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# Market Integration and the Law of One Price in Ghana[1]


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Abstract

Using a new dataset on the prices of perishable commodities traded across several markets and associated transport costs, we investigate the extent of market integration in Ghana and test the law of one price. We find support for market integration: prices at different markets are correlated, and most price series are co-integrated. Moreover, we find evidence that shocks in markets near production regions (supply shocks), are transmitted to markets near consumption regions, while the reverse can not be confirmed with our data. However, direct tests of Law of One Price show that the shocks are transmitted at a much lower level than standard theory predicts.



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## 1. Introduction

The development economics literature forks based on whether or not one believes that smooth price adjustments or frictions are at play in an economy. For example, limited supply frictions, perfect competition, and assuming demand for a commodity is universal imply that the law of one price (LOP) should hold: the difference between equilibrium prices across markets and time is attributable only to transaction cost differentials across those markets.[2] We investigate the LOP for a number of perishable goods across time and geographic space in Ghana using unique new datasets. The first, obtained from the Ministry of Food and Agriculture in Ghana, provides weekly data on perishable commodity prices across 15 main markets over seven years. The second, collected by the Center for Technology and Economic Development (CTED) at NYU Abu Dhabi in collaboration with Esoko (a company based in Accra specializing in data collection and information delivery to rural regions), provides data on transportation costs.[3] These datasets allow us to investigate timeless questions relating to the LOP in a manner that the previous literature on the subject could not. Specifically, we can investigate the LOP for several perishable commodities over time across Ghana. Previous research mostly concentrated on testing LOP for a single commodity. Further, we are able to condition our analyses on a variable that is an indicator of whether a pair of markets is a trading pair or not since we observe transportation

[2] Cournot (1838) states that transaction costs consist "*not only the price of necessaries and the wages of the agents by whom the transportation is mechanically carried out, but also insurance premiums, and the profits of the merchant, who ought to obtain in his business the interest on the capital employed and a proper return for his industry*."

[3] Both datasets are augmented with data on the distance between markets.

costs between markets. Methodologically, these data allow us to employ existing techniques more broadly and expand on them as well.

We first follow an existing tradition in the literature exemplified by Abdulai (2000) who examined maize markets in Ghana. Those markets were found to be well integrated using data on maize prices, threshold autoregression techniques and the assumption that agents only act to move to equilibrium when the benefits of doing so exceed costs. Ragasa et al (2018) also analyze maize production in Ghana, specifically the role of contract farming arrangements. In contrast we analyze a number of commodities and directly observe transportation costs and therefore speak to the Ghanaian agriculture markets broadly and target specific tests of the LOP, our main contribution to the literature.

That the LOP may not hold due to a number of frictions at play in developing country contexts is at the heart of Allen (2014)'s analysis. The friction analyzed there is information, specifically costly search processes for producers who try to determine where to sell produce in the Philippines. Allen (2014) finds that much of observed price dispersions can be accounted for by these frictions. The importance of information frictions in explaining price dispersion is also an important component of Aker (2010) who finds that the introduction of cellular phone service reduced price dispersion for grain in Niger. The same focus on informational frictions and possible alleviation due to the introduction of telecommunications in developing countries is found in Jensen (2007) who analyzed the case of Kerala, India and found a near perfect adherence to the LOP. The use of technology to assist in poverty reduction schemes is discussed at length in Ainembabazi et al (2018); the focus of CTED in partnering with such firms (e.g. Esoko) allows also for unique data collection as we report below.

A key friction that the introduction of communication and information technologies cannot overcome is of course the state of the transportation infrastructure in a developing country. Atkin and Donaldson (2015) augment their price data from Ethiopia and Nigeria with estimates of cost pass through (to account for imperfect market structures) and product origin locations to identify trade costs. Not doing so would bias downwards their estimates of the cost of distance. They find that the effect of (log) distance on trade costs in Nigeria and Ethiopia is four to five times than that in the United States. Bergquist (2017) uses experimental evidence from Kenya to shed light on the market structure of intermediaries who Atkin and Donaldson (2015) find capture the majority of surplus, with surplus shares rising for more distant locations. In a pair of analyses, Casaburi, Glennerster and Suriy (2013) and Casaburi and Reed (2017) further show that road infrastructure impacts crop prices. Our dataset with directly observed prices, transport costs and data on distances allows us to estimate pass through rates.[4] The ability to observe transportation costs directly is an important aspect of our contribution to the literature since it allows us to construct variables that clearly identify trading pairs in addition to being able to employ transportation cost data in empirical analyses of the LOP.

We find that in terms of simple summary statistics, correlations, co-integration and Granger causality tests that the LOP does weakly hold conditional on the distance between markets and if a market pair is identified to be a trading pair or not. Correlations, while a simple technique, are a first step in empirically investigating any LOP hypothesis under the assumption that any price differentials might simply be noise reflecting unobserved transaction costs. Next,

[4] Comprehensive literature reviews on market integration, the LOP and issues related to trade within developing countries are available in Dillon and Dambro (2017) and Rashid and Minot (2010).

assuming that the LOP holds for instance, a correlation declining with distance may be a consequence of noisy trade costs, a natural factor in developing country contexts. However, further investigation of our data, in computing pass through rates as is common in the literature and connecting destination market prices to origin market prices, we find no reason to conclude that the LOP holds across the Ghanaian economy. Finally, we find an important role for what would be considered to be supply shocks vs. demand shocks given the structure of our data.

The paper is organized as follows. Section 2 describes our data. Section 3 studies correlations, co-integration of prices, and our Granger causality tests in order to sequentially build evidence on the nature of perishable commodity markets in Ghana. In Section 4 we tackle the geographical pattern of our data and inferences we can make as a result. In Section 5 we discuss pass through rates and regressions related to testing the LOP directly. Section 6 concludes.

## 2. The Data

The Ministry of Food and Agriculture in Ghana (MOFA)'s representatives inquire about and record wholesale prices for commodities sold at various locations throughout Ghana.[5] The dataset contains prices, denoted $P_{cit}$, for commodities ($c \in \{1, \dots, 19\}$), and markets ($i \in \{1, \dots, 15\}$) at a weekly frequency from January 2009 through December 2015 ($t \in \{1, \dots, 364\}$). Table 1 presents summary statistics on these price data, in price per kilogram measured in local currency units. Each row of Table 1 below is constructed from a panel, across markets and time, for a particular commodity (i.e. $P_{it}$.for each $c$).

[5] Distances between markets were calculated using Google API.

Table 1. Summary Statistics (MOFA Data)

| Commodity | Average | Std. Dev. Overall | Std. Dev. Between | Std. Dev. Within | Average T | N |
|---|---|---|---|---|---|---|
| Cassava | 0.401 | 0.236 | 0.196 | 0.133 | 325.07 | 4876 |
| Cocoyam | 1.099 | 0.740 | 0.657 | 0.331 | 262.73 | 3941 |
| Cowpea | 1.790 | 0.820 | 0.769 | 0.291 | 343.60 | 5154 |
| Groundnuts | 2.870 | 1.298 | 1.257 | 0.333 | 339.87 | 5098 |
| Maize | 0.808 | 0.376 | 0.334 | 0.177 | 347.67 | 5215 |
| Millet | 1.224 | 0.451 | 0.414 | 0.183 | 346.33 | 5195 |
| Onion | 3.025 | 1.577 | 1.502 | 0.504 | 228.33 | 3425 |
| Oranges | 0.497 | 0.332 | 0.282 | 0.185 | 322.07 | 4831 |
| Palm fruit | 0.734 | 0.527 | 0.458 | 1.566 | 260.13 | 3902 |
| Palm oil | 2.505 | 1.340 | 1.274 | 0.435 | 340.40 | 5106 |
| Pepper (dried) | 11.552 | 5.953 | 4.268 | 4.256 | 315.40 | 4731 |
| Pepper (fresh) | 4.704 | 2.623 | 2.419 | 1.123 | 295.00 | 4425 |
| Plantain (apem) | 1.373 | 0.937 | 0.877 | 0.330 | 313.07 | 4696 |
| Plantain (apentu) | 1.010 | 0.716 | 0.642 | 0.331 | 338.53 | 5078 |
| Rice (imported) | 2.432 | 1.153 | 1.139 | 0.188 | 347.53 | 5213 |
| Rice (local) | 1.638 | 0.756 | 0.723 | 0.222 | 326.20 | 4893 |
| Sorghum | 1.017 | 0.401 | 0.339 | 0.218 | 334.60 | 5019 |
| Tomatoes | 3.066 | 2.278 | 2.077 | 0.966 | 345.33 | 5180 |
| Yam | 0.876 | 0.430 | 0.394 | 0.181 | 328.40 | 4926 |

Table 1 demonstrates variation of prices of each commodity both across markets (non-zero between standard deviations) and time (non-zero within standard deviations). It further indicates that the panel data for each commodity is incomplete on the time dimension since the average observations per market are not equal to the maximum possible time periods between January 2009-December 2015 (second to last column of Table 1, Average T, is not uniformly 364): while for Cassava there are 325 observations on average per market, not so for Onions for which there are 228 observations on average per market.

We supplement the data from MOFA with data on transportation costs collected by a company called Esoko in collaboration with Center for Technology and Economic Development (CTED) at New York University Abu Dhabi. Representatives from Esoko were asked by CTED to conduct a survey at many markets across Ghana. They collected data from each interviewee on commodities and their unit of measure (e.g. kilograms or tubers), source and destination markets for those commodities, the type of vehicle employed in transportation, and most critically, the cost of transportation ($TC_{cijt}$). Esoko representatives also recorded the date and source of the information itself, which can be a driver, trader or the Ghana Private Road Transport Union association. The survey took place between April 2013 and December 2014 with observations recorded on a weekly basis. Table 2 below provides summary statistics on this data in a manner analogous to Table 1 holding commodities fixed (i.e. $TC_{ijt}$.for each $c$).

Table 2. Summary Statistics (CTED Data)

| | | Std. Dev. | | | | |
|---|---|---|---|---|---|---|
| Commodity | Average | Overall | Between | Within | Average T | N |
| Bambara beans | 0.104 | 0.070 | 0.060 | 0.039 | 24.33 | 1022 |
| Cassava (chips) | 0.353 | 0.108 | 0.039 | 0.120 | 10.20 | 153 |
| Cassava (gari) | 0.201 | 0.191 | 0.174 | 0.113 | 10.69 | 310 |
| Cowpea | 0.115 | 0.183 | 0.121 | 0.368 | 20.14 | 1531 |
| Groundnuts | 0.144 | 0.190 | 0.146 | 0.368 | 23.61 | 1653 |
| Maize | 0.208 | 0.819 | 0.516 | 0.497 | 22.46 | 2021 |
| Millet | 0.129 | 0.107 | 0.081 | 0.123 | 19.54 | 1270 |
| Onion | 0.143 | 0.051 | 0.028 | 0.061 | 7.07 | 106 |
| Rice (local) | 0.117 | 0.055 | 0.020 | 0.153 | 17.22 | 947 |
| Shea (butter) | 0.228 | 0.200 | 0.141 | 0.144 | 15.71 | 267 |
| Shea (nuts) | 0.135 | 0.096 | 0.076 | 0.060 | 23.75 | 950 |
| Sorghum | 0.097 | 0.063 | 0.051 | 0.056 | 26.36 | 1186 |
| Soya bean | 0.100 | 0.046 | 0.032 | 0.036 | 21.10 | 1055 |
| Tomato (cooking) | 0.136 | 0.043 | 0.017 | 0.089 | 10.18 | 112 |
| Yam | 0.143 | 0.261 | 0.070 | 0.394 | 20.12 | 1368 |

Table 2 demonstrates variation of transport costs of each commodity both across markets (non-zero between standard deviations) and time (non-zero within standard deviations); however these are substantially smaller standard deviations when compared to prices. This is understandable as it is highly unlikely that transport costs vary as much as commodity prices would on a weekly basis. Table 2 also indicates that the panel data for each commodity is incomplete on the time dimension since the average observations per market are not equal to the maximum possible time periods between April 2013-December 2014: while for Groundnuts there are 24 observations on average per market, not so for Onions for which there are 7 observations on average per market.

The above datasets cover different commodities over different markets and time periods. Merging the two eliminates some commodities, however, is needed for some of the analyses we conduct in the next sections. The summary statistics for the merged data are presented in Table 3 below, we make a distinction for the two main variables of interest in subsequent analyses.

Table 3. Summary Statistics (Merged Data)

| Transportation Costs | | | | | | |
|---|---|---|---|---|---|---|
| | | Std. Dev. | | | | |
| Commodity | Average | Overall | Between | Within | Average T | N |
| Cowpea | 0.098 | 0.034 | 0.021 | 0.032 | 22.33 | 804 |
| Groundnuts | 0.122 | 0.039 | 0.019 | 0.040 | 29.04 | 813 |
| Maize | 0.111 | 0.056 | 0.040 | 0.052 | 24.94 | 873 |
| Millet | 0.120 | 0.056 | 0.045 | 0.037 | 19.17 | 556 |
| Onion | 0.133 | 0.041 | 0.029 | 0.034 | 11.13 | 89 |
| Rice (local) | 0.105 | 0.035 | 0.018 | 0.030 | 21.43 | 450 |
| Sorghum | 0.082 | 0.032 | 0.018 | 0.076 | 29.69 | 475 |
| Yam | 0.122 | 0.115 | 0.040 | 0.256 | 21.52 | 538 |

| Price Differences | | | | | | |
|---|---|---|---|---|---|---|
| | | Std. Dev. | | | | |
| Commodity | Average | Overall | Between | Within | Average T | N |
| Cowpea | 0.051 | 0.840 | 0.531 | 0.627 | 22.33 | 804 |
| Groundnuts | 0.579 | 0.791 | 0.585 | 0.552 | 29.04 | 813 |
| Maize | 0.216 | 0.275 | 0.148 | 0.273 | 24.94 | 873 |
| Millet | 0.265 | 0.403 | 0.257 | 0.294 | 19.17 | 556 |
| Onion | 0.510 | 0.879 | 0.726 | 1.520 | 11.13 | 89 |
| Rice (local) | 0.052 | 0.660 | 0.469 | 0.478 | 21.43 | 450 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Sorghum | 0.229 | 0.364 | 0.189 | 0.311 | 29.69 | 475 |
| Yam | 0.339 | 0.391 | 0.240 | 0.287 | 21.52 | 538 |

The same patterns observed for individual datasets are present in the merged data as well: lower variation for costs vs. price differences and incompleteness of data over time, even though the average values for transport costs and price differences are of similar magnitudes. Formal tests presented next analyze the relationship between these two variables.

**3. Tests of the Law of One price**

As discussed, in this section we proceed in steps from the simplest evaluations of price differentials (correlations) to the Granger causality tests discussed previously in the literature, for the sake of comparison.

If an identical commodity is sold on two spatially separated markets, our understanding of market integration implies that the commodity will be transported from the market where the price is lower to the market where the price is higher until the difference in prices will be no more than the transaction costs required for a trader to transport and sell the good in one market to the other. In particular, if we define $i$ and $j$ to be indexes for two separate locations, $c$ as the commodity index, and $t$ as the current time period, the law of one price (LOP) states:

$$P_{cjt} - P_{cit} \leq \tau_{cijt} \qquad (1)$$

where $P_{cjt}$ and $P_{cit}$ are prices for commodity $c$, and $\tau_{cijt}$ is the associated transaction cost. We therefore view $\tau_{cijt}$ in this section as being unobserved transaction costs.

Under the assumption that unobserved transaction costs are random, the LOP in (1) under equality implies that prices in different markets should co-move.[6] The extent of co-movement of prices can be investigated using three popular methods in the existing literature. The first is a correlation analysis: prices for the same commodity in different markets should be significantly correlated (e.g. Li (2000)). The second method is co-integration testing: prices for the same commodity in different markets should be co-integrated (e.g. Alexander and Wyeth (1994)). The third method is Granger Causality testing: prices for the same commodity in different markets should Granger cause each other (e.g. Fafchamps and Gavian (1996)).

Each of the above tests need also to be conditioned on the fact that in Ghana the transport network is still at a developing country phase with poor road quality and so the distance between markets may be more important than in developed countries. Moreoever, since we anticipate distance to be an important variable, we also distinguish between all market pairs and those market pairs that specifically are trading pairs. That is to say, market pairs for which we know there is an exchange of goods, this variable assists in evaluating the extent of market integration.

Distance therefore introduces a geo-spatial dimension to our data. That is, prices in markets far away from each other might be correlated less, be less co-integrated and not Granger cause each other as much, and we can evaluate each in turn given identification of trading pairs.

[6] In a section below, we demonstrate that in our data a significant number of markets trade as evidenced by recorded transportation costs across goods, origin-destination markets and time. This is why we modify the LOP in (1) to an equality statement for the analyses reported in this section.

We now turn to each of these tests with attention paid to the distance between markets and whether a market pair is a trading pair or not.

### 3.1. Correlation Analyses

The simplest possible measure of price co-movement is the correlation of prices across markets. We first compute correlations between prices across all pairs of markets using our MOFA dataset. Since we have 15 markets, there are 105 total pairs $\left(\frac{15\times14}{2}\right)$ of markets that could be trading. Next, using our transport costs dataset that we collected, we can surmise whether all possible pairs of markets trade for each commodity or not. That is, for each commodity, we know there is trade between a market pair if traders stated that they moved a commodity from one market to another at least once in the ESOKO survey. Therefore we can compute correlations for each commodity across all market pairs and also only across those pairs for which we can identify existence of trade as described above; Table 4 presents the average and standard deviation of correlations for each commodity, i.e., fixing the commodity dimension and a market pair, a correlation is calculated between the price series for the market pair. We report the average (and standard deviation) across market pairs for a given commodity. The third and fourth columns report the average (standard deviation) when the average across market pairs is for all pairs, whereas the sixth and seventh column report the same when the average is taken for only those market pairs that we identify as being trading pairs.

Table 4. Correlations across Commodities and Market Pairs

| Commodity | | Average (all) | Std. Dev. (all) | # of trading pairs | Average (trading) | Std. Dev. (trading) |
|---|---|---|---|---|---|---|
| Cassava | 105 | 0.616 | 0.210 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Cocoyam | 100 | 0.518 | 0.401 | | | |
| Cowpea | 105 | 0.852 | 0.065 | 33 | 0.851 | 0.061 |
| Groundnuts | 105 | 0.886 | 0.068 | 27 | 0.909 | 0.027 |
| Maize | 105 | 0.867 | 0.060 | 30 | 0.863 | 0.071 |
| Millet | 105 | 0.832 | 0.090 | 28 | 0.828 | 0.062 |
| Onion | 105 | 0.653 | 0.219 | 8 | 0.740 | 0.207 |
| Oranges | 105 | 0.493 | 0.211 | | | |
| Palm fruit | 78 | 0.314 | 0.327 | | | |
| Palm oil | 105 | 0.797 | 0.084 | | | |
| Pepper (dried) | 105 | 0.416 | 0.224 | | | |
| Pepper (fresh) | 104 | 0.343 | 0.312 | | | |
| Plantain (apem) | 105 | 0.479 | 0.205 | | | |
| Plantain (apentu) | 105 | 0.565 | 0.166 | | | |
| Rice (imported) | 105 | 0.900 | 0.070 | | | |
| Rice (local) | 105 | 0.794 | 0.128 | 20 | 0.814 | 0.090 |
| Sorghum | 105 | 0.843 | 0.078 | 15 | 0.844 | 0.075 |
| Tomatoes | 105 | 0.622 | 0.159 | | | |
| Yam | 105 | 0.646 | 0.147 | 25 | 0.604 | 0.175 |
| Total | 1962 | 0.655 | | 186 | 0.807 | |

Table 4 indicates that average correlations are higher among trading pairs, demonstrating the fact that prices at markets that have a direct connection are more likely to be correlated. Next, correlations between markets close to each other could be high, while correlations between distant markets should be low given that the transport infrastructure in Ghana is underdeveloped. Thus, we estimate a regression of the correlation of prices between markets on the distance between markets. Previous studies (e.g. Fafchamps and Gavian (1996)) used a similar approach, however, they analyzed the relationship for each commodity separately. We employ a panel approach and estimate the following commodity fixed effects regression:

$$Corr_{cij} = \alpha + \beta \mathrm{DST}_{ij} + \mu_c + \varepsilon_{ij}, \quad (2)$$

where $Corr_{cij}$ is the price correlation between a market pair for commodity $c$, $DST_{ij}$ is the distance between the pair scaled by a factor of 100 (i.e. $DST = 1$ indicates markets are 100 km apart), $\mu_c$ is the commodity fixed effect, and $\varepsilon_{cij}$ is the idiosyncratic error; regression results are provided in Table 5 below.

Table 5. Correlation and Distances

| | Estimate | Std. Err. | \|t\|-stat. |
|---|---|---|---|
| Distance (100km) | -0.0213 | 0.00214 | 9.91 |
| Constant | 0.733 | 0.00851 | 86.15 |
| Obs. | 1,962 | | |
| Groups | 19 | | |
| F-stat. for $H_0$ of fixed effects | 106.00 | | |

We see that the effect of distance on correlation is highly significant and that an extra 100 km decreases correlations by 2.1%. This confirms our hypothesis that correlations between markets close to each other are high, while correlations between distant markets are lower.

Next, we include in the regression (2) a dummy variable that is equal to 1 if traders stated that they moved a commodity $c$ from market $i$ to market $j$ or from market $j$ to market $i$.

$$Corr_{cij} = \alpha + \beta \mathrm{DST}_{ij} + T_{cij} + \mu_c + \varepsilon_{ij}, \qquad (3)$$

The results are presented below in Table 6.

Table 6. Correlation and Distances (Trading Pairs)

| | Estimate | Std. Err. | \|t\|-stat. |
|---|---|---|---|
| Distance (100km) | -0.0213 | 0.0021 | 9.93 |
| Trading pairs | 0.0116 | 0.0163 | 0.71 |
| Constant | 0.732 | 0.0085 | 85.21 |
| Obs. | 1,962 | | |
| Groups | 19 | | |
| F-stat. for $H_0$ of fixed effects | 99.50 | | |

We note that while distance still matters, whether a pair is trading or not is not significant. This result speaks to the effect of the general nature of transport networks reported in Table 6.

### 3.2. Cointegration Analyses

As argued by Harris (1979) and Blyn (1973) and emphasized by Ravallion (1986) there is a danger in using correlation analysis for market integration analyses since price series in two markets could be affected by a third variable (e.g. oil prices) and of course seasonality and related trends. An alternative approach therefore suggests a test for co-integration of price series vs. correlation analyses (Alexander and Wyeth (1994)). Much of the development literature argues that prices are commonly integrated of degree 1. Alexander and Wyeth (1994) state that when two price series are co-integrated, it follows that the markets are integrated (in the economic sense) in the long run. Our investigation proceeds in stages. We first check if individual price series are non-stationary, then check for stationarity of price differences. If price series are non-stationary, but their difference is stationary then we can conclude that markets are integrated.

Our price series are first tested for integration of degree one using an Augmented Dickey Fuller test. We estimate the following regression for each price series and market:

$$\Delta y_t = \alpha + \beta\, y_{t-1} + \sum_{j=1}^{k-1} \varphi_j \Delta y_{t-j} + \varepsilon_t \qquad (3)$$

where $y_t$ is the natural logarithm of a price series.[7] Testing for integration of degree 1 in these settings is equivalent to testing the hypothesis $H_0: \beta = 0$. For 49 out of 282[8] price series (17%) we reject the unit root hypothesis at a 5% confidence level in contrast to Fafchamps and Gavian (1996) who found that less than 5% of price series were stationary in their data. To test that our

[7] Our lag selection procedure is standard: we first estimate the model with a maximum lag $k = k_{max} = 12$ weeks, if the last lag coefficient $\varphi_k$ is insignificant, the model is re-estimated with $k = k - 1$ and the process repeated until the last lag coefficient is significant.

[8] Prices for Cocoyam in Bogatanga and Palm Fruit for Bolgatanga and Wa were not available for enough time periods to perform reliable unit root tests, thus tests were performed for 282 price series (15×19-3).

series are not integrated of degree 2 we take the first difference of prices and test them for stationarity using the same method. We find that 281 out of 282 differenced series are stationary. We therefore conclude that the majority of our price series are integrated of degree 1.

Next, we test for the stationarity of price differences for all combinations of commodity-market 1-market 2 for which both price series are non-stationary. We find that only 1392 of 1,954 combinations (71%) can be tested for co-integration. For these series, we compute price differences $PD_{cijt} = P_{cit} - P_{cjt}$ and test these series for unit roots. If the null hypothesis of a unit root is rejected, the two series are co-integrated. We find that among those 755 series (55%) are co-integrated.[9]

Differentiated by commodities, these results are presented in Table 7 (columns 2, 3 and 4). Columns 2-4 partition all price series for a given commodity into three sets: both series are non-stationary, only one price series is non-stationary, and both price series are stationary. Column 5 presents results for the co-integration tests, which were only conducted if price series for both markets were non-stationary. Columns 6 and 7 present the results only among trading pairs.

Table 7. Unit Roots and Co-Integration

| Commodity | Both non-stationary | One stationary | Both stationary | Co-integrated (all) | Both nonst. among trading | Co-integrated (trading) |
|---|---|---|---|---|---|---|
| Cassava | 91 | 14 | 0 | 29 (32%) | | |
| Cocoyam | 78 | 26 | 1 | 16 (21%) | | |
| Cowpea | 105 | 0 | 0 | 75 (71%) | 33 | 28 (85%) |
| Groundnuts | 105 | 0 | 0 | 69 (66%) | 27 | 18 (67%) |

[9] The remaining 562 (29%) combinations cannot be tested for co-integration: for 464 (23%) pairs only one market is non-stationary, and co-integration tests do not make sense (the difference should always be non-stationary). For the remaining 139 pairs (6%) both price series are stationary, and, therefore, co-integration tests cannot be conducted as well.

| | | | | | | |
|---|---|---|---|---|---|---|
| Maize | 105 | 0 | 0 | 63 (60%) | 30 | 16 (57%) |
| Millet | 105 | 0 | 0 | 81 (77%) | 28 | 23 (82%) |
| Onion | 55 | 44 | 6 | 32 (58%) | 1 | 1 (100%) |
| Oranges | 66 | 36 | 3 | 44 (67%) | | |
| Palm fruit | 45 | 50 | 10 | 22 (49%) | | |
| Palm oil | 105 | 0 | 0 | 40 (38%) | | |
| Pepper (dried) | 66 | 36 | 3 | 27 (41%) | | |
| Pepper (fresh) | 10 | 50 | 45 | 4 (40%) | | |
| Plantain (apem) | 45 | 50 | 10 | 21 (47%) | | |
| Plantain (apentu) | 55 | 44 | 6 | 32 (58%) | | |
| Rice (imported) | 105 | 0 | 0 | 51 (49%) | | |
| Rice (local) | 91 | 14 | 0 | 49 (54%) | 19 | 7 (37%) |
| Sorghum | 105 | 0 | 0 | 49 (47%) | 15 | 3 (20%) |
| Tomatoes | 10 | 50 | 45 | 10 (100%) | | |
| Yam | 45 | 50 | 10 | 34 (76%) | 9 | 6 (67%) |
| Total | 1392 | 464 | 139 | 748 (54%) | 162 | 104 (64%) |

Again, we observe significant heterogeneity among commodities. We can see that the highest number of co-integrated series is for millet (81) followed by cowpea (75) and then groundnuts (68) and maize (63). Also, notice that 76% of yam price series and 100% of tomato price series are co-integrated, although the number of series we can test for yam and tomatoes is low.

At the same time, co-integration among trading pairs is higher than among all pairs. We can see that 64% of trading pairs are co-integrated compared to 54% of co-integrated pairs among all pairs.[10] To show that this difference is significant, we estimate a logit regression where on the left-hand side is the probability that the two series are co-integrated, and on the right-hand side is the distance between markets and the dummy variable for trading pairs.

[10] 52% of non-trading pairs (652 out of 1244) are co-integrated.

$$Pr\{CI_{cij}\} = \Lambda\left(\alpha + \beta DST_{ij} + \gamma TR_{cij}\right) \quad (4)$$

Where $(i, j)$ is a pair of markets; $c$ is the commodity index, $CI_{cij}$ equals 1 if markets $i$ and $j$ are co-integrated for commodity $c$, $DST_{ij}$ is the distance in kilometers between the pair scaled by a factor of 100, and $TR_{cij}$ is a dummy variable that is equal to 1 if for commodity $c$ market pairs $i$ and $j$ are a trading pair of markets. The results of the regression are presented in the table below.

Table 8. Logit regression for co-integration and distances

| | Estimate | Std. Err. | t-stat |
|---|---|---|---|
| Distance (100 km) | -.146 | .0275 | -5.32 |
| Trading pairs | .56 | .176 | 3.17 |
| Constant | .598 | .111 | 5.40 |
| Num. obs. | 1392 | | |
| Pseudo $R^2$ | .0193 | | |

These estimation results show that there is a significant relationship between price co-integration and distances between markets. Markets that are close to each other are more likely to be integrated, markets that are far from each other are less likely to be integrated. If a market pair is a trading pair it has a higher probability of being integrated.

### 3.3 Granger Causality

Another test of MI that is widely used in the literature is the Granger causality test. Granger causality is a concept that is used to determine if one statistical variable is useful in forecasting the other variable. If markets are integrated, we expect that price shocks in one market are useful in determining prices in the other market, therefore, it is also an indirect test of equation (1), which says that prices in two markets should be connected by transportation/transaction costs.

To test for Granger causality between two markets (call them $X$ and $Y$), we use the following model.

$$\Delta y_t = \alpha + \sum_{j=1}^{k} \beta_j \Delta y_{t-j} + \sum_{j=1}^{k} \gamma_j \Delta x_{t-j} + \varepsilon_t \qquad (5)$$

where $y_t$ and $x_t$ are prices for markets $Y$ and $X$. The null hypothesis, that is, price changes in market $X$ do not cause price changes in market $Y$, is formulated as all $\gamma_j = 0$ (for all $j \in [1, k]$).

$$H_0\colon \gamma_j = 0 \; for \; all \; j \in [1, k] \qquad (6)$$

Since we have weekly data, we take $k = 12$ weeks to include information on three past months. The specification in (5) and the hypothesis test in (6) is valid irrespective of whether the prices $x_t$ and $y_t$ are stationary by themselves or not, so we conduct tests for all combinations of commodity-market1-market2 in both directions.

The results are as follows: for 1135 pairs of markets (57%) price changes in one market cause price changes in the other market. Out of those, for 317 pairs (16%) the causality runs both ways. Among trading pairs the causality is 72%. The results organized by commodities are presented in Table 9; trading market pairs have a higher percentage of Granger causality.

Table 9. Granger Causality Tests

| Commodity | Total pairs | At least one way Granger causality | Two way Granger causality | Trading pairs | At least one way |
|---|---|---|---|---|---|
| Cassava | 105 | 44 (42%) | 8 | | |
| Cocoyam | 105 | 44 (42%) | 7 | | |
| Cowpea | 105 | 60 (57%) | 21 | 33 | 21 (64%) |
| Groundnuts | 105 | 79 (75%) | 15 | 27 | 20 (74%) |
| Maize | 105 | 94 (89%) | 38 | 30 | 29 (97%) |
| Millet | 105 | 64 (61%) | 19 | 28 | 21 (75%) |
| Onion | 105 | 79 (75%) | 19 | 8 | 6 (75%) |
| Oranges | 105 | 62 (59%) | 18 | | |
| Palm fruit | 105 | 18 (17%) | 3 | | |
| Palm oil | 105 | 54 (51%) | 13 | | |

| | | | | | |
|---|---|---|---|---|---|
| Pepper (dried) | 105 | 51 (49%) | 16 | | |
| Pepper (fresh) | 105 | 58 (55%) | 16 | | |
| Plantain (apem) | 105 | 55 (52%) | 13 | | |
| Plantain (apentu) | 105 | 71 (68%) | 24 | | |
| Rice (imported) | 105 | 62 (59%) | 19 | | |
| Rice (local) | 105 | 51 (49%) | 7 | 20 | 9 (45%) |
| Sorghum | 105 | 46 (44%) | 14 | 15 | 6 (40%) |
| Tomatoes | 105 | 77 (73%) | 22 | | |
| Yam | 105 | 66 (63%) | 22 | 25 | 16 (64%) |
| Total | | 1135 (57%) | | 170 | 123(69%) |

**Note**: The third column: total pairs where at least one market Granger-causes the other; the fourth column: total pairs where both markets Granger-cause each other. The fifth column: total number of trading pairs. The sixth column: total pairs (among trading) where at least one markets Granger-causes the other market.

The most integrated market is the market for maize: for 94 out of 105 pairs of markets we cannot reject causality at 5% confidence level.

Since whether a market pair is trading or not matters, we next let $G_{cij}$ be a dummy variable that is equal to 1 if for commodity $c$ prices in market $i$ either cause or are being caused by prices in market $j$. To evaluate if distance and a trading relationship between markets affect whether a pair of markets is integrated or not we estimate:

$$Pr\{G_{cij} = 1\} = \Lambda\left(\alpha + \beta DST_{ij} + \gamma TR_{cij}\right) \quad (8)$$

Table 10: results of the regression (8)

| | Estimate | Std. Err. | z-stat |
|---|---|---|---|
| DST | -0.096 | 0.017 | -5.67 |
| TR | 0.480 | 0.114 | 4.21 |
| Constant | -0.268 | 0.067 | -4.02 |

Number of obs = 3,990

Pseudo $R^2$ = 0.0068

Now we consider only commodities for which there are non-zero trading pairs, among those we calculate how many have at least one-way Granger causality, Granger causality from origin to destination and Granger causality from destination to origin markets. This allows us to differentiate between variations in origin vs destination markets affecting our Granger causality tests. Results are provided below.

Table 11. Trading pairs and Granger Causality Tests

| Commodity | At least one way Granger causality | Trading pairs | At least one way (among trading pairs) | Origin causes dest-n | Dest-n causes origin |
|---|---|---|---|---|---|
| Cowpea | 60 | 32 | 21 | 17 | 13 |
| Groundnuts | 79 | 27 | 20 | 14 | 9 |
| Maize | 94 | 28 | 27 | 22 | 17 |
| Millet | 64 | 28 | 21 | 14 | 14 |
| Onion | 83 | 12 | 9 | 5 | 7 |
| Oranges | 62 | 3 | 3 | | 3 |
| Sorghum | 46 | 14 | 6 | 4 | 3 |
| Yam | 66 | 26 | 16 | 10 | 9 |

If prices at the origin market Granger-cause prices at the destination market, we conjecture that this is the effect of the supply shocks since goods are mostly transported from production areas to consumption areas. If, on the other hand, prices at the destination market Granger-cause prices at the origin market, we conjecture that this is the effect of the demand shocks. To test both hypotheses, we introduce a dummy variable $GC_{cij}$ which is equal to 1 if prices at market $i$ cause prices at market $j$, and dummy variable $GBC_{cij}$ that is equal to 1 if prices at market $i$ are being caused by prices at market $j$. Also, we let $F_{cij}$ be a dummy variable that is equal to 1 if $i$ and $j$ are trading pairs and the direction of trade is from $i$ to $j$. Then we specify

$$Pr\{GC_{cij} = 1\} = \Lambda(\alpha + \beta DST_{ij} + \gamma F_{cij}) \quad (9)$$

$$Pr\{GBC_{cij} = 1\} = \Lambda(\alpha + \beta DST_{ij} + \gamma F_{cij}) \quad (10)$$

Results of estimating these specifications are provided below, first for the specification (9) and then (10).

Table 12

| cause | Coef. | Std. Err. | z | p-value |
|---|---|---|---|---|
| DST | -0.095 | 0.017 | -5.57 | 0.00 |
| F | 0.592 | 0.157 | 3.94 | 0.00 |
| Constant | -0.254 | 0.066 | -4.03 | 0.00 |

Number of obs = 3,990
Pseudo R2 = 0.0068

Table 13

| beingcaus | Coef. | Std. Err. | z | p-value |
|---|---|---|---|---|
| DST | -0.093 | 0.017 | -5.49 | 0.00 |
| F | 0.226 | 0.154 | 1.47 | 0.14 |
| Constant | -0.254 | 0.066 | -3.83 | 0.00 |

Number of obs = 3,990
Pseudo R2 = 0.0087

We find that demand shocks are not significant, in contrast to the supply shocks which are significant at any level. Distance always decreases the probability that markets are connected.

To summarize, we find that shocks are transmitted from market to market (confirming integration), however we expected that the trading pair indicator would be more important. Finally, the direction of shock transmission comes from the supply shocks (from origin to destination).

**4. The Geographical Pattern of Market Integration**

In the context of the three measures of market connectedness, we analyze what they say about market integration across geographical space. We examine whether certain markets are more likely to be integrated with others, thereby identifying groups of markets that are jointly integrated as well as markets that are isolated.

First, we look at the average correlation for a given market.[11] The results are presented in the Table 14. Sorting the results by markets we can say which markets have the highest and lowest correlation on average. We see that the markets in the southern coastal areas of Ghana, many of which are large urban centers, are much more correlated with all other markets. At the same time, standard deviations indicate that this measure is imprecise, and the differences between markets are insignificant.

Table 14. Average Correlation

| Market | Average correlation | Standard deviation |
|---|---|---|
| Mankessim | 0.725 | 0.206 |
| Accra | 0.714 | 0.232 |
| Kumasi | 0.708 | 0.227 |
| Cape Coast | 0.693 | 0.285 |
| Sekondi | 0.690 | 0.268 |
| Koforidua | 0.688 | 0.233 |
| Ejura | 0.665 | 0.237 |
| Sunyani | 0.662 | 0.255 |
| Wa | 0.648 | 0.263 |
| Tema | 0.644 | 0.247 |
| Techiman | 0.641 | 0.234 |
| Ho | 0.620 | 0.246 |
| Obuasi | 0.611 | 0.268 |
| Bolgatanga | 0.595 | 0.348 |
| Tamale | 0.587 | 0.341 |

Our co-integration results show that the market that is co-integrated the most with other markets is Mankessim. Mankessim is a market on the Southern coast of Ghana, directly connected to Accra, the capital of Ghana, and Kumasi, the capital of Ashanti region, sometimes

[11] We average correlations across all market pairs that connect to this market and across all commodities.

called the second capital of the country. High in the list are also Koforidua, Ejura and Secondi, probably because of their direct connection to large markets.

The results for co-integration are reported in Table 15.

Table 15. Percentage of co-integrated series by market

| Market | # of series that can be tested for co-integration | # of co-integrated series | % of co-integrated series |
|---|---|---|---|
| Mankessim | 196 | 120 | 61.22 |
| Koforidua | 209 | 117 | 55.98 |
| Ejura | 186 | 111 | 59.68 |
| Sekondi | 209 | 111 | 53.11 |
| Tamale | 174 | 107 | 61.49 |
| Tema | 181 | 105 | 58.01 |
| Obuasi | 156 | 103 | 66.03 |
| Kumasi | 187 | 102 | 54.55 |
| Ho | 194 | 100 | 51.55 |
| Accra | 176 | 97 | 55.11 |
| Cape Coast | 191 | 97 | 50.79 |
| Wa | 191 | 90 | 47.12 |
| Bolgatanga | 184 | 88 | 47.83 |
| Techiman | 175 | 83 | 47.43 |
| Sunyani | 175 | 79 | 45.14 |

Table 16 summarizes Granger causality tests, showing for each market the number of markets that are Granger-caused by a market (column 2) and that Granger-cause that market (column 3).

Table 16. Granger-causality by market

| Market $i$ | # of series that are Granger-caused by prices in market $i$ | # of series that Granger-cause prices in market $i$ | $Column\ 2 + Column\ 3$ | $\frac{Column\ 2}{Column\ 3}$ |
|---|---|---|---|---|
| Bolgatanga | 100 | 66 | 166 | 1.52 |
| Tamale | 110 | 77 | 187 | 1.43 |
| Cape Coast | 99 | 87 | 186 | 1.14 |
| Sekondi | 90 | 82 | 172 | 1.10 |
| Tema | 106 | 101 | 207 | 1.05 |
| Kumasi | 108 | 105 | 213 | 1.03 |
| Obuasi | 106 | 107 | 213 | 0.99 |

| | | | | |
|---|---|---|---|---|
| Koforidua | 100 | 103 | 203 | 0.97 |
| Wa | 79 | 83 | 162 | 0.95 |
| Mankessim | 95 | 100 | 195 | 0.95 |
| Ho | 86 | 95 | 181 | 0.91 |
| Accra | 100 | 111 | 211 | 0.90 |
| Techiman | 94 | 107 | 201 | 0.88 |
| Ejura | 87 | 103 | 190 | 0.84 |
| Sunyani | 96 | 129 | 225 | 0.74 |

These markets are sorted by the ratio of "cause to being caused" by other markets, and the interpretation of this ratio is as follows. Markets with a high ratio of cause to being caused are likely to be the source of price shocks that spread across country. The highest ratio belongs to the most northern market in Ghana, Bolgatanga. This is the origin for most crops in Ghana. Surprisingly, another northern market, Wa, does not have high ratio of cause / being caused. We attribute this to the fact that Wa is more isolated than other markets.

Overall, we conclude that markets in Ghana are generally integrated but there do exist geographical areas (Wa, Ho) where markets are poorly integrated. We conjecture that the main reason is bad road infrastructure. More critically, markets that are closer to each other are much more likely to be integrated according to all criteria.

**5. Pass-Through Rates and Tests of the LOP**

Our tests above indicate that shocks are transmitted from market to market, indicating market integration. The law of one price, however, states that shocks should be perfectly transmitted from market to market. e.g., one dollar decrease in origin should lead to one dollar decrease in destination. In the literature, the coefficient of how much price shocks are transmitted from one market to another is called the 'pass-through rate'. We estimate this rate using the regression below for each trading pair (origin and destination):

$$P_{d,t} = \alpha + \beta t + \rho P_{o,t} + \varepsilon_t \quad (11)$$

We do so for each trading pair and take estimates $\rho_{od} = \hat{\rho}$ for each trading pair. If we have reverse traffic, i.e., records of transportation in both directions, we take the most popular direction. Under the law of one price, we would expect $\rho$ be equal to 1. The plot below provides a description of these pass through rates.

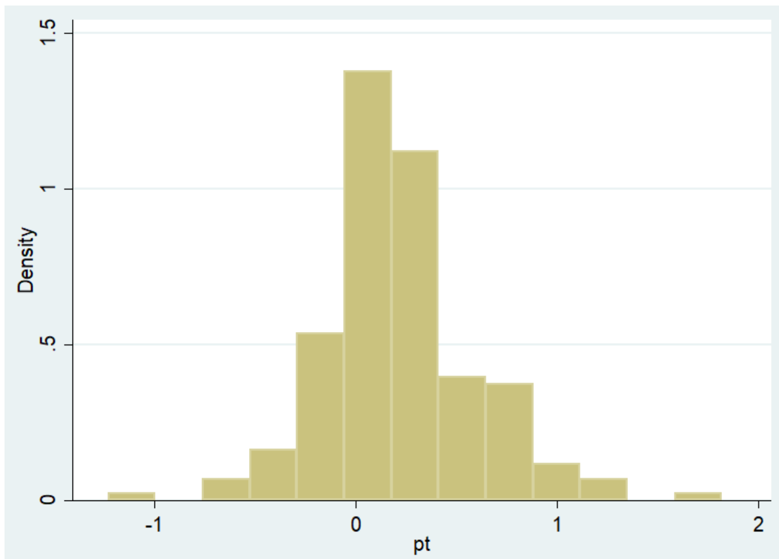


Figure 1. Pass Through Rates

The pass-through rates are clearly not clustered around the value consistent with the LOP (i.e. 1) implying that it is not the strongest description of our data as per this measure. Further, there is some mass in the distribution in the negative range which we attribute to measurement errors in the data.

We therefore next estimate a very straightforward regression specification to test the LOP and the deviation of these pass through rates from one. We regress destination market prices on time, origin market prices, transport costs, oil prices and commodity fixed effects:

$$P_{d,t} = \alpha + \beta t + \rho P_{o,t} + T_{cij} + OIL_t + \mu_c + \varepsilon_t \qquad (12)$$

Table 17. LOP Regression Results

| Variable | Estimate | Std. Err. |
|---|---|---|
| Constant | 0.6560 | 0.0778 |
| Time | -0.0022 | 0.0010 |
| Porigin | 0.2862 | 0.0160 |
| Costkg | 2.2139 | 0.1376 |
| Oil price | 0.0035 | 0.0004 |
| $R^2$ | 0.8401 | |

The estimates provided in Table 17 clearly demonstrate that the LOP does not hold as predicted by conventional competitive markets theory. While the fit of the specification is high, we would have expected the estimates to be consistent with the difference between destination and origin prices to be exactly a function of transport costs (i.e. transport costs having a coefficient of 1). We can conclude that the pattern of pass through rates and direct tests of the LOP given our unique data do not allow us to conclude that the LOP holds.

**5. Conclusion**

An important consideration in evaluating the extent to which market frictions exist in development contexts is whether simple relationships like the law of one price (LOP) hold. Empirical investigation of even such basic relationships is hampered by the fact that high quality data are generally not available, especially on transportation costs. In this paper, we collected such data and evaluated the extent to which markets in Ghana are integrated and the LOP holds. We found that generally a case can be made for integration: prices at different markets are correlated, most price series are co-integrated, and shocks at markets near production regions are transmitted to the markets near consumption regions. Moreover, shorter distance and our indicator of market pairs in which trade is known to take place, in general indicates for higher level of integration. This latter feature is important in the Ghanaian context given our data on numerous perishable quantities.

The LOP, however, is weakly supported at best. Our data indicates that shocks are transmitted at much lower rate than one to one as suggested by LOP.

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