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Abstract: *We analyze the effect of global financial conditions of developed and emerging economies on economic activity in Colombia. To accomplish this task, we estimate financial conditions indices for the stock markets of developed and emerging countries using principal components analysis. Then, we include the estimated indices as regressors in a traditional vector autoregression (VAR) that includes series of economic activity in Colombia; that is, we carry out a factor-augmented vector autoregression (FAVAR) analysis with one unobservable factor and one observable variable accounting for real economic activity to evaluate the influence of international financial conditions on macroeconomic variables in Colombia. Using monthly data, we find that the stock market conditions of emerging economies have a positive effect on macroeconomic performance in Colombia.*

Keywords: *stock prices, financial conditions indices, factor-augmented vector autoregression, dynamic factor models*

JEL Classification: *G10, G15, C38, E44*

Efectos de los índices accionarios de los mercados desarrollados y emergentes sobre la actividad económica en Colombia: una aproximación FAVAR

Resumen: *Analizamos el efecto de las condiciones financieras de economías emergentes y desarrolladas sobre el comportamiento de la economía colombiana. Para ello, estimamos índices de condiciones financieras para mercados accionarios de países desarrollados y emergentes usando análisis de componentes principales. Posteriormente, estos índices se incluyeron como regresores en un modelo tradicional de vectores auto-regresivos (VAR); es decir, estimamos un modelo de vectores auto-regresivos aumentado con factores (FAVAR) que incluye un factor no observable y una variable observable de la actividad económica real con el fin de evaluar el efecto de las condiciones financieras internacionales sobre las variables macroeconómicas colombianas. De esta manera, encontramos que las condiciones accionarias de los países emergentes tienen un efecto positivo sobre el comportamiento macroeconómico de Colombia cuando se lleva a cabo el análisis con datos mensuales.*

Palabras clave: *precios de acciones, índices de condiciones financieras, vectores auto-regresivos aumentados con factores, modelos de factores dinámicos*

Clasificación JEL: *G10, G15, C38, E44*

Les effets des indices boursiers des pays développés et émergents sur l'économie colombienne: Une approche FAVAR

Résumé: *Nous analysons l'effet des conditions financières des économies émergentes et développées sur la performance économique de Colombie. Pour ce faire, nous estimons des indices des conditions financières pour les marchés boursiers des pays développés ainsi que pour les émergents, tout en utilisant l'analyse en composantes principales. Ces indices sont ensuite considérés en tant que régresseurs dans un modèle traditionnel de vecteurs autorégressifs (VAR), c'est-à-dire que nous estimons un modèle vectoriel autorégressif augmenté par des facteurs (FAVAR), y compris un facteur non-observable et un facteur observable (l'activité économique réelle), afin d'évaluer l'effet des conditions financières internationales sur les variables macroéconomiques colombiennes. Lors de la réalisation de l'analyse avec des données mensuelles, nous constatons que les conditions boursières des pays émergents ont un effet positif sur la performance macroéconomique de Colombie.*

Mots-clés: *prix des actions, indices des conditions financières, modèle vectoriel autorégressif augmenté par des facteurs, modèles à facteurs dynamiques*

Classifcation JEL: *G10, G15, C38, E44*

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–Introduction. –I. Literature Review. –II. Methodology. –III. Data. –IV. Results –Conclusions. –References.

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Introduction

Financial markets have recently gained importance as one of the main factors behind the evolution of the real economy. Globalization and technological advances of information systems have enhanced the commercial and financial relationships among markets. Having more interconnected financial markets brings positive consequences for economies: agents have access to a higher number of financial assets, a wider range of portfolio diversification and risk management possibilities, and greater investment opportunities for national firms, among others. The relationship between different financial markets has also consequences on the real economy, as highlighted, for example, by Prasad, et al. (2004). Many of the ways in which financial and real

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markets interact remain as open questions; however, after the global financial crisis of 2007-2010, this interaction has become a first order interest in the academic agenda around the world.

Most studies regarding the effects of financial performance on the real economy have focused on studying the behavior of national financial markets, without considering the impact that international financial markets may have on national conditions. For example, Gómez, Murcia and Zamudio (2011) and Gerdrup and Hammersland (2006) recognize the relevance of national financial markets on the real economy. These authors also take into account the role of asset prices and financial indices as predictors of macroeconomic conditions. Other authors analyze the relationship between financial markets and the real economy in the context of economic and financial cycles. For instance, Angeloni and Faia (2009), Christiano, Motto and Rostagno (2010), Meh and Moran (2010), Cúrdia and Woodford (2010), and Claessens, Kose and Terrones (2012) highlight the importance of including financial variables into real business cycles analyses in order to consider financial dynamics in the estimation of the effectiveness of monetary and fiscal policy.

Nevertheless, we highlight the relevance of also analyzing the effect of international financial conditions on the real economy. There is evidence to suggest that international financial conditions have consequences on national financial markets and the real economy. These consequences are especially important during periods of financial distress where pass-through events and financial contagion can arise, as emphasized by Balakrishnan, et al. (2009).

Since many variables such as asset prices, interest rates, bonds, derivatives, among others, may potentially determine national or international financial conditions, we could summarize the information contained in them by means of an appropriate index. Hence, we analyze if the performance of international stock markets affect macroeconomic conditions in Colombia. To accomplish this objective, we first estimate financial conditions indices (FCIs) for developed and emerging economies using their national stock market indices.

Subsequently, we analyze the impact of international stock market conditions on the economic activity in Colombia using a factor-augmented vector autoregression (FAVAR) analysis as proposed by Stock and Watson (2002a) and Bernanke, Boivin and Eliasz (2005). We perform this analysis by differentiating between financial conditions of developed and emerging countries.

Our main results show that stock market conditions of emerging economies have a positive effect on economic activity in Colombia. In contrast, we find that financial conditions of developed economies do not have a statistically significant effect on economic performance in Colombia.

This paper is organized as follows. In section I, we present the literature review. Section II contains the methodology and econometric framework employed in the analysis. In section III, we present the data, and in section IV the estimation results. The last section concludes.

I. Literature Review

A financial conditions index compiles information on different financial variables that affect the economy's performance. In the last thirty years, many authors have explored and developed the estimation of FCIs, identifying two different approaches to their construction.

One approach consists of the estimation of FCIs considering only a few financial factors chosen among a wide group of variables, according to a theoretical framework or the researcher's necessity. Weighted averages of cross correlations of variables and a CAPM approach are some of the methodologies that researchers use to estimate FCIs in this fashion. Balakrishnan et al. (2009) use these methodologies to estimate joint FCIs for developed and emerging economies. These authors construct a measure that summarizes and describes the financial dynamics of a group of countries according to their classification into developed or emerging markets. Although the indices estimated by these authors permit to analyze some important aspects of the financial performance of the economy, in many cases they do not reflect the complexity of the dynamics of such conditions. Hence, FCIs estimated taking into account a limited number of factors could potentially misestimate the financial performance of the overall economy.

An alternative estimation approach considers as many factors as possible, exploiting the information available regarding financial conditions. Moreover, under the hypothesis that many international variables influence the financial performance of a specific economy, it is convenient to consider as much information as possible in order to capture the dynamics of the financial environment of the economy. This approach considers different methods that reduce the dimension of the information set, incorporating several factors in the construction of the financial indices. These models are known as factor models, and the most common methodologies to estimate them are principal components analysis (PCA) and singular value decomposition (SVD).

Stock and Watson (2002a), Hatzius et al. (2010) and Gómez et al. (2011) use principal components methodologies to estimate FCIs for different economies. All these studies consider several variables to build an FCI that properly describes the dynamics of financial conditions of the economies studied.

Since most of the financial variables are available on a high frequency basis, Brave and Butters (2011) estimate a high frequency FCI for Norway and the United States using dynamic factor models. The methodology proposed by the authors considers cross-correlations between variables, and the estimated index captures well-known episodes of crashes and crises.

Gómez et al. (2011) use factor models to estimate an FCI for Colombia. These authors construct the index considering financial variables such as interest rates, credit aggregates and expected inflation surveys. These authors evaluate the performance of the estimated index as a leading indicator and by its capacity to predict the behavior of some macroeconomic variables.

Regarding the effect of the FCI on the performance of the real economy, Stock and Watson (2005) propose a methodology to predict the behavior of macroeconomic variables using indices estimated by factor models. This method, called FAVAR, attempts to measure the impact of the behavior of different sectors on macroeconomic variables by combining the indices estimated through PCA with a vector autoregression analysis.

This methodology permits to capture the international interaction within financial markets by analyzing the effect of the FCIs, estimated using as much information as possible, on the performance of the economy. Therefore, we aim to analyze the influence of stock market conditions of developed and emerging countries on Colombia's economy. To summarize international financial conditions, we estimate an FCI for a group of developed and emerging countries using dynamic factor models. These models permit to include as many countries as possible in the sample. Then, we analyze the influence of the performance of international stock markets on Colombia's real activity using a FAVAR approach.

II. Methodology

Historically, applied work on macroeconomic and financial modeling has focused on a small set of variables. On the contrary, policymakers, economists, traders and practitioners usually examine a large number of variables when studying the possible evolution of a national economy following variations in national and international markets. The use of many series to analyze fluctuations in the economy suggests that those series contain more information than the one that is offered by major macroeconomic aggregates. Hence, it is convenient to consider a methodology that allows extracting most of the information provided by these series without facing the difficulties derived from working with a large number of variables.

Stock and Watson (2002a; 2006) study these methodologies and propose to use PCA for summarizing the main sources of variation and co-variation among a big set of variables. This is a way of reducing the dimensionality of the dataset while taking into account as much information as possible. PCA is used to sum up information from different sectors such as housing, banking, energy, and finance to construct sectorial indicators.

If the interest of the researcher is to study the influence of different sectors on the economy, it is plausible to consider these indicators into the framework provided by a VAR analysis. This allows us to make impulse-response analysis without facing the issues related to the loss of degrees of freedom, usually derived from working with many variables. Bernanke et al. (2005) propose this approach to analyze monetary policy.

As proposed in Bernanke et al. (2005), we use a FAVAR approach to study the influence that financial conditions from developed and emerging economies may have on Colombia's macroeconomic variables.

A. Factor-Augmented Vector Autoregression

Following Bernanke et al. (2005), let $\boldsymbol{Y}_t$ be an $M \times 1$ vector of observable economic variables. According to the standard approach, we can estimate a VAR, a Structural VAR (SVAR) or other multivariate time series model only using data for $\boldsymbol{Y}_t$. Nevertheless, in many economic and financial applications additional information could be relevant when modelling the dynamics of $\boldsymbol{Y}_t$. This additional information can be summarized by $\boldsymbol{f}_t$, a $r \times 1$ vector of unobserved factors, with r small. In this document, $\boldsymbol{f}_t$ summarizes the financial conditions of developed or emerging economies that are not easily represented by a small number of series:

$$\begin{pmatrix} \boldsymbol{f}_t \\ \boldsymbol{Y}_t \end{pmatrix} = \boldsymbol{\Phi}(\boldsymbol{L}) \begin{pmatrix} \boldsymbol{f}_{t-1} \\ \boldsymbol{Y}_{t-1} \end{pmatrix} + \boldsymbol{v}_t, \tag{1}$$

where $\boldsymbol{\Phi}(\boldsymbol{L})$ is a polynomial in $\boldsymbol{L}$, the lag operator of finite order d. It contains theoretical restrictions imposed by the researcher as in the SVAR literature. The error term $\boldsymbol{v}_t$ has mean zero and covariance matrix $\boldsymbol{Q}$.

Equation (1) is a structural VAR in $(\boldsymbol{f}_t, \boldsymbol{Y}_t)$. It could be transformed into a standard VAR in $\boldsymbol{Y}_t$, by letting the coefficients of $\boldsymbol{\Phi}(\boldsymbol{L})$ that relate $\boldsymbol{f}_{t-1}$ to $\boldsymbol{Y}_t$ to be all equal to zero. If this is not the case, the equation (1) is called FAVAR. Equation (1) offers a way to analyze the influence of the information contained in $\boldsymbol{f}_t$ on the observed variables in $\boldsymbol{Y}_t$.

Equation (1) cannot be directly estimated since the factors included in $\boldsymbol{f}_t$ are unobservable in nature. However, if we consider the factor as representing dynamics that potentially influence many economic variables, we would be able to infer these dynamics from a large group of different economic and financial time series. This assumption is summarized by the dynamic factor models presented in the following section.

B. Dynamic Factor Models

Following the methodology proposed by Stock and Watson (2002a), the most important assumption of dynamic factor models (DFM) is that the co-variation among economic time series can be summarized by a few underlying unobserved factors. Disturbances affecting these factors would represent major aggregate shocks to the economy. DFMs express observed time series as functions of a number of unobserved and common factors, plus an idiosyncratic error term as follows:

$$\boldsymbol{X}_{it} = \boldsymbol{\lambda}_i \left(\boldsymbol{L}\right) \boldsymbol{f}_t + \boldsymbol{u}_{it}, \tag{2}$$

where $\boldsymbol{f}_t$ is a $r \times 1$ vector of unobserved factors, $\boldsymbol{\lambda}_i(\boldsymbol{L})$ is a lag polynomial called "dynamic factor loadings", and $\boldsymbol{u}_{it}$ is the idiosyncratic disturbance. The factors and idiosyncratic disturbances are assumed to be uncorrelated at all leads and lags, which is:

$$E\left(\boldsymbol{f}_t \boldsymbol{u}_{is}\right) = 0 \quad \text{for all} \quad i, s. \tag{3}$$

The unobserved factors can be modeled as following a linear dynamic process:

$$\boldsymbol{\Gamma\Sigma L}) \, \boldsymbol{f}_t \boldsymbol{\eta}_t, \tag{4}$$

where $\boldsymbol{\Gamma\Sigma L})$ is a matrix lag polynomial and $\boldsymbol{\eta}_t$ a $r \times 1$ disturbance vector.

There are different approaches to the estimation of the dynamic factor; for example, we could estimate the unobservable factor in a state-space setting using the Kalman filter or we could use PCA instead. We prefer the latter approach because it is easily implementable in terms of computational costs and shows good statistical properties that are extensively documented by Stock and Watson (2002b).

C. Dynamic Factor Model Estimation by Principal Components Analysis

If $\boldsymbol{\lambda}_i(\boldsymbol{L})$ have finite order p, equation (2) can be written as:

$$\boldsymbol{X}_t = \boldsymbol{\Lambda F}_t + \boldsymbol{u}_t, \tag{5}$$

where $\boldsymbol{F}_t = \left[\boldsymbol{f}'t, \boldsymbol{f}'t - \mathbf{1}, \ldots, \boldsymbol{f}'t - \boldsymbol{p} + \mathbf{1}\right]'$, $\boldsymbol{u}_t = [\boldsymbol{u}_{1t} \ldots u_{nt}]$, and $\boldsymbol{\Lambda}$ is a matrix containing the coefficients of $\boldsymbol{\lambda}_i(\boldsymbol{L})$.

Equation (5) rewrites the DFM as a static factor model, in which there are q static factors consisting of the current and lagged values of the r dynamic factors, where $q \leq rp$.

Since $\boldsymbol{F}_t$ and $\boldsymbol{u}_t$ are uncorrelated at all leads and lags, the covariance matrix of $\boldsymbol{X}_t$ can be written as follows:

$$\boldsymbol{\Sigma}_{\boldsymbol{XX}} = \boldsymbol{\Lambda}\boldsymbol{\Sigma}_{\boldsymbol{FF}}\boldsymbol{\Lambda}' + \boldsymbol{\Sigma}_{\boldsymbol{uu}}, \tag{6}$$

where $\boldsymbol{\Sigma}_{\boldsymbol{FF}}$ and $\boldsymbol{\Sigma}_{\boldsymbol{uu}}$ are the covariance matrices of $\boldsymbol{F}_t$ and $\boldsymbol{u}_t$.

Under the assumption that the eigenvalues of $\boldsymbol{\Sigma}_{\boldsymbol{uu}}$ are O(1) and $\boldsymbol{\Lambda}'\boldsymbol{\Lambda}$ is $O(n)$, the first q eigenvalues of $\boldsymbol{\Sigma}_{\boldsymbol{XX}}$ are O(n) and the remaining eigenvalues are O(1). This implies that the first q principal components of X can serve as estimators of $\boldsymbol{\Lambda}$, which in turn can be used to estimate $\boldsymbol{F}_t$.

We can consider the estimation of $\boldsymbol{\Lambda}$ and $\boldsymbol{F}_t$ by solving the nonlinear least squares problem:

$$\max_{F_1 \ldots F_T} T^{-1} \sum_{t=1}^{T} (\boldsymbol{X}_t - \boldsymbol{\Lambda}\boldsymbol{F}_t)'(\boldsymbol{X}_t - \boldsymbol{\Lambda}\boldsymbol{F}_t) \quad \text{subject to} \quad \boldsymbol{\Lambda}'\boldsymbol{\Lambda} = \boldsymbol{I}_r \tag{7}$$

Note that in this procedure $F_1 \ldots F_T$ are treated as fixed parameters to be estimated. The first order conditions to maximize equation (7) show that estimators must satisfy

$$\widehat{\boldsymbol{F}}_t = \left(\widehat{\boldsymbol{\Lambda}}'\widehat{\boldsymbol{\Lambda}}\right)^{-1} \widehat{\boldsymbol{\Lambda}}'\boldsymbol{X}_{\boldsymbol{t}}. \tag{8}$$

Substituting equation (8) in (7) it yields

$$T^{-1} \sum_{t=1}^{T} \boldsymbol{X}_t' \left[\boldsymbol{I} - \boldsymbol{\Lambda}(\boldsymbol{\Lambda}'\boldsymbol{\Lambda})^{-1}\boldsymbol{\Lambda}'\right] \boldsymbol{X}_t. \tag{9}$$

Minimizing equation (9) is equivalent to maximizing

$$tr\left\{\left(\boldsymbol{\Lambda}'\boldsymbol{\Lambda}\right)^{-1/2'} \boldsymbol{\Lambda}'\widehat{\boldsymbol{\Sigma}}_{\boldsymbol{XX}}\boldsymbol{\Lambda}\left(\boldsymbol{\Lambda}'\boldsymbol{\Lambda}\right)^{-1/2}\right\}, \tag{10}$$

where $_{\boldsymbol{XX}} = \boldsymbol{T}^{-1} \sum_{t=1}^{\boldsymbol{T}} \boldsymbol{X}_t \boldsymbol{X}_t'$.

The latter procedure is equivalent to maximizing

$$\Lambda'\Sigma_{\boldsymbol{XX}}\Lambda\Sigma \text{ subject to } \Lambda'\Sigma\Lambda\Sigma = \boldsymbol{I}_r. \tag{11}$$

The solution to (11) is to set $\Lambda\Sigma$ to be the first q eigenvalues of $_{\boldsymbol{XX}}$. The resulting estimator for the factors is:

$$\boldsymbol{F}_t = \Lambda'\Sigma\boldsymbol{X}_t. \tag{12}$$

$\boldsymbol{F}_t$ contains the first q principal components of $\boldsymbol{X}_t$. The matrix in (13) is diagonal with elements that equal the largest q ordered eigenvalues of $_{\boldsymbol{XX}}$:

$$T^{-1} \sum_{t=1}^{T} \boldsymbol{F}_t \boldsymbol{F}' t. \tag{13}$$

III. Data

We selected 46 countries to estimate two FCIs, one for 23 developed economies and one for 23 emerging markets in our sample (See Table 1). We selected the countries in the sample mainly because of data availability. The stock price indices used are those calculated by Morgan Stanley Capital International (MSCI), and we retrieved them from Datastream. These indices measure the behavior of asset prices traded in the stock market of each country without accounting for dividends. In addition, Morgan Stanley constructs their indices in a standard way for each country, thus permitting an adequate use of the methodology we apply.

We use two data frequencies: the first one is quarterly, with the sample period starting in the first quarter of 2000 and finishing in the third quarter of 2013; the second one is monthly, with the sample period starting in December 1994 and finishing in November 2013. We estimate FCIs for the two groups of markets with each frequency. We name the FCI for the developed countries the Stock Market Developed Index (SMDI), and the FCI for the emerging countries the Stock Market Emerging Index (SMEI).

Table 1. *List of Countries and Their Acronyms*

Developed Countries		Emerging Countries	
US	United States	MA	Morocco
JP	Japan	LK	Sri Lanka
DE	Germany	PK	Pakistan
GB	Unites Kingdom	IN	India
AU	Australia	CN	China
FR	France	BR	Brazil
IT	Italy	ZA	South Africa
SG	Singapore	ID	Indonesia
CA	Canada	MY	Malaysia
ES	Spain	MX	Mexico
CH	Switzerland	RU	Russian Federation
HK	Hong Kong	TW	Taiwan
NL	Netherlands	AR	Argentina
SE	Sweden	CO	Colombia
AT	Austria	CZ	Czech Republic
BE	Belgium	HU	Hungary
FI	Finland	TH	Thailand
NZ	New Zealand	TR	Turkey
NO	Norway	CL	Chile
PT	Portugal	EG	Egypt
DK	Denmark	PE	Peru
IE	Ireland	PL	Poland
IL	Israel	KR	Republic of Korea

Source: own elaboration.

The gross domestic product (GDP) is the macroeconomic variable used to evaluate the effect of the quarterly SMDI and SMEI on Colombia's economic activity. Data for this variable are retrieved from the National Administrative Department of Statistics (DANE, for its acronym in Spanish). The sample spans from the first quarter of 2000 to the third quarter of 2013.

The monthly index of economic activity in Colombia (IMACO, for its acronym in Spanish)[1] is the macroeconomic variable used to evaluate the effect of the monthly SMDI and SMEI on Colombia's real activity. Data for this index were obtained from the Central Bank of Colombia (Banrep).[2] The data begin in December 1994 and finish in November 2013.

IV. Results

A. FAVAR of the Quarterly SMDI and SMEI on GDP

We assume for the estimation of the SMDI and SMEI that the series are cointegrated. This assumption is necessary in order to be able to apply the DFM methodology using series in levels. Traditional tests for cointegration are not suitable in this case due to the high frequency of the data. Theoretical motivation for this procedure is found in the works by Bai and Ng (2004) and Peña and Poncela (2006). The latter provide a rigorous discussion of why it is a better strategy to use series in levels provided that they share a common trend.

We construct the two indices applying the DFM methodology exposed in section III. The index is equivalent to the first principal component. In the case of developed countries, the first factor explains 57.59% of the overall

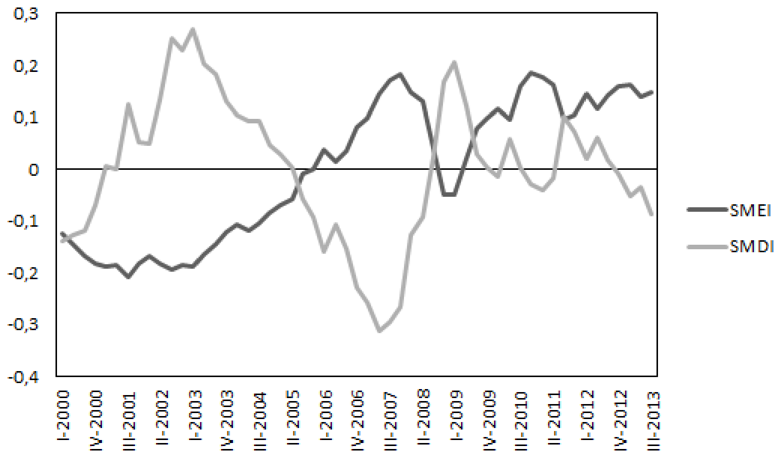
[1] The IMACO is a leading indicator of Colombia's economic activity. The Banrep constructs it using sectorial variables. The index can anticipate the behavior of annual GDP by five months.

[2] The IMACO is a generated variable as conceived in Pagan (1984). This could lead to inefficient estimations. But, given that it is extracted using principal components, it can be used to obtain subsequent consistent estimations (as if it was a non-generated variable) as showed in Stock and Watson (2002b) and Bai and Ng (2002, 2008). Moreover, we use non-parametric techniques in the construction of our confidence intervals for the impulse-response functions.

variance of the data. For emerging countries, the first factor explains 79.41% of data variability.

Figure 1 depicts the estimated SMDI and SMEI. The SMEI presents a positive growth tendency until the last quarter of 2007. After this period, the effect of the subprime crisis can be observed in the behavior of the index since it falls considerably until a valley in the first quarter of 2009. Afterwards, the SMEI increases to approach its pre-crisis value and then it stays at a constant level.

Figure 1. *Quarterly Stock Market Developed Index (SMDI) and Quarterly Stock Market Emerging Index (SMEI), 2000-I to 2013-III*



Source: own elaboration.

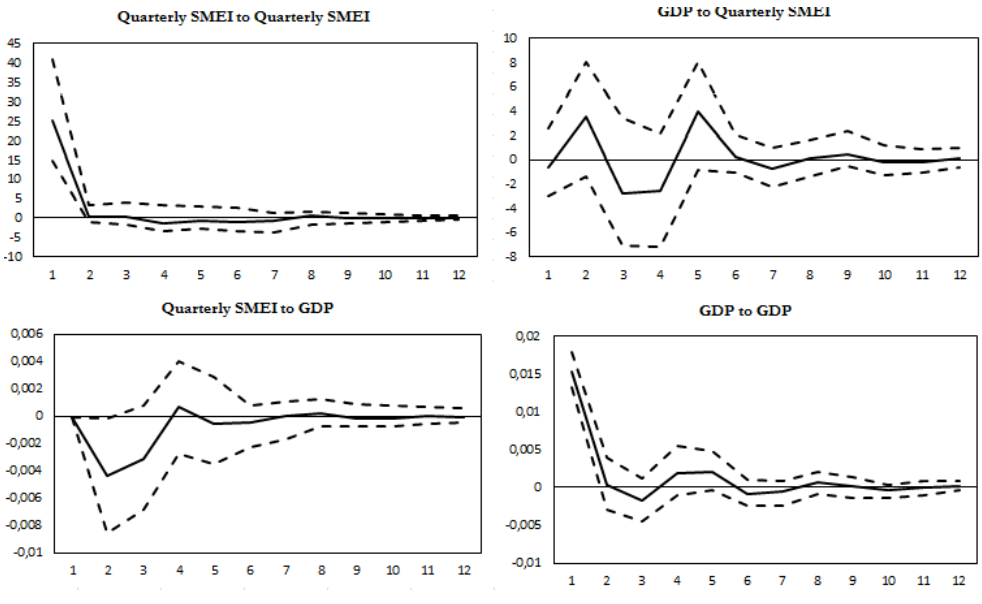
The SMDI grows until the first quarter of 2003. It decreases until the beginning of 2007, and then has an increment until 2009. This behavior does not capture the dot com and the housing price bubbles presented in the United States market. However, the SMDI does capture the European tourmoil faced by some countries of this continent, since the value of the index decreases from 2011 till 2013.

After constructing the indices, we estimate a bivariate vector autoregression (VAR). Following equation (1), $\boldsymbol{f}_t$ is the SMEI and $\boldsymbol{Y}_t$ is GDP. We estimate the VAR with four lags to capture the effects of shocks on the variables in one year, since the data has quarterly frequency.

We identify the SVAR using the Cholesky decomposition by imposing one restriction over the matrix of contemporaneous effects of the variables. We suppose that the contemporaneous effect of the SMEI on GDP is zero because, theoretically, it is expected that GDP be a slow moving variable.

Figure 2 shows the impulse response function (IRF) and confidence intervals of the quarterly SMEI and GDP VAR estimated. The GDP shocks have no statistically significant effects on the SMEI, nor has the SMEI shocks on GDP.

Figure 2. *Impulse Response Functions and Confidence Intervals of Quarterly SMEI and GDP*



Note: the confidence intervals were elaborated by bootstrapping with a 90% percentile.
Source: own elaboration.

Although we theoretically expect that the behavior of a small economy have no effect on the performance of the stock markets of developed economies, we estimate the effects of the SMDI on GDP using a bivariate FAVAR without imposing strong exogeneity assumptions; that is, considering that Colombia's economic activity may affect the stock market performance of developed countries. This constitutes a plausible consideration since Colombia has strong real and financial relationships with regional economies.

The IRFs estimated show that the effect of GDP on the SMDI is not statistically significant. This corresponds to what was theoretically expected. Conversely, the estimated effect of the SMDI on GDP is not statistically significant either. One possible explanation for this result could be that, in the construction of SMDI, we consider several developed economies that do not have strong economic relations with Colombia.

The lack of effects found between the SMEI, SMDI and GDP may be a consequence of the frequency of the data on a quarterly basis, because a lot of information regarding the behavior of the markets might be lost. This can be explained by the fact that financial markets are more efficient incorporating shocks than markets in the real sector. Hence, the former incorporate information faster than the latter.

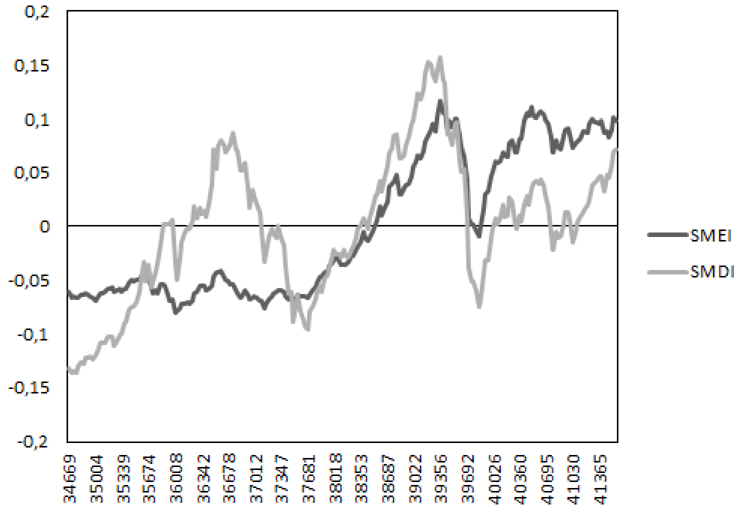
In order to capture this fact into our analysis, we estimate the indices using monthly data and perform the VAR analysis using a macroeconomic variable with a monthly frequency. We present the results in the next section.

B. FAVAR of the Monthly SMDI and SMEI on the IMACO

As we presented with the quarterly index, the monthly index is equivalent to the first principal component. In the case of developed countries, the first factor explains 57.80% of the overall variance of the data. For emerging countries, the first factor explains 76.29% of the data variability.

Figure 3 presents the monthly SMDI and the SMEI. The SMDI captures the bubbles arising before the dot com crisis (2000) and the subprime crisis (2007). The SMEI presents a stable pattern around the values of -0.1 and -0.5 since the beginning of sample until August 2003. From 2003 until 2007, the index also captures the bubble of housing prices in the United States.

Figure 3. *Monthly Stock Market Developed Index (SMDI) and Monthly Stock Market Emerging Index (SMEI), December 1994 to November 2013*

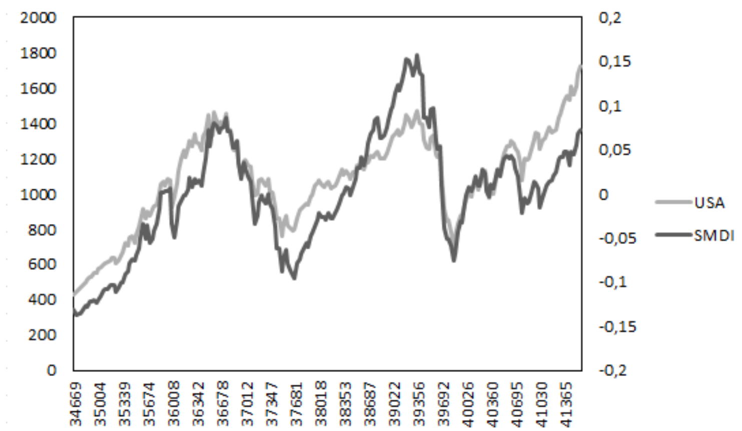


Source: own elaboration.

From 1994 to 2003, the indices present different behaviors; but from 2004 onwards, they exhibit similar paths. This result is in accordance with the results found in Uribe and Fernandez (2014). These authors identify periods of bubbles in several stock markets, and find that approximately before 2002, once a bubble exploded in the United States, the flight of capitals to emerging economies fostered the formation of bubbles in these markets. After this period, the bubbles formed in the United States stock markets were concordant with the bubbles formed in emerging economies. Hence, the indices we constructed are related to these periods of overvaluation.

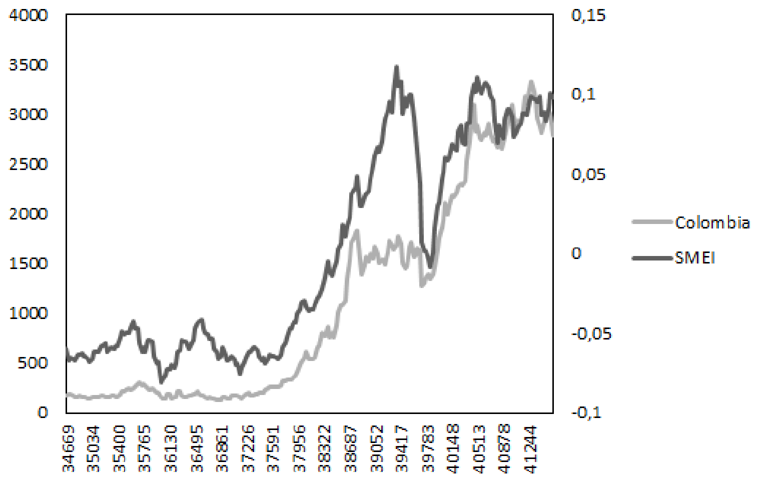
The SMDI and the United States MSCI price index are presented in figure 4. The behavior of these indices is very similar during the full sample period. In contrast, the pattern of the SMEI and the Colombia MSCI price index is quite different during the period analyzed. However, since 2009 the indices tend to have a more similar behavior (figure 5).

Figure 4. *Monthly Stock Market Developed Index (SMDI) and United States MSCI Price Index, December 1994 to November 2013*



Source: own elaboration.

Figure 5. *Monthly Stock Market Emerging Index (SMEI) and Colombia MSCI Price Index, December 1994 to November 2013*



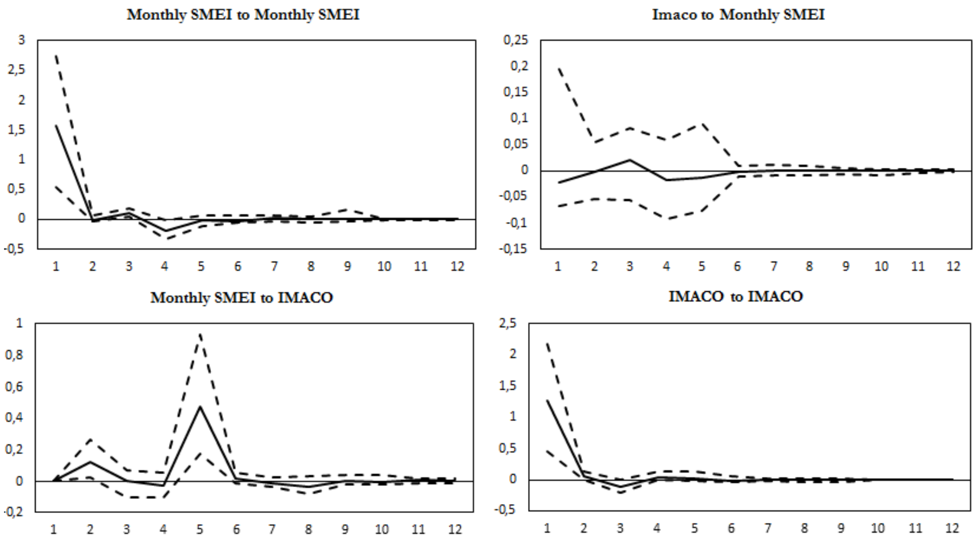
Source: own elaboration.

After constructing the indices, we estimate a bivariate VAR. Following equation (1), f_t is the SMEI and Y_t is the IMACO. Using information criteria, the best specified model is a VAR with four lags.

Once again, the SVAR is identified using the Cholesky decomposition. We suppose that the contemporaneous effect of the SMEI on the IMACO is zero because, theoretically, it is expected that the IMACO be the variable that moves slower than the index.

Figure 6 presents the IRF and confidence intervals of the estimated VAR of monthly SMEI and the IMACO. The IMACO shocks have no statiscally significant effects on the SMEI. However, the SMEI shocks do have a significant effect on the IMACO. Specifically, a shock on the SMEI affects positively the IMACO five months later.

Figure 6. *Impulse Response Functions and Confidence Intervals of Monthly SMEI and IMACO*



Note: the confidence intervals were elaborated by bootstrapping with a 90% percentile.
Source: own elaboration.

We also estimate the effect of the monthly SMDI on economic activity in Colombia without imposing the strong exogeneity assumption, as explained before. The impulse response functions estimated are not statistically significant. The lack of effect of IMACO on the SMDI is theoretically expected. Conversely, there is no effect of the SMDI on the IMACO either. These results could obey to the number of developed economies considered in the estimation of SMDI, as many of these countries do not have strong commercial or financial ties with Colombia.

As a robustness exercise, we estimated the VAR using the Indicador de Seguimiento de la Economía (ISE) calculated by the DANE. The ISE is the macroeconomic variable used to evaluate the effect of the monthly SMDI and SMEI. We found similar results as the ones found with IMACO, so we do not report them.

Conclusions

During the last decades, globalization of financial markets has increased considerably due to integration treaties between countries, availability of new technologies, and access to information and new markets. Furthermore, recent episodes of financial crises, such as the 2008 subprime crisis, have highlighted the importance of the effects of financial markets on the economic activity of nations. Hence, it is relevant to analyze the effects of international financial markets on the behavior of macroeconomic variables in Colombia.

This paper advances in this direction applying a FAVAR approach. Using the stock prices of 23 developed countries and 23 emergent markets, we construct FCIs for each group of markets. The indices were constructed by DFMs, estimating them by principal components. Then, we estimate a VAR using the FCIs of the emerging and developed economies with a macroeconomic variable for Colombia.

We use two data sets with different frequencies to estimate the FAVAR. The first one is a set of quarterly data. The indices used to construct the FCIs are the MSCI price indices and the macroeconomic variable for Colombia is quarterly GDP. The IRFs estimated from the bivariate VAR indicate that shocks on GDP have no statistically significant effects on the FCIs (emerging and developed economies), nor have the FCIs shocks on GDP.

The lack of effect found between the variables may be because the index was constructed using quarterly data, and a lot of information on the behavior of markets is lost. In order to capture this fact in our analysis, we estimate the indices using monthly data, and conduct the VAR analysis using the IMACO, a monthly variable that captures Colombia's economic activity.

In this case, the FCIs are related to periods of bubbles in financial markets. The FCI of developed economies captures the dot com bubble and the increment in housing prices before the subprime crisis. The FCI of the emerging economies has a relative stable behavior during the first eight years of analysis, and then the index captures the bubble arising before the subprime crisis. Before 2004, the indices differ considerably in their behavior, evidence that is consistent with the results found in Uribe and Fernandez (2014).

The IRFs of the estimation of the bivariate VAR including the FCI of the emerging markets and the IMACO indicates that the latter does not have a statistically significant effect on the index, but the index does have a positive effect on the IMACO five months after the original shock. The IRF of SMDI on the IMACO shows that the effect of the index over Colombia's economic performance is not statistically significant and, as expected theoretically, the IMACO does not affect the SMDI.

In conclusion, the results we find are consistent with the starting hypothesis that the analysis of economic activity must take into account the performance of international financial markets, in this case stock markets. The results are also consistent with the importance of using as much information as possible in the construction of indices, and the posterior analysis of their effects on the economy.

Future extensions in the literature should aim to increase the dimension of our model including other variables such as interest rates, exchange rates or commodity prices that could potentially interact significantly with the indexes constructed here. In this way, one should be able to enrich the analysis of the system's dynamics after a structural shock is observed in the financial markets or the real economy.

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