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

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Abstract

We quantify the relationship between Tanzanian and external maize markets while also accounting for domestic influences. We conclude that external influences on domestic prices originate from regional, rather than global, markets. We also show that, compared to external factors, domestic factors exert a greater influence on Tanzanian maize markets. Further, the mechanisms through which trade policies influence maize markets involve interactions with both external market shocks and domestic weather shocks. Overall, we provide evidence that the intermittent imposition of export bans in Tanzania has had adverse impacts on its maize markets, and consequently, on the development of its agrarian economy.

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1 Introduction

What drives food price changes in developing countries? This question has received considerable attention in the aftermath of the post-2005 spikes in international food prices. Much of that attention has focused on the influence of world markets.[1] In contrast, we develop a tractable empirical framework that measures and accounts for the influence of both external and domestic drivers of maize prices in Tanzania.[2]

We show that all 18 Tanzanian maize markets (for which we examine monthly price changes between August 2002 and July 2012) adjust to changes in maize 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 view that African and world food markets are weakly integrated (e.g. Minot (2011)).

We also find that export bans delay the adjustment towards long-run equilibrium in local maize markets. Weather shocks and harvest cycles also influence the adjustment process and are a major source of short-term price variability. However, we show that the magnitude of their influence is contingent on whether an export ban is imposed. Further, the impacts of weather shocks and harvest cycles are less pronounced in markets that are connected to regional and international trade hubs. Together, our results support the idea that restrictive trade policies exacerbate the impact of domestic weather shocks.

Though the welfare consequences of increases in food price levels are still the subject of policy debate, the welfare consequences of price uncertainty are less ambiguous: greater price uncertainty discourages smallholder farming households from incurring investments that raise their agricultural productivity. Our analysis points to two mechanisms that may reduce price uncertainty arising from domestic sources. First, investments that engender a shift away from primitive agrarian techniques and towards more modern production and marketing methods may partially mitigate the impact of domestic weather shocks. Second, and perhaps more importantly, a more open trade policy regime will lessen the influence of domestic shocks.

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 geographic and agroecological zones. Second, food self-sufficiency varies

[1] While Ivanic and Martin (2008) and von Braun (2008) have suggested that the 2008 food price spike had a strong impact, Aksoy and Hoekman (2010) and Headey (2013) note that the impact was muted. Swinnen (2011) reviews this literature.

[2] Tanzania comprises the mainland and Zanzibar. The mainland and Zanzibar follow different food policies. They also have different food staples: maize on the mainland and rice in Zanzibar. This paper is specifically focused on maize policies, in the mainland of Tanzania.

widely across different parts of the country - notably, the remote and fertile Southern zone is the major food surplus area.[3] Third, trade routes (potentially) involve coastal and inland water transport as well as road transport, both within the country and the region. Fourth, the eight countries that border Tanzania vary in terms of their net food import needs. Fifth, while the government influences prices through export bans, prices within the country are determined by market forces. Consequently, the 18 Tanzanian markets we study cover several different types of food staple markets that exist in Sub-Saharan Africa, rendering our analysis relevant to many types of local food markets across the continent.

The paper proceeds as follows. Section 2 presents an overview of the Tanzanian maize market, including its physical and policy aspects. Section 3 describes the framework relevant to the estimation of long-term trends and short-term dynamics. Sections 4 and 5 discuss results on the price and non-price factors affecting domestic maize prices. Section 6 examines the mechanisms through which the export ban influences domestic prices. Section 7 focuses on the 2011 export ban by estimating the path that domestic prices would have followed had Tanzania not imposed the ban. Section 8 concludes.

2 The Tanzanian Maize Market

Tanzania, Sub-Saharan Africa's sixth most populous nation, borders eight countries, three lakes, and the Indian Ocean. 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 of Tanzania's maize exports. Other major destinations include Malawi and Mozambique, and occasionally other countries in the region.

Physical Characteristics of the Tanzanian Maize Market
Maize has been cultivated in East Africa since the 17th century as a garden crop. The early 20th century saw a major shift in the types of maize cultivated, reflecting 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 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, contributing almost half of the country's total calorie intake. It accounts for 40 percent of the country's cropped area, with

[3] USAID's Famine Early Warning System Network (FEWS NET) provides a clear quantitative description of Tanzanian food markets : `http://www.fews.net/east-africa/tanzania`.

an estimated 85 percent of farmers cultivating the crop on plots of less than one hectare.[4] It is a rainfed crop produced with limited use of modern inputs, mostly cultivated by hand hoe, and vulnerable to weather shocks; productivity is low, at less than one ton per hectare compared to a world average of more than 5 tons per hectare.[5]

During 2010-14, Tanzania's annual maize production averaged 4.5 million tons, up from 2.5 million a decade earlier (Figure 2). Global maize production averaged about 800 million tons during this period, rendering Tanzania a small country in terms of its relevance in the global maize market.

Maize is grown in all five of Tanzania's agroecological zones and sold in 18 markets (Figure 1). Nearly one third of national output is produced in the Southern zone (Table 1), 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 having no convenient access to a port. Mbeya and Songea export maize to Malawi and Mozambique, most notably to Nampula in northern Mozambique; this trade often goes unrecorded (FEWSNET (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 other major food-deficit markets: Arusha and Moshi are close to Nairobi while Tanga is close to the Kenyan port of Mombasa, in addition to having Tanzania's second largest port.[6] 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, Mtwara, and Morogoro, only the latter is an important maize producer.

The relative isolation of the Southern zone surplus markets, combined with the long distances from markets to consumption centers and ports, and poor transport and storage infrastructure, subjects Tanzania's maize sector to seasonal influences.

The Policy Environment

The increased importance of maize in the local diet after World War II attracted government intervention. To secure food grain supplies during WWII, Kenya and Tanganyika (now mainland Tanzania) established a Cereals Board to control food grain trade. Gov-

[4] Government of Tanzania.

[5] USDA, psdonline : https://apps.fas.usda.gov/psdonline/.

[6] Arusha has historically been one of Tanzania's most important transport hubs (Iliffe (1979)).

ernment intervention continued well after WWII 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 not only became the sole marketer and trader of food crops but also instituted a pan-seasonal and pan-territorial pricing mechanism. 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 two successive poor harvests in 1961 and 1962; the National Agricultural Products Board was established in 1964 with responsibilities very similar to those of the post-WWII Grain Storage Department. Almost 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.[7] Although some changes were introduced in marketing and pricing policies in the early 1980s, the government continued to intervene in the maize sector through ad hoc export bans, which were typically imposed in response to food security and price volatility concerns, but some were attributable to political pressures (Edwards (2014)).

Several authors have highlighted the negative long-term consequences of restrictive trade policies in the Tanzanian context. For example, Lofchie (1978) linked the collapse of the agrarian economy to the high taxes on agricultural production and exports imposed during the two decades following the (1967) Arusha Declaration. Even President Julius Nyerere, the chief architect of the Arusha Declaration, acknowledged (in 1979) that weak economic incentives may have been responsible for the decline in agricultural productivity.[8] Suzuki and Bernard (1987, p 87) made a compelling case in favor of more open trade policies, arguing that: "Tanzania will not be completely self-sufficient in subsistence food for some years, but it can move towards that goal by producing surplus food in the areas that can support it. The most efficient policy would be to sell that surplus to neighboring countries to buy much needed inputs ...".

Despite these warnings and assessments, export bans continued to be imposed as recently as 2011. During the past decade five bans were imposed on maize exports, with an average duration of 13 months. The first and second of these spanned January 2005 to January 2007, with a three-month hiatus at the beginning of 2006. A five-month ban was in place in 2008 and another during 2009-10. The duration of the most recent ban was less

[7] The policy changes of the early 1970s were undertaken in conjunction with the campaign to replace the traditional system of rural settlements with large villages. This villagization policy was introduced in 1963 and within a decade had been expanded to the entire countryside. Between 1973 and 1976 as many as 11 million people moved, either voluntarily or forcibly (Mapolu et al. (1990)).

[8] Edwards (2014) discusses the broader policy context under which Tanzania's restrictive agricultural policies were implemented.

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 concerns about food security and price volatility, the bans were introduced when maize prices were high and removed when prices were low (Figure 3). The inflation-adjusted price of maize has been, on average, 28 percent lower in the last month of each ban than in the first (Table 2). Further, prices fall more rapidly when export bans are in effect, especially during the harvest season (Figure 4). In the next section, we outline a framework that quantifies both the overall impact of export bans on price changes, and the mechanisms through which export bans engender these price changes.

3 The Estimation Framework

Seasonality, weather shocks, and export bans, above and beyond the effects of external market conditions, are all likely to have important effects on the price determination process of maize. Moreover, the effects of these factors may differ across markets. We develop a model that captures the response of domestic prices to external market signals and also accounts for the factors mentioned above as well as fuel costs and inflation.

Early studies measured the strength of the relationship between external and domestic commodity markets through the following equation[9]

$$p_t^i = \mu + \beta p_t^E + \epsilon_t^i \tag{1}$$

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 ϵ_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, such an approach has two shortcomings. First, nonstationary prices may overstate the strength of the price transmission estimates. Second, in primary commodity markets such as those in Tanzania, with high trade costs, seasonality, policies, and other domestic influences, it is unlikely that external and domestic prices will differ only by an i.i.d. $N(\mu, \sigma^2)$ term.

[9] Although our framework builds on estimation techniques used in the market integration and law of one price literature, our focus is on what causes price changes in local markets - not whether these markets are "efficient". These are related but not identical concepts. For example, a low degree of market integration could reflect trade frictions engendered by a host of factors, including geography, poor infrastructure, or policies. For a comprehensive literature review on market integration see Fackler and Goodwin (2001). Meyer and Cramon-Taubadel (2004) survey the literature on asymmetric adjustment. Goodwin and Piggott (2001) employ a threshold cointegration technique that estimates market integration while adjusting for unobserved transport costs.

With respect to the nonstationarity concern, one could examine the order of integration of the error term in equation (1). Under nonstationary prices, the existence of a stationary error term implies co-movement between the two prices. However, if $\beta \neq 1$, the uniqueness of the co-integration parameter in the bivariate case implies that the corresponding price differential would be growing and that such growth would not be accounted for, even though prices may move in a seemingly synchronous manner. Hence the stationarity of the error term of equation (1), while establishing co-movement, should not be considered as a testable form equivalent to $\beta = 1$. In fact, a number of authors have warned, in a non-stationary context, against interpreting a non-unity slope coefficient as a sign of market integration (e.g. Baffes (1991); Barrett (1996); Baffes and Gardner (2003)).

To account for the non-unity slope coefficient we impose $\beta = 1$, in which case the problem is equivalent to testing for a unit root in the following univariate process:

$$(p_t^i - p_t^E) \sim I(0) \tag{2}$$

Stationarity as defined in equation (2) implies that external price signals are transmitted to domestic markets in the long run. The assumption (or finding) that the co-integration parameter is unity is crucial, because it ensures that no other non-stationary component is influencing domestic prices. The absence of co-integration (with unity slope coefficient in the present setting) can be attributed to omitted non-stationary variables. Therefore, equation (2) cannot serve as a substitute for $\beta = 1$ in equation (1); it can only serve as an intermediate step in establishing its validity.

In order to model a more realistic price dynamic process, we generalize equation (1) in three ways. As a first step, we introduce an auto-regressive structure by appending one lag for each price as follows:

$$p_t^i = \mu + \beta_1 p_t^E + \beta_2 p_{t-1}^E + \beta_3 p_{t-1}^i + u_t^i \tag{3}$$

where u_t is i.i.d. $N(\mu, \sigma^2)$ and $\beta_3 < 1$. Hendry et al. (1984) discuss a number of testable hypotheses resulting from corresponding restrictions on the parameter space of equation (3). The most important of which is long-run proportionality, which ensures that external price movements will eventually be transmitted to domestic markets. Under long run proportionality, which can be tested through the restriction, $\sum_i \beta_i = 1$, equation (3) can be reparameterized as follows:

$$(p_t^i - p_{t-1}^i) = \mu + (1 - \beta_3)(p_{t-1}^E - p_{t-1}^i) + \beta_1(p_t^E - p_{t-1}^E) + \mu_t^i \tag{4}$$

Because of the equivalence of the existence of co-integration and the error correction model, stationarity of the price differential in equation (2) implies the existence of an error correction mechanism as defined in equation (4), and vice versa.[10] On the other hand, the restriction $|\beta_3| < 1$ implies that $0 < 1 - \beta_3 < 2$.[11]

In equation (4), 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 world-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 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 price convergence.

As a second step, we allow for the (potential) influence of domestic factors by extending equation (4) as follows:

$$\Delta p_t^i = \mu + \gamma_1(p_{t-1}^E - p_{t-1}^i) + \gamma_2 \Delta p_t^E + F_t[\cdot] + u_t^i \tag{5}$$

To simplify the notation, we employ the difference operator (Δ) and also set $\gamma_1 = (1 - \beta_3)$ and $\gamma_2 = \beta_1$. $F_t[\cdot]$ is defined as follows:[12]

$$F_t[\cdot] \;=\; \gamma_3 \Delta p_t^F + \gamma_4 \Delta p_t^I + \gamma_5^S \sin\left(\frac{2\pi t}{12}\right) + \gamma_5^C \cos\left(\frac{2\pi t}{12}\right) + \gamma_6 NDVI_t + \gamma_7 I_{BAN_t} \tag{6}$$

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.[13] As a proxy for disturbances in weather conditions, $NDVI_t$ represents the monthly anomaly at time t in the Normalized Difference Vegetation Index and varies by month and agroecological zone. Finally, I_{BAN} is the export ban, taking the value of one when a 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, a key cost of production and transport, has a positive impact on maize prices. The consumer price index, which captures other cost pressures

[10] This follows the Engle-Granger representation theorem (Engle and Granger (1987)).

[11] 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.

[12] The explanatory power of the model increases by almost four-fold when we include these variables: the R-squared of a panel fixed model (for all 18 markets) increases from 0.059 to 0.199.

[13] In contrast to a dummy variable specification, this specification minimizes the potential impact of outliers, which is an especially useful feature in view of the relatively small number of harvest cycles (either 12 or 24) in our sample. Further, this specification uses a priori information that seasonal influences are smooth and cyclical. More than two trigonometric functions could be used to capture seasonality (e.g. Shumway and Stoffer (2011)). However, we use two, so that specification remains parsimonious.

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 expected 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, and vice versa.

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 affect, $I_{NO\_BAN} = 1$ otherwise), by restating equation (6) within a panel framework as follows:

$$\Delta p_t^i = \mu + \gamma_3 \Delta p_t^F + \gamma_4 \Delta p_t^I + \sum_{TR} I_{TRt} * \Big[\gamma_1^{TR}(p_{t-1}^E - p_{t-1}^i) + \gamma_2^{TR} \Delta p_t^E + \gamma_5^{S_{TR}} \sin\left(\frac{2\pi t}{12}\right) + \gamma_5^{C_{TR}} \cos\left(\frac{2\pi t}{12}\right) + \gamma_6^{TR} NDVI_t \Big] + u^i + \epsilon_t^i, \qquad TR \in \{BAN, NO\_BAN\} \tag{7}$$

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 (7) in square brackets can be viewed as the trade regime dependent process (RD_t), and as such, it sheds light on the channels through which export bans influence domestic prices:

$$\Delta p_t^i = \underbrace{\gamma_3 \Delta p_t^F + \gamma_4 \Delta p_t^I}_{\text{Price Controls}} + \underbrace{RD_t}_{\text{Regime Dependent Process}} + \underbrace{u^i}_{\text{Market Fixed Effect}} + \underbrace{\epsilon_t^i}_{\text{Idiosyncratic Error}}$$

where,

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

In the following three sections 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 estimate maize price dynamics for each of the 18 markets. We employ the panel specification (i.e. the third step) to identify the channels through which export bans affect domestic price dynamics in each agroecological zone.[14]

[14] We employ a panel specification in order to gain statistical power. However, this increased statistical power comes at the cost of assuming that parameters within an agroecological zone are homogenous.

4 Price Transmission

We begin by applying unit root tests to price levels (without and with a trend) and first differences using the Augmented Dickey-Fuller (ADF, Dickey and Fuller (1979)) and the Phillips-Perron (PP, Phillips and Perron (1988)).[15] Unit root results are reported in Table B1. Stationarity in log levels without a trend (first two columns) 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 (last two columns) 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 (equation 5) rather than an autoregressive structure (equation 3).

Selecting the Appropriate External Market

The first step of the analysis involves identification of the appropriate maize price anchor. The most commonly used world price 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 exports; it comes from a less liquid market, but is in a net maize deficit area and in physical proximity to Tanzania (Figure 5 depicts all three prices in US Dollar nominal terms).[16]

We begin the analysis by examining the long-run relationship between the Tanzanian maize markets and each of the three external price indicators. The full results are available in Appendix B, while Table 4 provides a summary of these results.

Using the U.S. Gulf price, the parameter estimates we obtain are significant for all 18 markets (all slope parameter estimates are significantly different from zero at the 1 percent level), with a median R-square of 0.69. However, the parameter estimate of equation (1) is well below unity (the median across markets is 0.78). And while 30 of the 36 unit root statistics of equation (1) support co-integration at the 5 percent level, only 20 support

[15]The data description and sources can be found in the Appendix A. Table 3 presents summary statistics on maize prices in domestic Tanzanian markets as well as key external markets.

[16]As Table 3 documents, average maize prices in Nairobi over the sample period were between 10 percent and 30 percent higher than prices in local Tanzanian markets (Figure 6 compares the Nairobi and Dar es Salaam price time series). In contrast, prices were lower in U.S. Gulf and South African markets than in Tanzanian markets.

stationarity of the price differential.

Using the South African maize price, we obtain estimates for β in equation (1) 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 1 percent level but the median R-square is 0.60 — lower than with the U.S. Gulf price. Furthermore, about half of the unit root statistics of equation (1) do not confirm a long-run relationship at the 5 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.

Using the Nairobi maize price, we find that all the parameter estimates are highly significant and much closer to unity (the median across 18 markets is 0.97) than their counterparts based on either U.S. Gulf or South African prices, and with a median R-square of 0.78 — much higher than with the other two prices. The unit root statistics of equation (1) confirm co-integration. The price differential is stationary as well, in most cases at the 1 percent level (the only exception is the ADF test for Bukoba): this is expected since the co-integration parameter is very close to unity. Based on these results, we choose the price in Nairobi as our reference for the external market influence.

Quantifying Price Relationships

Table 5 reports parameter estimates consistent with the error correction specification (6). This model explains about 30 percent of domestic price changes, with the R-square ranging from 0.20 in Songea, a surplus market in the Southern zone, to 0.37 in Arusha, a deficit market in the Northern zone. The error correction term, γ_1, is significant in 17 of the 18 markets: in 15 markets at the 1 percent level and in 2 markets at the 5 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 averages a little more than 0.13 across all 18 markets, implying that, on average, 13 percent of the price gap between Tanzania and Nairobi prices will be eliminated in the second (and every subsequent) period.[17]

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 5 percent level in 13 markets. The short-run effect in these 13 markets averages 0.25, implying that only one quarter of the adjustment to external price shocks is transmitted instantaneously.

To better understand the adjustment process, we combined the short-run and feedback effects into a single summary statistic.[18] Figure 8 depicts the cumulative adjustment for

[17]Figure 7 shows prices in Dar es Salaam, Songea (lowest average real prices for our sample) and Mwanza (highest average real prices). Although domestic prices move together, there are differences in terms of price levels, the influence of harvest cycles as well as anomalous movements (also see Table 3).

[18]The cumulative adjustment is calculated as follows. Let, k be the amount of adjustment that takes place

the first three months and shows that the adjustment exceeds two thirds in only one market (Bukoba), but exceeds 50 percent in another seven markets. The median adjustment across all markets is 0.40. Of the markets that adjust more quickly to external price shocks, some represent surplus and some 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 importance of geographic features in explaining market behaviour is consistent with a growing literature on the determinants of spatial differences in food prices. Several studies, including Versailles (2012) and Brenton et al. (2014), find significant border effects as well as large trade costs across space.

We also control for changes in fuel prices and the consumer price index. Although the cost of energy is expected to be captured by fluctuation in the external maize price, the large distances among Tanzanian markets make it likely that domestic fuel prices also play a role in domestic price determination.[19] We find that the effect of changes in fuel costs is mixed. In contrast to coastal markets and food surplus markets, food deficit markets that are in the interior are typically influenced by changes in fuel prices. Market prices in Dodoma and Morogoro, both in Tanzania's interior and with reasonable road connectivity, are the most sensitive to changes in fuel prices. In addition, Musoma, Mwanza, and Moshi are also influenced by changes in fuel prices in the short run.

The inclusion of the Consumer Price Index (CPI) to control for inflation ensures that the influences of the other drivers do not merely reflect co-movement due to general inflationary pressures.[20] The CPI parameter estimate is statistically different from zero in several markets. Maize prices are more strongly associated with inflation in the Northern, Lake, and Central zones, and less so, or not at all, in the Southern and Coastal zones.

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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 $k = 1 - (1 - \gamma_2)(1 - \gamma_1)^n$. Figures 8 and 9 report the three-month cumulative adjustment with Nairobi and the US Gulf, respectively, i.e., $n = 2$. For $k = 0.5$, n gives the half-life of a shock.

[19] We also examined whether world crude oil prices influence the domestic fuel prices. While we find that the world fuel price and the Dar es Salaam fuel price are cointegrated, the short-run magnitude of the external influence is quantitatively small. In the short run, a 10 percent increase in global crude prices is associated with a 0.9 percent increase in the local fuel prices in Dar es Salaam. After 3 months, just 35 percent of the shock is dissipated. Consequently, even after considering the impact of global crude price changes, we conclude that global commodity markets still exert a weak short-run influence on domestic markets in Tanzania.

[20] We also estimated the specifications by deflating all prices with the CPI, and the results are quantitatively very similar.

The implication is that maize prices are more detached from general inflation in the food-surplus Southern markets and the better connected Coastal markets.

We also calculated the three-month cumulative adjustment to the U.S. Gulf price. The results, shown in Figure 9, confirm that all Tanzanian maize markets adjust to changes in the Nairobi price much more quickly than they do to changes in the U.S. Gulf price.[21] This suggests that although external shocks influence domestic price movements, their impact is not as strong as typically assumed and comes mostly from the regional, not the global, market. These results are consistent with several studies that have previously examined Tanzanian maize markets.[22]

Yet, full price transmission, especially in the context of the 2008 and 2011 price spikes, is widely assumed. For example, Ivanic and Martin (2008) assume full transmission from world market prices 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 Sub-Saharan Africa) 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 such drivers and quantifies their impact.

5 Non-Price Determinants

The error correction model includes three non-price factors: export bans, seasonality, and weather. The rest of this section discusses the influence of these drivers.

Export Bans

The parameter estimate for the export ban dummy is negative and significantly different from zero at the 10 percent level in 11 of the 18 markets, with estimates ranging from -2.52

[21]The parameter estimates of the error correction model are not reported here.

[22]Suzuki and Bernard (1987) and Minot (2010) provide insightful descriptive analyses, while several authors have provided econometric analysis. Kilima et al. (2008) employ an ARCH-m model to link remoteness with greater maize price volatility. The World Bank (2009) provides econometric 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. Dillon and Barrett (2014) also find that world maize price movements do not influence domestic maize price movements in Tanzania. Although they find that world crude prices have an influence, they do not account for the influence of any domestic factor. To the best of our knowledge, no previous study has simultaneously measured the influence of external and domestic factors or has shown that the magnitudes of their impacts depend on trade policies.

(t-statistic = 1.81) in Dodoma to -5.36 (t-statistic = 1.71) in Lindi. 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 Tanzania's 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). Markets in the Southern zone are remote maize surplus markets with prices considerably lower than elsewhere; these features are likely to attenuate the impact of an export ban. In the southern ports, as well, prices are unlikely to reflect the full impact of official trade restrictions, because market participants can circumvent formal trade channels (FEWSNET (2008),FEWSNET (2014)).

Export bans have been studied elsewhere, both in the context of domestic-world price linkages and as a cause of the 2008 and 2011 food price spikes. 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 using a Markov switching model, concluded that such policies reduced the degree of integration with world markets and also increased domestic price variability. Further, numerous authors have noted that restrictive export policies were key contributors to the price spikes of 2008 and 2011 (see, among others, Timmer (2008); Abbott (2012); and Martin and Anderson (2011)).

Seasonality

We measure and control for the likely impact of harvest cycles on maize prices by employing a trigonometric specification that captures periodicity in the price time series (Shumway and Stoffer (2011)). We find that in most markets at least one of the two seasonality parameter estimates differs significantly from zero at the 5 percent level. Yet the magnitude of the seasonal changes differs across markets and zones. Even for Southern zone markets that exhibit strong seasonal patterns, the magnitude of the seasonal influence differs across markets. Prices in Songea begin increasing in September and reach their peak in February. As the harvest approaches, prices increases first moderate, and then prices fall rapidly from April through June (they decline nearly 6 percent during these months). On a cumulative basis, harvest cycles cause prices to be 20 percent lower in June than in February, and 20 percent higher in December than in August. This is consistent with a 40 percent gap between the lean season peak and the harvest season bottom.

While Mbeya is also a food surplus market in the Southern highlands with harvest cycles that occur in similar months, in contrast to Songea, Mbeya is less remote. As a result, compared to Songea, the influence of harvest cycles on local food prices in Mbeya is less pronounced (with a peak of a little more than 4 percent and with less than a 30 percent gap between the lean season peak and harvest bottom).

Evidence in support of seasonal influences on food prices, especially in the context of Sub-Saharan Africa, where it appears to be more pronounced than in other parts of the world, has been reported elsewhere. Sahn et al. (1989) highlighted the influence of seasonality in the context of developing-country agriculture. More recently, Kaminski et al. (2014) have shown that the seasonal component represents a significant share of total food price variability. Indeed, in Tanzania's case, the share is up to 20 percent (see also FEWSNET (2008),FEWSNET (2014), and Tschirley and Jayne (2010)).

Weather Anomalies

Vegetation anomalies provide estimates for domestic supply shocks which are, in turn, inversely related to local price changes.[23] The NDVI anomaly parameter estimate differs significantly from zero (at a 10 percent confidence level) in 14 markets, including several food-deficit markets. Exceptions are Mwanza, Musoma, and Shinyanga, which are located in the Lake zone and better connected, and Iringa, in the Southern Highlands.[24]

The other relatively isolated maize-surplus markets in the Southern Highlands — Songea, Sumbawanga, Morogoro, and Mbeya — exhibit the strongest price response to weather shocks. In Songea a 10 percent increase in the NDVI index, as experienced in December 2012, is associated with a 10.6 percent decline in prices. In contrast, Mbeya's price decline is only 5.1 percent; although Mbeya is a food-surplus area it has a better connected and developed market than does Songea and hence it benefits from greater absorption of surplus production by other markets. Consistent with this, seasonal price changes are smaller in Mbeya than in Songea (Figure 10).

Similarly, prices in Dar es Salaam are less responsive to local weather anomalies. Dar es Salaam is much better connected than Mbeya (in addition to being food-deficit) and consequently its vulnerability to weather shocks are muted. A 10 percent increase in the

[23] The weather disturbances in this study were estimated using satellite-derived Normalized Difference Vegetation Index (NDVI) imagery over cultivated areas as a proxy (c.f. Tucker (1979)). Brown (2014) reviews the literature that has examined the relationship between weather anomalies that are detected using satellite imagery and food prices. Johnson (2014) provides evidence in support of the informativeness of NDVI anomaly signals in the context of predicting the impacts of shocks to (county and state-level) grain yields in the United States.

[24] The reasons behind the non-significant result for the Iringa market are unclear; it is possible that transport, storage and food processing facilities may be relatively better in Iringa (since it connects the Southern Highlands to Dodoma and Arusha to the North and Dar es Salaam to the East), or this may be caused by measurement noise.

NDVI index is associated with just a 2.7 percent decline (t-statistic = 4.51) in prices in Dar es Salaam — about half Mbeya's magnitude.

The relationship between weather vulnerability and market connectivity also helps explain why restrictive trade policies exacerbate the impact of rainfall shocks, as the next section notes.

6 Price Dynamics under Export Bans

The previous two sections provide strong evidence that export bans exert downward pressure on local prices. In this section we examine the mechanisms through which export bans depress local prices. In particular, we show that export bans dampen adjustments to changes in the price in Nairobi and exacerbate responses to favorable weather shocks.

Table 6 reports results from a panel benchmark model that is similar to the specification in Table 5. The effects of the export ban are more muted in the Southern zone, but the effects on price changes are significantly different from zero across all zones and in the aggregate. 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. Weather anomalies influence price dynamics across all zones, producing the largest impacts in the major maize producing areas. In the Southern zone, a 10 percent decline in the NDVI (during the growing season) 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 above average: a 10 percent decline in the NDVI is associated with a 4.8 percent increase in prices. Price dynamics in all zones are also influenced by the lagged price difference from Nairobi. On average, if Nairobi prices are 10 percent higher than Tanzanian prices, the latter will increase by 1.6 percent (z-statistic = 9.23) to move towards equilibrium. All zones except for the Coastal zone are also influenced by changes in Nairobi prices in the short run. The largest short-run influence is felt in the Northern zone where a 10 percent change in the Nairobi price translates into a 3.3 percent change in the local maize price.

The results on adjustment differences under the two trade regimes are reported in Table 7. For the country as a whole, a 10 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 regime. These estimates are statistically different from zero and from each other at the 1 percent significance level.

The adjustment magnitudes under a ban, implied by Table 7, also point to the presence of substantial informal trade between countries. This is consistent with Tschirley and Jayne (2010) and FEWSNET (2014), who also suggest that export bans delay, but do not eliminate, price arbitrage between countries. Taken together, the results suggest that after three months, 52 percent of a given shock is dissipated when there is no ban – compared to 42 percent under a ban (Figure 11).

As expected, the influence of weather anomalies on local price changes is exacerbated during an export ban.[25] 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 and also from each other at the 1 percent level. The Southern and Northern zones, the main maize export areas, experience the largest differential impacts of weather disturbances under the two trade regimes. It is worth noting that the mechanisms through which export bans influence market prices involve changes in the impacts of both external and domestic shocks and not merely lower price levels (as shown in table 5).

In the case of the Northern and Southern zones, which are the main export areas, bans exacerbate weather shocks and consequently engender greater price uncertainty during the harvests. Consequently, maize producers are adversely affected by both lower prices at harvest as well as greater uncertainty due to the larger impacts of domestic shocks.

7 The Impact of the 2011 Export Ban

What path would maize prices have taken in the absence of export bans? This question is important because it constitutes an essential first step to understand the welfare impacts of trade policies. Answering this question precisely is difficult because of the likely endogeneity of export bans. First, ad-hoc agricultural trade policies may exert an adverse long-run influence on economies through mechanisms that disrupt market institutions and engender sub-optimal investments along the supply chain.[26] Indeed, the majority of Tanzanian maize markets analyzed in this study are characterized by price volatility that is significantly higher than external markets (Table 3), suggesting that these mechanisms may indeed be at work. This type of endogeneity is systemic, and has been a feature of Tanzania's maize sector all along, so it is not expected to bias our results. It would, however, be a more relevant concern in the context of cross-country comparisons.

Second, the timing of the imposition of a particular ban may be endogenous as well. As noted earlier, bans are more likely to be imposed when prices are elevated. Though our econometric analysis accounts for harvest shocks and consequently removes one (po-

[25] 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).

[26] Tschirley and Jayne (2010) discuss the adverse long-term consequences of discretionary (and unpredictable) trade policy regimes.

tential) source of omitted-variable bias, this type of endogeneity may exert an influence through other channels. We leave further examination of these channels to future research.

Because the circumstances under which export bans are imposed are different, and have complex interactions with other variables affecting domestic price movements, we isolate the impact of the last export ban from earlier ones by providing a separate estimate (Table 8).[27] For the country as a whole, the 2011 export ban caused the monthly price to be 8.7 percentage points lower, for every month that it was in effect, than they would have been without the ban. While all five zones experienced a large and significant impact, the effect of the ban was weakest in the Southern zone, most likely because of its poor transport and market infrastructure.

To better understand the impact of the 2011 ban, with the caveats above, we use the results in Table 8 to estimate counterfactual maize price changes in Dar es Salaam and Songea under a no-ban scenario. The counterfactual price path is estimated in the following manner. First, 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 adjusted by the last period's price difference with Nairobi.[28] Then, we use the counterfactual change to calculate the counterfactual level for the first period. Last, we repeat these steps recursively to generate the counterfactual price path.

Figures 12 and 13 show 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.[29] After the ban's removal, actual and counterfactual prices took several months to converge.

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[27] The difference in the magnitude of the impacts is statistically significant both across the full sample and across all zones. There are two reasons for the relatively larger impact of the 2011 export ban. First, prices in Nairobi were especially elevated during this ban. Second, there were significant investments in transport infrastructure during the late 2000s and this may have resulted in lower natural trade costs. As a consequence, the last export ban may have exerted a larger influence on both maize trade flows and local maize markets.

[28] The results for the specification with a separate export ban (in 2011) are very similar to those reported Table 6. The adjustment parameter is 0.15 (instead of 0.13) in the Northern zone and 0.13 (instead of 0.12) in the Southern zone. Similarly, the short run effect is 0.33 (instead of 0.32) in the Northern zone and the same (0.21) in the Southern zone. All these parameters for both specifications are significantly different from zero at a 1 per-cent level of significance.

[29] Although the estimated coefficients for Dar es Salaam and Songea are similar, the export ban does in fact have a much larger impact on levels in Dar es Salaam than in Songea. These differences reflect the fact that Dar es Salaam is better connected and has better functioning markets. There are two mechanical reasons why (apparently) similar coefficients translate into large level differences. First, because Dar es Salaam prices (without the ban) are higher than Songea prices, percentage changes translate into larger level changes. Second, our analysis is in terms of percentage changes (i.e. log differences) and the differences are compounded every month.

As the previous section shows, the impacts of weather shocks are more pronounced during a ban. Given that weather anomalies across Tanzania were large and positive for the maize planting and growing season at the end of 2011, had the export ban remained in place in 2012, maize prices would have fallen sharply with the 2012 maize harvests. This would have lowered farm incomes, and more importantly, weakened smallholders' incentives to make investments that improve their agricultural productivity.

8 Conclusions

We have shown that, in the long run, Tanzanian maize price movements are influenced by price movements in Nairobi. We also document that the impacts of movements in South African and U.S. Gulf prices, both commonly used in the literature on the subject, are far more muted. However, in the short run, maize prices are governed by a constellation of domestic factors. Export bans exert downward pressure on domestic maize prices. Both weather shocks and harvest cycles also have a strong short-run influence on local prices.[30] Together, these results underscore the importance of measuring and accounting for the influence of domestic drivers of local food prices.

We also find that the mechanisms through which trade policies influence maize markets involve interactions with both external market shocks and domestic weather shocks. Responses to weather shocks are less pronounced in markets that are connected to regional and international trade networks—suggesting that trade mitigates the influence of local shocks. Consistent with this, an export ban amplifies domestic weather disturbances. Restrictive trade policies delay, but do not eliminate, the adjustment towards a long-run equilibrium with external markets. These results complement attempts to identify local and global food crises (see, for example, Cuesta et al. (2014)). In this context, our study may be viewed as an attempt to better understand the mechanisms that lead to domestic food price spikes.

In addition, there is substantial variation in market linkages and behaviour across the 18 markets we study. This large sub-national variation has two important implications. First, although export bans are often imposed with the goal of protecting (better-connected) urban consumers, as transport costs decrease, the adverse impacts on rural producers will be larger, thus exacerbating the tradeoffs implicit in agricultural trade policies. Second, given the large differences in price differentials and adjustment speeds with external markets, measures of agricultural protection (e.g. the ones reported by Anderson and Valenzuela (2008)) gloss over large sub-national differences. Consequently, our results speak to the importance of incorporating sub-national differences into the design

[30] The strength of these relationships are consistent with poor storage and transport infrastructure.

of any policy that impacts domestic food markets.

Further, a better understanding of the relationship between weather shocks and food markets may improve our understanding of the mechanisms behind the well documented causal relationship between climate shocks and conflict (e.g. Sambanis (2002), Burke et al. (2015)).[31] Perhaps more fundamentally, Brückner and Ciccone (2011) document a causal relationship between adverse rainfall and transitions to democracy in Africa, while Dell et al. (2012) link positive temperature anomalies to lower growth rates in developing countries. Our study contributes to this literature by documenting a relationship between weather shocks and food prices, and by extension, food availability and rural incomes, both of which are related to conflict and economic growth.

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)). As a result, food markets with pronounced seasonality and greater sensitivity to weather anomalies are likely to be those more seriously affected if climatic changes intensify. For example, Rowhani et al. (2011) have shown that maize yields in Tanzania are affected by shifts in the growing season as well as by greater intra-seasonal variability. Cross-border food trade flows are an important mechanism through which some of the impacts associated with greater climate variability may be mitigated. It is therefore important to deepen our understanding of the influence that agricultural trade policies have on local food prices. Such an understanding will inform policies that aim to reduce the impact that climate change will have on the most vulnerable people in the developing world.

[31] Related, Brückner and Ciccone (2010) show that negative shocks to commodity export demand may engender conflict in (the relevant countries) in Sub-Saharan Africa. In addition, Nunn and Qian (2014) show that US food aid extends the duration of civil conflict in Africa. However, they do not examine the channels through which food aid impacts local food markets.

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Table 1
Key Physical Characteristics of Tanzanian Maize Markets

		Maize statistics on				Time and distance via major roads to			
	FEWS NET Categorization	**Production** *(000m 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	na	na	na	na
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	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	na	na	na	na
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). Road travel is less relevant for markets in the lake and coastal zones.

Table 2
Maize Prices during Export Bans

	--------------- Export ban's duration ---------------			------- 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).

Table 3
Summary Statistics of Maize Prices in Tanzania (June 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	248	272	219	6.9	7.1	6.6
South Africa	282	297	264	8.1	8.1	8.1
Nairobi	400	394	409	9.6	9.9	9.3
Tanzania, average	332	333	332	12.9	12.0	13.6
Central						
Dodoma	356	351	362	10.1	8.8	11.1
Singida	333	330	336	11.2	10.2	12.0
Tabora	343	351	334	13.2	13.6	12.5
Coastal						
Dar es Salaam	357	362	349	10.2	9.4	10.7
Lindi	356	361	350	20.0	19.1	21.0
Morogoro	349	342	357	13.3	13.6	12.6
Mtwara	353	351	355	21.9	20.5	23.5
Lake						
Bukoba	359	361	357	11.3	12.0	10.2
Musoma	378	384	370	11.4	11.3	11.2
Mwanza	385	390	380	10.3	10.0	10.3
Shinyanga	353	353	352	10.2	8.4	11.5
Northern						
Arusha	334	324	346	9.6	8.7	10.0
Moshi	348	337	362	10.3	9.0	11.1
Tanga	333	330	336	14.0	12.3	15.4
Southern Highlands						
Iringa	279	277	282	13.2	12.8	13.7
Mbeya	281	292	267	10.2	9.6	10.9
Songea	242	237	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, 64 correspond to Ban and 80 to No ban regimes.

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

	U.S. Gulf	South Africa	Nairobi
Conventional statistics, equation (1)			
Median R^2	0.69	0.60	0.78
Lowest R^2	0.59	0.50	0.64
Highest R^2	0.78	0.72	0.88
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

Notes: This table summarizes conventional and stationarity statistics reported in tables B2 (U.S. Gulf), B3 (South Africa), and B4 (Nairobi), reported in Appendix B.

Table 5
Parameter Estimates for Error Correction Model, Nairobi

	Arusha	Bukoba	Dar es Salaam	Dodoma	Iringa	Lindi	Mbeya	Morogoro	Moshi
μ	-0.02 (1.57)	-0.03* (1.83)	-0.01 (1.01)	-0.02 (1.25)	-0.04* (1.79)	-0.00 (0.19)	-0.02 (1.08)	-0.03 (1.59)	-0.02 (1.22)
$(p_{t-1}^E - p_{t-1}^i)$	0.12*** (2.97)	0.31*** (4.60)	0.13*** (3.53)	0.09*** (3.20)	0.11*** (2.64)	0.30*** (3.11)	0.05 (1.44)	0.15**** (3.05)	0.13*** (3.13)
Δp_t^E	0.32** (4.75)	0.37*** (3.93)	0.21** (2.50)	0.22*** (3.49)	0.37*** (3.19)	-0.07 (0.37)	0.17** (1.99)	0.41*** (2.75)	0.32*** (5.05)
Δp_t^F	0.21 (1.40)	0.21 (1.14)	0.21 (1.05)	0.42*** (2.69)	0.20 (0.81)	-0.31 (1.03)	-0.12 (0.67)	0.36* (1.83)	0.28* (1.82)
Δp_t^I	3.03*** (3.07)	1.96* (1.69)	1.98** (2.24)	2.90*** (3.26)	1.04 (0.97)	-0.22 (0.12)	1.90** (1.99)	2.75** (2.10)	2.48*** (3.33)
I_{BAN}	-3.31* (1.73)	-3.48** (2.16)	-3.29** (2.13)	-2.52* (1.81)	-1.46 (0.73)	-5.36* (1.71)	-1.24 (0.74)	-1.58 (0.75)	-2.68* (1.75)
$Cos\left(\frac{2\pi t}{12}\right)$	0.03** (2.19)	0.03 (1.58)	-0.03** (2.37)	0.04*** (2.95)	0.05*** (2.98)	0.10*** (3.36)	-0.04** (2.58)	0.05** (2.61)	0.02 (1.53)
$Sin\left(\frac{2\pi t}{12}\right)$	0.01 (1.15)	-0.05*** (-4.00)	0.00 (0.05)	0.01 (0.57)	0.01 (0.38)	-0.02 (0.53)	0.03*** (3.05)	0.00 (0.30)	0.03*** (2.97)
$NDVI_t$	-0.46*** (2.79)	-0.38*** (-4.46)	-0.27** (4.51)	-0.29*** (-5.45)	-0.43 (1.55)	-0.62*** (2.75)	-0.54*** (2.70)	-1.02*** (4.74)	-0.29** (2.47)
R-square	0.37	0.31	0.29	0.39	0.21	0.29	0.24	0.33	0.34

Notes: See next page.

Table 5 (continued)
Parameter Estimates for Error Correction Model, Nairobi

	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)
$(p_{t-1}^{E} - p_{t-1}^{i})$	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_t^E	-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_t^F	-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_t^I	-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)
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)
$Cos\left(\frac{2\pi t}{12}\right)$	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)
$Sin\left(\frac{2\pi t}{12}\right)$	-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)
R-square	0.26	0.22	0.28	0.25	0.28	0.20	0.23	0.26	0.34

Notes: Each regression has 144 monthly observations. The dependent variable is the change in the logarithm of the nominal price in market *i*. Absolute (robust) t-statistics in parentheses, significance level, * = 10 percent, ** = 5 percent, *** = 1 percent.

Table 6
Parameter Estimates for Panel Specification with Simple Dummy, Nairobi

	Central	Coastal	Lake	Northern	Southern	National
μ	-0.02*** (8.38)	-0.02*** (3.20)	-0.00 (0.68)	-0.02*** (7.54)	-0.05** (4.66)	-0.02*** (5.33)
$(p_{t-1}^E - p_{t-1}^i)$	0.13*** (8.26)	0.23*** (5.76)	0.20*** (4.93)	0.13*** (19.82)	0.12** (7.02)	0.16*** (9.23)
Δp_t^E	0.21*** (6.90)	0.12 (1.52)	0.26*** (5.23)	0.33*** (21.13)	0.21*** (4.52)	0.21*** (6.75)
Δp_t^F	0.33*** (8.00)	0.01 (0.11)	0.32*** (5.01)	0.26*** (14.92)	0.09 (1.55)	0.20*** (4.37)
Δp_t^I	2.78*** (67.95)	0.77 (1.09)	1.70*** (4.33)	2.40*** (7.81)	1.25*** (7.30)	1.68*** (6.61)
I_{BAN}	-2.78*** (15.77)	-3.49*** (6.93)	-3.83*** (17.23)	-2.75*** (11.13)	-2.07*** (2.75)	-3.09*** (12.72)
$Cos\left(\frac{2\pi t}{12}\right)$	0.04*** (15.43)	-0.07*** (4.30)	0.03*** (7.14)	0.04*** (2.64)	0.05*** (9.68)	-0.05*** (8.20)
$Sin\left(\frac{2\pi t}{12}\right)$	-0.01 (0.81)	-0.01 (1.62)	-0.03*** (4.63)	0.02*** (4.54)	-0.03** (2.35)	-0.01** (2.32)
$NDVI_t$	-0.23*** (8.13)	-0.38*** (2.95)	-0.19*** (2.66)	-0.48*** (4.64)	-0.65*** (6.30)	-0.31*** (7.42)
R-square	0.28	0.22	0.24	0.32	0.18	0.20

Notes: The dependent variable is the change in the logarithm of the nominal price in market *i*. All regressions employ a (market) fixed effects methodology with bootstrapped standard errors (1,000 replications). Robust absolute z-statistics in parentheses, significance level, * = 10 percent, ** = 5 percent, *** = 1 percent; significance levels are different than typical due to clustering adjustment of the standard errors. The bootstrapped standard errors are clustered at the market level.

Table 7
Parameter Estimates for Panel Specification with Interaction Dummies, Nairobi

	Central	Coastal	Lake	Northern	Southern	National
μ	-0.04*** (9.10)	-0.03*** (5.83)	-0.02*** (4.01)	-0.04*** (18.49)	-0.05** (4.34)	-0.04*** (8.80)
$(p_{t-1}^E - p_{t-1}^i)^* I_{BAN}$	0.10*** (6.46)	0.18*** (5.40)	0.14*** (7.09)	0.12*** (12.58)	0.10** (4.11)	0.13*** (7.98)
$(p_{t-1}^E - p_{t-1}^i)^* I_{NO\_BAN}$	0.17*** (10.80)	0.31*** (5.89)	0.25*** (5.03)	0.19*** (70.44)	0.15*** (7.62)	0.21*** (9.30)
$\Delta p_t^E{}^* I_{BAN}$	0.22*** (6.56)	0.15 (1.58)	0.26*** (5.65)	0.34*** (27.60)	0.23*** (4.69)	0.23*** (7.60)
$\Delta p_t^E{}^* I_{NO\_BAN}$	0.22*** (6.73)	0.14 (1.51)	0.26*** (5.68)	0.35*** (27.00)	0.22*** (4.71)	0.23*** (7.51)
Δp_t^F	0.36*** (9.60)	0.04 (0.29)	0.35*** (4.70)	0.29*** (15.11)	0.17** (2.27)	0.23*** (4.82)
Δp_t^I	2.89*** (9.99)	0.40 (0.43)	1.75*** (3.84)	2.76*** (8.46)	0.65*** (3.15)	1.61*** (4.97)
$Cos\left(\frac{2\pi t}{12}\right)^* I_{BAN}$	0.04*** (13.09)	0.08*** (3.43)	0.03*** (3.84)	0.05*** (2.72)	0.06*** (5.95)	0.05*** (7.45)
$Cos\left(\frac{2\pi t}{12}\right)^* I_{NO\_BAN}$	0.04*** (6.23)	0.09*** (5.24)	0.03*** (5.58)	0.04** (2.57)	0.06*** (8.10)	0.05*** (7.54)
$Sin\left(\frac{2\pi t}{12}\right)^* I_{BAN}$	0.00 (0.10)	-0.02 (1.24)	-0.02*** (3.35)	0.04*** (7.22)	-0.03** (2.33)	-0.01 (1.07)
$Sin\left(\frac{2\pi t}{12}\right)^* I_{NO\_BAN}$	-0.02*** (3.66)	0.00 (0.36)	-0.03*** (5.56)	0.00 (1.14)	-0.03** (2.58)	-0.02** (3.47)
$NDVI_t{}^* I_{BAN}$	-0.28*** (8.16)	-0.37*** (3.07)	-0.27* (1.74)	-0.59*** (5.55)	-0.86*** (3.98)	-0.38*** (6.18)
$NDVI_t{}^* I_{NO\_BAN}$	-0.19*** (3.17)	-0.40** (2.37)	-0.13** (2.01)	-0.43*** (3.73)	-0.21 (1.36)	-0.27*** (5.03)
R-square	0.27	0.23	0.24	0.30	0.21	0.20
Chi-square tests						
Difference in adjustment	0.07	0.14	0.11	0.07	0.05	0.08
Diff in Adj-Chi	29.56***	20.92***	11.16***	70.93***	21.05***	47.58***
Difference in NDVI	0.09	0.03	0.14	0.17	0.65	0.11
Diff in NDVI-Chi	1.31	0.05	0.95	6.39***	3.36**	3.30*

Notes: The dependent variable is the change in the nominal price in market *i*. All regressions employ a (market) fixed effects methodology with bootstrapped standard errors (1,000 replications). Robust absolute z-statistics in parentheses, significance level, * = 10 percent, ** = 5 percent, *** = 1 percent; significance levels are different than typical due to clustering adjustment of the standard errors. The bootstrapped standard errors are clustered at the market level. 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, respectively, under Ban and No ban regimes.

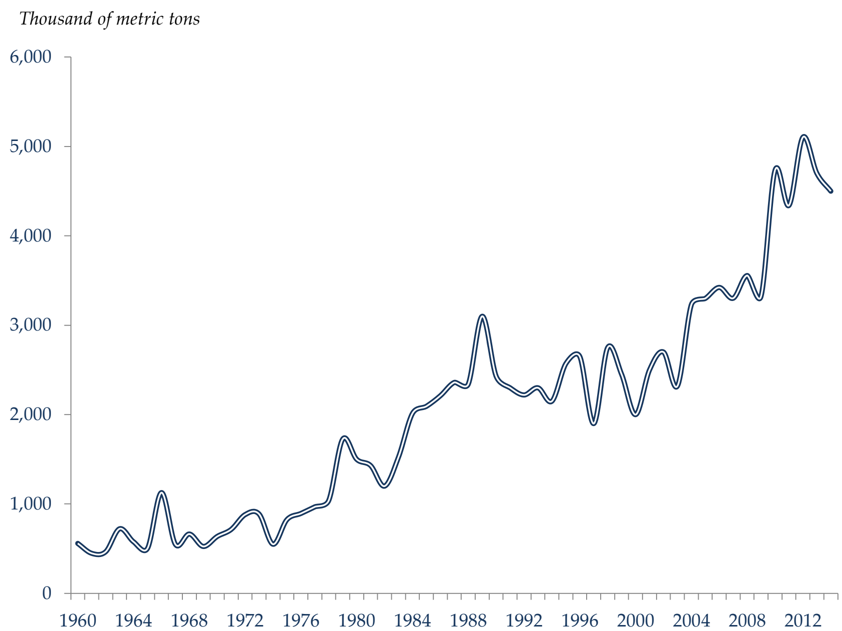
Table 8
Separating the Impact of the 2011 Export Ban

	Central	Coastal	Lake	Northern	Southern	National
Estimate reported in Table 6 (sixth row)						
I_{BAN}	-2.78***	-3.49***	-3.83***	-2.75***	-2.07***	-3.09***
	(15.77)	(6.93)	(17.23)	(11.13)	(2.75)	(12.72)
Specification separating the impact of the 2011 export ban						
I_{BAN}, *excluding 2011*	-2.27***	-2.80***	-3.30***	-2.01***	-1.62***	-2.52***
	(14.43)	(4.27)	(18.22)	(9.48)	(2.36)	(10.46)
2011 BAN	-7.94***	-10.57***	-9.00***	-9.17***	-7.28***	-8.87***
	(10.28)	(4.09)	(10.92)	(12.47)	(3.31)	(12.25)

Notes: The dependent variable is the change in the logarithm of the nominal price in market *i*. All regressions employ a (market) fixed effects methodology with bootstrapped standard errors (1,000 replications). Robust absolute *z*-statistics in parentheses; significance level, * = 10 percent, ** = 5 percent, *** = 1 percent; significance levels are different than typical due to clustering adjustment of the standard errors. The bootstrapped standard errors are clustered at the market level. The top row shows the parameter estimates of the export ban reported in Table 6. The second and third rows provide estimates of the bans prior to 2011 and the 2011 ban, respectively, which were estimated together with a similar specification to that of the model reported in Table 6.

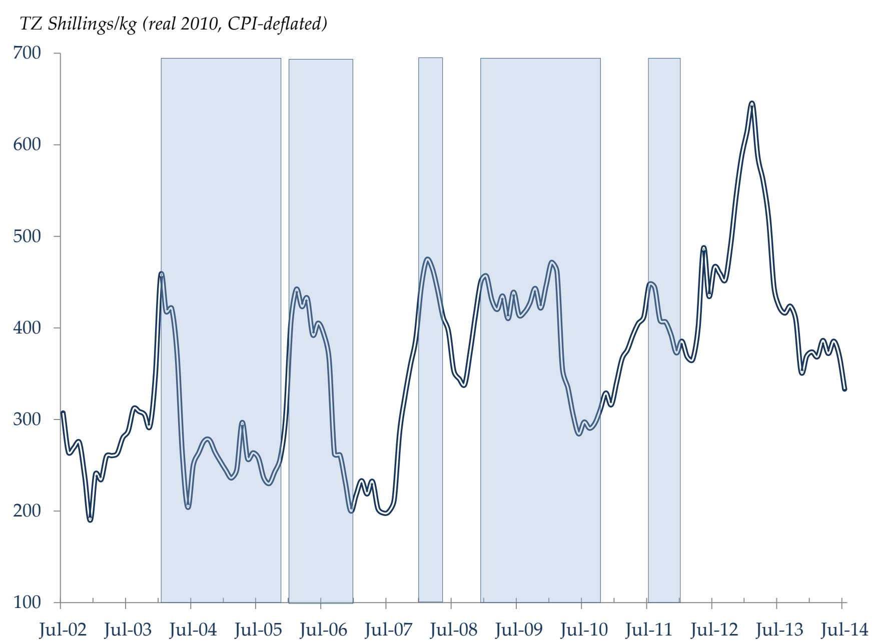
Figure 1
Maize Markets in Tanzania

Figure 2
Maize Production in Tanzania



Source: U.S. Department of Agriculture

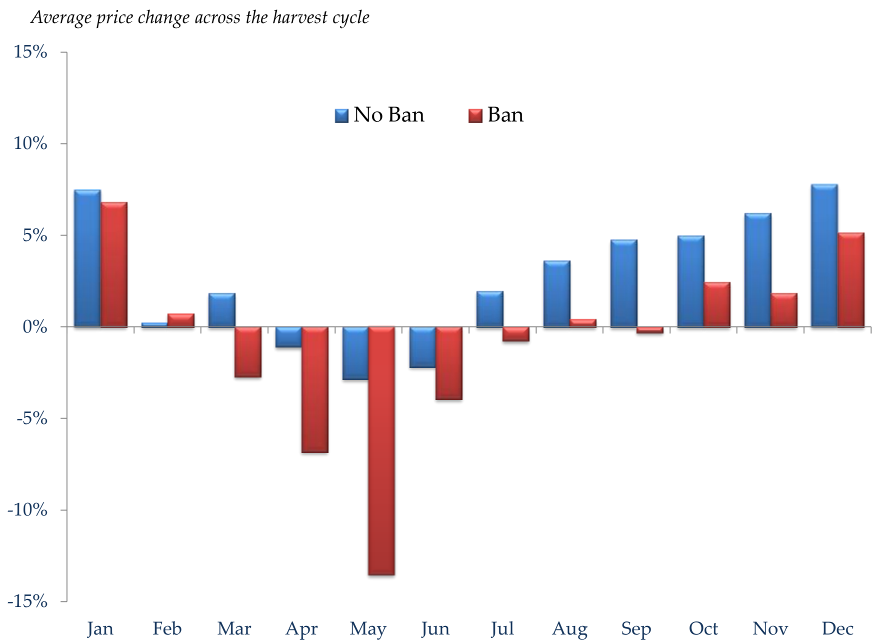
Figure 3
Maize Price in Dar es Salaam and Export Bans



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

Figure 4

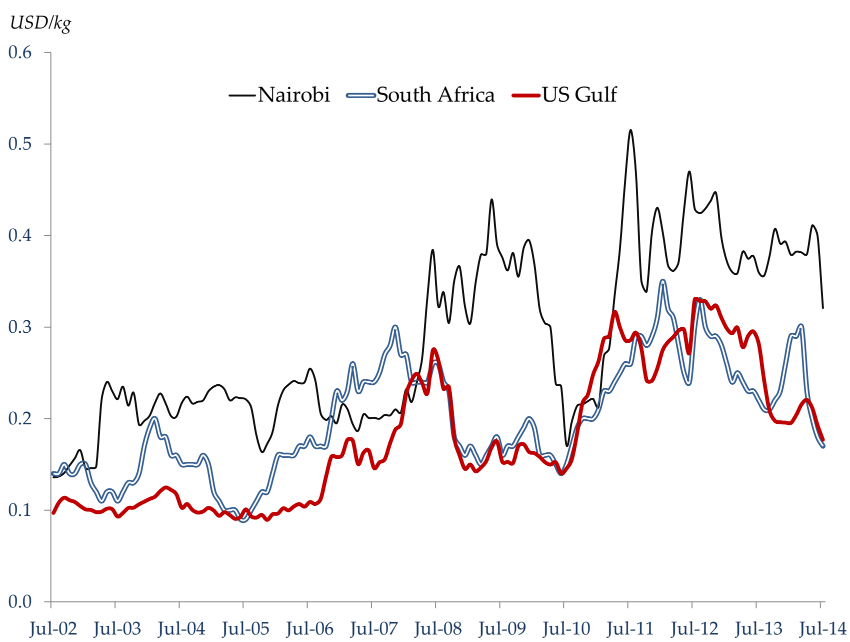
Average Price Changes during Ban and No Ban Periods



Source: Authors' calculation based on *unadjusted* price data.

Figure 5

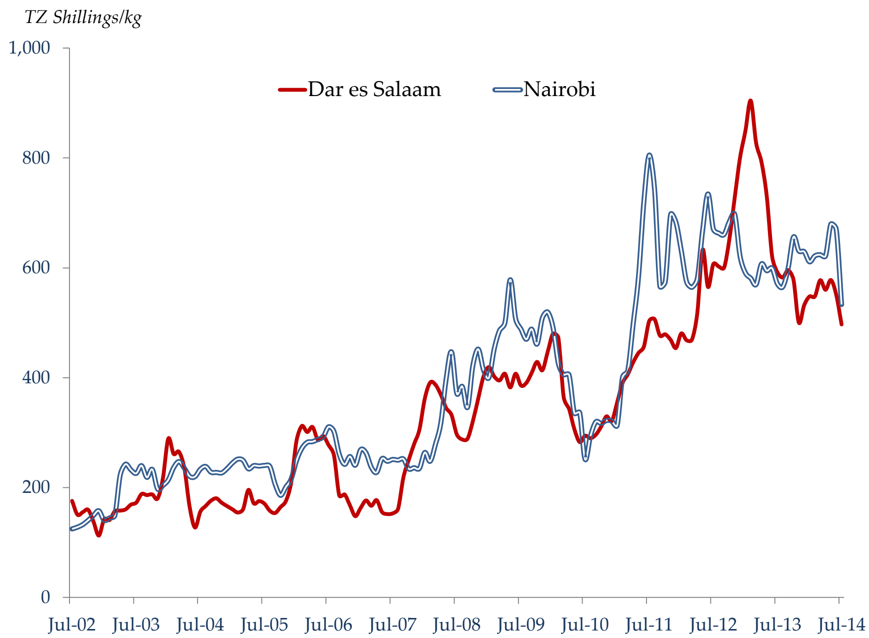
Nominal Maize Prices, International Comparison



Source: Ministry of Industry and Trade, Tanzania, FAO GIEWS, World Bank

Figure 6

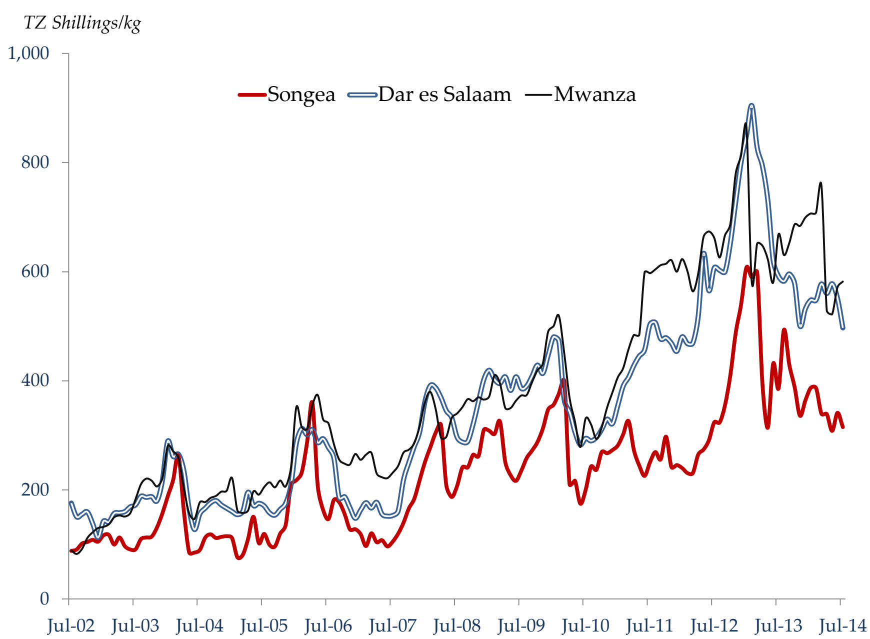
Nominal Maize Prices, Dar es Salaam and Nairobi



Source: Ministry of Industry and Trade, Tanzania

Figure 7

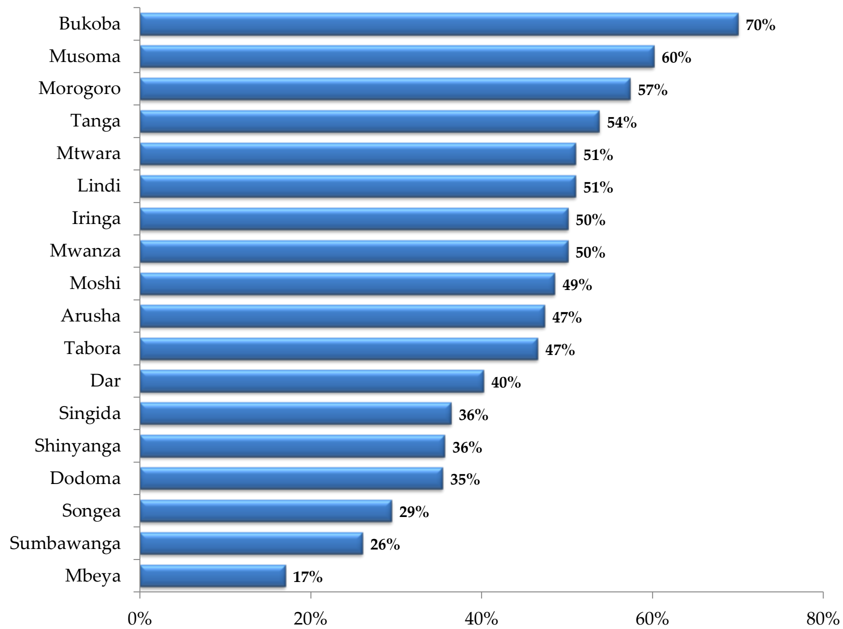
Nominal Maize Prices, Domestic Comparison



Source: Ministry of Industry and Trade, Tanzania

Figure 8

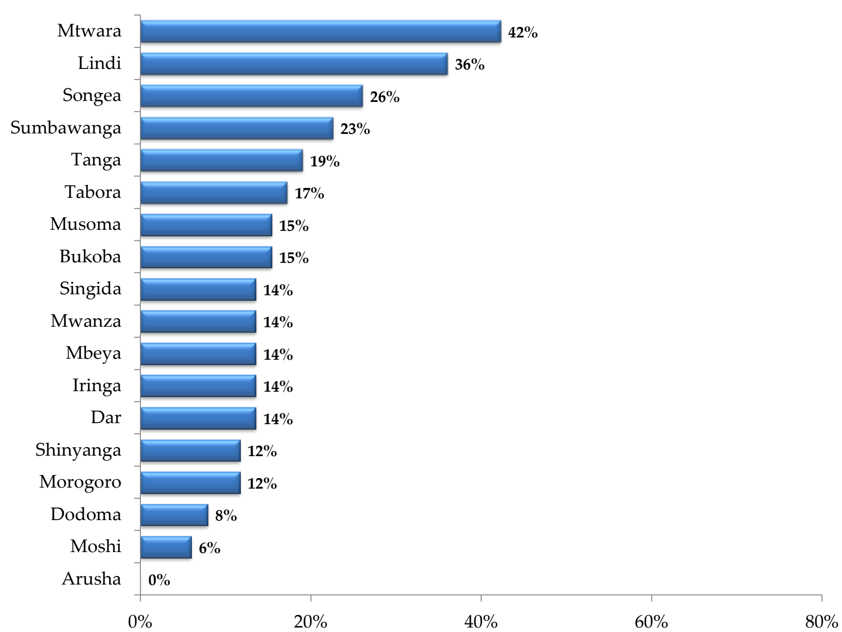
Price Adjustment Achieved within 3 Months (percent), Nairobi



Source: Authors' calculation based on parameter estimates

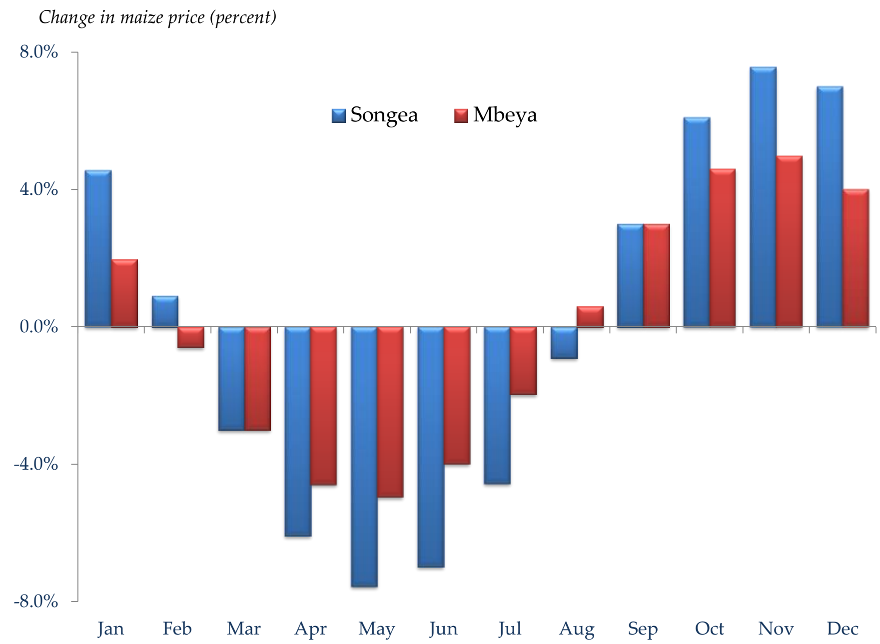
Figure 9

Price Adjustment Achieved within 3 Months (percent), US Gulf



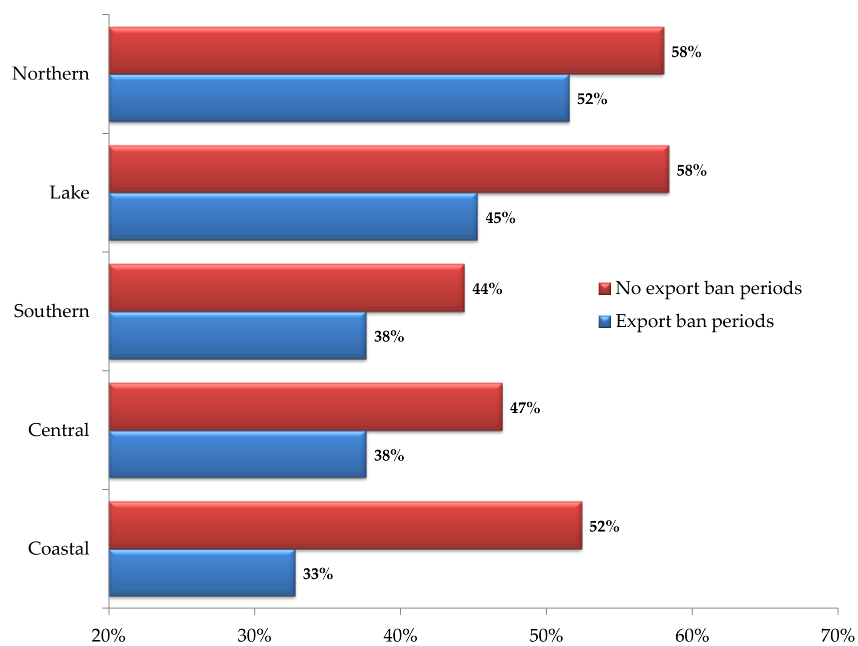
Source: Authors' calculation based on parameter estimates

Figure 10
Seasonal Influence on Maize Price Changes: Songea and Mbeya



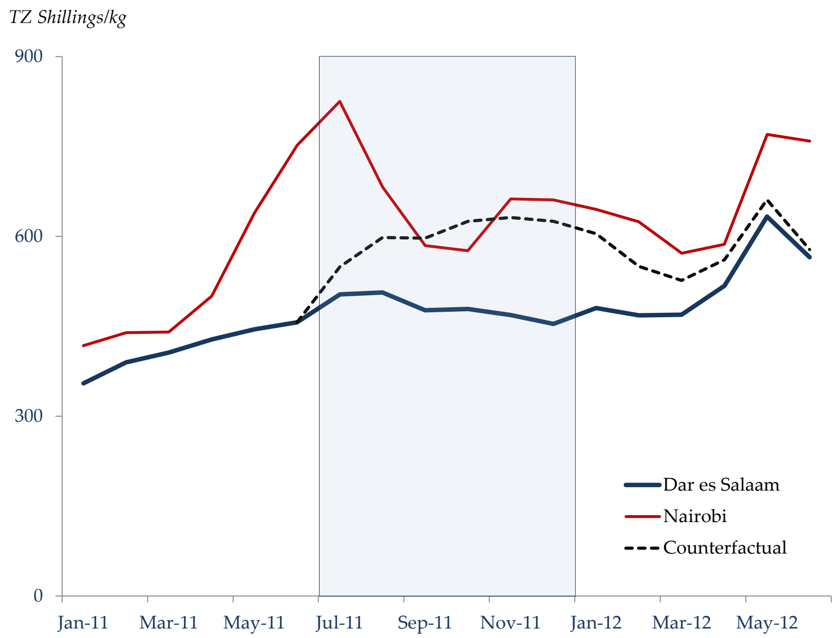
Source: Authors' calculation based on parameter estimates

Figure 11
Price Adjustment Achieved within 3 Months (percent), Asymmetric



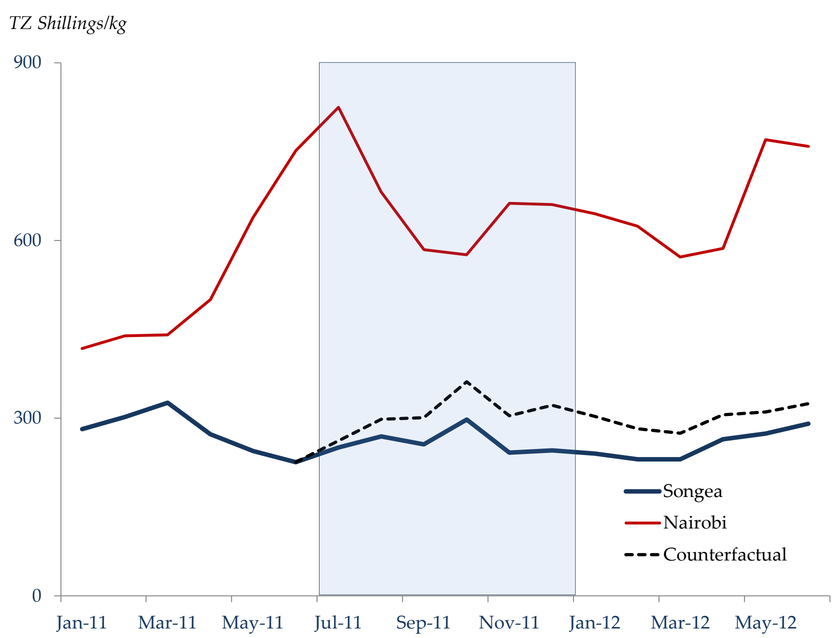
Source: Authors' calculation based on parameter estimates

Figure 12
Impact of the 2011 Export Ban in Dar es Salaam



Source: Authors' calculations based on parameter estimates

Figure 13
Impact of the 2011 Export Ban in Songea



Source: Authors' calculations based on parameter estimates

Appendix A : Data Description and Sources

Domestic Prices

Wholesale white maize prices in Tanzania are monthly averages, expressed in TZ shillings per kg, collected by Tanzania's Ministry of Industry and Trade in 18 markets. These markets are grouped into five zones and cover the entire country. Data on domestic fuel prices and CPI are collected by Tanzania's National Bureau of Statistics (NBS).

External Prices

Wholesale white maize prices in Nairobi (Kenya), Randfontein (South Africa), and Nampula (Mozambique) are sourced from FAO GIEWS (`http://www.fao.org/giews/english/index.htm`); U.S. Maize prices represent no. 2, yellow, f.o.b. Gulf ports. Crude oil price is the average of Brent (U.K. 38^0 API), West Texas Intermediate (WTI 40^0 API), and Dubai (Fateh 32^0 API) equally weighted. World prices for maize and oil were taken from the World Bank's pink sheet (`http://go.worldbank.org/4ROCCIEQ50`).

Export Ban

An export ban is represented by a dummy variable taking the value of 1 when the ban was effective and zero otherwise. The ban was effective during the following months: Jan—Dec 2005, Mar 2006—Jan 2007, Jan—May 2008, Jan 2009—Oct 2010, Jul 2011 (introduction was announced informally in Mar 2011)—Dec 2011 (lifting was announced informally in Oct 2011). This was sourced from FAO GIEWS, newspaper articles, and interviews with industry representatives.

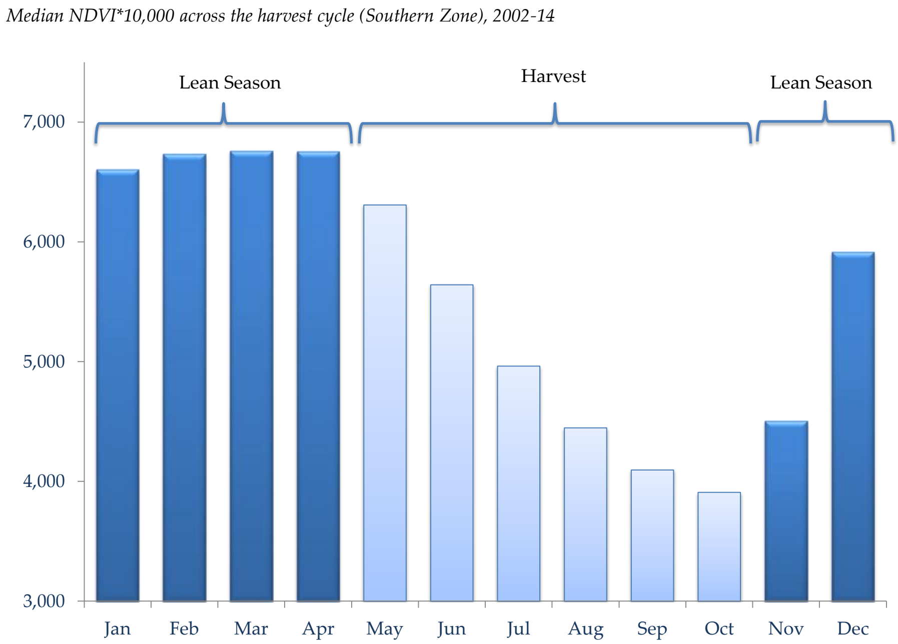
Normalized Difference Vegetation Index anomaly

Weather disturbances in this study were estimated using satellite-derived Normalized Difference Vegetation Index (NDVI) imagery over cultivated areas as a proxy. NDVI is derived from the visible and near-infrared portions of the electromagnetic spectrum and the contrast between the two provides a strong indication of vegetative health and plant productivity (c.f. Tucker (1979)). In an agricultural context, NDVI captured during the heart of the growing season, and thus anomalies of it from normal, have been shown related to crop productivity (Becker-Reshef et al. (2010); Johnson (2014); Brown (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 and, conversely, below normal NDVI values suggestive of lower than typical yields.

The NDVI data used in this research was collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard the NASA polar orbiting satellite Aqua from July 2002 to July 2014. MODIS provided an NDVI estimate every eight days at an approximately 250 meter ground sample (pixel) resolution across the entire study area. To isolate the NDVI signal to only those areas where crops are expected the time series was 'masked' by the Croplands and Cropland/Natural Vegetation Mosaic categories found within the IGBP land cover classification (c.f. Loveland et al. (2000)). Next, to reduce potential pixel-level noise (both in time and space) and simplify the modeling efforts, the measurements were aggregated to monthly values at a 5 kilometer grid cell size. And finally, the values were spatially averaged further to each of study areas in order to directly link them with the economic data.

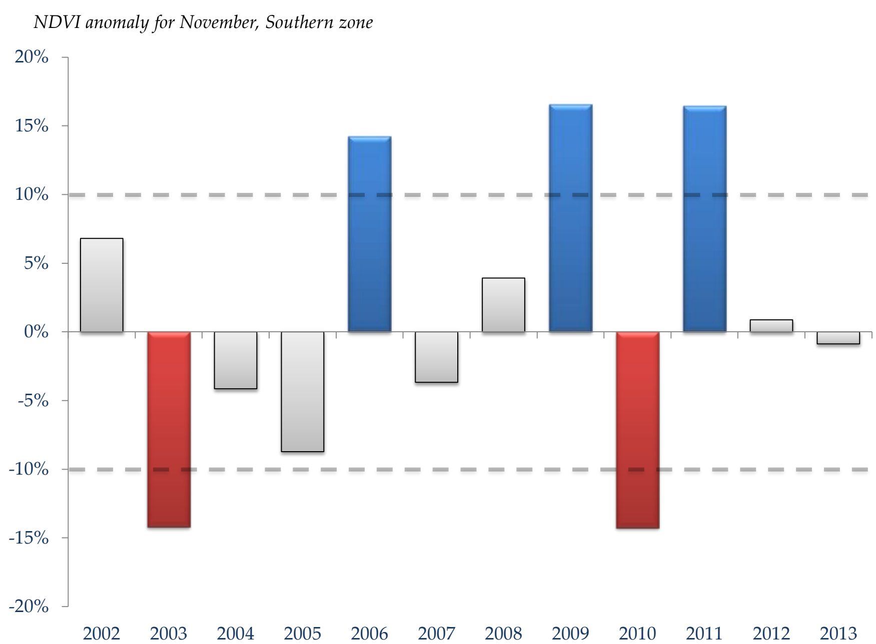
Figure A1 depicts the NDVI values across the harvest cycle for the Southern zone (multiplied by 10,000 as per convention). Each bar represents the median NDVI value for the relevant month for the 12 years of the sample. The median NDVI values range from a low of 3,910 in October (the last month of the harvest season) to a high of 6,761 in March (which is towards the end of the lean season that ends in April. For example, the November median value of 4505 reported in Figure A1 ranges between a low of 3,866 in 2003 to a high of 5,247 in 2011. Figure A2 depicts Southern zone's NDVI anomaly for the month of November. The (positive) anomaly equals 14.2 percent in 2006, calculated as the deviation of the NDVI value of 5,148 from the median of 4,506. Note that of the 12 observations shown in Figure A2, only five values lie outside the [-10 percent, +10 percent] interval, which are the ones which are assigned non-zero values for the NDVI anomaly used in the estimation; the rest are set to zero. Figures A3 and A4 depict the values of the NDVI anomaly used for the Northern and Southern zone, respectively. In the Northern zone, twenty months are assigned a non-zero NDVI anomaly, seven of which are negative (representing worse-than-normal weather conditions) while 13 are positive (representing better-than-normal weather conditions). In contrast, only seven months are assigned non-zero values in the Southern zone, three corresponding to better and four corresponding to worse than normal weather conditions.

Figure A1
NDVI Values across the Harvest Cycle in the Southern Zone



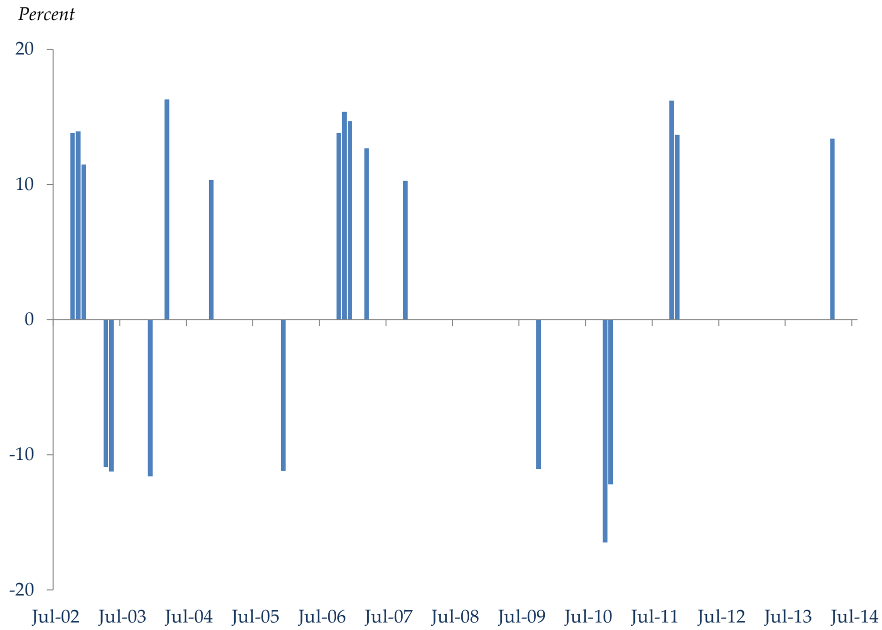
Source: Authors' calculation based on NDVI data

Figure A2
NDVI Anomalies for November in the Southern Zone



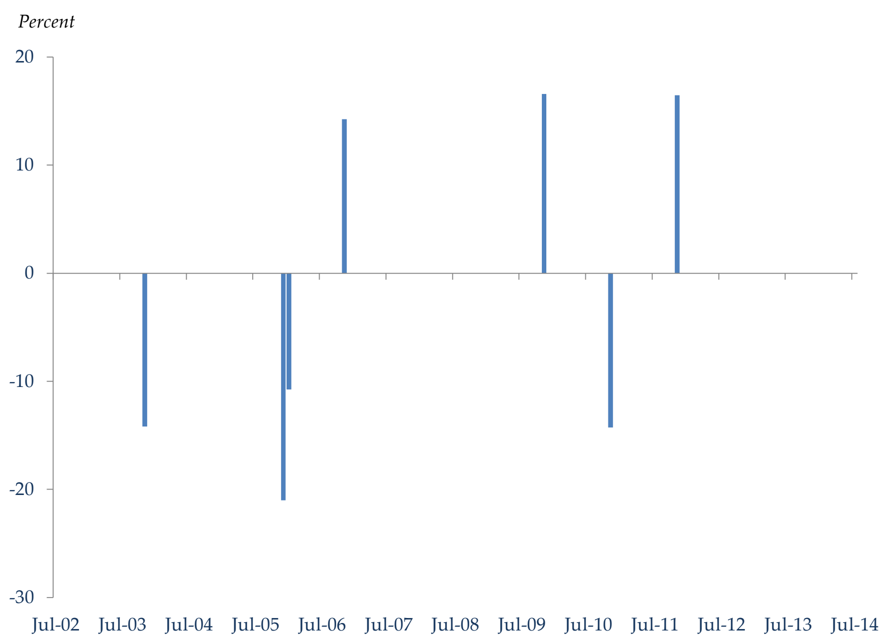
Source: Authors' calculations based on original NDVI data

Figure A3
NDVI Anomaly, Northern Zone



Source: NASA and authors' calculations

Figure A4
NDVI Anomaly, Southern Zone



Source: NASA and authors' calculations

APPENDIX B: Stationarity Properties and Parameter Estimates of Equation (1) and (2) for the three External Price Indicators

Table B1: Stationarity Properties

	-- Log-levels without trend --		-- Log-levels with trend --		-- First differences of logs --	
	ADF	*PP*	*ADF*	*PP*	*ADF*	*PP*
U.S. Gulf	-1.59	-1.46	-1.83	-1.76	-3.04	-9.65***
S. Africa	-2.00	-1.70	-2.58	-2.21	-3.54**	-8.88***
Nairobi	-1.14	-2.01	-3.25*	-3.22*	-3.91***	-10.04***
Arusha	-1.66	-2.23	-3.51**	-3.01	-4.53***	-7.94***
Bukoba	-1.10	-1.83	-3.91**	-3.53*	-4.01***	-11.24***
Dar es Salaam	-1.23	-1.30	-3.37*	-3.03	-4.28***	-8.87***
Dodoma	-1.57	-1.96	-3.90**	-2.89	-4.47***	-6.81***
Iringa	-1.35	-2.12	-3.45**	-3.13*	-4.47***	-8.72***
Lindi	-1.16	-2.45	-3.92**	-4.38***	-4.19***	-14.77***
Mbeya	-1.11	-1.37	-3.78**	-2.87	-4.23***	-8.09***
Morogoro	-1.85	-2.05	-3.36*	-2.78	-4.07***	-7.50***
Moshi	-1.47	-1.70	-3.35*	-2.79	-3.67***	-8.91***
Mtwara	-1.41	-2.99	-3.17*	-4.74***	-3.22**	-16.58***
Musoma	-0.89	-2.21	-4.20***	-3.52*	-4.56***	-9.34***
Mwanza	-1.24	-2.27	-4.28***	-3.57*	-4.52***	-10.65***
Shinyanga	-1.26	-2.91	-4.18***	-4.16***	-4.04***	-8.70***
Singida	-1.41	-2.48	-4.19***	-3.17*	-4.43***	-9.83***
Songea	-1.65	-2.11	-3.83**	-3.59**	-4.19***	-11.08***
Sumbawanga	-1.22	-1.65	-3.36*	-3.23*	-4.18***	-9.98***
Tabora	-1.54	-2.34	-4.23***	-3.30*	-3.98***	-11.09***
Tanga	-1.62	-2.39	-3.22*	-2.91	-3.94***	-7.58***

Notes: All variables are expressed in logarithms. ADF and PP denote the Augmented Dickey-Fuller and Phillips-Perron statistic for unit roots, respectively. The ADF statistic was based on 12 lags, while the spectral estimation for the PP statistics was based on the Bartlett kernel method. Significance level of stationarity: * = 10 percent, ** = 5 percent, *** = 1 percent.

Table B2: Parameter Estimates of Equation (1) and Stationarity Properties of Equation (2) between Tanzanian Markets and U.S. Gulf

	----------------------- Regression results, eq. (1) -----------------------					--- Price spread, eq. (2)---	
	μ	p_t^W	*R-square*	ADF	PP	ADF	PP
Arusha	2.72***	0.76***	0.68	-2.90**	-2.91**	-2.53	-2.67*
	(7.28)	(20.55)					
Bukoba	2.79***	0.76***	0.75	-3.00**	-3.21**	-2.85*	-2.99**
	(9.60)	(26.00)					
Dar es Salaam	2.44***	0.79***	0.73	-2.64*	-2.85*	-2.61*	-2.92**
	(7.91)	(25.56)					
Dodoma	2.03***	0.83***	0.67	-3.07**	-2.76*	-2.95**	-2.72*
	(4.81)	(19.84)					
Iringa	2.38***	0.77***	0.67	-3.03**	-3.20**	-2.86*	-3.03**
	(6.02)	(19.60)					
Lindi	2.80***	0.76***	0.62	-3.27**	-3.96***	-3.26**	-3.46**
	(5.94)	(16.22)					
Mbeya	1.38***	0.87***	0.78	-2.96**	-2.99**	-2.07	-3.05**
	(4.32)	(27.39)					
Morogoro	2.86***	0.75***	0.65	-3.18**	-2.97**	-2.58*	-2.83*
	(7.09)	(18.69)					
Moshi	2.71***	0.76***	0.65	-2.70*	-2.51	-2.53	-2.49
	(6.64)	(18.94)					
Mtwara	3.30***	0.70***	0.59	-2.92**	-4.42***	-2.65*	-3.99**
	(6.67)	(14.43)					
Musoma	2.93***	0.75***	0.73	-2.93**	-3.28**	-2.78*	-2.95**
	(8.40)	(21.66)					
Mwanza	2.14***	0.83***	0.77	-3.17**	-3.24**	-2.96**	-3.09**
	(5.72)	(22.52)					
Shinyanga	2.51***	0.78***	0.70	-2.86*	-3.59***	-2.61*	-3.24**
	(5.63)	(17.84)					
Singida	2.03***	0.83***	0.71	-3.27**	-3.24**	-2.99**	-3.08**
	(4.49)	(18.65)					
Songea	2.80***	0.72***	0.60	-3.27**	-3.40**	-2.92**	-3.19**
	(6.56)	(16.74)					
Sumbawanga	2.49***	0.75***	0.69	-2.90**	-3.23**	-2.73*	-3.12**
	(6.23)	(18.62)					
Tabora	2.51***	0.78***	0.73	-3.57***	-3.43**	-2.90**	-3.16**
	(6.32)	(19.85)					
Tanga	2.48***	0.78***	0.63	-3.01**	-3.13**	-2.74*	-2.96**
	(5.60)	(17.85)					

Notes: ADF and PP denote the Augmented Dickey-Fuller and Phillips-Perron statistic for unit roots, respectively. The numbers in parentheses are absolute t-statistics. Significance levels: * = 10 percent, ** = 5 percent, *** = 1 percent.

Table B3: Parameter Estimates of Equation (1) and Stationarity Properties of Equation (2) between Tanzanian Markets and Randfontein (South Africa)

	----------------------- Regression results, eq. (1)				-----------------------	--- Price spread, eq. (2)---	
	μ	p_t^W	*R-square*	ADF	PP	ADF	PP
Arusha	1.59***	0.86***	0.57	-2.85*	-2.77*	-3.10**	-2.79*
	(2.87)	(15.72)					
Bukoba	1.19***	0.91***	0.69	-2.43	-3.03**	-2.70*	-3.09**
	(3.16)	(24.00)					
Dar es Salaam	1.25***	0.90***	0.60	-2.63*	-2.48	-2.88**	-2.65*
	(2.82)	(20.06)					
Dodoma	0.87	0.93***	0.55	-2.83*	-2.62*	-2.95**	-2.65*
	(1.42)	(15.36)					
Iringa	1.21**	0.88***	0.55	-2.79*	-2.97**	-3.08**	-3.01**
	(2.37)	(17.17)					
Lindi	1.49**	0.87***	0.53	-3.32**	-3.72***	-3.68***	-3.74***
	(2.50)	(14.91)					
Mbeya	-0.19	1.02***	0.68	-2.53*	-2.66*	-2.48*	-2.64*
	(0.47)	(24.50)					
Morogoro	1.74***	0.85***	0.53	-2.98**	-2.86*	-3.16**	-2.92**
	(3.19)	(15.62)					
Moshi	1.61**	0.86***	0.53	-2.73*	-2.34	-3.00**	-2.43
	(2.56)	(13.92)					
Mtwara	20.7***	0.82***	0.51	-3.10**	-4.18***	-3.52***	-4.10***
	(3.31)	(13.34)					
Musoma	1.52***	0.88***	0.64	-2.62*	-3.11**	-3.03**	-3.14**
	(2.96)	(17.23)					
Mwanza	0.29	1.00***	0.72	-2.79*	-3.11**	-2.79*	-3.11**
	(0.58)	(20.33)					
Shinyanga	0.76	0.95***	0.66	-2.49	-3.59***	-2.63*	-3.58***
	(1.31)	(16.61)					
Singida	0.54	0.96***	0.62	-2.82*	-3.12**	-2.90**	-3.12**
	(0.86)	(15.51)					
Songea	1.68***	0.82***	0.50	-3.11**	-3.19**	-3.43**	-3.23**
	(3.08)	(14.87)					
Sumbawanga	0.95**	0.89***	0.63	-3.14**	-3.08**	-3.50**	-3.16**
	(1.99)	(18.48)					
Tabora	0.69	0.95***	0.70	-3.16**	-3.60***	-3.27**	-3.62***
	(1.35)	(18.76)					
Tanga	1.37**	0.88***	0.52	-2.92**	-3.03**	-3.14**	-3.04**
	(2.17)	(14.02)					

Notes: ADF and PP denote the Augmented Dickey-Fuller and Phillips-Perron statistic for unit roots, respectively. The numbers in parentheses are absolute (robust) t-statistics. Significance levels: * = 10 percent, ** = 5 percent, *** = 1 percent.

Table B4: Parameter Estimates of Equation (1) and Stationarity Properties of Equation (2) between Tanzanian Markets and Nairobi

	----------------------- Regression results, eq. (1) -----------------------					--- Price spread, eq. (2)---	
	μ	p_t^W	*R-square*	ADF	PP	ADF	PP
Arusha	-0.28	1.01***	0.87	-5.38***	-3.73***	-5.36***	-3.72***
	(0.84)	(32.24)					
Bukoba	0.19	0.97***	0.88	-2.30	-4.20***	-2.45	-4.20***
	(0.68)	(37.49)					
Dar es Salaam	-0.07	0.99***	0.82	-3.65***	-3.98***	-3.69***	-3.99***
	(0.17)	(24.56)					
Dodoma	-0.99**	1.08***	0.81	-4.88***	-3.33**	-4.39***	-3.21**
	(2.30)	(26.28)					
Iringa	0.08	0.96***	0.73	-3.54***	-3.31**	-3.69***	-3.32**
	(0.17)	(21.70)					
Lindi	0.46	0.94***	0.69	-3.54***	-4.52***	-3.71***	-4.52***
	(0.79)	(17.34)					
Mbeya	-0.63	1.03***	0.77	-3.56***	-3.22**	-3.41**	-3.17**
	(1.34	(22.90)					
Morogoro	0.19	0.97***	0.78	-4.50***	-3.46**	-4.54***	-3.49***
	(0.43)	(23.24)					
Moshi	-0.64*	1.05***	0.88	-4.29***	-3.94***	-4.19***	-3.79***
	(1.88)	(32.54)					
Mtwara	1.19*	0.87***	0.65	-4.45**	-4.58***	-3.58***	-4.81***
	(1.87)	(14.49)					
Musoma	0.28	0.97***	0.87	-3.63***	-4.69***	-3.74***	-4.73***
	(0.92)	(33.51)					
Mwanza	-0.54	1.05***	0.87	-3.34**	-4.44***	-3.18**	-4.35***
	(1.55)	(31.79)					
Shinyanga	-0.06	0.99***	0.81	-3.84***	-3.94***	-3.86***	-3.94***
	(0.14)	(22.66)					
Singida	-0.66	1.04***	0.81	-5.38***	-3.71***	-5.15***	-3.68***
	(1.46)	(24.42)					
Songea	0.76	0.88***	0.64	-3.90***	-3.77***	-4.15***	-3.80***
	(1.46)	(17.61)					
Sumbawanga	0.90*	0.87***	0.66	-3.25**	-3.38***	-3.76***	-2.46**
	(1.66)	(16.79)					
Tabora	0.61	0.93***	0.74	-4.07***	-3.50***	-4.24***	-3.52***
	(1.35)	(21.52)					
Tanga	-0.45	0.93***	0.78	-4.76***	-3.49***	-4.67***	-3.48**
	(0.98)	(23.40)					

Notes: ADF and PP denote the Augmented Dickey-Fuller and Phillips-Perron statistic for unit roots, respectively. The numbers in parentheses are absolute (robust) t-statistics. Significance levels: * = 10 percent, ** = 5 percent, *** = 1 percent.