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Abstract*

This paper examines how financial fluctuations and macroeconomic stability interact in the case of Venezuela, acknowledging that financial conditions deteriorating the macroeconomic environment can arise with both good and bad macroeconomic performance. An empirical methodology is provided that constructs two indexes, which are fully interpretable and are constructed with a minimum set of assumptions applied to a large number of financial time series. Structural interpretation of indexes is pursued using a structural VAR (SVAR) that associates macroeconomic stability with financial indexes. For Venezuela, a deterioration of procyclical financial conditions relates to financial margin reductions and expansions in banks' balance sheets, which are mostly triggered by unexpected increases in net primary money creation. Such expansions tend to appear in situations of declining macroeconomic stability. Worse countercyclical financial conditions are instead associated with situations of rising bank profitability, deleveraging and increased banking instability. In this case, fragility tends to materialize in periods of ameliorated macroeconomic stability.

JEL classifications: E30, G10, E00
Keywords: Financial cycle, Financial conditions index, Macroeconomic stability

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1. Introduction

There is no doubt that financial fluctuations are intrinsically related to macroeconomic conditions. But the way economists have conceptualized that relationship has changed over time and has also affected the way financial fluctuations have been understood. During the great moderation, causality was conceived mainly to run from macroeconomic policy to the financial sector: the achievement of price stability was considered an important determinant of financial stability. After the sub-prime crisis, the emphasis partly turned to understanding the events that were originated within the financial system but had vast consequences on systemic financial and macroeconomic stability. In this paper, we aim to understand this twofold relationship between financial fluctuations and macroeconomic stability using Venezuela as a case of study. The comprehension of this association acknowledges that the financial conditions deteriorating the macroeconomic environment can arise alongside both good and bad macroeconomic performance. To convey this idea, we provide an empirical methodology that measures financial fluctuations with two financial conditions indexes constructed from a large set of banking information. These two indexes are the procyclical financial condition index (*PFCI*), which summarizes the financial conditions that behave procyclically with respect to macroeconomic stability, and the countercyclical financial condition index (*CFCI*), which captures the state of countercyclical financial conditions.

Why measure countercyclical financial conditions? The general agreement in the literature is that financial conditions are inherently procyclical. According to most theoretical models, the financial system is procyclical with respect to the real cycle. That is, small macroeconomic shocks can be amplified and can lead to significant impacts on output due to the existence of financial frictions (mainly asymmetric information problems), as in the financial accelerator models of Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). These mechanisms are particularly relevant for situations of poor macroeconomic performance where endogenous financial responses prolong and deepen real downturns.[1] But there also are more empirically-based narratives where relatively stable macroeconomic conditions can foster financial decisions that equally pave the road for future undesirable consequences. For instance, situations of real expansions can lead to a deterioration of credit standards that fuel credit booms

[1] Athanasoglou, Daniilidis and Delis (2014) provide a comprehensive survey on the causes and consequences of the procyclicality of the banking sector.

(Jiménez and Saurina, 2006). Alternatively, financial conditions might deteriorate because of increasing risk-taking by financial institutions (Adrian and Shin, 2014; Altunbas, Gambacorta and Márques-Ibañez, 2010) While in Adrian and Shin (2014) risk-taking increases during real upturns, due to a reduction in the value at risk of assets, in Altunbas et al. (2010) banks' risk positions might be encouraged by loose monetary policy in periods of relatively stable macroeconomic conditions. All these descriptions suggest that fragile financial conditions may arise during optimistic valuations of the macroeconomic environment, even though these conditions would eventually turn into banking crises or have negative effects on economic activity. In a strict sense, these descriptions also imply that some financial conditions are countercyclical rather than procyclical, not only because they mildly compensate or dampen real expansions, but also because they arise during positive, or at least stable, macroeconomic performance.

Another crucial piece of information, which provides a meaningful interpretation for the potential countercyclicality of financial conditions, refers to the assessment of the macroeconomic environment and the notion of macroeconomic stability. For example, take the case of credit booms and loose credit standards that operate during economic expansions. Strictly speaking, while credit is in its upward phase, real activity is likely to continue its growth, but possibly at the cost of increasing inflation, or weakening the current account balance. In this case, the behavior of real output is not actually capturing the full distinct effects of credit innovations. Other variables might be signaling the early deterioration of the macroeconomic performance. This also means that the negative effects of countercyclical financial conditions can only be properly assessed if our evaluation of the macroeconomic environment is multidimensional.

Therefore, because looking only at the response of real activity gives an incomplete understanding of the effects of both procyclical and countercyclical financial fluctuations, in this paper we also construct a macroeconomic index that gauges macroeconomic stability. This index conveys information about the economy in different key areas (external, real, monetary and fiscal) while providing a judgment for overall economic performance. This multidimensional appraisal is also justified by the presumption that financial responses to the macroeconomic environment, i.e., banks' decisions and expectations regarding the economy, depend on the information of several macroeconomic variables.

According to our measure, macroeconomic performance of greater real growth and falling inflation improves macroeconomic stability, if fundamental balances in the economy do not deteriorate. The presumption is that a stable macroeconomic performance takes place when the economy is subject to positive supply shocks that simultaneously improve (or do not harm) its fundamental balances, i.e., the account balance, the fiscal balance and the goods market balance. Implicitly, this belief also suggests that for instance, a situation of large positive demand shocks, which likely generate output growth with rising current account and fiscal deficits, cannot be characterized as a situation of improved macroeconomic stability. That is, stability cannot be expected to increase if fundamental balances are weakening. Nor is it the case that an assessment of future economic performance can be totally optimistic if fundamental balances are jeopardized.

Methodologically, our measurements of financial fluctuations and macroeconomic stability aim to relate to one key idea developed in the econometric literature (Stock and Watson, 1999, 2002a, 2002b): statistical strategies that tend to use more information are usually better for predicting a future state of the economy. This idea has also reached financial analysis, and since the work of Hatzius et al. (2010) measuring financial conditions through a principal component has become a popular procedure. Nonetheless, a single principal component tends to be difficult to interpret because it only represents a means to summarize a large set of information. Our methodology attempts to combine several principal components of a large financial dataset to generate fully interpretable financial indexes through the implementation of a minimum set of assumptions. In a general sense, this methodology tries to balance the trade-off between applying a pure statistical procedure that might not deliver a fully interpretable outcome and measuring financial fluctuations through a predetermined, sometimes ad hoc notion.

Because the two financial indexes that describe financial fluctuations (*PFCI* and *CFCI*) are a combination of several principal components, they should be properly differentiated. Identification of indexes is pursued in the context of a structural VAR (SVAR) that associates macroeconomic stability with financial indexes. The identification strategy consists of combining financial components in such a way that structural responses to shocks have specific directions (signs). In other words, financial regressors (indexes) are selected in order to produce orthogonal macroeconomic and financial innovations that satisfy some expected impulse-responses. Restricting the sign of these impulse-responses ensures a minimum structural interpretation for the indexes. Specifically, because both indexes' innovations affect negatively macroeconomic stability, increases in financial indexes are interpreted as signaling a deterioration of financial conditions. Alternatively, since the response of indexes to macroeconomic stability innovations can be either negative or positive, a worsening of financial conditions can occur with both a deteriorated and an improved macroeconomic environment. The combination of these restrictions allows us to define indexes' cyclicality. The *PFCI* index measures procyclical financial conditions because a deterioration of macroeconomic stability also causes a worsening of financial conditions that further weakens stability. Contrarily, the *CFCI* index captures countercyclical financial conditions since an improvement in macroeconomic stability causes a deterioration of financial conditions that tends to abate or reverse the initial rise in stability.

Comparing the dynamics of these two indexes provides analysts with information of what type of disturbances (procyclical or countercyclical) might be driving the state of the financial system at different time periods. Based on the evaluation of the variables' loads on each index, analysts can deduce a stylized characterization of what indexes describe. For Venezuela, procyclical financial conditions exhibit a large deterioration when banks' balance sheets and deposits expand, leverage increases, and interest rates and financial margins tend to decline. In contrast, countercyclical financial conditions significantly worsen during episodes of high banking profitability that simultaneously relate to low leverage, tight liquidity and diminished banking stability. Estimations show that overall, procyclical financial conditions have been more important since 2003. This is because fragility was more on the side of the expansion of banks' balance sheets and deposits rather than on the side of increased profitability and instability. Such balance sheet expansions are mostly triggered by net primary money creation, which describes the combined monetary effects of fiscal spending and foreign exchange allocation.

Because the financial cycle (*CYCLE* indicator) is defined as the combined behavior of procyclical and countercyclical financial conditions, i.e., the sum of *PFCI* and *CFCI*, its dynamics characterize moments of greater or lower financial distress. This information, jointly analyzed with the dynamics of macroeconomic stability, can establish to what extent financial conditions precede or follow the deterioration of macroeconomic stability.

One important byproduct of the methodology presented in this paper is that practitioners can characterize either how specific financial variables respond to macroeconomic stability shocks or which exogenous adjustments in financial variables deteriorate stability. These two pieces of information also provide an assessment about the cyclicality of all financial variables included in the data, without the estimation of further models. Overall, this information completes our understanding of how individual variables' dynamics affect or are affected by macroeconomic stability.

In the comparison of the *CYCLE* indicator with a standard Financial Conditions Index (*FCI*) constructed as in Hatzius et al. (2010), we observe that our financial fluctuations' diagnosis is very different. This is probably related to the fact that the first component of the data does not necessarily contain all the relevant information for adequately assessing financial fluctuations. Moreover, the first component summarizes an important dimension of the data that could be helpful in forecasting output growth, but it does not have a clear interpretation in terms of which aspect of financial fluctuations it is capturing.

The paper is organized as follows. In the next section, we develop the core of the paper. We address the notion of financial fluctuations and macroeconomic stability respectively, and provide statistical models to estimate them. In Section 3, we explain the estimation with Venezuelan data and interpret the resulting indexes. In Section 4, we show how to use the estimated model to obtain information on how specific variables' dynamics affect or are affected by macroeconomic stability. Section 5 deals with other statistical aspects of financial indexes, i.e., the robustness of estimations to different types of information. Section 6 concludes.

2. Defining Financial Fluctuations and Macroeconomic Stability

The notion of financial fluctuations is widely used in the literature, but its definition is elusive or at least variable, depending on the context. In some cases, the characterization of financial fluctuations relies on the theoretical model employed, while in other cases, it depends on the analyst's prior about the relevance of a particular financial variable for explaining the business cycle. For example, in the model of Adrian and Boyarchenko (2012), financial cycles are described in terms of leverage cycles and the share of intermediated credit. In this case, the leverage cycle is the result of the risk-based funding constraints faced by financial intermediaries during the occurrence of macroeconomic shocks. Alternatively, Drehmann, Borio, and Tsatsaronis (2012), through empirical techniques, associate the financial cycle with the behavior of the low frequency of the credit-GDP ratio and property prices. In their work they claim that these variables are fundamental for explaining the business cycle: business cycle busts preceded by financial cycle booms are more severe. In this case, the financial cycle is explained by the interaction of monetary factors affected by the processes of financial liberalization and the implementation of different monetary regimes.

Another common way practitioners tend to conceptualize financial fluctuations is through the construction of FCIs, as in Hatzius et al. (2010). Under their approach, financial fluctuations are related to the co-movement of many financial variables that help predict the performance of economic activity. But because the index seeks precisely to improve the forecast of economic activity, it is not clear whether that index can really be interpreted as portraying or characterizing financial fluctuations. On the one hand, in the process of constructing the index, there is nothing that guarantees that the first principal component of those variables contains enough information to describe short-run financial fluctuations. On the other hand, although there is an effort to acknowledge the endogeneity between financial variables and macroeconomic conditions, the interpretation of that first principal component is only attained if the researcher has a strong understanding of the expected relationship between the index and each of the variables contained in it.[2] That is, interpreting the component requires taking a strong stand based on a priori knowledge of how variables should behave along the financial cycle.

In the absence of a theoretical model that can be applicable to different countries and realities, we can resort to an empirical methodology that measures financial fluctuations. But that methodology has to balance the following trade-off: clearly addressing what it is actually trying to measure, in order to give the resulting financial index a neat interpretation, versus not requiring strong a priori assumptions about the definition of the financial cycle. In this section, we intend to provide an empirical methodology that balances the above trade-off based on the idea that financial variables and macroeconomic stability are dynamically intertwined. That is, financial variables contain two basic types of information: the information that responds to changes in macroeconomic conditions, and the information that contains the innovations taking place within the financial system and that end up affecting the macroeconomic environment. In this context, financial fluctuations refer to all changes in financial conditions (a combination of multiple variables) that are dynamically related to macroeconomic stability.

[2] To ensure that a given principal component is interpretable, all its loads need to satisfy certain (sign) conditions. When the number of variables included is very large, the interpretation of the component becomes intricate.

This understanding of the endogeneity between financial variables and macroeconomic conditions also brings forward the idea that financial variables can behave procyclically or countercyclically with respect to the real cycle. Conceptually, this evaluation of financial variables' cyclicality entails understanding the direction of both the response and the effect of financial variables with respect to the real cycle. In this paper, we intend to exploit a similar notion, but applied to financial indexes: *PFCI*, an index that behaves procyclically with respect to macroeconomic stability, and *CFCI*, an index that captures countercyclical financial conditions. Identification of these two indexes is achieved by establishing the sign of both their response to macroeconomic stability innovations and their impact on macroeconomic stability. In this way, each index becomes a composite variable that exhibits procyclical or countercyclical dynamics with respect to macro stability. These two indexes, when added, describe all the financial fluctuations that are dynamically relevant for macroeconomic stability. Next, we describe in detail our methodology.

2.1. A Model of Financial Fluctuations

Let *W* be the set of *N* standardized financial variables of dimension T and F^F the set of the f first principal components of *W*, being $f < N$. Define W_t as a N x 1 vector of variables; F_t^F a 1 x f vector of chosen components; Q^F as a matrix of dimension f x f that satisfies $Q^F Q^{F'} = Q^{F'} Q^F = I$. That is, Q^F contains f orthogonal vectors with norm equal to one that can rotate the normal basis formed by the components F^F.[3] Consider the first two column-vectors of Q^F, denoted as q^1 and q^2 respectively, both of which represent potential linear combinations of the components F^F. For $t = 1, 2, \dots, T$, the dynamics of financial variables is described by the following model:

$$W_t = \alpha\, PFCI + \beta\, CFCI + \xi_t$$
$$V^{-1} \begin{bmatrix} MS_t \\ PFCI_t \\ CFCI_t \end{bmatrix} = \Gamma_1 \begin{bmatrix} MS_{t-1} \\ PFCI_{t-1} \\ CFCI_{t-1} \end{bmatrix} + \cdots + \Gamma_p \begin{bmatrix} MS_{t-p} \\ PFCI_{t-p} \\ CFCI_{t-p} \end{bmatrix} + \epsilon_t \qquad (1)$$

[3] Rubio-Ramírez, Waggoner, and Zha (2010) use a similar matrix Q to implement sign restriction identification of structural shocks in SVARs. This rotation matrix is obtained by applying the QR decomposition to a random matrix of standard normally distributed realizations.

where $PFCI_t \equiv F_t^F\, q^1$ and $CFCI_t \equiv F_t^F\, q^2$ are the unobserved composite variables that capture procyclical and countercyclical financial conditions respectively; α and β are N x 1 vectors of parameters; and *MS* is a variable that describes the state of macroeconomic stability. The equation: $W_t = \alpha\, PFCI + \beta\, CFCI + \xi_t$ resembles a factor equation where the bulk of the financial variables variability is described by the two unobserved financial factors *PFCI* and *CFCI*. These factors, differently from the standard dynamic factor model, are weakly correlated due to the variance structure of the F^F components used for their construction.[4] Coefficients α and β are analogous to factor loadings and relate the unobserved factors with each of the financial variables. These coefficients represent not only the co-movement between factors and variables, but also the importance of each variable for each factor.[5] Vector ξ_t contains (weakly correlated) financial idiosyncratic disturbances that are interpreted as the noise in financial variables.[6]

Because the unobserved financial indexes and *MS* are mutually endogenous, their dynamics is represented by a structural VAR (*p*). The matrices V and Γ represent the structural parameters of the system, and the vector ϵ_t contains the structural shocks, which by definition have identical variance and are orthogonal (have covariance matrix equal to the identity matrix). Because the SVAR(*p*) also has a reduced form representation:

$$Z_t = \mathrm{A}\, Z_{t-1} + e_t \qquad (2)$$

where Z_t contains the adequate arrangement of present and lagged endogenous variables, e_t is the vector of reduced-form residuals with covariance matrix Σ. Structural impulse-responses at any horizon *h* can be written as:

$$SIR(h) = A^{h-1}\, V \qquad for \quad h = 1, \ldots, T \qquad (3)$$

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[4] Weak contemporaneous correlation between financial indexes exists, even when using a particular realization of *Q*. This is the case, because the origin of such correlation lies in the variance-structure of components, and not on the properties of *Q*. Recall that $E\left(F_t^{F\prime}\, F_{t\ t}^F\right)$ is given by the eigenvalues $\lambda_1 > \lambda_2 \ldots > \lambda_f$ of the spectral decomposition for the covariance matrix $E(W_t W_t{}')$. Therefore, $E(PFCI_t{}'\, CFCI_t) = E(q^{1\prime} F_t^{F\prime}\, F_{t\ t}^F q^2) = q^{1\prime} E(F_t^{F\prime}\, F_t^F) q^2 = q^{1\prime} \begin{pmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_f \end{pmatrix} q^2$. Because $E(F_t{}'\, F_t)$ is diagonal, but with different diagonal elements, $E(PFCI_t{}'\, CFCI_t) \neq 0$, although $q^{1\prime}\, q^2 = 0$ is guaranteed.

[5] Coefficients α and β are obtained through standard OLS estimation. While factor loadings represent correlations between factors and standardized observed variables, α and β are proportional to correlations since they provide the association of variables in *W* (in standardize units) per unit of factor.

[6] This weak correlation of residual is similar to the assumption held in approximate dynamic factor models.

where $SIR(1) = V \equiv \begin{bmatrix} \frac{\partial MS}{\partial \epsilon_1} & \frac{\partial MS}{\partial \epsilon_2} & \frac{\partial MS}{\partial \epsilon_3} \\ \frac{\partial PFCI}{\partial \epsilon_1} & \frac{\partial PFCI}{\partial \epsilon_2} & \frac{\partial PFCI}{\partial \epsilon_3} \\ \frac{\partial CFCI}{\partial \epsilon_1} & \frac{\partial CFCI}{\partial \epsilon_2} & \frac{\partial CFCI}{\partial \epsilon_3} \end{bmatrix}$. This matrix represents the contemporaneous effects of structural shocks on system's variables. Structural errors are related to reduced-form residuals through V, being $e_t = V\,\epsilon_t$ and $E(e_t e_t{}') = V\,V' = \Sigma$.

In our model, identification of the unobserved financial indexes (*PFCI* and *CFCI*) is achieved by imposing zero and sign restrictions on the elements of V. That is, regressors of the VAR are selected (or components F^F are rotated) such that the expected restrictions are satisfied. Because there is no single way to identify regressors, this identification procedure also requires obtaining a sufficiently large number of realizations (*dr*) of the rotation matrix Q (i.e., $[q^{1(1)} \quad q^{2(1)}]$, $[q^{1(2)} \quad q^{2(2)}], \dots,$ $[q^{1(dr)} \quad q^{2(dr)}]$), such that all possible rotations satisfy the following conditions:

a) $\frac{\partial MS}{\partial \epsilon_2}, \frac{\partial MS}{\partial \epsilon_3} \leq 0$: responses of macroeconomic stability to a positive innovation in both *PFCI* and *CFCI* is negative. Or equivalently, an unexpected innovation in financial conditions, through either *PFCI* or *CFCI*, deteriorates macroeconomic stability. This assumption guarantees that exogenous increases in both indexes can be interpreted as more detrimental financial conditions.

b) $\frac{\partial PFCI}{\partial \epsilon_1} \leq 0, \frac{\partial CFCI}{\partial \epsilon_1} \geq 0$: responses of financial conditions to a positive macroeconomic stability shock, are negative for *PFCI* and positive for *CFCI*. That is, we presume that an unexpected improvement in macro stability would also improve the financial conditions reflected in *PFCI*, while it would worsen the financial conditions captured by *CFCI*. These restrictions are crucial for distinguishing *PFCI* from *CFCI*.

c) $\frac{\partial PFCI}{\partial \epsilon_3}, \frac{\partial CFCI}{\partial \epsilon_2} = 0$: contemporaneous responses of each index to innovations in the other index are null. This also entails assuming that each index does not depend on the contemporaneous value of the other index, or that cross-responses of financial indexes to their innovations are orthogonal.

Notice that while assumptions in a) are important for improving the interpretability of financial indexes, assumptions in b) are crucial for differentiating the two financial indexes in terms of their statistical properties and for characterizing their cyclicality. This is the case because cyclicality consists of having differentiated responses of the indexes to macroeconomic stability. In particular, we define cyclicality as follows:

1) Index *PFCI* is procyclical with respect to macro stability because $\downarrow MS \xrightarrow{\frac{\partial PFCI}{\partial \epsilon 1} \leq 0} \uparrow PFCI \xrightarrow{\frac{\partial MS}{\partial \epsilon 2} \leq 0} \downarrow MS$. In other words, a deterioration of macroeconomic conditions causes a deterioration of financial conditions that worsens stability further.
2) Index CFCI is countercyclical with respect to macro stability because $\uparrow MS \xrightarrow{\frac{\partial CFCI}{\partial \epsilon 1} \geq 0} \uparrow CFCI \xrightarrow{\frac{\partial MS}{\partial \epsilon 3} \leq 0} \downarrow MS$. That is, an improvement in macroeconomic conditions causes a deterioration of financial conditions that tends to reverse the initial increase in macro stability. In this case, *CFCI* reflects the combined behavior of those variables that during periods of macroeconomic stability create adverse financial conditions that later undermine stability.

Assumptions in c) basically guarantee that the orthogonal innovations in either index are passed through to the other one only with a lag. These assumptions, although not decisive for the identification of indexes, provide a justification for considering the addition of the two indexes as a representation of all financial fluctuations.

Because the pair of column-vectors obtained from each realization of the rotation matrix generates two fully-characterized financial indexes, this identification procedure generates some degree of uncertainty in its regressors and structural parameters, or that is to say, it delivers an overidentified model.[7] To convey such uncertainty in the estimation of financial regressors, we simply compute the final indicators *PFCI* or *CFCI*, as the median trajectory of all possible indicators satisfying impulse-response restrictions. Another possibility would be to choose a particular realization of the matrix Q, whose pair of column-vectors generates financial indexes close to the median indexes, as Fry and Pagan (2011) would suggest. However, even for a large

[7] Overidentification of structural parameters also occurs when structural shocks are identified using sign restrictions. For a discussion of identification of model with sign restrictions see Rubio-Ramírez, Waggoner and Zha (2010).

enough number of realizations, the procedure suggested by these authors is going to deliver results that are very sensitive to realizations. That is, small variations in the elements of Q might translate into important variations in the dynamics of indexes. Instead, selecting the median trajectory of all possible indexes is equivalent to using the median properties of the column vectors of Q to construct the indexes. In this case, the dynamics of indexes tend to be very robust to changes in the number of realizations and do not affect the existence of a weak correlation between financial indexes.

Finally, the financial cycle is defined as: $CYCLE_t \equiv PFCI_t + CFCI_t$. Because financial indexes are characterized through an SVAR, each index can be represented as a moving average of contemporaneous and lagged innovations in the system. For each index, new information at time t corresponds to its own contemporaneous innovation (assumptions c) and the effect of contemporaneous macroeconomic innovations (assumptions b). On the one hand, this means that $CYCLE_t$ accurately reflects all relevant financial disturbances since it precisely contains the sum of the orthogonal innovations ϵ_{2t} and ϵ_{3t}. On the other hand, because $CYCLE_t$ also comprises the effect of past macroeconomic and financial innovations, it represents the net effect of all innovations on overall financial conditions. As a consequence, if the joint assessment of procyclical and countercyclical financial conditions exhibits an increasing slope, it is likely that the deterioration of the financial system can have large impacts on macroeconomic stability.

2.2. A Notion of Macroeconomic Stability

Theoretically, a stabilized economy improves agents' expectations regarding the current and future performance of the economy. When these expectations are internalized, current decisions might contribute to increasing macroeconomic stability further. According to the World Bank, policies that aim to achieve stability usually have a positive connotation and imply economic growth. A stabilized economy could also mitigate the effects of external shocks and potentially sustain growth.

In practical terms nonetheless, assessing macroeconomic stability can be difficult. In many cases, macroeconomic stability is simply defined as the volatility of key macroeconomic variables (growth of GDP, inflation, current account deficit). Other possible variables usually used to capture the state of macroeconomic stability are the standard deviations of the GDP per capita, private consumption growth, and real exchange rate growth. The IMF and the EU have also emphasized that indicators such as inflation, long-term interest rate, debt/GDP ratio, fiscal deficit and monetary aggregates growth, help to signal macroeconomic stability.[8]

In our view, using volatility indicators to measure macroeconomic stability does not reflect whether the changes in variables are actually signaling an improvement or a deterioration of macroeconomic performance. Any assessment of the macroeconomic environment in relation to the financial sector needs to at least determine whether current economic performance can be regarded as positive or negative by economic agents. But agents are rational and tend to use all available information, not only real output performance information, to generate that assessment. This probably implies that macroeconomic stability needs to consider information regarding the degree of achievement of different economic balances, because they usually summarize how well the economy can sustain its current performance. But the question that arises is then, which balances might be relevant for measuring macroeconomic stability?

Because the primary role of the financial system is to intermediate between those that provide funds and those that need funds, all factors affecting agents' decisions in the economy (firms, households and government) should also have, directly or indirectly, an impact on the decisions and the state of the financial system. In that sense, most important balances in the economy are potentially relevant for the financial sector. Likewise, financial innovations probably produce economic effects that pervade overall macroeconomic performance and not only output performance.

On this account, we define macroeconomic stability as a positive assessment of the current macroeconomic performance that does not entail a weakening of different fundamental balances: the current account balance, the fiscal balance and the goods market balance. For most Latin American economies, such satisfactory performance is usually understood as achieving both a strong economic growth and a falling inflation, while improving (or not deteriorating) external, goods market and fiscal balances. Conceptually, we could argue that this assessment of the macroeconomic environment is equivalent to observing expansionary supply shocks whose surrounding conditions do not worsen fundamentals.

The construction of an index that measures macroeconomic stability requires then that all the above conditions be satisfied. That is, high values of the index should reflect good performance in terms of output growth, inflation and domestic currency valuation, without

[8] Krueger (2006).

deteriorating external, fiscal and goods market balances. In the next section, we explain the methodology for constructing that index.

2.3. An Index of Macroeconomic Stability (MS)

In Eickmeier, Gambacorta, and Hofmann (2014), the authors broadly define global liquidity as the availability of funds for purchases of goods or assets from a global perspective. In that paper, they construct an index of global liquidity conditions based on the identification of several common factors from a large number of quantity and price-based liquidity variables. That is, their procedure solves the problem of how to combine multiple dimensions of a large dataset into a single index that relates to some of its variables in predetermined ways. Next, we apply a similar identification technique to compute our composite macroeconomic index. The main idea is to combine a set of macroeconomic components to construct an index that relates to some macroeconomic variables in pre-determined ways. Our implementation of this procedure departs from Eickmeier et al. (2014) in some aspects that are going to be pointed out in the course of the description.

Start by defining X as set of M standardized macroeconomic variables of dimension T, and F^M as the set of the m first principal components of X, being $m < M$. Let X_t be an M x 1 vector of variables; F_t^M a 1 x m vector of chosen components and Q^M a m x m rotation matrix that satisfies: $Q^M Q^{M'} = Q^{M'} Q^M = I$. Let also q^1 be the first column-vector of Q^M. For $t = 1, 2, \dots, T$, the macroeconomic stability index (*MS*) satisfies the linear equation:

$$X_t = \gamma \, MS_t + \zeta_t \qquad (4)$$

where $MS_t \equiv F_t^M q^M$, ζ_t is the M x 1 vector of macroeconomic idiosyncratic disturbances and γ is an M x 1 vector of coefficients that relate macroeconomic variables to the unobserved *MS* index. The elements of the vector of coefficients satisfy some restrictions, i.e., some $\gamma_i \gtrless 0$. Because the *MS* index is a linear combination of the first m principal components of the macroeconomic data, this procedure is equivalent to finding the appropriate rotation of the orthogonal set of macro components that satisfies all the expected sign restrictions in the estimated linear model (4). In this way, the *MS* index has the properties imposed according to a theoretical framework or the notion subject to measurement. Notice that in this methodology, the restrictions are imposed on the response of the same variables that are summarized through the components.

In Eickmeier et al. (2014), when applying this procedure to global monetary, credit and financial variables, they previously clean or purge such variables from the effect of some macroeconomic indicators (inflation and growth). Consequently, their estimated linear model contains two regressors: the liquidity index that is being identified and the macroeconomic variables used in the purging process. In our case, this particular cleaning procedure is not necessary because the endogeneity existing between macroeconomic and financial variables is taken into consideration when constructing financial indexes. At this point, we only want to ensure that the index has the expected interpretation by satisfying the sign restrictions imposed on regression coefficients.

Because there are several rotation matrices that satisfy the restrictions imposed on (4), we can obtain as many rotation matrices as we choose. Each of these rotation matrices generates a different *MS* indicator. This implies that there is a degree of uncertainty or overidentification. To convey that uncertainty, we simply compute the final indicator *MS*, as the median trajectory of all possible indicators satisfying the chosen γ-restrictions.

3. Estimations for Venezuela

3.1. Estimation of the Macroeconomic Stability Index

The macroeconomic data used to compute the macroeconomic stability index for Venezuela comprise a total of 19 variables that include information from several economic sectors: goods market (output growth, inflation and unemployment), monetary (two variables that measure the monetary effects of fiscal and exchange rate actions), external (growth rates of exchange rate, international reserves, oil exports, imports, the current account balance and a capital inflow index) and fiscal (fiscal expenditures growth and balance). All growth rates are calculated in annual terms. The sample period for macroeconomic information is 2003:01 to 2014:12.

This data also includes a measure of excess demand in the goods market, denominated the goods market unbalance (*GMU*), as defined in Pagliacci (2016). Opposed to output gaps measures, which intend to capture the mere occurrence of demand shocks, the goods market unbalance is a measurement of excess demand in a framework where both supply and demand shocks can have short-run impacts on output. That is, excess demand can take place not only because expansionary demand shocks are occurring, but also because contractionary supply shocks take place. Operationally, this variable is computed as the difference or wedge between the supply and demand components of output growth, both of which are obtained out of the historical decomposition of supply and demand shocks identified within a bi-variate SVAR on output growth and inflation. Because this measure of excess demand captures situations of marked adjustments in inflation caused by the inconsistent reactions of firms and households to shocks, it is potentially an important notion for the performance of the financial system. In particular, one could presume that in situations of excess demand ($GMU > 0$), some financial conditions might deteriorate due to rapid credit expansions that are not necessarily accompanied by a larger supply of goods. Supply and demand components are also included in the macro data set.

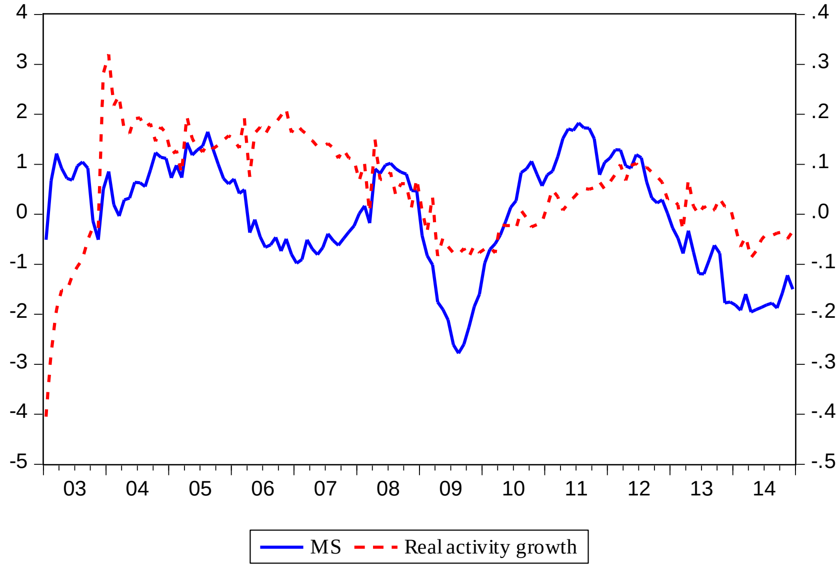
As suggested in Section 2.2, the macroeconomic stability notion relevant for the financial sector could vary, depending on the priors held by the researcher. For instance, in Drehmann, Borio and Tsatsaronis (2012) the financial cycle is strictly associated with the business cycle. In Hatzius et al. (2010), the *FCI* is purged from the effect of real output growth and inflation, because these variables allegedly affect financial conditions more importantly. In this paper, we contend that a broad notion of macroeconomic stability is potentially more suitable for capturing the macroeconomic conditions that affect the financial system. Therefore, as already proposed, we define *MS* as an index of macroeconomic stability that includes information on several fundamental balances. This index is computed based on the selection of the first six principal components of the macro data set, which account roughly for 85 percent of the common variability of series. The sign restrictions imposed on regression coefficients of the linear equation (4) are given by Table 1. In Figure 1, we compare *MS* with the growth rate of real activity.

Table 1. Restrictions Imposed on the Macroeconomic Stability Index

Implicit notion of macro stability	**Restrictions on macro variables' coefficients**
Expansionary supply shocks that do not harm fundamental balances (*MS*)	$\gamma_y \geq 0$, $\gamma_{pi} \leq 0$, $\gamma_{dep} \leq 0$, $\gamma_{FB} \geq 0$,$\gamma_{RCA} \geq 0$, $\gamma_{GMU} \leq 0$

Sub-indices represent the following variables. y: real output growth, pi: inflation; dep: domestic currency depreciation; FB: fiscal balance, calculated as a share of domestic expenditures; RCA: relative current account balance, defined as the ratio between the current account surplus and oil exports; GMU: goods market excess demand, measured as the difference between the demand and the supply components of output growth.

Figure 1. Comparisons of the Macroeconomic Stability Index with Real Activity Growth



According to the restrictions imposed, *MS* registers that the economy is more stable when expansionary supply shocks are not accompanied by a strong weakening of any of the fundamental balances (fiscal, current account and goods market). In this definition, stability can rise only if the economic indicators restricted are, on average, increasing.

In Figure 1, it is shown that the index *MS* provides a different story than the growth of real activity. For example, *MS* indicates that during the period 2006-2007, there is a deterioration of macroeconomic stability, in spite of the positive growth and relatively stable inflation. For that period the current account surplus fell importantly. On the contrary, by the end of 2011, macroeconomic stability increased because of the improvement of some of the fundamental balances: an increased CA surplus, a smaller fiscal deficit and a minor excess demand in the goods markets (a reduced GMU).

3.2. Estimation of Procyclical and Countercyclical Financial Conditions Indexes

The dynamic performance of macroeconomic stability is captured through the *MS* index, which is computed as shown in the previous section. This is our benchmark indicator for the estimation of financial indexes.

The data used to estimate financial indexes consist of series of performance indicators that are constructed from monthly information published by banks in financial reports. The sample includes 12 banks, which in June 2016 represented around 90 percent of the system's assets. We also complete this set of performance indicators with bank-aggregated information in order to characterize the whole banking system. The total number of financial variables considered is 473; these include capitalization ratios, coverage of non-performing loans, implicit interest rates, margins, returns, and the growth rate of main assets along with their allocation. Growth rates are all computed in annual terms. Leverage and capitalization are seasonally adjusted. The sample period for financial information covers from 1997:07 through 2015:03.

The estimation of financial indexes uses the information of the first 13 principal components, which explain 86 percent of the common variability of the set of 473 financial variables. The VAR employed for the identification of the financial indexes has a 2-lag length (as suggested by the Hannan-Quinn criterion) and satisfies stability conditions.

Structural decomposition of the covariance matrix Σ (the matrix *V* used in expression (3)) is obtained through several steps within the identification process. For a given draw $[q^{1(dr)} \quad q^{2(dr)}]$ of *Q*, which represents a set of potential financial indexes candidates, first a reduced VAR is estimated, a Cholesky decomposition is applied to Σ , impulse responses are computed and then restrictions on impulse responses are checked. We only keep those draws of *Q* that satisfy all restrictions. In this process, the order of variables reflects the structure of the theoretical SVAR: the macroeconomic stability index is ordered first, which means that innovations in financial indexes affect macroeconomic stability with a lag, while macroeconomic stability innovations can affect financial indexes contemporaneously. In other words, because macroeconomic conditions presumably adjust more slowly than financial conditions to shocks, it takes at least one month for financial innovations to be reflected in macroeconomic stability. Some sign restrictions on impulse-responses are imposed for two consecutive periods. Succinctly, the restrictions imposed are as follows:

$$SIR(1) = \begin{bmatrix} NR & 0 & 0 \\ \leq 0 & NR & 0 \\ \geq 0 & \simeq 0 & NR \end{bmatrix} \quad , \quad SIR(2) = \begin{bmatrix} NR & < 0 & < 0 \\ < 0 & NR & NR \\ > 0 & NR & NR \end{bmatrix}$$

where NR means that no restrictions were placed on those elements. Recall also that restrictions on SIR-elements (1,2) and (2,1) identify the *PFCI* index, while restrictions on elements (1,3) an (3,1) identify the *CFCI* index. Notice that *SIR*(1) represents a decomposition of Σ that has an additional zero restriction on the elements below the diagonal than the standard Cholesky decomposition. In *SIR*(2), we choose the financial regressors that exhibit the greatest responses on variables: elements (1,2), (2,1), (1,3) and (3,1) satisfy strict inequalities. That is, we choose the responses whose absolute values are above the median response.[9] This additional restriction on impulse-responses ensures that the magnitude of the responses is sufficiently large.

Because of a limited availability of macroeconomic data with respect to financial variables, we implement the above procedure for the estimation period 2003:01 to 2014:12. However, principal components of the financial data are calculated over the whole sample (1997:07 to 2015:03), as well as financial indexes.

3.3. Interpretation of Financial Indexes

Figure 2 presents the dynamics of the financial indexes for the Venezuelan case. A general evaluation of both indexes indicates that prior to 2004, financial fragility seemed to be dominated by countercyclical financial conditions. Afterwards, with the exception of 2011 and 2012, it was dominated by procyclical financial conditions. Interestingly enough, it was at the beginning of 2003, when an exchange rate control was implemented, and the price and allocation to the economy of foreign exchange currency became an administrative decision.[10] The relevant question is then, what is the particular interpretation of these two financial conditions indexes for the Venezuelan case?

One way to interpret financial indexes is by determining which financial variables have the larger loads. In model (1), this information is given by the size of α and β, which also indicate the direction of the correlation between specific financial variables and financial indexes. Table 2 shows some estimated coefficients associated with bank-aggregated financial variables.

[9] Once we obtain the empirical distribution of responses, we keep the half part of the distribution whose magnitudes of responses are further away from zero. This criterion is less arbitrary than choosing an absolute threshold value.

[10] This policy change implied the emergence of a non-official (dual) exchange rate market and an important reduction in the share of oil earnings allocated to the private sector.

Figure 2. Procyclical and Countercyclical Financial Conditions Indexes

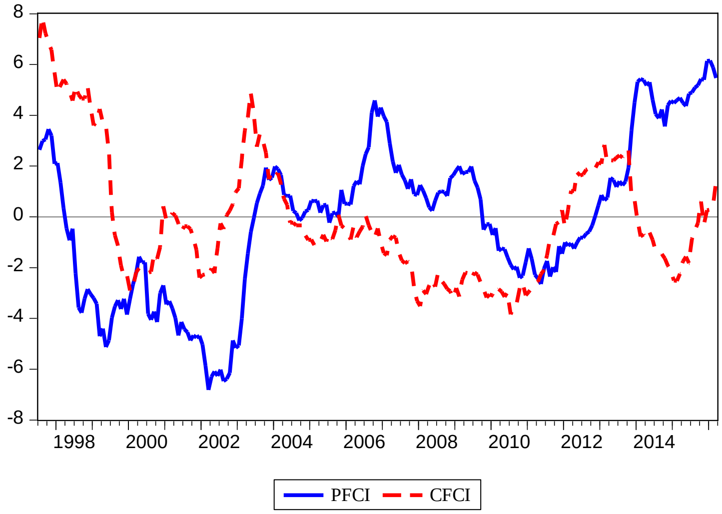


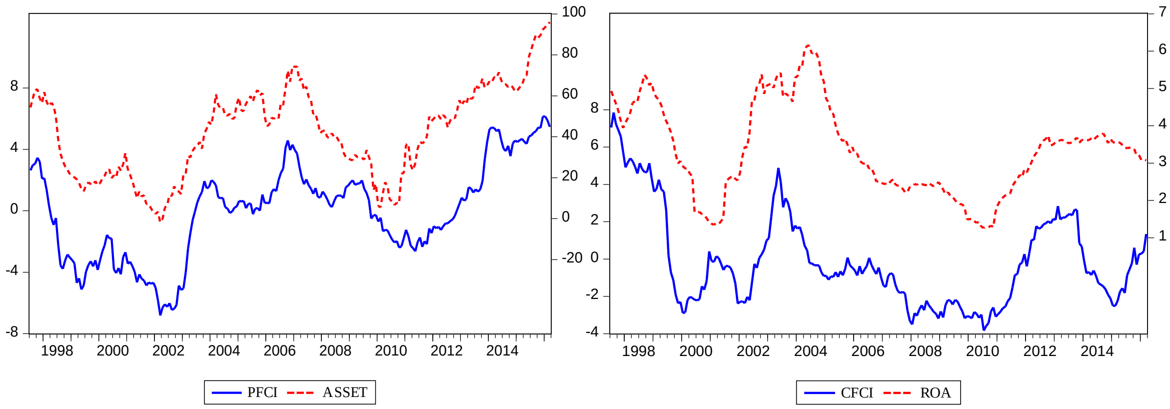
Table 2. Estimated Coefficients for Selected Bank-Aggregated Variables

Variable i	α_i	β_i
ASSET	0.28	0.08
CAP	-0.18	0.20
CML	0.21	0.09
CNL	0.18	0.05
COVNPL	0.22	-0.01
DEP	0.28	0.09
INT	-0.08	-0.04
K	0.22	0.12
LBCOSTS	-0.26	0.09
LEV	0.23	-0.12
LOAN	0.23	0.09
MGL	0.02	0.05
MARGIN	-0.23	0.16
RATE (LOAN)	-0.23	0.12
ROA	0.01	0.26
SEC	0.01	0.04
SHCML	-0.04	0.18
SHCNL	0.06	-0.18
SHLIQ	0.08	-0.10
SHLOANS	0.04	-0.01
SHMGL	0.01	-0.18
SHSEC	0.10	-0.09
ZETA	-0.01	-0.13

ASSET: annual growth rate of nominal assets; CAP: capitalization ratio; CML: annual growth rate of nominal commercial loans; CNL: annual growth rate of nominal consumption loans; COVNPL: ratio of loan provisions to non-performing loans; DEP: annual growth rate of nominal deposits; INT: intermediation (loans/deposits); K: annual growth rate of nominal capital; LBCOSTS: labor costs as a proportion of total assets; LEV: leverage (assets/capital); LOAN: annual growth rate of nominal loans; MGL: annual growth rate of nominal mortgage loans; MARGIN: financial margin computed as the difference of implicit rates; RATE (LOAN): implicit loan rate; ROA: returns on assets; SEC: annual growth rate of nominal securities; SHCML: share of commercial loans on total loans; SHCNL: share of consumption loans on total loans; SHLIQ: share of liquid assets on total assets; SHLOANS: share of loans on total assets; SHMGL: share of mortgage loans on total loans; SHSEC: share of securities on total assets; ZETA: median bans' zeta-score.

Parameter estimations in Table 2 point out that the larger positive associations arise between the *PFCI* and the growth rate of aggregated nominal banking assets ($\alpha_{ASSET} > 0$), and between the *CFCI* and the system profitability ($\beta_{ROA} > 0$). Figure 3 shows these conspicuous associations.

Figure 3. Associations of Financial Indexes with Particular Financial Variables



However, indexes are a combination of many bank-specific and aggregated variables. Other prominent variables' associations with indexes are the following. Procyclical financial conditions exhibit a large deterioration when banks' balance sheets and deposits expand ($\alpha_{ASSET}, \alpha_{DEP} > 0$), leverage increases ($\alpha_{LEV} > 0$), and interest rates and financial margins tend to decline ($\alpha_{RATE}, \alpha_{MARGIN} < 0$). In contrast, countercyclical financial conditions significantly worsen during episodes of high profitability and margins ($\beta_{ROA}, \beta_{MARGIN} > 0$) that simultaneously relate to low leverage ($\beta_{LEV} < 0$), low liquidity ($\beta_{SHLIQ} < 0$) and diminished stability ($\beta_{ZETA} < 0$).[11] Fragile countercyclical financial conditions can also be related to a reallocation of loans in favor of commercial loans ($\beta_{SHCML} > 0$) and to the detriment of both consumption loans ($\beta_{SHCNL} > 0$) and mortgage loans ($\beta_{SHMGL} > 0$).

Because *PFCI* and *CFCI* exhibit a close to zero contemporaneous correlation (0.02), it is probable that these two stylized characterizations tend to emerge at different points in time. Moreover, because of the prevalence of *PFCI* over *CFCI* after to 2003, we could state that, after the implementation of the exchange rate control, fragility was more on the side of the expansion of banks' balance sheets and deposits rather than the side of increased profitability and

[11] Stability is measured by the median zeta-score of the banking system, computed out of individual zeta-scores for banks.

instability. In terms of their relation to macroeconomic stability, indexes' correlations with *MS* reflect the assumptions used for their construction: *PFCI* is negatively correlated with *MS* (-0.64), while *CFCI* is positively correlated with *MS* (0.13). But a second pressing question that arises is: what are the specific macroeconomic conditions that are related to a deterioration of each financial condition index?

To answer the above question, we take a look at the individual correlations that arise between the financial indexes and each of the 19 macroeconomic variables employed to construct the index of macroeconomic stability (*MS*).[12] We find that for the *PFCI*, the highest individual correlation (0.58) corresponds to a monetary variable that measures net primary money creation in the economy. Specifically, this monetary variable captures the net monetary effect that results from the money creation associated with fiscal domestic spending and the monetary drain that occurs when the Central Bank allocates foreign exchange currency to the private sector. This means that procyclical financial conditions deteriorate when net primary money creation increases, because either the fiscal monetization has increased or the foreign exchange monetary drain has fallen.[13] For the *CFCI*, the highest correlations refer to the rate of domestic currency depreciation in the non-official market (0.29) and to the allocation of foreign exchange (0.18). In this case, one feasible interpretation would be that a significant allocation of foreign exchange currency that fuels domestic currency depreciation tends to deteriorate countercyclical financial conditions.

These associations between the financial indexes and particular variables of the macroeconomic environment finds some support in the work of Carvallo and Pagliacci (2016). In that paper, monetary shocks taking place through fiscal and foreign exchange policy decisions also have a sizable impact on the banking system, particularly bank stability. They claim that, under the current monetary and exchange rate arrangement in Venezuela, fiscal domestic expenditures tend to increase banks' funding and deposits, while foreign exchange allocation diminishes them. As a result, positive innovations in net primary money not only bring about loose general monetary conditions for the economy, but also increase banks' funds and deposits. Finally, bank stability is positively related to banks' funding expansions. This evidence, provided by Carvallo and Pagliacci (2016), completes our interpretation of results as follows. Higher net

[12] For the sake of brevity, these correlations are not reported, but can be available upon request.
[13] In particular, *PFCI* is positively correlated with the fiscal monetization and negatively correlated with the foreign exchange liquidation (0.28 and -0.29 respectively).

primary money creation would cause a deterioration of procyclical financial conditions because it expands banks' liabilities and main assets, while it reduces interest rates and margins. During this process leverage rises and labor costs are compulsorily reduced. In these situations, the fragility of the banking system seems to have its origin in the difficulty of maintaining adequate levels of profitability for intermediating larger quantities of funds. Alternatively, a deterioration of countercyclical financial conditions would occur with large foreign exchange liquidations because banks presumably finance their clients' acquisition of foreign currency. During this process, a reallocation of banks' assets takes place. This asset reorganization is characterized by a reduction in the relative size of liquid assets in favor of commercial loans, while liabilities tend to dwindle. Likewise, higher returns are generated, while bank leverage declines and stability drops. In this case, the source of the financial fragility seems to lie in the high volatility of banks' profitability.

Another way to complete the interpretation of financial indexes is by analyzing the variance decomposition of shocks in the SVAR defined according to model (1). As mentioned in the specification of this model, high positive innovations of indexes reflect financial conditions that undermine macro stability. But also, financial indexes are distinguished by their response to macroeconomic innovations. Although these properties are guaranteed in the identification process, the definite size of the impact of indexes on macroeconomic conditions, or the impact of the latter on the former, is an empirical matter that we can observe through variance decompositions. Once indexes have been computed, we estimate a two-lag VAR according to model (1), and compute accumulated variance decompositions. Table 3 shows these results.

Table 3. Variables' Variance Decomposition to Shocks

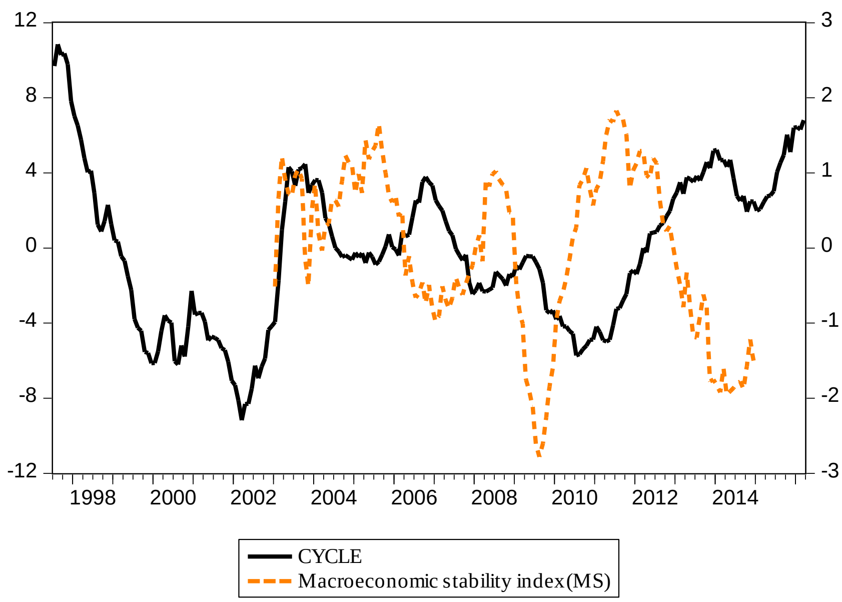
	MS decomposition			PFCI decomposition			CFCI decomposition		
period	MS shock	PFCI shock	CFCI shock	MS shock	PFCI shock	CFCI shock	MS shock	PFCI shock	CFCI shock
1	100%	0%	0%	3%	97%	0%	2%	2%	97%
2	93%	2%	5%	2%	97%	0%	3%	1%	96%
3	88%	4%	8%	2%	97%	1%	4%	1%	95%
4	84%	7%	9%	1%	97%	2%	4%	2%	94%
5	80%	10%	10%	1%	96%	3%	5%	3%	92%
6	77%	13%	11%	1%	94%	4%	6%	5%	90%
12	62%	23%	15%	1%	83%	16%	8%	18%	74%
24	48%	25%	28%	2%	63%	35%	9%	41%	51%

In Table 3, we can observe that both financial indexes have sizable impacts on macroeconomic stability and can account for about half of its variance after 24 months. Oppositely, because financial indexes' variability is mostly explained by *PFCI* and *CFCI* innovations, it also means that macroeconomic stability innovations are not able to explain a great deal of financial conditions' variability. So, what could be a possible source of these exogenous financial innovations?

As we mentioned before, the variables fiscal monetization and foreign exchange allocation are importantly correlated to indexes and can actually explain part of their dynamics. Therefore, one likely conjecture is that innovations in financial indexes can be accounted for by these two variables, which in fact do not strongly relate to macroeconomic stability. Both net primary money creation and foreign exchange liquidations are weakly correlated with the macroeconomic stability index (-0.31 and 0.44, respectively). This implies that these two variables presumably display a great deal of exogenous innovation (with respect to the *MS* index) that might explain financial indexes' innovations. Overall, what is actually interesting is that these strong associations between indexes and the monetary dimensions of fiscal and FX policy variables are arising in the data without imposing them ex ante. In fact, we have only imposed the relation of financial indexes with a general notion of macroeconomic stability, which is not extremely correlated with any of these two variables either.

A last bit of information that can be used for interpreting financial indexes is their analysis through the variable *CYCLE*. Because *CYCLE* results from the addition of the two financial indexes, it reflects the overall state of financial conditions that would affect macroeconomic stability. Then, if *CYCLE* exhibits an increasing slope, it is likely that the deterioration of the financial system can have large impacts on the macroeconomic environment. This is because the innovations of each of its two components also have a negative association with stability. In Figure 4, we show this index in contraposition to macro stability.

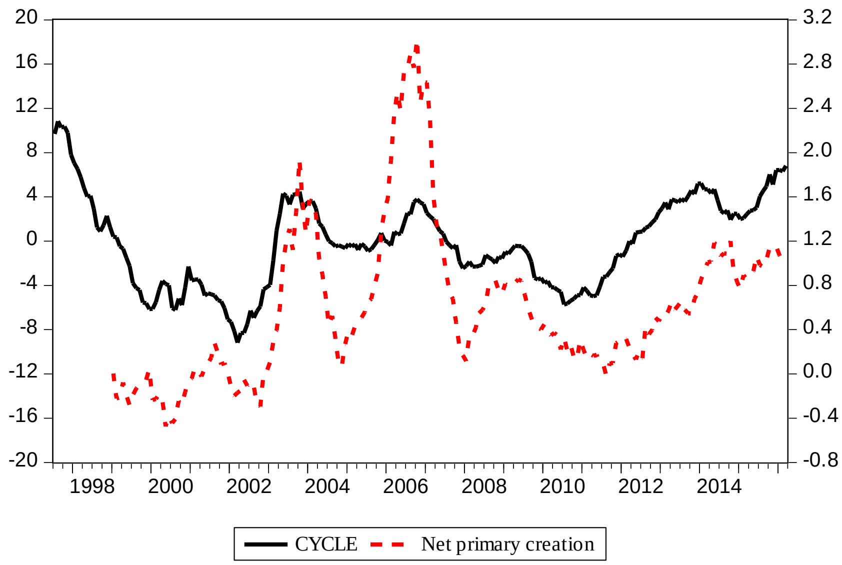
Figure 4. Financial Cycle and Macroeconomic Stability



The contemporaneous correlation between *CYCLE* and *MS* for the sample period is -0.32, which represents a linear combination of the correlations individually held by *PFCI* and *CFCI* with *MS* (-0.64 and 0.13 respectively). This means that overall financial conditions improve with greater macro stability. In terms of the level of the variable *CYCLE*, periods of maximum deterioration in financial conditions correspond to: in 1996-97, the exit of the exchange rate control implemented in 1994; in 2003, the implementation of the new exchange rate control; in 2006, a year of significant real growth but low stability; and finally in 2015-16, the last months of the sample. In terms of their synchronicity, the troughs (peaks) of *CYCLE* appear to slightly precede the peaks (troughs) of macroeconomic stability. This could suggest that the information in *CYCLE* might be also valuable for predicting macroeconomic stability.

Given the importance of net primary money creation to explain *PFCI*'s behavior, in Figure 5, we show the variable *CYCLE* in contraposition to that one. As previously suggested, because of the prevalence of *PFCI* over *CFCI* after 2003, the peaks of greater financial deterioration seem to coincide with the peaks of maximum primary monetary creation. However, in the context of a regime change, fragility could turn out to rely more on the behavior of countercyclical financial conditions, as it did prior to 2003.

Figure 5. Financial Cycle and Net Primary Money Creation



4. Financial Variables Analysis

Once we estimate the complete model in (1) and have both the size of the impulse-responses and parameter estimates from the factor equation, we can analyze the relation of particular financial variables to macroeconomic stability without estimating other models.

Recall the factor equation, $W_t = \alpha\, PFCI_{\,t} + \beta\, CFCI_t + \xi_t$, where coefficients α and β allow us to evaluate the co-movement between variables and indexes. In particular, given the i_{th} elements $\alpha_i = \frac{\partial W_i}{\partial PFCI}$, $\beta_i = \frac{\partial W_i}{\partial CFCI}$ then $\frac{\partial PFCI}{\partial W_i} = \sigma^2_{PFCI}\, \alpha_i$, $\frac{\partial CFCI}{\partial W_i} = \sigma^2_{CFCI}\, \beta_i$, being σ^2_{PFCI} and σ^2_{CFCI} the variances of the computed financial indexes.[14] As a result, any response or shock in financial indexes can be translated into movements of observable financial variables. That is, we can answer how particular financial variables respond to structural macroeconomic stability shocks (ϵ_1), through the impact of such shocks on indexes. Conversely, we can establish which

[14] Recall that the elements of α and β are estimated by the expression $\frac{cov(W_i, index)}{\sigma^2_{index}}$.

exogenous adjustments in financial variables deteriorate stability, through the evaluation of the impact of financial indexes' shocks (ϵ_2, ϵ_3) on macro stability. When these two pieces of information are analyzed jointly, they also provide a characterization of the cyclicality of each financial variable included in the system. This information could be very valuable in detecting patterns of variables' behavior that could be at odds with theoretical models or expectations and to examine the causes of such behavior. Overall, these exercises complete our understanding of the dynamics of financial variables in relation to macroeconomic stability.

Using the above concepts, we can characterize financial variables according to three criteria. Next we show how to implement calculations.

1) Financial variables' responses to shocks in macroeconomic stability ($\frac{\partial W_i}{\partial \epsilon_1}$).
   $\frac{\partial W_i}{\partial \epsilon_1} = \frac{\partial W_i}{\partial PFCI}\frac{\partial PFCI}{\partial \epsilon_1} + \frac{\partial W_i}{\partial CFCI}\frac{\partial CFCI}{\partial \epsilon_1} = \alpha_i \frac{\partial PFCI}{\partial \epsilon_1} + \beta_i \frac{\partial CFCI}{\partial \epsilon_1} \gtrless 0$, given that $\alpha_i, \beta_i \lesseqgtr 0$; and $\frac{\partial PFCI}{\partial \epsilon_1} \leq 0, \frac{\partial CFCI}{\partial \epsilon_1} \geq 0$. Notice that the terms $\frac{\partial PFCI}{\partial \epsilon_1}, \frac{\partial CFCI}{\partial \epsilon_1}$ represent the value of impulse-responses in model (1) for any chosen horizon. The general interpretation of the expression is that the response of a variable to a macroeconomic shock is a linear combination of the financial indexes' responses, where weights are given by the variable's loads.

   Variables that increase with positive innovations in macro stability satisfy: $\frac{\partial W_i}{\partial MS} > 0$.

2) Macroeconomic stability responses to shocks in financial variables ($\frac{\partial MS}{\partial W_i}$).
   $\frac{\partial MS}{\partial W_i} = \left(\frac{\partial MS}{\partial \epsilon_2}\frac{1}{\sigma_{PFCI}}\right)\frac{\partial PFCI}{\partial W_i} + \left(\frac{\partial MS}{\partial \epsilon_3}\frac{1}{\sigma_{CFCI}}\right)\frac{\partial CFCI}{\partial W_i} = \frac{\partial MS}{\partial \epsilon_2}\sigma_{PFCI}\, \alpha_i + \frac{\partial MS}{\partial \epsilon_3}\sigma_{CFCI}\beta_i \gtrless 0$, given that $\alpha_i, \beta_i \lesseqgtr 0$ and $\frac{\partial MS}{\partial \epsilon_2} \leq 0, \frac{\partial MS}{\partial \epsilon_3} \leq 0$. In this case, because impulse responses ($\frac{\partial MS}{\partial \epsilon_2}, \frac{\partial MS}{\partial \epsilon_3}$) refer to changes in *MS* caused by one standard deviation of indexes, we translate them into responses per unit of financial indexes (by dividing such responses by the standard deviation of indexes). Results are later translated into responses of macro stability per unit of the financial variable (by multiplying the expressions in parentheses by $\frac{\partial PFCI}{\partial W_i}, \frac{\partial CFCI}{\partial W_i}$ respectively). The interpretation of the resulting expression is that the response of the macro stability to a variable's shock is a linear combination of the

responses to financial indexes' shocks. Weights are the correlations between the variable and the indexes.[15]

Variables whose shocks rise macro stability satisfy: $\frac{\partial MS}{\partial W_i} > 0$.

3) Cyclicality of financial variables.
A variable is procyclical, if $\frac{\partial W_i}{\partial \epsilon_1} x \frac{\partial MS}{\partial W_i}$>0. Otherwise is countercyclical, i.e. $\frac{\partial W_i}{\partial \epsilon_1} x \frac{\partial MS}{\partial W_i} < 0$. This classification follows the same logic employed for defining cyclicality of financial indexes. In this case, procyclicality can be achieved by having either $\frac{\partial W_i}{\partial \epsilon_1} > 0$, $\frac{\partial MS}{\partial W_i} > 0$ or $\frac{\partial W_i}{\partial \epsilon_1} < 0$, $\frac{\partial MS}{\partial W_i} < 0$. In the latter case, it means that if a variable decreases with an unexpected macroeconomic improvement, a further reduction of the variable should enhance macro stability. In other words, a financial variable is procyclical if its variation (in the same direction of its response to a macroeconomic shock), reinforces the initial change in macroeconomic stability.

According to parameters estimates for Venezuela, variables characterization is summarized in Tables 4 and 5. There are multiple analyses that we could undertake using the information of these two tables. We will only focus on the variables that were mentioned to interpret *PCFI* and *CFCI* in Section 3.

[15] Note that correlations are $corr(w_i,\ index) = \frac{cov(w_i, index)}{\sigma_{index}}$.

Table 4. Financial Variables Characterization

	Growth rates/flows	Financial ratios
Variables that increase with an unexpected improved macro stability $\frac{\partial W_i}{\partial \epsilon_1} > 0$	LBCOSTS RATES MARGIN ROA ASSET, ASSETR LOAN, LOANR MGL, CNL, CML SEC, SECR DEP, DEPR K, KR	CAP SHCML
Variables that decrease with an unexpected improved macro stability $\frac{\partial W_i}{\partial \epsilon_1} < 0$	SEC, SECR	INT LEV COVNPL SHLIQ ZETA SHLOANS SHCNL, SHMGL SHSEC
Variables' innovations that improve macro stability $\frac{\partial MS}{\partial W_i} > 0$	LBCOSTS RATES MARGIN	CAP INT ZETA SHLIQ SHMGL, SHCNL
Variables' innovations that weaken macro stability $\frac{\partial MS}{\partial W_i} < 0$	ROA ASSET, ASSETR LOAN, LOANR CNL, CML MGL DEP, DEPR SEC, SECR K , KR	LEV COVNPL SHLOANS SHCML SHSEC

LBCOSTS: labor costs as a proportion of total assets; RATES: implicit loan and deposit rates; MARGIN: financial margin computed as the difference of implicit rates; ROA: returns on assets; ASSET (R): annual growth rate of nominal (real) assets; LOAN(R): annual growth rate of nominal (real) loans; MGL: annual growth rate of nominal mortgage loans; CNL: annual growth rate of nominal consumption loans; CML: annual growth rate of nominal commercial loans; SEC(R): annual growth rate of nominal (real) securities; DEP(R): annual growth rate of nominal (real) deposits; K(R): annual growth rate of nominal (real) capital; CAP: capitalization ratio; SHCML: share of commercial loans on total loans; SHCNL: share of consumption loans on total loans; SHMGL: share of mortgage loans on total loans; SHLIQ: share of liquid assets on total assets; SHLOANS: share of loans on total assets; SHSEC: share of securities on total assets; ZETA: median bans' zeta-score; INT: intermediation (loans/deposits); LEV: leverage (asset/capital); COVNPL: ratio of loan provisions to non-performing loans.

Recall that deteriorated procyclical financial conditions are related to banks' balance sheets expansions due to a growth in deposits that reduce margins and interest rates. Regarding this case, Table 5 shows that a positive growth rate of nominal aggregate assets (ASSET) and deposits (DEP) reduces macro stability ($\frac{\partial MS}{\partial W_i} < 0$), while a fall in interest rates (RATES) and financial margins (MARGIN) weakens stability ($\frac{\partial MS}{\partial W_i} > 0$). Therefore, innovations in the main components (variables) of the index cause the expected effect on macro stability. Alternatively, worse countercyclical financial conditions are associated with the rising profitability (ROA) that takes place in situations of increased instability (lower ZETA), in combination with reductions in the shares of liquid assets in total assets (SHLIQ), of consumption loans in total loans (SHCNL) and of mortgage loans in total loans (SHMGL). In this case, Table 4 corroborates that a higher ROA decreases stability ($\frac{\partial MS}{\partial W_i} < 0$), while a lower ZETA, SHLIQ, SHCNL and SHMGL diminish stability as well ($\frac{\partial MS}{\partial W_i} > 0$).

Another way to use the information in Table 4 is to determine if variables' behaviors are in line with macroprudential prescriptions in the literature. For example, because increasing capitalization (CAP) can improve macroeconomic stability ($\frac{\partial MS}{\partial W_i} > 0$), prescriptions related to the accumulation of capital buffers, especially during good times, could be considered appropriate for the Venezuelan economy. Another example: since reducing leverage (LEV) could contribute to improving macro stability ($\frac{\partial MS}{\partial W_i} < 0$), recommendations that lean toward monitoring or controlling the escalation of banking leverage also seem also reasonable for Venezuela. However, there are other prescriptions arising from Table 4 that are not so common. For instance, an increase in financial margins (MARGIN), interest rates (RATES), systemic stability (ZETA) and intermediation (INT) could help to enhance macroeconomic stability (all of them exhibit $\frac{\partial MS}{\partial W_i} > 0$). But again, these results should be interpreted as a summary of the historical behavior of the local banking system, which could also depend on specific features of the Venezuelan monetary and institutional arrangement.

Table 5. Variables' Cyclicality with Respect to Macroeconomic Stability $\left(\frac{\partial W}{\partial \epsilon_1} x \frac{\partial MS}{\partial W_i} \gtrless 0\right)$

	Growth rates/flows	Financial ratios
Procyclical financial variables $\frac{\partial W}{\partial \epsilon_1} x \frac{\partial MS}{\partial W_i} > 0$	LBCOSTS (+, +) RATES (+, +) MARGIN (+,+) SEC, SECR (-,-)	CAP (+,+) COVNPL (-,-) LEV (-,-) SHLOANS (-,-) SHSEC (-,-)
Countercyclical financial variables $\frac{\partial W}{\partial \epsilon_1} x \frac{\partial MS}{\partial W_i} < 0$	ROA (+,-) ASSET, ASSETR (+,-) LOAN, LOANR (+,-) CML, CNL, MGL (+,-) DEP, DEPR (+, -) K, KR (+,-)	INT (-,+) SHLIQ (-,+) SHCML (+,-) SHMGL, SHCNL (-,+) ZETA (-,+)

LBCOSTS: labor costs as a proportion of total assets; RATES: implicit loan and deposit rates; MARGIN: financial margin computed as the difference of implicit rates; ROA: returns on assets; ASSET (R): annual growth rate of nominal (real) assets; LOAN(R): annual growth rate of nominal (real) loans; MGL: annual growth rate of nominal mortgage loans; CNL: annual growth rate of nominal consumption loans; CML: annual growth rate of nominal commercial loans; SEC(R): annual growth rate of nominal (real) securities; DEP(R): annual growth rate of nominal (real) deposits; K(R): annual growth rate of nominal (real) capital; CAP: capitalization ratio; SHCML: share of commercial loans on total loans; SHCNL: share of consumption loans on total loans; SHMGL: share of mortgage loans on total loans; SHLIQ: share of liquid assets on total assets; SHLOANS: share of loans on total assets; SHSEC: share of securities on total assets; ZETA: median bans' zeta-score; INT: intermediation (loans/deposits); LEV: leverage (assets/capital); COVNPL: ratio of loan provisions on non-performing loans. Note: the value of impulse responses used correspond to the accumulated responses in a year, i.e., $\sum_{h=1}^{12} SIR(h)$.

Based on Table 5, we can assess cyclicality of several variables and compare it with results in the literature. We can extract, for instance, that capitalization in Venezuela is procyclical, as has been argued to be the case for many emerging markets. However, in this case procyclicality means not only that capitalization increases with stability, but also that a higher capitalization strengthens macroeconomic stability. This is a different assessment from most papers studying the cyclicality of capital or capital buffers, which contend that capital is procyclical because capitalization is reduced when real output expands.[16] Another interesting example is leverage, which is also procyclical, but apparently for the wrong reasons. Leverage tends to diminish when macroeconomic stability improves, and its reduction further promotes stability. Or conversely, leverage is likely to increase when macroeconomic stability deteriorates, and its upsurge deepens instability. A third result that could be compared with the literature is the

[16] These papers typically look at the coefficient of the reduced-form estimation of capitalization explained by a real variable (output growth or output gap). However, these works do not test whether an increase in capitalization actually reduces real output growth. Then, procyclicality entails finding that the estimated coefficient of the reduced-form equation is negative. But, it can be the case that reduced-form coefficients might actually be capturing a mix of double effects not adequately separated.

case of profitability. For Venezuela, profitability increases when macroeconomic stability is enhanced, while in the literature its increase is mostly attributed to a real expansion. But this rise in profitability is prone to cause a reduction in macroeconomic stability, at least for Venezuela. Therefore, ROA ends ups being countercyclical, and not procyclical as one could expect.

We do not believe that the results just described are universally valid. On the contrary, they are probably very specific to the Venezuelan institutional arrangement and to its monetary, fiscal and foreign exchange policies. However, these results come along with a more general and interesting reflection: that the characterization of cyclicality is crucially determined by both the assessment of the macro environment used and a clear understanding of the endogeneity of financial variables with respect to macroeconomic conditions. Therefore, our understanding of how financial variables behave along the financial cycle simply using their association with the real cycle could be misleading because we are either neglecting other dimensions of the macroeconomic performance or assuming that causality runs in only one direction.

5. Robustness Exercises: A Sensitivity Analysis for Financial Indexes

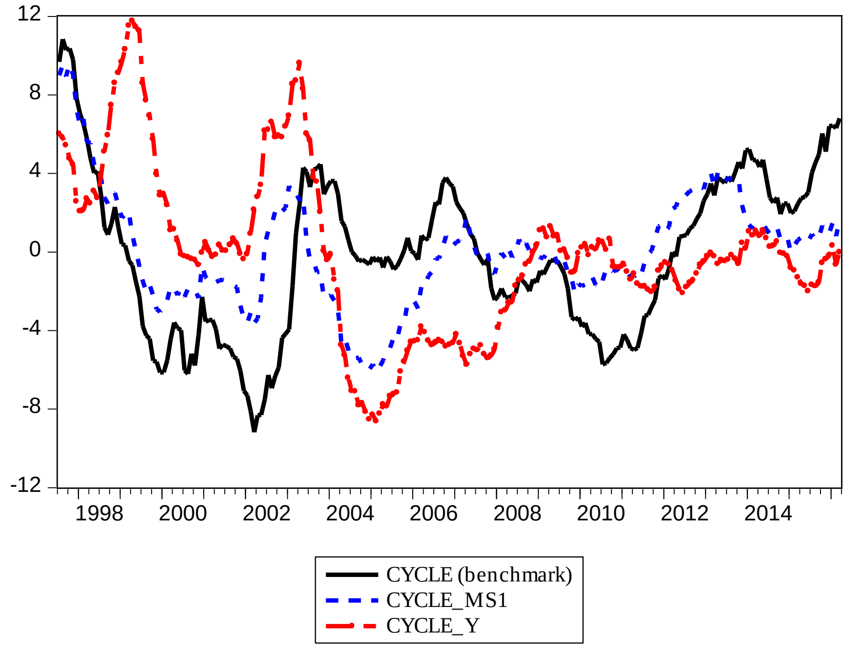
5.1. The Role of Macroeconomic Stability

It has been argued that using an ample notion of macroeconomic stability not only helps to identify countercyclical fluctuations, but also contributes to understanding the responses and effects of the financial system to different dimensions of the macroeconomic environment. In our next exercise, we compare financial cycle indicators (*CYCLE*) constructed with different notions or assessments of the macroeconomic environment.

We use two alternative notions for measuring the macro environment. The first refers to the growth of real activity itself. In this case, the economy is better off if its production increases. The second notion is labeled *MS1*, and it summarizes the environment only through the behavior of real activity and inflation. This is a narrower notion of macroeconomic stability that is built using the whole set of macro-variables, but establishing fewer restrictions.[17] For *MS1*, the assessment of the macroeconomic environment improves whenever expansionary supply shocks take place, by increasing output and reducing inflation. If a positive output performance occurs at the cost of rising inflation, then stability might not necessarily improve.

[17] In this case the restrictions imposed on the coefficients of equation (4) are: $\gamma_y \geq 0$, $\gamma_{pi} \leq 0$.

Figure 6. Comparisons of *CYCLE* Indicators with Different Underlying Notions of the Macroeconomic Environment

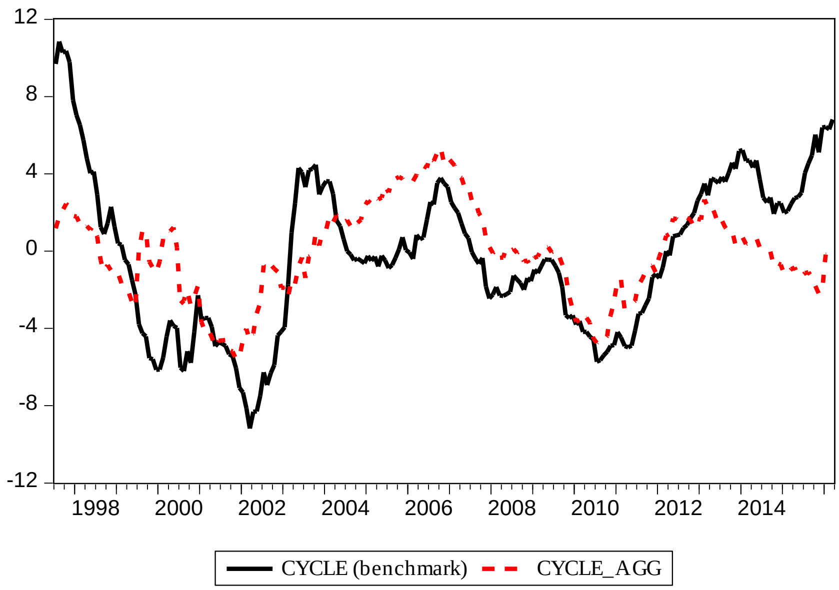


In Figure 6, besides our benchmark indicator (the one that uses the ample notion of macro stability *MS*), we also provide indexes computed with the narrower notion of macro stability (*MS1*) and with the growth of real output (*Y*). The general examination of that figure indicates that the selection of the macroeconomic dimension is fundamental in defining the trajectory of the financial indicator. In fact, all three indicators are different, but the indexes constructed with *MS* and *MS1* are closer to each other (they have a correlation of 0.58). The index *CYCLE_Y* has a correlation of 0.48 with *CYCLE_MS1* and -0.03 with *CYCLE_MS*). Our interpretation of this comparison is that the use of a larger set of macroeconomic variables, even without imposing all restrictions on variables, already produces a financial indicator closer to our benchmark. As a consequence, choosing a multidimensional notion of macro performance (such as *MS*) seems of utmost importance for getting an adequate characterization of financial conditions.

5.2. Aggregate versus Bank-Specific Information

Because we include aggregated and bank-specific information in the financial dataset for constructing financial indexes, one could ask whether systemic (aggregated) information is sufficient for adequately characterizing financial fluctuations. In Figure 7, it is clearly shown that the variability of the index computed out of pure aggregate information is much lower. In addition, some peaks of financial fragility are missed, in particular at the beginning and the end of the sample.

Figure 7. Comparisons of CYCLE Indicators Using Different Sets of Bank Information



5.3. Sensitivity to the Number of Financial Factors

Another important issue to consider for the construction of financial indexes is the number of principal components employed. Our methodology uses several components that explain about 85 of the data variability. As opposed to our strategy, the *FCI* constructed by Hatzius et al. (2010) uses only the first component of the financial data, after controlling or purging the effects of real output and inflation. In this section we present two comparisons. One, in Figure 8, shows the differences between our *CYCLE* indicator and a standard *FCI*, constructed as in Hatzius et al. (2010). The other, in Figure 9, presents whether our indicator *CYCLE* changes with the reduction or addition of components.

In Figure 8 we can observe that a standard *FCI* has a very different dynamics than our benchmark index. In particular, not only is its variability much lower, but also the dynamic of financial deterioration is divergent to our evaluation. This is probably related to the fact that the first component of the data does not necessarily contain all the relevant information to assess financial fluctuations. Moreover, the first component summarizes an important dimension of the data that could be helpful in forecasting output growth. However, that first component does not have a clear interpretation.

Figure 8. Comparison of *CYCLE* Indicator with a Standard *FCI*

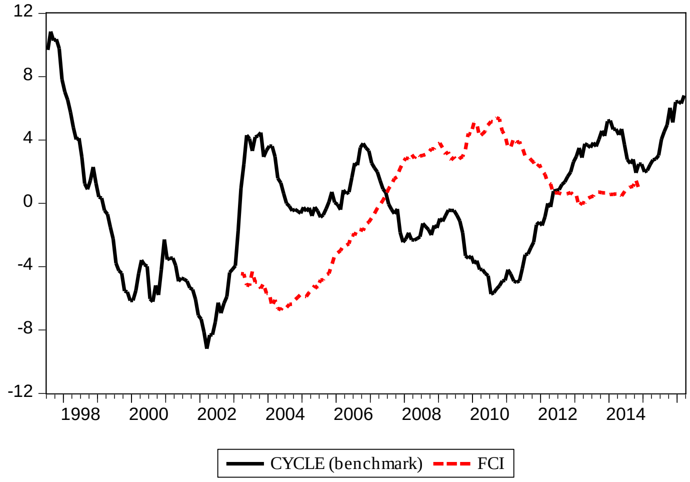
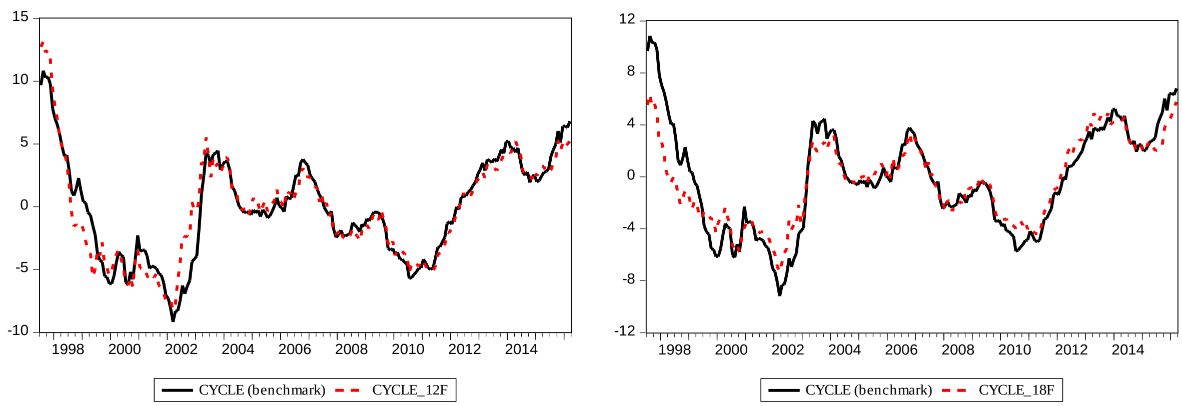


Figure 9. Comparisons of *CYCLE* Indicators Constructed with Different Numbers of Principal Components



In Figure 9, we observe that using 12 or 18 components for the construction of indexes does not bring about substantial changes in the diagnosis provided by the benchmark index. But using less information (fewer than 12 components) induces changes in the behavior of the estimated indexes. Our interpretation is that after a certain number of components, indexes tend to be robust to the addition of new ones because the relative importance of the information introduced is decreasing. This is exactly the logic of principal components. Therefore, for the application of our methodology the general recommendation is to consider as many components as necessary to avoid substantial changes in the indexes' dynamics. For practical purposes, we believe that using the number of components necessary to explain 85 percent of the data variability is a good threshold for robustness evaluation.

6. Summary and Concluding Remarks

In this paper we have put forward the idea that financial fluctuations are not only procyclical as typically thought, but can also be countercyclical. The motivation for talking about countercyclical financial fluctuations emerges from ideas already suggesting that good macroeconomic performance can lead to undesirable financial choices. Taking this idea as a starting point, we have developed a methodology that identifies procyclical and countercyclical financial conditions using two indicators with meaningful interpretation and policy implications.

We have learned three key ideas regarding the relationship between financial fluctuations and macroeconomic stability. First, a proper assessment of cyclicality needs to consider the endogeneity of financial variables with respect to the macroeconomic environment, i.e., cyclicality must evaluate both the response and the effect of financial variables. Second, assessment of the macroeconomic environment should be broad and cannot be restricted to a mere evaluation of the real cycle. Third, procyclical and countercyclical financial fluctuations capture two different meaningful financial phenomena that can help trace the origin of different sources of financial fragility.

The use of a broad notion to characterize the macroeconomic environment is justified by the same twofold relationship between financial and macroeconomic variables. Regarding the impact of macro-variables on the financial system, it is more likely than not that the evaluation, expectations and decisions of the financial system are based on the assessment of multiple dimensions of the macroeconomic environment. The larger the information set the financial system has, the more accurate its evaluation on future economic conditions might be. Concerning the consequences of financial decisions on the macroeconomic environment, looking only at real output effects offers an incomplete and possibly misleading interpretation of events. Perhaps this is one reason why testing the relationship of financial variables with the real cycle has sometimes become problematic. These two explanations suggest that a proper evaluation of procyclical and countercyclical financial conditions cannot be done without a multidimensional measurement of the state of the macroeconomic environment. In this regard, this paper offers a measurement of macroeconomic stability, the *MS* index, based on the use of a large set of macroeconomic information. We have also shown that using a narrow notion for the macroeconomic environment leads to very different financial indexes.

The specific interpretation of Venezuelan financial indexes comes mainly from the evaluation of the contributions of variables to indexes. We have discovered that a deterioration of procyclical financial conditions is associated with banks' balance sheet expansions that increase leverage and reduce interest rates and margins. These asset expansions are basically set off by positive innovations in primary money creation that result from the combined monetary effect of domestic expenditures financed with oil revenues and foreign currency allocation. Therefore, the procyclical fragility of the banking system seems to have its origin in the difficulty of maintaining adequate levels of profitability for intermediating larger quantities of funds. This component of financial fluctuations has dominated the dynamics of financial conditions in Venezuelan recent history, especially since the implementation of the exchange rate control in 2003.

In contrast, a deterioration of countercyclical financial conditions is related to situations of rising bank profitability that induce some degree of deleveraging and increased instability in tandem with a strong rearrangement of banking assets. These situations can be partly prompted by an increase in foreign exchange liquidations. In this case, the source of the financial fragility seems to lie in the volatility of banks' profitability. However, the importance of countercyclical financial conditions seems to have diminished after the implementation of the exchange rate control, with the exception of very few periods.

The relevance of the abovementioned policy-related variables has been established by evaluating the correlations between financial indexes and the macroeconomic variables used in the *MS* index. On average, peaks of net primary money creation are prone to occur during a deterioration of macroeconomic stability, while larger foreign currency allocations tend to coincide with periods of greater stability. A general interesting reflection from these results is that the associations between financial indexes and these policy-related variables have emerged without imposing them on the data. Hence, the methodology has allowed the discovery of relationships among financial and macroeconomic variables that reveal the importance of Venezuelan monetary, fiscal and foreign exchange institutional arrangements.

From an econometric perspective, the methodology developed employs a large set of financial (aggregated and bank-specific) information to gauge procyclical and countercyclical financial fluctuations. Operationally, these fluctuations are disentangled by two different combinations of the more important principal components of the financial data. The proper identification of these two indexes is achieved by giving economic content to the responses of financial indexes and macroeconomic stability to their own innovations. That is, financial indexes are constructed to satisfy certain sign restrictions on the impulse-responses described by the SVAR model of financial indexes and macroeconomic stability.

From the methodology itself, we have also learned two important ideas in contraposition to other procedures measuring financial fluctuations. The first is that indexes can have a concise economic interpretation even though they are constructed with combinations of principal components. This is because composite indexes are built to satisfy a general economic definition of cyclicality, instead of dealing with the interpretation of their particular components. While each single principal component is only a means to summarize different (orthogonal) dimensions of the data—and does not have a specific interpretation—the resulting indexes do have one. Moreover, because indexes combine several dimensions of the data, they represent a more comprehensive measure of financial fluctuations than financial condition indexes constructed from one single principal component. The second idea is that indexes allow analysts to discover the patterns of all financial variables included in the data set, in terms of their cyclicality and relation to macroeconomic stability, without recurring to the estimation of other models.

The policy implications that can be derived from the particular analysis of the Venezuelan case tend to point at modifications of the Venezuelan institutional arrangement in order to circumvent the monetary effects of fiscal and foreign exchange actions on money creation, as it has been already suggested in Carvallo and Pagliacci (2016) and Chirinos and Pagliacci (2017).

But a more general policy implication could also be drawn from Venezuelan findings. If procyclical or countercyclical financial conditions were in general related to the expansion of banks' balance sheets, then the variables that determine monetary conditions in economies could explain a sizable part of these fluctuations. In inflation targeting regimes, because exchange rates tend to float and interest rates are the instrument to anchor inflation expectations, one could deduce that those financial fluctuations are exclusively driven by monetary policy decisions.[18] However, this is a presumption that actually needs to be empirically tested. A methodology such as this one could be very useful for examining if financial conditions are fundamentally a monetary phenomenon and which variables best explain them.

[18] In contrast, we could contend that interest rate decisions are not necessarily the single determinant of monetary conditions. Other factors might affect monetary conditions as well.

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