specification & baseline sample		Excluding oil producers	Excluding the period of commodity price hikes	Income-level groups based on percentiles	Controlloing for other determinants of TFP
Dependent variable	Value-added growth rate	TFP_b growth rate	TFP growth rate			
	(1)	(2)	(3)	(4)	(5)	(6)
d.Temp.	0.290	0.231	0.073	0.012	0.498	-0.423
	(0.239)	(0.183)	(0.415)	(0.425)	(0.487)	(0.379)
Low-income country dummy × d.Temp.	-2.876***	-2.519***	-1.567*	-1.744**	-2.375***	-2.378***
	(1.092)	(0.673)	(0.951)	(0.695)	(0.428)	(0.604)
Middle-income country dummy × d.Temp.	-0.992**	-0.489	-0.965***	-0.637*	-1.217**	-0.884
	(0.473)	(0.482)	(0.320)	(0.353)	(0.598)	(1.661)
d.Rainfalls	2.856*	2.210	-5.792	-4.479	-6.107	4.355***
	(1.617)	(2.176)	(7.315)	(8.954)	(7.538)	(1.570)
Low-income country dummy × d.Rainfalls	3.235	3.152	11.70	10.79	10.45	9.867
	(2.201)	(3.396)	(7.462)	(10.140)	(7.893)	(6.912)
Middle-income country dummy × d.Rainfalls	-2.037**	-0.837	6.552	6.151	8.087	-4.732**
	(1.028)	(2.005)	(7.614)	(9.207)	(7.442)	(2.045)
Observations	4,066	3,410	2,661	2,423	3,242	1,382
Countries	158	147	141	141	141	61
R-squared	0.025	0.023	0.017	0.012	0.013	0.038
Linear combination of coefficients, Temperature effects						
Low-income countries	-2.586**	-2.288***	-1.494*	-1.732***	-1.877***	-2.801***
	(1.044)	(0.636)	(0.842)	(0.427)	(0.383)	(0.473)
Middle-income countries	-0.702	-0.258	-0.892	-0.625	-0.719	-1.307
	(0.521)	(0.551)	(0.489)	(0.267)	(0.732)	(1.854)
Linear combination of coefficients, Rainfall effects						
Low-income countries	6.092**	5.361**	5.907***	6.311***	4.345**	14.222**
	(2.648)	(2.722)	(1.302)	(3.377)	(1.769)	(6.739)
Middle-income countries	0.820	1.373	0.760	1.672	1.980	-0.377
	(1.014)	(1.125)	(1.300)	(1.805)	(1.700)	(1.312)

Notes: All regressions include income-level dummies interacted with year fixed effects. Robust standard errors, clustered in two ways, at the country-level and the region-level, are in parentheses. Temperatures are in degrees Celsius and rainfalls are in units of 100 mm per month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. See the main text for data sources.

many observations as possible and to have a benchmark year from earliest years in the sample, we choose 1995 as our base year to define country groups.

[28] Additional explanatory variables in column (6) include the capital-to-labor ratio, the taxes-to-value added ratio, and the subsidies-to-value added ratio. These variables are taken from the EORA and available for a large number of countries. We do not introduce fertilizers & pesticides and the political instability index because these variables are not available for many of LICs and adding these significantly limits the number of observations.

C. Importing Inputs Mitigates the Negative Weather Effects: Theory

The previous sections consider the impact of imported inputs and weather shocks individually, by closely following regression models from the literature. We further investigate interactions between these two factors in explaining agricultural TFP. This section presents a simple theoretical model helps clarify how imported inputs and weather shocks interact to affect TFP.

We start from the agricultural production function in Section II:

$$Y_{it} = A_{it}(K_{it})^{\alpha_{it}^K}(L_{it})^{\alpha_{it}^L}(T_{it})^{\alpha_{it}^T},$$

where agricultural TFP, A_{it}, is now described as a function of local temperatures $Temp_{it}$, local rainfalls $Rain_{it}$, and quality of intermediate inputs ϕ_{it}:[29]

$$A_{it} = A(Temp_{it}, Rain_{it}, \phi_{it}).$$

The overall quality of intermediate inputs ϕ_{it} is a weighted average of quality of domestic inputs ϕ_{it}^D and that of imported inputs ϕ_{it}^{Im}:

$$\phi_{it} = \vartheta_{it}^D\phi_{it}^D + \vartheta_{it}^{Im}\phi_{it}^{Im},$$

where the weights are the share of domestic inputs to the total value of inputs, $\vartheta_{it}^D = I_{it}^D/(I_{it}^D + I_{it}^{Im})$ and $\vartheta_{it}^{Im} = I_{it}^{Im}/(I_{it}^D + I_{it}^{Im})$ is the share of imported inputs.

We argue that a higher share of imported inputs reduces TFP's sensitivity to weather shocks. In other words, because higher temperatures reduce TFP, $\partial A_{it}/\partial Temp_{it} < 0$, and rainfalls increase TFP, $\partial A_{it}/\partial Rain_{it} > 0$, we have $\frac{\partial^2 A_{it}}{\partial Temp_{it}\partial\vartheta_{it}^{Im}} > 0$ and $\frac{\partial^2 A_{it}}{\partial Rain_{it}\partial\vartheta_{it}^{Im}} < 0$. Although the directions of the effects are opposite between the two weather shocks, the exact same discussions apply to these two. Therefore, this section focuses on the effect of temperature shocks only.

The effect of rising temperatures on agricultural TFP is obtained by differentiating TFP A_{it} with respect to $Temp_{it}$:

$$\frac{\partial A_{it}}{\partial Temp_{it}} = \frac{\partial A}{\partial Temp_{it}} + \frac{\partial A}{\partial \phi_{it}}(1-\vartheta_{it}^{Im})\frac{\partial \phi_{it}^D}{\partial Temp_{it}} + \frac{\partial A}{\partial \phi_{it}}\vartheta_{it}^{Im}\frac{\partial \phi_{it}^M}{\partial Temp_{it}},$$

where we plugged $\vartheta_{it}^D = 1 - \vartheta_{it}^{Im}$. The first term is the direct effect of rising temperatures on agricultural TFP; the second term indicates the indirect effect through the quality domestic inputs; and the third term is the indirect effect through the quality of imported inputs. Assuming that local temperature shocks do not affect quality of imported inputs, $\partial\phi_{it}^M/\partial Temp_{it} = 0$, the previous equation becomes:

$$\frac{\partial A_{it}}{\partial Temp_{it}} = \frac{\partial A}{\partial Temp_{it}} + \frac{\partial A}{\partial \phi_{it}}(1-\vartheta_{it}^{Im})\frac{\partial \phi_{it}^D}{\partial Temp_{it}}.$$

By differentiating this equation with respect to ϑ_{it}^{Im}, we obtain

[29] The previous section estimates the impact of weather shocks on the TFP growth rate and Appendix E provides a theoretical background for the regression equation. The theoretical setup in this section becomes consistent with the empirical model by specifying the TFP function as follows: $A_{it} = A(Temp_{it}, Rain_{it}, \phi_{it}) = A_{it-1}D(Temp_{it}, Rain_{it}, \phi_{it})$, TFP from the previous year times a damage function from weather shocks. Many other potential factors may affect TFP. However, we focus on these three variables as determinants of TFP.

$$\frac{\partial^2 A_{it}}{\partial Temp_{it}\partial\vartheta_{it}^{Im}} = \underbrace{\frac{\partial^2 A}{\partial Temp_{it}\partial\vartheta_{it}^{Im}}}_{\substack{Direct\\ productivity\ effect}} + \underbrace{\left(-\frac{\partial A}{\partial\phi_{it}}\frac{\partial\phi_{it}^{D}}{\partial Temp_{it}}\right)}_{\substack{Diversification\\ effect}} + \underbrace{\frac{\partial A}{\partial\phi_{it}}(1-\vartheta_{it}^{Im})\frac{\partial^2\phi_{it}^{D}}{\partial Temp_{it}\partial\vartheta_{it}^{Im}}}_{\substack{Synargies\ between\\ domestic\ and\ imported\ inputs}}.$$

where we assume $\partial^2 A/(\partial\phi_{it}\partial\vartheta_{it}^{Im}) = 0.$[30] Because higher temperatures reduce agricultural TFP, $\partial A_{it}/\partial Temp_{it} < 0$, and a greater share of imported inputs reduces the negative temperature effects, we argue $\partial^2 A_{it}/(\partial Temp_{it}\partial\vartheta_{it}^{Im}) > 0$.

This positive cross derivative comes from three effects. First, a greater share of imported inputs directly reduces the negative temperature effects, $\partial^2 A/(\partial Temp_{it}\partial\vartheta_{it}^{Im}) > 0$. Better production technologies embedded in imported inputs increase productivity, making agricultural production technology less sensitive to weather shocks. As shown in Section IV, a greater share of imported inputs increases agricultural TFP. Although we do not examine the direct effect on the climate sensitivity, we suppose a greater TFP makes agricultural production less sensitive to weather shocks. We refer to this effect as the direct productivity effect.

Second, a greater share of imported inputs increases the share of inputs that are not affected by local temperature shocks. As a result, this de-localization of inputs reduces the sensitivity of agricultural TFP to weather shocks, reflected in the second term: $-\frac{\partial A}{\partial\phi_{it}}\frac{\partial\phi_{it}^{D}}{\partial Temp_{it}}$, which is positive because $\partial\phi_{it}^{D}/\partial Temp_{it} < 0$. This is the same mechanism as Caselli et al. (2015), showing that a country can reduce exposure to domestic shocks therefore income volatility by diversifying source countries of imports. Their analyses include all macroeconomic shocks but there must be similar mechanisms in the context of weather shocks. We call this second channel the diversification effect.

Third, the last term of the previous equation is positive if $\partial^2\phi_{it}^{D}/(\partial Temp_{it}\partial\vartheta_{it}^{Im}) > 0$ because $\frac{\partial A}{\partial\phi_{it}}(1-\vartheta_{it}^{Im}) > 0$. This captures synergies between domestic inputs and imported inputs. A local final good producer is an intermediate good provider for other local final good producers. Therefore, increased productivity of domestic intermediate good producers raises productivity of domestic final good producers, making them less sensitive to weather shocks.[31] We refer to this as synergies between imported inputs and domestic inputs.

[30] This means that a change in the share of imported inputs does not affect the elasticity of agricultural TFP, A_{it}, with respect to the overall quality of intermediate inputs ϕ_{it}.

[31] This effect is present in a model where all final good varieties are used as intermediate inputs as in Eaton and Kortum (2003). Goldberg et al. (2010) find that new imported inputs facilitate domestic product creation. A greater number of domestically produced varieties due to new imported inputs would increase productivity of domestic firms if its production function is a CES form as in Kasahara and Rodrigue (2008).

D. Importing Inputs Mitigates the Negative Weather Effects: Evidence

We have clarified the channels a higher share of imported inputs makes countries less sensitive to weather shocks. This section investigates if imported inputs have such effects by only using observations from LICs where we find significant effects of weather shocks.

In order to test the theoretical possibilities, we estimate the following equation:

$$g_{i,t}^{TFP} = \pi_0 + \pi_1 d.Temp_{i,t} + \pi_1^{LowIm}\left[d.Temp_{i,t} D_i^{LowIm}\right] + \\ + \pi_2 d.Rain_{i,t} + \pi_2^{LowIm}\left[d.Rain_{i,t} D_i^{Low}\right] + D_i^{LowIm} + D_i^{LowIM}\theta_t + u_{i,t}, \tag{4}$$

where $g_{i,t}^{TFP}$, $d.Temp_{i,t}$, and $d.Rain_{i,t}$ follow the same definitions as for equation (3). $u_{i,t}$ denotes an error term. D_i^{LowIm} is a dummy variable taking unity if country *i*'s imported inputs-to-total inputs share is less than the 50th percentile of LICs in the start year of the sample (1991). We use the data from 1991 to construct D_i^{LowIm} in order to deal with possible endogenous changes in the share of imported inputs due to weather shocks. Interaction terms between D_i^{LowIM} and year dummies θ_t are also introduced. π_0, π_1^{LowIm}, π_2, and π_2^{LowIm} are coefficients to be estimated.

Table *6*: Weather Shocks and Imported Inputs, LICs

	Baseline specification & baseline sample			Excluding oil producers	Excluding the period of commodity price hikes	Controlloing for other determinants of TFP
Dependent variable	TFP growth rate	Value-added growth rate	TFP_b growth rate	TFP growth rate		
	(1)	(2)	(3)	(4)	(5)	(6)
d.Temp.	0.631	0.554	0.479	0.898	-0.525	0.618
	(0.849)	(0.639)	(0.755)	(0.612)	(0.493)	(0.811)
Lower share of imported inputs × d.Temp.	-4.915***	-5.429***	-4.546***	-4.790***	-1.811**	-4.963***
	(0.977)	(1.780)	(1.065)	(0.402)	(0.817)	(0.971)
d.Rainfalls	1.593	3.646	1.578	0.748	1.198	1.580
	(2.465)	(3.792)	(3.118)	(0.844)	(2.529)	(2.466)
Lower share of imported inputs × d.Rainfalls	11.96***	8.574*	12.02**	8.142*	14.27***	11.99***
	(4.563)	(4.905)	(4.689)	(4.576)	(4.904)	(4.587)
Lower share of imported inputs dummy	-0.377	0.356	-0.381	-0.051	-0.890*	-0.245
	(0.626)	(0.567)	(0.567)	(0.576)	(0.482)	(0.388)
Observations	557	621	557	498	415	557
Countries	24	24	24	21	24	24
R-squared	0.086	0.086	0.086	0.096	0.069	0.094
Linear combination of coefficients, Temperature effects						
Lower share of imported inputs	-4.284***	-4.875***	-4.067***	-3.891***	-2.336***	-4.345***
	(0.850)	(1.559)	(0.940)	(0.471)	(0.678)	(0.868)
Linear combination of coefficients, Rainfall effects						
Lower share of imported inputs	13.56***	12.22***	13.60***	8.889*	15.46***	13.57***
	(3.943)	(3.639)	(3.751)	(4.802)	(4.920)	(4.001)

Notes: All regressions include country dummies interacted with year dummies and use observations from LICs only. Robust standard errors, clustered at the country-level, are in parentheses. Temperatures are in degrees Celsius and rainfalls are in units of 100 mm per month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. See the main text for data sources.

Because we use a sample from LICs only and introduce the interaction term, $d.Temp_{i,t}D_i^{LowIm}$, the coefficient π_1 measures the temperature effect in LICs with higher share of imported inputs. π_1^{LowIm} captures "the temperature effect for countries with lower shares of imported inputs" minus "that for those with higher share of imported inputs". As a result, a linear combination of coefficients, $\pi_1 + \pi_1^{LowIm}$, is the temperature effect for LICs with lower shares of imported inputs. A similar interpretation applies to the rainfall variables.

Table 6 presents estimation results. Column (1) shows that a 1℃ increase in average temperatures reduces the TFP growth rate by 4.3 percent in countries with lower shares of imported inputs (see the linear combination of coefficients in the bottom of the table). Moreover, a 100 mm increase in monthly rainfalls increases the TFP growth rate by 13.6 percent. The results also suggest that weather shocks have no significant effects on countries with higher share of imported inputs even though all countries in the sample are from LICs.

Columns (2) and (3) use the same sample and the same explanatory variables as for column (1) but they use the value-added growth rate and the TFP_b growth rate. respectively. Results are essentially the same as for column (1). Columns (4)-(6) use the same dependent variable as for column (1) but they employ different samples of observations or controlling for additional explanatory variables as we have done in the previous section.[32] Again, results are robust.

One may claim that imported inputs actually do not mitigate weather shocks and the variable is just working as a proxy of something else. We consider three possibilities that our baseline results are spurious. First, it is possible that (Imported inputs)/(Total inputs) merely captures the countries' openness to import. Because imports in general have pro-competitive effects and increase productivity, the results may just be capturing countries' propensity to import from abroad, not the impact of imported inputs.

Second, possibly relatively richer countries within the LICs tend to use more imported inputs and these countries are less sensitive to weather shocks for some other reason. If that is the case, our baseline results could be coming from countries' initial income levels, not the share of imported inputs. Third, a higher share of imported inputs may be related with countries' initial technology levels and countries with better production technologies are possibly less vulnerable to weather shocks. If so, the results may just be showing different temperature effects stemming from countries' differences in initial technology levels.

In order to examine if these concerns are valid, we estimate the following equation:

$$g_{i,t}^{TFP} = \rho_1 d.Temp_{i,t} + \rho_1^{LowIm}\left[d.Temp_{i,t}D_i^{LowIm}\right] + \rho_2 d.Rain_{i,t} + \rho_2^{LowIm}\left[d.Rain_{i,t}D_i^{LowIm}\right] + \rho_1^{LowAggIm}\left[d.Temp_{i,t}D_i^{LowAggIm}\right] + \rho_2^{LowAggIm}\left[d.Rain_{i,t}D_i^{LowAggIm}\right] \quad (4)$$

[32] The same set of additional explanatory variables as for column (6) in Table 5 is introduced.

$$+ D_i^{LowIm} + D_i^{LowAggIm} + \rho_0 + \tilde{u}_{i,t},$$

where $D_i^{LowAggIm}$ denotes a dummy variable taking unity if the country's aggregate imports-to-GDP ratio is less than the 50th percentile among LICs in 1991; ρ_0, ρ_1, ρ_1^{LowIm}, $\rho_1^{LowAggIm}$, ρ_2, ρ_2^{LowIm}, and $\rho_2^{LowAggIm}$ are parameters to be estimated; $\tilde{u}_{i,t}$ indicates an error term.

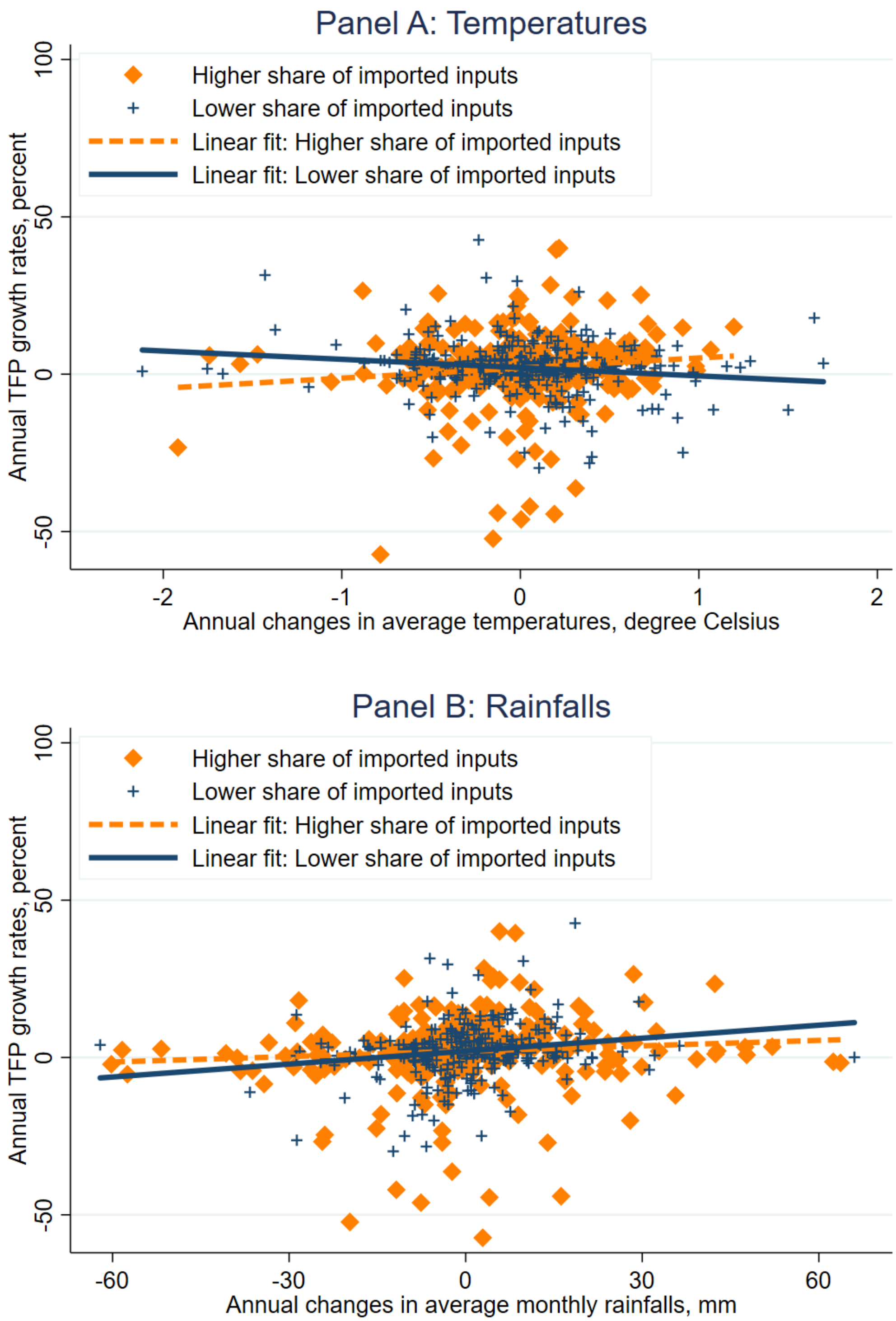
Table *7*: Weather Shocks and Imported Inputs, LICs, Robustness Checks

Dependent Variable = 100 times Annual Agricultural TFP Growth Rate

	Imports-to-GDP ratio		Initial income levels		Initial TFP levels	
	(1)	(2)	(3)	(4)	(5)	(6)
d.Temp.	-4.281*	-1.001	-0.947	1.234*	-2.619	0.568
	(2.529)	(3.014)	(1.168)	(0.747)	(1.763)	(2.157)
Lower share of imported inputs × d.Temp.		-4.619***		-4.568***		-4.933***
		(1.298)		(1.335)		(0.961)
Lower imports-to-GDP ratio × d.Temp.	3.259	2.580				
	(2.283)	(2.710)				
Lower initial income level × d.Temp.			-3.625***	-1.809		
			(1.302)	(1.303)		
Lower initial TFP level × d.Temp.					0.421	0.178
					(3.224)	(3.067)
d.Rainfalls	15.96***	12.03***	7.688	5.752	5.778	1.826
	(4.684)	(4.287)	(7.803)	(6.199)	(4.280)	(3.128)
Lower share of imported inputs × d.Rainfalls		12.20***		17.11***		11.99**
		(2.944)		(5.899)		(4.767)
Lower imports-to-GDP × d.Rainfalls	-14.90**	-15.41***				
	(6.049)	(5.144)				
Lower initial income level × d.Rainfalls			-3.900	-12.02*		
			(7.447)	(6.588)		
Lower initial TFP level × d.Rainfalls					-0.032	-1.724
					(8.487)	(7.708)
Observations	557	557	557	557	557	557
Countries	24	24	24	24	24	24
R-squared	0.084	0.098	0.077	0.092	0.071	0.086
Linear combination of coefficients, Temperature effects						
Lower share of imported inputs		-5.620**		-3.334***		-4.366**
		(2.853)		(1.283)		(1.841)
Lower imports-to-GDP ratio	-1.022***	1.579				0.746
	(0.271)	(0.812)				(1.134)
Lower initial income levels			-4.573***	-0.575		
			(0.332)	(1.435)		
Lower initial TFP levels					-2.198	
					(1.771)	
Linear combination of coefficients, Rainfall effects						
Lower share of imported inputs		24.23***		22.86***		13.82***
		(5.155)		(5.922)		(4.797)
Lower imports-to-GDP ratio	1.062	-3.375***				
	(2.280)	(1.284)				
Lower initial income levels			3.788***	-6.270		
			(1.325)	(6.060)		
Lower initial TFP levels					5.746	0.102
					(5.876)	(5.897)

Notes: The dependent variable is the TFP growth rate. All regressions include a constant term and interaction terms between year dummies and each of the dummy variables. It uses observations from LICs only. Robust standard errors, clustered at the country-level, are in parentheses. Temperatures are in degrees Celsius and rainfalls are in units of 100 mm per month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. See the main text for data sources.

Figure *6*: Weather Shocks and Annual TFP Growth Rates, LICs



Notes: The figures show the relationship between annual TFP growth rates – in the vertical axis – and annual changes in temperatures (Panel A) and rainfalls (Panel B) – in the horizontal axis. The sample comes from LICs during 1991-2015.

Estimating equation (4) answers if the first story is the main cause of the baseline results. In order to examine if the second and third stories are true, we make a dummy variable taking unity if the country's initial GDP per capita is less than the 50th percentile among LICs, $D_i^{LowGDPpc}$, and a dummy variable taking unity if the country's initial TFP level is less than the 50th percentile among the group of countries, D_i^{LowTFP}. Estimating equation (4) by replacing $D_i^{LowAggIm}$ with $D_i^{LowGDPpc}$ (or D_i^{LowTFP}) answers if the second (or the third) concern is valid or not.[33] These dummy variables are constructed based on the data from the WDI and our TFP estimates.[34]

Regression results are shown in Table 7. Columns (1) and (2) display results from estimating regressions controlling for the aggregate imports-to-GDP ratio. Column (1) introduces interaction terms with the aggregate imports-to-GDP ratio only and shows temperature effects are not statistically different across the two groups of countries – countries with higher aggregate imports-to-GDP ratio and those with lower ones. It also shows that the rainfall effects are greater for countries with lower aggregate imports-to-GDP ratio. Column (2) controls for both the imported inputs-to-total inputs ratio and the aggregate imports-to-GDP ratio. However, the effect of imported inputs remain significant. These results imply that our results are not coming from cross-country differences in propensity to import from abroad in general.

Finally, columns (5) and (6) consider the initial agricultural TFP levels. Results in column (5) imply that there is no systematic difference in weather shocks across low TFP countries and high TFP countries within the LICs. Furthermore, column (6) shows that, even after controlling for the initial TFP levels, the effects of imported inputs are similar to the baseline result. These considerations support the idea that our baseline results are caused by cross-country differences in the share of imported inputs. Appendix G conducts more robustness checks using different samples and concerning the way we construct the dummy variables.

Figure 6 visually describe the baseline results, where Panel A shows the relationship between the TFP growth rate and annual changes in temperatures and Panel B presents the one for rainfalls. It indicates that steeper temperature effects and rainfall effects come from countries employing lower shares of imported inputs.

We acknowledge that our results come from reduced-form regression analyses, exploiting historical variations in weather and agricultural TFPs. Therefore, the analysis focuses on the impact of weather shocks on a particular aspect of the economies – agricultural TFP – and the

[33] One may concern about multicollinearities between the dummy variable on the share of imported inputs, D_i^{LowIm}, and the dummies $D_i^{LowAggIm}$, $D_i^{LowGDPpc}$, and D_i^{LowTFP}, leading to an unreliable regression result. However, correlation between these dummies is low. Based on the sample of 30 LICs, $Corr\left(D_i^{LowIm}, D_i^{LowAggIm}\right) = -0.0455$, $Corr\left(D_i^{LowIm}, D_i^{LowGDPpc}\right) = 0.3030$, and , $Corr(D_i^{LowIm}, D_i^{LowTFP}) = -0.0318$. Therefore, there is no issue arising from multicollinearities between these dummies.

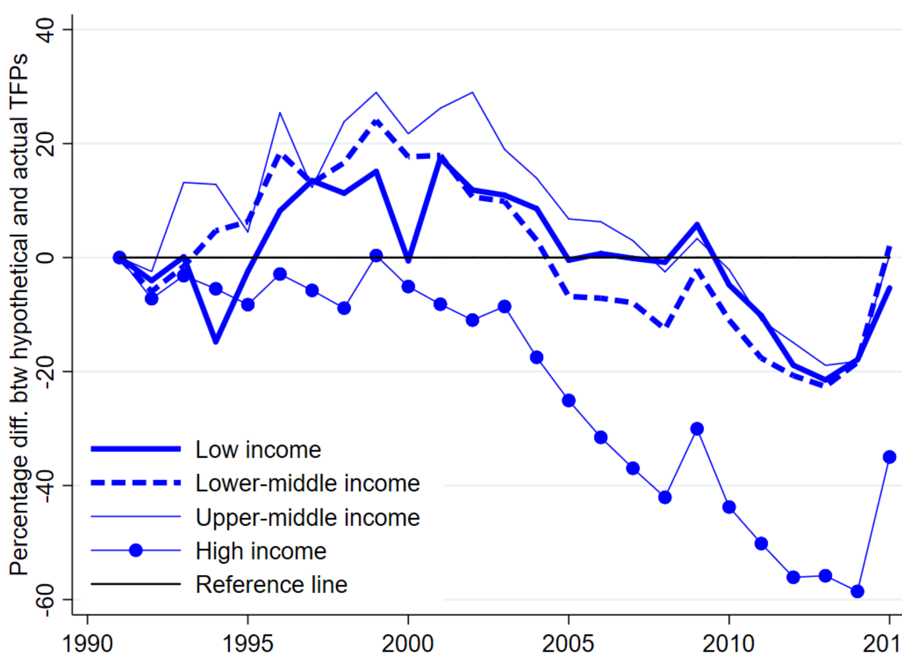
[34] The dummy variable capturing countries' propensity to import in general is based on the share of total imports in goods and services to GDP obtained from the WDI. The dummy variable on the initial income levels is based on GDP per capita (constant US dollars) retrieved from the WDI. The dummy variable on the initial agricultural TFP is constructed using our TFP estimates.

estimated impacts are considered as the short-run effects because we estimate countries' contemporaneous responses to short-run fluctuations in weather. In this sense, our analysis differs from ones in natural science fields employing estimates of future climate change and a General Circulation Model (GCM). These studies tend to find more pessimistic projections regarding the impact of climate change in the future. See Dell et al. (2014) and Auffhammer (2018) for more details.

V. Counterfactuals

The last set of analyses examines the magnitude of estimated impacts of imported inputs and weather shocks. Our analysis is simple. First, we estimate the regression $\ln(TFP_{i,t}) = \beta_0 + \beta_1 Inputs_{i,t} + \mathbb{X}_{i,t}\boldsymbol{\beta}_2 + e_{i,t}$ with our baseline model using IV. Second, we find counterfactual TFP levels, keeping $Inputs_{i,t}$ at their 1991 level, $\hat{y}_{i,t}^{1991} = \hat{\beta}_0 + \hat{\beta}_1 Inputs_{i,1991} + \mathbb{X}_{i,t}\widehat{\boldsymbol{\beta}}_2 + \hat{e}_{i,t}$.[35] Third, the gap between the counterfactual TFP and the actual TFP is computed $Gap_{i,t}^{1991} = 100 \times [\hat{y}_{i,t}^{1991} - \ln(TFP_{i,t})]$, which is a percentage deviation from the actual TFP level. If the gap is positive, then it means that actual changes in the share of imported inputs worked to reduce agricultural TFP and vice versa. We use the regression coefficients from column (4) of Table 2 to find counterfactual TFPs.

Figure 7: Counterfactual TFPs without Change in the Share of Imported Inputs since 1991

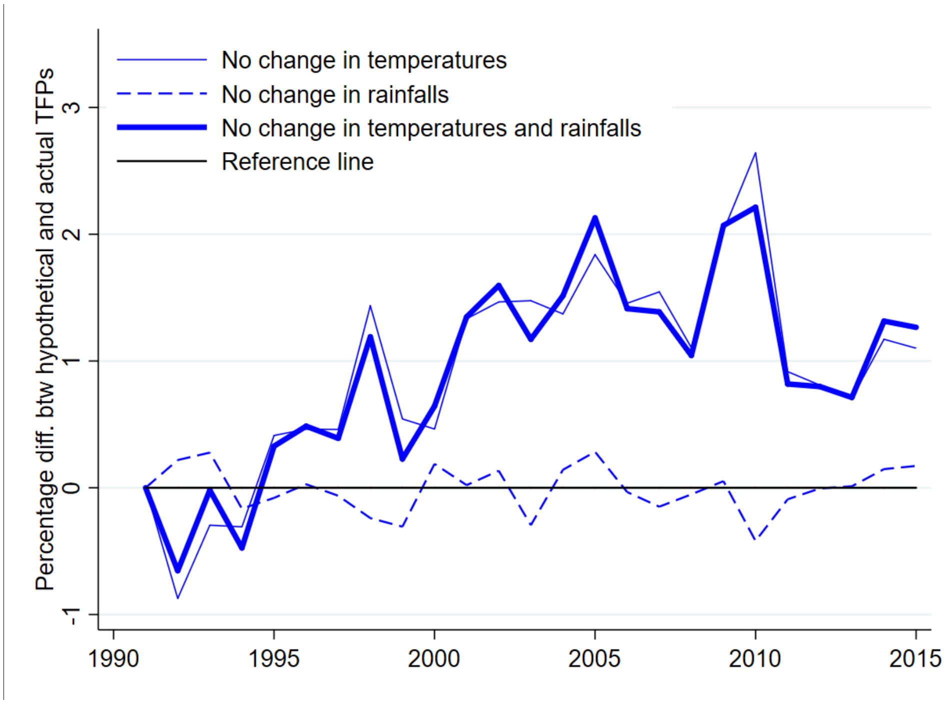


Notes: The figure shows percentage gaps between counterfactual TFP levels computed based on baseline regression result reported in column (4) of Table 2 and actual TFP levels, for the four groups of countries. Counterfactual TFP levels are estimated by assuming that the share of imported inputs did not change since 1991.

[35] Note that even residuals $\hat{e}_{i,t}$ are added to find counterfactuals because the purpose of this analysis is to isolate the impact of changes in the share of imported inputs.

Figure 7 shows the estimated gap between counterfactual TFPs and actual TFPs for the four groups of countries. It shows that changes in the share of imported inputs in the 1990s worked to reduce agricultural TFP in lower income countries. In 2002, for example, if the share of imported inputs stayed at the 1991 level, upper-middle income countries would have had 20 percent higher agricultural TFP and low-income and lower-middle income countries would have had 10 percent greater TFP than the actual TFP.

Figure *8*: Counterfactual TFPs without Weather Shocks, LICs



Notes: The figure shows differences between actual TFP levels and counterfactual TFP levels for the three scenarios. The thinner solid line, the dashed line, and the thicker solid line are based on Scenario 1: No change in temperatures, Scenario 2: No change in rainfalls, and Scenario 3: No change in temperatures and rainfalls since 1991.

The gap between the counterfactual and actual TFPs turned to be negative around 2004 for lower-middle income countries, and around 2010 for LICs and upper-middle-income countries. In 2014, LICs and middle-income countries would have about 20 percent lower TFP if the share of imported inputs stayed at the 1991 level. These results come from the fact that the share of imported inputs was declining in 1990s and it started to increase in early 2000s as shown in Figure 3. For high-income countries, the share of imported inputs continuously increased throughout the period, which contributed to the increase in TFP by about 60 percent in 2014.

We conduct a similar counterfactual analysis for weather shocks. First, we estimate equation (2) and find parameter estimates. Second, find counterfactual TFP growth rate when climatic conditions stayed at the 1991 level by assuming $d.Temp_{i,t} = 0$ and $d.Rain_{i,t} = 0$. Third, we find counterfactual TFP level in 1992, $\widehat{TFP}_{i,1992}^{1991}$, by using the counterfactual TFP growth rate in

1992 and the actual TFP level in 1991: $\widehat{TFP}_{i,1992}^{1991} = (1 + \hat{g}_{i,1992}^{TFP}/100) \times TFP_{i,1991}$ and then find TFP levels in the following years as follows: $\widehat{TFP}_{i,t}^{1991} = \left(1 + \hat{g}_{i,t}^{TFP}/100\right) \times TFP_{i,t-1}$ for t = 1993, 1994, …, 2015. Forth, the gap between the counterfactual TFP and actual TFP is computed $Gap_{i,t}^{1991} = 100 \times [\ln(\widehat{TFP}_{i,t}^{1991}) - \ln(TFP_{i,t})]$, which is a percentage deviation from the actual TFP level.

Table *8*: Actual Agricultural Value-Added and Counterfactual Value-Added under Scenario 1

		Year	Actual agricultural value-added (million USD) (1)	Hypothetical agricultural value-added (million USD) (2)	Difference, (2) minus (1) (million USD) (3)	Percentage difference, [(2) - (1)]/(1)×100 (4)
Afghanistan	AFG	2010	2,639	2,772	133	5.0%
Burundi	BDI	2005	456	471	14	3.2%
Benin	BEN	2010	1,388	1,420	32	2.3%
Burkina Faso	BFA	2010	2,530	2,587	58	2.3%
Central African Rep.	CAF	2010	660	675	15	2.3%
Gambia, The	GMB	2010	222	227	5	2.1%
Haiti	HTI	2015	902	918	16	1.7%
Liberia	LBR	2010	707	716	9	1.2%
Madagascar	MDG	2009	1,053	1,122	69	6.6%
Mali	MLI	2010	3,583	3,719	136	3.8%
Malawi	MWI	2010	1,545	1,594	49	3.2%
Niger	NER	2010	2,009	2,064	56	2.8%
Nepal	NPL	2010	3,193	3,319	126	3.9%
Rwanda	RWA	2010	1,258	1,288	30	2.4%
Senegal	SEN	2010	1,570	1,607	37	2.3%
Sierra Leone	SLE	2010	1,124	1,139	15	1.3%
Syria	SYR	2010	5,219	5,479	260	5.0%
Chad	TCD	2010	3,415	3,483	68	2.0%
Togo	TGO	2010	1,032	1,055	23	2.2%
Tanzania	TZA	2010	6,421	6,569	148	2.3%
Uganda	UGA	2010	3,297	3,413	117	3.5%
Total			44,223	45,636	1,413	3.2%

Notes: The table shows actual agricultural value added (million USD, constant 2005 prices) and counterfactual agricultural value added based on counterfactual TFPs estimated based on Scenario 1 for LICs. Some LICs are missing from the table due to data availability constraint.

Counterfactuals are found only for LICs where we find significant effects of weather shocks. We consider three scenarios. Scenarios 1 and 2 are the cases where temperatures and rainfalls did not change since 1991, respectively. Scenario 3 is when both temperatures and rainfalls did not change since 1991. Figure 8 shows results and suggests that weather shocks worked to reduce agricultural TFP in LICs. About 2 percent agricultural TFP were lost in 2005 and 2010 because these two years had the warmest average temperatures (NOAA National Centers for Environmental Information, 2011). The figure shows that the temperature effect is much more sizable than the rainfall effect. Scenario 1 (no change in temperatures) and Scenario 3 (no change in temperatures and rainfalls) imply similar results while Scenario 2 (no change in rainfalls) leads to a relatively smaller difference in actual TFP and hypothetical TFP.

In order to quantify its effects on agricultural value-added, we estimate hypothetical agricultural value-added based on counterfactuals under Scenario 1 (no change in temperatures). The hypothetical agricultural value-added is estimated by plugging the counterfactual TFP to the Cobb-Douglas production function: $Y_{i,t}^{C} = A_{i,t}^{C}(K_{it})^{\alpha_{it}^{K}}(L_{it})^{\alpha_{it}^{L}}(T_{it})^{\alpha_{it}^{T}}$. Table 8 presents results for each of LICs from the year where the difference between the actual value-added $Y_{i,t}$ and the hypothetical value-added $Y_{i,t}^{C}$ is the largest. In many LICs, damages from higher temperatures are the greatest mostly in the year 2010 because the global average temperature was the record high in the year.

In terms of absolute value, the largest losses in agricultural value-added come from Syria, Tanzania, and Mali – 260 million USD, 148 million USD, and 136 million USD agricultural value-added were lost, respectively. In terms of percentage, the largest losses are from Madagascar (6.6%), Afghanistan (5.0%), Syria (5.0%), and Nepal (3.9%). In LICs as a whole, 3.2 percent of total agricultural value-added, which is equivalent to 1.4 billion USD, were lost if we collect the largest damages throughout the sample period 1991-2015. These results suggest that rising temperatures have economically sizable effects on agricultural value-added.

VI. Conclusions

This paper has estimated agricultural TFP for 162 countries from 1990 to 2015 and examined the determinants of TFP by focusing on the role of imported inputs and weather shocks. We have three major findings – (1) An increase in usage of imported inputs has a significant impact on the level of TFP; (2) rising temperatures and rainfall shortages negatively influenced the agricultural TFP growth rate; (3) within LICs, a greater share of imported inputs works to reduce the negative effects of weather shocks.

While these results may imply that an optimistic view on the impact of future climate change because importing inputs would help LICs to deal with negative effects of weather shocks. However, we once again acknowledge that our results come from reduced-form regressions relating annual TFP growth rates with short-run fluctuations in weather. Therefore, this paper is silent about the impact of future climate change, which is projected to lead to more severe rises in temperatures and more radical changes in precipitation patterns compared with historical variations in the last two decades.

We have also conducted counterfactual analyses to understand the economic magnitudes of these impacts. The results suggest that an increase in the share of imported inputs explain at most 60 percent of agricultural TFP in high-income countries and 20 percent of that in low-income and middle-income countries. The economic magnitude of the impact of weather shocks is also sizable. Our results suggest that, colleting the cumulative losses in the warmest years during the sample period, in total 3.2 percent of agricultural value-added, which is equivalent to 1.4 billion USD, were lost due to a rise in temperatures in LICs as a whole.

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Appendix

A. List of Countries

We follow the World Bank's classification of income-level of countries. In a broader definition, lower-middle income and upper-middle countries are classified as middle-income countries.

Low-income countries (LICs)

No.	ISO	Country	Region
1	AFG	Afghanistan	South Asia
2	BDI	Burundi	Sub-Saharan Africa
3	BEN	Benin	Sub-Saharan Africa
4	BFA	Burkina Faso	Sub-Saharan Africa
5	CAF	Central African Rep.	Sub-Saharan Africa
6	COD	Congo, Dem. Rep.	Sub-Saharan Africa
7	ERI	Eritrea	Sub-Saharan Africa
8	ETH	Ethiopia	Sub-Saharan Africa
9	GIN	Guinea	Sub-Saharan Africa
10	GMB	Gambia, The	Sub-Saharan Africa
11	HTI	Haiti	Latin America & Caribbean
12	LBR	Liberia	Sub-Saharan Africa
13	MDG	Madagascar	Sub-Saharan Africa
14	MLI	Mali	Sub-Saharan Africa
15	MOZ	Mozambique	Sub-Saharan Africa
16	MWI	Malawi	Sub-Saharan Africa
17	NER	Niger	Sub-Saharan Africa
18	NPL	Nepal	South Asia
19	RWA	Rwanda	Sub-Saharan Africa
20	SEN	Senegal	Sub-Saharan Africa
21	SLE	Sierra Leone	Sub-Saharan Africa
22	SYR	Syria	Middle East & North Africa
23	TCD	Chad	Sub-Saharan Africa
24	TGO	Togo	Sub-Saharan Africa
25	TJK	Tajikistan	Europe & Central Asia
26	TZA	Tanzania	Sub-Saharan Africa
27	UGA	Uganda	Sub-Saharan Africa
28	YEM	Yemen, Rep.	Middle East & North Africa

Lower-middle-income countries

No.	ISO	Country	Region
1	AGO	Angola	Sub-Saharan Africa
2	BGD	Bangladesh	South Asia
3	BOL	Bolivia	Latin America & Caribbean
4	BTN	Bhutan	South Asia
5	CIV	Cote d'Ivoire	Sub-Saharan Africa
6	CMR	Cameroon	Sub-Saharan Africa
7	COG	Congo, Rep.	Sub-Saharan Africa
8	CPV	Cabo Verde	Sub-Saharan Africa
9	DJI	Djibouti	Middle East & North Africa
10	EGY	Egypt, Arab Rep.	Middle East & North Africa
11	GEO	Georgia	Europe & Central Asia
12	GHA	Ghana	Sub-Saharan Africa
13	HND	Honduras	Latin America & Caribbean
14	IDN	Indonesia	East Asia & Pacific
15	IND	India	South Asia
16	KEN	Kenya	Sub-Saharan Africa
17	KGZ	Kyrgyz Republic	Europe & Central Asia
18	KHM	Cambodia	East Asia & Pacific
19	LAO	Lao PDR	East Asia & Pacific
20	LKA	Sri Lanka	South Asia
21	LSO	Lesotho	Sub-Saharan Africa
22	MAR	Morocco	Middle East & North Africa
23	MDA	Moldova	Europe & Central Asia
24	MMR	Myanmar	East Asia & Pacific
25	MNG	Mongolia	East Asia & Pacific
26	MRT	Mauritania	Sub-Saharan Africa
27	NGA	Nigeria	Sub-Saharan Africa
28	NIC	Nicaragua	Latin America & Caribbean
29	PAK	Pakistan	South Asia
30	PHL	Philippines	East Asia & Pacific
31	PNG	Papua New Guinea	East Asia & Pacific
32	SLV	El Salvador	Latin America & Caribbean
33	STP	Sao Tome and Principe	Sub-Saharan Africa
34	SWZ	Swaziland	Sub-Saharan Africa
35	TUN	Tunisia	Middle East & North Africa
36	UKR	Ukraine	Europe & Central Asia
37	UZB	Uzbekistan	Europe & Central Asia
38	VNM	Vietnam	East Asia & Pacific
39	VUT	Vanuatu	East Asia & Pacific
40	ZMB	Zambia	Sub-Saharan Africa

Upper-middle-income countries

No.	ISO	Country	Region
1	ALB	Albania	Europe & Central Asia
2	ARM	Armenia	Europe & Central Asia
3	AZE	Azerbaijan	Europe & Central Asia
4	BGR	Bulgaria	Europe & Central Asia
5	BIH	Bosnia and Herzegovina	Europe & Central Asia
6	BLR	Belarus	Europe & Central Asia
7	BLZ	Belize	Latin America & Caribbean
8	BRA	Brazil	Latin America & Caribbean
9	BWA	Botswana	Sub-Saharan Africa
10	CHN	China	East Asia & Pacific
11	COL	Colombia	Latin America & Caribbean
12	CRI	Costa Rica	Latin America & Caribbean
13	DOM	Dominican Republic	Latin America & Caribbean
14	DZA	Algeria	Middle East & North Africa
15	ECU	Ecuador	Latin America & Caribbean
16	FJI	Fiji	East Asia & Pacific
17	GAB	Gabon	Sub-Saharan Africa
18	GTM	Guatemala	Latin America & Caribbean
19	GUY	Guyana	Latin America & Caribbean
20	IRN	Iran, Islamic Rep.	Middle East & North Africa
21	IRQ	Iraq	Middle East & North Africa
22	JAM	Jamaica	Latin America & Caribbean
23	JOR	Jordan	Middle East & North Africa
24	LBN	Lebanon	Middle East & North Africa
25	LBY	Libya	Middle East & North Africa
26	MDV	Maldives	South Asia
27	MEX	Mexico	Latin America & Caribbean
28	MKD	Macedonia, FYR	Europe & Central Asia
29	MNE	Montenegro	Europe & Central Asia
30	MUS	Mauritius	Sub-Saharan Africa
31	MYS	Malaysia	East Asia & Pacific
32	NAM	Namibia	Sub-Saharan Africa
33	PER	Peru	Latin America & Caribbean
34	PRY	Paraguay	Latin America & Caribbean
35	RUS	Russian Federation	Europe & Central Asia
36	SUR	Suriname	Latin America & Caribbean
37	THA	Thailand	East Asia & Pacific
38	TKM	Turkmenistan	Europe & Central Asia
39	TUR	Turkey	Europe & Central Asia
40	VEN	Venezuela, RB	Latin America & Caribbean
41	WSM	Samoa	East Asia & Pacific
42	ZAF	South Africa	Sub-Saharan Africa

High-income countries

No.	ISO	Country	Region
1	ARG	Argentina	Latin America & Caribbean
2	AUS	Australia	East Asia & Pacific
3	AUT	Austria	Europe & Central Asia
4	BHS	The Bahamas	Latin America & Caribbean
5	BHR	Bahrain	Middle East & North Africa
6	BRB	Barbados	Latin America & Caribbean
7	BEL	Belgium	Europe & Central Asia
8	BRN	Brunei Darussalam	East Asia & Pacific
9	CAN	Canada	North America
10	CHL	Chile	Latin America & Caribbean
11	HRV	Croatia	Europe & Central Asia
12	CYP	Cyprus	Europe & Central Asia
13	CZE	Czech Republic	Europe & Central Asia
14	DNK	Denmark	Europe & Central Asia
15	EST	Estonia	Europe & Central Asia
16	FIN	Finland	Europe & Central Asia
17	FRA	France	Europe & Central Asia
18	DEU	Germany	Europe & Central Asia
19	GRC	Greece	Europe & Central Asia
20	HKG	Hong Kong SAR, China	East Asia & Pacific
21	HUN	Hungary	Europe & Central Asia
22	ISL	Iceland	Europe & Central Asia
23	IRL	Ireland	Europe & Central Asia
24	ISR	Israel	Middle East & North Africa
25	ITA	Italy	Europe & Central Asia
26	JPN	Japan	East Asia & Pacific
27	KOR	Korea, Rep.	East Asia & Pacific
28	KWT	Kuwait	Middle East & North Africa
29	LVA	Latvia	Europe & Central Asia
30	LTU	Lithuania	Europe & Central Asia
31	LUX	Luxembourg	Europe & Central Asia
32	MLT	Malta	Middle East & North Africa
33	NLD	Netherlands	Europe & Central Asia
34	NZL	New Zealand	East Asia & Pacific
35	NOR	Norway	Europe & Central Asia
36	OMN	Oman	Middle East & North Africa
37	PAN	Panama	Latin America & Caribbean
38	POL	Poland	Europe & Central Asia
39	PRT	Portugal	Europe & Central Asia
40	QAT	Qatar	Middle East & North Africa
41	SAU	Saudi Arabia	Middle East & North Africa
42	SGP	Singapore	East Asia & Pacific
43	SVK	Slovak Republic	Europe & Central Asia
44	SVN	Slovenia	Europe & Central Asia
45	ESP	Spain	Europe & Central Asia
46	SWE	Sweden	Europe & Central Asia
47	CHE	Switzerland	Europe & Central Asia
48	TTO	Trinidad and Tobago	Latin America & Caribbean
49	ARE	United Arab Emirates	Middle East & North Africa
50	GBR	United Kingdom	Europe & Central Asia
51	USA	United States	North America
52	URY	Uruguay	Latin America & Caribbean

B. Data Sources and Summary Statistics

Data sources are summarized in the following table.

Variables	Unit	Data sources
Agricultural value-added (Agriculture, Forestry, and Fishing)	Value USD, 2005 prices, millions	FAOSTAT
Gross Production Value (Agriculture, PIN)	Value USD, Constant 2004-2006, millions	FAOSTAT
Net Capital Stocks (Agriculture, Forestry and Fishing)	Value US$, 2005 prices, millions	FAOSTAT
Population, total	Persons	WDI
Employment to population ratio, 15+, total (modeled ILO estimate)	% of total population	WDI
Employment in agriculture (modeled ILO estimate)	% of total employment	WDI
Agricultural area	1000 ha	FAOSTAT
Value of imported inputs	Current USD	The authors' calculation based on the data from EORA
Value of total intermediate inputs	Current USD	The authors' calculation based on the data from EORA
Fertilizer consumption	Kilograms per hectare of arable land	WDI
Pesticides (total use)	Tons of active ingredients	FAOSTAT
Value-added in the agricultural sector (EORA sector 1)	Current USD	EORA Database
Subsidies on production in the agricultural sector (EORA sector 1)	Current USD	EORA Database
Taxes on production in the agricultural sector (EORA sector 1)	Current USD	EORA Database
Capital-to-labor ratio (EORA sector 1)	Current USD over current USD	The authors' calculation based on the data from EORA
Political instability index (Freedom house index, civil liberty)	Index, from 1 to 7	Freedom House
Tariff rate, applied, weighted mean, all products	%	WDI
FDI inflows to Agriculture, Forestry and Fishing	Value US$, 2005 prices, millions	FAOSTAT
Real effective exchange rate index	Index, 2010 = 100	WDI
Temperatures	Degree Celsius	World Bank's Climate Change Knowledge Portal
Rainfalls	mm	World Bank's Climate Change Knowledge Portal
Gross Domestic Product	Value USD, 2005 prices	FAO
Oil rents	% of GDP	WDI
IMF Commodity Price Index	Index, 2005 = 100	IMF

Table A1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent variables					
ln(TFP)	3,914	-0.02	1.06	-3.89	3.72
ln(TFP_b)	4,114	-0.52	0.88	-3.79	2.02
ln(Value-added)	4,774	7.02	2.16	-0.35	12.94
TFP growth rate	3,751	2.44	14.02	-80.03	384.96
TFP_b growth rate	3,943	1.85	10.32	-71.17	197.92
Value-added growth rate	4,747	2.35	10.91	-80.78	167.06
Explanatory variables					
Imported inputs/Total inputs×100	4,420	16.62	16.62	0.00	99.96
Fertilizer & Pesticide	1,957	0.31	0.52	0.00	5.25
Capital-to-labor ratio	4,152	26.23	55.44	0.02	561.62
Taxes/Value-added×100	4,199	3.87	3.69	0.00	18.73
Subsidies/Value-added×100	4,199	3.08	6.74	0.00	50.81
Political instability index	3,720	3.42	1.78	1	7
Instruments					
Tariffs for all products	2,919	7.36	10.62	0	421.50
Tariffs for manufacturing goods	2,919	7.25	6.98	0	150.92
Tariffs for primary goods	2,919	7.93	21.02	0	917.75
FDI/Value added×100	1,050	0.82	2.69	-30.00	27.86
ln(Effective exchange rate/100 + 1)	2,030	0.69	0.11	0.27	1.82
Climate variables					
Average temperature in degree Celsius	4,160	19.26	8.35	-7.06	29.75
Average monthly rainfalls in 100 mm	4,134	1.00	0.73	0.01	3.75
Yearly change in average temperature	4,160	0.03	0.55	-3.64	2.93
Yearly change in average monthly rainfalls	4,134	0.00	0.22	-1.35	1.99
Dummies for all countries					
Hot country dummy	4,160	0.50	0.50	0	1
Agricultural country dummy	4,758	0.25	0.43	0	1
Oil producer dummy	4,186	0.10	0.30	0	1
Dummies for low-income countries					
Lower share of imported inputs dummy	780	0.50	0.50	0	1
Lower total imports-to-GDP ratio dummy	702	0.52	0.50	0	1
Lower income country dummy	806	0.48	0.50	0	1
Lower TFP dummy	650	0.48	0.50	0	1

Notes: The table shows summary statistics of variables employed in the regression analyses. The authors' calculation. See the main text and Appendix B for data sources.

C. Growth Accounting Results

This section provides tables showing growth accounting results presented in the main text.

Table A2: Growth Accounting Results, LICs, 1991-2015

		Value-added	Decomposition			
			TFP	Capital stock	Employ ment	Land area
Mali	MLI	7.69	3.49	2.21	1.71	0.29
Chad	TCD	6.85	3.60	2.06	1.15	0.04
Liberia	LBR	6.20	1.84	3.54	0.71	0.11
Burkina Faso	BFA	6.00	3.95	3.38	-1.33	0.00
Mozambique	MOZ	5.25	1.68	2.81	0.70	0.05
Niger	NER	4.70	3.46	-0.03	0.28	0.99
Benin	BEN	4.32	2.79	0.36	0.56	0.61
Rwanda	RWA	3.87	2.97	0.69	0.25	-0.04
Tanzania	TZA	5.09	-0.50	5.23	0.33	0.03
Guinea	GIN	3.73	1.18	1.73	0.78	0.04
Yemen, Rep.	YEM	3.67	2.39	1.15	0.13	-0.01
Uganda	UGA	3.29	0.99	1.05	1.04	0.21
Malawi	MWI	3.25	1.98	0.10	0.81	0.36
Nepal	NPL	3.05	2.41	0.29	0.36	-0.01
Senegal	SEN	2.68	2.51	-0.85	1.02	0.00
Togo	TGO	2.48	0.61	0.92	0.73	0.21
Gambia, The	GMB	1.99	1.80	-0.61	0.78	0.03
Congo, Dem. Rep.	COD	1.59	1.61	-1.04	1.01	0.01
Madagascar	MDG	1.58	0.31	0.17	0.94	0.16
Sierra Leone	SLE	0.61	-0.45	0.16	0.52	0.38
Syria	SYR	0.43	-0.29	1.07	-0.38	0.03
Afghanistan	AFG	-0.40	0.58	-1.73	0.75	0.00
Central African Rep.	CAF	0.18	0.00	-0.30	0.46	0.02
Burundi	BDI	-0.04	-0.14	-0.36	0.51	-0.05
Haiti	HTI	-0.80	-0.27	-0.84	0.14	0.17

Notes: The table shows annualized average growth rates of each component over 24 years, 1991-2015. Countries' income levels are based on the World Bank's classification. See the main text for data sources.

Table A3: Growth Accounting Results, Lower-Middle Income Countries, 1991-2015

		Value-added	Decomposition			
			TFP	Capital stock	Employ ment	Land area
Angola	AGO	6.65	4.50	0.36	1.76	0.03
Nigeria	NGA	6.24	4.24	1.63	0.22	0.15
Myanmar	MMR	6.21	3.09	3.29	-0.40	0.23
Vietnam	VNM	3.94	4.23	0.50	-0.87	0.07
Lao PDR	LAO	3.88	0.90	2.44	0.13	0.41
Cambodia	KHM	3.78	2.04	2.12	-0.61	0.23
Djibouti	DJI	3.75	1.63	1.34	0.48	0.29
Nicaragua	NIC	3.68	2.27	0.51	0.63	0.28
Ghana	GHA	3.60	3.12	-0.30	0.53	0.25
Cameroon	CMR	3.54	1.81	0.86	0.79	0.07
Bangladesh	BGD	3.51	1.58	2.23	-0.16	-0.14
Papua New Guinea	PNG	3.49	2.28	2.52	-1.30	0.00
Pakistan	PAK	3.24	1.89	0.65	0.66	0.03
Egypt, Arab Rep.	EGY	3.16	1.09	0.97	0.26	0.85
Sao Tome and Principe	STP	3.14	2.77	0.39	-0.21	0.20
Indonesia	IDN	3.09	2.61	0.21	-0.32	0.58
India	IND	3.01	1.68	1.60	-0.26	0.00
Honduras	HND	3.00	2.06	0.49	0.51	-0.06
Congo, Rep.	COG	2.98	1.92	-0.08	1.13	0.01
Sri Lanka	LKA	2.95	2.44	0.81	-0.49	0.19
Vanuatu	VUT	2.91	-0.02	2.01	0.67	0.25
Bolivia	BOL	2.76	2.14	0.47	0.11	0.04
Kenya	KEN	2.59	0.58	0.87	1.14	0.00
Morocco	MAR	2.45	0.62	1.45	0.37	0.01
Tunisia	TUN	2.42	1.90	1.02	-0.55	0.06
Bhutan	BTN	2.41	1.06	1.27	0.07	0.00
Philippines	PHL	2.27	1.84	0.16	0.08	0.18
Cabo Verde	CPV	2.16	-0.45	2.10	0.32	0.18
Mauritania	MRT	1.99	0.85	0.31	0.83	0.00
Cote d'Ivoire	CIV	1.87	1.83	-0.61	0.46	0.18
El Salvador	SLV	1.52	1.89	0.22	-0.72	0.14
Lesotho	LSO	1.44	2.89	1.09	-2.52	-0.02
Mongolia	MNG	1.26	0.21	1.42	-0.10	-0.28
Swaziland	SWZ	0.28	0.18	-0.28	0.39	0.00
Zambia	ZMB	0.26	-0.44	-0.20	0.74	0.16

Notes: The table shows annualized average growth rates of each component over 24 years, 1991-2015. Countries' income levels are based on the World Bank's classification. See the main text for data sources.

Table A4: Growth Accounting Results, Upper-Middle Income Countries, 1991-2015

		Value-added	Decomposition			
			TFP	Capital stock	Employ ment	Land area
China	CHN	7.07	3.52	5.04	-1.50	0.01
Iraq	IRQ	5.42	5.47	-0.05	0.05	-0.07
Algeria	DZA	5.09	3.88	1.21	-0.11	0.11
Albania	ALB	5.02	5.25	0.71	-0.99	0.05
Lebanon	LBN	4.45	2.58	0.77	1.00	0.10
Paraguay	PRY	4.41	3.55	0.15	0.00	0.71
Guyana	GUY	4.12	4.34	1.13	-1.31	-0.03
Peru	PER	3.91	2.46	0.25	1.20	0.00
Ecuador	ECU	3.66	4.46	-0.03	0.18	-0.95
Brazil	BRA	3.61	4.51	0.01	-1.20	0.29
Belize	BLZ	3.46	2.17	0.80	0.19	0.30
Dominican Republic	DOM	3.24	3.15	0.58	-0.47	-0.03
Guatemala	GTM	2.96	0.42	0.72	1.97	-0.14
Gabon	GAB	2.59	1.42	0.23	0.95	0.00
Costa Rica	CRI	2.50	2.14	1.16	-0.81	0.00
Thailand	THA	2.43	3.35	0.35	-1.30	0.03
Iran, Islamic Rep.	IRN	2.35	3.43	0.12	-0.03	-1.17
Jordan	JOR	2.23	2.30	-0.88	0.81	0.01
Turkey	TUR	1.88	2.41	0.46	-0.92	-0.08
Maldives	MDV	1.80	-0.81	3.13	-0.51	-0.02
Mexico	MEX	1.65	2.21	-0.16	-0.41	0.01
Jamaica	JAM	1.54	1.56	0.44	-0.42	-0.04
Suriname	SUR	1.53	-0.20	1.66	0.08	-0.01
Venezuela, RB	VEN	1.30	0.85	0.23	0.25	-0.02
South Africa	ZAF	1.26	3.42	-0.49	-1.67	0.00
Colombia	COL	1.20	1.13	0.02	0.07	-0.02
Botswana	BWA	1.09	-2.37	2.12	1.34	0.00
Mauritius	MUS	0.77	1.89	0.51	-1.40	-0.24
Malaysia	MYS	0.75	-0.20	1.21	-0.42	0.15
Fiji	FJI	0.72	0.58	0.34	-0.20	0.00
Namibia	NAM	0.67	0.96	-0.04	-0.24	0.00
Samoa	WSM	-1.62	0.38	-0.38	-1.10	-0.52
Bulgaria	BGR	-2.85	-3.99	2.66	-1.29	-0.22
Libya	LBY	-3.80	-5.30	-0.23	1.73	-0.01

Notes: The table shows annualized average growth rates of each component over 24 years, 1991-2015. Countries' income levels are based on the World Bank's classification. See the main text for data sources.

Table A5: Growth Accounting Results, High Income Countries, 1991-2015

		Value-added	Decomposition			
			TFP	Capital stock	Employ ment	Land area
Kuwait	KWT	10.68	8.92	0.90	0.84	0.02
Chile	CHL	4.52	5.59	0.00	-1.07	0.00
Oman	OMN	3.93	2.35	0.56	0.79	0.23
Qatar	QAT	3.88	1.79	1.75	0.32	0.01
Brunei Darussalam	BRN	3.23	3.00	1.12	-1.19	0.31
Bahrain	BHR	3.03	1.06	1.55	0.40	0.02
Norway	NOR	3.00	4.67	-0.43	-1.23	0.00
Australia	AUS	2.97	2.48	1.19	-0.63	-0.07
Denmark	DNK	2.69	3.92	-0.10	-1.13	0.00
Israel	ISR	2.27	3.81	0.36	-1.90	0.00
Panama	PAN	2.24	1.42	0.51	0.23	0.08
United States	USA	2.17	1.80	1.07	-0.70	0.00
United Arab Emirates	ARE	2.13	3.96	0.80	-2.87	0.24
New Zealand	NZL	2.04	1.14	1.41	-0.29	-0.22
Argentina	ARG	1.88	-0.59	0.71	1.61	0.14
Uruguay	URY	1.84	-1.63	1.95	1.57	-0.05
Saudi Arabia	SAU	1.52	2.20	-1.54	0.71	0.15
Korea, Rep.	KOR	1.46	4.24	0.27	-3.06	0.00
France	FRA	1.33	3.56	0.00	-2.22	0.00
Austria	AUT	1.26	0.86	0.74	-0.33	0.00
Canada	CAN	1.21	2.26	0.17	-1.17	-0.05
Finland	FIN	1.01	2.57	-0.42	-1.14	0.00
United Kingdom	GBR	0.67	1.08	0.78	-1.16	-0.04
Sweden	SWE	0.67	1.10	0.53	-0.96	0.00
Iceland	ISL	0.29	0.90	0.54	-1.15	0.00
Portugal	PRT	0.08	1.13	0.86	-1.91	0.00
Spain	ESP	-0.09	1.90	-0.09	-1.87	-0.03
Italy	ITA	-0.19	2.17	-0.01	-2.35	0.00
Japan	JPN	-0.19	1.05	-0.16	-0.84	-0.25
Malta	MLT	-0.39	-0.19	0.91	-1.11	0.00
Ireland	IRL	-0.39	0.29	0.12	-0.81	0.00
Greece	GRC	-0.67	-0.63	1.06	-1.11	0.00
Netherlands	NLD	-0.73	-1.45	1.29	-0.57	0.00
Switzerland	CHE	-0.74	-0.34	-0.18	-0.22	0.00
Cyprus	CYP	-0.79	-0.21	-0.01	-0.33	-0.25
Barbados	BRB	-1.18	0.62	-0.79	-0.66	-0.35
Trinidad and Tobago	TTO	-1.41	0.12	0.00	-1.32	-0.21
Bahamas, The	BHS	-1.42	-2.85	0.97	0.21	0.25
Singapore	SGP	-1.69	-7.10	-0.48	5.97	-0.07
Germany	DEU	-2.72	-0.66	0.31	-2.38	0.00
Hong Kong SAR, China	HKG	-4.87	-0.99	-0.18	-3.43	-0.27

Notes: The table shows annualized average growth rates of each component over 24 years, 1991-2015. Countries' income levels are based on the World Bank's classification. See the main text for data sources.

D. Estimating Agricultural TFP

D.1 Factor Shares

We obtain data on labor compensation and capital compensation from the EORA database. It provides data on payments to capital (consumption of fixed capital), payments to labor (compensation of labor), and value-added. The capital shares are estimated as $\alpha_{i,t}^{K} = \frac{payments\ to\ capital_{i,t}}{value-added_{i,t}}$ and the labor shares are $\alpha_{i,t}^{L} = \frac{payments\ to\ labor_{i,t}}{value-added_{i,t}}$. By assuming a CRS production technology, land shares are found as $\alpha_{i,t}^{T} = 1 - \alpha_{i,t}^{K} - \alpha_{i,t}^{L}$.
Table A6 summarizes average values of factor shares for four groups of countries in 1990 and 2015. These computations lead to reasonable numbers.

Table A6: Average Capital Shares, Labor Shares, and Land Shares

	1990			2015		
	Capital share	Labor share	Land share	Capital share	Labor share	Land share
Low income countries	0.397	0.338	0.265	0.417	0.307	0.276
Lower-middle income countries	0.300	0.416	0.284	0.305	0.399	0.297
Upper-middle income countries	0.298	0.408	0.294	0.316	0.379	0.305
High income countries	0.376	0.510	0.114	0.387	0.499	0.114

Notes: The authors' calculation based on the data from the EORA.

D.2 Estimating Cobb-Douglas Production Function

Our baseline TFP estimates use factor share parameters calculated using the data from the EORA. We also provide alternative measure of TFP using factor share parameters obtained by estimating a Cobb-Douglas production, which we call TFP$_b$. This section discusses how the parameters are estimated and presents estimation results.

We assume a Cobb-Douglas agricultural production function:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha_K} L_{i,t}^{\alpha_L} T_{i,t}^{\alpha_T} ,$$

where $Y_{i,t}$ denotes agricultural value-added of country *i* in year *t*; $A_{i,t}$, $K_{i,t}$, $L_{i,t}$, $T_{i,t}$ are agricultural TFP, capital stock, labor employment, and land area, respectively. α_K, α_L and α_T are the shares of capital, labor, and land, respectively. The production function exhibits constant returns to scale (CRS), therefore $\alpha_K + \alpha_L + \alpha_T = 1$.

By dividing the both sides by $L_{i,t}$, we can express the production function in intensive form as:

$$\tilde{Y}_{i,t} = A_{i,t} \tilde{K}_{i,t}^{\alpha_K} \tilde{T}_{i,t}^{\alpha_T},$$

where tilde indicate "per worker" – $\tilde{Y}_{i,t} = Y_{i,t}/L_{i,t}$, $\tilde{K}_{i,t} = K_{i,t}/L_{i,t}$, and $\tilde{T}_{i,t} = T_{i,t}/L_{i,t}$. This production function is transformed to a linear form by taking natural logs:

$$\ln(\tilde{Y}_{i,t}) = \ln(A_{i,t}) + \alpha_K \ln(\tilde{K}_{i,t}) + \alpha_T \ln(\tilde{T}_{i,t}).$$

The labor share is obtained by exploiting the CRS assumption: $\alpha_L = 1 - \alpha_K - \alpha_T$. This structural equation could in principle be estimated using the panel data from all 170 countries available in the sample. Nevertheless, the matched data with other variables in the regression leads to a sample of 162 countries only, and the balanced panel dataset between 1991 and 2015 is only available for 144 countries.

Table A7 presents estimated input shares with the Cobb-Douglas assumption. It shows that the capital share is 0.378 and the land share is 0.521. The CRS assumption implies that the labor share is $1 - \alpha_K - \alpha_T = 0.100$.

Table A7: Growth Accounting Results, by Income-Levels of Countries, 1991-2015

	(1)
α_K	0.378***
	(0.062)
α_T	0.521***
	(0.097)
Observations	4,114
Countries	170
R-squared	0.585
F-statistic	211.15
p-value of F-statistic	0.000
Labor share by assuming CRS	
$1 - \alpha_K - \alpha_T$	0.100*
	(0.056)

Notes: The table reports the result from estimating countries' agricultural production functions. The regression includes a constant term and country fixed effects. Standard errors, clustered at the country-level, are in parentheses.

E. Level Effects and Growth Effects

E.1 The effect on the level of TFP

We estimate the effect of imported inputs on the level of TFP by closely following empirical specifications in the literature on determinants of TFP (e.g., Alene, 2010; Craig et al., 1997; Amiti and Konings, 2007; Olper et al., 2017). They implicitly assume that agricultural production function of country *i* of year *t* is:

$$Y_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} T_{it}^{\alpha_T},$$

where

$$A_{it} = \exp(\mathbb{X}_{it}\boldsymbol{\beta} + a_i + \varepsilon_{it}).$$

The level of TFP A_{it} is a function of various factors in a vector $\mathbb{X}_{it}$ and time-invariant country fixed effect a_i and the error term ε_{it}. By taking natural logs, we find

$$\ln(A_{it}) = \mathbb{X}_{it}\boldsymbol{\beta} + a_i + \varepsilon_{it}, \tag{A.1}$$

which is the regression equation we estimated in Section IV.

E.2 The effect on the growth rate of TFP

Equation (A.1) tests if regressors $\mathbb{X}_{it}$ have the effect on the level of TFP. We allow weather shocks to affect the growth rate of TFP by closely following previous empirical studies on the effect of climate (Dell et al., 2012; Hsiang and Jina, 2014; Moore and Diaz, 2015; IMF, 2017). We explain a simple theoretical background following Dell et al. (2014).

The evolution of TFP is written as:

$$A_{it} = A_{it-1}\exp(D_{it}),$$

where D_{it} denotes a damage function of weather shocks in country *i* of year *t*. Greater economic damages due to weather shocks are related with a smaller value of D_{it}. The current level of TFP A_{it} depends upon the previous level of TFP A_{it-1} as well as damages from weather shocks described in the function D_{it}. Weather shocks affect the current level of TFP by altering its growth path from the previous period.

Taking natural logs leads to:

$$\ln(A_{it}) = \ln(A_{it-1}) + D_{it}.$$

We assume a linear functional form for the damage function, $D_{it} = \gamma_0 + \gamma_1 d.Temp_{it} + \gamma_2 d.Rainfalls_{it} + u_{it}$ where $d.Temp_{it}$ and $d.Rainfalls_{it}$ are annual changes in average temperatures and average monthly rainfalls from the previous year; u_{it} denotes the error term; γ_0, γ_1, and γ_2 are parameters to be estiamted. Given this assumption and by re-arrainging the previous equation, we find:

$$\ln(A_{it}) - \ln(A_{it-1}) = \gamma_0 + \gamma_1 d.Temp_{it} + \gamma_2 d.Rainfalls_{it} + u_{it}, \qquad \text{(A.2)}$$

which is the baseline regression model in Section V.

Dell et al. (2012), Hsiang and Jina (2014), Moore and Diaz (2015), and IMF (2017) estiamte the effect of climate on GDP growth rates by implicitely building upon this theoretical background. We assume that a similar argument applies in the context of agricultural production and estimate the impact on agricultural TFP.

F. Correlation between Temperatures and Rainfalls

One may concern about a multicollinearity between temperatures and rainfalls. However, there is no strong correlation between these two variables. Table A8 shows correlations between the regressors used in the regression analysis: changes in temperatures and changes in rainfalls.

Table A8: Correlations between *d.Temp* and *d.Rainfall*

	All countries		Low-income countries	
	1970-2015	1990-2015	1970-2015	1990-2015
Correlation coefficient	-0.0860	-0.0885	-0.1512	-0.0959
Observations	7,110	3,950	1,170	650

Notes: The authors' estimation.

It shows that there is virtually no correlation between the two variables. Using a sample of all countries, the correlation coefficient is -0.0860 and -0.0885 for the period 1970-2015 and 1990-2015, respectively. Restricting the sample to LICs only leads to correlation coefficients of -0.1512 and -0.0959, for 1970-2015 and 1990-2015, respectively, which are quite low. Therefore, there is no multicollinearity.

G. Robustness Checks on the Interactive Effects

This section presents robustness checks on the climate change mitigation effect of imported inputs. Table A9 summarizes results from six additional regressions concerning various possible critiques. All of these regressions use equation (3) in the main text and employ the sample of LICs only.

Column (1) cuts observations with extreme temperature changes where these are defined as observations where *d.Temp* is greater than the 95th percentile or less than the 5th percentile of *d.Temp* among observations from LICs after 1991. Column (2) drops observations with extreme rainfall changes where these are defined using the same cutoffs for *d.Rainfalls*. Columns (3) cuts observations from both extreme temperature changes and extreme rainfall changes. None of these treatments changes our results qualitatively.

Column (4)-(6) now use the baseline sample but we change the way we construct the imported input dummy. In the regressions in the main text we use the data from 1991 to make the imported inputs dummy. However, in column (4), it is constructed based on the data on $\frac{Imported\ inputs}{Total\ inputs}$ in 1995 using the same threshold as for the baseline, the 50th percentile. In column (5), the dummy variable is constructed based on the country mean of $\frac{Imported\ inputs}{Total\ inputs}$ during 1991-1995. Again, results are similar to our baseline results.

Column (6) introduces a continuous variable of $\frac{Imported\ inputs}{Total\ inputs}$ and its interaction term. Because countries with higher share of imported inputs are less sensitive to weather shocks, the coefficient of the interaction term $d.Temp \times \frac{Imported\ inputs}{Total\ inputs}$ is expected to have a positive sign and the one for changes in temperature, $d.Temp$, should be negative. We expect opposite signs for rainfall variables – the coefficient of the interaction term $d.Rainfalls \times \frac{Imported\ inputs}{Total\ inputs}$ is expected to have a negative sign and the one for changes in temperature, $d.Rainfalls$, should be positive. Results are as expected. The results show that our baseline results are robust.

Table A9: Weather Shocks and Imported Inputs, LICs, More Robustness Checks

	Dropping extreme changes in d.Temp	Dropping extreme changes in d.Rain	Dropping extreme changes in d.Temp & d.Rain	Input dummy based on the data from 1995	Input dummy based on mean during 1991-1995	Continuous input variable
	(1)	(2)	(3)	(4)	(5)	(6)
d.Temperature	-2.720	1.337	-2.903***	0.158	0.302	-2.831***
	(1.764)	(0.872)	(1.100)	(0.829)	(1.021)	(0.657)
Lower share of imported inputs × d.Temperature	-3.458**	-5.321***	-2.586**	-4.405***	-4.409***	0.055*
	(1.586)	(0.926)	(1.261)	(1.017)	(0.979)	(0.029)
d.Rainfalls	0.698	16.91***	18.71***	3.877***	4.383***	6.136
	(2.343)	(6.417)	(4.453)	(0.735)	(0.553)	(3.982)
Lower share of imported inputs × d.Rainfalls	12.00***	3.769	3.930	3.072	1.500	-0.025
	(3.777)	(10.150)	(7.929)	(6.892)	(5.501)	(0.228)
Lower share of imported inputs dummy	-0.053	0.125	0.357	-0.993	-0.991	-0.013
	(0.408)	(0.849)	(0.495)	(0.833)	(0.838)	(0.015)
Observations	499	513	459	557	557	557
Countries	24	24	24	24	24	24
R-squared	0.095	0.11	0.122	0.079	0.08	0.072
Linear combination of coefficients, Temperature effects						
Lower share of imported inputs	-6.177***	-3.985***	-5.489***	-4.247***	-4.107***	
	(1.247)	(0.792)	(1.238)	(1.003)	(0.819)	
Linear combination of coefficients, Rainfall effects						
Lower share of imported inputs	12.70***	20.68***	22.64***	6.949	5.883	
	(3.080)	(5.266)	(4.906)	(7.188)	(5.666)	

Notes: All regressions include a constant term and use the observations from LICs only. Robust standard errors, clustered at the country-level, are in parentheses. Temperatures are in degrees Celsius and rainfalls are in units of 100 mm per month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. See the main text for data sources.