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A Dynamic spatial modeling of agricultural price transmission: Evidence from Niger millet market

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ABSTRACT

Spatial interactions are essential drivers of price transmission mechanisms and may significantly affect any food policy's outcomes. However, spatial aspects seem to be generally overlooked when analyzing price transmission. This paper attempts to fill this gap by highlighting the usefulness of spatial interaction and models for market integration analysis. A Spatial Dynamic Panel Data model is presented and applied to Niger's millet market. Empirical results show that (1) the millet market is partly integrated, (2) locally traded commodities (millet and sorghum) are linked by a cross-commodity price transmission, (3) most imported cereals prices, which for Niger is maize and rice, did not affect the millet market, and (4) no cross-regions price transmission occurred for the millet market.

Keywords: Spatial econometrics, panel data, agricultural commodities, market integration, Niger.

1. Introduction

In recent years, agricultural products have undergone huge price variation in international markets. Such variation in world markets is not without effect on local markets. The extent of these shocks vary across countries as some are more dependent on international markets than others. A number of factors determine the degree of price transmission in a country, such as trade flows, transactions costs, trade policies, availability of price information across markets, and installed infrastructures. For example, if domestic products dominate the local markets, price transmission will be less severe than in markets where foreign goods dominate local goods. In addition,

¹<u>A.goundan@cgiar.org</u> ²<u>M.tankari@cgiar.org</u> transaction costs (transport, margins, risk premium, cost of information), distance, quality of infrastructure and trade barriers reduce price transmission by limiting trade flows.

Price transmission analysis measures how well different spatially separated markets are connected. If markets are perfectly integrated, price signals are transmitted from a selected location to other locations. This implies a price adjustment in response to existing excess supply and demand conditions in other locations of the integrated area. There is extensive theoretical and applied research on the mechanisms of price transmission. As applied studies often focus on policy implications, a large portion of the literature deals with methodological improvements in the fields of price transmission analysis. Therefore, various approaches can be found in the literature. The first studies began using correlation coefficients of prices to test market integration between spatially separated markets (Jones, 1972). Other research employed regression based models (Monke and Petzel, 1984), or time-series analysis techniques such as dynamic regression (Ravallion 1986)and cointegration analysis (Baulch 1997). Furthermore, a number of studies have proposed nonlinear approaches (Meyer and Cramon-Taubadel 2004, Greb et al. 2013). The common feature of these approaches is that they are mainly based on time-series analysis.

Since price transmission occurs between different locations, it is essential to include spatial interactions in price transmission models. The failure to take this fact into account may bias the results of an analysis. For example, Lesage (1999) stated that, due to spatial dependence and heterogeneity, Gauss-Markov assumption is violated. Spatial econometrics that successfully model those issues and draw appropriate inferences is a straightforward solution for price transmission analysis. Unfortunately, this tool seems to be rarely used in price transmission analysis. To the best of our knowledge, Keller and Shiue (2007) presented the only research that used the spatial econometric approach to study market integration for China's rice market.

Spatial features are accordingly important as they influence the degree of market integration. In addition, the price dynamic in a given location is influenced by its neighboring prices (Keller and Shiue 2007). LeSage and Pace (2009) pointed out five reasons to include spatial features (spatial autoregression) in a regression model: (a) a time-dependence motivation; (b) an omitted variables motivation; (c) a spatial heterogeneity motivation; (d) an externalities-based motivation; and (e) a model uncertainty motivation. Interestingly, these motivations are relevant in market integration analysis. Therefore, the main aim of this paper is to add to the literature by highlighting the usefulness of the spatial econometrics approach for price transmission analysis.

The remainder of this paper continues as follows. Section 2 presents the dynamic spatial panel framework. Section 3 provides the results of the application of the proposed frameworkto millet market in Niger. The final section is devoted to conclusion and policy implications.

3. Methodological framework

An appealing spatial econometrics models for price transmission analysis is the Spatial Dynamic Panel Data (SDPD) model proposed by Lee and Yu (2010). This framework allow three types of interactions in price transmission. First, temporal dependency is taking into account. Previous price is allowed to affect the following period price level in a specific location. This is particularly what time series modeling do. Second, endogenous interaction effects is also integrated. The price level in a specific location is assumed to be impacted by adjacent locations price level. This is an interesting characteristic of our framework since separated markets are connected through trade flows and price information. Third, exogenous interaction effects is also integrated. While exogenous variables are present in the price transmission model, our framework is able to account for the observed exogenous variables in adjacent locations.

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Let Y_t^k be the vector of price for *N* locations at time *t* for commodity *k* and X_t stand for exogenous variables, which could be the price of other products or weather variables. The SDPD setup is:

 $\boldsymbol{y}_{t}^{k} = \tau \boldsymbol{y}_{t-1}^{k} + \rho \boldsymbol{W} \boldsymbol{y}_{t}^{k} + \eta \boldsymbol{W} \boldsymbol{y}_{t-1}^{k} + \boldsymbol{x}_{t} \boldsymbol{\theta} + \boldsymbol{W} \boldsymbol{x}_{t} \boldsymbol{\beta} + \boldsymbol{\mu} + \alpha_{t} \boldsymbol{l}_{N} + \boldsymbol{v}_{t}(1)$

This model is known as a dynamic spatial Durbin model (Debarsy et al., 2012). μ is a vector spatial fixed effects, α_t stands for time fixed effects, while l_N is a vector of ones. Wx_t is the exogenous interaction effects term, y_{t-1}^k is the lagged of the dependent variable in time, Wy_t^k represents the contemporaneous endogenous interaction effects, Wy_{t-1}^k is the lagged endogenous interaction effects.

Based on the proprieties of model 1, it can be classified into three different cases depending on the value of $\tau + \rho + n$. According to Lee and Yu (2010), model 1 is stable if this value is less than one, cointegrated if it equals one and explosive otherwise. To estimate model 1, we followed Yu et al. (2008), Lee and Yu (2010), and Yu et al. (2012), who used a bias-corrected quasimaximum likelihood (BC-QML) estimator. This method produces consistent parameter estimates when the model is stable. However, when this stability condition is not satisfied, a data transformation is needed to consistently estimate model 1 using BC-QML. In fact, when the stability condition is not satisfied, Lee and Yu (2010) and Yu et al. (2012) proposed the spatial firstdifference transformation of model 1 using the matrix (**I-W**) where **I** denotes the N x N identity matrix. See Elhorst (2014) for more details.

To interpret the effect of a change in an explanatory variable in this SDPD framework, one has to compute the reduced form of (1), which is presented

$$y_{t} = [(I - \rho W)^{-1} (\tau I + \eta W)] y_{t-1} + (I - \rho W)^{-1} [x_{t}\theta + W x_{t}\beta] + (I - \rho W)^{-1} [\mu l_{N} + \alpha_{t} l_{n} + v_{t}]$$
(2)

The short-term impacts of a change in a specific explanatory variable x_i (or the lagged endogenous variable) on the dependent variable can be computed as:

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}_{i}} = [(\mathbf{I} - \rho \mathbf{W})^{-1} (\mathbf{x}_{i} \theta + \mathbf{W} \mathbf{x}_{i} \beta)$$

$$\frac{\partial \mathbf{y}}{\partial \mathbf{y}_{t-1}}] = [(\mathbf{I} - \rho \mathbf{W})^{-1} (\tau \mathbf{I} + \eta \mathbf{W})]$$
(4)

The results of (4) are named the convergence effects (impact of the lagged endogenous variables). These partial derivatives (3) and (4)are*N*x*N*matrixes. As noticed in Debarsy et al. (2012), diagonal elements of equation (3) are different for each cross section, and off-diagonal elements differ from zero and the matrix is nonsymmetric. This model is richer than the traditional linear model. The average of diagonal elements represent own-partial derivatives (called direct effects), meaning the impactof a change in the selected explanatory variable in location *i*on the dependentvariable in this location. The average of the off-diagonal elements (cross-derivative elements) of (3)-(4) is thus labeled indirect effects and showsthe response of the dependent variable in location *i* to a change in explanatory variables in any of the other locations.

In price transmission framework, direct effects of (4) gives the extent of price transmission across years in the same region. It is to say how a price change for a selected market (millet, rice

...) in a location affects futureprices for this market in this location. The indirect effects of (4) shows the response of price in a region to a previous price change in any of the other regions. Therefore, price transmission analysis in our framework helps to know if a price shock originated from one location is transmitted only inside this location or to neighboring locations. Thus, price transmission has two components: intra-region price transmission and cross-regions price transmission. When price of substitute commodities were used as explanatory variables, a cross-region and cross-commodities price transmission can be examined. Such situation is examined in this study, which analyzed millet's market integration accounting for sorghum, maize and rice prices. One issue here is that these price series are clearly endogenous. The price of sorghum may affect the price of millet and vice-versa or both prices may be affected by unobserved factors. In this paper, we addressed this issue by using the average of m^3 previous observations of the prices of sorghum, maize and rice.

4. Millet's market price transmission in Niger

In this section, the SDPD model was applied to analyze price transmission on cereals market in the eight regions of Niger (Agadez, Diffa, Dosso, Maradi, Niamey, Tahoua, Tillaberi and Zinder), with a special focus on millet, which is the most consumed cereal (food) in Niger (FAO, 2009). The attention paid to the millet market is justified because this cereal represents 78 percent of cereals consumption and 62 percent of food consumption in Niger (FAO, 2009). In addition, the millet consumed in Niger is totally produced locally (USDA, 2016). According to USDA database, around 2 percent of sorghum consumption are from imports, while maize and rice's consumption depend mainly on imports with more than 80 percent of demand satisfied by imports.

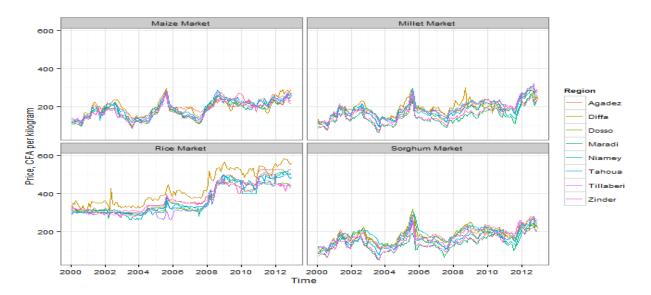


Figure4.1*Trends in Niger cereals prices, 2000–2012* Source: SIMA, 2013

³We also used the average of the three, four, and five previous months

Price series used in this study were provided by the Niger's System of Agricultural Market Information (SIMA). Established in 1989, SIMA is a specialized service of the government of Niger, which is operated by the Ministry of Trade and Private Sector Promotion. The main mission of SIMA is to collect, process, and disseminate information about agricultural markets for better decision making by policy makers. Prices used here concerned monthly retailer prices over 2000-2012 (per kg price level in local currency, CFA) for the main cereals consumed in Niger, namely millet, sorghum, maize and rice. The dynamics of various cereals prices considered are depicted in Figure 4.1.

Table 4.1 presents the results of price transmission analysis on Niger's millet market when accounting for other cereal prices. The results, as stated in the table's heading, are related to the spatial firstdifference of model (1) since the latter is found unstable. Due to space constraints, we don't present nor discuss the results of the direct estimation of model (1) here. For these details and others, the interested reader is referred to the *Discussion Paper* version of this study (Goundan and Tankari, 2016).

Column (1) of Table 4.1 reports the estimation results of the spatial firstdifference of model (1), columns (2) to (4) show the results for the direct, indirect and total effects of explanatory variables as formulated in section 3. The t-statistics of the derived effects are obtained by carrying out a Monte Carlo simulation experiment over the estimated parameters.

Only four parameters over the nine estimated are significant (column 1). They are the first three parameters related to the endogenous variables and the one related to sorghum as own region's sorghum price observed at current period. The temporal lagged millet price seems to have a positive and significant correlation with its next period level (**0.68**). The second and third parameters correspond to cross-region millet price transmission. They are both significant with different signs. The contemporaneous millet price of adjacent locations has a positive impact (0.28) while its lagged term has a negative (-0.23). This fact may lead a neutral indirect effect (to be confirmed by results in columns 2 to 4). The last significant parameter equals 0.09, which means sorghum price could have a positive direct effect on the millet price. Other parameters are not significantly different from zero. These results have to be confirmed by results in columns 2 to 4.

Table 4.1 Millet market integration resultsusing SDPD

	Spatial first-differences SDPD and effects estimates			
Explanatory variables	Coef	Direct	Indirect	Total
	(1)	(2)	(3)	(4)
Millet (-1)	0.68	0.67	-0.00	0.67
	24.4	17.58	-0.49	16.6
W*Millet (-1)	-0.22			
	-3.26			
W*Millet	0.28			
	3.71			
Maize	0.02	0.02	0.000	0.02
	0.60	0.50	-0.06	0.48
Rice	0.04	0.051	-0.00	0.05
	1.15	1.04	-0.22	1.00
Sorghum	0.09	0.10	0.00	0.10
	3.96	2.63	0.79	2.57
W*Maize	-0.01			
	-0.34			
W*Rice	-0.02			
	-1.10			
W*Sorghum	0.01			
	0.50			
Number of				
Observations	1057			
Fisher Stat	0.26			
tau+rho+eta	0.79			
Wald-test	23.35			
P-value Wald test	0.00			

Source: Authors' calculations.

Note: The numbers in (.) are the asymptotic t-statistic.

The convergence effect, the effect due to the temporal or spatial lag of the dependent variable, here the millet price, showed a positive and significant direct effect (**0.68**) and a non-significant indirect effect. The direct convergence effect means that there is a price transmission over time of **68** percent for Niger millet market. An increase in the previous price of millet is transmitted to its current level for about 68 percent. This parameter is the price transmission elasticity of millet price from one period to the next. Since the indirect convergence effect is not significant, this 68 percent price transmission is only a region specific price transmission. There is no cross-regions price transmission in Niger millet market. Concerning the impact of the price of millet's substitute commodities (maize, sorghum, and rice), we found that a change in the price of maize or rice had no direct nor indirect impacts on the millet price. Conversely, an increase of the price of sorghum significantly increased the price of millet. In fact, the direct effect of sorghum is transmitted to millet price for about 10 percent. This finding could be seen as evidence of the fact sorghum is a substitute for millet.

Two interesting findings are from these results. First, there is no cross-regions price transmission for millet market in Niger. This means that a price change in one location had likely no effect on price level in other locations. Many reasons could be given to explain such situation. Among them, we found (1) high transportation cost, (2) malfunctioning transport service (lagged transmission), (3) imperfect substitution of goods, (4) lack of price information, and (5) installed infrastructures (Badiane and Shively 1998, Ghosh 2011, Rashid et al. 2008, Minot 2010). Even though each of these factors could explain the inexistence of price transmission across regions, transport-related factors and infrastructure would be the most important factors in Africa in general and Niger specifically. Limited road infrastructure is available in Africa. Therefore, transports costs are high compared to other regions of the world (Macchi and Raballand , 2009; Teravaninthorn and Rabelland, 2009). Due to a lack of adequate infrastructure, the transportation of commodities took too much time. This situation could constitute a caveat for price transmission since traders cannot access readily available price information.

Second, only sorghum, a locally produced and consumed cereal (less than 2% of imports), affects the price of millet. Maize and rice, which mainly depend on imports, have no impact on millet market. Even though each of the aforementioned cereals were natural substitutes, their availability on local markets and the associated prices would determine consumers' choices. Millet and sorghum, which are locally produced and consumed, are likely to be the first choices of the population. Results also confirmed that Niger's top cereal imports, rice and maize, are not substitutes for locally traded commodities such as millet and sorghum. In the local market, exception to rice, these cereals have similar prices and dynamics (Figure 4.1). Therefore, the inexistence of price transmission from maize to millet is likely due to availability and consumers behavior. For rice, this could be explained by the price gap—rice price is about 2 to 4 times the price of millet (SIMA, 2013)— and the fact that in many West African countries, rice is considered a luxury good, and is generally only consumed during special events (FAO, 2009).

5. Conclusion

Price transmission is an important research topic from a scientific and policy perspective. The recurring commodity price spikes, especially the recent food price crisis, have revived the debate on the issue of market integration and best policy response. Price transmission occurs from one period to another and between separate locations. This study is one of few that suggest the use of a dynamic spatial econometrics framework for the analysis of price transmission and thus the integration of markets. As an application, the SDPD model has been used to analyze the price

transmission on the millet market. Our results revealed (i) a cross commodities price transmission between locally traded commodities (millet and sorghum) and regionally, or internationally traded cereals (rice and maize), and (iii) nosignificant spillover or diffusion effects (cross regions price transmission) for cereals market. These findings have some policy implications. Since absence of cross regions price transmission (market integration) is due to poor infrastructures and institutional facilities, government of Niger should strategically invest in appropriate infrastructures that will improve cereal markets integration. Millet and sorghum are essential for food security in Niger, and given the fact they are segmented from most imports cereals, it would be interesting for government to promote their production, which may be a good resilience strategy for consumers. In addition, storage facilities development can reduce their post-harvest losses and allow a better food availability in the country.

REFERENCES

- Aker, J. C. (2010). Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger. *American Economic Journal: Applied Economics* 2 (3): 46–59.
- Badiane, O. and Shively, G. E. (1998). Spatial integration, transport costs, and the response of local prices to policy changes in Ghana, *Journal of Development Economics*, Elsevier, vol. 56(2), 411-431.
- Baulch, B. (1997). Testing for Food Market Integration Revisited. *The Journal of Development* Studies 33 (4):512–534.
- Beekhuis, G. and I. Laouali. (2007). Cross-border Trade and Food Markets in Niger: Why Market Analysis is Important for Humanitarian Action. *Humanitarian Exchange Magazine* 38: 25–27.
- Chirwa, E. W. (2001). Food Pricing Reforms and Price Transmission in Malawi: Implications for Food Policy and Food Security. Unpublished. University of Malawi, Zomba..
- Debarsy, N., C. Ertur, and J. P. LeSage. (2012). Interpreting Dynamic Space–Time Panel Data Models. *Statistical Methodology* 9 (1): 158–171.
- DIVA-GIS. (2013). Free Spatial Data. http://www.diva-gis.org/datadown.
- Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*. New York: Springer.
- FAO (Food and Agriculture Organization of the United Nations). (2009). Profil Nutritionnel du Niger. Division de la Nutrition et de la Protection des Consommateurs. Rome.
- Ghosh, M. (2011). Agricultural Policy Reforms and Spatial Integration of Food Grain Markets in India. *Journal of Economic Development* 36 (2): 15-37.
- Goundan, A., M. R. Tankari. (2016). A Dynamic spatial modeling of agricultural price transmission: Evidence from Niger millet market". Washington: International Food Policy Research Institute, *forthcoming*.
- Greb, F., von Cramon-Taubadel, S., Krivobokova, T., &Munk, A. (2013). The estimation of threshold models in price transmission analysis. *American Journal of Agricultural Economics*, 95 (4): 900-916.
- Jones, W. O. (1972). *Marketing Staple Food Crops in Tropical Africa*. Ithaca, NY, US: Cornell University Press.

- Keller, W., and C. H. Shiue. (2007). The Origin of Spatial Interaction. *Journal of Econometrics* 140 (1): 304–332.
- Lee, L.-f., and J. Yu. (2010). Some Recent Developments in Spatial Panel Data Models. *Regional Science and Urban Economics* 40 (5): 255–271.
- LeSage, J. P. (1999). *The theory and practice of spatial econometrics*. University of Toledo. Toledo, Ohio, 28, 33.
- LeSage, J., and, R. K. Pace. (2009). *Introduction to Spatial Econometrics*. CRC Press/Taylor & Francis Group.
- Macchi, P., and G. Raballand. (2009). Transport Prices and Costs: The Need to Revisit Donors' Policies in Transport in Africa. Bureau for Research & Economic Analysis of Development, Working Paper No. 190. Washington, DC: World Bank. http://ssrn.com/abstract=1511190
- Meyer, J., and S. Cramon-Taubadel. (2004). Asymmetric Price Transmission: A Survey. *Journal of Agricultural Economics* 55(3):581–611.
- Minot, N. (2010). Transmission of world food price changes to markets in Sub-Saharan Africa. Washington: International Food Policy Research Institute.
- Monke, E., and T. Petzel. (1984). Market Integration: An Application to International Trade in Cotton. *American Journal of Agricultural Economics* 66(4):481–487.
- Rashid, S., A. Gulati, and R. Cummings Jr. (2008). Grain marketing parastatals in Asia: Why do they have to change now? In *From Parastatals to Private Trade: Lessons from Asian Agriculture*, 51–76. Baltimore: John Hopkins University Press.
- Ravallion, M. (1986). Testing Market Integration. *American Journal of Agricultural Economics* 68(1):102–109.
- Shin, M. (2010). A Geospatial Analysis of Market Integration: The Case of the 2004/5 Food Crisis in Niger. *Food Security* 2 (3): 261–269.
- SIMA (Système d'Information sur les Marchés Agricoles du Niger). (2013). Cereals price data. http://www.simaniger.net/
- Teravaninthorn, S., G. Raballand. (2009). Transport Prices and Costs in Africa : A Review of the International Corridors. Directions in Development; Infrastructure. Washington, DC: World Bank.https://openknowledge.worldbank.org/handle/10986/.
- USDA (United States Department of Agriculture). (2016). Market and Trade Data.

Available at: https://apps.fas.usda.gov/psdonline/psdDownload.aspx

- Yu, J., R. de Jong, L.-f Lee. (2008). Quasi-maximum Likelihood Estimators for Spatial Dynamic Panel Data with Fixed Effects when Both N and T are Large. *Journal of Econometrics* 146 (1): 118–134.
 - . (2012). Estimation for Spatial Dynamic Panel Data with Fixed Effects: The Case of Spatial Cointegration. *Journal of Econometrics* 167 (1): 16–37.