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The Cost of Collateralized Borrowing in the Colombian Money Market: Does Connectedness Matter?¹

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Abstract

Under the view that *the market* is a weighted and directed network (Barabási, 2003), this document is a first attempt to model the Colombian money market within a spatial econometrics framework. By estimating two standard spatial econometric models, we study the cost of collateralized borrowing (i.e. sell/buy backs) among Colombian financial institutions, and its relationship with the effects induced by traditional variables (leverage, size and borrowing levels), and by spatial variables resulting from observed linkages among financial institutions. The model that best fits the data is the Spatial Durbin Model, whose main findings indicate that (i) traditional variables are of low explanatory power by themselves; (ii) there exists a significant spatial dependence with regard to the cost of collateralized borrowing; (iii) the inclusion of spatial lags of the same traditional factors results in a model able to explain the existence of borrowing spreads that vary across financial institutions despite the collateralized nature of sell/buy backs; (iv) direct and spill-over effects from the spatially lagged value of financial leverage are the most significant for determining the cost of collateralized borrowing. Results are valuable since making connectedness an explanatory variable breaks with the traditional (reductionist) understanding of financial markets, which concurs with the current interest in the macro-prudential perspective of financial stability.

JEL: C31, G21, G32.

Keywords: money market, interbank, collateral, collateralized borrowing, spatial econometrics.

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I. Introduction

As presented in León (2012), collateralized borrowing is the most important source of liquidity for financial institutions in the Colombian money market, where the most commonly used collateral is local sovereign securities (i.e. TES).⁴ Based on 2010, 2011 and 2012 daily averages, the two main money market operations are repos with the Central Bank and sell/buy backs (*simultáneas*) between financial institutions, where they account for about 60.3% and 32.9% of the money market liquidity, respectively. Unlike other countries, the contribution of non-collateralized borrowing as a liquidity source in the Colombian case is rather low (6.5%).

Since the cost of repos with the Central Bank does not follow active credit risk monitoring considerations, and due to the subsidiary role of non-collateralized borrowing and other types of money market operations (e.g. repos between financial institutions)⁵, the most appropriate source of money market information for inferring credit quality is sell/buy backs transactions. Thus, in the sense of Rochet and Tirole (1996) and Calomiris (2003), sell/buy backs might be particularly effective as sources of market discipline data for monitoring purposes because similar institutions might be expected to identify a peer's risk best.

Consequently, information corresponding to sell/buy backs may be useful to analyse the cost of borrowing among financial institutions participating in the local money market. Explanatory variables (i.e. risk factors) that are commonly used for analysing the cost of borrowing are related to idiosyncratic or institution-centric metrics of credit risk, such as leverage, asset value and liquidity. In this sense, as may be inferred from Berndsen (1992), a traditional model of the cost of borrowing would rely on a reductionist approach to a complex system, where it would be customary to find the introduction of *ceteris paribus* conditions, summarizing or ignoring feedback loops, and making assumptions about the order of magnitude of counteracting effects.

However, as has been prompted after the global crisis that begun in 2007, connectedness is a risk factor worth including in models that deal with complex systems, where the latter are characterized by their connectedness and hierarchical structure (Casti, 1979). In this sense, making connectedness an explanatory variable is important because (i) it concurs with the view that *the market* is not a

⁴ For instance, based on approximate figures, in 2012 79% of collateralized money market transactions (i.e. sell/buy backs and repos, excluding Central Bank's repos) used sovereign local securities (i.e. TES) as collateral, whereas 17% used other fixed income securities, and 4% used equities; if Central Bank's repos are considered, sovereign local securities represent about 93%. All estimations and analysis in this document are restricted to sovereign local securities.

⁵ After excluding Central Bank's repos, sovereign securities sell/buy backs are the most important source of credit risk monitoring and market discipline, with 2010, 2011 and 2012 daily averages value of transactions around 83% of the total, whereas repos between financial institutions account for about 1%, and non-collateralized borrowing around 16%, respectively.

mythical entity that mediates all economic interactions, but a weighted and directed network of institutions (Barabási, 2003), and (ii) it breaks with the traditional –reductionist- understanding of financial markets, which concurs with the current interest in the macro-prudential perspective of financial stability.

Accordingly, Krugman (1996) acknowledges the shortcomings of mainstream economics: *How do economists routinely deal with the question of how the economy organizes its use of space? The short answer is that mostly they do not deal with the question at all.* Traditional econometric models are non-spatial in nature, where the multidirectional dependence among the sample observations is ignored. Nevertheless, some econometric models have acknowledged the importance of spatial concepts, such as distance, adjacency or links between the observations, where such models have been labelled as *spatial econometrics*.

This document is a first attempt to make connectedness an explanatory variable of the cost of collateralized borrowing in the Colombian money market by means of spatial econometrics, in which connectedness is defined by the existence of collateralized borrowing/lending flows (i.e. transactions) between financial institutions. This attempt consists of (i) using local sovereign securities sell/buy backs' spreads over the Central Bank's reference rate as the cost of collateralized borrowing in the Colombian money market, as suggested by León (2012); (ii) using the Colombian local sovereign securities sell/buy backs operations' network as the connectedness variable for the models; and (iii) implementing two basic specifications of spatial econometric models (i.e. Spatial Autoregressive and Spatial Durbin Model), where their selection resulted from the convenience of decomposing spatial effects (network effects) into their direct and indirect constituents.

Besides being a novel approach to understanding financial networks and the money market in the Colombian case, results (i) confirm the relevance of connectedness for analysing financial markets, along with the importance of macro-prudential approaches to financial stability; (ii) confirm the importance of understanding direct and indirect network effects in the borrowing costs of the Colombian collateralized borrowing money market; and (iii) verify that local sovereign securities fail to offset credit risk in collateralized borrowing among financial institutions, as suggested by León (2012).

This document is structured as follows. The next (second) section introduces spatial econometric models, with emphasis on the selected specifications (i.e. Spatial Autoregressive and Spatial Durbin Model). The third section describes the datasets, and the fourth presents the results of the

estimations. The last section presents some relevant remarks about the results, along with several potential research avenues.

II. Spatial Econometrics models

Spatial econometric models are mostly used to examine data that exhibit a spatial dependence related to the notion of geographic distance. Spatial dependence in data is a concept that can be easily understood as the case in which the value taken by the dependent variable of a cross sectional unit is affected by the value taken by the dependent variable of another cross sectional unit.

An analogy with traditional time-series analysis is illustrative. In time-series models the basic building blocks are constructed with the help of the time lag operator, whereas in spatial models a network lag operator plays a similar role, only along a different dimension; the time-lag operator shifts a variable by one period and its power refers to events more distant in time, whereas a network-lag of a variable is the average of values from neighbouring nodes (Signori and Gençay, 2010).

The spatial dependence is a feature that has been usually attributed to the existence of heterogeneity and spatial autocorrelation. The absence of homogeneity in a sample (i.e. heterogeneity) is a concept composed by '*structural instability*' and '*heteroscedasticity*'. Structural instability is noticeable in parameters and functional forms that particularly depend on the localization of each region, whereas the heteroscedasticity could emerge from omitted variables and specification errors. The spatial autocorrelation can be explained by the multidirectional dependence among the sample observations, and is usually attributed to: (i) measurement errors; (ii) interaction phenomena; (iii) and spill-over effects (Moreno and Vayá, 2002).

The first formalizations in this topic go back to the work of Anselin (1980, 1988), who developed the Spatial Autoregressive model (SAR), and the Spatial Error model (SEM); two models that closely resemble the autoregressive model and the moving average model of time series, respectively, but within a spatial context. Since 1993, with the developing of some alternative specifications, such as the Manski model, this strand of theoretical econometrics completed the set of models known so far. However, the empirical application of these models has been scarce because of the difficulties implied by the computation of some of these specifications.

A. Defining the weights matrix

Spatial autocorrelation in data invalidates the assumption of spherical errors, and is usually explained as a multidirectional dependence among the units of study that occur by the mutual affectations that emerge among contiguous units, like regions. The multidirectional dependence could be properly quantified by means of a spatial weights matrix among units (W) (Moreno and Vayá, 2002).⁶

This matrix, also known as connectivity matrix, is row-stochastic⁷ and squared, with a dimension that depends on the number of units, and is formed by elements (w_{ij}) that replicate the *intensity of interdependence* that exist between pairs of units (i and j).⁸

The matrix C , displayed below, represents the connectivity among four entities. For instance, element (1,2) indicates that entity E_1 is first order connected to E_2 , and this element coincides with the one located in the position (2,1) of the matrix; therefore, in this case, matrix C is also symmetrical.

$$C = \begin{bmatrix} & E_1 & E_2 & E_3 & E_4 \\ E_1 & 0 & 1 & 0 & 0 \\ E_2 & 1 & 0 & 1 & 0 \\ E_3 & 0 & 1 & 0 & 1 \\ E_4 & 0 & 0 & 1 & 0 \end{bmatrix}$$

The zeroes capture the absence of contiguity between non-connected entities (e.g 1,3) or the impossibility of finding self-connected entities. The weights matrix may be normalized, adjusting the rows so that each of them will individually sum one (i.e. row-stochastic). Hence, the matrix (W) will allocate the same weight to each neighbour region (LeSage and Pace, 2009):

$$W = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

⁶ According to these authors, in the temporal context, the autocorrelation is defined by a unidirectional dependence, because the past explains the future. The time series lag operator (L) is commonly used to capture this unidirectional effect. In the spatial context this function (now multidirectional) is fulfilled by the weights matrix.

⁷ A matrix being row-stochastic corresponds to a matrix of non-negative real numbers, with each row summing to 1. It is also known as a probability or transition matrix.

⁸ Regarding the usage of *intensity* as a connectedness variable, Simon (1962) acknowledges that intensity reconciles the interaction between dissimilar types of networks, in which physical and biological networks are better described in terms of spatial terms (e.g. distance, contiguity), whereas social networks are in interaction terms (e.g. friendship, partnership, acquaintance).

The vector of spatial lags ‘ Wy ’ is defined by the product of the matrix (W) and the vector of entities (y):

$$W \times y = \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 \\ 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 1 & 0 \end{bmatrix}}_W \underbrace{\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix}}_y = Wy = \begin{bmatrix} y_2 \\ (y_1 + y_3)/2 \\ (y_2 + y_4)/2 \\ y_3 \end{bmatrix}$$

In the spatial econometrics literature, the definition of the spatial weights lack of a common criterion. However, any definition should, undoubtedly, establish positive weights. The weights in this matrix are typically constructed using geographical measures of distance, such as the Euclidean distance. In the example presented above, the matrix W is symmetrical given that the weights are based on spatial distances among units. However, in other cases this feature and the normalization of rows might not be necessary. For instance, some studies of social phenomena have used indicators of distance based on information of democracy, trade and social distance. Other notions of distance are based on networks and linkages among observations (Beck, Glenditsch and Beardsley, 2006).

B. The Spatial Autoregressive Model (SAR model)

One of the simplest approximations to the analysis of spatial data is provided by the Spatial Autoregressive model (SAR), in which the spatial autocorrelation only affects the endogenous variable; thus, it is also known as the Spatial Lag model. This condition could also be understood as the case in which the dependent variable of the other units of analysis could affect the dependent variable of the unit under study (Neumayer and Plümer, 2010). Therefore, the spatial effect is composed by the weighted average of the values taken by the dependent variables of other units:

$$y = \rho Wy + X\beta + \varepsilon \quad (1)$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

In this model:

- y is the vector of endogenous or dependent variables, of dimension $(n \times 1)$
- ρ is the scalar spatial autoregressive parameter of the dependent variable
- β is the traditional (i.e. non-spatial) vector of parameters
- W is the matrix of spatial weights, of dimension $(n \times n)$
- X is an $(n \times k)$ matrix of exogenous explanatory variables

ε is the $(n \times 1)$ vector of residuals
 I_n identity matrix of dimension $(n \times n)$

As pointed out by LeSage and Pace (2009), the parameter ρ could be considered as the correlation coefficient between the vector ‘ y ’ and the vector of spatial lags ‘ Wy ’. Despite the similarity of this spatial parameter with the standard correlation coefficient, this parameter is not constrained by the bounds $-1/+1$. In fact, the range in which this parameter should fall is determined by the matrix of weights designated to account for the spatial dependence among units.

Solving equation (1) and reorganizing the terms, we can get the implied data generating process (DGP), where the term $(I_n - \rho W)$ is non-singular for all $\rho \in (-1, 1)$ (LeSage and Pace, 2009):

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} \varepsilon \quad (2)$$

Equation (3) is a compact version of equation (2) which allows for decomposing the dependent variable y in terms of two matrix expressions: $S_r(W)$ and $V(W)$

$$y = \sum_{r=1}^k S_r(W) x_r + V(W) \varepsilon \quad (3)$$

The first of these expressions ($S_r(W)$) is a $(n \times n)$ multiplier matrix *that* captures all impacts (direct and indirect) generated by changes in the r -th non-constant explanatory variable:

$$S_r(W) = V(W) I_n \beta_r \quad (4)$$

$V(W)$ is an infinite series expansion of $(I_n - \rho W)^{-1}$ that affects both, the vector of estimated parameters β_r and the vector of residuals:

$$V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \dots \quad (5)$$

For the cases where the spatial autoregressive parameter of the dependent variable (ρ) takes a value lower than one, in absolute terms, the impact estimates of the series expansion will decline.

From the above, it follows that the interpretation of the effects that a unit change in an exogenous variable x_j has on dependent variable y cannot be done directly on the estimated regression coefficient. In this context, if we want to interpret the effect that a change in the independent variable that entity j has on the dependent variable of other entities, we have to examine the following expression:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} = V(W)I_n\beta_r = (I - \rho W)^{-1}I\beta_j \quad (6)$$

According to Corrado and Fingleton (2010), the average total effect corresponds to equation (7), in which the term q corresponds to a $(N \times 1)$ vector of ones:

$$N^{-1} \sum \frac{\partial y_i}{\partial x_{jr}} = N^{-1}q'(I - \rho W)^{-1}I\beta_jq \quad (7)$$

The average total effect is explained by the direct and indirect effects. The direct effects are in the diagonal elements of the multiplier matrix $S_r(W)$, whereas the indirect effects can be found in the off-diagonal elements of the same matrix.

The average direct effect of a unit change in x_{rj} on y_r is given by equation (8). Accordingly, the direct effect does not exactly correspond to the estimated parameter (β_j) because a change in x_{rj} impacts y_r , the dependent variable of this region will affect another region $y_s (s \neq r)$ and so on. In the end, this impact returns to the former unit and produces an additional effect on y_r .

$$N^{-1} \sum_r^N \frac{\partial y_r}{\partial x_{rj}} = N^{-1} \text{trace}[(I - \rho W)^{-1}I\beta_j] \quad (8)$$

Likewise, the average indirect effect can be explained by the difference between the total effect and the direct effect. In matrix algebra, this effect equals the mean of the off-diagonal elements of the matrix $(I - \rho W)^{-1}I\beta_j$:

$$N^{-1} \sum \frac{\partial y_r}{\partial x_{sj}} = N^{-1}(q'(I - \rho W)^{-1}I\beta_jq - \text{trace}[(I - \rho W)^{-1}I\beta_j]) \quad (9)$$

C. The Spatial Durbin Model (SDM)

Under a similar structure to that exhibited by the SAR model, the SDM not only includes the spatial effect of other entities on the dependent variable (as captured by ρ), but it also considers spatial lags of the independent variables by means of including the term $WX\theta$ in equation (1), where the effect of other entities on the independent variables is captured by θ . As in LeSage and Pace (2009):

$$y = \rho W y + X\beta + WX\theta + \varepsilon \quad (10)$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

For this model the corresponding DGP is given by:

$$y = (I_n - \rho W)^{-1}(I_n\beta + W\theta)X + (I_n - \rho W)^{-1}\varepsilon \quad (11)$$

But equation (11) could be re-expressed in terms of $V(W)$ and $S_r(W)$, as follows:

$$y = \underbrace{\frac{(I_n - \rho W)^{-1}(I_n\beta + W\theta)}{V(W)}}_{S_r(W)} + \frac{(I_n - \rho W)^{-1}\varepsilon}{V(W)} \quad (12)$$

Again, the multiplier matrix $S_r(W)$ summarizes the direct and indirect impacts caused by the explanatory variables, in its diagonal and off-diagonal elements, respectively:

$$y = \sum_{r=1}^k S_r(W)x_r + V(W)\varepsilon \quad (13)$$

Therefore, the DGP (13) in matrix form will be given by the following expression:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \sum_{r=1}^k \underbrace{\begin{bmatrix} S_r(W)_{11} & S_r(W)_{12} & \dots & S_r(W)_{1n} \\ S_r(W)_{21} & S_r(W)_{22} & \dots & S_r(W)_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_r(W)_{n1} & S_r(W)_{n2} & \dots & S_r(W)_{nn} \end{bmatrix}}_{S_r(W)} \begin{bmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{bmatrix} + V(W)\varepsilon$$

From the matrix expression below one can extract a measure of the impact generated on the i -th unit:

$$y_i = \sum_{r=1}^k [S_r(W)_{i1}x_{1r} + S_r(W)_{i2}x_{2r} + \dots + S_r(W)_{in}x_{nr}] + V(W)_i\varepsilon \quad (14)$$

Hence, the effect that a change in the independent variable that entity j has on the dependent variable of all other entities (the cross-partial derivative) will be given by:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \quad (15)$$

Likewise, the effect that a change in the independent variable that an entity has over its own dependent variable (the own-partial derivative) is represented by:

$$\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii} \quad (16)$$

This last result demonstrates that the entity i will affect other entities, but at the same time, the change in its own independent variable may perhaps affect this entity again. The magnitude of the total impact could depend on: (i) the connectivity to other entities; (ii) the strength of spatial

dependence measured by ρ ; (iii) the parameters β and θ ; and (iv) the elements in the diagonal of matrix $S_r(W)$ (LeSage and Page, 2009).

With regard to equations (10) and (11), it is important to remark that the parameter interpretation should be done with caution. In absence of spatial dependence, the interpretation of the estimated coefficients is usually executed under the notion of partial derivatives. In presence of spatial dependence the estimation of coefficients employs a weights matrix which ends by transforming X_r using $S_r(W)$. In words of LeSage and Page (2009), the concept of partial derivatives cannot be used to interpret the parameters of these models because from its specification it is clear that “*any change to an explanatory variable in a given observation can affect the dependent variable in all observations through the matrix inverse*”. For that reason, the inferences for the SDM model should be made from equations (15) and (16).

Although it is common to find other alternative models in spatial econometrics literature (e.g. SEM, SDEM, SAC and Manski model)⁹, for the purpose of this study the most convenient are SAR and SDM models since their specifications enable to compute the direct and indirect network effects resulting from connectedness.¹⁰

D. Methods of estimation

The empirical literature on spatial econometrics has warned that the ordinary least squares (OLS) method is not appropriate for estimating models with spatial dependent data, given that this procedure ignores the spatial interdependence among units. If this condition is ignored the variance-covariance matrix obtained through OLS will be inappropriate, which could weaken the inferences based on the estimated parameters. In other words, under spatial dependence the assumption of spherical errors required to perform both the individual and joint significance tests, will not hold.

Unlike the OLS method, the Maximum Likelihood will generate a consistent estimation of the spatial parameters, even in cases in which the error term does not follow a normal distribution. In

⁹ Some of the alternative models are more parameterized, whereas others are based on a structure with spatial dependence parameters affecting the residuals.

¹⁰ For details on other spatial econometric models, like SEM (Spatial Error Models), SDEM (Spatial Durbin Error Model) and SAC (General Spatial Model, also known as Kelejian Prucha model), see LeSage and Page (2009) and Elhorst (2010).

addition to guaranteeing consistency, this method of estimation will produce asymptotically efficient parameters (Moreno and Vayá, 2002; Franzese and Hays, 2004).¹¹

III. Data description

The dependent variable was defined as the collateralized borrowing spread (*spr*) for each financial institution in the local money market, which corresponds to the value-weighted average of the MEC (Mercado Electrónico de Colombia) and OTC (over the counter) sell/buy backs' (i.e. *simultáneas*) margin over the Central Bank's intervention rate for each financial institution, as estimated by León (2012).¹² This average corresponds to short-term (1 to 3 days) sell/buy backs transactions taking place in a six-month period extracted from June 2011 to May 2012, where only transactions collateralized with sovereign securities (i.e. TES) were considered.¹³

As before, sell/buy backs consist of two sell and buy transactions simultaneously contracted, with the same principal amount and security, with both parties obliged to take the inverse position at maturity (i.e. the buyer becomes the seller), where the property of the collateral is transferred to its buyer.¹⁴ As previously stated, sell/buy backs are the second most important source of money market liquidity (second to Central Bank's liquidity), and are the most appropriate source of money market information for inferring credit quality under some intuitive –yet sound- assumptions, namely (i) excluding transactions not conveying market discipline information; (ii) excluding non-proprietary (i.e. on behalf of clients) transactions; (iii) and using the Central Bank intervention rate as a threshold to capture money-demanding transactions, as suggested by León (2012).

The set of independent variables (X) comprises traditional (i.e. institution centric) factors such as (i) financial leverage, (ii) total value of assets and (iii) total value of sell/buy back borrowing. The measure of financial leverage was computed as the ratio of total liabilities to total assets, with data from each institution's financial statements. This variable was included with the aim of testing

¹¹ Some alternative methods, not based in the normality assumption of the residuals, such as that of the instrumental variables –S2SLS-IV and the generalized method of moments –GMM- are very useful for cases with spatial dependence that includes more than one explanatory variable (different from those spatially lagged) that requires to be instrumented (Elhorst, 2010).

¹² As presented in León (2012), unlike SEN (Sistema Electrónico de Negociación), MEC and OTC sell/buy backs convey information concerning the credit quality of the counterparties, and thus it is useful as a source of market discipline. Additionally, since not all sell/buy backs or repo transactions result from equal motivations (Cardozo et al., 2011; Hördahl and King, 2008), the Central Bank's intervention rate is used as a threshold to capture (discard) those sell/buy backs that are related to money-demanding (securities-demanding) transactions.

¹³ Lack of precision regarding the six-month period used follows disclosure reasons. Likewise, the names of financial institutions included in the model are not disclosed.

¹⁴ Unlike repos, haircuts and mobility limitations are not imposed on collateral, which may explain why Colombian financial firms prefer sell/buy backs to other sources, including repos with the Central Bank during some periods.

whether the leverage of a financial institution and the market's perception of counterparty risk move in tandem, as commonly found in corporate finance literature (Merton, 1974), and as suggested by simple intuition.

The total value of assets is a simple metric for the size of each financial institution, measured in monetary terms (i.e. Colombian pesos), as reported in their financial statements. Based on the too-big-to-fail criteria, which recognizes the willingness of financial authorities to aid large financial institutions in distress, it is expected that the larger the borrower, the lower the cost of borrowing. Total value of sell/buy back borrowing is also measured in monetary terms, and serves the purpose of testing whether financial institutions' borrowing level in the money market affects their cost of borrowing; intuitively, the higher the borrowing level, the higher the cost.¹⁵ Traditional summary statistics of the cost of collateralized borrowing (*spr*) and the non-spatial explanatory variables (X) are presented in Appendix A.

It is worth highlighting that the statistical significance of any of these variables, spatial or non-spatial, would verify the findings of León (2012) regarding the existence of borrowing spreads that vary across financial institutions despite they all use rather homogeneous and low credit risk collaterals (i.e. sovereign's local securities denominated in local currency). In other words, securitization would not offset counterparty risk in the Colombian market, where possible explanations for this finding may be related to local sovereign securities not being an ideal collateral (i.e. a security that functions like cash) in the sense of Gorton and Metrick (2010), or to the potential cost of having the collateral trapped in a bankruptcy proceeding (French et al., 2010).¹⁶

For the estimation of the spatial models we used a row-standardized weights matrix that was constructed using the value of the transactions (sell/buy backs) among the participants in the selected set of sell/buy backs transactions. This matrix is non-symmetrical given that lending reciprocity is not warranted (i.e. the value of the lending from one participant to another may not correspond to the value of the lending in the opposite direction).

¹⁵ Since the OTC market is bilateral (i.e. non-anonymous), it is rather evident that the higher the borrowing, the higher the cost. Despite being an anonymous trading platform, MEC allows users to define a quota or exposure limit for each other potential counterparty, where this limit follows active credit risk assessment from the liquidity-offering firm. Thus, it is intuitive that an institution heavily borrowing in the selected collateralized money market will face increasing marginal funding costs.

¹⁶ According to Gorton and Metrick (2010), the ideal collateral is a security that functions like cash: this is, collaterals must be information-insensitive securities by design, with their price being immune to adverse selection whenever they are traded. Therefore, if collaterals are not information-insensitive securities, concerns arise about the ability to recover the collateral value when sold in the market if the counterparty did default. French et al. (2010) highlights that despite pledged collateral is senior to the claims of other creditors, if failure is a concern the potential cost of having the collateral trapped in a bankruptcy proceeding for even a short period is large relative to the interest due on a one-day loan.

The total number of financial institutions reported by León (2012) is 38. However, since the model requires that each row of the weights matrix has at least one non-zero element, the number of financial institutions available drops to 21. This set of financial institutions comprises seven banks, ten brokerage firms, two insurance firms, one financial corporation and one investment fund.

IV. Estimation results

In this section we present the summary estimates obtained from the Spatial Autoregressive model (SAR) and the Spatial Durbin Model (SDM). Let spr be a column vector of dimensions $(n \times 1)$ containing the value-weighted average of collateralized borrowing spread (spr) for each financial institution in the local money market; X a $(n \times 4)$ matrix with each column containing a column of ones (for the intercept term), financial leverage, total value of assets and total value of sell/buy back borrowing, respectively. The SAR and SDM models were estimated as follows:

$$\text{SAR} \quad \quad \quad spr = \rho W spr + X\beta + \varepsilon \quad (17)$$

$$\text{SDM} \quad \quad \quad spr = \rho W spr + X\beta + WX\theta + \varepsilon \quad (18)$$

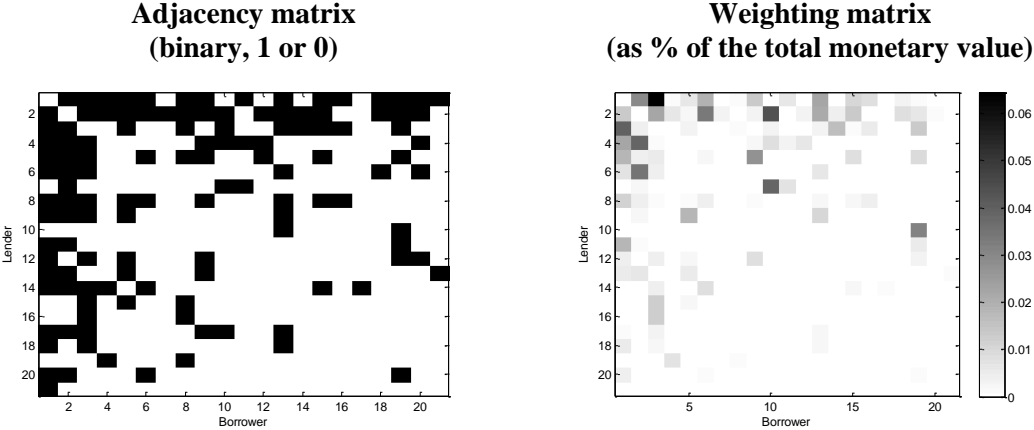
For the estimation of the SAR as well as for the SDM we used a weights matrix (W) constructed using the datasets previously described. The left hand side of Graph No.1 corresponds to the original (i.e. non-row-stochastic) adjacency or connectivity matrix, which exhibits the presence (filled) or absence (blanks) of a link between financial institutions, where an element c_{ij} represents i lending to j (i.e. j borrowing from i).¹⁷ The right hand side of the graph displays the intensity plot of the weighting matrix, where an element w_{ij} represents i lending to j (i.e. j borrowing from i) as a percentage of the total lending (borrowing) between the considered financial institutions. Financial institutions in both matrices are ordered based on the total lending they provide to the system, with most (least) contributing in the upper-left (lower-right) corner of each matrix.

Despite analysing the static complexity (i.e. connectedness and hierarchical structure) of the sell/buy backs network is outside the scope of this paper, it is worth noting some evidence arising from the visual inspection of Graph No.1. For instance, the adjacency and weighted matrices tend to be sparse (i.e. blanks dominate both matrices), thus the network appears to be of low density.

¹⁷ The absence of self-links (i.e. empty diagonal) results from discarding non-proprietary (i.e. on behalf of clients) sell/buy backs.

Moreover, since both matrices are ordered based on the total lending they provide to the system, easily distinguishing zones or blocks suggests the presence of some sort of clustering, where particularly dense areas in the upper-left corner suggests the presence of tiering. Additionally, both matrices display that some participants are particularly important as concentrators of transactions, either measured by the number of links or the value of the corresponding transactions, which suggests the presence of some sort of skewed distribution (e.g. power-law) beneath the connectivity structure of the sell/buy backs network, as documented by León, Machado and Murcia (2013). These preliminary suggestions concur with financial network’s literature.

Graph No. 1 The weights matrix



Source: authors’ design.

With the aim of guaranteeing consistency and efficiency in the estimated parameters, the estimation of these models used the Maximum Likelihood method. Table No. 1 presents the estimated parameters of OLS, SAR and SDM models, along with their standard errors and the summary of test results. From the diagnostic tests executed on the residuals of these models, the problems of heteroscedasticity, non-normality and specification can be discarded from the results. The analysis of the results reported in the first two columns of Table No. 1 evidence the poor fit of the OLS model for this data; such low explanatory power of traditional (i.e. non-spatial) variables concur with the corresponding scatter diagrams that relate the collateralized borrowing spread (*spr*) and the financial leverage, total assets and borrowing in Appendix B. Besides, the statistical significance of the scalar parameter ρ and the parameters provided by the SAR and SDM models along with the reported results of the tests for spatial dependence supports the premise that in presence of spatial

patterns in data, OLS parameter estimates will be biased, and could also be inconsistent and inefficient.¹⁸

Table No. 1 Results of Spatial Autoregressive and Spatial Durbin models

| | OLS | | SAR model | | SDM model | |
|---|--------------|--------------------|----------------------|--------------------|----------------------|--------------------|
| | Coefficient | Standard error | Coefficient | Standard error | Coefficient | Standard error |
| Financial leverage | 0.34 | 0.876 | 0.22 | 0.615 | -0.26 | 0.584 |
| Total assets | 0.00 | 1.18E-08 | 0.00 | 8.31E-09 | 0.00 | 6.55E-09** |
| Borrowing | 0.00 | 2.75E-04 | 0.00 | 1.93E-04 | 0.00 | 0.0002 |
| W_financial leverage | | | | | -4.80 | 1.349*** |
| W_total assets | | | | | 0.00 | 1.36E-08 |
| W_total borrowing | | | | | 6.5E-04 | 0.0003** |
| Constant | 6.57 | 0.481*** | 1.31 | 1.191 | 5.67 | 2.38** |
| $\hat{\rho}$ | | | 0.80 | 0.174*** | 0.63 | 0.262** |
| Acceptable Range for ρ : | | | -1.9745 < ρ < 1 | | -1.9745 < ρ < 1 | |
| Noise variance parameter ($\hat{\sigma}^2$) | | | 0.47 | | 0.36 | |
| Log Likelihood value | | | -15.24 | | -9.21 | |
| \hat{R}^2 | 0.096 | | 0.155 | | 0.659 | |
| \hat{R}^2 adjusted | | | 0.061 | | 0.545 | |
| TEST | Value | Probability | Value | Probability | Value | Probability |
| Spatial Error Correlation | | | | | | |
| GLOBAL Moran MI | | | 0.30 | (0.003)*** | 0.12 | (0.153) |
| Spatial Lag Correlation | | | | | | |
| LM Lag (Anselin) | | | 29.60 | (0.000)*** | 5.57 | (0.02)** |
| General Spatial Correlation | | | | | | |
| LM Spatial Correlation (LMErr+LMLag_R) | | | 401.16 | (0.000)*** | 22.48 | (0.00)*** |
| Heteroscedasticity Tests | | | | | | |
| Cameron and Trivedi | 5.82 | (0.758) | | | | |
| Hall-Pagan LM Test: $E2 = \hat{Y}$ | | | 1.78 | (0.182) | 2.00 | (0.158) |
| Hall-Pagan LM Test: $E2 = \hat{Y}^2$ | | | 1.81 | (0.178) | 2.17 | (0.140) |
| Hall-Pagan LM Test: $E2 = \hat{Y}^2_{t-1}$ | | | 1.75 | (0.185) | 1.82 | (0.177) |
| Jarque-Bera LM Test | | | | | | |
| Skewness | 3.21 | (0.359) | 2.61 | (0.271) | 1.63 | (0.443) |
| Kurtosis | 2.13 | (0.145) | | | | |
| Ramsey Specification Test | 0.72 | (0.555) | 0.83 | (0.376) | 3.43 | (0.087) |

Statistically significant at 5% (**) and 1% (***)

Source: authors' calculations

For both spatial models, SAR and SDM, the coefficient of spatial dependence (ρ) resulted statistically significant at 1% confidence level, with estimated values for such exponent within the estimated acceptable range [-1.97, 1], where this range is calculated for the selected weights matrix.¹⁹ The significance of ρ , along with the overall results obtained with other spatial

¹⁸ The poor fit of the cost of collateralized borrowing provided by the OLS estimation resulted in a very low goodness of fit measure. In fact, the adjusted \hat{R}^2 results in a negative value.

¹⁹ According to Kelejian and Prucha (2010), the range for ρ provides a compact interval that contains the true parameter space.

correlations tests (i.e. Spatial Error Correlation, Spatial Lag Correlation, General Spatial Correlation)²⁰, suggest that the existence of general spatial autocorrelation could be mostly attributed to the spatial dependence of the cost of acquiring financial funds (*spr*). The statistical significance and the positive sign of the spatial dependence coefficient (ρ) in both spatial models (SAR and SDM) suggests that in response to an exogenous shock that increases (decreases) the cost of borrowing of an entity in the collateralized money market, the remaining participants will also experience increments (reductions) in the cost of access to liquidity, which is an intuitive finding that may be caused by the prominence of overall market liquidity conditions on institutions' individual borrowing costs. In other words, this parameter (ρ) can be considered as a broad measure of the intensity of interdependence among entities with regard to the cost of collateralized borrowing, whose positive sign suggests the existence of spillover effects and positive feedbacks.

About the specification of the model, a quick comparison of the results reported in Table No.1 suggests that the model that best fits the data is the SDM, given that the spatially lagged variables of financial leverage (*W_financial leverage*) and total borrowing (*W_total borrowing*) are significant, and also, due to the fact that excluding them from the estimation will result in the existence of spatial dependence in the residuals, as the GLOBAL Moran's I statistic indicates for the SAR model. Hence, although the model mostly used for data with spatial dependence is the SAR (because of its simplicity), the inferences that we could draw from this model will be inaccurate, given that its coefficients estimates suffer from omitted variable bias. Moreover, for the data under analysis, the overall explanatory capabilities of the SDM surpass those of the SAR model, as demonstrated by the adjusted \hat{R}^2 and the log likelihood value attained by each model.²¹

As mentioned before, the SDM (as well as the SAR model) allow for estimating the effects generated by changes in the explanatory variables by means of decomposing them into direct and indirect effects. In regard to our specifications, changes in the set of spatial or non-spatial explanatory variables of a financial institution may cause direct effects, corresponding to the impact on the borrowing cost of the financial institution, along with indirect effects, corresponding to the impact on the borrowing cost of all other financial institutions.

At traditional levels of significance (5%), only three of the six included parameters in the SDM are significant. These parameters are the total assets, and the spatial lag variables of financial leverage and total borrowing. However, given that the estimated coefficients for the total assets and the

²⁰ These tests determine whether the spatial effects emerge from spatial lag dependence (LM lag -Anselin), from residual spatial dependence (Global Moran MI) or from both (General Spatial Autocorrelation).

²¹ As stated by LeSage and Pace (2009), a further advantage of the SDM is that this is the only model that will produce unbiased coefficient estimates under all four possible data generating process (SAR, SEM and SAC).

spatial lag total borrowing are nil, the marginal effects can be mostly attributed to the spatial lag of financial leverage and especially to the component arising from other financial institutions (indirect effect) (tables No. 1 and 2).

Table No. 2 Marginal effects from the SDM

| | Estimated Beta | Total effect | Direct effect | Indirect effect |
|----------------------|------------------|--------------|---------------|-----------------|
| Financial leverage | -0.26 | -0.24 | -0.09 | -0.15 |
| Total assets | 0.00** | 0.00 | 0.00 | 0.00 |
| Borrowing | 0.00 | 0.00 | 0.00 | 0.00 |
| W_financial leverage | -4.80*** | -4.50 | -1.76 | -2.74 |
| W_total assets | 0.00 | 0.00 | 0.00 | 0.00 |
| W_borrowing | 6.5E-04** | 6.0E-04 | 2.0E-04 | 4.0E-04 |

Statistical significance at 5% (**) and 1% (***)

Source: authors' calculations

According to the results of the total effects, the variable that contributes most to explain the cost of acquiring financial funds (*spr*) is the spatial lag variable of financial leverage, with a total parameter impact of -4.50, where the negative sign implies that the more (less) leveraged a financial institution is, the less (more) costly it is able to lend in the money market. Despite being somewhat odd at first, the sign of the coefficient agrees with corporate finance basics: *ex-ante*, debt is always cheaper than equity because it is less risky (Quiry, Dallochio, Le Fur, Salvi, 2005). In this sense, highly leveraged firms have a lower weighted cost of capital, which would allow them to have a lower cost of opportunity of their liquid funds, and –therefore- to lend at a lower rate; however, it is well known that the weighted cost of capital as a function of leverage displays some non-linear features that may limit the validity of this result and its interpretation to leverage levels close to those observed for the selected financial institutions (i.e. debt to assets ratio around 0.68).²²

Hence, consistent with the direct effect for the spatial lag variable of financial leverage (-1.76), it is reasonable to expect that a more leveraged institution will be able to provide less costly liquidity to other participants in the money market and, consequently, this institution will have access to cheaper liquidity from its counterparties. Likewise, the spatial spill-over (indirect effect) impact of financial leverage (-2.74) suggests that increments in the leverage of a financial institution could yield reductions in the cost of access to liquidity of the remaining entities in the market, which will

²² The optimal tradeoff between debt and equity that attains the lowest weighted cost of capital is not a trivial goal; for instance, above a certain level of leverage the risk of bankruptcy will prompt the market to demand higher returns on equity, cancelling out the positive impact of debt financing. In this sense, as in Quiry et al. (2005), the “real world” shows that an optimal capital structure can be achieved with some, but not too much leverage.

result in a general cost reduction of borrowing across the market. Again, this concurs with corporate finance basics, but may be limited to leverage levels close to those observed for the selected financial institutions.²³

The impact decomposition for the remaining significant spatially lagged variable (i.e. lag variable of borrowing) suggests that the indirect effects produce a greater influence on the dependent variable (*spr*) than those that were directly generated (0.0002); the positive sign is intuitive since it suggests that an institution increasing its borrowing will face increasing marginal funding costs. However, given that the estimated parameter for this variable is extremely low, there will be no gains from using the analysis of impact decomposition for this parameter to explain the cost of financial funds.

Finally, consistent with the findings of León (2012) regarding the existence of borrowing spreads that vary across financial institutions despite the collateralized nature of sell/buy backs transactions, several factors considered are statistically significant. This confirms that securitization does not offset counterparty risk in the Colombian market, where traditional (i.e. the size) and spatial (i.e. spatial lag of leverage and total borrowing) factors are explanatory of borrowing cost differences across financial institutions in the Colombian money market; again, this finding may be related to securities not being an ideal collateral (Gorton and Metrick, 2010), or to the potential cost of having the collateral trapped in a bankruptcy proceeding (French et al., 2010).

V. Final remarks

As suggested by the macro-prudential approach to financial systems' analysis, where the complexity arising from financial institutions' connectedness should not be ignored, results confirm the importance of the impact estimates (i.e. direct and indirect effects) in the borrowing costs of the Colombian collateralized borrowing money market. Traditional factors, such as size, leverage and borrowing levels are of low explanatory power by themselves. The inclusion of spatial effects (network effects) of the same traditional factors results in a model able to explain the existence of borrowing spreads that vary across financial institutions despite the collateralized nature of sell/buy backs transactions.

²³ Spatial spill-overs have been recognised earlier in other applied spatial econometric works as those impacts (network spill-overs) that emerge from the characteristics of other entities (neighbours in the network) that ultimately end by affecting the entity under study, as in Signori and Gençay (2010).

Therefore, results not only highlight the importance and significance of connectedness, but also stress the need for implementing models that consider spatial effects in economic analysis. In this sense, this document provides a first attempt to implicitly modelling connectedness for the analysis and understanding of the Colombian financial market within an econometric framework.²⁴

Regarding the limitations of the document, some are worth stating. First, despite the overall fit of the selected spatial models is promising, the number of financial institutions available for implementing the model (i.e. 21) is low, and potentially problematic; unfortunately, the number of financial institutions available depends on market dynamics, and surmounting this limitation may be difficult. Second, results may be dependent on the period analysed; however, this limitation can be easily conquered by implementing the proposed analysis on a frequent basis. Third, as acknowledged by León (2012), sell/buy backs spreads may contain non-credit risk factors (e.g. operational, liquidity and market risks) that affect the estimations; yet, as the collaterals used in the considered transactions are rather homogenous, and since the overall fit of the selected spatial models is adequate, these effects are expected to be secondary for analytical purposes. Fourth, available information does not include transactions where corporate or equity securities act as collaterals; despite local sovereign securities collateralized transactions are unarguably the most important by volume, it would be interesting to account for other types of –less homogeneous– collaterals.

New research avenues arise from some unexploited results. For instance, since coefficient ρ measures the spatial effect of other entities on the dependent variable, its level and dynamics may capture the degree and evolution of potential contagion among money market participants, respectively; this is, the spatial component of borrowing costs among financial institutions could serve as a measure of the potential effect of connectedness.

Likewise, taking into account the promising results here reported, it may be interesting to implement an analogous approach for other types of financial institutions' borrowing, with non-collateralized borrowing data as the most obvious candidate for such implementation. However, a comprehensive implementation should aim at simultaneously considering the three main sources of money market liquidity: collateralized (e.g. sell/buy backs, repos), non-collateralized and Central Bank's collateralized liquidity facilities. We expect to undertake such task in the near future.

²⁴ Non-econometric approaches (i.e. network analysis) for modeling connectedness in the Colombian financial markets may be found elsewhere (e.g. León and Machado, 2013; León and Pérez, 2013; León and Murcia, 2012; León et al., 2012; Cepeda, 2008).

Additionally, based on the new evidence of sovereign local securities not providing a fair offset of credit risk in collateralized borrowing in the Colombian money market, it is worth examining the causes of those securities failing to be ideal collateral (i.e. a security that functions like cash) in the sense of Gorton and Metrick (2010). Some preliminary explanations for such failure may be related to sovereign local securities not being information invariant (León, 2012); market participant's concerns about the potential cost of having the collateral trapped in a bankruptcy proceeding for even a short period of time (French et al., 2010), even when the applicable local legal framework deals with such issue; or the existence of quotas or exposure limits for each other potential counterparty in collateralized money markets.

Finally, since analysing the static complexity (i.e. connectivity and hierarchy) of the collateralized borrowing network is outside the scope of this paper, the preliminary suggestions made based on the visual inspection of the adjacency and weighting matrices (fourth section) should be properly addressed. This is particularly relevant to gain a deeper understanding of the Colombian money market.

VI. References

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Appendix A (Summary Statistics)

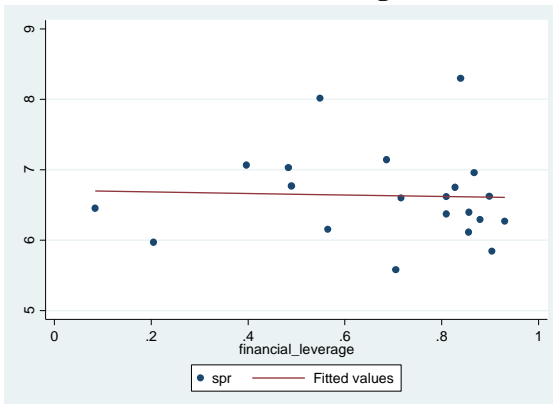
Summary statistics of variables used in the estimations

| | Mean | Standard deviation | Minimum | Maximum |
|--------------------|-----------|--------------------|---------|------------|
| SPR | 6.63 | 0.65 | 5.58 | 8.30 |
| Financial leverage | 0.68 | 0.24 | 0.08 | 0.93 |
| Total assets | 8,181,987 | 15,800,000 | 11,770 | 58,400,000 |
| Borrowing | 718.70 | 732.34 | 18.85 | 2,358.37 |

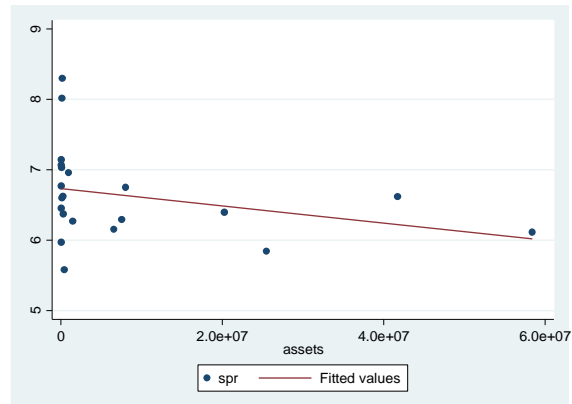
Source: authors' calculations.

Appendix B (Scatter plots)

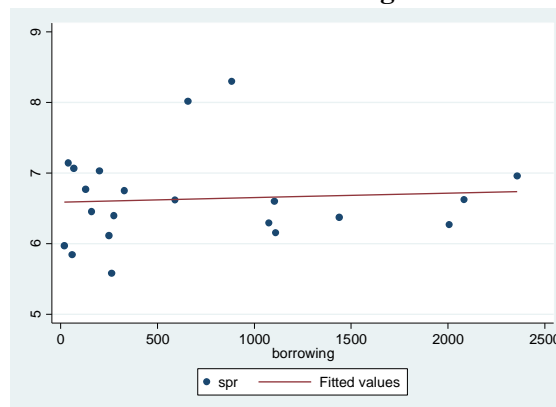
Collateralized Borrowing Spread (*spr*) and Financial Leverage



Collateralized Borrowing Spread (*spr*) and Total Assets



Collateralized Borrowing Spread (*spr*) and Total Borrowing



Source: authors' calculations.