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


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**Abstract**

This paper estimates agricultural total factor productivity (TFP) in 161 countries and investigates the effect of temperatures on agricultural TFP growth rates by exploiting year-to-year variations in weather and TFP growth rates during the period 1992-2015. We provide the new evidence that higher temperatures impede TFP growth, particularly in low-income countries (LICs) with lower shares of imported inputs. Our central estimates imply that a 1 degree Celsius rise in annual average temperatures reduce the TFP growth rate by 5.4 percentage points in that group of countries while temperatures have insignificant effects in other countries. It suggests that a higher import component of intermediate inputs mitigates the negative effect of weather shocks. We argue imported inputs have such effects because inputs from abroad embed advanced technologies and less sensitive to climate and a higher share imported inputs make overall inputs less sensitive to local climate shocks.



*Key Words*: Agricultural TFP, Imported Inputs, Weather Shocks, Climate Change Mitigation, LICs
*JEL codes*: F14, F18, Q17, Q54


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# 1 Introduction

Rising temperatures have been shown to influence many aspects of economies such as production (Dell et al., 2012), migrations (Peri and Sasahara, 2019), local conflicts (Bosetti et al., 2018), and mortality (Burgess et al., 2014), especially in developing countries. In addition, the average temperatures are expected to rise by 4 degree Celsius by 2800-2100 (e.g., IPCC, 2014; World Bank, 2018). Such change is likely to have severe effects on agricultural production as documented in a large number of existing studies (e.g., Burke and Emerick, 2016; Colmer, 2019).[1] Therefore, it is critical to understand likely impacts of climate change and how to cope with its effects on economies.

The goal of this paper is to investigate the effect of rising temperatures on one of the most climate-sensitive parts of economies, agricultural productivity, with focusing on the role of imported inputs in mitigating negative effects of rising temperatures. Using the data from 161 countries during the period 1992-2015, we observe strong inverse effects of weather shocks in low-income countries (hereafter LICs) using less imported inputs. Higher temperatures 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 reasons to believe that imported inputs have such effects. First, imported inputs tend to be higher quality and embed better technologies. As a result, these work to reduce vulnerability of agricultural production to weather shocks. Second, a greater share of imported inputs to total intermediate input usage makes the overall quality of inputs less sensitive to local weather shocks, because local climate has no effects on the quality of imported inputs.[2] Third, local final good producers are intermediate good suppliers because there are sectoral linkages. Local final good producers' productivity gains from imported inputs have positive effects on domestic intermediate goods. The interactions through sectoral linkages contribute to make domestic input quality less climate sensitive, which in turn leads to more climate-robust agricultural sectors.

The share of imported inputs to total input usage in agricultural sectors varies substantially across countries. According to the data from the EORA database (Lenzen et al., 2012; Lenzen et al., 2013), the average share of imported inputs is about 13% for LICs in the beginning of the sample period, 1990. However, this figure is 18% for other countries. Even within LICs, there are large variations in the share of imported inputs. For example, the share of imported inputs is less than 3% in Afghanistan, Burkina Faso, Niger, Syria, and Yemen for almost entire sample period 1990-2015. We argue that these cross-country differences in prevalence of imported inputs is one reason why the effects of temperatures differ across countries.

There are many factors determining countries' propensity to import intermediate inputs. For example, the average tariff rate in 2005 is 12% in LICs and this figure is about 9% and 4% for middle-income and high-income countries, respectively, according to the World Development Indicators of World Bank (2018). These figures suggest that, on average, LICs are applying higher tariffs than other countries. Furthermore, according the Doing Business Database (World Bank, 2019), the average costs to import per container

[1] Burke and Emerick (2016) estimate that, in the U.S., corn yield will decline by 15% by 2050 due to climate change. Colmer (2019) finds that, using the data from India, a 1°C increase in temperatures reduce agricultural yield by 12.4% and the value of production by 12.5%.

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

in 2006 is 5,000 USD in LICs and this figure is about 3,000 USD and 1,400 USD for middle-income and high-income countries, respectively. These data show that producers in LICs face higher costs to import products due to tariffs and non-tariff barriers.[3] All of these are associated with propensity to import intermediate inputs, which in turn affects growth paths of agricultural TFP by altering the effect of temperatures.

In order to examine the effect of imported inputs on sensitively of agricultural TFP to climate, we run regressions by employing agricultural TFP growth rates as the dependent variable and changes in annual average temperatures as an explanatory variable with control variables including rainfalls and other potential factors affecting TFP growth. Our analysis allows different responses to temperature shocks across four groups countries, (1) LICs importing a fewer inputs, (2) LICs importing more inputs, (3) non-LICs importing a fewer inputs, and (4) non-LICs importing more inputs. We find a severe negative impact of higher temperatures in the first group of countries, LICs importing less inputs. Our baseline results suggest that a 1°C increase in temperatures reduces the agricultural TFP growth rate by 5.4 percentage points in that group of countries. Because the average TFP growth rate in LICs during the sample period is 2.4%, one standard deviation rise in annual temperatures, 0.55 degree Celsius, leads to almost zero growth of TFP in that year. In contrast, we find that higher temperatures do not have statistically significant effects on TFP growth in other groups of countries.

Our results are robust to a wide range of sub-samples and specifications. It includes regressions (1) concerning possibility that outliers are causing our baseline results by dropping observations with extreme temperature changes, extreme rainfall changes, oil-producers, the period of commodity price hikes; (2) using different imported input dummies constructed using data from different years; (3) changing thresholds dividing LICs into two groups, lower share and higher share of imported inputs; (4) introducing lags of temperature variables; and (5) addressing possible correlations between countries' propensity to import inputs and other characteristics of countries such as aggregate imports, initial income levels, and initial TFP levels. We find that our results are robust to these considerations.

We further examine imported inputs in which sectors have stronger climate change mitigation effects by defining the share of imported inputs purchased from a certain sector abroad to the total value of inputs purchased from the same sector. Results show that imported inputs from manufacturing sectors particularly matter. It suggests that manufacturing imported inputs embeds better technologies from abroad and making manufacturing sectors in LICs more capital intensive, reducing the effect of higher temperatures on agricultural productivity growth rates.

One may claim that the estimated negative effect of higher temperatures on TFP comes from noise in the data and it does not necessarily capture interactions between imported inputs and temperature effects. In order to address this potential critique, we generate 1,000 sets of randomly selected of 13 countries where 13 is the number of countries defined as LICs using a fewer share of imported inputs. By using the 1,000 sets of countries, we generate 1,000 different dummy variables and run 1,000 regressions by employing our baseline specification. We find that none of the 1,000 regressions leads to a similar

[3] Plant-level evidence includes Kugler and Verhoogen (2009) and Kasahara and Rodrigue (2008). They find that a fraction of plants import intermediate inputs. By working with data from Colombia, Kugler and Verhoogen (2009) show that importing plants produce greater output, pay higher wages, and are more productive. Kasahara and Rodrigue (2008) document that, using the data from Chile, plants using imported inputs employ more labor, more capital, and produce more output, suggesting that there are costs of importing inputs and only larger firms are afford to pay those costs.

coefficient as our baseline result. The actual point estimate of temperature effects, 5.4 percentage points, is far less than the lowest values of the falsification parameters, suggesting that indeed imported inputs matter in explaining differences in temperature effects across countries within LICs.

Lastly, we estimate the same regressions by replacing the dependent variables with agricultural value-added growth rates, agricultural gross output growth rates, and GDP growth rates, respectively, to show that our results are not caused by particular assumptions we made to estimate agricultural TFP. Results show that higher temperatures reduce these growth rates in LICs using a fewer imported inputs as consistent with our baseline results. The estimated magnitudes of temperature effects are smaller for these dependent variables. This is consistent with our prior because these dependent variables includes effects of production factors, such as capital and labor, and non-agricultural sectors, making it difficult to observe a clear-cut temperature effect.

This paper contributes to the literature on the impacts of weather shocks on agricultural sectors. The previous work on this issue focuses on a certain areas of the world (e.g., Burke et al., 2015, for the U.S.; Ashenfelter and Storchmann, 2006, for Germany; Wang et al., 2009, for China; Colmer, 2019, for India) 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. In this regard, this paper is attuned to recent studies finding significant effects of weather shocks in LICs (e.g., Dell et al., 2012, for GDP growth rate; Cattaneo and Peri, 2016, for emigration from countries; and Peri and Sasahara, 2019, for internal migrations).

We go beyond the existing literature by documenting that prevalence of imported inputs reduces countries' vulnerability to weather shocks. This insight is new to the international trade literature documenting positive effects of imported inputs on importing countries. For example, Amiti and Konings (2007) find that cutting tariffs on intermediate inputs has a greater effect on firm productivity using the data from Indonesia. Kasahara and Rodrigue (2008) also show that becoming an importer of intermediate goods increases the firm's productivity using the data from Chile. Halpern et al. (2015) find positive productivity effects of imported inputs due to imperfect substitution between domestic and imported inputs. Goldberg et al. (2010) document that importing inputs create new domestic varieties. This paper differs from these prior studies because we focus on agricultural sectors instead of manufacturing sectors and find that importing inputs mitigates the negative effect of rising temperatures on agricultural TFP growth rates.

The rest of the paper is organized as follows. The next section explains data sources and presents summary statistics. Section 3 clarifies possible theoretical channels through which imported inputs and temperatures interact to determine TFP growth rates. Section 4 empirical assesses the effect of imported inputs and weather shocks on agricultural TFP. Section 5 concludes.

# 2 Data

## 2.1 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 TFP estimates are presented.

As in Herrendorf et al. (2015) and many others,[4] country $i$'s agricultural production function in year $t$ is described by a Cobb-Douglas production function subject to constant returns to scale (CRS):[5]

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

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. $\alpha_{it}^K$, $\alpha_{it}^L$, and $\alpha_{it}^T$ 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 FAOSTAT of FAO (2018) and data on agricultural employment come from WDI of World Bank (2018). We take the capital share and the labor share data from the EORA database (Lenzen et al., 2012; Lenzen et al., 2013). It provides the data on payments to capital (consumption of fixed capital), payments to labor (compensation of labor), and value-added.[6] We compute the capital share as $\alpha_{it}^K = \frac{\text{payments to capital}_{it}}{\text{value added}_{it}}$ and the labor share as $\alpha_{it}^L = \frac{\text{payments to labor}_{it}}{\text{value added}_{it}}$. 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: $A_{it} = Y_{it}/(K_{it})^{\alpha_{it}^K}(L_{it})^{\alpha_{it}^L}(T_{it})^{\alpha_{it}^T}$.[7]

Our sample includes 161 countries in the world — 28 LICs, 40 lower-middle-income countries, 41 upper-middle-income countries, and 52 high-income countries. Figure 1 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.

## 2.2 Imported Inputs and Weather Shocks

We find the share of imported inputs based on the data obtained from the EORA database (Lenzen et al., 2012; Lenzen et al., 2013). It provides input-output tables for 190 countries in the world during 1990-2015 at annual frequency. These input-output tables are constructed using the data from the UN Comtrade database, EuroStat, IDE/JETRO input-output tables, and data from countries' statistical authorities. Figure 2 shows average shares of imported inputs to total purchase of intermediate goods in the agricultural sector for the four groups of countries. It indicates that high-income countries have higher average share of imported inputs and LICs have the lowest share in almost entire period. The share of imported inputs is declining in the 1990s and it increases since early 2000s. There is a sharp decline in the share of imported inputs during 2008-2010 due to the global financial crisis.

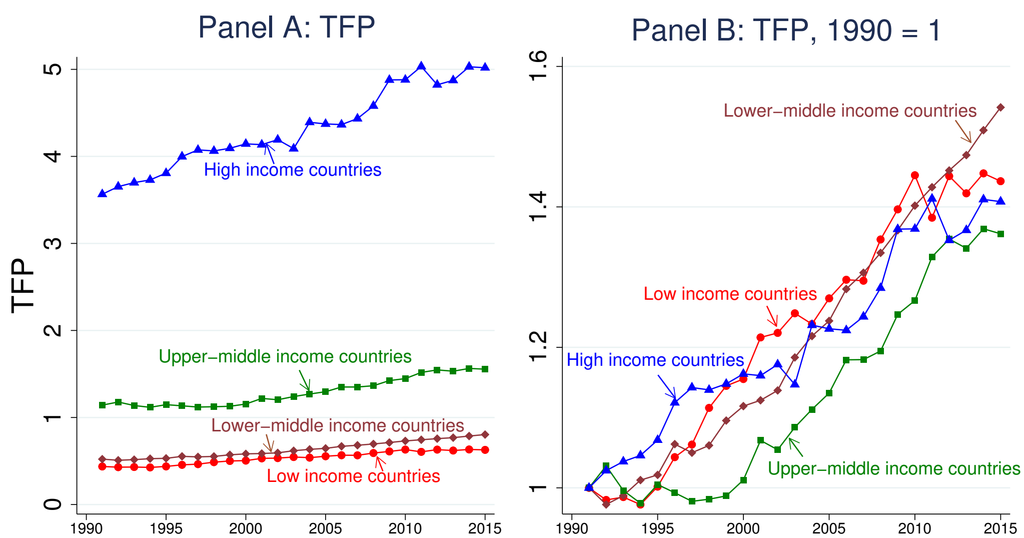
[4]Herrendorf et al. (2015) examine structural transformation in the postwar United States by estimating Cobb-Douglas production functions for the agriculture industry. Other studies assuming a Cobb-Douglas production includes Macours and Swinnen (2000), Gollin and Rogerson (2014), and Craig et al. (1997).

[5]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.

[6]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.

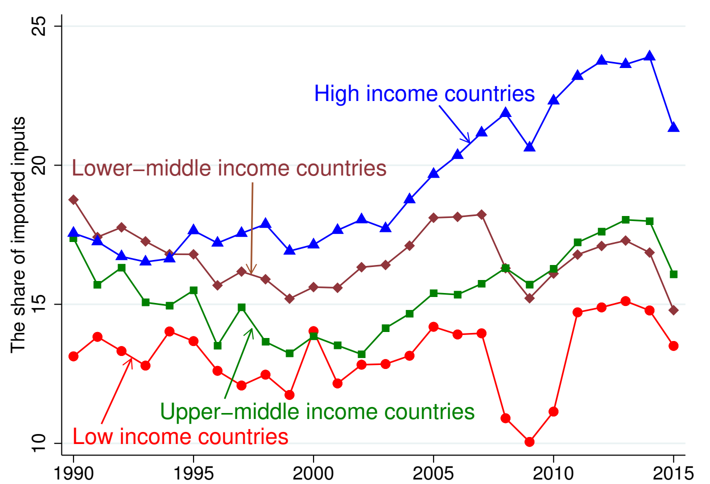
[7]See Appendix B for more details on data. See Appendix C.1 for calculated factor shares.

**Figure 1: 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.

**Figure 2: Share of Imported Inputs by Income-Level of Countries, 1990-2015**

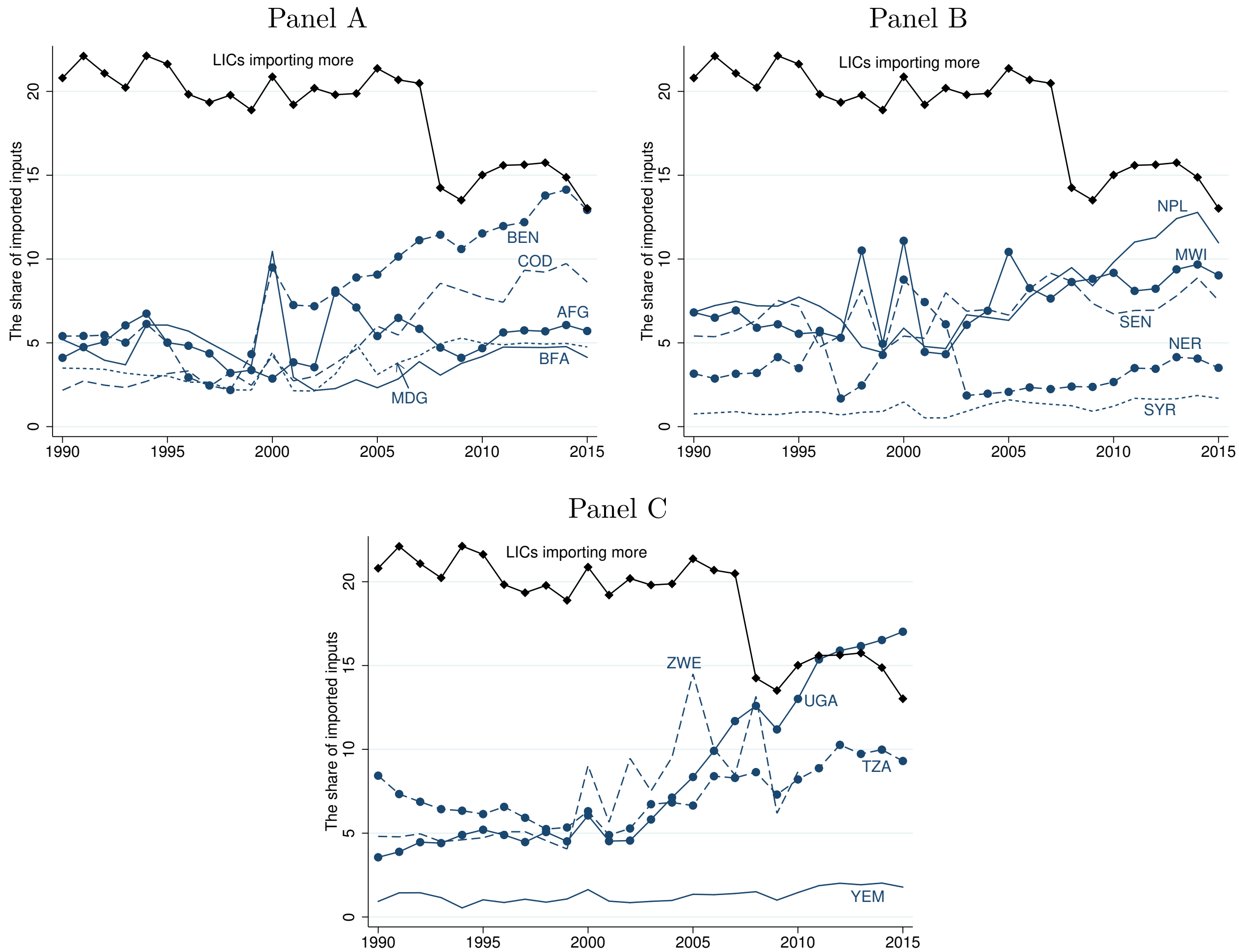



*Notes*: The figure shows simple averages of the share of imported inputs to total inputs for the four groups of countries. The authors' calculation based on the data from EORA (Lenzen et al., 2012; Lenzen et al., 2013).

We further break down the sample of 28 LICs in three panels in Figure 3. We divide the LICs into two groups, ones using higher shares of imported inputs and others using lower shares of imported inputs by using the 50th percentile of the distribution of the share of imported inputs to total input usage in the beginning of the sample period 1991.[8] One exceptional country in LICs is Ethiopia where its share of

[8]The data on the share of imported inputs in total input purchase are available since 1990. However, the data on TFP are available since 1991 and we have TFP growth rates since 1992. Therefore, our regressions are based on the data between 1992 and 2015. For this reason, we chose 1991 as our benchmark year to define dummy variables for lower and higher shares of imported inputs.

**Figure 3: Share of Imported Inputs in LICs, 1990-2015**




*Notes*: The figure shows the share of imported inputs to total input usage in the agricultural sector. The sample of LICs is divided into based on the median value in 1990. The average value of LICs importing more inputs (above median) is described by the dark line with square symbols. Individual countries' import shares are shown by the navy lines. The authors' calculation based on the data from EORA (Lenzen et al., 2012; Lenzen et al., 2013).

imported inputs in the beginning of the period is very low but it suddenly increases in 1993 and becomes even greater than the average share of LICs importing more inputs. Therefore, we include Ethiopia in the group of LICs using higher share of imported inputs.

Panel A of Figure 3 shows the average share imported inputs of LICs using higher shares of imported inputs and five countries included in the group of LICs importing lower shares of inputs, Afghanistan (AFG), Benin (BEN), Burkina Faso (BFA), Dem. Rep. of Congo (COD), and Madagascar (MDG). Panel B shows other five countries in the group of LICs importing less, Malawi (MWI), Niger (NER), Nepal (NPL), Senegal (SEN), and Syria (SYR). Lastly, Panel C describes the share of imported inputs in Uganda (UGA), Syria (SYR), Tanzania (TZA), and Zimbabwe (ZWE).[9] These three graphs show that countries included in the group of LICs with lower shares of imported inputs indeed have low shares — the shares of imported inputs are 10% of total input usage for most of these countries — and the shares

[9]Zimbabwe is not included in regressions in the later section because it does not have the data on agricultural TFP.

remain low throughout the sample period.[10]

Data on weather variables, temperatures and rainfalls come from the *Climate Change Knowledge Portal* of World Bank (2018). Table 1 shows summary statistics of variables used in regressions based on our baseline sample, 3,213 observations. We use three different dependent variables, value-added growth rates, gross output growth rates, and GDP growth rates, for robustness checks and these variables have different sample sizes. Our baseline sample exclude outliers of TFP growth rates, which are defined as top 0.5% and bottom 0.5% of TFP growth rates. Outliers of the other dependent variables, defined using the same thresholds, are also excluded from regressions.

**Table 1: Summary Statistics**

| | Obs. | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| *Dependent variables* | | | | | |
| TFP growth rates, % | 3,213 | 2.24 | 9.22 | -36.43 | 48.29 |
| Value-added growth rates, % | 4,020 | 2.21 | 8.71 | -33.54 | 46.62 |
| Gross output growth rates, % | 3,052 | 2.05 | 8.34 | -31.86 | 53.33 |
| GDP growth rates, % | 4,016 | 3.56 | 5.01 | -23.98 | 29.70 |
| *Explanatory variables* | | | | | |
| Imported inputs/Total inputs×100, % | 3,213 | 15.77 | 14.35 | 0.52 | 94.07 |
| Capital-to-labor ratio (thousand USD per worker) | 3,213 | 26.15 | 53.45 | 0.02 | 561.62 |
| Taxes/Value-added×100, % | 3,213 | 4.29 | 5.64 | 0.00 | 61.59 |
| Subsidies/Value-added×100, % | 3,213 | 4.27 | 9.72 | 0.00 | 54.84 |
| *Climate variables* | | | | | |
| Average temperature in degree Celsius | 3,213 | 18.89 | 8.27 | -7.02 | 29.75 |
| Average monthly rainfalls in 100 mm | 3,213 | 0.93 | 0.67 | 0.01 | 3.16 |
| Yearly change in average temperature | 3,213 | 0.03 | 0.55 | -2.48 | 2.93 |
| Yearly change in average monthly rainfalls | 3,213 | 0.00 | 0.20 | -1.35 | 1.99 |

*Notes:* The table shows summary statistics on variables used in regressions. The sample is restricted to observations that are used in baseline regressions. The dependent variables used in robustness checks, value-added growth rates, gross output growth rates, and GDP growth rates have different sample sizes and these different sample sizes are applied to regressions using these variables dependent variables.

## 3 Possible Theoretical Mechanisms

This section presents a simple theoretical model helps clarify how imported inputs and weather shocks interact to affect TFP growth rates. We start from the agricultural production function in Section 2, $Y_{it} = A_{it}(K_{it})^{\alpha^K_{it}}(L_{it})^{\alpha^L_{it}}(T_{it})^{\alpha^T_{it}}$, where agricultural TFP, $A_{it}$, is now described as a function of local

[10]There are many reasons why the share of imported inputs differs across countries. For example, LICs tend to impose higher tariffs than other countries. The average tariff rate applied by LICs in 2005 is 12% while it is 9% and 4% in middle-income and high-income countries, respectively, according to the World Development Indicators (World Bank, 2018). Furthermore, the data from the Doing Business Database (World Bank, 2019) show that non-tariff barriers, including legal procedures and transport infrastructure, tend to be higher in LICs — the average costs to import per container is about 5,000 USD in LICs while they are 3,000 USD and 1,400 USD in middle-income and high-income countries, respectively. There would be many other country-specific costs associated with costs to import. All of these are associated with cross-country differences in propensities to import inputs. However, we do not seek to understand the factors determining the share of imported inputs because it is beyond the scope of the paper.

temperatures $Temp_{it}$, local rainfalls $Rain_{it}$, and quality of intermediate inputs $\phi_{it}$:

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

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

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

where the weights are the share of domestic inputs to the total value of inputs, $\omega_{it}^D = I_{it}^D/(I_{it}^D + I_{it}^{Im})$ and $\omega_{it}^{Im} = I_{it}^{Im}/(I_{it}^D + I_{it}^{Im})$ 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 $\frac{\partial^2 A_{it}}{\partial Temp_{it} \partial \omega_{it}^{Im}} > 0$ and $\frac{\partial^2 A_{it}}{\partial Rain_{it} \partial \omega_{it}^{Im}} < 0$. 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 $Temp_{it}$:

$$\frac{dA_{it}}{dTemp_{it}} = \frac{\partial A_{it}}{\partial Temp_{it}} + \frac{\partial A_{it}}{\partial \phi_{it}}(1 - \omega_{it}^{Im})\frac{\partial \phi_{it}^D}{\partial Temp_{it}} + \frac{\partial A_{it}}{\partial \phi_{it}}\omega_{it}^{Im}\frac{\partial \phi_{it}^{Im}}{\partial Temp_{it}},$$

where we plugged $\omega_{it}^D = 1 - \omega_{it}^{Im}$. 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, $\partial \phi_{it}^{Im}/\partial Temp_{it} = 0$, the previous equation becomes:

$$\frac{dA_{it}}{dTemp_{it}} = \frac{\partial A_{it}}{\partial Temp_{it}} + \frac{\partial A_{it}}{\partial \phi_{it}}(1 - \omega_{it}^{Im})\frac{\partial \phi_{it}^D}{\partial Temp_{it}},$$

By differentiating this equation with respect to $\omega_{it}^{Im}$, we obtain

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

where we assume $\partial^2 A/(\phi_{it} \partial \omega_{it}^{Im}) = 0$.[11] Because higher temperatures reduce agricultural TFP, we have $\partial A_{it}/Temp_{it} < 0$, and a greater share of imported inputs reduces the negative temperature effects, we argue $\frac{d^2 A_{it}}{dTemp_{it} d\omega_{it}^{Im}} > 0$. This positive cross derivative comes from three effects. First, a greater share of imported inputs directly reduces the negative temperature effects, $\frac{\partial^2 A_{it}}{\partial Temp_{it} \partial \omega_{it}^{Im}} > 0$. Better production technologies embedded in imported inputs increase productivity, making agricultural production technology 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

[11]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 $\phi_{it}$.

temperature shocks. As a result, this de-localization of inputs reduces the sensitivity of agricultural TFP to weather shocks, reflected in the second term: $-\frac{\partial A_{it}}{\partial \phi_{it}} \frac{\partial \phi_{it}^D}{\partial Temp_{it}}$, which is positive because $\frac{\partial A_{it}}{\partial \phi_{it}} > 0$ and $\frac{\partial \phi_{it}^D}{\partial Temp_{it}} < 0$. 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 $\frac{\partial^2 \phi_{it}^D}{\partial Temp_{it} \partial \phi_{it}^{Im}} > 0$ because $\frac{\partial A_{it}}{\partial \phi_{it}} > 0$. 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.[12] We refer to this as synergies between imported inputs and domestic inputs.

# 4 Regression Analysis

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 estimating regressions. First, we outline the regression model. Second, baseline results are presented and discussed. Third, we conduct additional analyses to show that the results are robust.

## 4.1 Regression Model

Our regressions use the data from 161 countries and allow countries to respond to weather shocks differently. We do so by making four groups of countries, (1) LICs importing lower share of imported inputs, (2) LICs importing higher share of imported inputs, (3) non-LICs importing lower share of imported inputs, and (4) non-LICs importing higher share of imported inputs. Dummy variables for the first three groups are denoted as $D_{LIC}^L$, $D_{LIC}^H$, and $D_{NonLIC}^L$, respectively. The forth group of countries is chosen as benchmark. Using these dummies, we estimate the following equation:

$$
\begin{aligned}
g_{it}^{TFP} = {} & \beta_1 \Delta Temp_{it} + \beta_{NonLIC}^L (D_{NonLIC,i}^L \Delta Temp_{it}) + \sum_{g \in \{H,L\}} \beta_{LIC}^g (D_{LIC,i}^g \Delta Temp_{it}) \\
& + \gamma_1 \Delta Rain_{it} + \gamma_{NonLIC}^L (D_{NonLIC,i}^L \Delta Rain_{it}) + \sum_{g \in \{H,L\}} \gamma_{LIC}^g (D_{LIC,i}^g \Delta Rain_{it}) \\
& + \mathbf{X}_{it} \boldsymbol{\beta} + u_{it},
\end{aligned} \tag{2}
$$

where $g_{it}^{TFP} = 100 \times (TFP_{it} - TFP_{it-1})/TFP_{it-1}$ denotes the TFP growth rate; $\Delta Temp_{it} = Temp_{it} - Temp_{it-1}$ indicates year-to-year changes in temperatures, and $\Delta Rain_{it}$ is year-to-year changes in rainfalls. $D_{NonLIC,i}^L$ indicates the dummy variable taking unity if country $i$ is a non-LIC and the share of imported inputs is less than the 25th percentile among non-LICs in the beginning of the sample period, 1991. $D_{LIC,i}^L$

[12] This effect is present in a model where all final good varieties are used as intermediate inputs. 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).

and $D^H_{LIC,i}$ are the dummy variables taking unity if country $i$ is a LIC and the share of imported inputs are less than or greater than the 50th percentile among LICs, respectively. $\mathbf{X}_{it}$ is a vector of variables including a constant term, interaction terms between year dummies and $D^L_{NonLIC,i}$, $D^L_{LIC,i}$, and $D^H_{LIC,i}$, respectively. $u_{it}$ denotes an error term. The data on TFP are available since 1991 and our dependent variable is the TFP growth rate. As a result, the sample starts 1992 and the end year is 2015.

Regarding the temperature effects, because we omit interaction term with the dummy taking one for non-LICs using a higher share of imported inputs which we call the benchmark group, the coefficient for $Temp_{it}$, $\beta_1$, measures the effect of temperatures on agricultural TFP in this group of countries. A coefficient of an interaction term quantifies the difference between the temperature effect of the benchmark group and the group of countries identified by the dummy variable. A linear combination of $\beta_1$ and a coefficient from an interaction term measures the temperature effect for that group. For example, $\beta_1 + \beta^L_{NonLIC}$, is the effect of temperatures on agricultural TFP in non-LICs using a lower share of imported inputs. The same interpretation applies to the rainfall coefficients, $\gamma$'s. We also run regressions including an interaction term between $\Delta Temp_{it}$ and a hot country dummy where hot countries are defined as those with temperature levels greater than median in the beginning of the sample, and an interaction term between $\Delta Temp_{it}$ and a agriculture-based country dummy where such countries are defined as those agricultural value-added shares are greater than the 75th percentile among the sample countries in the beginning of the sample.

**Table 2: Unit Root Tests and Cointegration Tests**

Panel A: Unit Root Tests

| | TFP growth rate | $\Delta Temp$ | $\Delta Rain$ |
|---|---|---|---|
| All countries | -30.16* | -34.31* | -35.55* |
| LICs | -13.10* | -14.48* | -15.11* |
| LICs with lower shares of imported inputs | -9.37* | -10.52* | -10.70* |

Panel B: Cointegration Tests for TFP growth rate, $\Delta Temp$, and $\Delta Rain$

| | 1 Lag | 2 Lags | 3 Lags |
|---|---|---|---|
| All countries | -31.76* | -11.86* | -10.13* |
| LICs | -21.21* | -7.00* | -6.91* |
| LICs with lower shares of imported inputs | -15.57* | -5.31* | -3.78* |

*Notes:* Panel A reports Z-t-tilde-bar statistics from Im-Pesaran-Shin unit-root tests for three variables, TFP growth rates, $\Delta Temp$, and $\Delta Rain$, respectively. The null hypothesis of the test is all panels contain unit roots. Panel B shows Augmented Dickey-Fuller t-statistics for a combination of the three variables, with 1 lag, 2 lags, and 3 lags, respectively. The null hypothesis of the test is that there is no cointegration. * indicates statistical significance at the 1% level. These tests require a dataset to be strongly balanced. As a result, these tests are based on 135 countries for TFP growth rates and 115 countries for $\Delta Temp$ and $\Delta Rain$.

Before presenting regression results, we show that the variables used in regressions are stationary. Panel A of Table 2 shows results from panel unit root tests for each of our three main variables, TFP growth rates, $\Delta Temp$, and $\Delta Rain$. The tests require data to be strongly balanced. Therefore, these are based on 135 countries for TFP growth rates and 115 countries for $\Delta Temp$ and $\Delta Rain$. We report results from three sets of observations, all countries, LICs, and LICs with lower shares of imported inputs, for each of the three variables. For all of the nine tests, we reject the null hypothesis that all panels contain unit roots at the 1% significance level. Furthermore, we conduct cointegration tests for a set of the three variables, TFP growth rates, $\Delta Temp$, and $\Delta Rain$. Panel B presents results from nine tests for three sets of observations, all countries, LICs, and LICs with lower shares of imported inputs, and for three cases, with 1 lag, 2 lags, and 3 lags, respectively. All of these tests reject the null hypothesis that there is no cointegration. These results show that our dataset is stationary and there is no issue arising from serial correlation and other time-series characteristics of data.

### 4.2 Baseline Results

Table 3 presents estimation results. All regressions in the table are based on 3,213 observations from 140 countries. In addition to estimated coefficients, we report robust standard errors clustered at the country-level in parentheses and robust standard errors clustered in two-ways, at the country-level and region-year level, in brackets.[13] The bottom of the table report linear combinations of estimated coefficients showing temperature effects in each group of countries. While all regressions include rainfall variables in a symmetric way as for temperature variables, we do not report these coefficients because our focus is on the temperature effects and rainfalls are added as controls.

Column (1) shows that a 1°C increase in temperatures reduces the TFP growth rate by 0.84 percent in the benchmark group, non-LICs with a higher share of imported inputs. The coefficient is significant at the 5% level with the standard error in parentheses, clustered at the country-level, but it is insignificant with standard error in bracket, clustered at the region-year level. The interaction terms for non-LICs with a lower share of imported inputs and LICs with a higher share of imported inputs have insignificant coefficients under either standard errors, meaning that these groups do not have significantly different temperature effects. In contrast, the interaction term for LICs with a lower share of imported inputs has a negative sign and statistically significant at the 1% level in either standard error. The point estimate is -3.34 and its linear combination with $\hat{\beta}_1$ is -4.18. This means that a 1°C increase in temperatures reduces the TFP growth rate by 4.18% in LICs with a lower share imported inputs.

Columns (2) and (3) introduce the interaction term between temperatures and the hot country dummy, $D^{Hot}$, and the agriculture-based country dummy, $D^{Ag}$, respectively.[14] Column (4) introduces both of these interaction terms. These columns show that, in LICs with a lower share of imported inputs, a 1°C increase in temperatures reduces the TFP growth rate by 4.23%, 5.50%, and 5.36%, respectively. The estimation results are similar to column (1). Column (4) further adds the capital-to-labor ratio, the tax-to-value added ratio, and the subsidy-to-value added ratio. Again, the result is qualitatively remain similar as previous columns. Controlling for all of these variables, the temperature effect on agricultural TFP in LICs with a lower share of imported inputs becomes -5.37 and significant at the 1% level in either standard error.

Figure 4 plots temperature effects reported in Table 3. It shows that a higher temperature has the greatest negative effect on the TFP growth rate in LICs with a lower share of imported inputs (see the left panel). Looking at the temperature effects obtained by controlling for other determinants of TFP shown in the right part of each panel, the temperature effects become smaller in LICs with a higher share

[13] Dell et al. (2012) and other studies on weather shocks employ the same two-way clustering standard errors by Cameron et al. (2011).

[14] The hot country dummy helps to address non-linearity of the temperature effects documented in prior studies (e.g., Schlenker and Roberts, 2009; Burke et al., 2015).

**Table 3: Baseline Results**

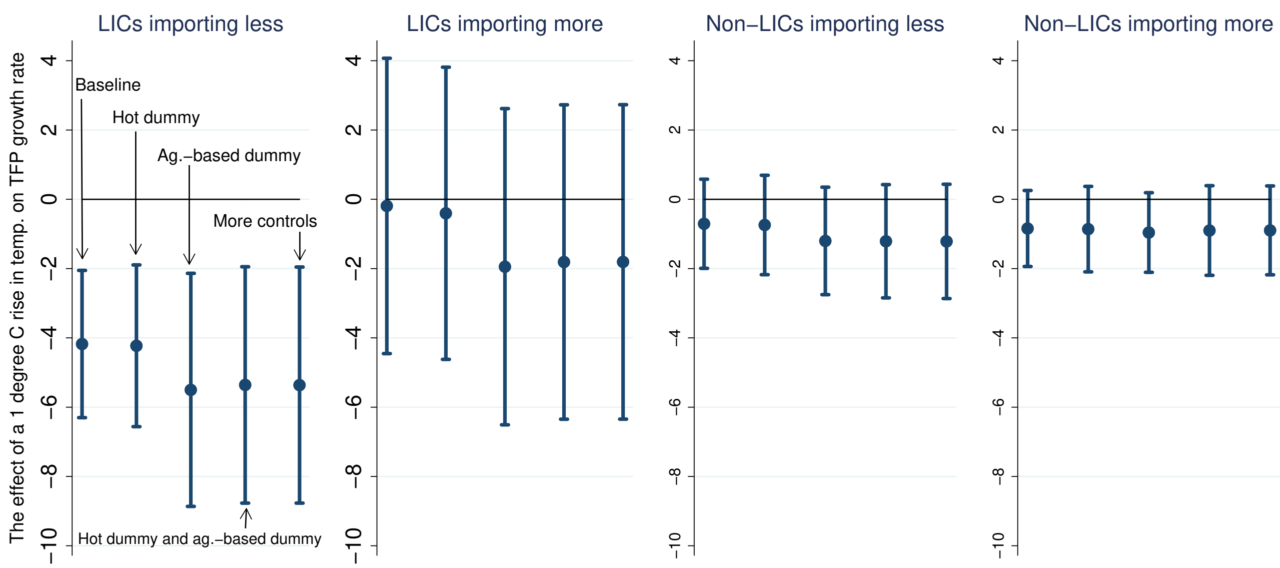
Dep. Var. $= 100\times(TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\Delta Temp$, $\beta_1$ | -0.843 | -0.861 | -0.959 | -0.901 | -0.896 |
| | (0.414)** | (0.454)* | (0.398)** | (0.437)** | (0.438)** |
| | [0.560] | [0.629] | [0.586] | [0.660] | [0.648] |
| $D^L_{NonLIC} \times \Delta Temp$, $\beta^L_{NonLIC}$ | 0.136 | 0.120 | -0.242 | -0.309 | -0.311 |
| | (0.708) | (0.716) | (0.788) | (0.814) | (0.816) |
| | [0.800] | [0.835] | [0.909] | [0.936] | [0.935] |
| $D^H_{LIC} \times \Delta Temp$, $\beta^H_{LIC}$ | 0.651 | 0.456 | -0.987 | -0.909 | -0.942 |
| | (2.064) | (2.057) | (2.285) | (2.249) | (2.252) |
| | [2.208] | [2.154] | [2.336] | [2.310] | [2.313] |
| $D^L_{LIC} \times \Delta Temp$, $\beta^L_{LIC}$ | -3.335 | -3.368 | -4.541 | -4.457 | -4.473 |
| | (0.996)*** | (1.090)*** | (1.528)*** | (1.532)*** | (1.534)*** |
| | [1.097]*** | [1.145]*** | [1.643]*** | [1.633]*** | [1.639]*** |
| $D^{Hot} \times \Delta Temp$, $\beta_2$ | | 0.263 | | -0.188 | -0.175 |
| | | (0.958) | | (1.005) | (1.005) |
| | | [1.072] | | [1.127] | [1.122] |
| $D^{Ag} \times \Delta Temp$, $\beta_3$ | | | 1.970 | 1.980 | 1.971 |
| | | | (1.253) | (1.282) | (1.284) |
| | | | [1.316] | [1.320] | [1.324] |
| Additional controls | | | | | Yes |
| $R$-squared | 0.034 | 0.044 | 0.041 | 0.052 | 0.053 |
| Linear combination of coefficients | | | | | |
| $\beta_1 + \beta^L_{NonLIC}$ | -0.706 | -0.741 | -1.201 | -1.210 | -1.216 |
| | (0.575) | (0.585) | (0.691)* | (0.696)* | (0.696)* |
| | [0.656] | [0.732] | [0.791] | [0.834] | [0.840] |
| $\beta_1 + \beta^H_{LIC}$ | -0.191 | -0.405 | -1.946 | -1.810 | -1.807 |
| | (2.022) | (2.041) | (2.254) | (2.227) | (2.229) |
| | [2.175] | [2.151] | [2.328] | [2.315] | [2.321] |
| $\beta_1 + \beta^L_{LIC}$ | -4.177 | -4.228 | -5.501 | -5.358 | -5.369 |
| | (0.906)*** | (1.065)*** | (1.481)*** | (1.515)*** | (1.516)*** |
| | [1.084]*** | [1.191]*** | [1.716]*** | [1.740]*** | [1.738]*** |

*Notes:* All regressions are based on 3,213 observations from 161 countries. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. $D^{Hot}$ indicates the hot country dummy taking unity if the temperature level is greater than medium in the beginning of the sample period, 1991. $D^{Ag}$ denotes the agriculture-based country dummy taking unity if the agricultural value added is greater than the 75th percentile in 1991. In the bottom of the table, $\beta_1 + \beta^L_{NonLIC}$ measures the effect of a 1°C increase in temperatures on agricultural TFP growth rates in non-LICs importing lower shares of imported inputs. $\beta_1 + \beta^H_{LIC}$ and $\beta_1 + \beta^L_{LIC}$ quantify the same effect in LICs with higher and lower shares of imported inputs, respectively.

of imported inputs. The temperature effects are even smaller in non-LICs with a lower share of imported inputs. Lastly, the effects are the smallest in non-LICs with a higher share of imported inputs. These results are consistent with the previous studies showing that economic development makes a country less sensitive to climate (e.g., Mendelsohn et al., 2001; Mendelsohn et al., 2006; and Dell et al., 2012). Furthermore, we find new evidence that countries employing lower shares of imported inputs are more severely affected by rising temperatures.

**Figure 4:** Plotting the Baseline Results




*Notes*: The figure shows the effect of a 1°C rise on the TFP growth rate with the corresponding 95 percent confidence interval shown in Table 3. Standard errors are clustered in two ways, at the country-level and the region-year level. The left panel shows the results for LICs with a lower share of imported inputs and the next panel shows the ones for LICs with a higher share of imported inputs. The last two panels are also organized in the same way.

### 4.3 Robustness Checks

This section conducts a number of robustness checks. We now focus only on LICs because the purpose of this section is to show that, among LICs, only countries employing lower share of imported inputs are more severely affected by rising temperatures. Our considerations include sub-samples of the baseline sample, different ways to construct input dummies, alternative thresholds to define countries employing a lower share of imported inputs, lag models, possible correlation of input status with other characteristics of countries, and other dependent variables.

#### 4.3.1 Different Samples and Different Input Dummies

We first show that baseline results are robust to a wide range of different sub-samples and specification. Table 4 summarizes results from seven regressions showing robustness. Panels A and B are based on the specifications in columns (1) and (5) of Table 3, respectively. Column (1) of Table 4 cuts observations with top 1% and bottom 1% temperature changes among observations from LICs in the sample period. Column (2) drops top 1% and bottom 1% rainfall changes. Columns (3) cuts both extreme temperature and rainfall changes dropped in columns (1) and (2). These address outliers of weather variables.

**Table 4: Different Samples and Different Input Dummies**

Dependent Variable = $100\times(TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$

| | Drop extreme $\Delta Temp$ | Drop extreme $\Delta Rain$ | Drop extreme $\Delta Temp$ & $\Delta Rain$ | Drop oil produ- -cers | Drop the periods of commodity price hikes | Input dummy based on the mean 1990-94 | Input dummy based on the data in 2000 |
|---|---|---|---|---|---|---|---|
| | | | | *Panel A: Without Controls* | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\beta_1 + \beta^H_{LIC}$ | -1.091 | -0.550 | -1.567 | -0.006 | -1.547 | -0.302 | -1.664 |
| | (2.014) | (2.132) | (2.143) | (1.949) | (1.874) | (2.307) | (2.767) |
| | [2.180] | [2.303] | [2.329] | [2.147] | [1.921] | [2.466] | [3.059] |
| $\beta_1 + \beta^L_{LIC}$ | -6.206 | -4.092 | -6.120 | -3.108 | -2.211 | -4.004 | -2.846 |
| | (1.469)*** | (0.906)*** | (1.487)*** | (0.945)*** | (0.843)*** | (0.908)*** | (1.111)** |
| | [1.499]*** | [1.088]*** | [1.516]*** | [1.270]** | [0.987]** | [1.035]*** | [1.235]** |
| | | | | *Panel B: With Controls* | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\beta_1 + \beta^H_{LIC}$ | -2.942 | -2.015 | -3.156 | -1.089 | -3.475 | -1.939 | -3.530 |
| | (2.469) | (2.369) | (2.615) | (2.115) | (2.061)* | (2.530) | (2.938) |
| | [2.508] | [2.444] | [2.650] | [2.346] | [2.155] | [2.592] | [3.154] |
| $\beta_1 + \beta^L_{LIC}$ | -7.912 | -5.303 | -7.580 | -4.162 | -3.701 | -5.480 | -4.129 |
| | (1.886)*** | (1.407)*** | (1.862)*** | (1.480)*** | (1.286)*** | (1.423)*** | (1.567)*** |
| | [1.971]*** | [1.636]*** | [1.954]*** | [1.870]** | [1.567]** | [1.658]*** | [1.691]** |
| Observations | 3,098 | 3,095 | 2,981 | 2,637 | 2,402 | 3,213 | 3,213 |

*Notes:* $\beta_1 + \beta^H_{LIC}$ measures the effect of a 1°C increase in temperatures on agricultural TFP growth rates in LICs with higher shares of imported inputs. $\beta_1 + \beta^L_{LIC}$ quantifies the same effect in LICs with lower shares of imported inputs. All regressions employ the specification reported in column (1) of Table 3. Observations come from 161 countries in all columns. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In addition, we exclude samples that may not be suited for analyses. Column (4) drops oil producers where oil producers are defined as countries with oil rent-to-GDP ratio is greater than the 90th percentile of the distribution in 1991 (16%). Column (5) cuts the period of commodity price hikes where it is 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. We also consider the data we use to construct the input dummies. In column (4), the lower share imported input dummy is constructed based on the average value of (Imported inputs)/(Total inputs) during 1990-1994, with the 50th percentile cutoff. In column (5), the dummy is generated based on the data on (Imported inputs)/(Total inputs) in 2000.

All of these considerations lead to results similar to our baseline results. Panel A shows that, by employing the specification in column (1) of Table 3, a 1°C increase in temperatures reduces the TFP growth rate by 2.2-6.2 percentage points in LICs employing lower shares of imported inputs. Panel B includes more controls by employing the same set of variables as in column (5) of Table 3 and show that the same increase in temperatures reduces the TFP growth rate by 3.7-7.9 percentage points in the countries. See Table A3 in Appendix for an associated regression table.

#### 4.3.2 Different Thresholds to Define the Dummy Variable for Imported Inputs

The dummy variables for countries importing less imported inputs $D^L$ and more imported inputs $D^H$ are defined by dividing using the 50th percentile cutoff. We show that our results are robust to slight changes in this cutoff. First, we consider five different thresholds, 45th, 40th, 35th, 30th, and 25th of distribution of (imported inputs)/(total inputs) in 1991. While our baseline model define 13 LICs as countries with lower shares of imported inputs, each of those alternative thresholds include 12, 10, 9, 7, and 6 countries as countries employing lower share of imported inputs. Panel A of Table 5 shows point estimates of the temperature effect in the two groups of LICs with these alternative thresholds. We use the same set of controls as column (5) of Table 3. The results show that these different thresholds lead to similar results our baseline results shown in the far left of the panels. A 1°C increase in temperatures reduces the agricultural TFP growth rate by 5.6-6.0 percentage points in either thresholds.

We also consider five additional different thresholds by increasing the number of countries included in the group of lower shares of imported inputs. Panel B describes results. In addition to the benchmark with the 50th percentile threshold reported in the far left, 55th, 60th, 65th, 70th, and 75th percentile thresholds are employed to divide LICs into two groups. With these thresholds, 13, 14, 16, 17, 19, and 20 countries are included in the group of lower shares of imported inputs, respectively. Panel B shows that our results remain almost unchanged for different thresholds. A 1°C increase in temperatures reduces the agricultural TFP growth rate by 4.0-5.6 percentage points in either thresholds. See Table A4 in Appendix for an associated regression table.

#### 4.3.3 Lag model

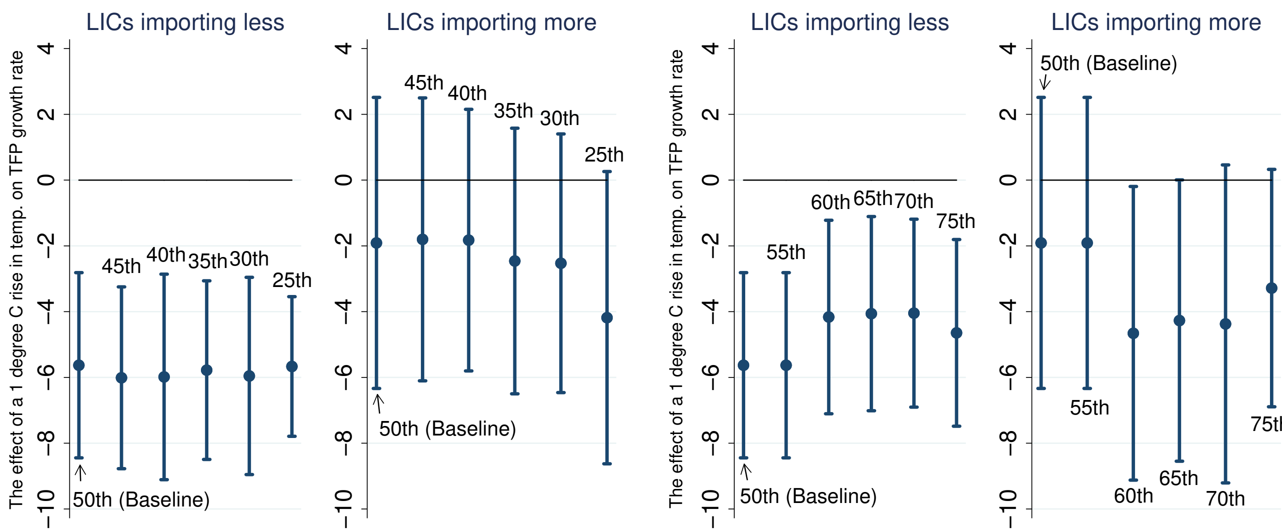
Our baseline model includes year-to-year changes in temperatures and rainfalls as explanatory variables but the estimates may depends on the initial level of temperatures in the previous year. In order to accommodate this consideration, we estimate a more flexible model with lagged levels of temperatures and rainfalls, taking dynamic impact of climate change into consideration. We estimate four additional regressions including 1 lag, 3 lags, 5 lags, and 10 lags, respectively. All regressions are based on 3,213 observations from 140 countries. Although we take lags, we do not use the number of observations because climate variables are available since 1980 and the sample period is 1991-2015. We use the same set of controls as column (5) of Table 3.

Figure 6 shows results. The point estimates in the far left location shows the baseline result with no lag as a reference. The next four point estimates come from lag models. We report linear combinations of all temperature coefficients including contemporaneous changes and lagged level variables, $\beta_1 + \sum_{s=0}^{T} \beta^g_{LIC,t-s}$ for $g = L, H$ and $T = 1, 3, 5,$ and 10. It shows that our results with lags are similar to the baseline results, meaning that our results are robust to inclusion of lagged level of temperatures. A 1°C increase in temperatures reduces the agricultural TFP growth rate by 5.6-5.8 percentage points in either model.

**Figure 5:** Different Thresholds to Divide the LIC Sample

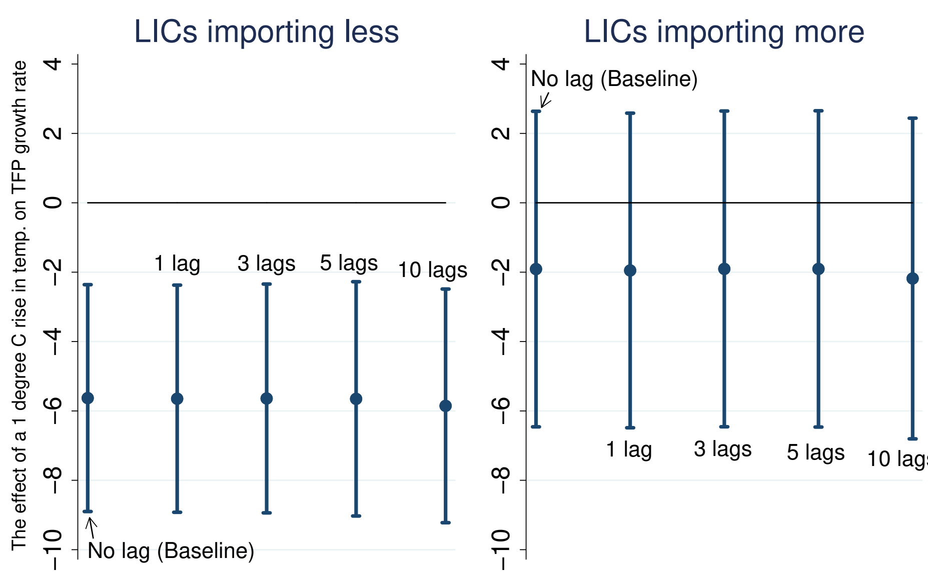
Panel A: Reducing the Thresholds

Panel B: Increasing the Thresholds




*Notes*: The figure shows the impact of a 1°C increase in temperatures on agricultural TFP growth rate with the 95 percent confidence intervals with two-way clustering robust standard errors. Panel A shows six different estimation results for the benchmark and five additional cases where an increasing number of LICs are included in the group of lower shares of imported inputs. Panel B shows five additional cases where a smaller number of LICs are included in the group of lower shares of imported inputs. All regressions are based on 3,213 observations from 161 countries. See Table A3 in Appendix for an associated regression table.

**Figure 6:** Lag Model




*Notes*: The figure shows the impact of a 1°C increase in temperatures on agricultural TFP growth rate with the 95 percent confidence intervals with two-way clustering robust standard errors. Each estimates include a different number of lagged temperature and rainfall variables. All regressions are based on 3,213 observations from 161 countries. Although we take lags, we do not use the number of observations because climate variables are available since 1980 and the sample period is 1991-2015. See Table A4 in Appendix for an associated table.

#### 4.3.4 Possible Correlation between Import Dummy and Other Characteristics

The next possible critique we address is potential correlation between input dummies and other characteristics of countries. For example, a possible story collapsing our main result is that countries employing lower shares of imported inputs tend to import agricultural goods more, increasing competition in the market, making it vulnerable to weather shocks.

In order to examine if this concern is valid, we estimate the following equation:

$$\begin{aligned} g_{it}^{TFP} \;=\;& \beta_1 \Delta Temp_{it} + \beta_{NonLIC}^{L}(D_{NonLIC,i}^{L}\Delta Temp_{it}) + \sum_{g\in\{H,L\}} \beta_{LIC}^{g}(D_{LIC,i}^{g}\Delta Temp_{it}) \\ & + \gamma_1 \Delta Rain_{it} + \gamma_{NonLIC}^{L}(D_{NonLIC,i}^{L}\Delta Rain_{it}) + \sum_{g\in\{H,L\}} \gamma_{LIC}^{g}(D_{LIC,i}^{g}\Delta Rain_{it}) \qquad (3) \\ & + \beta_{LIC}^{Im}(D_{LIC,i}^{Im}\Delta Temp_{it}) + \gamma_{LIC}^{Im}(D_{LIC,i}^{Im}\Delta Rain_{it}) + \mathbf{X}_{it}\boldsymbol{\beta} + e_{it}, \end{aligned}$$

where the interaction terms between climate variables and $D_{LIC,i}^{Im}$ are added to equation (2). $D_{LIC,i}^{Im}$ denotes the dummy variable taking one if the country is a LIC and its aggregate imports-to-GDP ratio is less than the 50th percentile among LICs in 1991. $\beta_{LIC}^{Im}$, and $\gamma_{LIC}^{Im}$ are parameters to be estimated; $e_{it}$ indicates an error term.

The first three columns of Table 5 show the result with the dummy $D_{LIC,i}^{Im}$. For simplicity, we report only linear combinations of coefficients capturing the temperature effects on the agricultural TFP growth rate. Column (1) introduces climate variables and the interaction terms between $D_{LIC,i}^{Im}$ only, without other dummies in the baseline model. It shows that LICs importing less are negatively affected by higher temperatures but the effect is insignificant. Column (2) introduces the dummies included in the baseline model, showing that the temperature effects on LICs with lower shares of imported inputs remain significant even after inclusion of interaction terms with $D_{LIC,i}^{Im}$.[15] Column (3) employs specification shown in column (5) of Table 3 and includes more controls. The temperature effect on the group of countries still remain significant. These two columns, (2) and (3) show that, even after controlling for countries' aggregate imports, a 1°C rise in temperatures reduce the TFP growth rate by 4.7-5.4 percentage points in LICs with lower shares of imported inputs.

The second possible story we address is that 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 this is the case, our baseline results could be coming from countries' initial income levels, not the share of imported inputs. In order to address this, we introduce a dummy variable taking unity if the country's initial GDP per capita is less than the 50th percentile among LICs, $D_{LIC,i}^{GDPpc}$.[16] Columns (4)-(6) of Table 5 show results with the dummy variable. Column (4) shows that the agricultural TFP growth rates of relatively poorer LICs are negatively affected by higher temperature and the effect is significant. However, as shown in columns (5) and (6), the temperature effect on this group of countries turn to be insignificant once the set of baseline dummies are introduced. The impact on agricultural TFP on LICs with lower shares of imported input is significant in these columns, showing that the baseline results are robust to inclusion of $D_{LIC,i}^{GDPpc}$.

Third, a higher share of imported inputs may be related with countries' initial agricultural production

[15] The dummy variable $D_{LIC,i}^{Im}$ is based on the share of total imports in goods and services to GDP obtained from WDI.

[16] The dummy variable $D_{LIC,i}^{GDPpc}$ is based on GDP per capita (constant US dollars) retrieved from WDI.

**Table 5: Introducing Additional Interaction Terms**

Dep. Var. $= 100\times(TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$

| *Added* | Imports-to-GDP ratio | | | Initial income levels | | | Initial TFP levels | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\beta_1 + \beta_{LIC}^{Added}$ | -0.362 | 1.216 | 0.431 | -3.348 | -2.459 | -3.670 | -1.185 | 0.236 | -0.804 |
| | (1.730) | (2.422) | (2.757) | (1.233)*** | (2.126) | (2.530) | (3.126) | (3.053) | (3.277) |
| | [1.804] | [2.725] | [3.221] | [1.273]*** | [2.364] | [2.816] | [3.232] | [3.307] | [3.580] |
| $\beta_1 + \beta_{LIC}^{H}$ | | -1.055 | -1.924 | | 0.655 | -1.091 | | -0.640 | -2.062 |
| | | (2.510) | (2.795) | | (1.853) | (2.124) | | (1.360) | (1.845) |
| | | [2.761] | [2.994] | | [2.121] | [2.389] | | [1.584] | [2.006] |
| $\beta_1 + \beta_{LIC}^{L}$ | | -4.731 | -5.416 | | -2.887 | -3.953 | | -3.999 | -5.046 |
| | | (2.010)** | (2.350)** | | (1.344)** | (1.669)** | | (1.322)*** | (1.753)*** |
| | | [2.190]** | [2.534]** | | [1.704]* | [2.030]* | | [1.599]** | [1.972]** |
| Controls | | | Yes | | | Yes | | | Yes |
| $R$-squared | 0.016 | 0.040 | 0.058 | 0.022 | 0.037 | 0.056 | 0.019 | 0.035 | 0.053 |

*Notes:* $\beta_1 + \beta_{LIC}^{Added}$ measures the effect of a 1°C increase in temperatures on agricultural TFP growth rates in the group of countries defined by the *Added* variable in LICs. $\beta_1 + \beta_{LIC}^{H}$ and $\beta_1 + \beta_{LIC}^{L}$ quantify the same effect in LICs with higher and lower shares of imported inputs, respectively. All regressions are based on 3,213 observations from 161 countries. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

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 check if this is the case, we estimate equation (3) by replacing $D_{LIC,i}^{Im}$ with $D_{LIC,i}^{TFP}$, a dummy variable taking unity if the country's initial TFP level is less than the 50th percentile among the group of countries.[17] The last three columns of Table 5 describe results and point estimates in columns (8)-(9) are similar to the baseline results. These considerations show that our baseline results are robust to inclusion of additional dummies that may be correlated with the imported input dummies.

One may concern about multicollinearities between the dummy, $D_{LIC,i}^{L}$, and the dummies $D_{LIC,i}^{IM}$, $D_i^{GDPpc}$, and $D_{LIC,i}^{TFP}$, leading to an unreliable regression result. However, correlation between these dummies is low. Based on the sample of 30 LICs, $Corr(D_{LIC,i}^{L}, D_{LIC,i}^{LowIm}) = -0.05$, $Corr(D_{LIC,i}^{L}, D_{LIC,i}^{GDPpc}) = 0.30$, and, $Corr(D_{LIC,i}^{L}, D_{LIC,i}^{TFP}) = -0.03$. Therefore, there is no issue arising from multicollinearities between these dummies.

#### 4.3.5 Effects of Imported Inputs by Sector

Imported inputs include many different varieties such as seeds, fertilizers, pesticides, tractors, machinery, and transport equipment. We investigate imported inputs from which sectors matter the most in determining the effect of temperatures on TFP growth rates. We create ten different variables measuring the share of imported inputs to total input usage in ten different sectors by using the data from the EORA database. The share of sector $s$'s imported inputs to total purchases of sector $s$'s inputs in country $i$ in

[17] The dummy variable $D_{LIC,i}^{TFP}$ is based on our agricultural TFP estimates.

year $t$ is $\omega(s)^{Im}_{it} = I(s)^{D}_{it}/(I(s)^{D}_{it} + I(s)^{Im}_{it})$ where $I(s)^{D}_{it}$ denotes the value of sector $s$'s inputs imported from abroad and $I(s)^{D}_{it}$ indicates the value of the same sector's inputs produced domestically. Based on the distribution of $\omega(s)^{Im}_{it}$ in the beginning of the sample period, 1991, we make dummy variables taking unity if the share of imported inputs is less than the 50th percentile of the distribution, $D(s)^{L}_{LIC,i}$, and the one taking unity if the share is greater than the 50th percentile, $D(s)^{H}_{LIC,i}$, for each sector $s$. Then we estimate ten different regression by replacing input dummies in the regression specification in column (5) of Table 3 with these sectoral input dummies, respectively.

**Table 6: Effects of Imported Inputs by Sector**

Dep. Var. $= 100\times(TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$

| | Agri-culture (1) | Fish-ing (2) | Food and bev--erages (3) | Textiles and apparel (4) | Wood and paper (5) |
|---|---|---|---|---|---|
| $\beta_1 + \beta^{H}_{LIC}$ | -3.100 | -2.658 | -3.780 | -3.466 | -0.969 |
| | (1.751)* | (1.281)** | (1.810)** | (1.487)** | (2.422) |
| | [2.304] | [1.588]* | [1.999] | [1.774]* | [2.548] |
| $\beta_1 + \beta^{L}_{LIC}$ | -1.206 | -1.597 | -1.216 | -1.160 | -2.930 |
| | (1.879) | (1.779) | (1.738) | (1.882) | (1.114)*** |
| | [2.029] | [1.932] | [1.883] | [2.042] | [1.302]** |

| | Chemical non-metallic product (6) | Electrical machi--nery (7) | Transport equip--ment (8) | Other manufa-cturing (9) | Financial intermed-iation (10) |
|---|---|---|---|---|---|
| $\beta_1 + \beta^{H}_{LIC}$ | -3.294 | -0.969 | -1.410 | -1.238 | 0.687 |
| | (1.897)* | (2.422) | (2.554) | (2.209) | (1.640) |
| | [2.199] | [2.570] | [2.721] | [2.376] | [1.819] |
| $\beta_1 + \beta^{L}_{LIC}$ | -1.319 | -2.930 | -3.067 | -3.130 | -4.359 |
| | (1.638) | (1.114)*** | (1.089)*** | (1.186)*** | (1.088)*** |
| | [1.869] | [1.330]** | [1.280]** | [1.397]** | [1.252]*** |

*Notes:* $\beta_1 + \beta^{H}_{LIC}$ measures the effect of a 1°C increase in temperatures on agricultural TFP growth rates in LICs with higher shares of imported inputs. $\beta_1 + \beta^{L}_{LIC}$ quantifies the same effect in LICs with lower shares of imported inputs. All regressions are based on 3,213 observations from 161 countries. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

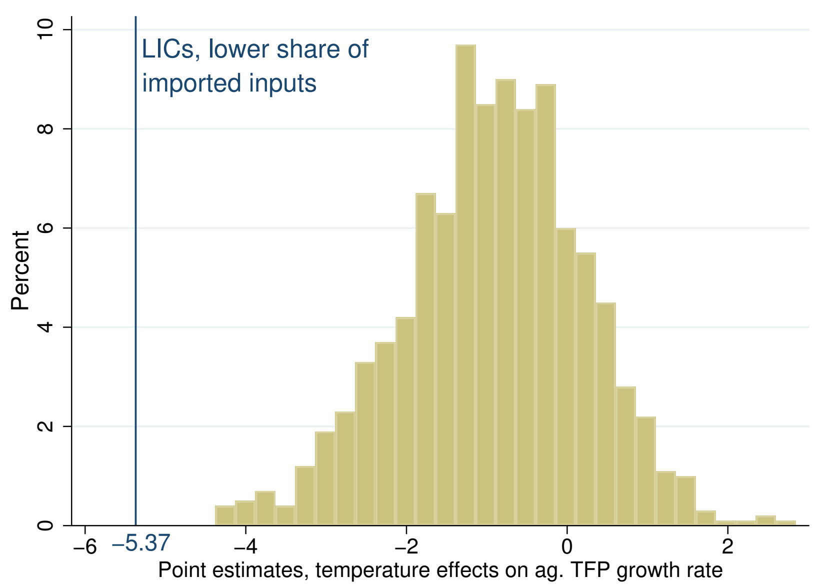
Table 6 summarizes results. It shows that all estimated temperature effects are negative in LICs using lower shares of imported inputs. The negative effects are statistically significant for sectors 'Wood and Paper', 'Electrical and machinery', 'Transport equipment', 'Other manufacturing', and 'Financial intermediation'. For example, a 1°C increase in temperatures reduces agricultural TFP growth rates by 2.9 percent in countries that are using lower shares of imported inputs from the 'electrical and machinery' sector and it is significant at the 1% level with standard errors clustered at the country level and significant at the 5% level with two-way clustered standard errors.

These results suggest that manufacturing inputs from abroad play a key role in mitigating the negative effects of higher temperatures. This is consistent with a number of prior studies documenting positive productivity effects of imported inputs in manufacturing sectors (e.g., Amiti and Konings, 2007; Halpern et al., 2015; and Kasahara and Rodrigue, 2008). Imported inputs from abroad are produced by better technologies and they are sophisticated and more capital-intensive. Therefore, imported inputs embedding better technologies have positive effects on productivity.

#### 4.3.6 Placebo Tests

One may argue that the estimated negative effect of temperatures is possibly coming from noise in the data and it does not necessarily capture interactive effects of imported inputs and temperatures. In order to respond to this possible critique, we created random 1,000 sets of 13 countries where it is the number of LICs using lower shares of imported inputs in our baseline regressions. Then we generate 1,000 different dummy variables corresponding to these randomly selected sets of countries. By using each of these 1,000 dummies, we estimate 1,000 different regressions to find the effect of temperatures on TFP growth rates in these 1,000 different sets of countries. We employ the specification presented in column (5) of Table 3.

**Figure 7:** Distribution of Falsification Parameters




*Notes*: The figure shows distribution of coefficients measuring the impact of a 1°C increase in temperatures on agricultural TFP growth rates estimated by using the specification presented in column (5) of Table 3 with 1,000 randomly selected sets of countries in the treatment group. The point estimate for LICs importing a fewer imported inputs, −5.63, is also shown in the figure.

Figure 7 presents distribution of 1,000 point estimates measuring the effect of a 1°C increase in temperatures on TFP growth rates. It shows that point estimates follow a normal distribution and the average point estimate is about -1, meaning that a 1°C increase in temperatures reduces TFP growth rates by one percentage point in a typical randomly selected group of countries. The average point estimate is negative as rising temperatures have a negative effect on agricultural TFP growth rates in most countries. It shows that the smallest point estimates are about −4. The actual point estimate we find from LICs importing a fewer intermediate inputs is −5.63, far below the lowest point estimates from the 1,000 regressions. The distribution of the 1,0000 point estimates and the actual point estimate show that our results — the negative temperature effects in LICs importing less — are not coming from noise of the data and imported inputs do matter in determining the effect of rising temperatures on TFP growth rates.

#### 4.3.7 Other Dependent Variables

This section shows that our results are not coming from particular assumptions we made to estimate TFP by estimating equation (2) by replacing the dependent variable with the growth rate of agricultural value-added, agricultural gross output, and GDP. The effects on the agricultural value-added growth rates are presented in columns (1)-(2) of Table 7. Linear combinations of coefficients, $\beta_1 + \beta^g_{LIC}$ for $g = H, L$, which correspond to the numbers reported in the bottom of columns (1) and (5) of Table 3. -4.18 and -5.63. By replacing the dependent variable with agricultural value-added, these point estimates change to -4.1 and -4.8, respectively. These point estimates are significantly different from zero. These results suggest that our results do not depend upon assumptions we made to estimate agricultural TFP.

The two columns in the middle show the effect of temperatures on agricultural gross output. These show that a 1°C increase in temperatures reduces the output growth rates by about 4.5 percentage points. These effects are significant in column (3). However, after adding controls, it turns to be insignificant with two-way robust standard errors as shown in column (4). The last two columns present the effect on the GDP growth rates. A 1°C increase in temperatures reduces the GDP growth rates by about 1 to 1.5 percentage points. Again, the effect of temperatures on the GDP growth rates is insignificant with two-way robust standard errors. The last two columns show the effect on the GDP growth rates, column (5) includes no controls and column (6) introduces controls. These show that a 1°C increase in temperatures reduces the output growth rates by about 1-1.4 percentage points. These results are consistent with Dell et al. (2012) showing that higher temperatures reduce GDP growth rates in LICs.

**Table 7: Other Dependent Variables**

| Dep. Var. | Ag. Value-Added | | Ag. Gross Output | | GDP | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta_1 + \beta^H_{LIC}$ | -0.607 | -1.439 | 0.998 | 1.079 | 0.472 | 0.695 |
| | (1.946) | (2.193) | (2.795) | (2.872) | (0.870) | (0.965) |
| | [2.102] | [2.347] | [2.940] | [3.047] | [0.956] | [1.185] |
| $\beta_1 + \beta^L_{LIC}$ | -4.144 | -4.813 | -4.435 | -4.564 | -1.407 | -0.963 |
| | (1.137)*** | (1.460)*** | (2.340)* | (2.652)* | (0.464)*** | (0.563)* |
| | [1.263]*** | [1.652]*** | [2.545]* | [2.979] | [0.593]** | [0.819] |
| Controls | | Yes | | Yes | | Yes |
| $R$-squared | 0.016 | 0.040 | 0.022 | 0.037 | 0.019 | 0.035 |
| Countries | 185 | 185 | 138 | 138 | 185 | 185 |
| Obs. | 4,020 | 4,020 | 3,052 | 3,052 | 4,016 | 4,016 |

*Notes:* $\beta_1 + \beta^H_{LIC}$ measures the effect of a 1°C increase in temperatures on agricultural TFP growth rates in LICs with higher shares of imported inputs. $\beta_1 + \beta^L_{LIC}$ quantifies the same effect in LICs with lower shares of imported inputs. All regressions employ the specification reported in column (1) of Table 3. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

To summarize, we obtain similar results by estimating regressions with replacing the dependent variable with other variables. The estimated magnitude of the negative impact is greatest for agricultural TFP growth rates, and then the agricultural value-added growth rates, the agricultural gross output growth rate, and the GDP growth rates follow. The order of the magnitudes are consistent with our prior that rising temperatures have particularly strong effects on agricultural sector and its productivity is most severely impacted.

## 5 Conclusions

This paper has estimated agricultural TFP and examined the effect of higher temperatures on TFP growth rates by focusing on the role of imported inputs in mitigating negative effects of higher temperatures. Our baseline results suggest that a 1°C increase in temperatures reduces TFP growth rates by 5.37 percentage points in LICs using lower shares of imported inputs while temperatures have an insignificant effect on other groups of countries. Our results are robust to a variety of considerations such as excluding outliers, introducing lagged climate variables, changing thresholds to grouping countries, and placebo tests. We also consider sectoral composition of imported inputs and the results suggest that manufacturing intermediate goods from abroad have particularly strong climate change mitigating effects. It implies that imported machinery, transport equipment, and other capital goods embed better technologies from abroad, making agricultural production more capital intensive and less vulnerable to higher temperatures.

Our results come from reduced-form regression analyses, exploiting historical variations in weather and agricultural TFP. Therefore, the estimated impacts are considered as the short-run effects because we estimate countries' contemporaneous responses to short-run fluctuations in weather. In addition, the analysis focuses on the impact of weather shocks on a particular aspect of the economies – agricultural TFP. As a result, 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. Nonetheless, this paper contributes to our understanding on the effects of weather shocks as it confirms results from existing studies finding negative temperature effects on LICs provides new evidence that importing more imported inputs mitigate such negative effects.

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# Appendix

## A List of Countries

This section presents a list of countries included in the regressions. We follow the World Bank's definition on country groups. Asterisk * indicates countries with lower shares of imported inputs. Low-income countries are following 28 countries:

> Afghanistan (AFG)*, Benin (BEN)*, Burkina Faso (BFA)*, Burundi (BDI), Central African Rep. (CAF), Chad (TCD), Dem. Rep. of Congo (COD)*, Eritrea (ERI), Ethiopia (ETH), The Gambia (GMB), Guinea (GIN), Haiti (HTI), Liberia (LBR), Madagascar (MDG)*, Malawi (MWI)*, Mali (MLI), Mozambique (MOZ), Nepal (NPL)*, Niger (NER)*, Rwanda (RWA), Senegal (SEN)*, Sierra Leone (SLE), Syria (SYR)*, Tajikistan (TJK), Tanzania (TZA)*, Togo (TGO), Uganda (UGA)*, and Rep. of Yemen (YEM)*.

Lower-middle income countries are following 40 countries:

> Angola (AGO), Bangladesh (BGD)*, Bhutan (BTN), Bolivia (BOL), Cabo Verde (CPV), Cambodia (KHM), Cameroon (CMR)*, Congo, Rep. (COG), Cote d'Ivoire (CIV)*, Djibouti (DJI), Egypt (EGY)*, El Salvador (SLV)*, Georgia (GEO), Ghana (GHA), Honduras (HND)*, India (IND)*, Indonesia (IDN), Kenya (KEN), Kyrgyz Republic (KGZ), Lao PDR (LAO), Lesotho (LSO), Mauritania (MRT), Moldova (MDA), Mongolia (MNG)*, Morocco (MAR)*, Myanmar (MMR)*, Nicaragua (NIC)*, Nigeria (NGA)*, Pakistan (PAK)*, Papua New Guinea (PNG)*, Philippines (PHL), Sao Tome and Principe (STP), Sri Lanka (LKA)*, Swaziland (SWZ), Tunisia (TUN)*, Ukraine (UKR)*, Uzbekistan (UZB), Vanuatu (VUT), Vietnam (VNM), and Zambia (ZMB).

Upper-middle income countries are following 41 countries:

> Albania (ALB), Algeria (DZA), Armenia (ARM), Azerbaijan (AZE), Belarus (BLR), Belize (BLZ), Bosnia and Herzegovina (BIH), Botswana (BWA), Brazil (BRA), Bulgaria (BGR)*, China (CHN)*, Colombia (COL), Costa Rica (CRI)*, Dominican Republic (DOM), Ecuador (ECU), Fiji (FJI), Gabon (GAB), Guatemala (GTM), Guyana (GUY), Iran (IRN), Iraq (IRQ), Jamaica (JAM), Jordan (JOR)*, Lebanon (LBN), Libya (LBY)*, Macedonia (MKD), Malaysia (MYS), Maldives (MDV), Mauritius (MUS), Mexico (MEX), Namibia (NAM), Paraguay (PRY), Peru (PER), Russia (RUS), Samoa (WSM), South Africa (ZAF), Suriname (SUR), Thailand (THA), Turkey (TUR), Turkmenistan (TKM), and Venezuela (VEN).

High-income countries are following 52 countries:

> Argentina (ARG)*, Australia (AUS), Austria (AUT), The Bahamas (BHS), Bahrain (BHR), Barbados (BRB), Belgium (BEL), Brunei Darussalam (BRN), Canada (CAN), Chile (CHL), Croatia (HRV), Cyprus (CYP), Czech Republic (CZE), Denmark (DNK), Estonia (EST)*, Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hong Kong SAR (China) (HKG), Hungary (HUN), Iceland (ISL)*, Ireland (IRL), Israel (ISR), Italy (ITA)*, Japan (JPN)*, Rep. of Korea (KOR)*, Kuwait (KWT), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), Netherlands (NLD), New Zealand (NZL), Norway (NOR), Oman (OMN), Panama (PAN), Poland (POL)*, Portugal (PRT), Qatar (QAT), Saudi Arabia (SAU), Singapore (SGP), Slovak Republic (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), Switzerland (CHE), Trinidad and Tobago (TTO), United Arab Emirates (ARE), United Kingdom (GBR), United States (USA)*, and Uruguay (URY).

# 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 USD, 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 population | WDI |
| Agricultural area | 1000 ha | FAOSTAT |
| Value of imported inputs | Current USD | EORA |
| Value of total intermediate inputs | Current USD | EORA |
| Fertilizer consumption | Kilograms per hectare of arable land | WDI |
| Value-added in the agricultural sector (EORA sector 1) | Current USD | EORA |
| Subsidies on production in the agricultural sector (EORA sector 1) | Current USD | EORA |
| Taxes on production in the agricultural sector (EORA sector 1) | Current USD | EORA |
| Capital-to-labor ratio in the agricultural sector (EORA sector 1) | % | EORA |
| Political instability index (Freedom house index, civil liberty) | Index (0 = the best, 7 = the worst) | Freedom House |
| Tariff rate, applied, weighted mean, all products | % | WDI |
| FDI inflows to Agriculture, Forestry and Fishing | Value USD, 2005 prices, millions | FAOSTAT |
| Real effective exchange rate index | Index, 2010 = 100 | WDI |
| Temperatures (monthly average) | Degree Celsius | CCKP |
| Rainfalls (montly total) | mm | CCKP |
| Gross Domestic Product | Value USD, 2005 prices | FAOSTAT |
| Oil rents | % of GDP | WDI |
| IMF Commodity Price Index | Index, 2005 = 100 | IMF WEO |

FAOSTAT indicates the database by the Food and Agriculture Organization of the United Nations.
WDI indicates the *World Development Indicators* of the World Bank.
EORA indicates the EORA Input-Output tables (Lenzen et al. 2012; Lenzen et al., 2013)
IMF WEO indicates the *World Economic Outlook* of the IMF.
CCKP indicates the *Climate Change Knowledge Portal* of the World Bank.

# C Estimating Agricultural TFP

## C.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 share is estimated as $\alpha_{it}^{K} = \frac{\text{payments to capital}_{it}}{\text{value added}_{it}}$ and the labor share is $\alpha_{it}^{L} = \frac{\text{payments to labor}_{it}}{\text{value added}_{it}}$. By assuming a CRS production technology, the land share is $\alpha_{it}^{T} = 1 - \alpha_{it}^{K} - \alpha_{it}^{L}$. Table A1 summarizes average values of factor shares for four groups of countries in 1990 and 2015. These computations lead to reasonable numbers.

**Table A1: Average Capital Shares, Labor Shares, and Land Shares by Income-level of Countries**

| | 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 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 A2 shows correlations between the regressors used in the regression analysis: changes in temperatures and changes in rainfalls. 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.

**Table A2: Correlations between $\Delta Temp$ and $\Delta Rain$**

| | All countries | | LICs | |
|---|---|---|---|---|
| | 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.

# E Tables Plotted in Figures in the Main Text

This section presents further robustness checks on our regression results in the main text.

**Table A3: Different Thresholds to Divide the LIC Sample**

Dependent Variable = $100\times(TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$

Panel A: Reducing the Threshold

| Threshold | (Baseline) 50th | 45th | 40th | 35th | 30th | 25th |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta_1 + \beta^H_{LIC}$ | -1.910 | -1.802 | -1.825 | -2.460 | -2.529 | -4.183 |
| | (2.258) | (2.195) | (2.029) | (2.060) | (2.006) | (2.267)* |
| | [2.320] | [2.257] | [2.101] | [2.156] | [2.111] | [2.296]* |
| $\beta_1 + \beta^L_{LIC}$ | -5.630 | -6.011 | -5.985 | -5.778 | -5.955 | -5.667 |
| | (1.436)*** | (1.410)*** | (1.594)*** | (1.386)*** | (1.530)*** | (1.083)*** |
| | [1.668]*** | [1.713]*** | [1.880]*** | [1.760]*** | [1.791]*** | [1.442]*** |
| LICs, low share of im. inputs | 13 | 12 | 11 | 10 | 8 | 7 |
| LICs, high share of im. inputs | 15 | 16 | 17 | 18 | 20 | 21 |

Panel B: Increasing the Threshold

| Threshold | (Baseline) 50th | 55th | 60th | 65th | 70th | 75th |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta_1 + \beta^H_{LIC}$ | -1.910 | -4.659 | -4.271 | -4.373 | -3.284 | -3.164 |
| | (2.258) | (2.278)** | (2.182)* | (2.467)* | (1.841)* | (1.765)* |
| | [2.320] | [2.429]* | [2.343]* | [2.648]* | [2.133] | [2.056] |
| $\beta_1 + \beta^L_{LIC}$ | -5.630 | -4.163 | -4.061 | -4.046 | -4.646 | -4.641 |
| | (1.436)*** | (1.501)*** | (1.506)*** | (1.458)*** | (1.448)*** | (1.439)*** |
| | [1.668]*** | [1.755]** | [1.763]** | [1.742]** | [1.683]*** | [1.655]*** |
| LICs, low share of im. inputs | 13 | 14 | 15 | 17 | 18 | 19 |
| LICs, high share of im. inputs | 15 | 14 | 13 | 12 | 10 | 9 |

*Notes:* All regressions are based on 3,213 observations from 161 countries and employ the specification reported in column (1) of Table 3. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Table A4: Lag Model**

| Dependent Variable = $100\times(TFP_{i,t} - TFP_{i,t-1})/TFP_{i,t-1}$ | | | | | |
|---|---|---|---|---|---|
| $T$ | No lag | 1 lag | 3 lags | 5 lags | 10 lags |
| | *Panel A: Without Controls* | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| $\beta_1 + \sum_{s=0}^{T} \beta_{LIC,t-s}^{H}$ | -0.191 | -0.259 | -0.208 | -0.234 | -0.416 |
| | (2.014) | (2.015) | (2.012) | (2.020) | (2.051) |
| | [2.145] | [2.141] | [2.133] | [2.135] | [2.171] |
| $\beta_1 + \sum_{s=0}^{T} \beta_{LIC,t-s}^{L}$ | -4.177 | -4.225 | -4.239 | -4.271 | -4.437 |
| | (0.903)*** | (0.905)*** | (0.906)*** | (0.918)*** | (0.958)*** |
| | [1.057]*** | [1.054]*** | [1.041]*** | [1.074]*** | [1.125]*** |
| | *Panel B: With Controls* | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| $\beta_1 + \sum_{s=0}^{T} \beta_{LIC,t-s}^{H}$ | -1.910 | -1.951 | -1.906 | -1.906 | -2.183 |
| | (2.258) | (2.249) | (2.231) | (2.237) | (2.243) |
| | [2.320] | [2.314] | [2.322] | [2.326] | [2.358] |
| $\beta_1 + \sum_{s=0}^{T} \beta_{LIC,t-s}^{L}$ | -5.630 | -5.647 | -5.641 | -5.652 | -5.854 |
| | (1.436)*** | (1.424)*** | (1.417)*** | (1.446)*** | (1.448)*** |
| | [1.668]*** | [1.670]*** | [1.683]*** | [1.723]*** | [1.718]*** |

*Notes:* All regressions are based on 3,213 observations from 161 countries. Robust standard errors clustered at the country-level are in parentheses. Robust standard errors clustered in two ways, at the country-level and the region-year level, are in brackets. Temperatures are in degrees Celsius. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.