The World Bank Economic Review, 2017, 1–25
doi: 10.1093/wber/lhx008
Article

What Drives Local Food Prices? Evidence from the Tanzanian Maize Market*

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Abstract

We examine the drivers of monthly changes in maize prices across 18 Tanzanian markets. Local prices respond three to four times faster to the main regional market (Nairobi) than to the international benchmark (US Gulf). More importantly, shocks from Nairobi account for only one third of the explained variation in domestic prices; the remaining two-thirds is accounted for by domestic influences (including harvest cycles, weather shocks, and trade policies). Further, we show that remoteness and the local agroecology systematically influence the behavior of food prices.

JEL classification: E31, O13, Q02, Q13, Q18

Key words: Food prices, Price transmission, Tanzania, Trade policies, Weather anomalies

I. Introduction

What drives food price changes in developing countries? This question has received considerable attention in the aftermath of the 2008 and 2011 spikes in international food prices. Much of that attention has focused on the influence of world markets.[1] Instead, we develop an empirical framework that measures and accounts for the influence of both external and domestic drivers of maize prices in Tanzania.

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1 While Ivanic and Martin (2008) and von Braun (2008) have suggested that the 2008 food price spike had a strong influence on domestic food markets, Aksoy and Hoekman (2010) and Headey (2013) found a muted impact. Swinnen (2011), who reviews this literature, also questions the official statements by several international organizations. These statements were justified by trade simulation models predicated on ad-hoc assumptions regarding the extent of price transmission.

More generally, and in contrast to the food market integration literature, our focus is on understanding price changes in local markets—not whether these markets are "efficient." These are different concepts. For example, a low degree of market integration could reflect trade frictions engendered by a host of factors, including geography, poor infrastructure, and policies.[2]

We show that all 18 Tanzanian maize markets (for which we examine monthly price changes from August 2002 to July 2014) adjust to changes in prices in Nairobi with a lag, but significantly faster than they do to changes in the U.S. Gulf and South African prices. This suggests that the impact of external markets is not as strong as typically assumed and comes mostly from regional, rather than global, markets. These findings are consistent with the weak linkages between domestic and world food markets reported elsewhere (e.g., Baffes and Gardner [2003], Minot [2011], and Brown and Kshirsagar [2015]). We also show that within-country variation in trade costs and agroecological conditions engenders systematic differences in the behavior of local maize prices. While we find that weather shocks and harvest cycles are a major source of short-term price variability across all markets, their influence is most pronounced in markets that are both remote and located in surplus producing regions.

Several features of Tanzania's agrarian economy lend themselves to a study of food staple markets that may be of broader interest. First, Tanzania is a large country with five distinct agroecological zones. Second, food self-sufficiency varies widely across different parts of the country. Third, there are diverse domestic and cross-border trade routes that involve water (ocean and lake) as well road transport. Fourth, the eight countries that border Tanzania vary in terms of their net food import needs. Fifth, while the government influences the relationship between domestic and external prices through trade policies, prices within the country are, for the most part, determined by market forces. Therefore, our analysis is relevant to understanding local food markets across developing countries.

The paper proceeds as follows. Section II presents an overview of Tanzanian maize markets. Section III describes the conceptual and empirical framework employed to estimate the impacts of the drivers of local food prices. Sections IV and V discuss price and non-price drivers by analyzing individual markets as well as market groups that are delineated across two dimensions: surplus versus deficit and remote versus connected markets. Section VI examines the channels through which trade policies may influence domestic prices. Section VII concludes.

II. The Tanzanian Maize Market

Tanzania, Sub-Saharan Africa's sixth most populous nation, borders eight countries, three lakes, and the Indian Ocean.[3] It has two major ports, Dar es Salaam and Tanga, and two smaller ones, Lindi and Mtwara (figure 1). Nairobi, East Africa's largest city and major commercial center, is a key destination for its maize exports. Other destinations include Malawi and Mozambique and occasionally other countries in the region.

Geographic and Historical Influences

Maize has been cultivated in East Africa since the 17th century. A major shift took place in the early 20th century in the types of maize cultivated, following the introduction of better-performing varieties from the United States, initially in South Africa and later in Southern and Eastern Africa including Tanzania (McCann [2005]). Two policy changes in the first half of the 20th century incentivized the expansion and commercialization of maize: the 1911 introduction by the London Corn Exchange of

2 Ravallion (1986) provides an insightful discussion on the relationship between local effects and transport costs during a three-year period that encompasses the 1974 famine in Bangladesh. Badiane and Shively (1998) show that reforms engendered decreases in local maize price volatility in Ghana.

3 While Tanzania comprises the mainland and Zanzibar, in this paper we study markets on the mainland.

Figure 1. Maize Markets in Tanzania

grading standards for African imports and the 1925 Rhodesian Maize Act, which codified the primary cultivation of white dent corn into law.

Today, maize is Tanzania's most important food staple.[4] During the 2007/08 season, 5.1 out of the 5.8 million agricultural households grew maize. However, maize is produced with limited use of modern inputs. Further, only three percent of maize area is irrigated.

4 Tanzania accounts for less than one percent of global maize production (USDA), therefore it does not influence the global market.

Table 1. Key Physical Characteristics of Tanzanian Maize Markets

		Maize statistics on				Time and distance via major roads			
	FEWS NET Categorization	Production (000 m MT)	Area (000 Ha)	Yield (MT/Ha)	Share (Percent)	Dar (Hours)	Nairobi (Hours)	Dar (Km)	Nairobi (Km)
Central									
Dodoma	Minor deficit	351	339	1.0	74	7:33	8:45	502	682
Singida	Minor deficit	190	150	1.3	53	10:24	8:14	673	578
Tabora	Minor deficit	376	292	1.3	68	12:51	11:35	886	873
Coastal									
Dar es Salaam	Deficit	4	6	0.7	55	0:00	11:43	0:00	913
Lindi	Minor deficit	63	76	0.8	59	5:57	17:31	457	1,362
Morogoro	Minor deficit	238	232	1.0	44	2:34	11:22	194	889
Mtwara	Minor deficit	63	78	0.8	67	7:17	18:51	562	1,467
Lake									
Bukoba	Deficit	121	100	1.2	71	18:29	12:30	1,415	960
Musoma	Minor deficit	117	65	1.8	69	15:25	6:44	1,149	495
Mwanza	Deficit	250	263	0.9	56	17:19	11:07	1,132	678
Shinyanga	Deficit	672	516	1.3	65	13:17	10:28	1,017	761
Northern									
Arusha	Deficit	210	124	1.7	95	8:25	3:33	647	272
Moshi	Minor deficit	150	108	1.4	94	7:21	4:32	567	349
Tanga	Surplus	273	188	1.5	na	4:39	8:32	356	619
Southern Highlands									
Iringa	Surplus	384	247	1.6	91	6:29	11:41	503	946
Mbeya	Surplus	495	271	1.8	72	10:32	15:23	829	1,165
Songea	Surplus	237	149	1.6	79	11:51	19:10	924	1,374
Sumbawanga	Surplus	351	224	1.6	70	18:51	19:00	1,215	1,466

Sources: FEWS NET categories from USAID's www.fews.net. Data for regional maize production from Tanzania's Agricultural Sample Census 2007/08 (2012). Road distances and time from Google Maps (estimated times assume no traffic, accessed on January 2015). Road travel is less relevant for markets in the lake and coastal zones.

Note: Share represents the share of crop area used for maize production.

Maize is grown in all five of Tanzania's agroecological zones (table 1). Nearly one-third of national output is produced in the Southern zone whose four surplus markets—Iringa, Mbeya, Songea, and Sumbawanga—are relatively isolated, being more than 500 kilometers away from Dar es Salaam (a major consumption market) and Nairobi (an export destination) and without convenient access to a port. However, Mbeya and Songea export maize to Malawi and Mozambique, most notably to Nampula in northern Mozambique; this trade often goes unrecorded (FEWS NET [2014]; Burke and Myers [2014]). Tanzania's Northern zone markets—Arusha, Moshi, and Tanga—account for almost 15 percent of maize output and are well connected to Nairobi. Arusha has historically been one of Tanzania's most important transport hubs (Iliffe [1979]). The Central zone markets of Dodoma, Singida, and Tabora account for about 20 percent of maize production. They are food-deficit markets but have good access to transport infrastructure. The four Lake zone markets—Bukoba, Musoma, Mwanza, and Shinyanga—are all food-deficit markets as well, with convenient access to the markets of Kenya and other neighboring countries. Last, in the Coastal zone, which includes the large market of Dar es Salaam along with Lindi, Morogoro, and Mtwara, only Morogoro is an important maize producer.

The limited use of modern inputs along with the small share of maize under irrigation renders Tanzania's maize production vulnerable to weather shocks. Furthermore, the remoteness of the Southern zone surplus markets, combined with the long distances from markets to consumption centers and ports, and poor transport and storage infrastructure, magnifies the influence of domestic factors.

Table 2. Export Bans and Maize Prices

	Export ban's effectiveness			Price (Tsh/kg, CPI-deflated, 2010)		
	First month	Last month	Duration (months)	First month	Last month	Percent change
First	January 2004	December 2005	24	457	302	−34%
Second	March 2006	December 2006	10	423	200	−53%
Third	January 2008	April 2008	4	445	442	−1%
Fourth	January 2009	September 2010	21	457	296	−35%
Fifth	July 2011	December 2011	6	447	373	−17%
Average			13	446	323	−28%

Notes: Prices refer to the Dar es Salaam market. Export bans were in effect for 65 months (out of 144 months in the sample).

The Policy Environment

During World War II, Kenya and Tanganyika (now mainland Tanzania) established a Cereals Board in order to control grain trade and secure food supplies. Government intervention continued well after the war under the aegis of a Cereals Pool jointly operated by Kenya, Uganda, and Tanganyika. Tanganyika withdrew from the pool in 1949 and established a Grain Storage Department that became the sole marketer and trader of food crops. This arrangement lasted until 1955, when, after a number of good harvests, the government's intervention in the food sector diminished (Suzuki and Bernard [1987]).

For the next seven years, maize was freely traded in Tanzania, but that changed following poor harvests in 1961 and 1962; the National Agricultural Products Board was established in 1964 with responsibilities very similar to those of the Grain Storage Department. A decade later, the National Milling Corporation took over marketing, trade, and storage aspects for most food commodities while the responsibility for price-setting stayed with the government. Although some interventions were removed in the early 1980s, the government continued to intervene through ad hoc policies in response to food security concerns and political pressures.

The negative consequences of Tanzania's restrictive trade policies are well known (e.g., Edwards [2014]). Lofchie (1978) linked the collapse of the country's agrarian economy to the high taxes on agricultural production that followed the (1967) Arusha Declaration. Even President Nyerere, the chief architect of the declaration, acknowledged (in 1979) that weak economic incentives may have been responsible for the decline in agricultural productivity. Suzuki and Bernard (1987) argued in favor of more open trade policies.[5]

Despite these warnings and assessments, ad-hoc trade policies were introduced as recently as 2011. Since 2004, five export bans were imposed on maize exports, with an average duration of 13 months (table 2). The first and second spanned January 2005 to December 2006, with a two-month hiatus at the beginning of 2006. A four-month ban was in place in 2008 and another (much longer ban) during 2009–10. The duration of the most recent one was less clear: it was announced in March 2011 and became effective in July; likewise, its removal was announced in October 2011 but did not take effect until December that year. Consistent with the government's concern about food security, the bans were introduced when maize prices were high and removed when prices were low (figure 2). The inflation-adjusted price of maize has been, on average, 28 percent lower in the last month of each ban than in the first.

5 For analyses of Tanzania's agricultural and trade policies in the context of the reforms that began in the mid-1990s, see Cooksey (2003) for agriculture, Mitchell (2004) for the cashew sector, and Baffes (2004, 2005a,b) for the cotton, coffee, and tea sectors, respectively.

Table 3. Summary Statistics of Maize Prices in Tanzania (August 2002 –July 2014)

	Average Price Tsh/kg, Real, Sep 2010 = 100			Volatility Standard deviation of logarithmic change		
	Full	No ban	Ban	Full	No ban	Ban
U.S. Gulf	256	277	229	6.7	6.6	6.9
South Africa	285	300	267	9.4	9.0	9.7
Nairobi	402	396	409	9.6	9.9	9.2
Tanzania, average	334	295	296	12.7	11.2	13.9
Central						
Dodoma	357	353	362	10.1	8.8	11.1
Singida	334	333	336	11.2	10.2	12.0
Tabora	345	353	334	13.2	13.6	12.5
Coastal						
Dar es Salaam	357	363	349	10.2	9.4	10.7
Lindi	357	364	350	20.0	19.1	21.0
Morogoro	350	344	357	13.3	13.6	12.6
Mtwara	355	354	355	21.9	20.5	23.5
Lake						
Bukoba	360	363	357	11.3	12.0	10.2
Musoma	379	387	370	11.4	11.3	11.2
Mwanza	387	393	380	10.3	10.0	10.3
Shinyanga	355	357	352	10.2	8.4	11.5
Northern						
Arusha	335	327	346	9.6	8.7	10.0
Moshi	349	339	362	10.3	9.0	11.1
Tanga	334	333	336	14.0	12.3	15.4
Southern Highlands						
Iringa	280	279	282	13.2	12.8	13.7
Mbeya	281	293	267	10.2	9.6	10.9
Songea	242	238	247	17.3	13.3	21.2
Sumbawanga	247	259	232	14.1	13.1	15.2

Notes: Both Tanzanian and external prices are expressed in real Tanzanian shillings (September 2010 = 100, deflated by the total CPI). Volatility is defined as standard deviation of logarithmic change, multiplied by 100. Out of the 144 monthly observations, 65 correspond to Ban and 79 to No ban regimes.

III. The Conceptual Framework And Data

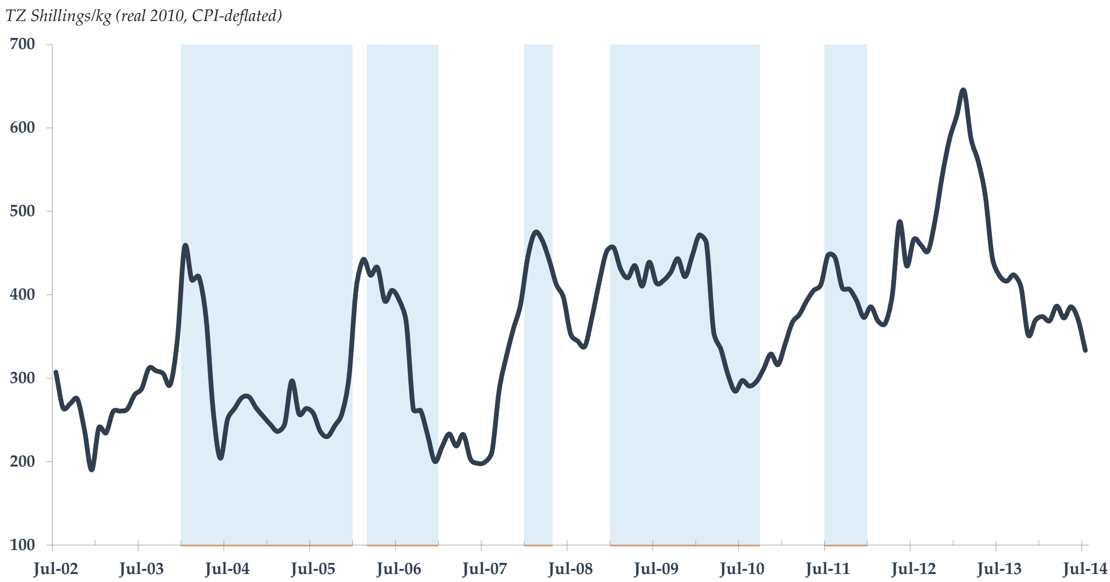
Food prices in developing countries often vary considerably across time and locations. At a given location, the near absence of local storage, coupled with harvest cycles, engenders seasonal variation in prices while weather anomalies induce deviations from these seasonal patterns. In addition to this temporal variation, large trade costs, due to poor transport infrastructure, coupled with agroecological variation and (often) trade restrictions, create substantial spatial price variation.

Local Food Price Formation in Developing Countries

In what follows, we develop a framework to understand spatial and temporal differences in local food prices. This framework augments the standard spatial equilibrium model by allowing for the influence of harvest cycles, production shocks, trade costs, and trade policies.[6]

6 In the spatial equilibrium framework, trade costs prevent price equalization even when arbitrage opportunities are exhausted (Samuelson [1952]).

Figure 2. Maize Prices in Dar es Salaam and Export Bans



Source: FAO GIEWS, newspaper articles, and interviews with industry representatives

First, we introduce two seasons, lean and harvest. In the absence of storage, the local market i is supplied entirely by the external market during the lean season. Therefore, the local price (P_L^i) depends on the exogenous external price (P^E) and the trade costs (T^i). The trade costs, which vary across markets, can be particularity large in remote areas (i.e., areas characterized by poor transport infrastructure and substantial distance from the external market):

$$P_L^i = P^E + T^i \tag{1}$$

The local price during the harvest season, P_H^i, is given by:

$$P_H^i = \begin{cases} P^E + T^i & \text{if} \quad P_H^{Ai} \geq P^E + T^i & \text{(2a)} \\ P_H^{Ai} & \text{if} \quad P_H^{Ai} \subset (P^E - T^i, P^E + T^i) & \text{(2b)} \\ P^E - T^i & \text{if} \quad P_H^{Ai} \leq P^E - T^i & \text{(2c)} \end{cases}$$

Equation (2a), relevant to a deficit market, shows that the local price is determined by the external price and trade costs. Equation (2b), relevant when trade with the external market does not take place, shows that the local price, which equals the autarky price (P_H^{Ai}), is determined by local demand and supply and fluctuates within the parity band ($P^E - T^i, P^E + T^i$). Equation (2c) refers to a surplus market, which exports to the external market, and, therefore, has a local price that is equal to the external price net of trade costs.

Second, we introduce an agroecological factor Z^i, which is inversely related to the cost of producing food and captures the influence of location-specific and time-invariant factors such as soil fertility, rainfall patterns, and the length of the growing season.

Third, we assume that local production is influenced by a time-varying production shock (α) with $\alpha > 1$ being consistent with a good harvest and $\alpha = 1$ associated with a bad harvest. Therefore, the autarky price is related to production shocks in good and bad states of nature as follows:

$$P_H^{Ai} = \frac{1}{\alpha Z^i} \tag{3}$$

Fourth, we assume that trade costs can increase from T^i to θT^i, where $\theta > 1$, due to factors such as trade policies. Therefore, the imposition of a restrictive trade policy widens the parity band from $(P^E - T^i, P^E + T^i)$ to $(P^E - \theta T^i, P^E + \theta T^i)$.

The above framework allows us to categorize markets as being *surplus* and *deficit* (relative to the external market), under normal trade costs. A *surplus* market imports food in the lean season and may export food during the harvest season. In contrast, a *deficit* market imports food during the lean season, may import food during the harvest season, and never exports food. In addition to the surplus-deficit distinction, markets are also delineated into *connected* and *remote* categories based on trade costs—which depend on distance from the external market, transport infrastructure, and trade policies. These categories enable us to relate the behavior of local prices to harvest cycles, production shocks, the external price, trade costs, and the agroecological factor, with the latter two varying across markets. Therefore, we categorize markets as follows: *surplus-remote*, *surplus-connected*, *deficit-remote*, and *deficit-connected.*

The local price in *surplus-remote* markets can be derived by combining equations (2b–c) and (3):

$$P_H^i = \begin{cases} \dfrac{1}{Z^i} & \text{if} \quad \dfrac{1}{Z^i} > P^E - \theta T^i \quad \text{and} \quad \alpha = 1 \qquad \text{(4a)} \\ \dfrac{1}{\alpha Z^i} & \text{if} \quad \dfrac{1}{\alpha Z^i} > P^E - \theta T^i \quad \text{and} \quad \alpha > 1 \qquad \text{(4b)} \\ P^E - \theta T^i & \text{if} \quad \dfrac{1}{Z^i} \leq P^E - \theta T^i \quad \text{and} \quad \alpha = 1 \qquad \text{(4c)} \\ P^E - \theta T^i & \text{if} \quad \dfrac{1}{\alpha Z^i} \leq P^E - \theta T^i \quad \text{and} \quad \alpha > 1 \qquad \text{(4d)} \end{cases}$$

Equations (4a–b) correspond to (2b) and equations (4c–d) correspond to (2c). Since the surplus-remote markets either export or do not trade during the harvest season, condition (2a) is not applicable. When trade costs are normal ($\theta = 1$), a favorable harvest ($\alpha > 1$) results in the same local price as an unfavorable harvest. In this context, local prices are equal in both states of nature because they are bounded from below by the effective export price (equations [4c] and [4d]). However, when trade costs are sufficiently large ($\theta > 1$) the local market will be in autarky when the external price, net of trade costs, falls below the autarky price. Consequently, with large trade costs, an increase in the quantity supplied (due to a favorable harvest) will engender a proportionate decrease in the local price (by α), as described by equations (4a) and (4b).

In contrast, a *surplus-connected* market will import during the lean season ($P_L^i = P^E + \theta T^i$) and export during the harvest season ($P_H^i = P^E - \theta T^i$), analogous to equations (2a) and (2c). These markets will continue to be unaffected by local production shocks. The local price in *deficit-connected* markets will be the same in both periods ($P_L^i = P_H^i = P^E + \theta T^i$) and will also be unaffected by local production shocks. A *deficit-remote* market will have higher prices during a poor harvest and the influence of restrictive trade policies is symmetric to that of a surplus-remote market. These markets will experience larger price increases during unfavorable harvests because the upper bound (formed by the effective import price) will be pushed higher when trade costs increase.

The next section develops an empirical framework that relates local prices to the five observable variables in the model—the exogenous external price and trade policies (both of which are not location-specific and vary across time), the local production shock (which is location-specific and varies across time), and the agroecological factor and trade costs (both of which are location-specific and time-invariant).

The Estimation Framework

Early studies measured the strength of the relationship between domestic and external commodity prices in a manner analogous to equation (1):[7]

$$p_t^i = \mu + \beta p_t^E + u_t^i \tag{5}$$

where p_t^i and p_t^E denote the logarithm of the nominal price in domestic market i and the external market at time t, while μ and β are parameters to be estimated and u_t^i is the error term. Full price transmission requires that $\beta = 1$, a hypothesis that could be tested and would also imply that $(p_t^i - p_t^E) \sim N(\mu, \sigma^2)$. However, equation (5) has two shortcomings. First, the presence of nonstationarity may overstate the strength of the price transmission estimates. Second, in commodity markets with characteristics such as those discussed earlier, it is unlikely that external and domestic prices will only differ by an i.i.d. $N(\mu, \sigma^2)$ term.

With respect to nonstationarity, we follow the common practice of examining the order of integration of the error term in equation (5). If prices are nonstationary, the existence of a stationary error term implies co-movement between the two prices. However, if $\beta \neq 1$, the price differential is growing and such growth would not be accounted for, even though prices are cointegrated. In fact, several authors have noted the weakness with interpreting a non-unity slope coefficient as a sign of market integration (e.g., Baffes [1991], Barrett [1996], Baffes and Gardner [2003]). Therefore, we impose the restriction $\beta = 1$, in which case the problem is equivalent to testing for a unit root in the following univariate process:

$$(p_t^i - p_t^E) \sim I(0) \tag{6}$$

In order to model a process which takes into account the factors described in the previous section, we generalize the above specification in three ways. As a first step, we introduce an auto-regressive structure by appending one lag for each price as follows:

$$p_t^i = \mu + \beta_1 p_t^E + \beta_2 p_{t-1}^E + \beta_3 p_{t-1}^i + u_t^i \tag{7}$$

where u_t is i.i.d. $N(\mu, \sigma^2)$ and $|\beta_3| < 1$.[8] Hendry et al. (1984) discuss a number of testable hypotheses resulting from restrictions on equation (7). The most important is long-run proportionality which requires $\sum_i \beta_i = 1$ and ensures that external price movements will *eventually* be transmitted to domestic markets. Then equation (7) becomes:

$$(p_t^i - p_{t-1}^i) = \mu + (1 - \beta_3)(p_{t-1}^E - p_{t-1}^i) + \beta_1 (p_t^E - p_{t-1}^E) + u_t^i \tag{8}$$

Because of the equivalence of the existence of co-integration and an error correction mechanism, stationarity of the price differential in equation (6) implies the existence of an error correction mechanism as defined in equation (8) and vice versa. This follows the Engle-Granger representation theorem (Engle and Granger [1987]).

In equation (8), β_1 indicates how much of a given change in the external price will be transmitted to domestic markets within the first period; $(1 - \beta_3)$ indicates how much of the external-domestic price spread will be eliminated in each subsequent period. The closer to unity is $(1 - \beta_3)$, the more rapidly prices will converge. It is worth emphasizing that $(1 - \beta_3)$, being different from zero, is a necessary and

7 For literature reviews on market integration, see Fackler and Goodwin (2001) and Meyer and Cramon-Taubadel (2004).

8 The restriction $|\beta_3| < 1$ implies that $0 < 1 - \beta_3 < 2$. In turn, the sign of β_3, or alternatively whether $(1 - \beta_3)$ falls within [0, 1] or [1, 2] intervals, signifies the type of convergence: monotonic in the former and oscillatory in the latter.

sufficient condition for long-run convergence. By contrast, a β_1 significantly different from zero is neither a necessary nor a sufficient condition for long-run convergence.

As a second step, we allow for the influence of domestic factors on short run dynamics by extending equation (8) as follows:

$$\Delta p_t^i = \mu + \gamma_1(p_{t-1}^E - p_{t-1}^i) + \gamma_2 \Delta p_t^E + F_t[\cdot] + u_t^i \tag{9}$$

To simplify notation, we employ the difference operator (Δ) and also set $\gamma_1 = (1-\beta_3)$ and $\gamma_2 = \beta_1$. $F_t[\cdot]$, which captures the influence of factors described in equations (3) and (4a–d), is defined as follows:

$$F_t[\cdot] = \gamma_3 \Delta p_t^F + \gamma_4 \Delta p_t^I + \gamma_5^S \sin\left(\frac{2\pi t}{12}\right) + \gamma_5^C \cos\left(\frac{2\pi t}{12}\right) + \gamma_6 NDVI_t + \gamma_7 I_{BAN_t} \tag{10}$$

p_t^F and p_t^I denote the logarithm of the price of fuel and the urban consumer price index, respectively. The trigonometric terms capture the periodic influence of harvest cycles (Sims [1974], Granger [1979]).[9] As a proxy for disturbances in weather conditions, $NDVI_t$ represents the *anomaly* at time t in the Normalized Difference Vegetation Index and varies by month and agroecological zone. Finally, I_{BAN} is a trade policy dummy, taking the value of one when an export ban is in effect and zero otherwise.

The parameter estimates of the lagged price difference between external and domestic markets are expected to be positive (or not significantly different from zero in the absence of co-integration). The price of fuel, an important component of the transport cost, has a positive impact on maize prices. The consumer price index, which captures other cost pressures such as increases in rural wages and costs of intermediate materials, is also expected to have a positive impact on maize prices. An export ban is likely to exert downward pressure on domestic prices since it increases the availability of domestic supplies. The trigonometric variables capture seasonal influences on food prices arising from the interaction of harvest cycles and inadequate storage and transport capacity. Finally, a positive NDVI anomaly during the growing season is expected to have a negative impact on prices.[10]

As a third step, we allow for different impacts of domestic and external factors under two trade policies ($I_{BAN} = 1$ when an export ban is in effect, $I_{NO\_BAN} = 1$ otherwise), by restating equation (10) within a panel framework as follows:

$$\begin{aligned} \Delta p_t^i = \mu + \gamma_3 \Delta p_t^F + \gamma_4 \Delta p_t^I + \sum_{TR} I_{TRt} * [\gamma_1^{TR}(p_{t-1}^E - p_{t-1}^i) + \gamma_2^{TR} \Delta p_t^E + \gamma_5^{S_{TR}} \sin\left(\frac{2\pi t}{12}\right) \\ + \gamma_5^{C_{TR}} \cos\left(\frac{2\pi t}{12}\right) + \gamma_6^{TR} NDVI_t] + u^i + \epsilon_t^i, \quad TR \in \left\{BAN, NO\_BAN\right\} \end{aligned} \tag{11}$$

where u^i denotes the market fixed effect, ϵ_t^i the idiosyncratic error clustered by market i, and I_{TR} the trade regime, as defined above. The part of equation (11) in square brackets can be interpreted as a trade regime dependent process:

$$\overbrace{\underbrace{\gamma_1(p_{t-1}^E - p_{t-1}^i)}_{\text{Adjustment}} + \underbrace{\gamma_2 \Delta p_t^E}_{\text{Short-Run Effect}}}^{\text{External(Price)Drivers}} \quad \overbrace{\underbrace{+ \gamma_5^S \sin\left(\frac{2\pi t}{12}\right) + \gamma_5^C \cos\left(\frac{2\pi t}{12}\right)}_{\text{Harvest Cycles}} + \underbrace{\gamma_6 NDVI_t}_{\text{Weather Anomalies}}}^{\text{Domestic(Non-Price)Drivers}}$$

9 In contrast to a dummy variable specification typically used in the literature, the trigonometric variables minimize the potential impact of outliers, and they are more appropriate given the smooth and cyclical nature of seasonality (e.g., Shumway and Stoffer [2011]).

10 Across markets, (4) implies that these effects are smaller when trade costs are lower. This corresponds to $\gamma_6 < 0$ in equation (10) and $\gamma_6^{BAN} < \gamma_6^{NO\_BAN}$ in equation (11).

As such, it sheds light on the channels through which export bans influence the impacts of external and domestic drivers of local prices.

The Data

The dataset consists of 144 monthly observations, covering the period August 2002 to July 2014. Domestic maize prices represent 18 wholesale markets and are expressed in Tanzanian shillings per kg. They are reported by Tanzania's Ministry of Industry and Trade. These 18 markets cover the entire country. Data on domestic fuel prices and the Consumer Price Index (CPI) are reported by Tanzania's National Bureau of Statistics. Wholesale maize prices in Nairobi (Kenya), Randfontein (South Africa), and Nampula (Mozambique) are sourced from FAO GIEWS; U.S. Maize prices represent no. 2, yellow, f.o.b. Gulf ports. U.S. Gulf maize prices were taken from the World Bank's pink sheet. The construction of the export ban dummy is based on information from FAO GIEWS, newspaper articles, and interviews with industry representatives.

Weather disturbances were estimated using satellite-derived Normalized Difference Vegetation Index (NDVI) imagery over cultivated areas as a proxy (Tucker [1979] and appendix S1 in the supplemental appendix, available at http://wber.oxfordjournals.org). We use the percentage deviation from the mean NDVI (for a given zone and month) as our measure of a local weather disturbance. In an agricultural context, NDVI captured during the heart of the growing season has been shown to be related to crop productivity (Becker-Reshef et al. [2010], Johnson [2014]). In other words, higher than expected values of NDVI during the growing season would be consistent with weather conditions that have been favorable to crop yields. Because the NDVI information is incorporated as anomalous deviations from monthly averages, this measure has no seasonal component and consequently is not collinear with seasonal variables.

In the following sections, we analyze the data using the three steps in the empirical framework discussed above. We employ the first two steps (i.e., the identification of an appropriate external market and estimation of the impacts of domestic and external shocks) in order to analyze maize price dynamics for each of the 18 markets. We then estimate the panel specification (i.e., the third step) to identify the channels through which trade policies affect domestic price dynamics for each market type, which also addresses concerns regarding endogeneity.

IV. Price Transmission

We begin by applying unit root tests to price levels using the Augmented Dickey-Fuller (ADF, Dickey and Fuller [1979]) and the Phillips-Perron (PP, Phillips and Perron [1988]) procedures (see the supplemental appendix tables S2.1-S2.4). Stationarity in log levels without a trend is overwhelmingly rejected in all cases. When a trend is included, the PP test indicates stationarity for some prices but the ADF does not. Taking first differences induces stationarity in all cases. Consequently, the long-term relationship between domestic and external prices should be examined on the basis of co-integration statistics, while short-run dynamics should be examined through an error correction model.

Selecting the Appropriate External Market

The first step of the analysis involves identification of the appropriate maize price anchor. The most commonly used indicator for maize is the U.S. Gulf price. It is the export price of the United States, the world's largest maize exporter, comes from the world's most liquid market; but it pertains to yellow maize, which is used primarily for animal feed. Another commonly used price benchmark in the context of Eastern and Southern Africa is the Randfontein (South Africa) white maize price, which is also associated with a liquid market and serves as a price discovery mechanism in the region (Traub and Jayne [2008]). A third choice would be the price in Nairobi, which is the main destination for Tanzania's maize

Table 4. Summary Indicators of the Relationship between 18 Domestic and 3 External Prices

	U.S. Gulf	South Africa	Nairobi
Conventional statistics, equation (1)			
Lowest R^2	0.59	0.50	0.64
Median R^2	0.69	0.60	0.78
Highest R^2	0.78	0.72	0.88
Median absolute deviation of β_1 from unity (%)	24	12	3
Stationarity statistics of equation (1), count out of 18			
ADF < 5%	15	8	17
PP < 5%	15	12	15
ADF < 1%	1	0	14
PP < 1%	3	4	14
Stationarity statistics of equation (2), count out of 18			
ADF < 5%	6	14	17
PP < 5%	14	13	18
ADF < 1%	0	2	15
PP < 1%	0	4	13
Durbin-Watson statistic for serial correlation, equation (5), R^2 of the respective regression in parenthesis			
Lowest	0.13 (0.69)	0.12 (0.53)	0.27 (0.77)
Median	0.22 (0.77)	0.19 (0.52)	0.37 (0.78)
Highest	0.47 (0.60)	0.37 (0.49)	0.65 (0.65)
3-month cumulative adjustment, percent			
Lowest	0	8	17
Median	14	28	47
Highest	42	59	70

Notes: This table summarizes conventional and stationarity statistics, reported in the online appendix tables.

exports; it comes from a less liquid market, but is in a net maize deficit area and in physical proximity to Tanzania.

Our analysis begins by examining the long-run relationship between the Tanzanian maize markets and each of the three external price indicators; table 4 provides a summary of these results (the full results are available in the supplemental appendix S2). The parameter estimates of equation (5), based on the US Gulf price, are significantly different from zero at the one percent level, with a median R^2 of 0.69. However, the coefficients are well below unity (the median across markets is 0.78). And while 30 of the 36 unit root statistics of equation (5) support co-integration at the five percent level, only 20 statistics support stationarity of the price differential (equation [6]).

Using the South African maize price, we obtain estimates for β in equation (5) that are much closer to unity (the median across the 18 markets is 0.9) than those based on the U.S. Gulf price. All are significantly different from zero at the one percent level but the median R^2 is 0.60, lower than the U.S. Gulf price. Furthermore, about half of the unit root statistics do not confirm a long-run relationship at the five percent level. The evidence based on the price spread is more supportive of the existence of a long-run relationship between the Tanzanian markets and the South African market.

Using Nairobi as the external benchmark renders the parameter estimates highly significant and much closer to unity, while the median R^2 increases to 0.78. The unit root statistics of equation (5) confirm co-integration. The price differential is stationary as well, in most cases at the one percent level. This is expected since the co-integration parameter is very close to unity. Based on these results, we choose Nairobi as the reference external market.

Table 5. Parameter Estimates for Error Correction Model

	Arusha	Bukoba	Dar es Salaam	Dodoma	Iringa	Lindi	Mbeya	Morogoro	Moshi
μ	−0.02	−0.03*	−0.01	−0.02	−0.04*	−0.00	−0.02	−0.03	−0.02
	(1.57)	(1.83)	(1.01)	(1.25)	(1.79)	(0.19)	(1.08)	(1.59)	(1.22)
$(p^E_{t-1} - p^i_{t-1})$	0.12***	0.31***	0.13***	0.09***	0.11***	0.30***	0.05	0.15****	0.13***
	(2.97)	(4.60)	(3.53)	(3.20)	(2.64)	(3.11)	(1.44)	(3.05)	(3.13)
Δp^E_t	0.32**	0.37***	0.21**	0.22***	0.37***	−0.07	0.17**	0.41***	0.32***
	(4.75)	(3.93)	(2.50)	(3.49)	(3.19)	(0.37)	(1.99)	(2.75)	(5.05)
Δp^F_t	0.21	0.21	0.21	0.42***	0.20	−0.31	−0.12	0.36*	0.28*
	(1.40)	(1.14)	(1.05)	(2.69)	(0.81)	(1.03)	(0.67)	(1.83)	(1.82)
Δp^I_t	3.03***	1.96*	1.98**	2.90***	1.04	−0.22	1.90**	2.75**	2.48***
	(3.07)	(1.69)	(2.24)	(3.26)	(0.97)	(0.12)	(1.99)	(2.10)	(3.33)
$\text{Cos}\left(\frac{2\pi t}{12}\right)$	0.03**	0.03	−0.03**	0.04***	0.05***	0.10***	−0.04**	0.05**	0.02
	(2.19)	(1.58)	(2.37)	(2.95)	(2.98)	(3.36)	(2.58)	(2.61)	(1.53)
$\text{Sin}\left(\frac{2\pi t}{12}\right)$	0.01	−0.05***	0.00	0.01	0.01	−0.02	0.03***	0.00	0.03***
	(1.15)	(−4.00)	(0.05)	(0.57)	(0.38)	(0.53)	(3.05)	(0.30)	(2.97)
$NDVI_t$	−0.46***	−0.38***	−0.27**	−0.29***	−0.43	−0.62***	−0.54***	−1.02***	−0.29**
	(2.79)	(−4.46)	(4.51)	(−5.45)	(1.55)	(2.75)	(2.70)	(4.74)	(2.47)
I_{BAN}	−2.31*	−3.48**	−3.29**	−2.52*	−1.46	−5.36*	−1.24	−1.58	−2.68*
	(1.73)	(2.16)	(2.13)	(1.81)	(0.73)	(1.71)	(0.74)	(0.75)	(1.75)
3-month adj (%)	47	70	40	35	50	51	17	57	49
R^2	0.37	0.31	0.29	0.39	0.21	0.29	0.24	0.33	0.34

	Mtwara	Musoma	Mwanza	Shinyanga	Singida	Songea	Sumbawanga	Tabora	Tanga
μ	−0.01	−0.00	−0.00	0.01	−0.02*	−0.09**	−0.05*	−0.03	−0.02
	(0.36)	(0.31)	(0.11)	(1.04)	(1.74)	(2.26)	(1.75)	(1.48)	(0.94)
$(p^E_{t-1} - p^i_{t-1})$	0.30***	0.24***	0.20***	0.13***	0.14**	0.16**	0.14***	0.15***	0.15***
	(3.72)	(3.69)	(4.06)	(3.37)	(3.01)	(2.52)	(3.02)	(2.88)	(2.98)
Δp^E_t	−0.03	0.31***	0.22**	0.15**	0.14	0.14	0.16	0.26**	0.36***
	(0.16)	(3.50)	(2.44)	(2.11)	(1.53)	(0.98)	(1.30)	(2.79)	(3.15)
Δp^F_t	−0.27	0.44**	0.49**	0.17	0.24	0.21	0.08	0.34	0.29
	(0.90)	(2.12)	(2.33)	(0.89)	(1.00)	(0.77)	(0.27)	(1.14)	(1.44)
Δp^I_t	−1.06	2.27*	2.21**	0.35	2.77***	1.03	1.03	2.74***	1.72
	(0.52)	(1.69)	(2.42)	(0.37)	(3.03)	(0.59)	(0.69)	(2.62)	(1.10)
$\text{Cos}\left(\frac{2\pi t}{12}\right)$	0.12***	−0.03*	0.03*	0.05***	0.04**	0.07**	0.04*	0.05**	0.08***
	(3.59)	(1.73)	(1.93)	(3.37)	(2.34)	(2.32)	(1.78)	(2.32)	(4.34)
$\text{Sin}\left(\frac{2\pi t}{12}\right)$	−0.01	−0.02	−0.02**	0.02*	0.00	−0.03*	−0.06***	−0.04**	0.02
	(0.25)	(1.48)	(2.15)	(1.78)	(0.24)	(1.72)	(4.07)	(2.49)	(0.98)
$NDVI_t$	−0.56**	−0.22	−0.16	−0.01	−0.23***	−1.06***	−0.61*	−0.16*	−0.71***
	(2.16)	(1.14)	(1.36)	(−0.06)	(3.12)	(−2.75)	(1.94)	(1.80)	(3.30)
I_{BAN}	−3.52	−4.58**	−3.65**	−4.19***	−3.03*	−0.52	−4.42*	−3.03	−3.32
	(1.09)	(2.51)	(2.43)	(2.66)	(1.84)	(0.19)	(1.98)	(1.56)	(1.58)
3-month adj (%)	51	60	50	36	26	29	26	47	54
R^2	0.26	0.22	0.28	0.25	0.28	0.20	0.23	0.26	0.34

Notes: The dependent variable is the change in the logarithm of the nominal price in market *i*. Each regression has 144 monthly observations. Absolute (robust) t-statistics in parentheses, significance level, * = 10 percent, ** = 5 percent, *** = 1 percent. $(p^E_{t-1} - p^i_{t-1})$ denotes the lagged difference between the price in Nairobi and the price in the domestic market *i*. Δp^E_t and Δp^i_t denote the first difference of the external and domestic market *i* price. Δp^F_t denotes the first difference of the fuel price. Δp^I_t denotes the first difference of the consumer price index. The Cos(•) and Sin(•) functions denote the seasonality variables. $NDVI_t$ represents the weather anomaly variable. I_{BAN} is the export ban dummy.

Table 6. Parameter Estimates for Panel Specification

	Northern markets (surplus, connected)	Southern markets (surplus, remote)	Other markets (deficit)	National aggregation
μ	−0.02***	−0.05**	−0.01***	−0.02***
	(7.54)	(4.66)	(3.78)	(5.33)
$(p^E_{t-1} - p^i_{t-1})$	0.13***	0.12**	0.19***	0.16***
	(19.82)	(7.02)	(7.25)	(9.23)
Δp^E_t	0.33***	0.21***	0.19***	0.21***
	(21.13)	(4.52)	(4.37)	(6.75)
Δp^F_t	0.26***	0.09	0.22***	0.20***
	(14.92)	(1.55)	(3.13)	(4.37)
Δp^I_t	2.40***	1.25***	1.66***	1.68***
	(7.81)	(7.30)	(4.19)	(6.61)
$\mathrm{Cos}\left(\frac{2\pi t}{12}\right)$	0.04***	0.05***	0.05***	0.05***
	(2.64)	(9.68)	(5.30)	(8.20)
$\mathrm{Sin}\left(\frac{2\pi t}{12}\right)$	0.02***	−0.03**	−0.01***	−0.01**
	(4.54)	(2.35)	(2.91)	(2.32)
$NDVI_t$	−0.48***	−0.65***	−0.27***	−0.31***
	(4.64)	(6.30)	(2.66)	(7.42)
I_{BAN}	−2.75***	−2.07***	−3.41***	−3.09***
	(11.13)	(2.75)	(12.24)	(12.72)
R^2	0.29	0.16	0.19	0.18
3-month adj (%)	49	39	47	44
No of markets	3	4	11	18
Observations	432	576	1,584	2,592

Notes: The dependent variable is the change in the logarithm of the nominal maize price. All regressions employ market dummies as fixed effects with bootstrapped standard errors which are clustered at the market level (1,000 replications). Robust absolute z-statistics in parentheses, significance level, * = 10 percent, ** = 5 percent, *** = 1 percent. The R^2s represent within-market R^2. $(p^E_{t-1} - p^i_{t-1})$ denotes the lagged difference between the price in Nairobi and the price in the domestic market *i*. Δp^E_t and Δp^i_t denote the first difference of the external and domestic market *i* price. Δp^F_t denotes the first difference of the fuel price. Δp^I_t denotes the first difference of the consumer price index. The Cos(•) and Sin(•) functions denote the seasonality variables. $NDVI_t$ represents the weather anomaly variable. I_{BAN} is the export ban dummy.

Quantifying Price Relationships

Table 5 reports parameter estimates consistent with the error correction specification (6) for all 18 markets. Table 6 reports panel estimates for the country as a whole (the last column) and the following three market-types (first three columns)[11]: first, the *surplus-connected* markets of the Northern zone (Arusha, Moshi, and Tanga) which have strong transport linkages to Nairobi; second, the *surplus-remote* markets of the Southern zone (Mbeya, Iringa, Songea, and Sumbawanga), which have relatively poor access to other markets; third, the remaining markets, all of which are *deficit-connected* or *deficit-remote*.

Equation (6) explains about 30 percent of local price changes, with the R^2 ranging from 0.20 in Songea, a remote-surplus market, to 0.37 in Arusha, a market close to Nairobi. The error correction term, γ_1, is significant in 17 of the 18 markets: in 15 markets at the one percent level and in two markets at the five percent level (Mbeya the exception). However, the estimates vary widely, from a low of 0.11 in Iringa (t-statistic = 2.64) to a high of 0.31 in Bukoba (t-statistic = 4.60). The error correction term for the national aggregation (panel specification) is 0.16, implying that 16 percent of the Tanzania-Nairobi price spread will be eliminated in the second (and every subsequent) period (table 6).

11 Our categorization is based on table 1 as well as Suzuki and Bernard (1987), Kilima et al. (2008), and Minot (2010).

Results on the short-run impact of the external price shocks are even more heterogeneous. The parameter estimate for γ_2 differs significantly from zero at the five percent level in 13 markets. The short-run effect in these 13 markets averages 0.25, implying that only one-quarter of the external price shock is transmitted instantaneously. The panel specification results confirm this weak short-run external influence (the short-run impact for the national aggregate is 0.21).[12]

To better understand the adjustment process, we combined the short-run and feedback effects into a single statistic.[13] The median three-month cumulative adjustment across all markets is 0.47. Of the markets that adjust faster to external price shocks, some represent surplus and others represent deficit regions, but most are either close to Nairobi (Bukoba and Musoma) or have access to a port (Tanga and Mtwara), suggesting that geography plays a key role in the price adjustment process. The panel specification also shows that the southern markets exhibit the slowest three-month adjustment.

The importance of geographic features in explaining market behavior is consistent with a growing literature on the determinants of spatial price differences, especially following the seminal study by Engel and Rogers (1996), which identified significant border effects, and the attendant failure of the law of one price, across the U.S.-Canada border. Indeed, Versailles (2012) and Brenton et al. (2014) find significant border effects as well as large trade costs across space in food commodity markets. For non-food products, Broda and Weinstein (2008) show that, at disaggregate product and market levels, price differences within countries may be of comparable magnitude to differences across national borders. Gopinath et al. (2011) find that national borders influence the transmission of shocks to production costs.

Although energy costs at the international level are expected to be captured by fluctuations in the external maize price (Baffes [2007]), the large distances among Tanzanian markets make it likely that changes in domestic fuel prices could also be relevant, and therefore fuel prices are included as a control in all specifications. The inclusion of the CPI as an additional explanatory variable to control for inflation ensures that the influences of the other drivers do not merely reflect co-movement due to general inflationary pressures.[14] Results on individual markets reported in table 5 show a diverse impact of CPI on maize prices—some markets exhibit a significant effect (e.g., Arusha and Moshi), while others do not (e.g., Lindi and Mtwara). The national aggregate from the panel results, however, gives a short run estimate of 1.68 with the impact in the Northern markets almost twice as much as in the Southern markets (2.40 and 1.25, respectively), with all parameter estimates being highly significant. We also estimated a specification whereby all prices were deflated with the CPI. Detailed results, which are included in table S2.6 in the supplemental appendix, are almost identical to those reported here. This follows from the fact that changes in the logarithmic CPI have very little variability around the mean, while logarithmic maize price changes are considerably more variable.

The results discussed above are consistent with several studies that have previously examined Tanzanian maize markets. Suzuki and Bernard (1987) and Minot (2010) provide insightful descriptive

12 We use the Donald and Lang (2007) small-group correction when reporting level of significance.

13 The cumulative adjustment is calculated as follows. Let, k be the amount of adjustment that takes place in n periods. In the current period, $n = 0$, k takes the value of γ_2 [also equal to $1 - (1 - \gamma_2)$], which is the short-run effect of the external price on the domestic price. In the next period, $n = 1$, k takes the value of $\gamma_2 + (1 - \gamma_2)\gamma_1$, which is the effect of the previous period, γ_2, plus the feedback effect, $(1 - \gamma_2)\gamma_1$. It can also be written as $(1 - (1 - \gamma_2)(1 - \gamma_1)\gamma_1$. For $n = 2$, k takes the value of the previous period, $[\gamma_2 + (1 - \gamma_2)]\gamma_1$, plus $\gamma_1(1 - \gamma_2 - (1 - \gamma_1)\gamma_2)$ [which can be written as $1 - (1 - \gamma_2)(1 - \gamma_1)^2$]. The terms of the second parenthesis form a geometric sequence with the ratio equal to $(1 - \gamma_1)$ and the nth term equal to $(1 - \gamma_1)^n$. Hence, the adjustment at period n will be given by $k = 1 - (1 - \gamma_2)(1 - \gamma_1)^n$. For $k = 0.5$, n gives the half-life of an external shock.

14 Changes in the CPI could be correlated with changes in domestic demand (see Abbott et al. (2014) in the context of imperfect price transmission in Vietnam). However, the monthly change in maize consumption is perhaps not sensitive to the monthly change in income (especially over a relatively short 12-year period). Nevertheless, this is an issue that merits further study, especially in the African context.

market analyses. Van Campenhout (2007) uncovers a secular trend toward lower spreads and greater adjustment between 1989 and 2000 for some markets but not for others. Kilima et al. (2008) find a link between remoteness and maize price volatility. The World Bank (2009) provides evidence on the poor linkages between four Tanzanian markets and world markets, as well as compelling descriptive evidence on the marketing and transport inefficiencies that plague Tanzania's maize sector. Mahdi (2012) discusses the impact of Tanzania's inadequate rural infrastructure on maize marketing at the household level. Dillon and Barrett (2016) also find that world maize price movements do not exert much influence on domestic maize price movements in Tanzania.[15]

Yet, full price transmission, especially in the context of the 2008 and 2011 price spikes, is widely assumed in trade simulation models that have constituted the basis for major policy pronouncements (Swinnen [2011]). For example, Ivanic and Martin (2008) assume full transmission from world to domestic prices, which in turn drives their assessment of the poverty impact of the 2008 food price spike. Nicita et al. (2014) also assume full price transmission in Sub-Saharan Africa in their analysis of the distributional biases of agricultural trade policies. The empirical relevance of the full price transmission assumption has been questioned in a broader context by Headey (2013) and Swinnen and Squicciarini (2012). Given that domestic maize prices in Tanzania (and, perhaps, many parts of the developing world) are only weakly influenced by external prices in the short run, any explanation of food price movements must include the influence of domestic drivers. The next section identifies three drivers (harvest cycles, weather anomalies, and trade policies) and quantifies their impact as described in section 3.[16]

V. Non-Price Determinants

Seasonality

We estimate the impact of harvest cycles by employing a trigonometric specification that captures periodicity. We find that, in 17 of the 18 markets, at least one of the two seasonality parameter estimates differs significantly from zero at the five percent level, in turn suggesting that short term maize price movements are influenced by harvest cycles.

Yet, the magnitude of the seasonal changes differs across markets, even within the same agroecological zone (figure 3). For example, harvest cycles in Songea are consistent with a 40 percent gap between the lean season peak (February) and the harvest season bottom (August)—the corresponding price gap in the better-connected market of Mbeya is 30 percent.

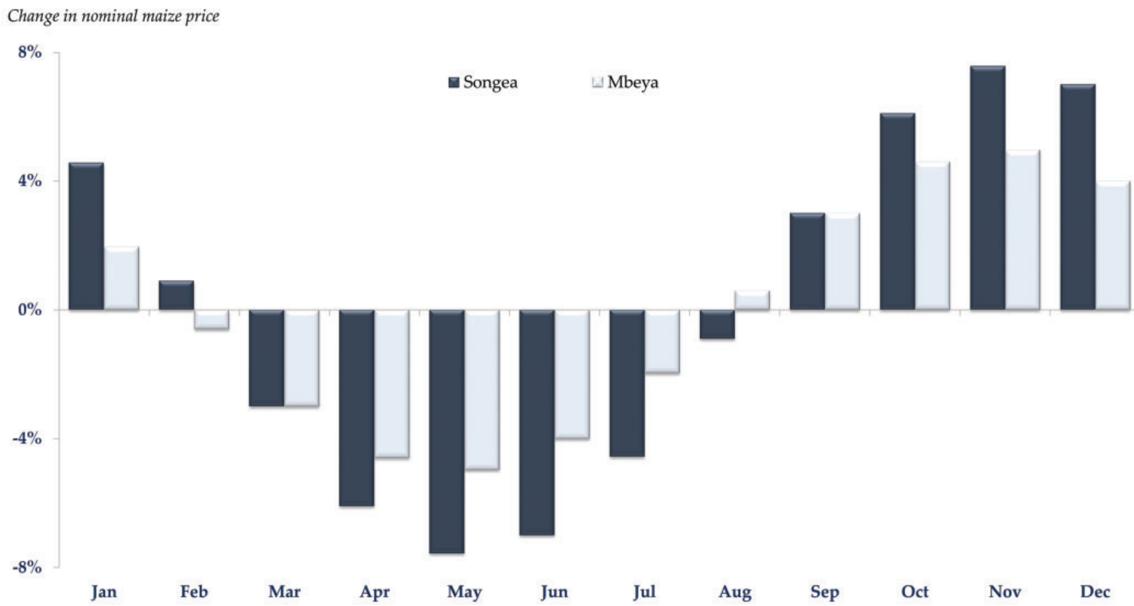
Evidence in support of seasonal influences on food prices in developing countries has been reported elsewhere. Sen (1981) and Ravallion (1987) discussed rice price seasonality in Bangladesh in particular and in a developing country context more generally. Sahn et al. (1989) also examined the influence of harvest cycles on prices and consumption in developing countries. In addition, Tschirley and Jayne (2010) discuss the impact of harvest cycles on local food markets in Africa while Kaminski et al. (2016) have shown that there is, on average, a 27 percent difference between seasonal high and low maize prices in Tanzania.

In addition to the direct impact on local prices, harvest cycles may influence other relationships. For example, adjustment parameters may also vary across seasons. As Delgado (1986) shows, the variance in food staple price spreads in Nigeria changes across seasons. In the supplemental appendix (table S2.8), we document that the linkages with Nairobi are much stronger during the Tanzanian harvest season. This supports our interpretation of the adjustment to the Nairobi price as an indicator of trade flows.

15 Dillon and Barrett (2016), however, find a strong impact of global oil prices on domestic maize prices in East Africa.

16 The influence of domestic (non-price) factors, such as seasonality, weather shocks and trade policies, feature prominently in the classic textbook treatment of food markets by Timmer et al. (1983).

Figure 3. Seasonal Influence on Maize Price Changes: Songea and Mbeya



Source: Authors' calculation based on parameter estimates

Weather Anomalies

Vegetation anomalies provide estimates for domestic supply shocks which are, in turn, inversely related to local price changes. The NDVI anomaly parameter estimate differs significantly from zero (at a ten percent confidence level) in 14 markets, including several food-deficit markets. Exceptions are the better connected markets in the Lake Zone (Mwanza, Musoma, and Shinyanga), and Iringa, a transport hub in the Southern Highlands.

The Southern markets exhibit the strongest price response to weather shocks. In Songea, for example, a ten percent increase in the NDVI index, as experienced in December 2012, is associated with a 10.6 percent decline in maize prices. Prices in the better-connected market of Mbeya declined by only 5.1 percent. Songea's greater vulnerability to weather shocks is consistent with more pronounced price declines during the harvest season. By contrast, prices in Dar es Salaam are much less responsive to local weather anomalies; a ten percent increase in the NDVI index is associated with just a 2.7 percent price decline, about half of Mbeya's magnitude. Dar es Salaam is better connected than Mbeya (in addition to being food-deficit) and consequently its vulnerability to weather shocks is muted.

While weather anomalies influence price dynamics across all markets, the surplus markets of the major maize producing areas appear to be affected the most. In the Southern zone, a ten percent negative deviation in the NDVI is associated with a 6.5 percent increase in prices—an impact that is more than twice as large as the national average of 3.1 percent. In the Northern zone, too, weather impacts are well above average: a ten percent negative deviation in the NDVI is associated with a 4.8 percent increase in prices.[17]

17 In the supplemental appendix (table S2.9), we estimate the influence of NDVI anomalies (and other factors) using a pooled sample where the coefficients are allowed to vary by market-groups. The parameter estimates for

Our results contribute to the emerging literature on the influence weather anomalies exert on food prices.[18] Brown and Kshirsagar (2015) examined 554 local commodity markets in over 50 developing countries and concluded that weather shocks exerted a significant impact on twice as many markets compared to the impact of international prices. Mawejje (2016) documented both the influence of weather anomalies on Ugandan food prices and the weak linkage with international prices. Götz et al. (2016) relate harvest failures to changes in local wheat prices in Russia.

Trade Policies

The parameter estimate for the export ban dummy is negative and significantly different from zero at the ten percent level in 11 of the 18 markets, with estimates ranging from -2.52 (t-statistic = 1.81) in Dodoma to -5.36 (t-statistic = 1.71) in Lindi (see table 5). The export ban is associated with a 3.29 percent monthly price decline in Dar es Salaam, which translates into a 20 percent cumulative price decline if a ban is in effect for six months. Of the seven markets whose prices are not affected by the ban, four are in the Southern zone (Mbeya, Songea, Iringa, and Morogoro); Tabora is in the Central zone; and the other two are the southernmost port (Mtwara) and the northernmost port (Tanga). The surplus markets in the Southern zone have prices that are considerably lower than elsewhere; these features are likely to attenuate the impact of an export ban. In the markets with ports, prices are unlikely to reflect the full impact of official trade restrictions, because market participants can circumvent formal trade channels (FEWS NET [2008], FEWS NET [2014]).

For Tanzania as a whole, holding other factors constant, an export ban is consistent with price changes that are 3.1 percent (z-statistic = 12.7) lower than with no ban (table 6). The effects of the export ban are more muted in the Southern zone (a monthly decrease of two percent compared to 2.8 percent in the Northern zone).

Export bans have been studied in the context of domestic-world price linkages.[19] Ihle et al. (2009) examined the influence of export bans on Tanzanian food prices and concluded that, in contrast to our results, the influence on markets was larger in the Southern than in the Northern zone. Our results may differ from theirs because we use observed export ban dummies instead of estimating the latent influence of unobserved export bans, or alternatively, because we account for weather shocks and harvest cycles. Götz et al. (2013) examined the effects of Russia's and Ukraine's export grain policies during 2007/08 and 2010/11 and concluded that such policies reduced the degree of integration with world markets and increased domestic price variability. Abbott (2012) provides a useful discussion on the cross-country variation in the imposition of export bans.

Assessing the Importance of Domestic Influences

The importance of domestic factors in explaining Tanzania's maize prices is highlighted in table 7, which reports parameter estimates based on equation (10) by starting with only the external price benchmark and progressively adding the domestic factors. Movements in the price of maize in Nairobi alone explain only six percent of the Tanzania's maize price changes ($R^2 = 0.06$ in first column). The inclusion of other domestic prices increases the explanatory power of the model to ten percent. When seasonality, weather anomalies, and the trade policies are included, the explanatory power increases to 14, 16, and 18

the NDVI anomalies are identical to those discussed above. Moreover, we find a statistically significant difference between the surplus group and the other groups.

18 While NDVI has been shown to be related to crop productivity (Becker-Reshef et al. [2010]; Johnson [2014]), the literature that has examined the influence of weather shocks on intra-annual changes in local food prices is less extensive. See Brown (2014) for a literature review (with a particular focus on remote sensed weather anomalies) and USAID (http://www.fews.net/) for policy-relevant analysis.

19 In the context of Tanzania, Gordon [1994]) concluded that the post-1985 policy reforms undertaken by the Government of Tanzania improved domestic market integration in the maize market.

Table 7. Parameter Estimates for Panel Specification, National Aggregation: Gains from the Inclusion of Domestic Factors

	Nairobi	+ Other prices	+ Seasonality	+ NDVI	+ Ban
μ	−0.02***	−0.04**	−0.04***	−0.04***	−0.02***
	(6.10)	(11.48)	(9.80)	(9.56)	(5.33)
$(p^E_{t-1} - p^i_{t-1})$	0.13***	0.14**	0.15***	0.16***	0.16***
	(8.80)	(9.31)	(8.89)	(9.13)	(9.23)
Δp^E_t	0.17***	0.21***	0.23***	0.23***	0.21***
	(21.13)	(4.52)	(7.18)	(7.32)	(6.75)
Δp^F_t		0.04	0.17***	0.21***	0.20***
		(0.70)	(3.90)	(4.44)	(4.37)
Δp^I_t		2.82***	1.02***	1.10***	1.68***
		(13.56)	(3.30)	(3.53)	(6.61)
$\mathrm{Cos}\left(\frac{2\pi t}{12}\right)$			0.05***	0.05***	0.05***
			(8.11)	(8.39)	(8.20)
$\mathrm{Sin}\left(\frac{2\pi t}{12}\right)$			−0.01**	−0.01**	−0.01**
			(2.16)	(2.32)	(2.32)
Weather				−0.33***	−0.31***
				(7.48)	(7.42)
Policies					−3.09***
					(12.72)
R^2	0.06	0.10	0.14	0.16	0.18
3-month adj (%)	37	40	44	46	44

Notes: The dependent variable is the change in the logarithm of the nominal market price. All regressions use 2,592 observations for 18 markets and employ (market) fixed effects with bootstrapped standard errors (1,000 replications). $(p^E_{t-1} - p^i_{t-1})$ denotes the lagged difference between the price in Nairobi and the price in the domestic market *i*. Δp^E_t and Δp^i_t denote the first difference of the external and domestic market *i* price. Δp^F_t denotes the first difference of the fuel price. Δp^I_t denotes the first difference of the consumer price index. The Cos(•) and Sin(•) functions denote the seasonality variables. $NDVI_t$ represents the weather anomaly variable. I_{BAN} is the export ban dummy. The first column reports panel estimates by including the Nairobi price only (i.e., the panel counterpart of equation [8]). The second column (+ other prices) includes other domestic prices. The third column (+ Seasonality) adds the two seasonality variables. The fourth column (Weather) includes the weather anomaly index. The last column (Policies) is identical to the last column of table 6.

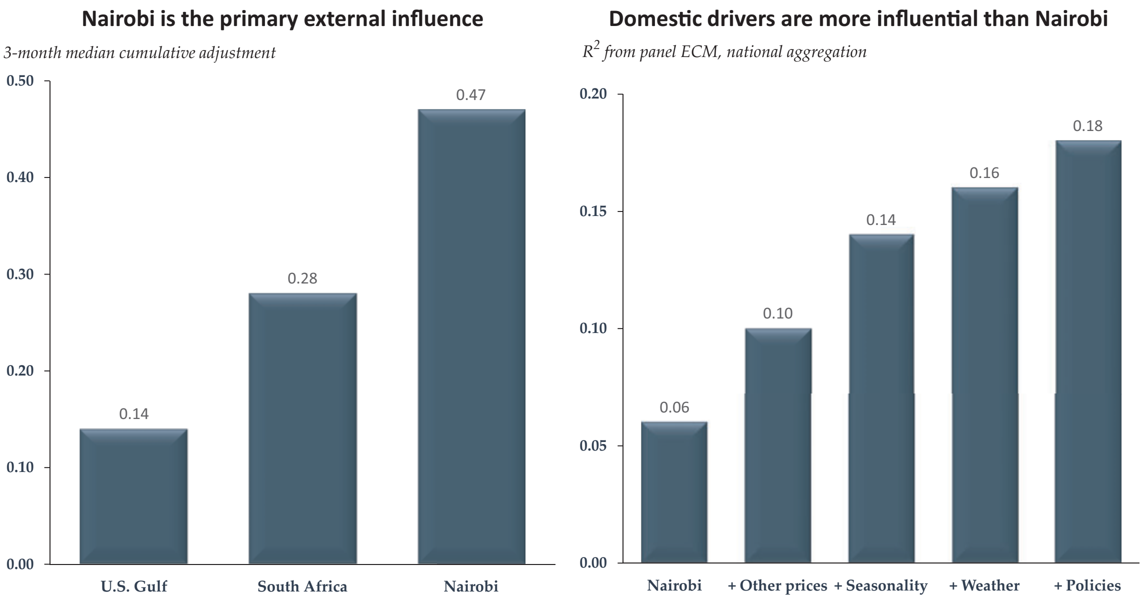
percent, respectively (figure 4, right chart). In other words, two-thirds of the changes in Tanzania's maize prices reflect domestic factors while only one-third is due to external influences.

These results are striking considering that the Nairobi price outperforms the US Gulf and South Africa benchmarks by a wide margin. For example, as shown earlier (table 4), the explanatory power of the log-level regressions increases moderately when the US Gulf price is replaced by the Nairobi one (from 69 to 78 percent in the case of median R^2). However, on only a few occasions (for regression [5]) and on no occasion (for price differential [6]) stationarity of the respective error term is satisfied at the one percent level of significance, indicating a weak degree of co-movement. Equally striking, the three-month cumulative adjustment increases more than threefold when the Nairobi price replaces that of US Gulf–from 14 to 47 percent (figure 4, left chart). These results underscore the merit in identifying regional price anchors that are perhaps more relevant than international benchmarks.

VI. Price Dynamics Under Different Trade Policies

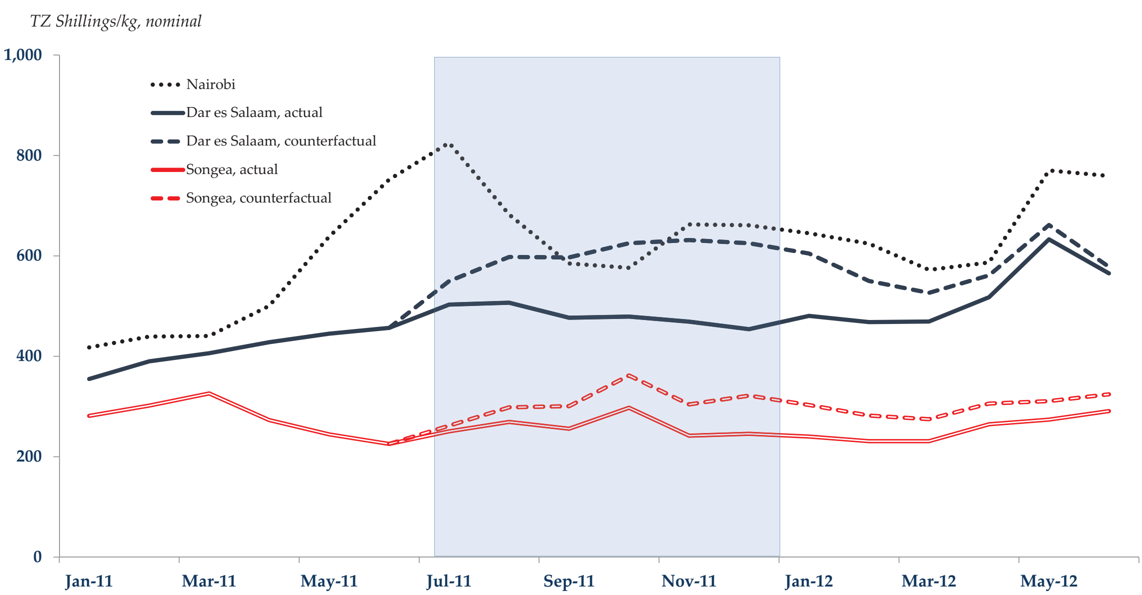
This section analyzes the mechanisms through which export bans depress local prices by documenting differences in adjustment across trade regimes, as well as differences in the sensitivity to local weather shocks. Results (consistent with equation [11]) are reported in table 8. A 10 percent decline in the NDVI is associated with a 3.8 percent increase in prices during a ban and only a 2.7 percent increase when there is no ban. These estimates are significantly different from zero (at a one percent level of significance) and also from each other at the ten percent significant level. The impacts of weather shocks are

Figure 4. The Relative Influence of External and Domestic Drivers



Source: Table 4, penultimate row (left chart) and Table 7, penultimate row (right chart)

Figure 5. Impact of the 2011 Export Ban in Dar es Salaam and Songea



Source: Authors' calculations based on parameter estimates

Table 8. Parameter Estimates for Panel Specification with Interaction Dummies

	Northern markets (surplus, connected)	Southern markets (surplus, remote)	Other markets (deficit)	National aggregation
μ	−0.04***	−0.05**	−0.03***	−0.04***
	(18.49)	(4.34)	(8.92)	(8.80)
$(p^E_{t-1} - p^i_{t-1})^* I_{BAN}$	0.12***	0.10**	0.15***	0.13***
	(12.58)	(4.11)	(7.17)	(7.98)
$(p^E_{t-1} - p^i_{t-1})^* I_{NO\_BAN}$	0.19***	0.15***	0.25***	0.21***
	(70.44)	(7.62)	(7.77)	(9.30)
$\Delta p^E_t{}^* I_{BAN}$	0.34***	0.23***	0.20***	0.23***
	(27.60)	(4.69)	(4.87)	(7.60)
$\Delta p^E_t{}^* I_{NO\_BAN}$	0.35***	0.22***	0.20***	0.23***
	(27.00)	(4.71)	(4.79)	(7.51)
Δp^F_t	0.29***	0.17**	0.25***	0.23***
	(15.11)	(2.27)	(3.70)	(4.82)
Δp^I_t	2.76***	0.65***	1.57***	1.61***
	(8.46)	(3.15)	(3.28)	(4.97)
$\mathrm{Cos}\left(\frac{2\pi t}{12}\right)^* I_{BAN}$	0.05***	0.06***	0.05***	0.05***
	(2.72)	(5.95)	(4.87)	(7.45)
$\mathrm{Cos}\left(\frac{2\pi t}{12}\right)^* I_{NO\_BAN}$	0.04**	0.06***	0.05***	0.05***
	(2.57)	(8.10)	(5.07)	(7.54)
$\mathrm{Sin}\left(\frac{2\pi t}{12}\right)^* I_{BAN}$	0.04***	−0.03**	−0.01*	−0.01
	(7.22)	(2.33)	(1.79)	(1.07)
$\mathrm{Sin}\left(\frac{2\pi t}{12}\right)^* I_{NO\_BAN}$	0.00	−0.03**	−0.02***	−0.02**
	(1.14)	(2.58)	(3.08)	(3.47)
$NDVI_t{}^* I_{BAN}$	−0.59***	−0.86***	−0.32***	−0.38***
	(5.55)	(3.98)	(8.35)	(6.18)
$NDVI_t{}^* I_{NO\_BAN}$	−0.43***	−0.21	−0.25***	−0.27***
	(3.73)	(1.36)	(4.87)	(5.03)
3-month adj*I_{BAN}	49	38	42	42
3-month adj*I_{NO_BAN}	57	44	55	52
R^2	0.33	0.20	0.21	0.20
No of markets	3	4	11	18
Observations	432	576	1,584	2,592
Chi-square tests				
Difference in adjustment	0.07	0.05	0.00	0.08
Diff in Adj-Chi	70.93***	21.05***	37.15***	47.58***
Difference in NDVI	0.17	0.65	0.24	0.11
Diff in NDVI-Chi	6.39***	3.36**	1.38	3.30*

Notes: The dependent variable is the change in the logarithm of the nominal market price. $(p^E_{t-1} - p^i_{t-1})$ is the lagged difference between the Nairobi and domestic market *i* price. Δp^E_t and Δp^i_t are the first differences of the external and domestic market *i* price. Δp^F_t and Δp^I_t denote the first difference of the fuel and consumer price index. Cos(•) and Sin(•) are the seasonality variables. $NDVI_t$ represents the weather anomaly variable. I_{BAN} is the export ban dummy. The *Diff in Adj-Chi* and *Diff in NDVI-Chi* provide the chi-squared statistics from a Wald test of the difference in the values taken by the adjustment coefficient and the NDVI anomaly, under Ban (I_{BAN}) and No ban (I_{NO_BAN}) regimes.

largest for remote-surplus market groups. These markets are most vulnerable to weather shocks because they produce a surplus *and* are remote.[20]

For the country as a whole, a ten percent average difference with the Nairobi price is associated with a 2.1 percent increase in the local price under no ban and a 1.3 percent increase under a ban. These

20 These results are similar to those of Burgess and Donaldson (2010), who found (based on 1875-1915 data for India) that the tendency of rainfall shortages to cause famines diminished as trade increased (as measured by railroad expansion).

estimates are statistically different from zero and from each other at the one percent significance level. After three months, 52 percent of a given shock is dissipated when there is no ban compared to 42 percent under a ban. The adjustment magnitudes under a ban also point to the presence of substantial informal trade between countries; consistent with Tschirley and Jayne (2010) and FEWS NET (2014), who also suggest that export bans delay, but do not eliminate, price arbitrage between countries.

To provide a sense of the magnitudes involved, we construct the maize price path in the absence of the most recent ban, which was in effect during the second half of 2011. This counterfactual price path is constructed as follows: first, we estimate the export ban coefficient for the 2011 separately, in order to specifically capture the effects of that ban, as opposed to the average effect across all bans (see table S2.5 in the supplemental appendix for the parameter estimates). Second, we assume that the counterfactual price change in the first period will differ from the actual price change by the size of the export ban coefficient and by the adjustment coefficient modified by the previous period's price difference with Nairobi. Third, we use the counterfactual change to calculate the price level for the first period. Fourth, we repeat these steps recursively to generate the counterfactual price path.

Figure 5 shows the actual and counterfactual maize prices in Dar es Salaam and Songea. Actual maize prices began to diverge from counterfactual prices at the start of the ban in July 2011. By December 2011, the last month of the ban, the estimates suggest that maize prices in Dar es Salaam would have been 38 percent higher than they were under the ban, while in Songea they would have been 31 percent higher. Following the ban's removal, actual and counterfactual prices took several months to converge.

Beyond documenting the differential impact of external and domestic shocks under different trade regimes, the results in table 8 are also relevant to determining whether export bans are endogenous. As noted earlier, export bans are imposed when prices are high and removed when prices are low. Therefore, it is natural to ask whether a third factor caused prices to fall and also triggered a trade policy response. In this context, it is worth highlighting two sets of facts that we document. First, the adjustments to price differentials with Nairobi (table 8) are much smaller when an export ban is imposed. Further, this difference is significant at the one percent level. Second, an export ban is associated with the smallest price decrease in the remote markets that have the weakest trade linkages with Nairobi.

VII. Conclusions

We have shown that, in the long run, Tanzanian maize price movements are mainly influenced by price movements in Nairobi (the regional hub) while international markets are much less important. In the short run, prices are governed by domestic factors (including harvest cycles, weather anomalies, and trade policies), the incorporation of which engenders a threefold increase in explanatory power. These results complement attempts to identify food crises (see, for example, Cuesta et al. [2014]), by measuring the influence of several important drivers of local food price movements. In this context, our study contributes to the literature that investigates the causes of domestic food market disturbances (Sen [1981] and Ravallion [1987]).

These results also have a bearing on the role policies could play in mitigating the impacts of climate change on food supply. There is evidence of an increase in climate variability in tropical Sub-Saharan Africa (e.g., Thornton et al. [2009], Feng et al. [2013], and Field et al. [2014]). For Tanzania, Rowhani et al. (2011) have shown that maize yields are affected by shifts in the growing season as well as by greater intraseasonal variability. Cross-border trade is an important mechanism through which some of the impacts associated with greater climate variability may be mitigated. Therefore, an improved understanding of the factors that reduce impediments to agricultural trade, both within and across countries, will inform policies that aim to reduce the impact that climate change will have on the most vulnerable people in the developing world.

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