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Climate change driven food inflation in Ethiopia?

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ABSTRACT

The research dealt with the relationships between temperature variability and price of food stuffs in Tigrai using 84 months collected time series data thereby applied a Univariate econometric tool and finite Distributed Lag Model in defining the variables and outcome of the study. As a result, the econometric regression analysis witnessed that a 1^{o}C temperature rise contributed the average price of food stuffs such as barley price rose up by 80 percent, maize 186 percent, sorghum close to 275 percent, wheat 60 percent, and 170 percent in white Teff over the years, ceteris paribus.

Contribution/ Originality

The current article contributes in literature in several ways, e.g. it examines the impact of temperature increment on food inflation using econometrics which was missing in Tigrai, Ethiopia. It also analyse the causality effect of temperature variability on food inflation in the Eastern Africa, Ethiopia opposite to what mostly descriptive.

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1. INTRODUCTION

Climate Change is the concern of both Less Developing countries (LDCs) and Developed countries (DCs). Although countries in the Southern hemisphere are not the main originators of climate change, they may suffer the greatest share of damage in the form of declining yields and greater frequency of extreme weather events (IMF and WB, 2011). Contrary to the 'green revolution ' in the late 1960s in Asia, staple food consumption price shocks will gloomy forecasted to rise by 2050 (Fischer *et al.*, 2014). It is also projected that in the coming near years the world Agricultural Gross Domestic Product (GDP) of staple foods to decrease by 16 percent in 2020 due to global warming. However, the impact on LDCs will be much more severe than DCs hence rely on agriculture. The effects of global warming on the production of cereals are not equally likely in crop type. Future projections on climate variability show that land suitable for wheat production, for example, may almost disappear in Africa due to climate change (cited in IMF and WB, 2011). The causing factors for staple food prices to increase on (corn, wheat, edible oil, soybeans, crude oil, and etcetera) items this time globally were due to high demand created by food in emerging economies, rising biofuel production, the slow supply adjustment to higher prices, wrong policy responses in some countries, higher input prices, export bans, and climate change (Woertz *et al.*, 2014). The rising staple food price soar harms for those who earn income below poverty line hence decrease their purchasing power parity (Tadesse, 2012). Staple food cereals are the most important foods and the diets of the most population of the world (Urgessa, 2011). Research results forecasted that in a group of more than 40 LDCs, especially in Sub-Saharan Africa (SSA), food cereal yields are expected to decline with mean losses of about 15 percent mainly due to climate change by 2080 (IMF and WB, 2011). Ethiopia by 2070-2099 even will experience an average daily rainfall reduction of 1.97 millimeters (mm) and the mean annual temperature will rise to 26.9^{o}C that cause aridity to increase as well as minimal agricultural productivity. The agricultural food cereals yield were reduced and impacts negatively welfares of many populations due to climate change using different methodologies in different districts (Weldesilassie *et al.*, 2015; Bezabih and Mekonen, 2014; and Gebreegziabher *et al.*, 2014). The researcher poses the study in Tigrai, to deal with the large debatable issue climate change driven food inflation? Estimating and forecasting the effect of climate change (temperature) on staple food prices in Tigrai regional state of Ethiopia is therefore the ultimate objective of this study.

2. LITRATURE REVIEW

2.1. Climate change and food inflation

Climate change is the root cause of the recent staple food price volatility in the World (Fischer *et al.*, 2014). The increasing climatic variability in SSA reduces crop production, increase land degradation, food inflation, and food insecurity in the region (Benedict *et al.*, 2013). A 1 to 2^{o}C increase in temperature decrease food crop yield in SSA though the exact level of yield production reduction is unknown (cited in Benedict *et al.*, 2013).The negative impacts of climate change varied from country to country and from cereal to cereal genetics, example, 65% of maize and 79% millet crop yield losses were registered in Africa. Crops yield in particular and the total agriculture yields were declined due to the annual average temperature increase (Gebreegziabher *et al.*, 2014). The negative impact of temperature rise was non-linear and heterogeneous on agricultural outputs unlike rainfall (Bezabih and Mekonen, 2014). Climate change caused a reduction in yield and profitability of cotton and sugarcane thereby producers' welfare. Especially, the impact of temperature increase share is higher as compared to rainfall in reducing the yields (Weldesilassie *et al.*, 2015). Fischer *et al.* (2014) revealed that scaling up to a higher rate of agricultural yield productivity through research and development can possibly support to combat the unanticipated shocks (though individually improbable) to the vulnerable people with lower socioeconomic status due to price spikes. On the same token, the greatest agricultural food yield productivity increase is possible through intensification in SSA where large yield gap is found. However, the scientists and farmers alike will be challenging in working to reduce the environment negative effect while using agricultural inputs. In LDCs large costs can be incurred due to small shifts in climate because of low levels of adaptive capacity, technology, and resources they have. Across Ethiopia over the past 50 years, the average temperature increases due to climate change and the length of the growing season have been reduced near to 15 percent (Ethiopia climate change case study, 2015). Climate change on agricultural production is forecasted more likely to reduce GDP by around 10 percent thereby raise income inequality through firing poverty in Ethiopia.

The price of wheat, coarse grains, rice and oil seed crops were rise up by close to 50 percent in 2005 to 2008 in the World due to complex and mutually reinforcing factors, climate change holds largest share (OECD, 2008). The yield of maize, rice, wheat, and soybean are declining globally this time because of insecticides, pests, and weeds. However, 29 percent reduction was recorded as a result of climate change (De Schutter and Frison, 2017).

Projections of future needs for staple food consumption show that high demands for feed grains will put pressure on the environment that will cause climate change. It will drive up prices of staple food cereals agricultural production as compared to meat and make it more challenge in affording adequate diet by LDCs (Keats and Wiggins, 2014). Loening *et al*., (2009) on their study revealed that inflation in Ethiopia is highly associated with the price shocks on staple foodstuffs including maize, Teff, sorghum, wheat, and barley. The exchange rate and World's price shocks explained a large percent in the Ethiopian inflation unlike to the prevailing view domestically born at most. To simplify, a one percent increase in world food prices proportionally soars up domestic food prices by one percent, unless the exchange rate changes though the realistic time span as evidence for this fact is three years. In fact, the evidence mentioned above, in the long run, is weak. Tadesse (2012), staple food cereals prices rose faster in Ethiopia as compared to other countries. The price soars created on food cereals is the prime source of food price inflation in the country and mainly due to climate change in major producing countries (Ibid). Keeping the current sorghum cultivars in Tigrai, the future yield of it is estimated to decline between 5 and 24 percent because of the temperature raise (Gebrekiros *et al*., 2016).

Mikemina (2013) witnessed that there exists a non-linear relationship between agricultural outputs and recorded rapid rainfall on the production year. Climate change impact simulations revealed that changes in climate attributes will reduce agricultural added value per acre of land ranging from 7.11 percent in 2025 climate scenario to 15.24 percent in 2050. Quiggin (2007) told to the world that an average temperature increase above 2^{o}C per annum would definitely reduce global agricultural production. Of which the lions share for the less production expected to be seen in LDCs. Stock and Watson (2000) have been introduced the distribution lag model in the context of estimating the dynamic causal effects on orange juice prices and weather using monthly collected time series data of 1950 to 2000, concluded that as the weather gets cold the price of juice gets higher over time. The Paris Agreement in California 2015 come up with ambitious potentially the best agreement to limit the World average temperature increases to 2^{o}C annually (Stewart *et al*., 2017). Although the Paris Agreement set goals, lacks legally enforcing conditions and might seems as the usual pseudo previous climate conferences. The negative consequences of climate change require therefore an integrated and rational world commitment to combat in action. LDCs and poor farmers are the earlier victims of the catastrophes of climate change in particular and agriculture thereby food security at large (FAO, 2017).

3. MATERIALS AND METHODS

3.1. Description of the study area

Tigrai is the Northern part of Ethiopia's federal states located at 12012' and 14032' North latitude and between 36030' and 40030' East longitude. The total population of Tigrai is expected to be more than five million with close to 25 to 30 % urban residents (BoFED, 2017).

3.2. Data type and source of data

The data was gathered from two secondary sources. These are: National Meteorology Agency of Ethiopia, Mekelle Directorate Branch, and Tigrai Agricultural Marketing Promotion Agency (TAMPA). Monthly collected time series data were used (data of 84 months) starting from January 2009 to December 2015.

3.3. Model specification and estimation

Time series data uses to estimate the dynamic causal effects and forecasting future situation based on the lag values (Stock and Watson, 2000). In the economics literature, the distributed lag models are highly useful for the consumer, producer and government behaviors economic units that had been implemented by different researchers (Roll, 1984; and Hamilton, 2005). Especially, distributed lag models are essential not only in estimating the previous year (lag value) but also useful in estimating current year value of defining a variable. The research is modeling univariate time series data (one variable temperature). Dynamic effects usually happened over time so that the econometric model used to estimate the dynamic causal effects require including lags. The paper is therefore categorized under the "finite distributed lag model" hence the number of years to go back is defined in years. Specified:

$$P_{iwt} = \beta_0 + \beta_1 P_{iwt-1} + \beta_2 P_{iwt-2} + \beta_3 P_{iwt-3} + \beta_4 P_{iwt-4} + \beta_5 P_{iwt-5} + \beta_6 P_{iwt-6} + \alpha_1 T_{iwt-1} + \alpha_2 T_{iwt-2} + \alpha_3 T_{iwt-3} + \alpha_4 T_{iwt-4} + \alpha_5 T_{iwt-5} + \alpha_6 T_{iwt-6} + \varepsilon_t \quad \text{………………} (1)$$

where,

P_t = the current prices of staple food items in the specified study area [1]

i= number of food items (maize, sorghum, Teff, wheat, and barley) used in the estimation

w = number of woreda's β_0 = constant t = time measured in months (years)

β_1= the immediate effect of a unit change in P_{iwt} on P_t holding constant past P_t (one period lag dynamic multiplier effect) short β_2= two-year dynamic multiplier, *ceteris paribus* Pt, Pt-1, Pt-2, Pt-3 …

β_3= three year dynamic multiplier effect of change in Pt-2 on P_{iwt}, *ceteris paribus* Pt, Pt-1, Pt-3, β_4 = four year dynamic multiplier effect of change in Pt-3 onP_{iwt}, *ceteris paribus*

β_6= six year dynamic multiplier effect of change in Pt-5 on P_{iwt}, *ceteris paribus*

T= the average monthly temperature of every woreda α_1= one year lag dynamic multiplier effect of temperature on P_{iwt} *ceteris paribus* α_2= two-year lag dynamic multiplier effect of temperature on P_{iwt} *ceteris paribus* α_6= six year lag dynamic multiplier effect of temperature on P_{iwt} *ceteris paribus*

ε_t= includes both measurement error and the effect of omitted determinants of P_{iwt}, or stochastic term.

A priori expectation is stated as follows: first, represent the coefficients to estimate the short term effects of variation in temperature on the dependent variable (price of staple food) that is β1… β6> 0, and the long run expectation is also stated as follows: α1 …> 0, and α6 > 0. (Gujarati, 2001) contended those parameters α, α0, α1, α2… α6 in distributed lag models can possibly be estimated using classical least square method. However, (Gujarati, 2001) criticizes certain points concerning to estimates in distributed lag models. First there is a difficulty to know a pre-information in the model regarding to how long the lag period will be; second, when a data set that can estimate the lag period is not set up, degree of freedom is continuously decreased, and the last important challenge is that variables decided as defining variables are in a multiple linear relationship. Consequently, the researcher applied Stock and Watson (2000) econometrics approach.

4. RESULTS AND DISCUSSION

4.1. Descriptive analysis

Cereals such as maize, Sorghum, Teff, barley, and wheat which are produced at the small scale level are the major food consumption items in the research area (Tigrai). Rashid (2011) also documented that more than 60% of Ethiopian food consumption, especially calorie intake were found from four staple bowls of cereal (maize, Teff, sorghum, and wheat) supplied by small farming households. Though not empirical conclusion, there was high variation of food prices every year in staple cereals due to climate change, *ceteris paribus*, over the seven years. Teff the mentioned domestic consumption of both urban and rural population has recorded the highest inflation (86 percent) from 2009 to 2015.

[1] Regional state of Tigrai in this context is an administrative structure of governance next to that of The Federal Democratic Republic of Ethiopia government

From Table 1 the price of white Teff increased from 982 Birr (45US$) in the past seven years to 1,825 Birr (83 US$). Whereas, the price of maize and sorghum were rise up by around 22 and 33 percent respectively in the same years. This might be more of due to production surplus, demand shift to Teff, income growth, increase the cost of agricultural inputs, and less climate vulnerability in maize and sorghum, *ceteris paribus*.

Table 1: Trends of staple food inflation in Tigrai (2009 to 2015)

Staple food items	Price in (Birr) 2009	Price in (Birr) 2015	Price in (US$) 2009	Price in (US$) 2015	% increase	Unit
Prbarley	584	924	27	42	58%	Qtl.
Prmaize	452	550	21	25	22%	Qtl.
Prsorghum	573	763	26	35	33%	Qtl.
Prteffmix	848	1420	39	65	67%	Qtl.
Prteffred	745	1196	34	54	61%	Qtl.
Prwhiteteff	982	1825	45	83	86%	Qtl.
Prwheat	738	1125	34	51	52%	Qtl.

Source: Computed from the collected secondary data, 2016
Note: A Quintal (Qtl.) the unit of measurement in our case is equivalent to one tenth of a ton. Thus, (1Qtl. =1/10 ton). Similarly, the current official money exchange rate in Ethiopia November 2016 was taken (1US$=22 Birr)

4.2. Econometric Analysis

4.2.1. Lag length selection process

We applied Final prediction error (FPE), Akaike information criterion (AIC), Schwarz's Bayesian information criterion (SBIC) and Hannan-Quinni information criterion (HQIC) in the selection of appropriate lag length. As a result, we select the best lag length at which the values of information criterions are minimal. AIC is the best parameter for because the data is collected monthly.

4.2.2. The direct effects of temperature on staple food items price

Lag length of the price of wheat was found in the 4th year (Table 2). As temperature in the region increase by at least 1^{o}C, the average price of wheat decreases close to six fold. Moreover, white Teff, barley, and maize cereals price were declined by 608, 565, and 483 percent respectively (See Tables 3 to 5), *ceteris paribus*.

Table 2: Lag length selection on price of wheat

The Direct Effect of Price of Wheat								
Lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-673	-	-	-	1126	17.36	17.3	17
1	-627	90.9	4	0.0	3912	16.21	16.7	16
2	-622	11.3	4	0.0	3748	16.7	16.8	16
3	-619	5.1	4	0.2	3896	16.1	16.5	16
4	-599	39.5*	4	0.0	265*	15.5*	16.*	16*
5	-596	6.7	4	0.1	2653	15.8	16.1	16
6	-592	7.3	4	0.1	2682	15.5	16.1	16

Source: Computed from the Collected Secondary Data, 2016

Table 3: Lag length selection on price of white Teff
The lag length for the price of white Teff was found in the 6th year

				The Direct Effect of Price of white Teff				
lag	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-736	-	-	-	58851	18.9	18.9	19
1	-643	187.9	4	0.0	5861	16.6	16.7	16
2	-629	27.7	4	0.0	4548	16.4	16.5*	16*
3	-626	7.4	4	0.0	4606	16.4	16.5	16
4	-619	13.5	4	0.0	4293	16.3	16.5	16
5	-615	8.3	4	0.1	4282	16.3	16.6	17
6	-608	12.6*	4	0.0	4043*	16.2*	16.5	17

Source: Computed from the Collected Secondary Data, 2016

We select second year as the best lag length for the price of barley. From Table 2 to 5 it can partly said that the staple food cereal prices were on average less sensitive to the temperature increment in the past seven years. Thus, there was no drought happenings (including El Nino and La Nino) in the study area over the specified years and the prices of these staple foods increase more due to less supply of outputs and high demand, *ceteris paribus*.

Table 4: Lag length selection on price of barley

				The Direct Effect of Price of Barley				
Lag	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-678	-	-	-	12835	17.4	17.4	17
1	-590	174.1	4	0.0	1510	15.2	15.3	15
2	-578	24.6	4	0.0	1220*	15.1*	15.2*	15*
3	-574	7.3	4	0.1	1232	15.1	15.2	15
4	-573	1.6	4	0.7	1337	15.4	15.3	15
5	-571	4.8	4	0.3	1395	15.2	15.4	15
6	-565	11.6*	4	0.0	1335	15.2	15.4	15

Source: Computed from the Collected Secondary Data, 2016

The lag length for the price of barley was found in the 2nd year.

Table 5: Lag length selection on price of maize

lag	**LL**	**LR**	**df**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-517	-	-	-	2076	13.3	13	13
1	-487	60	4	0.0	1064	12.6	12*	12*
2	-483	8	4	0.0*	1062*	12.6*	12	12
3	-482	2	4	0.7	1146	12.7	12	13
4	-478	6	4	0.1	1169	12.7	12	13
5	-473	9*	4	0.0	1147	12.7	13	13
6	-470	6	4	0.2	1176	12.7	13	13

Source: Computed from the Collected Secondary Data, 2016

The lag length for the price of maize was found in the 2nd year.

4.2.3. The augmented dickey-fuller test for unit root (ADFT)

In finding the robust regression result, econometricians advised testing stationarity as a prior pre-requisition in time series data. The researcher applied the test using ADFT model with constant and trends. In the end, the regression outcome revealed that sound.

The regressed ADFT result revealed that the Test Statistic Value Z (t) (3.96) is higher than that of these three critical values ranges from 2.59 to 3.5. As a result, the lags were non-stationary at level (normal regression), but become stationary after first difference (with change (d)). In the last seven years in Tigrai, a one-degree centigrade (1°C) temperature increase caused the average price of food barley to increase by 80 percent *ceteris paribus*.

Table 6: Augmented dicky-fuller test for unit root on the price of barley

dfuller dprbarley, regress lags(7) ADFT for unit root Number of observation = 75 ---------- Interpolated Dickey-Fuller ---------						
Test Statistic		1% Critical Value		5% Critical Value	10% Critical Value	
Z(t) -3.960		-3.545		-2.910	-2.590	
MacKinnon approximate p-value for Z(t) = 0.0016						
dpbarly	**Coef**	**Std.Err.**	**T**	**p>t**	**[95% Conf. Interval]**	
L1.	1.93	0.48	3.96	0.0**	-2.95	-.95
LD.	0.80	0.45	1.77	0.08*	-0.10	1.71
L2D.	0.67	0.41	1.61	0.11	-0.15	1.51
L3D.	0.35	0.37	1.08	0.28	-0.34	1.13
L4D.	0.11	0.29	0.39	0.69	-0.48	0.71
L5D.	0.24	0.23	1.06	0.29	-0.21	0.71
L6D.	0.23	0.17	1.29	0.20	-0.12	0.58
L7D.	0.21	0.11	1.84	0.07*	-0.02	0.45
_cons	0.40	1.4	0.29	0.77	-2.41	3.21

Note: ***, ** and* are statistically significant at 1%, 5% and 10%
Source: Computed from the Collected Secondary Data, 2016

Table 7: Augmented dicky-fuller test for unit root on the price of maize

dfuller dprmaize, regress lags(7) ADFT for unit root Number of observation = 75 ---------- Interpolated Dickey-Fuller ---------						
Test Statistic		1% Critical Value		5% Critical Value	10% Critical Value	
Z(t) -4.846		-3.545		-2.910	-2.590	
MacKinnon approximate p-value for Z(t) = 0.0000						
dpmaize	**Coef**	**Std. Err**	**T**	**P>t**	**[95% Conf. Interval]**	
L1.	3.07	0.63	4.85	0.0**	-4.38	-1.81
LD.	1.86	0.57	3.21	0.0**	0.71	3.01
L2D.	1.49	0.51	2.91	0.0**	0.47	2.52
L3D.	1.02	0.44	2.29	0.03*	0.13	1.90
L4D.	0.68	0.35	1.93	0.05*	-0.02	1.39
L5D.	0.47	0.26	1.79	0.07*	-0.07	1.01
L6D.	0.20	0.19	1.07	0.28	-0.17	0.58
L7D.	0.12	0.12	1.03	0.30	-0.12	0.36
_cons	1.07	1.37	0.79	0.43	-1.67	3.81

Source: Computed from the Collected Secondary Data, 2016

The regression output revealed that as one-degree centigrade (1°C) temperature increase because of climate change in the study area, the average price of maize crop was increased close to double (186 percent). The research outputs are consistent and valid with the previously done researchers (Stock and Watson, 2000; Quiggin, 2007; Erdal *et al*., 2009; Mikemina, 2013; and Fischer *et al*., 2014).

According to table 8, due to approximately one-degree centigrade temperature increment, more than 60 percent of the average wheat price increase was registered per unit of quintal over the past seven years in Tigrai, keeping other things into act.

Table 8: Augmented dicky-fuller test for unit root on the price of wheat

dfuller dprwheat, regress lags(7) ADFT for unit root Number of observation = 75 ---------- Interpolated Dickey-Fuller ---------						
Test Statistic	**1% Critical Value**		**5% Critical Value**		**10% Critical Value**	
Z(t) -4.347	-3.545		-2.910		-2.590	
MacKinnon approximate p-value for Z(t) = 0.0004						
dprwheat	**Coef**	**Std.Err**	**T**	**P>t**	**[95% Conf. Interval]**	
L1.	2.78	0.64	4.35	0.00	-4.06	-1.51
LD.	1.45	0.58	2.48	0.02	0.28	2.61
L2D.	1.21	0.52	2.36	0.02	0.19	2.24
L3D.	0.58	0.45	1.30	0.20	-0.31	1.48
L4D.	0.40	0.36	1.11	0.27	-0.32	1.18
L5D.	0.24	0.26	0.94	0.35	-0.27	0.76
L6D.	-0.06	0.19	-0.32	0.75	-0.44	0.32
L7D.	-0.06	0.12	-0.6	0.58	-0.29	0.17
_cons	1.55	1.06	1.45	0.15	-0.58	3.67

Note: ***, ** and * are statistically significant at 1%, 5% and 10%
Source: Computed from the Collected Secondary data, 2016

Table 9: Augmented dicky-fuller test on the price of white Teff

dfuller dprteffwh, regress lags(7) ADFT for unit root Number of observation = 75 ---------- Interpolated Dickey-Fuller ---------						
Test Statistic	**1% Critical Value**		**5% Critical Value**		**10% Critical Value**	
Z(t)-3.973	-3.545		-2.910		-2.590	
MacKinnon approximate p-value for Z(t) = 0.0016						
dprteff	**Coef**	**Std.Err**	**T**	**P>t**	**[95% Conf. Interval)**	
L1.	0.25	0.56	2.18	0.00	-3.65	-1.15
LD.	1.14	3.97	1.77	0.03	0.09	2.18
L2D.	0.83	0.52	1.08	0.08	-0.17	1.76
L3D.	0.43	0.46	1.06	0.28	-0.39	1.28
L4D.	0.35	0.41	0.67	0.29	-0.38	1.08
L5D.	0.16	0.34	0.21	0.50	-0.38	0.69
L6D.	0.17	0.25	0.84	0.00**	-0.32	0.48
L7D.	0.11	0.18	1.04	0.40	-0.15	0.36
_cons	1.08	0.12	1.051	0.34	-1.78	3.88

Source: Computed from the Collected Secondary Data, 2016

According to the regression output from table 9, close to double (170 percent) average prices of white Teff foods were recorded because of one degree centigrade ($1^{o}C$) temperature increase, *ceteris paribus*, in Tigrai over the past seven years and is consistent with the past researchers (Quiggin, 2007; Erdal *et al.*, 2009; Mikemina, 2013; Fischer *et al.*, 2014; Woertz *et al.*, 2014).

5. CONCLUSION

The Study tried to deal with the temperature variability impacts price of food stuffs in Tigrai using monthly collected Time Series data of 84 months. The average price of white food Teff increased from 45US$ (in 2009) to 83 US$ (in 2015) partly because of less than 1^{o}C change, *ceteris paribus*. The registered food price rise was equivalent to 67 percent. However, the price of maize and price of sorghum were recorded 22 and 33 percent respectively in the last seven years. The price of maize was rises up from 21US$ to 25US$ relatively the lower food inflation champion item as compared to the remaining staple foods in the past seven years. Moreover, the price of sorghum was increased from 26 US$ to 35 US$ over time due to climate change, ceteris paribus. On top of that, the average price of barley increased from 27 US$ to 42US$; price of mixed Teff soared from 39 US$ to 65US$; the price of wheat rose from 34 US$ to 51 US$; and price of red Teff increased from 34US$ to 54US$ in the years 2009 to 2015 because of close to 1^{o}C temperature increment, ceteris paribus in Tigrai.

Similarly, the ADFT econometric regression output revealed that over the past 84 months (7 years) one-degree centigrade temperature increase caused the average price of food barley to increase higher than 80 percent, maize 186 percent, sorghum close to 275 percent, 60 percent in wheat, and close to double (170 percent) in white Teff, ceteris paribus. Even though the prices of staple foods increase in general were large in the last seven years, but the temperature rise was less. However, this lower temperature change may not keep low over time.

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