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A spatio-temporal analysis of agricultural prices: An application to Colombian data*

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Abstract

This paper studies whether the geographical separation of markets constitutes a factor that helps explain the dynamics of agricultural prices. To do this, we employ a highly disaggregated dataset for Colombia that consists of weekly observations on wholesale prices for 18 agricultural products traded in markets scattered around the country. The sample period spans for almost a decade. According to our results, which are based on generalised impulse response functions, distance (and thus transportation costs) is a factor that helps explain the speed at which prices adjust to shocks in other locations, thus confirming that price adjustments take longer for markets farther apart.

JEL Classification: O18; Q13; R12.

Keywords: Price analysis, market integration, agriculture, Colombia.

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1 Introduction

Testing whether spatially separated markets are integrated is a topic that has received a great deal of attention over the years; see Fackler and Goodwin (2001) for a literature review. As indicated by Barrett (1996), spatial market integration is important because it helps define the extent of a market, and this, in turn, is essential for sectoral or macroeconomic analysis. The idea of spatial market integration is often expressed as the law of one price. This law asserts that in the presence of a competitive market structure, and in the absence of barriers to trade, such as transport costs and tariffs, prices of identical products sold in different markets will be the same when expressed in the same currency; see Froot and Rogoff (1995). The premise underlying this law is that market participants exploit goods-market arbitrage opportunities by purchasing (selling) a good in one market and selling (purchasing) it in another. Thus, no arbitrage profits are left unexploited by market participants. As a result, in spatially integrated markets a shock to the price in one market should propagate to other market's price as well, so that prices become dependent from each other. By contrast, the failure of prices of identical products to equalise between markets can be viewed as a sign that those markets are not fully spatially integrated or, put another way, that they are segmented (or fragmented). In such a case, "cross-sectional (...) aggregation of demand and supply loses its logical foundation" [Barrett (1996), p. 826].

This paper aims to study spatial price linkages in Colombian agricultural markets. The Colombian case is interesting because the diverse geographical and topographical conditions of the country have played a key role in defining regions that exhibit their own cultural and economic features.[1] Within this context, transportation costs may be substantial either because of the lack of an adequate transport and communications infrastructure, or because of the presence of factors that may

[1]Indeed, Colombia is often characterised by a "centre-periphery" dichotomy, where the central region (which includes the three main cities of the country, namely Bogotá, Medellín and Cali) comprises the largest concentration of population, economic activity and infrastructure; see Galvis (2007).

disrupt (or even interrupt) the normal functioning of the existing transportation network for extended periods of time (e.g. landslides caused by weather conditions). As a result, it is quite possible that a highly perishable agricultural good ends up being produced only for the purposes of local consumption.

The analysis of agricultural market integration has not been a subject of extensive research in Colombia. An exception is Ramírez (1999), who studies eight products in twelve cities, using annual data over the period 1928 to 1990. Ramírez relates the marked decline in the coefficients of variation of city price differentials during the 1930s, a decade characterised by the rapid expansion of the rail network, to the development of transport infrastructure, and concludes that in Colombia the lack of an adequate transportation network is an important factor restricting the integration of agricultural markets. In another study for Colombia, Iregui and Otero (2011) apply panel stationarity tests to monthly price data (January 1999 – December 2007) for fifty-four food products in thirteen cities, and find that i.) market integration is favoured when cities are similar in terms of both their population and economic sizes; and ii.) price adjustment to exogenous shocks or innovations is much faster the more perishable a food product is.

Our examination of spatial market integration is based on impulse response functions. Other studies that have used this econometric tool of analysis include, inter alia, Brorsen et al. (1985), Mjelde and Paggi (1989), Goletti and Babu (1994), Goodwin et al. (1999) and Williams and Bewley (1993). Fackler and Goodwin (2001) point out that a common criticism of these papers is that their results are based on the computation of orthogonalised impulse responses and these, in turn, depend on the adoption of a specific order of the variables in the system. In order to avoid this limitation, the modelling approach that we adopt in this paper relies on the Pesaran and Shin (1998) generalised impulse response functions, which are invariant to the order of the variables in the system. In a subsequent stage of our analysis, the resulting generalised impulse responses are used to obtain an estimate of the speed at which prices adjust to exogenous shocks (measured by the half-life of a shock). An important feature of our econometric modelling strategy is that we explicitly consider the role played by the distance between the locations where the goods are sold (and hence transportation costs), as a factor that helps explain the speed at which prices adjust to shocks in geographically separated markets. The specific hypothesis we aim to test is whether the price response in market i to price shocks in market j is positively related to the distance between i and j.

To carry out the empirical analysis, we take advantage of a large and unique database: highly disaggregated price data for 18 non-processed agricultural products sold in several wholesale markets, which are scattered around the country. The data have been collected on a weekly frequency over the period 01/04/2002 through 03/18/2011. It is worth noting that the product-by-product market-level high-frequency price data used in this paper can be viewed as a three-dimensional panel, based on the product, market and time dimensions. The distinctive feature of the data is that prices are in absolute terms, that is they are not representative price indices. This offers several important advantages compared to other studies available in the literature. First, we can perform comparisons based on identical goods rather than on product groups that consist of similar products. Thus, while the consumer price index includes, for instance, the product group labelled "potato", in this paper we analyse two specific potato varieties, namely "criolla" and "pastusa".[2] Second, prices are collected at the specific markets where products are sold, avoiding the risk of obtaining biased results due to market aggregation. In other words, instead of using price data for a product traded in the city of Cali, we use price information collected at the markets of Cavasa and Santa Elena, which are located in different areas of the city of Cali. Third, we expect that the high-frequency nature of a dataset that spans for almost a decade would allow us to capture rich dynamic patterns, and further our understanding of the time profile of shocks both over time and across markets.

[2] As another illustration of the product heterogeneity issue, the consumer price index includes the category "other fresh fruits", which is not particularly useful for the level of specificity that we wish to accomplish in this paper.

The plan of the paper is as follows. Section 2 presents a brief review of the relevant literature. Section 3 describes the dataset, investigates the time-series properties of the price series under consideration, and reports the results of the empirical analysis. Section 4 offers some concluding remarks.

2 Brief review of relevant literature

Several authors have studied the idea that the speed at which the price in one market adjusts to exogenous shocks in other markets is related to the distance between the markets. Engel and Rogers (1996) use consumer price data from 23 North American cities (14 in the United States and 9 in Canada) for 14 disaggregated consumer price indexes spanning over the period June 1978 through December 1994. They find that both distance and the existence of a border between countries matter for relative price variability. Parsley and Wei (1996) collect price data, from January 1975 to April 1992, on 51 traded and nontraded goods and services in 48 cities of the United States. They provide evidence that price convergence rates are slower for cities farther apart. In subsequent work, Parsley and Wei (2001) construct a three-dimensional panel data set of prices on 27 traded goods, over the period 1976Q1 through 1997Q4 (i.e. 88 quarters), across 96 cities in the United States and Japan. Their results indicate that the distribution of intra-national relative prices is markedly less volatile and on average closer to zero, than the comparable distribution for international relative prices. Baba (2007) also reaches the conclusion that price dispersion is related to geographical distance, by using panel data on monthly prices for 192 goods, that cover 47 cities in Japan and 36 cities in Korea, over the period 1999–2001.

Fackler and Goodwin (2001) survey more than sixty empirical studies on agricultural market integration. According to their method of analysis, these studies can be classified as those that have employed i.) simple correlation analysis; ii.) static regression models; iii.) dynamic regression models; iv.) vector autoregressive (VAR) models (including Granger causality tests, impulse response analysis and cointegration analysis); and v.) regime-switching models. Fackler and Goodwin point out that although the overwhelming majority of authors have focused on whether or not markets exhibit spatial integration, only a reduced number of them have explicitly evaluated the determinants of market integration, in particular the role played by distance as a factor that may affect the speed at which prices adjust to shocks. In the following part of this section we review some of the papers that belong to this (much smaller) second group.

Brorsen et al. (1985) present an early application of VAR models to study spatial and temporal relationships among selected grain markets in the United States. The authors use weekly price data for corn, sorghum and soybeans in Kansas City (a major domestic market), Texas High Plains (a nearly self-sufficient producing and consuming region), and Houston (an export market). Brorsen et al. point out that given that Kansas City is the centre for the interstate trade of grains and soybeans originating from the states of Iowa, Kansas, Missouri and Nebraska, Kansas City prices would be expected to have more impact on the prices of the other two locations than the other way around. Although they do not formally test for the effect of distance on price adjustment, they conclude that transportation may be a factor that reduces arbitrage activities and thus leads to slower adjustments in prices (this conclusion is based on results derived from the computation of multiplier effects that quantify the impact of one price on another). Another illustration, although not for an agricultural product, is Williams and Bewley (1993), who postulate a four-dimensional VAR model to study price arbitrage between cattle auctions in Queensland. The price series used by these authors refer the so-called Jap-Ox cattle market. This type of cattle is almost exclusively exported to Japan, and therefore meets specific requirements in terms of minimum weight, fat and muscle score (which allows them to avoid potential problems of cattle heterogeneity). The prices are defined by the following cattle auctions: i.) Monday meeting of Rockhampton saleyard; ii.) Tuesday meeting of Toowoomba saleyard; iii.) Wednesday meeting of Toowoomba saleyard and iv.) Wednesday meeting of Townsville saleyard. Although the authors do not carry out a formal test for the effect of distance, they observe that Townsville is the only auction market that reacts significantly and in a direct manner to its own past changes, and indicate that this finding reflects the fact that this market is geographically isolated. Prices in the other three auction markets appear to react not only to themselves but also to each other.

Gardner and Brooks (1994) and Goodwin et al. (1999) study spatial market integration after the collapse of the former Soviet Union. Gardner and Brooks (1994) study food price differentials using data on six products traded in fourteen cities in the Volga region. The products are beef, potatoes, sugar, vegetable oil, apples and eggs, and the price data were collected on a weekly frequency from February 1992 to April 1993. Their results indicate that price differentials can be explained by regional policy, measured by a dummy variable that takes the value of one if two cities are in the same "oblast" (or province), but not by the distance between markets. Goodwin et al. (1999) use weekly retail price data for four food products (i.e. eggs, milk, vegetable oil and potatoes) in five cities (i.e. Moscow, St. Petersburg, Krasnodar, Arkhangelsk, and Vladivostok) spanning from June 1993 to December 1994 (although the authors report that for some cities not all prices were available). Goodwin et al. point out that their results reveal the existence of spatial linkages not only for cities within the same oblast, but also among cities in different oblasts.

Goletti et al. (1995) analyse rice market integration in Bangladesh, using weekly wholesale price data over a period of three years (between 1989 and 1992) for sixty-four district headquarters. Goletti et al. find that distance has a negative effect on market integration, and argue that as transportation costs between markets farther apart increase, trade opportunities with closer markets start to be explored. Other variables that are also found to affect market integration are telephone density, transportation strikes and production shocks, where the latter consist mostly of adverse weather conditions and pest attacks. Goletti and Babu (1994) examine the extent of maize markets integration in Malawi using monthly price data collected at eight main locations: Blantyre, Lilongwe, Mzuzu, Zomba, Karonga, Nkhotakota, Msangu and Kamuzu (the sample period is January 1984 – December 1991). According to Goletti and Babu, even though market liberalisation and price stabilisation policies have served to enhance market integration, the extent of it will remain low unless further developments on infrastructure and communications take place.

3 Empirical analysis

3.1 Data

The dataset, obtained from the Servicio de Información Agropecuaria assembled by the Corporación Colombia Internacional (CCI), consists of weekly observations on wholesale prices for 18 agricultural products sold in markets scattered around the country. The products are (where the number of markets in which they are sold appears in parentheses): cucumber (22), coriander (21), tamarillo (20), red pepper (18), blackberry (17), celery (17), plantain (17), tomato (17), lettuce (16), snap pea (16), sweet corn (15), green bean (13), potato "pastusa" variety (13), spring onion (13), passion fruit (13), granadilla (12), naranjilla (12), and potato "criolla" variety (12). The sample period runs from 01/04/2002 to 03/18/2011, for a total of 481 time observations. The rationale for using the products mentioned above over this time period is based on the need to acquire a consistent dataset that guarantees the largest number of markets where each product is traded; a more detailed description of the dataset used in our analysis is provided in Appendix 1.[3] All price series are measured in Colombian pesos per kilo, and are subject to the logarithmic transformation; see Figure 1 for plots of the price series under consideration.

[3]The price series were provided electronically by CCI. However, they can also be downloaded using the data retrieval tools available at *www.cci.org.co/ccinew/SIA.html*.

3.2 Preliminary data analysis

We begin our empirical investigation with a preliminary analysis of the time series properties of the agricultural prices under consideration.[4] The order of integration of the price information is investigated using the augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979). This test continues to be one of the most commonly applied testing procedures for non-stationarity probably due to the fact that it is straightforward to compute. However, a common criticism of the ADF test is that it exhibits disappointing power properties, as reported, for instance, by DeJong et al. (1992). Thus, we also employ more powerful modifications of the ADF unit root test, namely the ADF_{max} test of Leybourne (1995), who suggests taking the maximum of two ADF test statistics calculated using both forward and reversed data, as well as the GLS-ADF test of Elliot et al. (1996), who use conditional generalised least squares.

Table 1 reports for each product the number of individual prices that are found to be stationary, based on the ADF and ADF_{max} test statistics. As can be seen from the table, there are only very few instances where we fail to reject the null of non-stationarity at the 10% significance level. This finding is irrespective of the number of lags of the dependent variable included in the test regressions, denoted p. Qualitatively similar results are obtained when employing the GLS-ADF test and also when a trend term is included in the test regression (these results are not reported here to save space).

Broadly speaking, the picture that emerges from applying the univariate ADF, ADF_{max} and GLS-ADF unit root tests is that the individual price series under consideration can be best described as stationary, i.e. $I \sim (0)$, processes during the period of analysis. This conclusion appears robust to the augmentation order of the test regressions, and irrespective of the deterministic components that are considered.

[4] All results were obtained using the econometric softwares RATS version 8.1 and EViews version 7.2.

3.3 Speed of price adjustment and distance

In this section we examine the dispersion of prices over time and across markets. The specific question we aim to answer is whether the geographical separation of markets constitutes a factor that helps explain agricultural price dynamics. Our empirical modelling exercise is based on the estimation of VAR models for each product under consideration. The use of a VAR-based modelling approach can be justified on two grounds. First, the results of the preliminary analysis of the data supported the view that the prices under consideration could be best characterised as stationary series over the study period. The finding of stationarity precludes the possibility of cointegrating relationships, and therefore makes the data suitable for modelling within a standard VAR framework. Second, it may prove difficult to identify for every product a specific market, say k, that is dominant in the sense that shocks to it propagate to the other markets, while shocks to the remaining markets have little effect on k. Such an analysis is further complicated by the fact that for some products we have price data in two markets of the same city.[5] Thus, adopting a VAR approach offers the advantage of treating all prices as potentially endogenous variables.

Once VAR models have been estimated, it is possible to examine the speed at which prices adjust to exogenous shocks or innovations, using half-life estimates based on impulse response functions. It is well known that in the case of a simple AR(1) process the half-life of a shock can be estimated using the formula $-\frac{\ln(2)}{\ln(\hat{\delta})}$, where $\hat{\delta}$ denotes the estimated value of the autoregressive coefficient.[6] However, for more complicated processes, such as a higher order AR process or an ARMA process, the previous formula is no longer valid, and thus impulse response functions should be preferred; see, for instance, Goldberg and Verboven (2005), Morshed et al. (2006) and Seong et al. (2006). Taking this aspect into consideration, we

[5]Indeed, notice for instance that several products are traded in the markets of Cavasa and Santa Elena,both ofwhich are located in different areas of the city of Cali.

[6]Parsley and Wei (1996) extend the basic AR specification by including distance as an additional regressor, so that the effect of transportation costs can be estimated simultaneously with the dynamic model of price adjustment.

employ the generalised impulse response functions (GIRF) developed by Pesaran and Shin (1998), which offer the advantage of being invariant to the way shocks in the underlying VAR model are orthogonalised. Thus, GIRF provide an extension to the traditional impulse response analysis, which is sensitive to the ordering of the variables included in the VAR; see e.g. Lütkepohl (2005).

An important initial stage in the analysis of VAR models is the selection of the optimal lag length. This involves selecting an order high enough such that one can be reasonably confident that the optimal order will not exceed it. Bearing in mind that for some products the sample size (481 observations) might turn out to be small relative to the number of variables in the VAR (for instance, cucumber and coriander are traded in 22 and 21 markets, respectively), we set 4 lags as the maximum order of the VAR models, and use the Schwarz information criterion (SIC) to select the optimal order of the models. Another model selection criterion commonly used in the econometrics literature is the Akaike information criterion (AIC). Although it may happen that the AIC picks up the same optimal lag order selected by the SIC, when this does not occur the model order selected with the latter tends to be smaller than the one selected with the former (or, in other words, SIC favours models containing fewer parameters). Hence, here we opt for the more parsimonious specification that results from using the SIC (qualitatively similar results are obtained when using the AIC to select the optimal lag length).

Having selected the optimal order of the VAR models, for each product we calculate the associated GIRF that describe the time profile of the effect of a shock observed in the respective market, as well as that of shocks that originate in a different market (shocks are measured by one standard deviation). For each market the resulting lag weights are then normalised so that they add up to one, and the half-life of a shock is calculated as the number of weeks required for 50 per cent (or the first half) of the adjustment to take place. Notice that there is no need for half-lives to be symmetric; that is, the half-life of a shock to price in market i on the price in market j, is not necessarily the same as the half-life of a shock to price in market j on the price in market i.

Table 2 compares average half-life estimates from GIRF for shocks observed in the respective market (own shock) with those that originate in a different market. The results reported in this table highlight an interesting spatial dimension on the dispersion of prices. Indeed, if we consider for instance the case of celery, the average half-life estimate of an own shock is approximately 8 weeks. By contrast, for the same product the average half-life estimate of the same shock on other markets takes much longer to dissipate, that is approximately 12 weeks. The difference between the latter and the former is positive and statistically different from zero. Similar findings are observed for the other products.

The results reported in Table 2 suggest that distance might be a factor that helps explain intermarket price dynamics. To formally test whether price adjustments take longer for markets farther apart, it would be ideal to have information on the amount of time it takes for a product to reach a specific destination. Unfortunately, such information is not available for Colombia. In order to overcome this limitation, we use Google Maps, the web mapping service application provided by Google, to estimate the distance between market pairs i and j (denoted D_{ij}). We are aware that by using this measure of distance, that is based on satellite information, we are implicitly assuming that the quality of the road transportation network is identical all over the country, which might be a strong assumption in the case of a developing country such as Colombia. Bearing in mind this limitation, for every product, k, we estimate a regression model where the estimated half-life of a shock to price in market i on the price in market j, H_{ij}, is regressed against an intercept and the (logarithm) of the distance between i and j, $\ln D_{ij}$. More formally:

$$H_{ij}^{(k)} = \beta_1^{(k)} + \beta_2^{(k)} \ln D_{ij} + \varepsilon_{ij}^{(k)}, \tag{1}$$

where in the case of own-price shocks, i.e. when $i = j$, we set $D_{ij} = 1$ so that $\ln D_{ij} = 0$.[7]

[7]We also estimated an alternative functional form specification, in which distance entered the regression model as a natural number and the square of it. However, in this case we found a modest

The regression model postulated in Eq. (1) is estimated by ordinary least squares (OLS) and then the White (1980) test for heteroskedasticity is performed. The results reported in Table 3 indicate that the null hypothesis of homoskedasticity is not rejected at a 10% significance level in the following ten products: tamarillo, red pepper, blackberry, plantain, tomato, lettuce, snap pea, green bean, passion fruit and potato "criolla" variety. In all cases except one, the estimate of the coefficient associated to $\ln D_{ij}$ has the expected positive sign and is statistically different from zero (the exception is tomato where the estimated coefficient is positive but not statistically different from zero). These findings confirm the view that the rates of convergence are slower for markets farther apart.

Regarding cucumber, coriander, celery, sweet corn, potato "pastusa" variety, spring onion, granadilla and naranjilla, heteroskedasticity-consistent standard errors are reported below the estimated coefficients. However, in an attempt to find an appropriate transformation to eliminate from the data this heteroskedasticity, we also consider weighted least squares (WLS) estimation. To implement this estimation method we divide both the dependent and explanatory variables (including the intercept term) by an estimate of the standard deviation of the half-life time, denoted $\hat{s}(\hat{H}_{ij})$, which in turn may be obtained using the bootstrap method.[8] For the purposes of this paper, the bootstrap estimates of $\hat{s}(\hat{H}_{ij})$ are computed using Hall's studentized method, based on 1000 bootstrap replications; see e.g. Lütkepohl (2005) for a description of this method. Table 4 summarises the results of estimating Eq. (1) by WLS. According to our findings, the estimated coefficient associated to $\ln D_{ij}$ is positive and significant in all eight cases. Moreover, the White (1980) test for heteroskedasticity applied to the residuals of the transformed models now reveals that they are homoskedastic.

increase in the explanatory power of the regressions and, in most cases, the estimated coefficient associated to the square of distance was not found to be statistically different from zero.

[8]Transforming a model to correct for heteroskedasticity often results in a regression that does not include an intercept term, and as a result care must be exercised when interpreting statistics such as the R^2. To avoid these difficulties, it is customary practice to include an intercept term in the transformed model; see e.g. Kennedy (2008), pp.126.

For some products, the coefficients of determination of the estimated models suggest that there may well be additional factors that help explain the variability of the dependent variable. For instance, Goletti et al. (1995) consider factors such as deficiencies in transportation, communication and commercialisation; these factors could be measured, for instance, by the density of paved roads, the density of (mobile) telephones, and the density of bank branches, respectively, where these density measures should ideally refer to the areas of influence of the markets. However, prices are the only information readily available at the level of disaggregation of our analysis (recall that prices refer to individual products sold in a specific location). Thus, any formal attempt to examine the possible effect of factors other than distance on spatial market integration would be at the expense of aggregating the dataset (either across products, markets or over time), and this is an aspect that is left for future research.

4 Concluding remarks

This paper applies generalised impulse response analysis to formally examine whether the price response in a market to price shocks in other markets is positively related to the distance between those markets. The empirical analysis relies on the use of a highly disaggregated dataset, which consists of weekly price information on individual products, sold in a specific location, over a period of almost a decade. The dataset used in the analysis offers several advantages, some of which are not present in the existing literature, including: i.) product heterogeneity is avoided; ii.) bias due to aggregation across markets is limited; and iii.) rich dynamic patterns may be captured because of the relatively long data span.

The results reveal an interesting spatial dimension on the diffusion of prices in Colombian agricultural markets, in the sense that distance (and thus transportation costs) is a factor that helps explain the speed at which prices adjust to shocks in other locations. This finding highlights the role played by transaction costs as a factor that may enhance market integration. Of course, we are aware that factors other than distance (e.g. deficiencies in transportation, communication and commercialisation) might also help explain the dynamics of agricultural price adjustment. However, we argue that these additional factors can only be formally incorporated into the analysis at the expense of aggregating the dataset, either along the product, market or time dimensions, and this is an aspect that is not pursued in the present work.

References

Baba, C. (2007). Price dispersion across and within countries: The case of Japan and Korea. *Journal of the Japanese and International Economies 21*, 237–259.

Barrett, C. B. (1996) Market analysis methods: Are our enriched toolkits well suited to enlivened markets? *American Journal of Agricultural Economics 78*, 825–829.

Brorsen, B. W., J.-P. Chavas, W. R. Grant, and A. W. Ngenge (1985). Spatial and temporal relationships among selected U.S. grain markets. *North Central Journal of Agricultural Economics 7*, 1–10.

DeJong, D. N., J. C. Nankervis, N. E. Savin, and C. H. Whiteman (1992). The power problems of unit root tests in time series with autoregressive errors. *Journal of Econometrics 53*, 323–343.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association 74*, 427–431.

Elliot, G., T. J. Rothenberg, and J. H. Stock (1996). Efficient tests for an autoregressive unit root. *Econometrica 64*, 813–836.

Engel, C. and J. T. Rogers (1996). How wide is the border? *American Economic Review 86*, 1112–1125.

Fackler, P. L. and B. K. Goodwin (2001). Spatial price analysis. In B. Gardner and G. Rausser (Eds.), *Handbook of Agricultural Economics. Volume I*, pp. 971–1024. Amsterdam: Elsevier Science.

Froot, K. and K. Rogoff (1995). Perspectives on PPP and long-run real exchange rates. In G. M. Grossman and K. Rogoff (Eds.), *Handbook of International Economics. Volume III*, pp. 1647–1688. Amsterdam: North Holland.

Galvis, A. (2007). La topografía económica de colombia. In J. Bonet (Ed.), *Geografía Económica Y Análisis Espacial En Colombia*, pp. 9–45. Colombia: Banco de la República.

Gardner, B. L. and K. M. Brooks (1994). Food prices and market integration in Russia: 1992-93. *American Journal of Agricultural Economics 76*, 641–646.

Goldberg, P. and F. Verboven (2005). Market integration and convergence to the law of one price: Evidence from the european car market. *Journal of International Economics 65*, 49–73.

Goletti, F., R. Ahmed, and N. Farid (1995). Structural determinants of market integration: The case of rice markets in Bangladesh. *The Developing Economies 33*, 185–202.

Goletti, F. and S. Babu (1994). Market liberalization and integration of maize markets in Malawi. *Agricultural Economics 11*, 311–324.

Goodwin, B. K., T. J. Greenes, and C. McCurdy (1999). Spatial price dynamics and integration in Russian food markets. *Policy Reform 3*, 157–193.

Iregui, A. M. and J. Otero (2011). Testing the law of one price in food markets: Evidence for Colombia using disaggregated data. *Empirical Economics 40*, 269–284.

Kennedy, P. (2008). *A Guide to Econometrics.* Malden MA: Wiley-Blackwell.

Leybourne, S. (1995). Testing for unit roots using forward and reverse Dickey-Fuller regressions. *Oxford Bulletin of Economics and Statistics 57*, 559–571.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis.* Heidelberg: Springer Verlag.

MacKinnon, J.G. (1991). Critical values for cointegration tests. In R.F. Engle and C.W.J. Granger (Eds.), *Long-run Economic Relationships: Readings in Cointegration*, pp. 267–276 Oxford: Oxford University Press.

Mjelde, J. W. and M. S. Paggi (1989). An empirical analysis of interregional price linkages. *Journal of Regional Science 29*, 171–190.

Morshed, A., S. Ahn, and M. Lee (2006). Price convergence among indian cities: A cointegration approach. *Journal of Asian Economics 17*, 1030–1043.

Parsley, D. and S.-J. Wei (1996). Convergence to the law of one price without trade barriers or currency fluctuations. *Quarterly Journal of Economics 108*, 1211–1236.

Parsley, D. C. and S.-J. Wei (2001). Explaining the border effect: The role of exchange rate variability, shipping costs, and geography. *Journal of International Economics 55*, 87–105.

Pesaran, M. H. and Y. Shin (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters 58*, 17–29.

Ramírez, M. (1999). *On Infrastructure and Economic Growth.* Ph. D. thesis, University of Illinois at Urbana-Champaign.

Seong, B., A. M. Morshed, and S. K. Ahn (2006). Additional sources of bias in half-life estimation. *Computational Statistics and Data Analysis 51*, 2056–2064.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and direct test for heteroskedasticity. *Econometrica 48*, 817–838.

Williams, C. H. and R. A. Bewley (1993). Price arbitrage between Queensland cattle auctions. *Australian Journal of Agricultural Economics 37*, 33–55.

Table 1: Number of rejections of the unit root test statistics

Product	ADF			$\text{ADF}_{\max}$		
	$p=1$	$p=2$	$p=3$	$p=1$	$p=2$	$p=3$
Cucumber	22 of 22	22 of 22	22 of 22	22 of 22	22 of 22	22 of 22
Coriander	21 of 21	21 of 21	21 of 21	21 of 21	21 of 21	21 of 21
Tamarillo	20 of 20	20 of 20	20 of 20	20 of 20	20 of 20	20 of 20
Red pepper	18 of 18	17 of 18	17 of 18	18 of 18	18 of 18	18 of 18
Blackberry	17 of 17	17 of 17	17 of 17	17 of 17	17 of 17	17 of 17
Celery	17 of 17	17 of 17	17 of 17	17 of 17	17 of 17	17 of 17
Plantain	12 of 17	13 of 17	12 of 17	13 of 17	12 of 17	13 of 17
Tomato	17 of 17	17 of 17	17 of 17	17 of 17	17 of 17	17 of 17
Lettuce	15 of 16	15 of 16	15 of 16	16 of 16	15 of 16	15 of 16
Snap pea	16 of 16	16 of 16	16 of 16	16 of 16	16 of 16	16 of 16
Sweet corn	15 of 15	15 of 15	15 of 15	15 of 15	15 of 15	15 of 15
Green bean	13 of 13	13 of 13	13 of 13	13 of 13	13 of 13	13 of 13
Potato “pastusa” variety	13 of 13	13 of 13	13 of 13	13 of 13	13 of 13	13 of 13
Spring onion	13 of 13	12 of 13	12 of 13	13 of 13	13 of 13	13 of 13
Passion fruit	13 of 13	13 of 13	13 of 13	13 of 13	13 of 13	13 of 13
Granadilla	12 of 12	12 of 12	12 of 12	12 of 12	12 of 12	12 of 12
Naranjilla	9 of 12	8 of 12	9 of 12	12 of 12	12 of 12	12 of 12
Potato “criolla” variety	12 of 12	12 of 12	12 of 12	12 of 12	12 of 12	12 of 12

Notes: The test regressions include an intercept term, and are augmented using (p) lags of the dependent variable. Each cell in the table indicates the number of times for which the corresponding test statistic is rejected at a 10% significance level. In the case of the ADF(p) test the critical values are taken from MacKinnon (1991), while for the $\text{ADF}_{\max}(p)$ test we use Leybourne (1995).

Table 2: Average half-life estimates from GIRF

Product	Shock in own market	Shock in other market	Diff.	(se)	t-stat.
Cucumber	4.409	6.043	1.634	(0.685)	2.386
Coriander	4.381	10.879	6.498	(2.468)	2.633
Tamarillo	10.300	13.892	3.592	(1.134)	3.168
Red pepper	7.056	10.608	3.552	(1.249)	2.844
Blackberry	7.118	11.684	4.566	(1.580)	2.890
Celery	7.882	11.875	3.993	(1.583)	2.522
Plantain	14.176	29.504	15.327	(3.108)	4.932
Tomato	4.294	5.026	0.732	(0.258)	2.836
Lettuce	8.313	11.821	3.508	(1.876)	1.870
Snap pea	6.188	8.938	2.750	(0.463)	5.940
Sweet corn	6.000	16.810	10.810	(1.892)	5.713
Green bean	2.923	3.788	0.865	(0.294)	2.943
Potato "pastusa" variety	13.308	15.712	2.404	(0.837)	2.872
Spring onion	7.692	11.372	3.679	(1.298)	2.835
Passion fruit	8.692	13.494	4.801	(1.405)	3.417
Granadilla	4.250	5.439	1.189	(0.879)	1.353
Naranjilla	15.333	23.553	8.220	(2.489)	3.302
Potato "criolla" variety	8.417	11.667	3.250	(0.911)	3.568

Table 3: OLS estimates of the relationship between half-life and distance

Product	Const.	$\ln D_{ij}$	Obs.	R^2	F_{hetero}	p-value
Cucumber	5.573	0.072	484	0.001	3.262	[0.039]
(*hcse*)	(0.464)	(0.081)				
Coriander	4.508	1.115	441	0.021	2.339	[0.098]
(*hcse*)	(1.056)	(0.221)				
Tamarillo	11.317	0.445	400	0.017	0.807	[0.447]
(*se*)	(0.754)	(0.141)				
Red pepper	7.177	0.629	324	0.032	1.484	[0.228]
(*se*)	(0.641)	(0.131)				
Blackberry	7.408	0.757	289	0.034	1.703	[0.184]
(*se*)	(0.820)	(0.157)				
Celery	5.833	1.092	289	0.070	6.473	[0.002]
(*hcse*)	(0.855)	(0.184)				
Plantain	13.321	2.859	289	0.122	2.203	[0.112]
(*se*)	(1.581)	(0.301)				
Tomato	4.831	0.031	289	0.002	2.101	[0.124]
(*se*)	(0.216)	(0.043)				
Lettuce	8.320	0.616	256	0.018	0.796	[0.452]
(*se*)	(1.053)	(0.211)				
Snap pea	5.508	0.654	256	0.253	0.603	[0.548]
(*se*)	(0.406)	(0.078)				
Sweet corn	6.245	1.942	225	0.173	2.922	[0.056]
(*hcse*)	(0.982)	(0.189)				
Green bean	2.509	0.235	169	0.150	2.008	[0.138]
(*se*)	(0.240)	(0.045)				
Potato "pastusa" variety	13.256	0.432	169	0.063	3.703	[0.027]
(*hcse*)	(0.817)	(0.144)				
Spring onion	7.395	0.716	169	0.075	5.815	[0.004]
(*hcse*)	(0.553)	(0.123)				
Passion fruit	7.155	1.195	169	0.157	0.055	[0.947]
(*se*)	(1.097)	(0.208)				
Granadilla	4.765	0.121	144	0.005	3.317	[0.039]
(*hcse*)	(0.499)	(0.106)				
Naranjilla	17.787	1.063	144	0.041	9.540	[0.000]
(*hcse*)	(1.868)	(0.409)				
Potato "criolla" variety	8.029	0.692	144	0.133	1.088	[0.340]
(*se*)	(0.640)	(0.123)				

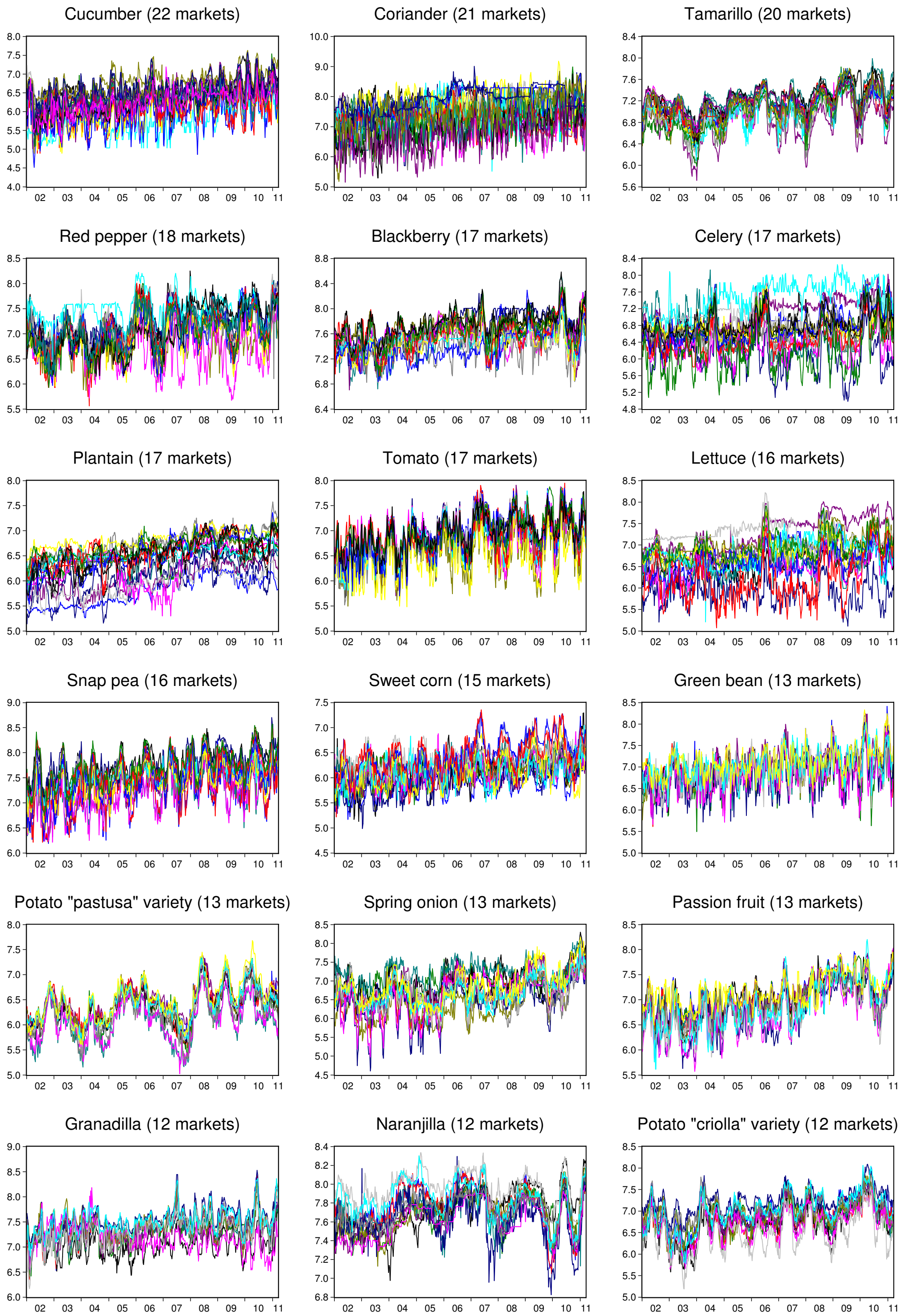
Notes: Estimation default and heteroskedasticity-consistent standard errors are (*se*) and (*hcse*), respectively. F_{hetero} is the White test for heteroskedasticity (with cross terms).

Table 4: WLS estimates of the relationship between half-life and distance

Product	Const.	$\frac{1}{\hat{s}(\hat{H}_{ij})}$	$\frac{\ln D_{ij}}{\hat{s}(\hat{H}_{ij})}$	Obs.	R^2	$F_{stat.}$	p-value	F_{hetero}	p-value
Cucumber	0.759	1.580	0.547	484	0.546	289.634	[0.000]	1.363	[0.237]
(se)	(0.056)	(0.138)	(0.040)						
Coriander	1.020	1.025	0.507	441	0.602	331.639	[0.000]	1.815	[0.109]
(se)	(0.051)	(0.047)	(0.046)						
Celery	0.445	2.201	1.194	289	0.703	337.81	[0.000]	1.845	[0.104]
(se)	(0.061)	(0.180)	(0.062)						
Sweet corn	1.051	1.715	0.951	225	0.357	61.569	[0.000]	1.341	[0.248]
(se)	(0.135)	(0.218)	(0.127)						
Potato "pastusa" variety	-0.059	6.934	1.690	169	0.833	414.763	[0.000]	1.728	[0.131]
(se)	(0.072)	(0.579)	(0.108)						
Spring onion	0.991	1.868	1.171	169	0.48	76.738	[0.000]	1.286	[0.272]
(se)	(0.119)	(0.294)	(0.129)						
Granadilla	0.954	2.089	0.332	144	0.559	89.274	[0.000]	1.460	[0.207]
(se)	(0.120)	(0.212)	(0.066)						
Naranjilla	0.481	2.478	2.020	144	0.466	61.437	[0.000]	1.118	[0.354]
(se)	(0.131)	(0.513)	(0.213)						

Notes: Standard errors in parentheses. $F_{stat.}$ is the joint test of the significance of the slope coefficients. F_{hetero} is the White test for heteroskedasticity (with cross terms).

Figure 1: Plot of the (logarithm) of the price series



Appendix 1

Market (City-Department)	Product																	
	a	*b*	*c*	*d*	*e*	*f*	*g*	*h*	*i*	*j*	*k*	*l*	*m*	*n*	*o*	*p*	*q*	*r*
El Retiro (Armenia-Quindío)							✓				✓							
Mercar (Armenia-Quindío)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Centroabastos (Bucaramanga-Santander)	✓		✓	✓	✓		✓			✓	✓	✓	✓	✓	✓	✓		✓
Centro (Bucaramanga-Santander)													✓					
Corabastos (Bogotá-Bogotá)	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓	✓
Barranquillita (Barranquilla-Atlántico)	✓	✓	✓		✓	✓	✓		✓			✓		✓				
Buenaventura (Buenaventura-Valle)	✓	✓		✓				✓							✓			
Cavasa (Cali-Valle)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	
Santa Elena (Cali-Valle)	✓	✓	✓	✓	✓		✓	✓		✓	✓		✓		✓	✓	✓	
Bazurto (Cartagena-Bolívar)	✓	✓	✓		✓	✓	✓		✓		✓	✓						
Cartago (Cartago-Valle)	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓		✓	✓	✓	✓	✓
Cenabastos (Cúcuta-Norte)	✓		✓	✓	✓	✓			✓	✓	✓		✓		✓		✓	✓
El Santuario (El Santuario-Antioquia)			✓							✓								✓
Ibagué (Ibagué-Tolima)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓	✓	✓
Ipiales (Ipiales-Nariño)	✓	✓		✓									✓					
Galería (Manizales-Caldas)	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓		✓
Marinilla (Marinilla-Antioquia)		✓		✓		✓		✓	✓		✓							
Central Mayorista (Itaguí-Antioquia)	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓
Mercado del Sur (Montería-Córdoba)	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓		✓	✓			✓
Sur Abastos (Neiva-Huila)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Palmira (Palmira-Valle)	✓			✓				✓										
Pasto (Pasto-Nariño)	✓	✓				✓			✓				✓			✓		
La Bella (Pereira-Risaralda)														✓				
Mercasa (Pereira-Risaralda)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓
Rionegro (Rionegro-Antioquia)											✓							
Santa Bárbara (Santa Bárbara-Antioquia)								✓										
Tuluá (Tuluá-Valle)	✓	✓	✓	✓	✓	✓	✓	✓		✓					✓	✓	✓	
Complejo del Sur (Tunja-Boyacá)	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓				✓
Central de Abastos (Villavicencio-Meta)		✓	✓	✓	✓		✓			✓	✓	✓	✓	✓	✓		✓	
Mercabastos (Valledupar-Cesar)	✓	✓	✓				✓							✓				

Products: *a*) Cucumber; *b*) Coriander; *c*) Tamarillo; *d*) Red pepper; *e*) Blackberry; *f*) Celery; *g*) Plantain; *h*) Tomato; *i*) Lettuce; *j*) Snap pea; *k*) Sweet corn; *l*) Green bean; *m*) Potato “pastusa” variety; *n*) Spring onion; *o*) Passion fruit; *p*) Granadilla; *q*) Naranjilla; and *r*) Potato “criolla” variety. The symbol ✓ indicates the availability of price data for a specific pair of product and market.