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Testing the law of one price in food markets: Evidence for Colombia using disaggregated data*

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Abstract

This paper applies stationarity tests to examine evidence of market integration for a relatively large sample of food products in Colombia. We find little support for market integration when using the univariate KPSS tests for stationarity. However, within a panel context and after allowing for cross sectional dependence, the Hadri tests provide much more evidence supporting the view that food markets are integrated or, in other words, that the law of one price holds for most products.

JEL Classification: C33; F32; F41.

Keywords: Law of one price; panel stationarity test; disaggregated price data, cross section dependence; Colombia.

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1 Introduction

The law of one price is one of the building blocks of the international economics literature. This law states that in the presence of a competitive market structure, and in the absence of transport costs and other barriers to trade, prices of identical products sold in different markets will be the same when expressed in terms of a common currency (see e.g. Froot and Rogoff (1995); Sarno and Taylor (2002)). The law of one price is based upon the idea that market participants exploit arbitrage opportunities by purchasing (selling) a good in one market and selling (purchasing) it in another.

Broadly speaking, in testing the law of one price several empirical tests of price convergence have been carried out, particularly in the international trade area (e.g. Frankel and Rose (1996); Doroodian, Jung, and Boyd (1999); Goldberg and Verboven (2005)), but also with reference to price indices across cities within a country, that is, a context characterised by the absence of trade barriers and exchange rate volatility (e.g. Parsley and Wei (1996); Cecchetti, Mark, and Sonora (2002); Esaka (2003); Sonora (2005); Morshed, Ahn, and Lee (2006)). Early empirical literature on the validity of the law of one price finds little support in favour of the hypothesis, in the sense that large and persistent deviations from the law of one price are found even in those cases where one would least expect them to occur, i.e. highly disaggregated price data for a number of traded goods (see, *inter alia*, Isard (1977); Milone (1986); Giovannini (1988)). In recent years, however, evidence coming from the exploitation of new data sets, either in the form of panel data or longer time series data, tend to support the view that the law of one price does hold in the long run; see, *inter alia*, Goldberg and Verboven (2005), Cecchetti, Mark, and Sonora (2002), Sonora (2005).

This paper aims to complement the body of literature of the law of one price by examining whether Colombian regions can be best described as fully integrated, so that the prices of the same food products in different cities maintain a long-run equilibrium relationship or, put it another way, the price differential is stationary. We believe that the study of the Colombian case is interesting because the country's diverse geography has played a fundamental role in defining regions that exhibit their own cultural and economic features. In fact, Colombian regions are 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)).

The analysis of market integration has not been a topic of extensive research in Colombia. Two exceptions are Ramírez (1999) and Barón (2004). Ramírez (1999), using annual data from 1928 to 1990 for 8 agricultural commodities in 12 cities, associates the marked decline in the coefficients of variation of city price differentials during the 1930s to the development of transport infrastructure (including the expansion of railways), and observes that after this period no major additional declines took place. Further analysis by Ramírez, based on Johansen (1988) cointegration tests, indicates that market integration in Colombia has been rather limited and is still restricted by the lack of adequate transportation networks. On the other hand, Barón (2004) examines the time series properties of aggregate consumer price indices for food and housing in 7 cities. Barón finds evidence of stationarity in relative prices for food (which can be thought of as a tradable good), supporting the view that relative purchasing power parity holds for these goods, while mixed results were found for housing (which can be thought of as a non-tradable good).

Our paper differs in two important aspects from these previous works. First, we test for stationarity of city relative prices using a large dataset for a panel of 13 cities and 54 food products. The use of a highly disaggregated dataset allows us to analyse the relationship between deviations from the law of one price and type of goods. Second, given that unit root tests applied to single series suffer from low power, in this paper we adopt a panel approach which offers a way forward in terms of enhanced test power. The most commonly used unit root tests applied to panels include Maddala and Wu (1999) (MW) and Im, Pesaran, and Shin (2003)

(IPS), which test the joint null hypothesis of a unit root against the alternative of at least one stationary series in the panel. These tests are based on augmented Dickey and Fuller (1979) (ADF) statistics across the cross-sectional units of the panel. However, IPS (2003, p.73) warn that due to the heterogeneous nature of the alternative hypothesis in their test, one needs to be careful when interpreting the results because the null hypothesis that there is a unit root in each cross section may be rejected when only a fraction of the series in the panel are stationary. A further issue here is that the presence of cross-sectional dependencies can undermine the asymptotic normality of the IPS test and lead to over-rejection of the null hypothesis of joint non-stationarity.

A distinctive feature of our analysis is that we apply the Hadri (2000) tests, which test the null hypothesis that all individual series are stationary, against the alternative of at least a single unit root in the panel. The Hadri tests offer the key advantage that if the null hypothesis is not rejected, we may conclude that all the city relative prices in the panel are stationary. In addition to this, an important novel feature of our analysis is that we allow for the presence of potential cross-sectional dependencies. More specifically, we consider a procedure based on a bootstrap of the Hadri tests because failure to account for cross-sectional dependencies leads to size distortion and over-rejection by the Hadri tests.

The paper is organised as follows. Section 2 presents an overview of the Hadri (2000) panel stationarity tests. Section 3 describes the consumer price indices and the results of applying the panel stationarity tests to the relative price of food products between major Colombian cities. Section 4 presents half-life estimates for shocks originated in the same city using generalised impulse response functions. Section 5 concludes.

2 Testing for stationarity in dynamic heterogeneous panel data

Hadri (2000) proposes residual-based Lagrange Multiplier tests for the null hypothesis that all the time series in the panel are stationary (either around a level or a deterministic time trend), against the alternative that some of the series are nonstationary. Following Hadri (2000), consider the models:

$$y_{it} = r_{it} + \varepsilon_{it} \tag{1}$$

and

$$y_{it} = r_{it} + \beta_i t + \varepsilon_{it} \tag{2}$$

where r_{it} is a random walk, $r_{it} = r_{i,t-1} + u_{it}$, and ε_{it} and u_{it} are mutually independent normal distributions. Also, ε_{it} and u_{it} are $i.i.d$ across i and over t, with $E[\varepsilon_{it}] = 0$, $E[\varepsilon_{it}^2] = \sigma_{\varepsilon,i}^2 > 0$, $E[u_{it}] = 0$, $E[u_{it}^2] = \sigma_{u,i}^2 \geq 0$, $t = 1, ..., T$ and $i = 1, ..., N$. The null hypothesis that all the series are stationary is given by $H_0 : \sigma_{u,i}^2 = 0$, $i = 1, ..., N$, while the alternative that some of the series are nonstationary is $H_1 : \sigma_{u,i}^2 > 0$, $i = 1, ..., N_1$ and $\sigma_{u,i}^2 = 0$, $i = N_1 + 1, ..., N$.

Let $\hat{\varepsilon}_{it}$ be the residuals from the regression of y_{it} on an intercept, for model (1) (or on an intercept and a linear trend term, for model (2)). Then, the individual univariate Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) stationarity test is:

$$\eta_{i,T} = \frac{\sum_{t=1}^{T} S_{it}^2}{T^2 \hat{\sigma}_{\varepsilon_i}^2}, \tag{3}$$

where S_{it} denotes the partial sum process of the residuals given by $S_{it} = \sum_{j=1}^{t} \hat{\varepsilon}_{ij}$, and $\hat{\sigma}_{\varepsilon_i}^2$ is a consistent estimator of the long-run variance of $\hat{\varepsilon}_{it}$ from the appropriate regression. In their original paper, KPSS propose a nonparametric estimator of $\hat{\sigma}_{\varepsilon_i}^2$ based on a Bartlett window having a truncation lag parameter of $l_q = \text{integer}\left[q\,(T/100)^{1/4}\right]$, with $q = 4, 12$. However, Caner and Kilian (2001) have pointed out that stationarity tests, like the KPSS tests, exhibit very low power after correcting for size distortions. Thus, in our paper we follow recent work by Sul, Phillips, and Choi (2005), who propose a new boundary condition rule that improves the size and power properties of the KPSS stationarity tests. In particular, Sul et al. suggest the following procedure. First, an AR model for the residuals is estimated, that is:

$$\hat{\varepsilon}_{it} = \rho_{i,1}\hat{\varepsilon}_{i,t-1} + ... + \rho_{i,p_i}\hat{\varepsilon}_{i,t-p_i} + \upsilon_{it}, \tag{4}$$

where the lag length of the autoregression can be determined for example using the GEneral-To-Specific (GETS) algorithm proposed by Hall (1994) and Campbell and Perron (1991). Second, the long-run variance estimate of $\hat{\sigma}^2_{\varepsilon_i}$ is obtained with the boundary condition rule:

$$\hat{\sigma}^2_{\varepsilon_i} = \min\left\{T\hat{\sigma}^2_{\upsilon_i}, \frac{\hat{\sigma}^2_{\upsilon_i}}{\left(1-\hat{\rho}_i\left(1\right)\right)^2}\right\}, \tag{5}$$

where $\hat{\rho}_i\left(1\right) = \hat{\rho}_{i,1}\left(1\right) + ... + \hat{\rho}_{i,p_i}\left(1\right)$ denotes the autoregressive polynomial evaluated at $L = 1$. In turn, $\hat{\sigma}^2_{\upsilon_i}$ is the long-run variance estimate of the residuals in equation that is obtained using a quadratic spectral window Heteroscedastic and Autocorrelation Consistent (HAC) estimator.[1]

The Hadri (2000) panel stationarity test statistic is given by the simple average of individual univariate KPSS stationarity tests:

$$\widehat{LM}_{T,N} = \frac{1}{N}\sum_{i=1}^{N}\eta_{i,T},$$

which after a suitable standardisation, using appropriate moments, follows a standard normal limiting distribution.[2] That is:

[1]Additional Monte Carlo evidence reported by Carrion-I-Silvestre and Sansó (2006) also indicates that the proposal in Sul, Phillips, and Choi (2005) is to be preferred since the KPSS statistics exhibit less size distortion and reasonable power.

[2]Asymptotic moments can be found in Hadri (2000) while finite sample critical values appear in Hadri and Larsson (2005).

$$Z = \frac{\sqrt{N}\left(\widehat{LM}_{T,N} - \bar{\xi}\right)}{\bar{\zeta}} \Rightarrow N(0,1), \tag{6}$$

where $\bar{\xi} = \frac{1}{N}\sum_{i=1}^{N}\xi_i$ and $\bar{\zeta}^2 = \frac{1}{N}\sum_{i=1}^{N}\zeta_i^2$ are the necessary moments required for standardisation.

The Monte Carlo experiments of Hadri (2000) illustrate that these tests have good size properties for T and N sufficiently large. However, Giulietti, Otero, and Smith (2009) show that even for relatively large T and N the Hadri (2000) tests suffer from severe size distortions in the presence of cross-sectional dependence, the magnitude of which increases as the strength of the cross-sectional dependence increases. This finding is in line with the results obtained by Strauss and Yigit (2003) and Pesaran (2007) on both the IPS and the MW panel unit root tests. To correct for the size distortion caused by cross-sectional dependence, Giulietti et al. apply the bootstrap method and find that the bootstrap Hadri tests are approximately correctly sized.

To implement the bootstrap method in the context of the Hadri tests, we start off by correcting for serial correlation using equation (4) and obtain $\hat{\upsilon}_{it}$, which are centred around zero. Next, as in Maddala and Wu (1999), the residuals $\hat{\upsilon}_{it}$ are resampled with replacement with the cross-section index fixed, so that their cross-correlation structure is preserved; the resulting bootstrap innovation $\hat{\upsilon}_{it}$ is denoted $\hat{\upsilon}_{it}^*$. Then, $\hat{\varepsilon}_{it}^*$ is generated recursively as:

$$\hat{\varepsilon}_{it}^* = \hat{\rho}_{i,1}\hat{\varepsilon}_{i,t-1}^* + ... + \hat{\rho}_{i,p_i}\hat{\varepsilon}_{i,t-p_i}^* + \upsilon_{it}^*,$$

where, in order to ensure that initialisation of $\hat{\varepsilon}_{it}^*$, i.e. the bootstrap samples of $\hat{\varepsilon}_{it}$, becomes unimportant, we follow Chang (2004) who advocates generating a large number of $\hat{\varepsilon}_{it}^*$, say $T+Q$ values and discard the first Q values of $\hat{\varepsilon}_{it}^*$ (for our purposes we choose $Q = 50$). Lastly, the bootstrap samples of y_{it}^* are calculated by adding $\hat{\varepsilon}_{it}^*$ to the deterministic component of the corresponding model, and the Hadri LM statistic is calculated for each y_{it}^*. The previous steps are repeated several times in order to derive the empirical distribution of the LM statistic, from which bootstrap probability values (or alternatively bootstrap critical values) may be obtained.

3 Data and empirical analysis

The data set, obtained from Departamento Administrativo Nacional de Estadística (DANE), consists of seasonally unadjusted monthly observations on consumer price indices for 54 food products in 13 major Colombian cities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales, Pasto, Pereira, Cúcuta, Montería, Neiva, Cartagena and Villavicencio. Food products can be further classified as non-processed food products (of which we have 17 products) and processed (or manufactured) food products (of which we have the remaining 37 products). For the purposes of our empirical analysis, we consider for each product two panels of relative prices. The first panel (Panel 1) consists of the six main cities, namely Medellín, Cali, Barranquilla, Bucaramanga, Manizales and Pasto, while the second panel (Panel 2) includes all 13 cities. The city of Bogotá provides a natural benchmark as it is both the national capital as well as the centre of the most important economic region in the country. Thus, the relative price of good k between city i and the benchmark city (Bogotá) at time t is defined as $y_{it}^k = \ln\left(p_{it}^k / p_{\text{Bogotá},t}^k\right)$, where both the numerator and the denominator are considered in logarithms. The variable y_{it}^k can be thought of as a city relative price (also referred to as a city real exchange rate). The sample period runs from January 1999 to December 2007, for a total of 108 time observations.[3]

It is worth noticing that finding stationarity in y_{it}^k implies that the (logarithms of the) price indices of product k in city i and the benchmark city, Bogotá in this case, are cointegrated with a cointegrating vector $(1, -1)'$. This result implies that the price indices in the cities under consideration must be linked by a long-run equilibrium relationship. In the short run city relative prices may deviate from

[3]This range of cities is dictated by the availability of consistent data with respect to the period of study.

the long-run equilibrium relationship, although not by an ever-growing amount, since economic forces may be expected to act so as to restore equilibrium; i.e. the discrepancy in the relationship must be integrated of order zero. This, in turn, is consistent with the view that arbitrage opportunities are only possible in the short but not in the long run.

The results of applying the KPSS univariate stationarity test, based on the model with intercept only, are reported in Tables 1 and 2. As indicated in the previous section, the long-run variance required to calculate the KPSS statistic is consistently estimated using the new boundary condition rule put forward by Sul, Phillips, and Choi (2005); see equation (5). Furthermore, to correct for possible serial correlation the autoregressive processes in (4) are estimated for up to $p = 18$ lags, and the optimal number of lags is chosen based on the GETS algorithm. This algorithm involves testing whether the last autoregressive coefficient is statistically different from zero (say, at the 5 per cent significance level); if this coefficient is not statistically significant, then the order of the autoregression is reduced by one until the last coefficient is statistically significant. As can be seen from the tables, the evidence here does not provide a clear indication supporting the view that the law of one price holds for the city relative prices of the different food products. Indeed, looking at the results for the 6 cities that conform Panel 1, there are only two processed food products (namely coffee and cooked meats) for which we do not reject the null hypothesis of stationarity (at the 5 per cent significance level) in any of the cities under consideration. In all other cases, the null hypothesis of stationarity is rejected (at the 5 per cent significance level) in at least one of the cities.

Next, we apply the Hadri panel stationarity test to the relative prices under consideration. The main motivation for testing stationarity in a panel of data instead of individual time series is that it has been noted that the power of the tests increases with the number of cross-sections in the panel. To allow for potential cross section dependence, we apply the bootstrap method to the Hadri tests as outlined in the previous section; it should be recalled that failure to account for potential cross section dependence will result in severe size distortion of the Hadri test statistics. The resulting Hadri test statistics are reported in Tables 3 and 4, along with their corresponding bootstrap $p-values$ in brackets, which in turn are based on 2,000 replications used to derive the empirical distributions of the test statistics. Focusing first on Panel 1, it is interesting to note that the null hypothesis of panel stationarity is not rejected (at the 5 per cent significance level) in 14 out of the 17 non-processed food products, and in 24 out of the 37 processed food products considered. These findings provide support to the view that the law of one price holds for most of the food products, implying that price differentials are stationary or, in other words, they do not increase (or decrease) by an ever-growing amount.

With regard to Panel 2, which extends Panel 1 by including 6 additional smaller cities, we find fewer products where the null hypothesis of panel stationarity is not rejected. Indeed, when considering the extended panel, evidence supporting the law of one price falls from 14 to 12 non-processed food products, and from 24 to 18 processed food products. These results suggest that market integration tends to occur less frequently when considering dissimilar cities in terms of their population and economic sizes. Thus, market participants may be able to make profits systematically.

4 Speed of adjustment and half-life

This section examines the speed at which city relative prices adjust to exogenous shocks or innovations, using half-life estimates based on the impulse response functions that result from the estimation of Vector Autoregressive (VAR) models. In particular, we focus on the products where we failed to reject the null hypothesis of panel stationarity in the previous section, since their city relative prices are all individually $\sim I(0)$ and hence are suitable for modelling in a VAR framework.

It is well known that in the case of simple AR(1) processes, the estimated value of the autoregressive coefficient, say $\hat{\beta}$, can be used to calculate the approximate half-life of a shock on the dependent variable based on the formula $-\ln(2)/\hat{\beta}$. However, for more complicated processes the previous formula is no longer valid, and thus impulse response functions should be preferred; see, for example, Goldberg and Verboven (2005). For our purposes, we specifically consider the generalised impulse response functions developed by Pesaran and Shin (1998). These functions offer the advantage of being invariant to the way shocks in the underlying VAR model are orthogonalised, and therefore provide an important extension to the traditional impulse response analysis, which is sensitive to the ordering of the variables in the VAR; see e.g. Lütkepohl (2005).

For the specification of the VAR model for each product, we consider the relative prices of the cities that conform Panel 1, namely Medellín, Cali, Barranquilla, Bucaramanga, Manizales and Pasto. An important initial stage in the analysis is the selection of the optimal order of the VAR models, which involves selecting an order high enough such that one can be reasonably confident that the optimal order will not exceed it. In the case of the present application we set 12 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 criteria often applied to select between time series models is the Akaike information criterion (AIC). In general, both criteria tend to pick up the same optimal order, although when they do not coincide the model order selected with the SIC tends to be smaller than the model order selected with the AIC. Bearing in mind that the sample size (108 observations) might be small relative to the number of variables in the VAR (6 relative prices), we favour the more parsimonious specification that results from using the SIC.

Having selected the optimal order of the VAR models, we calculate the associated generalised impulse responses that describe the time profile of the effect of a unit shock in the relative price of a city, measured by one standard deviation, on the relative price in the same city. The resulting lag weights for each city are then normalised so that they add up to one, and the half-life is calculated as the number of months required for 50 per cent (or the first half) of the adjustment to take place.

Lastly, half-lives are averaged across cities to obtain an estimate of a products' half-life to own price shocks. The main results are reported in Table 5, which classifies the resulting half-life estimates to own price shocks according to their persistence in time. According to this table, our half-life estimates appear to be related to how perishable a good is. Indeed, for 9 out of 14 non-processed food products half-life estimates lie below 3 months, whereas for 16 out of 24 processed food products half-life estimates range between 6 to 12 months.[4]

These rates of convergence could be compared with those estimated for Indian cities by Morshed, Ahn, and Lee (2006), who found that the half-life of any shock is close to 3 months, also using monthly data. In the case of Mexico, Sonora (2005) using monthly dissagregated data found half-life convergence rates ranging between one to two years approximately. In other studies, within-country price convergence is much slower. For instance, in the case of US cities, Parsley and Wei (1996) using quarterly commodity level price indices found that the half-life for tradables is about 4 to 5 quarters and 15 quarters for services, whereas Cecchetti, Mark, and Sonora (2002), using annual aggregate price indices, estimate a half-life of convergence of approximately 9 years. Cecchetti, Mark, and Sonora (2002) indicate that price convergence is faster within regions of a single country, since markets for both products and factors are more integrated.

5 Concluding remarks

This paper applies the Hadri (2000) tests for panel stationarity to examine evidence on market integration for a relatively large sample of food products in Colombia, using a dataset for a panel of 13 cities and 54 food products. The Hadri tests offer the key advantage insofar as we may conclude that all the city relative prices in the panel are stationary, if the joint null hypothesis is not rejected. In addition to this, another important feature of our analysis is that we allow for the presence of

[4]Qualitatively similar results are obtained when estimating half-lives using the 13 cities comprised in Panel 2 (these results are not reported here to save space, though).

serial correlation and cross-sectional dependency across the city relative prices in the panel, by means of the implementation of an AR-based bootstrap.

According to our results, the use of individual univariate KPSS tests for stationarity does provide very little support for the view that food markets are integrated or, in other words, food prices do not appear to maintain an equilibrium relationship in the long run. However, when we consider a panel for the seven main cities in the country, and after allowing for the potential effect of cross sectional dependency, we find much more evidence suggesting that food markets are integrated. When the panels are extended by including smaller cities (both in terms of economic activity and population size), fewer cases favouring market integration are found.

Our findings thus suggest that market integration is favoured by similarities in terms of both population and economic sizes. Lastly, we also found that the rate of convergence of price differentials to exogenous shocks or innovations, in a context in which trade barriers and exchange rate volatility are absent, is much faster the more perishable a food product is.

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Table 1. Univariate KPSS tests for mean stationarity: Non-processed food products

City / Product	Bar	Buc	Cal	Man	Med	Pas	Car	Cuc	Mon	Nei	Per	Vil
Bananas	2.56‡	1.84‡	0.91‡	0.16	0.89‡	0.52†	2.43‡	0.03	0.60†	0.38	0.20	0.31
Blackberry	0.42	0.29	1.03‡	0.19	0.82‡	0.34	0.13	0.09	0.15	0.25	0.33	0.06
Carrots	0.17	1.09‡	0.53†	0.26	0.56†	0.22	0.40	0.08	0.35	0.21	0.56†	0.25
Cassava	0.56†	0.79‡	0.56†	0.13	0.09	0.20	0.48†	0.16	0.93‡	0.56†	0.35	0.36
Eggs	0.19	1.32‡	0.20	0.59†	0.30	0.08	0.20	0.22	0.20	0.30	0.10	0.17
Kidney beans	0.08	0.61†	0.50†	0.12	0.59†	0.65†	0.12	0.33	0.07	0.90‡	0.16	0.72†
Onions	0.67†	0.26	0.22	1.05‡	0.18	0.13	0.81‡	0.22	0.59†	1.01‡	0.06	0.26
Oranges	0.31	0.15	0.24	0.23	0.20	0.71†	0.58†	0.08	0.10	0.15	0.10	0.36
Other dry vegetables	0.16	0.07	0.55†	0.70†	0.12	0.43	0.58†	0.18	0.10	0.72†	0.25	0.07
Other fresh fruits	0.09	0.32	0.12	0.12	0.66†	0.11	0.54†	0.16	1.20‡	0.17	0.23	0.52†
Other fresh vegetables	0.05	0.73†	0.54†	0.39	0.71†	0.31	0.08	0.13	0.11	0.68†	0.49†	0.12
Other roots and tubers	0.30	0.42	0.20	0.94‡	0.28	0.08	0.50†	0.25	1.90‡	0.34	0.17	0.30
Peas	0.24	0.24	0.52†	0.53†	0.51†	0.39	0.20	0.69†	0.60†	1.56‡	0.90‡	0.15
Plantains	1.76‡	0.50†	0.19	0.35	0.08	1.19‡	1.68‡	0.13	1.20‡	0.19	0.21	0.77‡
Potatoes	0.14	0.78‡	0.17	0.18	0.93‡	0.04	0.12	0.13	0.96‡	0.37	0.29	0.19
Tomatoes	0.42	0.73†	0.32	0.04	0.14	0.37	0.52†	0.26	0.44	0.71†	0.18	0.76‡
Tree tomato	0.22	0.16	0.31	0.64†	0.22	0.53†	0.13	0.12	0.05	0.11	0.09	0.49†

Note: † and ‡ denote statistical significance at the 5 and 1% levels, based on Sephton (1995).

Table 2. Univariate KPSS tests for mean stationarity: Processed food products

City Product	Bar	Buc	Cal	Man	Med	Pas	Car	Cuc	Mon	Nei	Per	Vil
Beef	2.18‡	1.20‡	0.31	1.57‡	0.91‡	0.59†	0.23	0.75‡	1.22‡	1.34‡	0.34	0.57†
Biscuits and cakes	0.18	0.05	0.21	1.07‡	0.30	1.07‡	0.34	4.46‡	0.46	1.16‡	0.12	0.35
Bread	0.62†	0.87‡	1.00‡	0.92‡	0.34	2.67‡	1.39‡	0.20	0.28	0.27	0.27	0.16
Breakfast cereals	1.66‡	0.13	2.14‡	0.41	0.61†	0.74‡	0.92‡	0.18	0.14	0.73†	0.11	1.50‡
Canteen meals	0.18	0.88‡	1.09‡	0.34	0.35	0.25	0.98‡	0.56†	8.22‡	0.20	2.69‡	2.08‡
Cheese	0.20	3.76‡	0.61†	0.23	0.37	0.63†	0.14	0.19	1.34‡	0.19	0.90‡	2.11‡
Chicken	1.99‡	0.74‡	0.35	0.17	0.48†	0.23	0.26	7.79‡	0.63†	0.96‡	0.09	0.11
Cocoa	0.91‡	0.71†	3.92‡	1.01‡	4.99‡	0.32	0.29	0.18	0.19	0.34	2.10‡	0.13
Coffee	0.09	0.22	0.11	0.04	0.12	0.22	0.16	0.32	0.78‡	0.29	0.35	0.23
Cold fast food	0.44	2.05‡	0.10	1.03‡	0.49†	0.92‡	1.47‡	0.08	1.05‡	2.18‡	1.79‡	0.41
Cooked meats	0.46	0.37	0.25	0.38	0.10	0.23	2.33‡	0.26	0.20	0.70†	0.17	0.47†
Cooking oil	0.30	0.51†	0.10	0.24	0.80‡	0.27	0.56†	0.35	0.09	0.17	0.26	0.54†
Dried pasta	0.23	0.47†	0.46	0.44	0.28	0.30	0.78‡	0.34	0.06	0.07	1.43‡	0.21
Fish (fresh and processed)	0.50†	0.13	0.13	0.49†	1.46‡	0.47†	0.63†	0.12	0.11	0.72†	0.13	0.11
Flour	1.94‡	1.56‡	0.68†	0.73†	0.29	0.66†	1.35‡	4.47‡	0.36	2.65‡	0.13	6.56‡
Fruit juices	1.15‡	2.95‡	0.23	0.19	0.36	0.26	0.74‡	0.82‡	0.61†	0.63†	0.38	0.93‡
Hamburgers	8.62‡	0.09	0.18	0.36	0.95‡	3.78‡	1.44‡	0.20	0.44	0.24	0.35	0.27
Hot fast food	1.77‡	0.97‡	0.44	0.22	0.93‡	0.53†	0.30	0.69†	0.73†	0.57†	0.53†	0.52†
Lunch (eating out)	1.57‡	0.93‡	2.32‡	1.00‡	4.47‡	0.85‡	1.38‡	1.81‡	11.02‡	0.13	4.89‡	10.34‡
Margarine, butter and other fats	0.42	0.69†	0.06	0.38	0.50†	0.07	0.48†	4.56‡	0.60†	0.14	0.22	0.22
Milk	0.24	0.46	0.29	0.15	0.59†	1.11‡	0.11	0.82‡	7.64‡	1.18‡	0.77‡	0.30
Other canned vegetables	0.34	1.01‡	0.41	1.13‡	0.67†	7.46‡	1.03‡	4.85‡	0.54†	1.62‡	1.34‡	0.18
Other condiments	0.44	1.02‡	0.17	0.77‡	0.54†	0.84‡	2.87‡	0.95‡	10.76‡	0.41	0.57†	1.51‡
Other dairy products	0.32	1.68‡	2.56‡	0.39	0.41	1.61‡	0.25	0.30	0.27	1.02‡	0.26	0.60†
Other food products	0.58†	0.18	0.33	0.16	0.31	0.11	0.84‡	0.68†	0.56†	0.10	0.14	1.87‡
Other non-alcoholic beverages	2.00‡	0.45	0.26	0.50†	0.47†	0.99‡	0.14	2.71‡	0.35	0.12	0.31	0.80‡
Other sea products	0.57†	0.12	0.39	1.13‡	0.15	0.34	0.43	0.19	0.31	0.91‡	0.14	0.87‡
Panela (sugar cane by-product)	1.65‡	0.78‡	1.98‡	1.72‡	2.23‡	1.21‡	8.55‡	4.23‡	0.34	2.68‡	3.67‡	2.36‡
Pork	0.26	1.57‡	0.46	0.20	0.32	1.08‡	0.19	0.39	1.16‡	1.44‡	0.59†	1.92‡
Rice	0.73†	0.68†	0.68†	0.45	0.07	1.02‡	0.49†	4.07‡	1.39‡	0.29	1.53‡	2.72‡
Salt	0.72†	3.23‡	0.23	0.34	0.40	0.19	0.15	2.05‡	2.25‡	0.36	1.46‡	1.61‡
Soft beverages	1.71‡	1.70‡	0.84‡	0.37	0.07	0.34	1.27‡	1.74‡	1.29‡	1.85‡	1.68‡	0.42
Soup cereals	0.77‡	0.24	0.22	0.17	0.44	0.35	0.95‡	0.42	0.32	0.53†	0.93‡	0.55†
Soups	0.45	0.80‡	0.67†	0.44	0.15	1.11‡	0.13	4.88‡	5.37‡	0.20	0.05	1.41‡
Sugar	0.19	0.10	0.95‡	0.25	0.49†	0.33	0.16	1.74‡	0.17	0.22	0.33	0.36
Tomato sauce and mayonnaise	0.90‡	1.40‡	0.39	0.40	0.92‡	2.92‡	0.23	18.47‡	1.19‡	0.66†	0.66†	0.16
Various jams	0.42	0.73†	0.21	1.09‡	0.50†	1.89‡	1.28‡	0.24	0.36	0.06	0.51†	0.26

Note: † and ‡ denote statistical significance at the 5 and 1% levels, based on Sephton (1995).

Table 3. Hadri tests for mean stationarity:
Non-processed food products

Product	Panel 1: 7 cities		Panel 2: 13 cities	
	Statistic	p-value	Statistic	p-value
Bananas	16.26	[0.00]	17.23	[0.00]
Blackberry	5.78	[0.13]	4.08	[0.27]
Carrots	5.05	[0.03]	5.23	[0.07]
Cassava	3.64	[0.11]	6.17	[0.03]
Eggs	4.63	[0.12]	3.62	[0.39]
Kidney beans	4.31	[0.64]	5.57	[0.57]
Onions	4.17	[0.11]	6.76	[0.04]
Oranges	2.28	[0.10]	2.34	[0.18]
Other dry vegetables	2.82	[0.64]	3.72	[0.66]
Other fresh fruits	1.11	[0.46]	4.35	[0.22]
Other fresh vegetables	4.76	[0.06]	4.56	[0.16]
Other roots and tubers	3.36	[0.46]	7.18	[0.28]
Peas	3.95	[0.14]	8.85	[0.06]
Plantains	8.50	[0.01]	12.24	[0.00]
Potatoes	3.41	[0.68]	4.46	[0.56]
Tomatoes	2.79	[0.05]	5.63	[0.01]
Tree tomato	2.95	[0.27]	2.05	[0.50]

Notes: Panel 1 comprises the following cities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales and Pasto. Panel 2 comprises the cities in Panel 1 plus Pereira, Cúcuta, Montería, Neiva, Cartagena and Villavicencio. All relative prices are measured with respect to Bogotá.

Table 4. Hadri tests for mean stationarity:
Processed food products

Product	Panel 1: 7 cities		Panel 2: 13 cities	
	Statistic	p-value	Statistic	p-value
Beef	15.96	[0.06]	18.03	[0.03]
Biscuits and cakes	5.19	[0.09]	15.18	[0.01]
Bread	14.98	[0.02]	13.66	[0.02]
Breakfast cereals	12.96	[0.47]	14.20	[0.40]
Canteen meals	5.75	[0.07]	30.97	[0.00]
Cheese	13.27	[0.01]	16.92	[0.01]
Chicken	8.17	[0.15]	23.05	[0.04]
Cocoa	30.04	[0.04]	25.59	[0.04]
Coffee	-0.57	[0.97]	1.81	[0.53]
Cold fast food	11.11	[0.03]	19.55	[0.01]
Cooked meats	2.18	[0.20]	7.64	[0.05]
Cooking oil	3.37	[0.22]	4.25	[0.25]
Dried pasta	3.26	[0.18]	5.98	[0.88]
Fish (fresh and processed)	6.05	[0.59]	5.88	[0.82]
Flour	13.46	[0.01]	37.95	[0.00]
Fruit juices	11.42	[0.28]	14.17	[0.22]
Hamburgers	35.96	[0.01]	29.22	[0.01]
Hot fast food	10.66	[0.11]	12.11	[0.06]
Lunch (eating out)	28.06	[0.01]	75.81	[0.01]
Margarine, butter and other fats	3.09	[0.16]	12.41	[0.13]
Milk	5.06	[0.07]	22.79	[0.04]
Other canned vegetables	27.78	[0.22]	36.39	[0.11]
Other condiments	7.68	[0.48]	36.93	[0.16]
Other dairy products	16.51	[0.02]	14.95	[0.01]
Other food products	1.81	[0.78]	7.52	[0.37]
Other non-alcoholic beverages	10.15	[0.04]	13.89	[0.05]
Other sea products	4.67	[0.04]	6.89	[0.11]
Panela (sugar cane by-product)	23.70	[0.09]	57.57	[0.04]
Pork	7.99	[0.06]	14.81	[0.01]
Rice	7.29	[0.08]	23.73	[0.09]
Salt	11.36	[0.04]	21.51	[0.02]
Soft beverages	11.12	[0.06]	22.06	[0.00]
Soup cereals	3.28	[0.61]	7.57	[0.69]
Soups	7.26	[0.08]	26.73	[0.08]
Sugar	3.59	[0.20]	6.42	[0.12]
Tomato sauce and mayonnaise	16.43	[0.03]	51.49	[0.03]
Various jams	10.62	[0.03]	10.84	[0.01]

Notes: Panel 1 comprises the following cities: Bogotá, Medellín, Cali, Barranquilla, Bucaramanga, Manizales and Pasto. Panel 2 comprises the cities in Panel 1 plus Pereira, Cúcuta, Montería, Neiva, Cartagena and Villavicencio. All relative prices are measured with respect to Bogotá.

Table 5. Half-life estimates from generalised impulse response functions

Food product	0 to 3 months	3 to 6 months	above 6 months
Non-processed			
Blackberry		★	
Cassava		★	
Eggs		★	
Kidney beans	★		
Onions	★		
Oranges	★		
Other dry vegetables			★
Other fresh fruits	★		
Other fresh vegetables	★		
Other roots and tubers		★	
Peas	★		
Potatoes	★		
Tomatoes	★		
Tree tomatoe	★		
Processed			
Beef			★
Biscuits and cakes			★
Breakfast cereals			★
Canteen meals			★
Chicken			★
Coffee	★		
Cooked meats		★	
Cooking oil		★	
Dried pasta		★	
Fish (fresh and processed)			★
Fruit juices			★
Hot fast food			★
Margarine, butter and other fats		★	
Milk		★	
Other canned vegetables			★
Other condiments			★
Other food products		★	
Panela (sugar cane by-product)			★
Pork			★
Rice			★
Soft beverages			★
Soup cereals		★	
Soups			★
Sugar			★