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Spatial equilibrium and price transmission between Southern African maize markets connected by informal trade ☆

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ABSTRACT

Policies regulating the international grain trade in Southern Africa (SA) are motivated by uncertainty regarding private sector performance and, in turn, private sector performance is generally constrained by the policy environment. We study spatial price transmission between SA maize markets where trade is dominated by informal product flows. This provides an opportunity to study private sector market performance in a largely unregulated market environment. Contrary to some existing evidence on the performance of SA grain markets connected by formal trade, we find that informally trading markets work quite well. Long-run price equilibrium is consistent with competitive trade, price transmission is rapid, and potential trade constraints have no disruptive impact on long-run relationships. Nevertheless, we do find evidence of occasionally high transfer costs that may impede informal trade flows. The conclusion is that a policy focus on encouraging informal trade and lowering informal trade costs would lead to improved market performance.

Introduction

Grain marketing policies in many countries in Southern Africa (SA) are frequently conditioned by skepticism about the private sector's performance in meeting food security goals (Mwanaumo et al., 2005; Tschirley and Jayne, 2008; Tschirley et al., 2004). On the other hand, many investigators have argued that discretionary grain marketing policies themselves, which include export bans, import licensing restrictions and internal trade restrictions, limit private sector activity and perpetuate "weak" private sector performance. For example, many studies conclude that grain markets in SA are not well-integrated with each other and with world markets, at least partially due to government policies and the transfer costs they impose (Keats et al., 2010; Myers and Jayne, 2012; Rashid and Minot, 2010).

Despite these government restrictions on formal cross-border trade, data collected in recent years shows a considerable amount of staple grains are traded across borders throughout the SA region through informal channels (FEWS NET, 2009). Informal traders deal in small quantities (usually just 50–100 kg at a time) without trading licenses and with no official record of their transactions. With hundreds or sometimes thousands of small informal traders operating daily, however, the aggregate volume of informal trade can be substantial. Reliable high frequency data on total informal trade throughout the region are not available, but estimated figures confirm the quantity of informally traded maize across some borders far exceeds that traded formally in recent years.[1] Thus the relationship between cross-border markets connected by informal trade may be very different than would be suggested by examining official trade data. The fact that informal transactions are difficult to regulate and occur outside the sphere of policy influence suggests the relationship between informal import and export markets can provide insights into how international markets within the region might perform in the absence of government trade regulations.

The objective of this paper is to analyze regional price transmission in SA by determining whether, and under what conditions,

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[1] Comparing data for informal trade from Zambia to DRC to the limited official monthly data on formal trade that exists from COMESA (Common Market for Eastern and Southern Africa) suggests that informal trade usually accounts for more than 90% of total trade and frequently 100% in a given month. Comparing this study's data to annual data reported to FAOstat confirms that, where periods fully overlap, recorded informal trade accounts for at least 80% of the maize traded between Malawi and Mozambique.

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0306-9192/

long-run spatial price equilibrium exists, and by measuring the speed at which price shocks are transmitted between surplus and deficit markets. In contrast with most previous studies on price transmission in SA that focus on international markets connected through formal trade, key features of this research are: (1) our focus on markets connected through informal trade; and (2) the use of monthly data on the quantity of informal trade to inform the analysis. The article provides useful new results that can be contrasted with existing spatial price transmission literature to provide new insights into how spatial markets in SA might perform in a less (or more consistently) regulated policy environment.

The method we use builds on the Myers and Jayne (2012) threshold autoregressive (TAR) model that incorporates trade volume. Specifically, we use the amount of cross-border informal trade as a threshold variable and allow the long-run spatial price equilibrium and speed of adjustment to differ across multiple trade regimes. As in Myers and Jayne (2012), transfer costs are explicitly incorporated into the model, rather than assumed constant as in most previous price transmission analyses (e.g. Aker, 2007; Balcombe et al., 2007; Goodwin and Piggott, 2001; Obstfeld and Taylor, 1997; Sephton, 2003). The number and location of regime defining thresholds are inferred from the data and selected based on the Gonzalo and Pitarakis (2002) penalty function approach.

We focus on two informal trade routes: (1) Kitwe in Zambia and Kasumbalesa in The Democratic Republic of Congo (DRC); and (2) Cuamba in Mozambique and Liwonde in Malawi. Kitwe is a major market situated along the route between Zambia's surplus production regions and deficit regions in DRC, and Kasumbalesa is the major entry point for grain informally imported to DRC from Zambia. Cuamba is situated within northern Mozambique's major surplus production zone and Liwonde is situated along the major trade route from northern Mozambique to the maize deficit areas of southern Malawi. A considerable amount of informal cross-border trade occurs between both of these market pairs so they are good candidates for examining spatial market efficiency and price transmission in SA in the presence of informal trade.

For both of the trade routes studied we find evidence of a single long-run price equilibrium that is consistent with competitive trading conditions and price transmission that is rapid compared to results from other studies. This is in stark contrast to the results of Myers and Jayne (2012) who found significant government involvement in formal cross-border trade led to a breakdown in spatial price transmission. Evidently, markets linked through relatively unregulated informal trade are not subject to the same kind of multiple trading regimes that limit price transmission and hinder adjustment in markets subject to heavy government regulation and control.

We also observe trade occurring occasionally during months when prevailing price differences between markets suggest it would be unprofitable, which may be caused by informational barriers inherent in the nature of informal trading, preemptive trade and storage (see Coleman, 2009), or economies of scope for traders dealing in multiple commodities. Relatedly, there are periods when the magnitude of price differences between markets is quite large, suggesting either abnormal returns to trade or very high, unobserved physical and institutional transfer costs. We discuss these anomalies further below.

Our results provide evidence that unregulated private sector markets in SA can be expected to adjust in a way that is generally consistent with spatial market equilibrium. Moreover, our analysis suggests that policies focused on encouraging informal trade, and lowering the cost of such trade, may be quite effective at bringing about trade flows and price transmission in ways that state-led trading has not. More generally, by combining data on informal trade, prices, and transfer costs, this article provides new evidence on the longstanding question of how effective spatial market price transmission is in SA. It is an example of what Barrett (1996) described as "level III" market analysis combining both trade and price data. While Barrett emphasized that such an approach would be necessary to understand agricultural markets in developing economies, they remain rare. Stephens et al. (2012), Amikuzuno and Donkoh (2012), and Myers and Jayne (2012) are other recent examples of level III analysis.

The next section will describe the markets and data used in this article, followed by a section outlining the methods employed. The penultimate section presents results and the final section has concluding comments.

Market descriptions and data

This article combines data on informal maize trade volumes, maize grain prices, diesel fuel prices and exchange rates from several sources.

Informal trade volumes

Informal trade flow data are collected and reported as national level statistics by the Famine Early Warning Systems Network (FEWS NET) in the monthly bulletin series "Informal Cross Border Food Trade in Southern Africa" (e.g. FEWS NET, 2009).[2] Due to the nature of this trade and the porous borders throughout the region, collecting accurate informal trade data presents numerous challenges. FEWS NET hires border monitors stationed at strategic border points identified through a consultant study as locations where the largest amount of informally traded maize crosses borders. These enumerators take a daily count of the number of bags informal traders carry across borders, usually on bicycles. Counts are then converted to tonnage in the monthly reports based on bag weights (the bags used to transport maize are designed to hold dry maize at specific size/weight ratios, most commonly the "50 kg bag") (FEWS NET, 2009, Mushinge, personal communication).

There are two monitored border locations in the area between Kitwe in Zambia and Kasumbalesa in DRC. We use the aggregate trade from both monitoring locations as an estimate of total maize traded between these markets. On the border between Mozambique and Malawi there are 11 monitor stations, 6 of which are in the area between the market pair of Cuamba and Liwonde. The data are not disaggregated by station, so we use the total trade volume from all 11 stations is a proxy for trade between the Cuamba and Liwonde areas. This is reasonable because the 6 stations in the area account for the majority of the informal trade between Malawi and Mozambique.

Unfortunately, this cannot be considered a complete measure of all the maize grain informally traded between the markets we analyze. FEWS NET staffers estimate they are counting roughly 80% of the trade between Mozambique and Malawi and about a third of the trade from Zambia to DRC. In both country pairs FEWS NET officials also believe that the proportion of trade measured is consistent on a month-to-month basis. This assertion is based on studies that have been conducted in recent years by external consultants. A 2005 review of the program states that the monitoring system "is clearly effective in terms of indicating directions, trends and magnitudes of flows" (FEWS NET, 2005). We therefore consider the figures reported to be a good measure of relative changes in total trade volume. That said, we also acknowledge that these trade data are more subject to measurement error than one might normally expect from a time-series, and that this may add to the

[2] In addition to the bulletins, much of the information in Section 'Informal trade volumes' comes from personal communication with Chansa Mushinge, Country FEWS NET Representative for Zambia and other members of the FEWS NET/Zambia staff whose assistance is greatly appreciated.

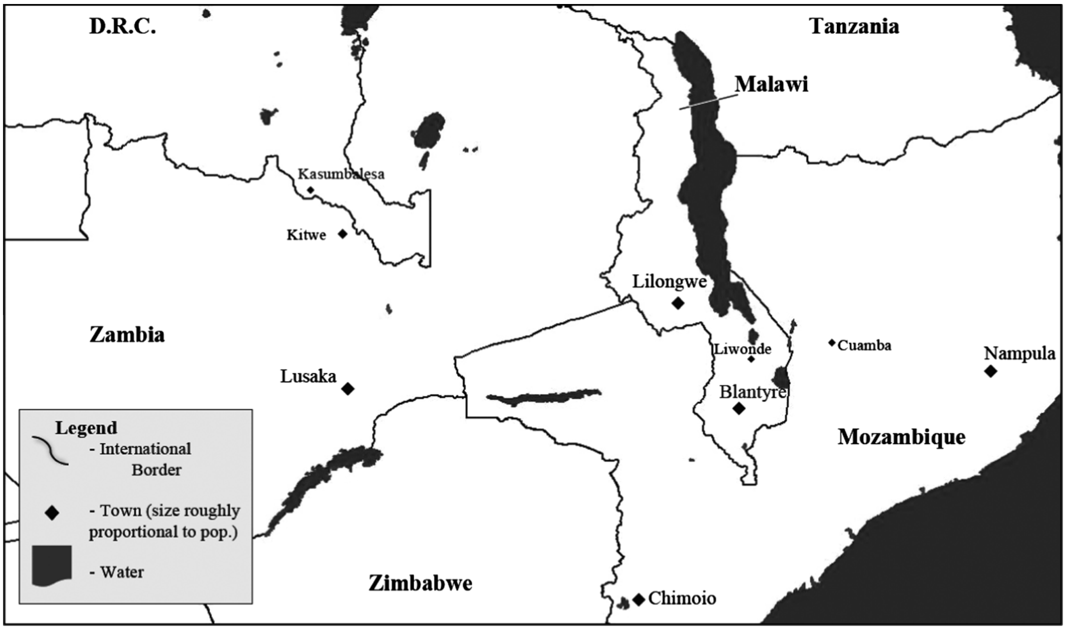

Fig. 1. Map of markets considered in the spatial price transmission analysis.

challenge of identifying trade thresholds that are discussed in Section 'Identifying the number of regimes and threshold values'. The data are from July 2004 to August 2010, providing 74 monthly observations.

Retail maize grain prices

We focus on the prices of local white maize. Although the quality of this maize may be inconsistent, there is also generally no formal grading system (especially for informally traded maize). Thus, there is very little price differential for variations in quality. Maize prices in markets within this region are typically publicly posted on a "per kg" basis and it is very uncommon for posted prices to differ much from one vendor to the next. Enumerators from various agencies visit these markets (usually weekly) to record and report these prices.

Maize prices in Zambia are collected weekly by the Central Statistics Office (CSO) and reported as monthly averages in nominal Zambian Kwacha (ZMK) through FEWS NET. Price data covering the same period covered by informal trade data are available for over 30 different markets in Zambia, including Kitwe.

FEWS NET provides price data for one market in DRC, Kasumbalesa, near its southern border with Zambia. Travelling on the tarmac road that connects them, Kasumbalesa is 98 kilometers (km) from Kitwe (Fig. 1). Price data collection in DRC did not begin until July 2005 (one year after the collection of trade data began), so the model for Kitwe and Kasumbalesa is estimated using 62 monthly observations.

The Ministry of Agriculture and Rural Development in Mozambique collects weekly retail maize grain prices in several northern markets near the Malawi border, including Cuamba, through its Agricultural Market Information System. The Ministry of Agriculture in Malawi collects weekly retail maize prices in various locations throughout the country, including Liwonde, as part of the Retail Price Survey. Liwonde is along the road from Cuamba to Blantyre (Malawi's largest southern city, Fig. 1). There are 258 km of road between Liwonde and Cuamba that is a combination of graded soil and tarmac.

There is one missing value in the Cuamba price series. This was replaced with an imputed value using the best subset regression of all other available prices, including several not used in the price transmission analysis. All prices are converted to the currency of the exporting market (ZMK or Mozambique New Metical (MZN) using monthly averages of daily exchange rates reported at oanda.com and fxtop.com. Although the DRC currency is the Congolese Frank, FEWS NET reports Kasumbalesa prices in USD. These are converted to Kwacha using the product of the Dollar-to-Franc and Franc-to-Kwacha exchange rates.[3]

Transfer costs

Diesel price could be an important time-varying component of transfer costs and will be included using diesel price per liter in Lusaka and Nampula for the Zambian and Mozambican models respectively.[4] The Energy Regulation Board reports Zambian diesel prices while Mozambican diesel prices come from Direccao Nacional de Energia.[5] Since fuel prices are tightly regulated in both countries, the Lusaka and Nampula prices accurately reflect diesel price movements in the exporting markets in our analysis.

Diesel may be an important component but it is unlikely that diesel prices alone will control for all transfer costs. For example, costs unrelated to transportation such as uncertainty premiums or search and price discovery costs are likely independent of diesel prices. Under informal trade there may be additional transfer costs for labor (e.g., if large shipments must be disassembled from a truck, transported by individuals over the border, then reassembled) and less scrupulous activities such as solicitation of bribes. Such costs are often difficult or impossible to observe. To the extent possible, including an intercept in the model specification described in the next section further controls for unobserved transfer costs.[6]

[3] It is important to first convert to Francs because the Dollar-to-Kwacha rate is not always the same as the product described here due to differences in the relative strength against the Dollar.

[4] Though most informally trade maize moves across borders on bicycles or other man and animal powered vehicles, some of it will have been transferred to and from the border crossing on diesel powered trucks or mini-vans.

[5] We thank the authors of Tostao and Brorsen (2005) for sharing Mozambican diesel price data.

[6] As one anonymous reviewer points out, the regression intercept only captures omitted transfer costs assuming the quasi-homotheticity of full, unobserved transfer costs as a function of observed costs.

Methods

The study of market integration and spatial price transmission has evolved substantially over the past few decades.[7] The class of models has grown from early work that focused on price correlation coefficients (Blyne, 1973; Cummings, 1967; Lele, 1967), to linear cointegration models (Harriss, 1979, and references therein), and more recently to non-linear models that allow for the presence of transfer costs that had previously been ignored. Two prevailing modeling approaches have emerged: Baulch's (1997) parity bounds model (PBM) and the threshold autoregressive model (TAR) introduced by Balke and Fomby (1997). For this article we use a recent version of the TAR model developed by Myers and Jayne (2012) because it allows for the possibility of different price transmission regimes under different trade flow situations. We also acknowledge, however, that PBM and TAR models both have their advantages and disadvantages, and each requires different sets of assumptions.

The core principle underlying the TAR approach revolves around the fact that there is a cost to moving commodities between spatially separated markets. When the difference in prices between markets exceeds that cost, traders may exploit an opportunity for spatial arbitrage by moving goods to the higher priced market. Eventually, of course, this will shift the supply curves in both markets, dictating that the price difference cannot exceed transfer costs in the long run (this is the Law of One Price). So long as the difference between prices in spatially segregated markets is below the cost of transferring goods between them, there is no opportunity for spatial arbitrage and prices will not be connected through trade. The cost of transferring a commodity thus acts as a threshold determining the relationship between market prices.

Traditional TAR models are estimated with a single threshold based on the size of the price difference between the two markets. Price transmission is allowed to occur at different speeds depending on whether the current price difference is above or below the threshold. The threshold in such models is estimated by evaluating the value that best fits the data, which is then interpreted as the transfer costs of getting product from one market to the other.

TAR models can be found in numerous prior applications[8] (Abdulai, 2000; Aker, 2007; Balcombe et al., 2007; Goodwin and Piggott, 2001; Obstfeld and Taylor, 1997; Sephton, 2003; Van Campenhout, 2007). However, traditional TAR models have their drawbacks. First, nearly all applications impose the (frequently implicit) assumption that transfer costs are constant over time in order to estimate the threshold parameter.[9] This simplifying assumption is often justified by stating that many of the factors driving transfer costs are unobservable, and it is better to assume constant transfer costs than to ignore them altogether. While this may be true, traditional TAR models leave no room to include time-varying factors driving transfer costs that are observable, such as the price of fuel.

Secondly, the traditional TAR model implicitly assumes existence of the same long-run equilibrium relationship between prices even when the price margin is below the estimated transfer cost. In reality, there is no reason to believe the equilibrium relationship between spatial prices should be the same with and without trade. Indeed, there are good reasons for believing the nature of this long-run equilibrium relationship (and perhaps even whether such a relationship exists at all) could be quite different with and without trade (Stephens et al., 2012). This may be a potential source of model misspecification.

Thirdly, traditional TAR models are estimated using observations on prices only while quantities traded are implicitly assumed to exist or not depending on whether price transmission occurs. If data are available, however, trade volume could provide more insight into the relationship between markets since trade, or perhaps even the flow of information and just the possibility of trade, could be the actual mechanism through which price transmission occurs (see Stephens et al., 2012 and Jensen, 2007, for examples of price transmission in the presence of information flows without trade).

There are several reasons one might expect different equilibrium price relationships across different trading regimes. The most intuitive threshold is zero, where a lack of trade indicates price differences lower than transfer costs and, with no opportunity for spatial arbitrage, the possibility of no equilibrium relationship between the two prices. Alternatively, we might find that as trade volume approaches the capacity limit for transportation between markets, the equilibrium price adjustment process may break down and switches to a different regime (Coleman, 2009). At intermediate trade volumes spatial arbitrage may work quite well to maintain a long-run equilibrium relationship between price differences and transfer costs, leading to yet another regime for the long-run equilibrium relationship (Myers and Jayne, 2012).

Price transmission with transfer costs and trade regimes

Myers and Jayne (2012) address some of these shortcomings of the traditional TAR approach by introducing a multiple-regime price transmission model which explicitly includes transfer costs and uses trade volume as the threshold variable. We follow their approach closely in the present article. Because the econometrics of the approach are already detailed in Myers and Jayne (2012) we limit ourselves here to summarizing key features of the model and briefly describing the estimation procedure. The key equation in the model is a multiple regime long-run equilibrium spatial price relationship that can be written as:

$$p_t^a = \beta_{0i} + \beta_{1i} p_t^b + \beta_{2i} k_t + u_{it} \quad (1)$$

where p_t^a is the price in market a in time $t = (1, 2, \ldots T)$, p_t^b is the price in market b in time t, k_t is the unit cost of transferring a good from market b to market a,[10] and u_{it} is a random shock whose properties are discussed later. The intercept and slope parameters β_{0i}, β_{1i} and β_{2i}, and the stochastic properties of the shock are allowed to vary across trade regimes, indexed by $i = (1, 2, \ldots I)$. If unit costs are not completely observable, k_t could alternatively be considered as a vector of observable components of transfer costs.

If a regime i features an error term that is nonstationary, then no long-run equilibrium relationship exists in that regime and any significant estimate of the intercept and slope parameters would represent spurious regression. If, on the other hand, the error is stationary in regime i a long-run equilibrium exists and perfect spatial arbitrage would imply $\beta_{0i} = 0$ and $\beta_{1i} = \beta_{2i} = 1$, but this is seldom observed empirically because there are a variety of unobserved factors that may cause deviations from the perfect spatial arbitrage conditions (Myers and Jayne, 2012 and Williams and Wright, 1991). For example, allowing $\beta_{0i} \neq 0$ addresses some of the difficulties of fully measuring transfer costs by enabling the model to control for costs that are time invariant and unobservable. If the

[7] See Fackler and Goodwin (2002) for a more thorough review of the methods for measuring price transmission and market efficiency over the past few decades. Also see Rashid and Minot (2010) for a review of price transmission literature focused on Africa.

[8] Of course, PBM models can be found in the literature as well (e.g., Baulch, 1997; Barrett and Li, 2002; Negassa and Myers, 2007).

[9] Van Campenhout (2007) allows the transfer cost threshold to adjust according to a linear time trend instead, which would at least account for trends in unobserved transfer costs.

[10] The unit transfer cost is not explicitly included in the notation in Myers and Jayne (2012), but including it is a straightforward extension.

error term is stationary and serially uncorrelated for a given regime, then adjustment to equilibrium is immediate after a shock. If there is autocorrelation, on the other hand, adjustment to equilibrium is a dynamic process whose duration depends on the structure of autocorrelation in u_{it}.

Myers and Jayne (2012), following Phillips and Loretan (1991), show that assuming nonstationary prices and allowing for the possibility of stationary but autocorrelated errors[11] (i.e., the presence of long-run equilibrium and gradual adjustment to equilibrium) leads to a single equation error correction model (SEECM) that is amenable to estimation.[12] The SEECM will also be regime dependent and takes the form:

$$\begin{aligned}\Delta p_t^a &= \mu_i + \beta_{1i}\Delta p_t^b + \beta_{2i}\Delta k_t + \lambda_i(p_{t-1}^a - \beta_{1i}p_{t-1}^b - \beta_{2i}k_{t-1}) \\ &\quad + \sum_{j=1}^{n} b_{ji}(\Delta p_{t-j}^a - \beta_{1i}\Delta p_{t-j}^b - \beta_{2i}\Delta k_{t-j}) + \rho_{1i}\Delta p_t^b \\ &\quad + \sum_{j=1}^{n} c_{ji}\Delta p_{t-j}^b + \rho_{2i}\Delta k_t + \sum_{j=1}^{n} d_{ji}\Delta k_{t-j} + \eta_{it} \qquad (2)\end{aligned}$$

The parameters λ_i, b_{ji}, c_{ji}, d_{ji}, ρ_{1i} and ρ_{2i} depend on regime-specific correlation and autocorrelation in the structural error terms, while the regime dependent long-run relationships between prices and transfer costs are still measured by β_{1i} and β_{2i}. The speed of adjustment parameter, λ_i, measures how quickly prices return to equilibrium after a shock in each trading regime, with $\lambda_i = 0$ indicating no long-run equilibrium exists (infinite adjustment). The μ_i are composite intercept terms that include β_{0i}. It is noteworthy that this formulation does not assume that import market prices or transfer costs are exogenous to export market prices. In other words, this form of the model is robust to violation of the "central market" assumption made by Ravallion (1986) and others. Moreover, most prior studies assume trade is unidirectional, which is an assumption we can relax since a switch in the direction of trade could potentially represent a regime threshold.

The number of lags included, n, is chosen to eliminate autocorrelation in the residual term, η_{it}. Given our small sample size, we begin with $n = 1$ and only add additional lags if tests suggest that autocorrelation remains. Within each regime, estimation via NLS (Nonlinear Least Squares) provides asymptotically optimal Gaussian inference (Phillips and Loretan, 1991).

Identifying the number of regimes and threshold values

To facilitate the discussion of how regimes and threshold values of informal trade are identified we re-write equation (2) as:

$$\Delta p_t^a = f(\mathbf{X_t}, \theta_i), \text{ if } \tau_{i-1} < q_t \leqslant \tau_i, \quad \text{for all} \quad i = (1 \ldots I) \qquad (3)$$

where $\boldsymbol{X_t}$ is a vector of the relevant variables from equation (2), θ_i is the associated regime dependent parameter vector and q is the threshold variable (the quantity of maize informally traded in our case). The threshold parameters, τ, represent the levels at which the price transmission process changes. Note that when trade is unidirectional (or bidirectional and measured as total trade) $\tau_0 = 0$, and in any case $\tau_I = \infty$.

Conditional on given thresholds, estimating parameters within each regime can be accomplished by applying NLS to (2) using the relevant sub-sample, as already discussed. Eq. (3), however, introduces I new parameters to identify: $(\tau_1 \ldots \tau_{I-1})$ and I itself. For any given number of regimes the threshold parameters can be identified employing the Gonzalo-Pitarakis (GP) penalized criterion function approach, where the threshold parameter(s) is (are) chosen to maximize the objective function:

$$Q_T(i-1) = \max_{\tau} \ln\left[\frac{SS_T}{SS_T(\tau)}\right] - \frac{g(T)}{T}K \cdot (i-1) \qquad (4)$$

where K is the number of parameters in the single-regime (i.e. no threshold) model,[13] SS_T is the sum of squared residuals for the single regime model.[14] and $SS_T(\tau)$ is the sum of squared residuals of the i-regime model. Defining a functional form for the penalty function $g(\cdot)$ ompletes the criterion. Gonzalo and Pitarakis (2002) simulate results for 5 alternative specifications of the penalty function including three Baysian Information Criteria (BIC, BIC2 and BIC3), an Akaike Information Criterion (AIC) and a Hannan-Quinn (HQ) criterion which respectively define $g(\cdot)$as $\ln(\cdot)$, $2\ln(\cdot)3\ln(\cdot)$, 2 and $2\ln(\ln(\cdot))$.

We use the GP approach because the distribution of a conventional likelihood-ratio test statistic to compare alternative regimes is unknown due to the nuisance parameter issue under the null hypothesis of no thresholds[15] (Gonzalo and Pitarakis, 2002 and Hansen, 1996). For any given i, the GP approach is analogous to the sup-Wald grid search employed by most single threshold studies for identifying the optimal threshold. Over a range of values of i, the right hand term of the GP function penalizes the objective function for model over-parameterization. Though there is not an explicit test available for the existence, number, or value of multiple-thresholds, the GP criterion is a direct method for allowing the data to discover the "best" multiple-threshold model.

Finally, to identify I, first note that we can restrict it to be some integer such that $I \in (1 \ldots I^*)$, where $I^* = \text{int } [(T-n-1)/(K+1+\delta(T-n-1))] - 1$. The numerator within the integer function (T-n-1) is the number of usable observations. The denominator $(K+1+\delta(T-n-1))$ is the minimum number of observations we will allow within each regime where $K + 1$ is number of observations needed for each regime to have enough degrees of freedom to estimate with inference and $\delta \in (0, 1)$ determines the additional share of the sample which will be included in each regime to avoid over-parameterization. Following the recommendation of Balke (2000) we will set $\delta = 0.15$. The resulting integer is thus the maximum number of regimes into which we could split our sample. We subtract 1 because there is one less threshold than there are regimes. Then, the GP criterion suggests that we can identify the optimal number of thresholds according to:

$$I = \arg\max_{0 \leqslant I \leqslant I^*} Q_T(I-1) \qquad (5)$$

In practice this approach can be employed either sequentially or non-sequentially. Sequential threshold estimation first identifies the optimal threshold under the assumption that only one exists, and then maintains that threshold while evidence of additional thresholds is examined. Non-sequential estimation abandons previously identified thresholds and begins the search anew each time the assumption on the number of thresholds is updated. Gonzalo and Pitarakis (2002) demonstrate that sequential identification is asymptotically consistent and it is certainly easier numerically.

[11] Evidence presented later in this article supports these assumptions for this application.

[12] There are a number of valid ways to estimate the structural system of equations represented by Eq. (2), including vector error correction models, which are used in some single-threshold models. See Myers and Jayne (2012) for explicit treatment of the structural model. The SEECM is convenient when considering *multiple*-threshold models.

[13] In our case when $n = 1$, $K = 9$.

[14] It is interesting to note that nonstationarity and cointegration restrictions have no impact in the GP criterion because they have no impact on value of either SS calculation in (4) In fact, even a linear regression of Δp_t^a on $\boldsymbol{X_t}$ provides the same SS for any within-regime model irrespective of nonstationarity or cointegration properties of the data, so we can employ OLS to execute maximization of Eq. (4).

[15] Hansen (2000) describes a Monte-Carlo approach for regime testing when i=2. However, implementation of that test has proven infeasible with our data, likely due to collinearity resulting from small within-regime sample sizes (Hansen, personal communication). This was true even when the threshold was held at the median value of the threshold variable (i.e. when the sample was split in half).

Since we have a fairly small sample size, however, we apply non-sequential identification that, incidentally, was found to give equivalent results to sequential identification in our applications.

Interpreting results

In price transmission studies the primary unit of analysis is often the half-life, h, of a shock, or the amount of time it takes for half of the adjustment back to long-run equilibrium to occur. Half-lives are computed either using the approximate formula when price differences follow an AR(1) process (e.g. Van Campenhout (2007) uses $h = \ln(0.5)/\ln(1 + \lambda)$), or via simulation (which will be appropriate in our case). It is also useful to examine the effect of a shock graphically, where we can see how the importing price would react to a one-time permanent shock in the price of the exporting market. In addition to quantifying the overall time it takes for shocks to dissipate, such graphs can show the path of adjustment back to equilibrium in a way that is more informative than just reporting half-lives.

Results

We examine each market pair in its own sub-section before summarizing our findings.

Kitwe and Kasumbalesa

Prices and trade data for Kitwe, Zambia and Kasumbalesa, DRC are examined descriptively in Fig. 2, where we plot trade volume on the left axis, and the price difference on the right axis. Fig. 2 shows there are no extended periods during our sample when there is zero informal trade between these markets, ruling out the possibility of a no trade regime. Graphically, it appears there is general co-movement between price differences and informal trade volume. For example, in January 2009 the price difference was negative (i.e. prices were higher in Zambia than in DRC) and informal trade was extremely low. Since DRC is not a surplus producer, this was likely a period when that country was importing from elsewhere and/or a positive price shock in Zambia raised Zambian prices sufficiently to eliminate the incentive to export. There is neither empirical nor anecdotal evidence suggesting maize trade (formal or informal) ever flowed from DRC back to Zambia during this period (Mushinge, personal communication). Around mid-2009 the Kasumbalesa price increased relative to Kitwe and we observe a corresponding surge in informal trade volume. After

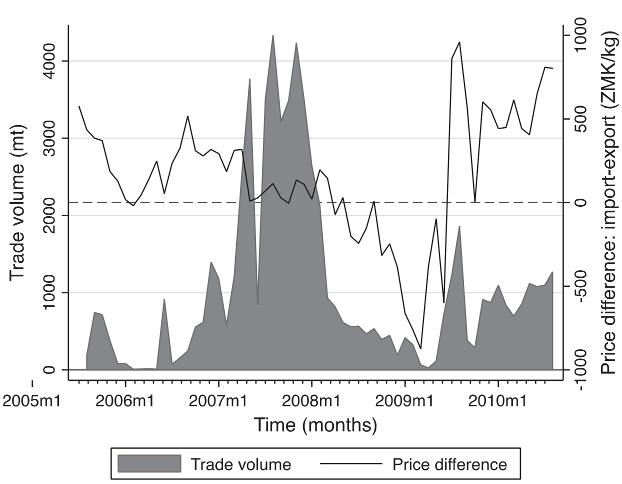

Fig. 2. Price difference between Kitwe and Kasumbalesa and informal trade levels.

a brief dip back to nearly zero, the price difference between these markets bounced around 500 Kwacha per kg (over \$0.11 at the mean exchange rate over this period of 4399.1 ZMK/USD), with corresponding movements in the volume of informal trade throughout the remainder of the sample period.

The price difference of 500 Kwacha per kg is on the high side of the distribution across our data, but not uncommon. If the price difference is entirely attributable to transport costs, that translates to roughly \$114 per ton, or \$1.16 per ton kilometer, which seems quite high. According to the World Bank's current documentation for assessing the performance of transport sector, efficient transport in similar areas would cost between \$0.20 and \$0.30 per ton per kilometer (World Bank, nd). The average price difference between these markets when the DRC price is higher than the Zambian price is 305 ZMK/kg, or \$0.73 per ton kilometer. Implications of these price differentials will be discussed in more detail later.

For small-scale traders, informal trade often occurs across official border crossings, where some of this cost may be attributable to corruption or bribery of border officials (on both sides). Some larger-scale (would-be formal) traders may also use these border crossings, but they disassemble their shipments and hire bicyclists to cross the border with 1-3 bags each to then reassemble the bulk load on the other side, imposing additional labor costs. Traders sometimes avoid official border crossings to circumvent labor and corruption costs, rather choosing to take smaller "bush roads", frequently at night. This choice, however, may also come with additional costs in the form of vehicle damage (most commonly tires) and extra pay for drivers, to name a few.

There are two periods in the sample where trade behavior may seem counterintuitive at first glance. First, during 2006 price differences were fairly high with a relatively small amount of trade, while in 2007 price differences were much closer to zero and trade volume was relatively high. These outcomes can be explained by Zambian maize production patterns. The 2006 Zambian maize harvest was below average at about 0.7 million metric tons (mmt), while the 2007 harvest was relatively high at 1.4 mmt (Mason et al., 2012). So while incentives for informal cross border trade existed in both years, there was much more surplus available for trade in 2007 and therefore higher trade volumes were recorded. In turn, these higher trade volumes appear to have driven prices in the two markets closer together, perhaps due to competition and reduced unit transfer costs. This suggests another potential cause for low trade thresholds may be limited supply availability.

The second unusual period occurs during 2008 when the price difference is negative but there is positive trade volume moving into the DRC. There are several possible explanations for this. The first is data aggregation. The price data are monthly averages and the trade volume data are monthly aggregates, but prices and flows can fluctuate within a month. Thus, on any given day price incentives may encourage trade to flow to DRC, even if on average over the month the incentive is not to trade. A second possible explanation is that uninformed traders were exporting to DRC during this period and made losses on these trades. Anecdotal evidence confirms that it is not uncommon for some traders to export grains based on ill-informed price expectations, and when it would have been more profitable to sell locally (Mushinge, personal communication). Imperfect information is one of the reasons we expect to see dynamics in the price transmission between markets at all.

Thirdly, while recorded prices reflect prevailing market prices, even on a given day the prevailing price is an aggregate across transactions. Unlike commodity markets in more developed regions, where buyers and sellers both tend to be the takers of prices determined by a larger number of transactions, price negotiations in less developed regions occasionally take place at the transaction level. Depending on the negotiating power of the

Table 1
Threshold selection for price transmission between Kitwe & Kasumbalesa.

Model	Threshold value (metric tons of traded maize)		Selection criterion				
			BIC	AIC	HQ	BIC2	BIC3
	τ_1	τ_2	GP values				
Two regime	1095		0.0268	0.3409	0.2181	−0.5874	−1.2015
Three regime	555	1095	−0.0858	0.5425	0.2968	−1.3141	−2.5424

traders, it is possible that some quantities traded represent a small amount of profitable trade taking place despite prevailing market prices indicating trade would be unprofitable.

Finally, there are at least two reasons that even a rational, well-informed trader might shift maize from Zambia to DRC during this time. First, sending maize across the border during times of negative price differentials could still be profitable if traders are able to store maize in DRC in anticipation of higher prices later on (Coleman, 2009). Alternatively, there may be economies of scope for traders transporting multiple commodities that make the cost of arbitrage lower than if they were trading just one commodity.

In general, the fact that price differences and trade volumes appear to move together suggests linked markets and price transmission, but for statistical testing we turn to the threshold SEECM. With the initial one lag ($n = 1$) model there are 9 parameters to estimate and 60 usable observations. Based on the criterion described in Section 'Methods', this implies we can investigate at most two thresholds and three regimes. Results from the GP selection process are presented in Table 1.

The first potential threshold identified is at the trade level of 1095 metric tons of maize. According to the BIC criterion (GP = 0.03) this model is slightly superior to the single regime model, while the AIC and HQ criteria lend more support with GP values of 0.34 and 0.22 respectively. On the other hand, the BIC2 and BIC3 criteria, which more heavily penalize over-parameterization, strongly favor the single-regime model (GP values of −0.59 and −1.20, respectively).

The three-regime model identifies optimal thresholds at 555 and 1095 metric tons of informally traded maize. The BIC, BIC2 and BIC3 criteria all have their lowest GP values for this model (−0.09, −1.31 and −2.54 respectively), and all would favor the single-regime over the triple-regime. On the other hand, the AIC and HQ criteria both have the highest GP values for the three-regime model (0.54 and 0.30 respectively).

Unfortunately, these results are not definitive. At least one of the GP criteria supports either the single regime model, the two-regime model, or the three-regime model. In simulations presented by Gonzalo and Pitarakis (2002) the BIC2 and BIC3 criteria have the best performance by far when the data generating mechanism (DGM) has no thresholds (correctly identifying the model in nearly 100% of the simulations). In the same simulations the AIC and HQ criteria perform rather poorly. When the DGM has two-regimes the criteria to most frequently correctly identify the model are AIC, HQ and BIC (in that order), but the BIC2 criterion also performs fairly well. Based on these results, they conclude "BIC and to a lesser extent BIC2 display the best overall performance, with an excellent ability to point to the true model even for moderately small sample sizes," such as the one used for this article.

Using an un-weighted average the BIC and BIC2 criteria favor the single-regime model. Even if we were to only consider the BIC criterion, support for the threshold model is fairly weak (i.e. the GP is very close to zero). Based on the sum of evidence, we thus choose a single-regime SEECM model without trade thresholds. While this leads to a conventional one-regime analysis without thresholds, here the single-regime model arises from extensive model evaluation as opposed to being imposed a priori.

Next we examine the stochastic properties of the price data under the single-regime assumption.[16] Table 2 summarizes the p-values from augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) unit root tests as well as Johansen cointegration tests. For each price series tests fail to reject the nonstationary (or non-trend-stationary) null hypothesis using either the ADF or PP tests. For Johansen's cointegration test, the Schwarz-Baysian (SB) and HQ criteria each suggest 1 lag which corresponds to a maximum rank of zero (no cointegration), but the likelihood ratio (LR), final prediction error (FPE) and AIC criteria each suggest 4 lags and a maximum rank of one (cointegration). Taken together, these results support the assumptions used in Section 'Methods' to derive the SEECM (i.e., nonstationary variables and cointegration).

Results for the full sample SEECM are presented in Table 3. First note from the Ljung-Box tests reported at the bottom of this table that there is no evidence of autocorrelation in the residuals, and thus no need to add additional lags to the model. Our estimate of β_1 is 0.999 with a p-value of 0.02 against the $\beta_1 = 0$ null hypothesis.[17] The t-test for whether this estimate is significantly different from 1 yields a p-value of 0.998 (i.e. this estimate is significantly different than zero, but not significantly different than one). The 95% confidence interval for this estimate is 0.13 to 1.86. These results suggest complete, one-to-one price transmission between these markets in the long-run.

Perhaps surprisingly, the estimate of β_2 is not statistically significantly different from zero at any meaningful level, suggesting that diesel prices do not explain any of the difference between Kitwe and Kasumbalesa maize prices. This may be a reflection of the fact that, although a national border separates them, these markets are less than 100 km of tarmac away from each other. Therefore, diesel costs for transportation between them may not change much with diesel price changes. Furthermore, at least a portion of the transportation is frequently done on the back of a bicycle, the cost of which is not directly associated with diesel price. As previously discussed, these added labor costs of transport may explain why the price differences can become very high.

The estimate for the speed of price transmission parameter, λ, is −0.2236, with a p-value of 0.03 and a 95% confidence interval of −0.424 to −0.023. Implications of this speed of adjustment are discussed below. Other parameter estimates have no meaningful economic interpretation individually (Myers and Jayne, 2012).

Fig. 3 simulates the effect of a one-time permanent shock to the Kitwe price on the Kasumbalesa price. The simulation is initiated holding Kitwe maize price, represented by the dashed line, and Lusaka diesel price (not shown) at their data means (1171 ZMK/kg and 5799 ZMK/liter respectively). The associated equilibrium price of maize in Kasumbalesa predicted by the model is 1329 ZMK/kg, which is reasonably close to the actual mean price over

[16] Under multiple regimes, analysis at this stage would be complicated by the discontinuities of each regime subsample. We omit any related discussion because it is not relevant here, but interested readers are referred to Myers and Jayne (2012) (in particular see the appendix).

[17] A key advantage to estimating Eq. (2) via NLS rather than the linear model in Eq. (1) via OLS is that standard inference is asymptotically valid because error dynamics have been incorporated into the model (Phillips and Loretan, 1991 page 423).

Table 2
Diagnostic tests for price series stochastic properties (Kitwe and Kasumbalesa).

Test	Kasumbalesa	Kitwe	Diesel
Unit root (Nonstationary null)			
ADF	0.61	0.24	0.19
ADF, trend	0.32	0.19	0.12
PP	0.41	0.30	0.41
PP, trend	0.18	0.52	0.48
Johansen (lag criteria)	Lags		Maximum rank
Cointegration			
LR	4		1
FPE	4		1
AIC	4		1
HQ	1		0
SB	1		0

Notes: MacKinnon (1994) approximate *p*-values reported for ADF and PP tests. Maximum rank determined using Johansen's trace statistic and the 5% critical level.

Table 3
Price transmission estimation results for Kitwe & Kasumbalesa.

Parameter	Estimate[a]	[95% Confidence Interval]	
μ: Constant	129.776 (212.85)	[−297.55, 557.10]	
β_1: Long-run price transmission	0.9988[**] (0.43)	[0.13, 1.86]	
β_2: Long-run diesel Price transmission	−0.0727 (0.16)	[−0.40, 0.25]	
λ: Speed of adjustment	−0.2236[**] (0.10)	[−0.42, −0.02]	
ρ_1	−0.6859[*] (0.14)	[−0.34, 0.22]	
ρ_2	0.1162 (0.41)	[−1.50, 0.13]	
b_1	−0.0617 (0.21)	[−0.26, 0.59]	
c_1	0.1633 (0.18)	[−0.24, 0.47]	
d_1	0.0614 (0.10)	[−0.14, 0.26]	
Goodness of fit:			
R^2			0.19
Adjusted-R^2			0.06
Residual autocorrelation[b]:			
Q(1)			0.86
Q(3)			0.62
Q(5)			0.49
Q(7)			0.43

Note:
[*] Significant at the 10% levels respectively.
[**] Significant at the 5% levels respectively.
[a] Standard errors in parentheses.
[b] Residual autocorrelation tests (*Q*(*j*)) are *p*-values for portmanteau tests for *j*th degree white noise in the residuals. Insignificant results suggest white noise (i.e. no autocorrelation).

the sample (1316 ZMK/kg). In the third month a one-time permanent increase in Kitwe price is introduced in the amount of 150 ZMK/kg (the average month-to-month change in Kitwe price over the sample period). We see rapid price transmission. The Kasumbalesa price begins to respond in the month of the shock itself, and by the end of the month following the shock, 67% of the adjustment back to equilibrium has occurred. From this month onward the shock adjustment gradually levels off so that by the 8th month after the shock (month 12 in Fig. 3), the Kasumbalesa price has effectively reached the new equilibrium price of around 1479 ZMK/kg. For comparison to the traditional measure of the speed of price transmission, note that half of the adjustment to the new equilibrium has occurred by roughly 2 weeks into the month after the shock so the half-life is 1.52.

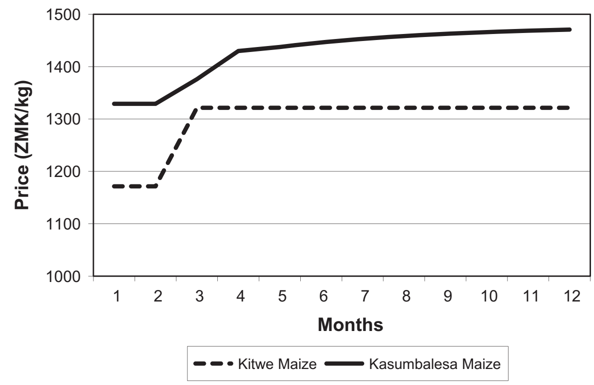

Fig. 3. Simulated shock to equilibrium prices in Kitwe and Kasumbalesa.

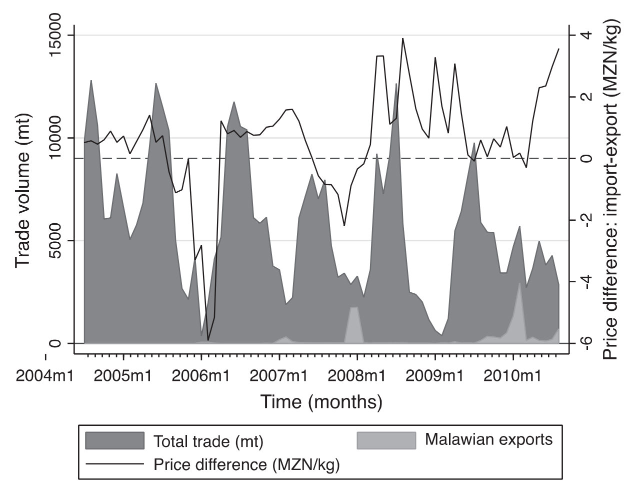

Fig. 4. Price difference between Liwonde and Cuamba and informal trade levels.

These results suggest that the informal trade which regularly takes place draws prices in these spatially separated markets towards an equilibrium relationship, and that the speed of adjustment is rapid. Moreover, after exhaustively searching the data for threshold effects, the evidence indicates that trade levels (high or low) do not disrupt the price transmission process. We will compare the speed of transmission estimated here to that between Mozambique and Malawi as well as to results from other studies in the following sub-section.

Cuamba and Liwonde

Next we examine the relationship between prices in Cuamba, Mozambique, and Liwonde, Malawi. Prices and trade data are examined descriptively in Fig. 4. Unlike the case with Zambia and The DRC, informal Malawian traders occasionally transport maize to sell in Mozambique. Thus, in Fig. 4 we plot both total trade volume and the amount of trade flowing from Malawi to Mozambique on the left vertical axis, and price difference on the right vertical axis. As in the previous case of trade between Zambia and DRC, there are a number of periods in which informal trade is flowing from Mozambique to Malawi even though the price difference is negative. In addition there are a small number of periods showing bidirectional trade flows. As before, these observations could be due to data aggregation, the presence of uninformed traders with imperfect information, or a small number of transactions taking place at prices other than the prevailing market price.

Table 4
GP threshold selection for price transmission between Cuamba and Liwonde.

Model	Threshold value (metric tons of traded maize)		Penalty criterion function				
	τ_1	τ_2	BIC	AIC	HQ	BIC2	BIC3
			GP values				
Two regime	2398.0		−0.2943	−0.0097	−0.1230	−0.8289	−1.3634
Three regime	2398.0	5608.6	−0.4913	0.0779	−0.1487	−1.5604	−2.6296

Table 5
Diagnostic tests for price series stochastic properties (Cuamba and Liwonde).

Test	Liwonde	Cuamba	Diesel
Unit root (Nonstationary null)			
ADF	0.27	0.05	0.29
ADF, trend	0.21	0.12	0.49
APP	0.27	0.04	0.39
APP, trend	0.16	0.08	0.61
Johansen (lag criteria)	Lags		Maximum rank
Cointegration			
LR	4	0	
FPE	2	1	
AIC	2	1	
HQ	1	1	
SB	1	1	

Notes: MacKinnon (1994) approximate p-values reported for ADF and PP tests. Maximum rank determined using Johansen's (1991) trace statistic and the 5% critical level.

Table 6
Price transmission estimation results for Cuamba and Liwonde.

Parameter	Estimate[a]	[95% Confidence Interval]
μ: Constant	-1.864^{**}	[−3.38, −0.35]
	(0.76)	
β_1: Long-run price transmission	0.822^{***}	[0.52, 1.12]
	(0.15)	
β_2: Long-run diesel Price transmission	0.336^{***}	[0.11, 0.57]
	(0.12)	
λ: Speed of adjustment	-0.246^{***}	[−0.42, −0.07]
	(0.09)	
ρ_1	-0.342^{**}	[−0.34, 0.16]
	(0.13)	
ρ_2	-0.310^{***}	[−0.63, −0.05]
	(0.14)	
b_1	−0.092	[−0.11, 0.19]
	(0.08)	
c_1	0.040	[−0.54, −0.08]
	(0.11)	
d_1	−0.040	[−0.20, 0.12]
	(0.08)	
Goodness of fit:		
R^2		0.62
Adjusted-R^2		0.57
Residual autocorrelation[b]:		
Q(1)		0.94
Q(3)		0.27
Q(5)		0.55
Q(7)		0.72

Notes:
** Significant at the 5% levels respectively.
*** Significant at the 1% levels respectively.
[a] Standard errors in parentheses.
[b] Residual autocorrelation tests (Q(*j*)) are *p*-values for portmanteau tests for *j*th degree white noise in the residuals. Insignificant results suggest white noise (i.e. no autocorrelation).

We proceed with empirical modeling with the minor difference that now we use net trade as our threshold variable.[18] With the initial one lag ($n = 1$) model there are 9 parameters to estimate and we have 72 usable observations, suggesting that we can allow for at most 2 thresholds and 3 regimes. Results from the GP selection process are presented in Table 4. These results almost exclusively favor the single regime model. The only exception is the three-regime model compared to the single regime model according to the AIC criterion. This produces a GP value of just less than 0.08, suggesting the threshold model is slightly superior. Based on the sum of the evidence, however, we conclude the single-regime model is most appropriate.

Next we examine the stochastic properties of these prices under the single-regime model. Table 5 presents the p-values from ADF and PP unit root tests as well as Johansen cointegration tests. For Liwonde maize price, we fail to reject the nonstationary null hypothesis using either the ADF or PP tests with and without including trends. For Cuamba maize price, ADF and PP do reject the nonstationary null at the 4-5% level, but only reject the non-trend-stationary hypothesis at the 12% and 8% levels respectively. Diesel price results clearly fail to reject the nonstationary null. Finally, 4 of the 5 lag selection criteria for Johansen's test lead to the conclusion of cointegration. As in the Zambia-DRC application, this evidence generally supports nonstationarity[19] and cointegration, which is consistent with specification of the SEECM in equation (2). NLS estimation results for the full-sample SEECM are reported in Table 6.

The Ljung-Box tests reported at the bottom of this table show no evidence of autocorrelation in the residuals, and thus no need to add further lags to the model. Our estimate of β_1 is 0.822 with a *p*-value of 0.00 and a 95% confidence interval of 0.52–1.12. This coefficient estimate is close to the $\beta_1 = 1$ value we would expect under perfect long-run price transmission. Furthermore, we fail to reject $H_0 : \beta_1 = 1$ with a *p*-value of 0.24.

Unlike the model for Kitwe and Kasumbalesa, here we find a statistically significant estimate of β_2. Given that these markets are much farther apart than Kitwe and Kasumbalesa, it is not surprising to see diesel price is significant in this model. That said, on a per ton kilometer basis, transfer costs appear to be lower between these markets than between the previously investigated Zambia-DRC markets. The average price difference when Malawian prices are higher, for example, is 1.24 MTN/kg, which translates to about $48.66 per ton at the period's mean exchange rate (25.53 MTN/$), or just $0.19 per ton kilometer. The highest price difference is 3.9 MTN/kg, translating to roughly $0.59 per ton kilometer. These are lower than the comparable figures for the market pair of Kitwe and Kasumbalesa, but keep in mind that the distance between markets here is much greater. That is, in addition to demonstrating a relatively efficient border crossing, this comparison might also come from spreading a similar border crossing cost over a longer distance.

[18] We also used total trade as an alternative threshold variable but this leads to the same conclusion regarding the presence of thresholds as using net trade.

[19] We acknowledge that we can only fail to reject that Cuamba price is nonstationary if we set the critical value at 3%, which may seem low. It is worth noting, though, that the Kwiatkowski et al. (1992) test on the null hypothesis that Cuamba price is stationary is rejected at the 3% level.

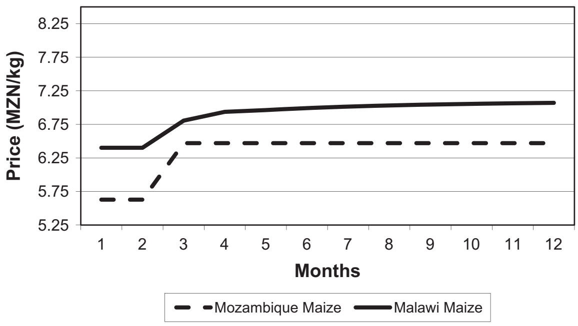

Fig. 5. Simulated shock to equilibrium prices in Cuamba and Liwonde.

The estimated speed of adjustment parameter, λ, is -0.246 with a p-value of 0.01 and a 95% confidence interval of -0.416 to -0.076. This estimate is similar to the Kitwe/Kasumbalesa estimate but the confidence interval is narrower in this case.

Fig. 5 shows the effect of a one-time permanent shock to the Cuamba price on the Liwonde price. The simulation is initiated with Cuamba maize price and Nampula diesel price (not shown) at their data means (5.63 MZN/kg and 27.91 MZN/liter respectively). The associated long-run equilibrium price of maize in Liwonde predicted by the model is 6.40 MZN/kg, which is reasonable but slightly higher than the actual mean price over the sample (6.18 MZN/kg). In the third month a one-time permanent increase in Cuamba price is introduced in the amount of 0.84 MZN/kg (the average month-to-month change in Cuamba price over the sample period). Once again we see fairly rapid price transmission. By the end of the month following the shock to Cuamba price, 77% of the adjustment back to equilibrium has occurred, which is slightly more than in the simulation for Kitwe/Kasumbalesa price transmission. From the month after the shock onward adjustment gradually levels off so that by the 8th month after the shock (month 12 in Fig. 5) the Liwonde price has effectively reached the new equilibrium price at around 7.09 MZN/kg. For comparison to the traditional measure of the speed of price transmission, note that half of the adjustment to the new equilibrium price occurs within the month of the shock itself. Specifically, the half-life in this simulation is 0.86 months.

The fact that only one regime was found, and that the regime features approximately one-for-one long-run price movements and rapid adjustment, suggests that, as in the case for Kitwe/Kasumbalesa, the informal trade is drawing these spatially separated markets towards long-run equilibrium and price transmission is fairly rapid. By comparison, Van Campenhout (2007) estimates maize grain price transmission half lives within Tanzania using the traditional TAR model. When price difference exceeds estimated transfer costs, that study estimates a 0.86 month half-life when markets are relatively close together (355 km) and up to 2.71 months for markets that are farther apart (503 km).[20] Myers and Jayne (2012) estimate speed of transmission between South Africa and Zambia at a half-life rate of 1.2–7.8 months, depending on trade regimes. Compared to these results and other studies, the simulation based half-life approximations of 1.52 and 0.86 months for Kitwe/Kasumbalesa and Cuamba/Liwonde respectively seem fairly rapid.

Overall, results suggest these two market pairs, where trade occurs relatively outside the realm of policy influence, appear to be connected as one would expect markets to be where price incentives frequently favor trade. Moreover, despite an exhaustive search, we find no compelling evidence of trade thresholds that would indicate capacity constraints or other frictions are altering these price transmission relationships. However, while the evidence on price *transmission* is consistent with well functioning markets, the evidence on the magnitude of price *differences* raises some concerns. In the case of Kitwe and Kasumbalesa, for example, the mean price difference when prices favor trade would translate to more than \$0.70 per ton kilometer. The price difference between Cuamba and Liwonde can be nearly \$0.60 per ton kilometer but has a mean of less than \$0.20 per ton kilometer. The fact that price differences are occasionally quite large indicates there may be large unobserved transfer costs (or inefficient trading decisions) that influence informal trade. High transfer costs could characterize many transactions in this region, even those within one country (e.g. Moser et al. (2009) indicate crime, remoteness and information asymmetries driving high transfer costs within Madagascar) In the case of informal trade, transfer costs could also be associated with corruption at border crossings, or other added capital and labor costs that come with being forced to use informal trading mechanisms (e.g. bicycle transporters or lower quality road networks).

To summarize, we found no evidence of regime shifting across trade thresholds and, together with the price transmission and speed of adjustment estimations for our full-sample (no threshold) model, this leads to the conclusion that spatial market price transmission between these market pairs connected by informal trade is complete and quite rapid. These results provide evidence that spatial price transmission between markets connected by informal (relatively unrestricted) trade can be expected to be quite effective. This is in notable contrast to similar studies that examine price transmission to these (and similar) countries at the global scale (Myers and Jayne, 2012; Minot, 2011). Moreover, our analysis suggests that policies focused on encouraging informal trade, and lowering the cost of such trade, may be quite effective at bringing about trade flows and price transmission in ways that state-led trading has not. For example, focusing on the legitimization of informal trade, investing in transportation infrastructure, and otherwise lowering transfer costs could have high long-run payoffs in these countries.

Summary and conclusion

The objective of this article was to analyze maize grain price transmission between countries in the SA region, focusing on informal trading routes between Zambia and the DRC as well as Mozambique and Malawi. Specifically, we sought to determine whether and under what conditions long-run spatial price equilibrium exists and the speed at which price shocks are transmitted between Kitwe and Kasumbalesa (in Zambia and DRC respectively), and Cuamba and Liwonde (in Mozambique and Malawi respectively).

The majority of the existing literature suggests SA grain markets are relatively isolated from outside price changes, due in part to government policies such as export bans and import licensing restrictions. There is less evidence available on how these markets could be expected to perform when and where these barriers are lower. The existence of largely unregulated informal maize trade provides an opportunity to examine how spatial markets in SA perform with relatively little influence from these government policies.

Following Myers and Jayne (2012) we employed a single-equation error correction price transmission model that allows for time varying transfer costs and for the equilibrium price relationship between markets to vary depending on trade thresholds. Thresholds may be expected, for example, if trade is very high and straining an exporter's transportation capacity, or if trade slows or stops due to poor price incentives or supply constraints.

[20] Van Campenhout (2007) reported half-lives in weeks (3.7 and 11.6 weeks respectively for those described here). The conversion to months assumes a 7-day week and a 30-day month.

After exhaustively searching our data for threshold trade levels, we conclude that no thresholds exist, and that in both market pairs there is only one price transmission regime. We argue this is exactly what one should expect in well-functioning spatial markets not subject to the influence of government trade restrictions, as is the case when trade is dominated by informal flows. Our inability to find evidence of thresholds could also be due to measurement error in the informal trade flow data, which we acknowledge is likely to be high. However, to the extent that our incomplete trade flow data still reflect trends and directions of change in the amount traded, results should provide useful insights into spatial market performance in SA under informal trade.

Our descriptive analysis shows that some trade does occur when price incentives would not seem to support it. This may be due to data aggregation across time and transactions, or to the actions of poorly informed traders, the presence of which is confirmed by anecdotal evidence (Mushinge, personal communication). Other explanations are that traders may be taking advantage of economies of scope in trading multiple commodities, or planning to store grain in the importing location until prices rise.

In the single-regime models estimated we find that estimates of long-run equilibrium parameters suggest perfect one-to-one long-run price transmission for both market pairs studied. The speed of price transmission was also similar in the two models estimated. The half-life of a transfer is computed via simulation to be roughly 1.52 months between Kitwe and Kasumbalesa and 0.86 months between Cuamba and Liwonde, both of which represent fairly rapid price transmission compared to other findings in the literature. Results show that one month after a shock to equilibrium is introduced, 67% (77%) of the total value of the shock will have transferred between Kitwe and Kasumbalesa (Cuamba and Liwonde).

Overall, the evidence shows that spatial price transmission is quite effective between SA maize markets connected by informal trade, and therefore largely unimpeded by trade regulations and restrictions. This is in notable contrast to similar studies that examine price transmission to these (and similar) countries at the global scale (Myers and Jayne, 2012; Minot, 2011). The markets studied here feature a long-run price equilibrium relationship consistent with competitive trade flows, price transmission that is quite rapid, and external trade thresholds have no measurably disruptive impact. In other words, spatial market arbitrage works well when unencumbered by policies such as export bans, exclusively state owned import rights and other license restrictions that that are typically placed on formal trade flows in the region.

That said, informal trade does seem sometimes burdened with high transfer costs. Consistent and more open trade policy could potentially reduce high labor and capital costs that may be associated with informal trading, and also reduce the incentives for bribery and corruption currently associated with moving informal trade across borders. Moreover, our results suggest that while formal trade restrictions may increase the cost of doing business, such policies do not necessarily stop informal trade from playing an important economic role. Focusing on the legitimization of informal trade, investing in transportation infrastructure, and otherwise lowering transfer costs of grains may have higher payoffs than formal trade regulations and state-led trading.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foodpol.2014.05.008.

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