Final report ETH-21091

January 2022

Inflation in Ethiopia: Supply-side drivers

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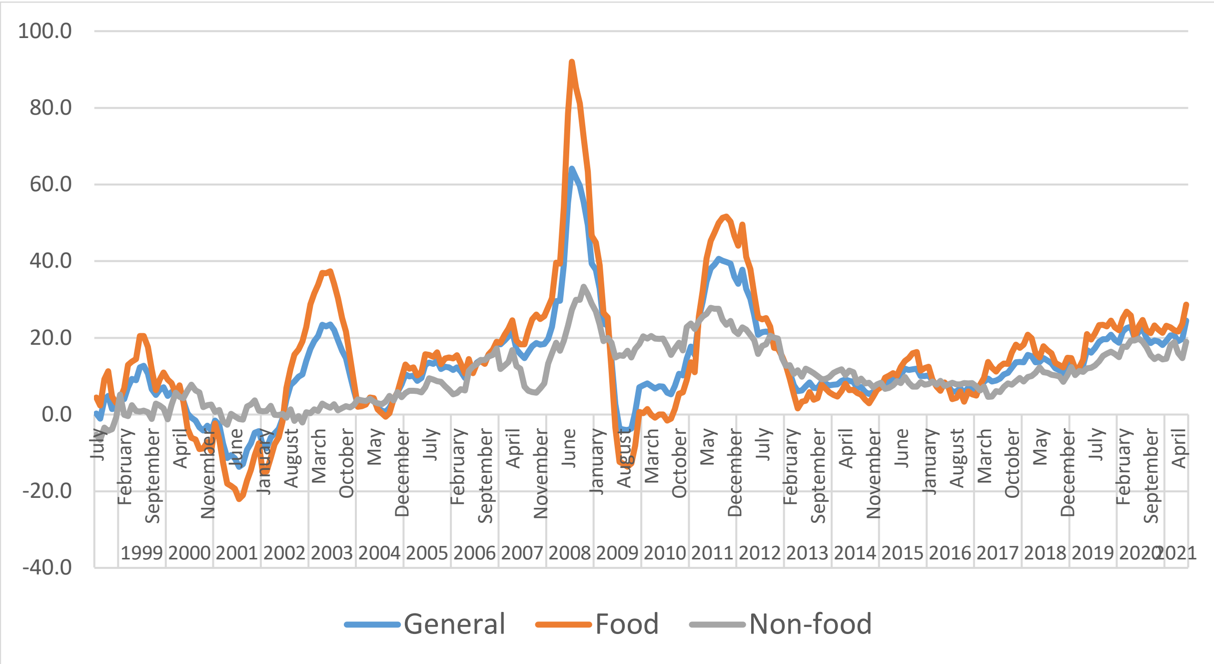
October 2021

1. Introduction

Understanding and addressing the recent rise in food inflation continues to be one of the most pressing macroeconomic policy issues. Since its unprecedented rise in 2006, inflation has been a subject of macroeconomic policy with various studies having been conducted to identify drivers both in the short and long-term. Over the past two decades, we have seen three episodes of high inflation. Ethiopia experienced drought in 2002/03 which led to high food inflation, and in turn meant high general inflation given the substantive weight of food in household expenditure. In 2007/08 and 2011/12, studies show that a combination of global food prices and demand-led growth policies explained the sharp rise in food price that drove overall inflation. Since early 2017, general inflation has witnessed a persistent upward trend, reaching 24%in June 2021. This latter persistent trend has triggered new concerns since it coincides with lower monetary growth and relatively stable global food prices. An IGC-funded research project took a macroeconomic approach to understanding drivers of recent trends and concluded that supply-side factors including yield variability, international price arbitrage play a major role in determining domestic food inflation, in addition to demand-side factor that anchor core inflation. This and other concerns have resulted in further questions surrounding the food market and drivers of food inflation.

Figure 1.1: Trends in general, food and non-food Inflation (2000 – 2021)



Source: Central Statistical Agency

This report presents results from an extension of the inflation project and focuses on attempting to understand dynamics in food markets. In particular, it analyses changes in marketable surplus of major food crops, food price dispersion across regions along with food price integration in different markets. It also attempts to identify micro-drivers of inflation, including changes in household demand (expenditure), and other price determinants including political unrest and transaction costs. The report presents a summary of the methodology employed, the results and the actionable policy recommendation. It also highlights what further work can be done. The report is organised as follows:

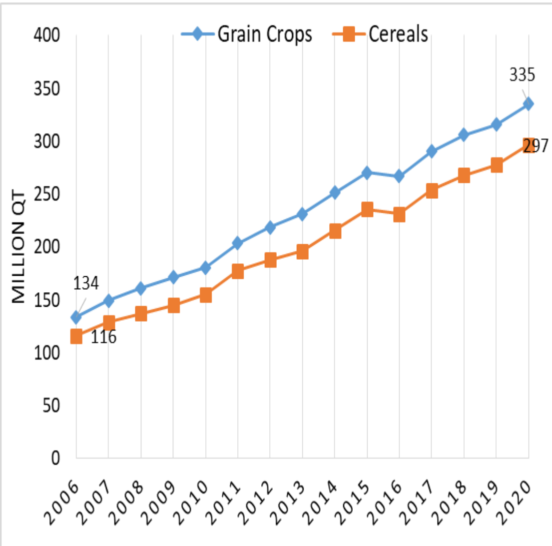
Section two discusses changes in marketable surplus and its relation to food prices. Section three presents analysis of food price dispersion and market integration. Section four presents events analysis. Each section will present a summary of the methodology before discussing the findings. The last section brings together the main findings and policy implications.

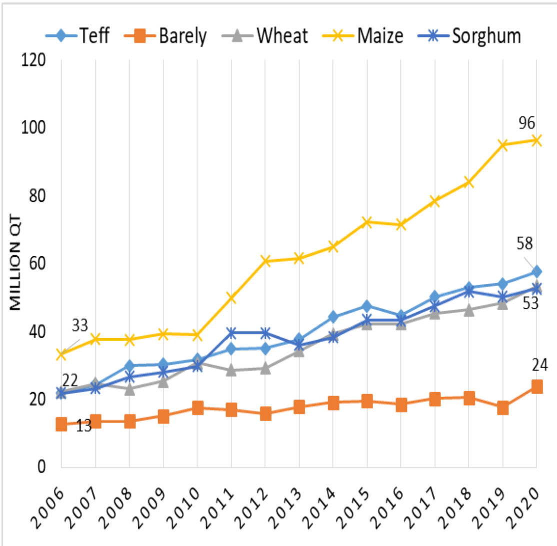
2. Marketable surplus, food prices, and supply chains

2.1 Cereals in Ethiopia: Overview of Production trends and Marketable Surplus

According to CSA's 2018/19 Agricultural Sample Survey, cereals constitute about 81% of Ethiopia's total grain crop area and more than 88% of total grain production. Teff, maize, sorghum, wheat, and barley are by far the most important staple crops in the country constituting about 24%, 19%, 14%, 14%, and 6 % of total grain area and about 17%, 30%, 16%, 15%, and 7% of total grain production respectively. As is depicted in Figure 2.1 below, production of each of the aforementioned grain crops and cereals has increased by more than 150% over the last decade and a half (2006-2020). During the same period, production of the major staples also grew considerably with teff (165%), maize (189%), sorghum (142%), and wheat (140%) experiencing more than double growth while production of barley grew by 87%. Similarly, pulses (136%), oilseeds (73%), vegetables (95%), and root crops (281%) also exhibited substantial growth during the same period (not showed in the figure). While these are all impressive growth rates, these rates, however, become less dramatic if we scale them by cumulative growth in population. During the same period, population grew by 46% -i.e., from 78million in 2006 to about 15million in 2020 (World Bank, 2021).

Figure 2.1: Grain production increased considerable over 2006-2020

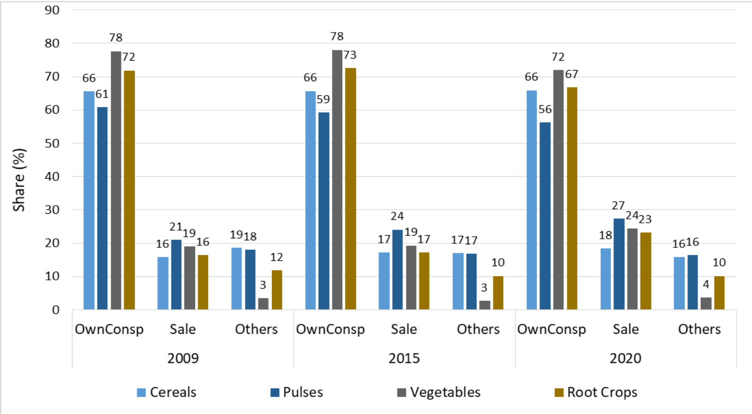




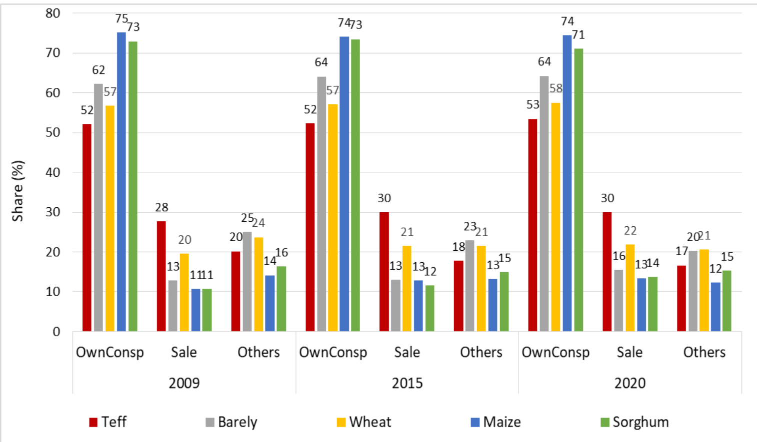
Source: Based on CSA's AgSS data (2006-2020)

Despite the increased production over the 2006-2020 period, the largest share of production is still auto-consumed by the smallholder producers that account for about 95% of overall grain production in Ethiopia. Based on CSA's Crop and Livestock Utilisation survey of different years, figure 2.2 (a) shows crop utilisation for three periods: 2009, 2015, and 2020. More than two-thirds (i.e., 66%) of cereal production is auto-consumed with no change over the period. Farmers seem to take a relatively small proportion (16-18%) of what they produce with the remaining proportion utilised for other purposes (e.g., seed, in-kind wage, and animal feed). The share of auto-consumption is larger for pulses and root crops. Similarly, as can be seen in figure 2.2 (b), producers of the major staples use a large part of their produce for own-consumption. With little change in the proportion over time, in 2020, a large proportion of what was produced was allotted for own-consumption in the case of teff (53%), wheat (58%), maize (74%), barely (64%), and sorghum (71%), with the farmers selling less than one third of their produce. In 2020, producers marketed about 30% of their teff produce, 22% of wheat, 13% of maize, 16% of barley, and 14% of sorghum. While marketable surplus increased overtime in absolute terms, the share of marketable surplus for the major staples, however, has showed little change (figure 2.2 (b)).

Figure 2.2: Biggest share of production is auto-consumed



(a)



(b)

Source: Based on CSA's crop utilization data (2009-2020)

More recently, the government has been exerting considerable effort to close the gap between production and demand by importing massive amounts of food items (e.g., in 2020/21 cereal imports were US$ 1.34 billion[1], 59% higher than the imports in 2019/20, and imports of 'other foods' such as cooking oil in 2020/21 reached US$ 843 million, 56% higher than the previous year). In 2020/21, the

[1]Approximately, cereal imports account for 10% of local cereal production but for about 50% of local marketable surplus (CSA, 2021a; CSA, 2021b; USDA, 2021). Wheat and rice imports almost exclusively constitute cereal imports into Ethiopia. For example, in 2020/21, Ethiopia imported more than 1.5 million MT of wheat - i.e., approximately 25% of domestic wheat consumption (USDA, 2021) while imports of rice (broken, husked, milled or paddy) were about 1.4million MT in 2019 (FAOSTAT, 2021). Imports of other cereals were relatively small: during same period, 2020/21, imports of maize, sorghum, and barley were 0.035 million MT, 0.025 million MT, and 0.004 million MT, respectively.

government initiated a programme aimed at substituting wheat imports with domestic production within three years. In the first year (20/21), the government has largely been able to increase the share of land under irrigation beyond '*Meher*' (the major production season) and produced 15 million quintals of wheat. Nonetheless, the lack of an increase in marketable surplus from smallholder production has been an important supply-side factor for food inflation.

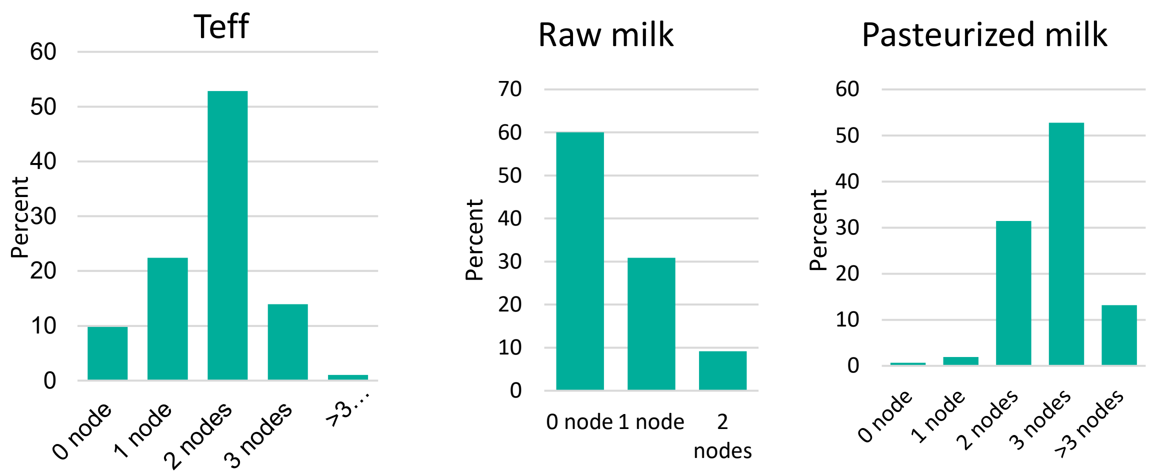
Finally, recent studies in Ethiopia (e.g., Worku et.al., 2017 ; Ahmed et.al., 2018; Minten et.al., 2020) show that households both in rural and urban areas are shifting towards consumption of such high valued items as animal sourced foods and vegetables. While the share of these items in overall basket of consumption goods is still relatively small to considerably drive the general inflation, their share in overall food consumption is increasing overtime. Worku et.al., (2017), for example, show that the share of animal sourced foods and vegetables in overall food consumption increased from 7.5% to 10.8% and from 3.7% to 6.4% between 1999 and 2011 respectively. Incorporating the latest (2016) round of Household Income, Consumption and Expenditure (HICE) Survey, a more in-depth analysis of shifts in consumption patterns is being undertaken to see if there have been similar shifts in the composition of food expenditures that would affect inflation. Preliminary results indicate that households, both in rural and urban areas, have increased their consumption of high-value foods including fruits and vegetables, suggesting a structural shift in demand for the high-value crops with high income elasticity compared to basic crops. This increased demand could help explain higher price increases in these high-value foods relative to subsistence food. This would be expected to be transitory as supply chains develop. In addition, any inflation effect would disappear when the CPI basket weights are appropriately adjusted. Nonetheless, it could impact food inflation in the interim phase.

2.2. Evidence on Supply Chains

Downstream. Research to date on select value chains in Ethiopia has shown variance in degree of efficiency at the downstream level. For several commodities, the supply chain is more efficient than expected. For example, for teff supply chain from the major teff producing areas to Addis Ababa, the number of middlemen is relatively small- in 85% of the cases, there are only two actors between rural producers and urban retailers (Figure 2.3 (a) below) and in 32% of the cases even shorter with urban retailers directly procuring from rural areas (Minten et.al, 2016). In the case of milk, involvement of middlemen in the value chain depends on whether the milk is 'fresh' or pasteurized (Figure 2.3 (b) & (c)). For example, for fresh milk (Figure 2.3 (b)), the role of middlemen is minimal as 60% of urban retailers directly purchase from rural producers and/or their own farms. In 30% of the cases, the value chain involves only one middleman and about 10% involve two middlemen. This is a sign of a well-functioning value chain. In the pasteurized milk value chain, however, we find longer supply chains (Figure 2.3 (c)). The most common route involves three actors between rural farmers and urban retailers (i.e., farmers sell to rural traders, who deliver to dairy processing companies, which then distribute to urban retailers through independent distributors or traders) (Minten et.al. 2020). The second most common structure (i.e., 32%) involves two actors (i.e., either processing firms using milk collectors and then distributing the pasteurized milk themselves or the processing firms procuring milk directly from dairy producers and then distributing the pasteurized product through independent traders and distributors). The evidence from both the teff (Minten et.al., 2016) and the dairy value chains (Minten et.al., 2020) show that each supply chains are rather short. This is an important finding given the blame for price spikes often placed on traders/brokers.

Figure 2.3: Value chain structure: number of actors between rural producers and urban retailers

(a) (b) (c)

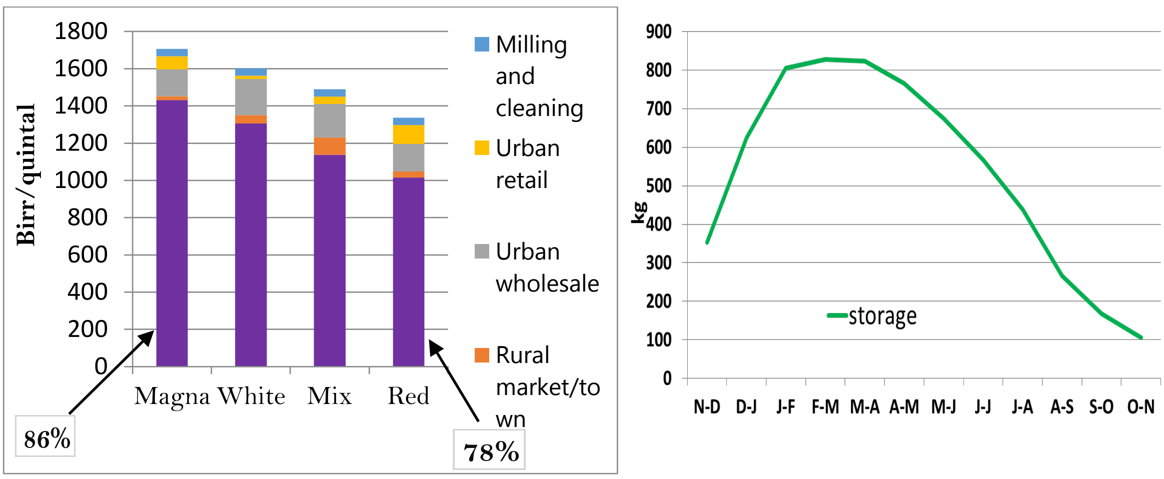


Source: (teff) Minten et.al. (2016); (milk) Minten et.al. (2020)

Minten et.al. (2016) also show that rural teff farmers, contrary to conventional wisdom, receive a relatively high share of retail prices in urban areas (Figure 2.4 (a)). The study shows that farmers receive between 78% in the case of red teff (the least preferred type) and 86% in the case of the 'magna' (the most preferred teff) type- hence, a relatively high share of value captured by the farmer. This result also shows that, at least in the case of teff, middlemen receive a small share of final price. The study also provides evidence that few farmers (about 10%) now engage in distress sale (Figure 2.4 (b)). Majority of the farmers pile up postharvest (November -March) and rather smoothly release their stock.

Figure 2.4: High share of farmgate price and less distress sale

(a) (b)

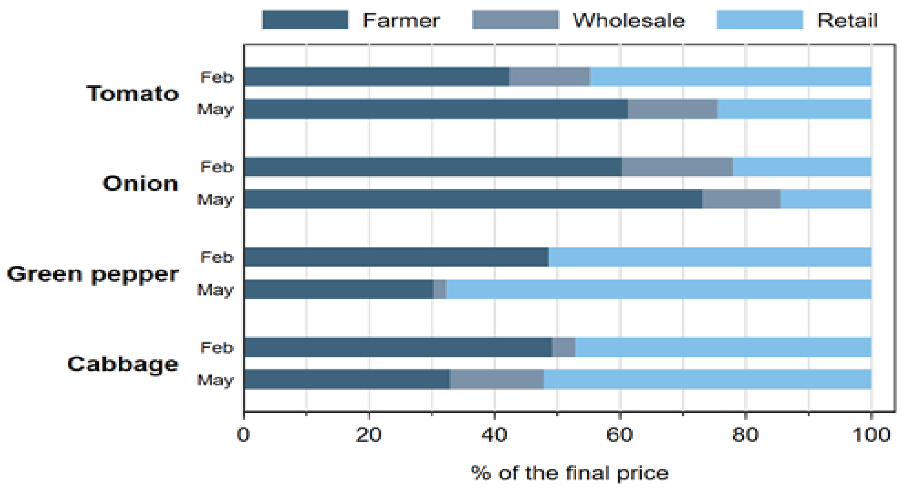


Source: Minten et.al. (2016)

A recent study by Hirvonen et.al. (2021) demonstrates that for vegetables, the gross margins at wholesale level are generally small relative to farm gate prices and to the gross margins in the urban retail sector (ranging from near zero for green peppers to 14 percent for onions).

Figure 2.5 presents vegetable price structure before and during the pandemic, by vegetable type. The figure shows marketing margins at different stages of the value chain as percentages of the final retail price. Strikingly, the observed changes in retail (consumer) prices during the pandemic are largely driven by increases or decreases in farm gate prices and not by wholesale or retail cost margins. It seems then that the various disruptions associated with the pandemic have not led to substantial increases in marketing margins (Hirvonen et.al., 2021). Rather increases in consumer prices in Addis may have stemmed from an increased reliance on more costly vegetables produced in the Central Rift Valley due to reductions in both international trade (e.g., onions from Sudan) and domestic trade between Oromia and Amhara region. At the same time, for vegetables, the retail margins can be quite high depending on the location of the wholesale markets relative to producing areas. For example, roughly three quarters of vegetables are produced in the Rift Valley where the current Addis market is conveniently located (Hirvonen et.al. 2021). However, the other quarter of vegetables coming from the north have additional transport costs to reach that wholesale market. Further analysis could be done to ascertain whether another wholesale facility (seasonally adjusted) could be in the northern part of Addis. It also will be important to consult with the retailers in making market location decisions to have a more comprehensive understanding of their incentives and increase the likelihood that retailers will avail themselves of the new markets[2].

Figure 2.5. Vegetable value chain marketing margins as a percentage of final retail price, by vegetable type



Source: Hirvonen et.al. (2021)

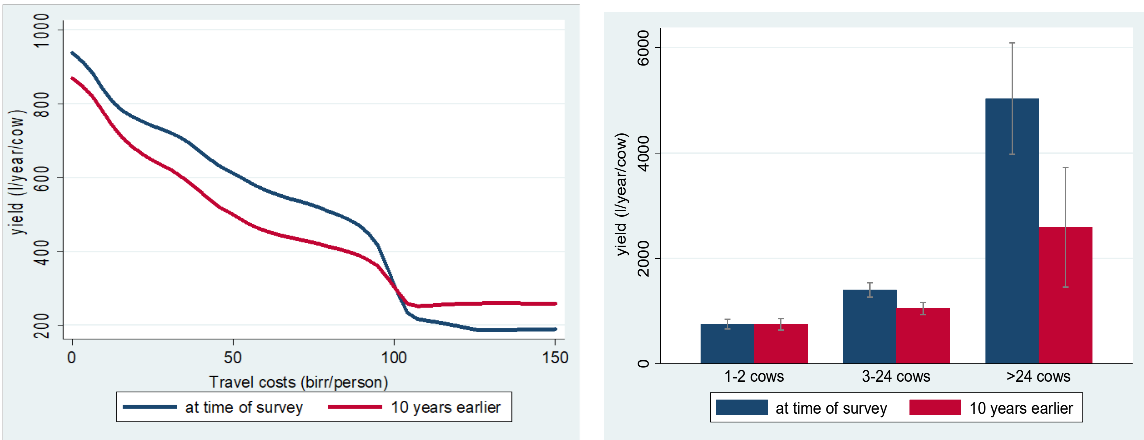
Upstream. The research on select value chains has pointed to upstream constraints, but those tend to be peculiar to the commodity as well as more structural. For example, in dairy, while expansion of milk processing for large producers as well as urban dairy farms has been impressive, milk yields remain low for the vast majority of small and/or remote dairy farmers (Minten et.al. (2020)). Proximity to urban centres (indicating access to important inputs) and farm size seem

[2] In addition, initial findings in the vegetable supply chain analysis suggest that the addition of a requirement that youth coops be used for the loading and unloading has perhaps inadvertently led to price increases. The loaded charges apparently are at times comparable to the total transportation cost (Hirvonen et.al., 2021)

to be strongly correlated with productivity (Figure 2.6 (a)). For example, farms near Addis Ababa get more than 5 times higher yield than those located in remote areas (i.e., within 250-300 km range). Similarly, big farms (>24 cows) get substantially larger yields and also their productivity rises overtime while small farms (1-2 cows) get about 10 times less with no productivity change over time (Figure 2.6 (b)).

Figure 2.6: Cow milk yield by distance from Addis Ababa and by farm size

(a) (b)



Source: Minten et.al.(2020b)

However, for these high value commodities, if measures were found to make supply chains more efficient in the short term, impact on overall price level would be muted, given that their share in the price index remains relatively small. In total, high value vegetables (tomato, onion, green pepper, cabbage, lettuce, spinach) and fruits total 3.6, 2.1, and 3.0, percent in Addis, Amhar, and Oromia, respectively.

Several supply chains are already more efficient than usually assumed. Nonetheless, supply chains can be improved through policy action. Rationalizing location and seasonality of the urban distribution infrastructure could result in decreased transaction costs at retail level. Also, there may be scope for rethinking policy on loading and reloading mandates. The expected increased access to and lower price of mobile phone services as part of telecom reform provides an opportunity to markedly increase farmers' access to price information, thereby strengthening their bargaining position vis-à-vis traders, as well as retailers' ability to shorten the supply chain. While the predominant supply chain factors are primarily of a medium- and longer-term structural nature, evidence suggests ongoing shocks from market-disrupting events can have an important short-term impact, notably, on grains price. This suggests the critical importance of a more continual flow of information from those monitoring agricultural markets to the macroeconomic policy makers, notably, the flagging of potentially disruptive events along the supply chain.

3. Regional food price dispersion and market integration

3.1 Regional food price dispersion

Commodity prices can differ from one place to another for various reasons. Primarily, differences in the cost of getting goods from one place to another can differ. In this sub-section, we look at the geographic dispersion of prices and its relationship with inflation. We undertake a descriptive analysis of trends in geographic food price dispersion in relation to inflation and track it over time. In addition to tracking trends, we conduct Granger causal estimation to assess whether underlying causes of dispersion is resulting in inflation or vice-versa.

Price dispersion can be affected by both time-varying and geographic factors (De Silva et. al., 2019). It is common to use retail price models to explain factors that affect price dispersion (Sheremirov, 2015, Crucini, 2003). In particular, costs related to geography including storage, transportation, differential tax rates determine geographic price dispersion. In addition, demand related drivers like geographic differences in income also determine relatively non-time varying price dispersion (Crucini, 2003, De Silva et al., 2019). In addition to the cost and income factors other market imperfections also explain price dispersions. Choi and Choi (2014) find that market frictions related to price stickiness contribute to the persistence of price dispersion in different cities in the US. Further, price dispersion can be affected by home bias where traders are biased towards selling in their home markets as opposed to other regions within the same country or other bordering countries. Chahruor and Stevens (2019) show that US producers are three times more likely to sell to retailers in their own region than in other regions of the US, with this finding being stronger for Canadian producers. Therefore, it is important to consider the role of administrative borders and the bias to sell in home regions. Importantly, studies that relate inflation and price dispersion mainly considering inflation as a factor that affects price dispersion dynamically.

A majority of the studies that assess the relationship between geographic dispersion of prices and inflation draw a unidirectional causality that runs from inflation to price dispersion. The findings largely show that price dispersion is increasing in inflation. Head and Kumar (2005) use a monetary search model in which consumers have fixed information friction to assess the relationship between inflation and price dispersion. They find that inflation and price dispersion are positively related and there may be some welfare gain if inflation-induced search results in erosion of market power.

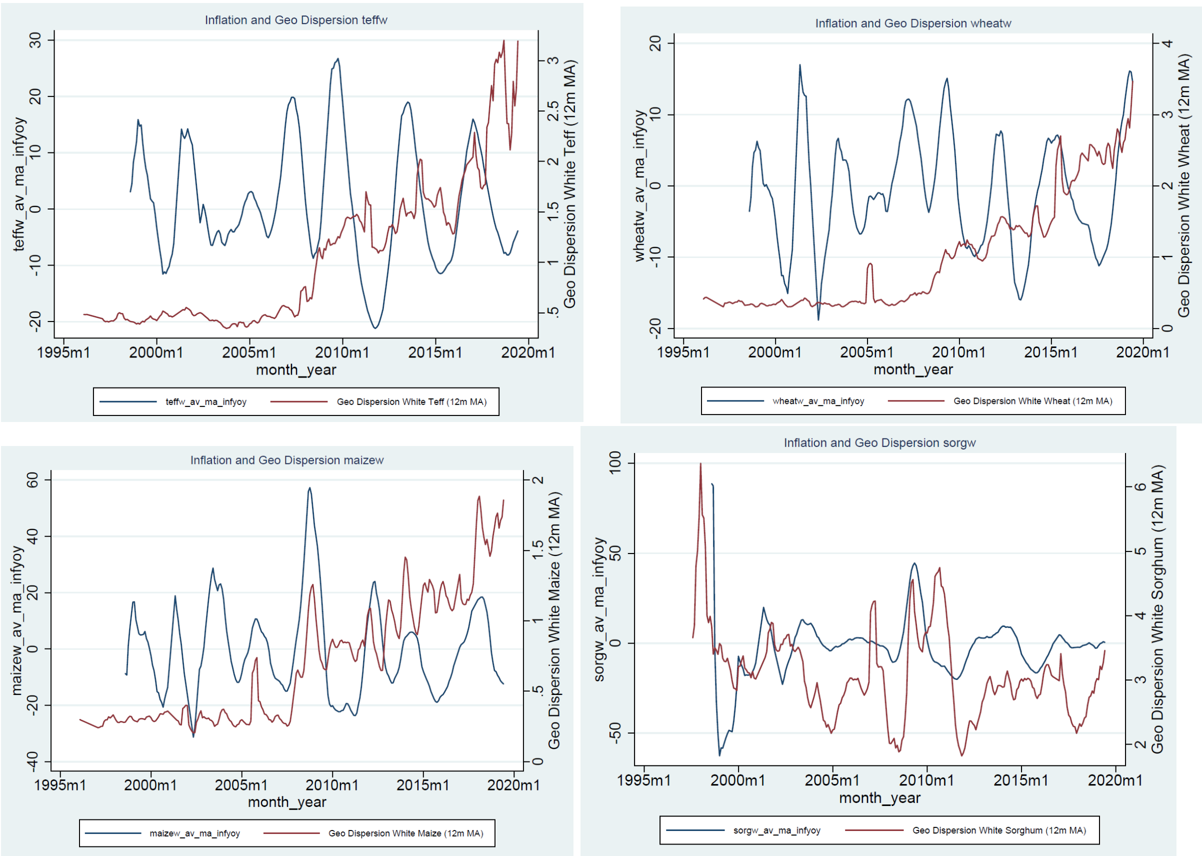
Price Dispersion and Inflation in Ethiopian Food Markets

In this section, we follow from the above analysis and characterize the relationship between geographic price dispersion and respective inflation rates for selected food crops in Ethiopia. As presented in the introduction and previous sections food inflation drives overall inflation with the two major food categories being bread and cereals, and fruits and vegetables. Out of these, the bread and cereals category has a higher household expenditure share and therefore, changes in this category is more consequential for changes in the food CPI. Thus, we consider major cereal crops like teff, wheat, maize, sorghum and other major crops and analyse retail price inflation and dispersion at the nominal level. A key focus is to see if there are notable differences in the recent episode of price inflation from the other episodes in 2008 and 2011. In particular, whether or not geographic factors that lead to inflation are reflected in the price dispersion will indicate whether non-monetary factors have relatively more impact on inflation.

We measure price dispersions as the standard deviation from the mean on retail prices for each month. For inflation, we calculate the year-on-year percentage change of average prices across regions. Figure 3.1 presents trends in inflation and price dispersion for teff, wheat, maize and sorghum. Teff prices mainly follow general food inflation trends ending at around 10% in September

2020 while wheat showcased high inflationary trends ending at around 32% in September 2020. Towards the end of the time series, we see a sharp increase in geographic price dispersion reaching above three standard deviations. This can be due to geographic factors that caused friction in price integration. This is exemplified by the stronger relationship between inflation and dispersion in the post-2015 period. Table 4 indicates that the correlation between inflation and price dispersion was more than double compared to the period before 2015.

Figure 3.1 : Trends in inflation and geographic price dispersions for selected crops



Source: Retail Price and Own Computation

Table 3.1 also confirms that for most of the major crops, inflation and price dispersion are positively correlated in similar vein to what has been documented in the literature. In particular, the correlations show positive trends in the post 2015 period. One hypothesis is that other factors that disproportionately affect different regions are accountable for variations in both the inflation and price dispersions. It is challenging to conduct a causal analysis without accounting for the time and geographic price determinants like income, transportation cost, and other similar such variables. These data are not available for the geographic level and time series that we are analyzing.

Table 3.1.- Correlation between inflation and dispersion for selected crops

	Nominal Prices		Real Prices	
Crops	**Before 2015**	**After 2015**	**Before 2015**	**After 2015**
Teff White	0.168	0.266	0.0089	0.0071
Teff Mixed	0.219	0.448	0.0458	0.1564

Teff Black	0.198	0.611	0.0917	0.2906
Wheat White	0.179	0.375	0.1017	0.2483
Wheat Red	0.315	0.619	0.0516	0.4302
Wheat Mixed	0.344		0.0366	
Maize White	0.301	0.52	0.1768	0.383
Barley White	0.273	0.622	0.1705	0.1131
Barley Mixed	0.33	0.647	0.2066	0.077
Sorghum Yellow	0.274	0.867	0.3378	0.5862
Average	**0.253**	**0.563**	**0.1228**	**0.254656**

Source: Retail Prices and Own Computation

To further investigate the dynamics between inflation and food price dispersion we conduct a Vector Autoregressive Model (VAR) estimation and to gauge the time variation precedence we conduct a Granger causality analysis. Conducting a VAR diagnostic involves optimal lag length selection that represents the relationship between inflation and dispersion.

Lag length selection results show that for the crops considered in this study the optimal lag length ranges from 2 to 4 lags. The selection is based on multiple results from the Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz's Bayesian Information Criterion (HBIC), and the Hannan Quinn Information Criterion (HQIC) optimal lag selection methods. The selection was done giving more weight to the latter three criterion and taking repeated lags in these tests.

Table 3.2.- Optimal Lag Lengths (AIC, HQIC, SBIC)

Crop	Optimal Lag	Crop	Optimal Lag
Teff White	4	Mango	2
Teff Mixed	2	Beef	2
Teff Black	2	Egg	3
Wheat White	2	Cheese	3
Wheat Red	3	Milk	4
Wheat Mixed	3	Carrot	2
Maize White	2	Garlic	2
Barley White	3	Kale	3
Barley Mixed	3	Onion	4
Sorghum Red	4	Potato	2
Sorghum White	3	Green Pepper	4
Sorghum Yellow	2		
Orange	4		
Papaya	4		
Banana	3		
Avocado	4		

Based on these lags we conduct a VAR model estimation followed by a Granger causal estimation. Granger causality tests the joint exclusion of the lags of a variable to test its causality on the other variable. Accordingly, we take up to four lags and test whether food price dispersion Granger causes inflation. Similar to the correlation we find distinct results for the post 2015 period as opposed to the pre 2015 period. The null hypothesis is that the explanatory variable (here price dispersion) *does not* Granger causes inflation. In most cases in Table 3.3 the null is rejected which means that in the post-2015 sample, statistical causality runs from price dispersion to inflation. Considering only the post 2015 period, the test rejects the exclusion of the lags of price dispersion in 5 out of the 27 food items including the major crops like mixed *teff*, red and white wheat, maize, banana, and beef. These results show that in the post-2015 period some major crops and animal products may depict significant relationship between geographic dispersion and inflation with the statistical causality running from dispersion to inflation. This shows the increasing importance of geographic factors in influencing inflation.

Table 3.3.- Granger causality results for post-2015 period

	Equation	Excluded	chi2	df	Prob > chi2
Teff Mixed	teffm_av_ma_inf~y	teffm_sd_ma	10.393	4	0.034
	teffm_sd_ma	teffm_av_ma_inf~y	17.378	4	0.002
Wheat White	wheatw_av_ma_in~y	wheatw_sd_ma	17.755	4	0.001
	wheatw_sd_ma	wheatw_av_ma_in~y	8.33	4	0.08
Wheat Red	wheatr_av_ma_in~y	wheatr_sd_ma	9.4717	4	0.05
	wheatr_sd_ma	wheatr_av_ma_in~y	13.568	4	0.009
Banana	banana_av_ma_in~y	banana_sd_ma	11.635	4	0.02
	banana_sd_ma	banana_av_ma_in~y	3.6603	4	0.454
Beef	beef_av_ma_infyoy	beef_sd_ma	14.492	4	0.006
	beef_sd_ma	beef_av_ma_infyoy	15.593	4	0.004
Milk	milk_av_ma_infyoy	milk_sd_ma	3.51	4	0.476
	milk_sd_ma	milk_av_ma_infyoy	19.373	4	0.001
Carrot	carrot_av_ma_in~y	carrot_sd_ma	2.3886	4	0.665
	carrot_sd_ma	carrot_av_ma_in~y	13.024	4	0.011
Pepper Green	peppergr_av_ma_~y	peppergr_sd_ma	6.5787	4	0.16
	peppergr_sd_ma	peppergr_av_ma_~y	12.545	4	0.014

Source: Retail prices and own computation

Although, it is difficult to surmise that price dispersions directly affect inflation, it is plausible to assume that the factor/s that affect price dispersion could also be resulting in inflation. These factors can range from geographically varying conditions of transportation and logistics or other factors. By indirectly measuring transactions costs, the next section will explore trends in market integration in recent years. To complement this, a further section we investigate the relationship between political unrest events and food prices.

3.2Food market integration

The previous sub-section addressed differences in prices by looking at the geographic dispersion of prices and its relationship with inflation. This sub-section looks at market integration across different markets.

For this study, we primarily used wholesale-level price data of the Ethiopian Grain Trade Enterprise (EGTE). The data is organized monthly, running from July 2001 to March 2020. We focused on the major staple crops: three types of teff (white, mixed, and red), white wheat, and maize[3].

One dimension is whether there is a price transmission between the traditional clearing hub (Addis Ababa market) and select regional markets. Those results are given below. On average, 10 regional wholesale markets are selected for white teff, mixed teff, red teff, white wheat, and maize, and each one is paired with Addis Ababa for a test of market integration between July 2001 and March 2020. The number of markets paired with Addis Ababa varies between 8 (white wheat) to 11 (white teff)[4]. For a reasonable analysis, we categorised the markets into the following three: surplus (crop-wise, amongst top-5 producing area), deficit (crop-specific low-producing area), and major hubs (non-deficit and big/secondary towns). About 50% of the selected markets are from the surplus areas, about 20% from deficit areas while the remaining represent major hub areas.

To measure the extent of market integration, we used a modified version of the Threshold Autoregressive (TAR) Model[5] as is used in Van Campenhout (2007) as outlined in the Annex. Markets would be integrated if price differences are fully explained by transaction costs of moving grains between one market and the other. In the absence of transaction cost data, this model allows us to estimate market integration using only available price data by introducing dynamics of the arbitrage process underlying interconnected markets (making assumptions regarding traders' arbitrage process and speed of adjustment over time) and measuring extent to which prices move back into a given threshold band. A major caveat is that the model cannot capture changes in transaction costs over time.

Relying on the TAR model, figure 3.2 below presents a summary of spatial market integration between Addis Ababa and regional markets. The analysis is performed for four periods: 2000-2005, 2006-2010, 2011-2015, and 2016-2020. For each of the four periods, the figure displays the proportion of regional markets that are found to be integrated with Addis Ababa. Between 2000 and 2015, estimates show that more and more regional markets have been integrated with Addis Ababa. However, since 2015, except for maize markets, regional markets for the other staples seem to have become less integrated with the capital city.

Another important dimension is the extent of market integration between secondary/tertiary towns and market. Ethiopia had seen massive road infrastructural improvements based on radial configuration (Addis Ababa as a focal point). However, more recently, there has also been considerable improvement in road infrastructure between regional towns/cities (see figure 3.3 below). With better access to roads (asphalted or all-weather roads) and rapid urbanisation of regional towns/cities, trade among these regional markets might have increased in lieu of going through Addis Ababa, a market that has traditionally been the major clearing hub. These factors might explain the measured decline in spatial market integration of regional markets with Addis Ababa in the post-2015 period rather than any conclusion that market integration overall worsened. Work to examine trends in market integration between these secondary/tertiary regional markets has yet to be finalized. Hence, no firm policy conclusions can be made at this stage. The next section also examines the role that nationwide political events (road blocks, demonstrations, civil unrest etc) may have played in spatial market integration.

Figure 3.2: Regional markets have been integrated with Addis Ababa up to 2015

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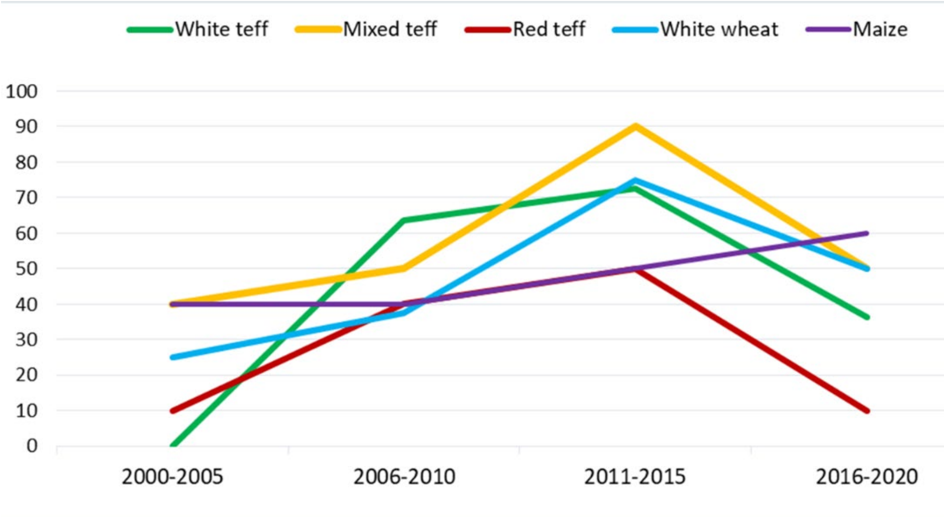
[3] Results for white barley and white sorghum can be accessed upon request

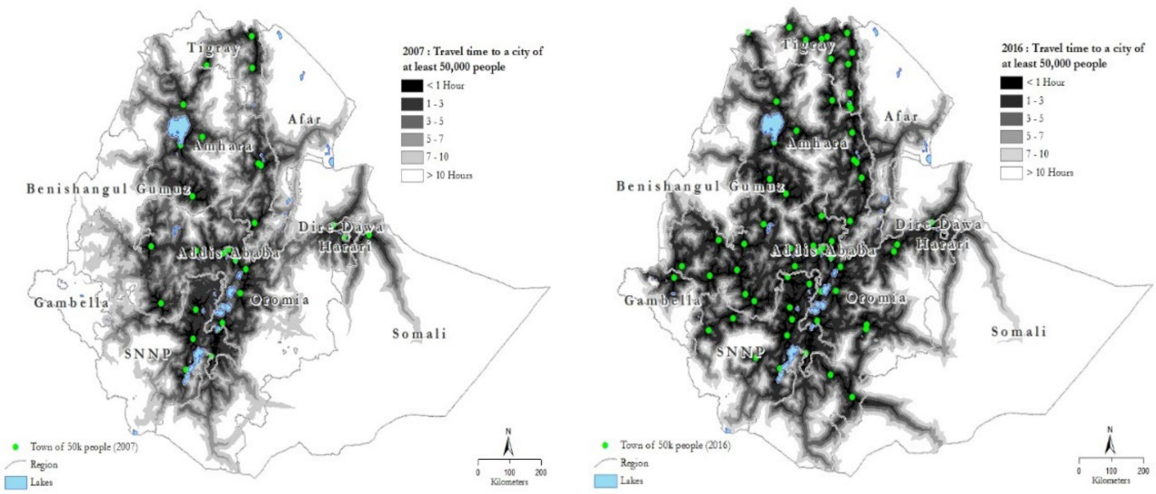
[4] The markets were selected based on two criteria: (i), markets with relatively more number of observations - i.e., 10 percent or less missing values, and (ii), based on a test of stationarity.

[5] More detailed descriptions on the model and on alternative models can be found in Van Campenhout (2007)



Source: TAR estimates based on EGTE's data

Figure 3.3: Rapid infrastructural improvements might have affected spatial market integration



Source: IFPRI GIS

4.Event Analysis

4.1 Introduction

In recent years, events like political instability, armed conflict, and violent protests have become common and they are expected to affect food prices through the supply chain. There is evidence that political instability leads to high volatility in prices (Aisen and Veiga, 2008). Ethiopia faced significant escalation in the number of incidents representing political instability especially since 2015/16. The number of incidents considered in this study increased from 9 incidents in 2010 to 237 in 2018. This started with continuous protests in the Oromia region dubbed the 'Oromo Protests'. This eventually led to the resignation of Prime Minister Hailemariama Desalegn and the coming to power of Prime

Minister Abiy Ahmed, ushering a period of political and economic reforms. Significant number of the events have continued to occur during the transition and until recently, with the situation being aggravated by the eruption of armed conflict in the Tigray region that led to significant damages in Tigray and neighbouring regions. The impact of political instability, in the form of different types of unrests, on prices needs to be investigated, especially in the context of supply-side analysis since unrests tend to be localised with significant implications for food supply.

In this report, we document the number and characteristics of political incidents that have occurred over the past 10 years and conduct analysis relating to prices at the zonal level for various food products in the consumer price baskets. We conduct a descriptive analysis and use impact evaluation methodology – a difference-in-difference estimation to assess the impact of incidents on prices. The following indicates the definition and source of data focussing on event measurement. We then follow with the descriptive analysis and the preliminary results of a difference-in-difference estimate of the impact of events on prices.

4.2 Events: data sources and results

In order to examine the impact of political instability on food price dynamics, the study combined three sources of data:(i) political instability and events data, (ii) annual agricultural production data and (iii) retail prices of food items. The sources of political instability data are primarily coming from Armed Conflict Location & Event Data (ACLED)[6]. ACLED is designed for analysis of disaggregated conflict and crisis mapping. This dataset codes the dates and locations of almost all reported political violence and protests that have occurred in different African countries. For Ethiopia, such compiled data are available for more than two decades (from 1997 to the present). The event data are derived from a variety of sources, including local and international media. These data also contain information regarding the type of events, range of actors and number of fatalities for each incident. The geographical coverage is graded into four levels: region, zone, woreda and towns (location), in descending order of the size of the conflicted regions.

Data on production for the main growing season (Meher) and food retail price was obtained from the Ethiopian Central Statistical Agency (CSA). We considered the recent data over the last ten years, starting from 2010 up until 2019. The Annual Agricultural Sample Survey (AGSS) is a large survey covering more than 40,000 private peasant holders engaged in growing crops and raising livestock in private or in combination with others. The survey covers the entire rural part of the country. On the other hand, the retail price data contains monthly unit price information for foods and non-food items in all parts of the country.

The event data are organised for specific year, month and date of the incident, and occurring in a specific location. However, since the production and price data we have is organized at zone level, we did the same thing for the event data, organising by zone for the years 2010-2019. The zone level event can be considered as the secondary level incident as it is derived from the event that occurred in a specific market location[7]. Thus, zones are considered to have political instability in a specific year if that event occurred at the specific market location within that given zone. The assumption is that a given location's incidents, whose coordinates are found with in a specific zone, are believed to distort

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[6] Data Export Tool | ACLED (acleddata.com)

[7] CSA has a total of 119 market places selected for the retail price survey. In each market place data collectors are assigned to undertake the data collection every month. We traced the market place in the event data by matching the name of location in the event data with the name of market places where we have price information.

the price of food items at the zone level as well. By doing so, we are finally able to merge a total of 39 zones, which encountered political unrest, with the corresponding zones of production and price data.

ACLED currently categorised six types of events and twenty-five types of sub-events, both violent and non-violent, that may occur during a period of political violence and disorder. Table 4.1 displays event and sub-event types that occurred for the 39 zones that were selected. Since we depend on sub-event types to see the effect on food price dynamics, we present the percentage of sub-event types that occurred between 2010 and 2019. Accordingly, the top three event types are peaceful protest (32.5%), armed clash (19.5%) and attack (14.9%). Excessive force against protestors accounts for 9%,violent demonstration takes 7.8 %, mob violence 4.5% and protest with intervention accounts for 3.9%. The percentages for the remaining events are insignificant, nearly close to 1%.

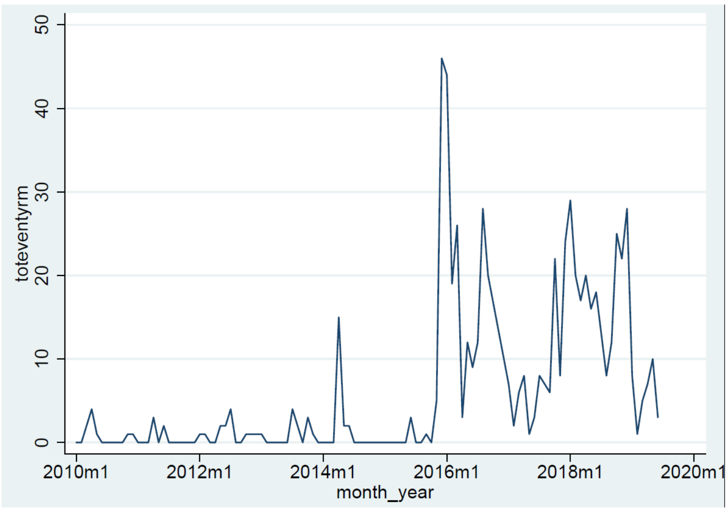
Table 4.1: Percentage of sub-event occurrence

General	Event type	Sub-event type	Percentage
Violent events	Battles	Armed Clash	19.5
		Government regions territory	0.0
		Non-state actor overtakes territory	0.0
	Explosions/Remote violence	Chemical weapon	0.0
		Air/drone strike	0.6
		Suicide bomb	0.0
		Shelling/artillery/missile attack	0.0
		Remote explosive/landmine/IED	0.6
		Grenade	1.9
	Violence against civilians	Sexual violence	1.9
		Attack	14.9
		Abduction/forced disappearance	0.7
Demonstration	Protests	Peaceful protest	32.5
		Protest with intervention	3.9
		Excessive force against protesters	9.1
	Riots	violent demonstration	7.8
		Mob violence	4.5
Non-violent actions	Strategic developments	Agreement	0.6
		Arrests	0.0
		Change to group/activity	0.7
		Disrupted weapons use	0.0
		Headquarters or base established	0.0
		Looting/property destruction	0.7
		Non-violent transfer of territory	0.0
		Other	0.0

Source: Author's computations

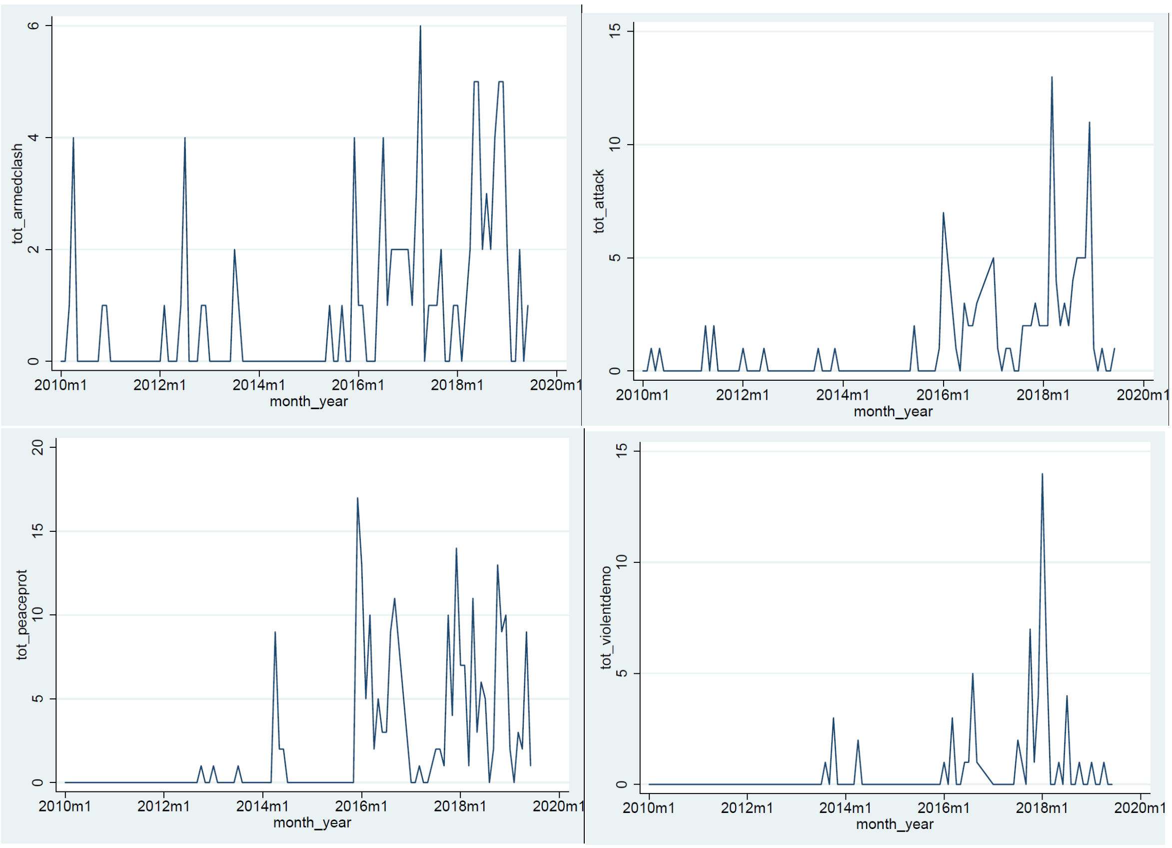
For this study, we focus on a subset of events that we assume had escalated enough to cause disruptions. These include armed conflicts, peaceful protests, attacks, excess force against protesters, violent demonstration, protests with interventions, mob violence, and looting and destruction. These represent significant numbers from the total incidents we aggregated. Accordingly, total number of incidents increased from 9 in 2010 to a high of 237 in 2018. As described above, the number of peaceful protests, armed clashes and attacks have large numbers accounting 66.9% of the total number of incidents. It is important to note that in this analysis, we are looking at the number of incidents and not the duration. The duration of the events can further affect an incident's impact on disruptions that lead to price instability. This would require more detailed data on the duration of incidents. In addition, the data does not indicate the intensity of disruption, particularly on economic institutions and thus for this study we assume that incidents affect prices equally. We try to account for intensity using different incidents. Figure 4.1 shows trends in the number of events. Number of incidents had a peak of around 45 in a month in 2016, but in general show elevated number of events through up until 2019.

Figure 4.1: Trend in number of political incidents (2010-2019)



Source: ACLED and authors own computation

Figure 4.2: Number of events by category (2010-2019)

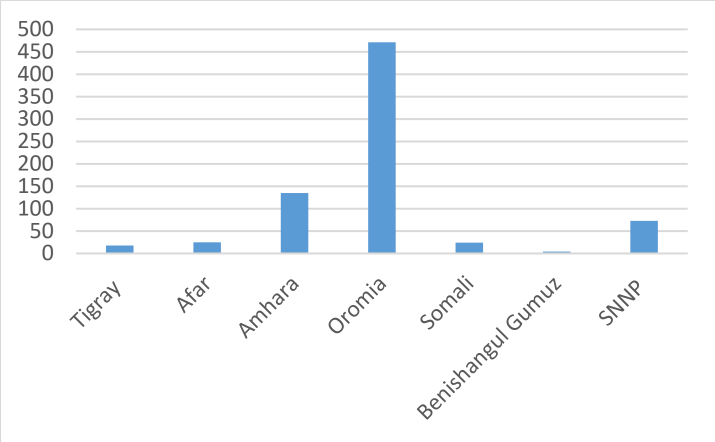


Source: ACLED and authors own computation

We can see that the incidents show significant escalation in the post-2015 period due to the protests and transition, although the number declines in 2019 with relative stability despite still remaining high. The majority of incidents are peaceful protests. These are peaceful in general but can signal instability, which may disrupt prices. Attacks followed by armed clashes and violent demonstrations may follow with, as expected, more serious consequences on prices. In areas with these events, it is expected that there will be transport disruptions making it difficult to get food items to the market. In addition, consumers tend to purchase more in anticipation of shortages when there are political events. Therefore, events affect both the supply and demand sides.

Regionally the Oromia region witnessed the majority of events amounting to 471 in total in the past ten years based on the data collected by the ACLED. This is expected since the majority of the political incidents that occurred during the period considered were organised by the Oromo Protest movement. The Amhara region follows with 135 total events over the ten year period. These two regions represent the largest food production regions particularly for cereals inEthiopia. Thus, the political unrest occurring in these regions affect not only the delivery of food to households but also the supply of crops to central markets in Addis Ababa. This increases the likely impact of events on prices of food items.

Figure 4.3: Regional Distribution of Events



Source: ACLED and author’s own computation

4.3 Impact of Events on Prices

Prices and political instability have had similar structural shifts in the last 10 years. The preliminary difference in difference estimates indicate that the events significantly influence food prices. The occurrence of an event for example, increased a kilo of teff price by Birr 6.50. At the current price this represents more than 10% of the price of teff which is around 60 Birr/kg, the price of wheat by Birr 5.73 (about 25% of the price), the price of maize by 6.35 Birr (about 30% of the price) and the price of barley by Birr 6.47 (about 40% of the price). These results are robust to time fixed effects. It should be noted that these estimates are preliminary and will be more precise with the inclusion of more control variables.

Results also show that the prices in regions with events have not been higher than in other regions, suggesting that it may be disruption to supply routes to the main markets that have been leading to the price increases rather than purely localized price impacts. Further work would include identifying whether the treated region is a net producer or net consumer region as well as whether the treated market is integrated to the central Addis or other markets.

Table 1: Difference in Difference Estimation

	(1) teff_w	(2) wheat	(3) maize	(4) barley
event2015	6.50***	5.73***	6.35***	6.47***
	(0.39)	(0.59)	(0.36)	(0.45)
PROD_TEFF	0.17			
	(0.11)			
PROD_WHEAT		0.27**		
		(0.12)		
PROD_MAIZE			0.06***	
			(0.01)	
PROD_BARLEY				0.14**
				(0.07)
_cons	12.40***	9.72***	13.36***	12.73***
	(1.45)	(2.18)	(0.40)	(1.09)
N	456	458	513	472
F_grang				

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In line with these results, research on supply side drivers (IGC, 2021) has also confirmed the role of market-disrupting events on food inflation. This includes for traditional grains, the bulk of the food consumption basket, where markets have integrated over time (for example, between net producing areas and central Addis market in the 2000-2015 period). This suggests the importance of minimizing disruptions along supply routes, notably when events are in net grain producer areas. There also may be short-term measures for protecting farmers planting and harvesting in conflict-affected areas (Box 1).

Box 1: Events—Managing Short Term Impact on Grain Prices

A recent event highlights the potentially negative short-term impact on prices of conflict in net producing areas The case was an ethnic conflict in East Wollega, the second most important zone for maize. This led to partial destruction of that region's maize crop with farmers fleeing the areas and trucks not willing to go into the conflict areas earlier in 2021. The security authorities responded promptly, thereby reducing the overall potential destruction. Nonetheless, destruction led to an increase in maize prices, both in the region and in the central market of about 300% as compared to the previous year, far exceeding the overall food price inflation of roughly 30%. However, uncertainty regarding the security situation remains.

This case highlights potential of mediation efforts focused on protecting farmers during planting and harvesting of crops in conflict-affected areas and

5. Main Findings and Policy Implications

This last section brings together the main findings of this research and builds a story around the food supply side factors driving inflation. It also highlights where policy makers may wish to focus attention in efforts to reduce inflation.

IGC's earlier inflation research stressed that inflation drivers in Ethiopia consist of both demand side (monetary and inflation expectations) factors as well as a set of supply-side or structural drivers (including market-disrupting events). That earlier research also noted persistence in food inflation (lagged inflation statistically significant for food price inflation, Adam et al (2021)). This has some additional policy implications related to the food price shocks.

- Inflationary expectations (short term). To manage inflationary expectations and mitigate against persistence in food inflation, it will be critical for authorities to communicate clearly the macroeconomic policy stance and any adjustments, for example, regarding monetary and credit aggregates.

A major conclusion of the further analysis is that marketable surplus of grains has not kept up with demand. Both cereal production and marketable surplus have increased in absolute terms over time (2009-2020), more than doubling. However, the share of production for own-consumption by smallholder producers remained high and that for marketable surplus increased only slightly (basically flat for teff, wheat, maize and oilseeds, within only pulses, vegetables and root crops showing increases). These producers account for about 95% of overall grain production in Ethiopia. There are several policy implications:

- Imports and production (short/medium term). Government's efforts regarding wheat imports will continue to have important short term effects, as will the role of price considerations in strategic grain reserve policy. For the medium and longer term, commercial investment in food production might be way forward. Other studies have identified a number of steps that could be taken to increase commercial food production which would be by and large marketable surplus with the exception of supply for seeds.
- Rural population growth (long term). A major factor preventing smallholder producers from marketing more of their grain production is growth in the rural household population. Despite a commendable effort in expanding family planning services, rural fertility rates remain high, thereby, putting pressure on both rural and urban population through migration. A concerted effort to make family planning services more effective could reduce this pressure.
- Productivity of arable land and support for the rural economy (medium term). Other studies have identified projects and policies aimed at enhancing productivity of arable land. These could be accelerated. This includes productivity of smallholder farmers, including those rural households that are net buyers of food particularly in the lean season; a rural jobs policy that can keep youth engaged in agricultural production; and reduction of other constraints (such as access to credit) to enhance production and marketable surplus.
- Protection of farmers planting/harvesting crops (short term). A major focus of mediation efforts could include a moratorium during the planting or harvesting seasons in conflict-affected areas

Preliminary results indicate that high value food items such as fruits and vegetables have high income elasticity. Increased incomes over the past decade changed the composition of food expenditure from grains towards a higher share for those high value items which also experienced higher price increases, explaining some of the inflation. Price increases would be expected to be transitory as supply chains develop which suggests the following on the policy side:

- Facilitating supply chain development. Avoid restricting development of supply chains in high value food items, especially since recent analysis of several supply chains (dairy, vegetables) shows that they are more efficient than usually assumed. Rationalizing location and seasonality of the urban distribution infrastructure could decrease transaction costs at retail level. Also, there may be scope for rethinking policy and loading and reloading mandates.

Geographic price dispersion across a range of food items has increased, with causality tests suggesting this has contributed to inflation in select food items. While there is some evidence of increased market integration to 2015, analysis is incomplete and inconclusive as to more recent trends. Nonetheless, this suggests several policy directions:

- Transport infrastructure (medium term). It will be critical to maintain improved transport infrastructure which presumably increased integration and decreased dispersion. However, more analysis of recent trends including integration among regional markets is needed before being more definitive on the role of trunk vs regional infrastructure.
- Marketing margins (medium term). There is considerable scope to leverage the growing telecom network to make it easier to share real-time market data among farmers and reduce monopoly power and, hence, margin between farmgate and market prices. Focus needs to be on not only access to mobile phones but also pricing and mobile applications.

A tentative conclusion of the analysis is that disruptive events in food surplus areas have played a role in the supply side drivers of inflation. This can lead to high inflation knock-on with non-localized large costs to the economy overall. We continue to work on role of disruptive events as this can have implications for policy.

- Disaggregated measurement of inflation (short term). A policy implication is for macroeconomic policy makers to monitor inflation in a disaggregated way. Surprisingly, events in select regions of the country appear to exacerbate inflation in rest of the country rather than in the source zone when events are in surplus regions. It would be helpful to isolate those local inflationary developments and how they link to the broader economy through the transport and marketing of production surpluses. That would give authorities a broad brush assessment as to how much of the inflation surge is directly event/conflict related rather than other macroeconomic factors. There indeed will be indirect effects as well, but these would be more complex to untangle.
- Mitigation of the economic consequences of disruptive events (short/medium term). Another policy implication is the importance of trying to mitigate such kinds of events, whether in the political, security or economic sphere. This could include minimizing disruptions along supply routes, notably when events are in net producer areas, and improving broad-based dialogue and communication to preserve confidence in the state's capacity to secure economic activity.

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Appendix: Lag Length Selection [YOU MAY WANT TO MOVE EVEN MORE OF THE DETAILS ON THIS FROM BODY OF THE NOTE]

```
. varsoc  teffw_av_ma_infyoy      teffw_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1210.87				181.63	10.8777	10.8901	10.9083
1	-361.172	1699.4	4	0.000	.092298	3.29302	3.33003	3.38469
2	-151.466	419.41	4	0.000	.014587	1.44812	1.5098*	1.60091*
3	-150.233	2.4662	4	0.651	.014954	1.47294	1.55929	1.68684
4	-141.328	17.81*	4	0.001	.014311*	1.42895*	1.53997	1.70397

```
   Endogenous:  teffw_av_ma_infyoy teffw_sd_ma
    Exogenous:  _cons

. varsoc  teffm_av_ma_infyoy      teffm_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1192.59				154.17	10.7138	10.7261	10.7444
1	-304.78	1775.6	4	0.000	.05566	2.78727	2.82427	2.87894
2	-84.6556	440.25*	4	0.000	.008012*	.84893*	.910609*	1.00172*
3	-82.5474	4.2166	4	0.377	.008149	.865896	.952247	1.0798
4	-80.0995	4.8957	4	0.298	.008264	.879816	.990839	1.15483

```
   Endogenous:  teffm_av_ma_infyoy teffm_sd_ma
    Exogenous:  _cons

. varsoc  teffb_av_ma_infyoy      teffb_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1241.12				238.243	11.149	11.1614	11.1796
1	-424.556	1633.1	4	0.000	.162957	3.86148	3.89849	3.95316
2	-199.165	450.78*	4	0.000	.022375*	1.87592*	1.9376*	2.02871*
3	-197.628	3.0729	4	0.546	.022875	1.89801	1.98436	2.11192
4	-197.312	.6334	4	0.959	.023645	1.93105	2.04207	2.20606

```
   Endogenous:  teffb_av_ma_infyoy teffb_sd_ma
    Exogenous:  _cons

. varsoc  wheatw_av_ma_infyoy     wheatw_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1241.95				240.033	11.1565	11.1689	11.1871
1	-400.788	1682.3	4	0.000	.131674	3.64832	3.68533	3.74
2	-146.196	509.18*	4	0.000	.013914	1.40086	1.46254*	1.55365*
3	-142.065	8.2614	4	0.082	.013898*	1.39969*	1.48604	1.61359
4	-139.658	4.8137	4	0.307	.014098	1.41397	1.525	1.68899

```
   Endogenous:  wheatw_av_ma_infyoy wheatw_sd_ma
    Exogenous:  _cons

. varsoc  wheatr_av_ma_infyoy     wheatr_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1304.17				419.391	11.7146	11.7269	11.7451
1	-349.088	1910.2	4	0.000	.082818	3.18464	3.22165	3.27631
2	-68.8869	560.4	4	0.000	.006955	.707506	.769185	.860294*
3	-59.3371	19.1*	4	0.001	.006618*	.657732*	.744083*	.871635
4	-57.38	3.9142	4	0.418	.006741	.676054	.787077	.951073

```
   Endogenous:  wheatr_av_ma_infyoy wheatr_sd_ma
    Exogenous:  _cons

. varsoc  wheatm_av_ma_infyoy     wheatm_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1216.29				190.686	10.9264	10.9387	10.9569
1	-407.224	1618.1	4	0.000	.139498	3.70605	3.74306	3.79772
2	-197.732	418.99*	4	0.000	.022089*	1.86306*	1.92474*	2.01585*
3	-196.788	1.8875	4	0.756	.022703	1.89047	1.97682	2.10438
4	-194.065	5.446	4	0.245	.022966	1.90193	2.01295	2.17694

```
   Endogenous:  wheatm_av_ma_infyoy wheatm_sd_ma
    Exogenous:  _cons

. varsoc  maizew_av_ma_infyoy     maizew_sd_ma

   Selection-order criteria
   Sample:  1998m5 - 2019m6, but with gaps      Number of obs      =       223
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1222.99				202.496	10.9865	10.9988	11.017
1	-412.7	1620.6	4	0.000	.14652	3.75516	3.79216	3.84683
2	-147.343	530.71	4	0.000	.014058	1.41115	1.47283	1.56393*
3	-137.809	19.068*	4	0.001	.013377	1.36151	1.44786*	1.57542
4	-133.596	8.4254	4	0.077	.013352*	1.35961*	1.47063	1.63462

```
   Endogenous:  maizew_av_ma_infyoy maizew_sd_ma
    Exogenous:  _cons
```

Appendix : Granger Causality

Appendix: Threshold Autoregressive (TAR Model) in Van Campenhout (2007)

A modified version of the Threshold Autoregressive (TAR) Model[8] as used in Van Campenhout (2007) is used to test price transmission between Addis Ababa and carefully selected regional markets. The TAR model can be described as follows:

Consider

$$d_t = P^i{}_t - P^j{}_t \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

P_t^k : price in k (k= i, j) market at time t

d_t : price difference between markets i and j at time t

Given this, consider an AR process in which two spatially separated markets are said to be integrated when deviations in d_{t-1}, the previous period's price difference between two markets, is transmitted to current period.

$$\Delta d_t = \rho d_{t-1} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots. (2)$$

Where ρ is the speed of adjustment (The error correction term, ρ, should have a negative sign to indicate a move back to the long-run equilibrium. A positive sign indicates a move away from equilibrium. As the coefficients should lie between 0 and 1, 0 suggests no adjustment while 1 indicates full adjustment of the process back to its equilibrium position.). ε_t is the error term

The above specification is based on assumption of symmetry and linearity and also disregards transaction costs as it implicitly assumes deviation is always above a parity bound (Dercon and Campenhout 1999). However, it has been noted (Tong 1980; Enders and Sikilos 2001) that for most price series, given markets are integrated, deviations from a given equilibrium is corrected in an asymmetric manner (and also non-linear due to such factors as reversals in direction of trade flow (Amikuzuno 2009)).

Efficient arbitrage is said to occur when $| d_t | >= TC_{ij}$ where $| d_t |$ is the absolute value of price difference between markets i and j, and TC_{ij} is transaction cost of moving a given commodity between

[8] More detailed descriptions on the model and on alternative models can be found in Van Campenhout (2007)

markets i and j. Accordingly, if the price difference of a commodity between two markets is greater than the transaction cost between them, TC_{ij}, traders can make profit by shipping the commodity from the market with a lower price to the market with the higher price.

As usually the case, it is difficult to get transaction cost data and market integration related inference is usually limited to available price data (According to Barrett (1996), studies that rely on price data alone are labeled level I). However, spatial integration between markets can be undertaken by categorizing specifications into three regimes to account for the invisible transaction costs depending on whether $d_{t-1} > TC_{ij}$, $d_{t-1} <- TC_{ij}$, or $| d_{t-1} | < TC_{ij}$; **w**here: TC_{ij}, is transaction cost between markets i and j. In the first (second) scenario, there is profitable arbitrage that has not been exploited by traders in moving commodities from market i to j (or j to i); while the third case, given markets are integrated, can be considered as a condition for efficient arbitrage and a state where it is unprofitable for traders to engage in arbitrage (Campenhout 2007). Accordingly, d_{t-1} can be considered as a long run process returning to a band [- TC_{ij}, TC_{ij}] and arbitrage occurs outside the band until the threshold values on the band, TC_{ij}, are reached. Consequently, upon returning to the band, there will be some non-linear autoregressive process and the magnitude of the adjustment process is a percentage of the deviations in each period, i.e., $\Delta d_t = d_t - d_{t-1}$. The process can be expressed as:

$$\Delta d_t = \begin{cases} \rho^{out} d_{t-1} + \varepsilon_t : & d_{t-1} > \theta \\ \rho^{in} d_{t-1} + \varepsilon_t : & \theta < d_{t-1} + \theta \ldots \ldots (3) \\ \rho^{out} d_{t-1} + \varepsilon_t : & d_{t-1} < -\theta \end{cases}$$

Where: ε_t is a white noise with N (0, δ^{in2}), ρ^{out} is the speed of adjustment towards the band, ρ^{in}, the speed of adjustment inside the band and θ is the threshold. The threshold value, (θ), is estimated through a grid search which is super consistent (Chan 1993). However, this specification too has its shortcoming as it assumes constant threshold value (transaction cost) over the study period. However, in reality transaction costs could vary depending on season, direction of trade, quality of roads and fuel prices among others.

$$\Delta d_t = \begin{cases} \rho^{out} d_{t-1} + \rho^{out}{}_t d_{t-1} + \varepsilon_t & : \quad d_{t-1} > \theta_t \\ \varepsilon_t & : -\theta_t \le d_{t-1} \le \theta_t \ldots \ldots \ldots \ldots \ldots \ldots (4) \\ \rho^{out} d_{t-1} + \rho^{out}{}_t d_{t-1} + \varepsilon_t & : \quad d_{t-1} < \theta_t \end{cases}$$

where d_t is the difference between the wholesale price in Addis Ababa and other regional markets at the same level. That is, $d_t = P_t, A - P_t, O$, where P_t, A is cereals price in Addis Ababa and P_t, O is the corresponding wholesale level price in other markets at time t. $\Delta d_t = d_t - d_{t-1}$ while ε_t is the estimated residual. t denotes the time trend and θ is an approximation for transaction costs[9]. ρ^{out} is the adjustment factor[10] for prices outside of the transaction cost band (that is –θ to θ).

[9] Following Van Campenhout (2007), the threshold is modeled as a simple linear function of time: θ_t=θ_0 + $\frac{(\theta_T - \theta_0)}{T}$. t where t is the time running from 0 to T, and like the standard TAR model the thresholds are estimated through a grid search which is super consistent (Chan 1993).

[10] If ρ^{out}= -1 it means there is perfect integration (i.e., deviations from the long run equilibrium are transferred) and adjustment is instant. If ρ^{out} =0, it means that there is no integration and hence no adjustment in the near future. Consequently, the closer ρ is to -1, the higher the degree of integration and the lower the speed of adjustment. If ρ is positive however, it means that markets are drifting apart and it is an indication that the markets in discussion are not integrated in the short run.

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
teffw_av_ma_inf~y	teffw_sd	1.7277	4	0.786
teffw_av_ma_inf~y	ALL	1.7277	4	0.786
teffw_sd	teffw_av_ma_inf~y	2.842	4	0.585
teffw_sd	ALL	2.842	4	0.585

(output written to Graphs\Granger_teffw.tex)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
teffm_av_ma_inf~y	teffm_sd	1.112	4	0.892
teffm_av_ma_inf~y	ALL	1.112	4	0.892
teffm_sd	teffm_av_ma_inf~y	.44435	4	0.979
teffm_sd	ALL	.44435	4	0.979

(output written to Graphs\Granger_teffm.tex)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
teffb_av_ma_inf~y	teffb_sd	.25734	4	0.992
teffb_av_ma_inf~y	ALL	.25734	4	0.992
teffb_sd	teffb_av_ma_inf~y	2.6826	4	0.612
teffb_sd	ALL	2.6826	4	0.612

(output written to Graphs\Granger_teffb.tex)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
wheatw_av_ma_in~y	wheatw_sd	2.9208	4	0.571
wheatw_av_ma_in~y	ALL	2.9208	4	0.571
wheatw_sd	wheatw_av_ma_in~y	2.816	4	0.589
wheatw_sd	ALL	2.816	4	0.589

(output written to Graphs\Granger_wheatw.tex)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
wheatr_av_ma_in~y	wheatr_sd	5.0317	4	0.284
wheatr_av_ma_in~y	ALL	5.0317	4	0.284
wheatr_sd	wheatr_av_ma_in~y	2.4128	4	0.660
wheatr_sd	ALL	2.4128	4	0.660

(output written to Graphs\Granger_wheatr.tex)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
wheatm_av_ma_in~y	wheatm_sd	4.4055	4	0.354
wheatm_av_ma_in~y	ALL	4.4055	4	0.354
wheatm_sd	wheatm_av_ma_in~y	.42777	4	0.980
wheatm_sd	ALL	.42777	4	0.980

(output written to Graphs\Granger_wheatm.tex)

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
maizew_av_ma_in~y	maizew_sd	7.4262	4	0.115
maizew_av_ma_in~y	ALL	7.4262	4	0.115
maizew_sd	maizew_av_ma_in~y	3.6599	4	0.454
maizew_sd	ALL	3.6599	4	0.454

(output written to Graphs\Granger_maizew.tex) www.theigc.org