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The Financial Conditions Index as an Additional Tool for Policymakers in Developing Countries: The Mexican Case

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Abstract

The nature of the financial crisis in 2008 posed new challenges for macroeconomic theory and policy-makers. In this context, a financial conditions index (FCI) could be a useful tool to identify the state of financial conditions in a country. We construct three FCIs for Mexico to analyse the role of financial asset prices in formulating monetary policy under an inflation-targeting regime. Using monthly data from 1995 to 2017, we estimate FCIs with three different methodologies and build the index by taking into account the mechanism of transmission of monetary policy and incorporating the most relevant financial variables. Our results show that, likewise for developing countries such as Mexico, an FCI could be a useful tool for managing monetary policy in reducing macroeconomic fluctuations.

Keywords: Financial conditions index, VAR model, ARDL model, TVP-VAR model.

JEL classification: C32, G01, E44, O54

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1. Introduction

The nature and intensity of the 2008 financial crisis has launched a new challenge for macroeconomic theory and policy-makers. Following the crisis, the high level of uncertainty, financial instability and economic depression have raised the need to reevaluate the relationship between financial conditions and real economic activity. The events resulting from the Lehman Brothers crash, and all other following crises such as the debt crises in 2010 and, more recently, the markets stress for the economic consequences of the Covid_19 pandemic and the Ucranian war have increasingly signalled that over the long term the instability of financial markets can dangerously hamper economic growth, not only in fragile developing countries but also in more solid advanced economies. Due to the decades-long absence of major global financial crises, this basic fact had been long neglected by monetary authorities and markets worldwide. In the context of renewed awareness of the relevance of the interplay between financial and real variables like GDP growth and unemployment, the role of financial asset prices in the formulation of monetary policy has gained strength, as has the need to develop new tools to implement monetary policy actions and forecasts. Hence the recent interest in the Financial Conditions Index (FCI).

Summarising information from different financial sources, the FCI is able to identify the state of the financial conditions in a country. In theory, the index may include any variable that characterises the supply or demand of financial instruments relevant to economic activity and may detect episodes of financial stress or the emergence of factors causing large shocks in financial markets (Armendariz and Ramirez, 2017; Hatzius, Hooper, Mishkin, Schoenholtz, and Watson, 2010). Yet, in most instances, the FCI encompasses information from the most representative financial variables (such as interest rates, stock prices, exchange rates and credit markets) with the ultimate aim of measuring the impact of exogenous financial shocks on future economic activities. On such premises, it may be argued that this index is the natural evolution of the Monetary Conditions Index (MCI) which, instead, was formulated to detect the effects on the economy of purely monetary variables.

The idea of employing a synthetic monetary indicator to measure the impact of exogenous shocks or policy measures on the economy goes back to the late 1960s. In 1967, Brunner and Meltzer envisaged a monetary indicator which was expressed as the minimum of a function of social utility, weighting the variables that serve as an instrument for monetary policy. In the early-mid 1990s, the central banks used a combination of the short-term interest rate and exchange rate, called the Monetary Conditions Index (MCI). The MCI works as an indicator of monetary conditions, as an operational target or as a leading indicator. The limit of the MCI as an operational target is that the predicted inflation rate is obtained from the dynamics of the explanatory variables, including interest rates and real exchange rates whose effects are substitutes for each other. The FCI attempts to overcome the MCI's limits by encompassing financial variables.

Galati and Moessner (2013) identify four categories of indicators of financial stress: 1) balance sheet and market indicators, 2) early warning indicators, 3) vector autoregression (VAR) models for forecasting financial distress, and 4) macro stress tests used to evaluate the response of the financial system to unexpected exogenous shocks. Some of these indices focus only on banking variables and fail to predict distant future conditions of overall financial markets. Others are based on credit and asset markets, and have proved useful in forecasting over 1-4 year horizons. An additional advantage of such indicators is that they reflect the interaction between the financial sector and the real economy.

Over the last years, economists have designed for many countries various indices of financial stress and volatility and have found that in many instances those are good predictors of inflation and monetary variables.

We add to the literature by building an FCI for Mexico. The idea is to provide a solid financial condition index that allows the monetary transmission policy to be monitored in a country which in recent decades has suffered from major financial and monetary crises. Using monthly data from the Inter-

American Development Bank, the World Bank and the National Institute of Statistics and Geography of Mexico, we cover a long interval of time, 1990M1 to 2017M5, witnessing two major financial crises: the Mexican currency crisis in 1994 and the 2008 global financial crises. To build our FCI, we consider numerous financial and monetary variables: real interest rate, real exchange rate, a stock market index, an index of private credit, the monetary aggregate M2, a degree of credit dollarization, an emerging markets bond index (EMBI), a measure of risk spread, and agriculture raw material index.

To allow for the interdependence between the variables and to take into account the intertemporal dynamics of the series, we estimate the weights of the financial variables to include in the FCI by means of a vector autoregression (VAR) model with impulse response functions and the autoregressive distributed lag (ARDL) model. We also build (the results are in the Appendix A2) an FCI by employing a Factor-Augmented Vector Autoregression model (FAVAR). As a result, we obtain three FCIs which capture different features of the monetary and financial cycle.

Apart from building a predictor of possible financial stress, our objective was to construct an FCI for a central bank that pursues inflation-targeting and to analyse the role of financial asset prices in formulating monetary policy. Hence, we also attempt to find out whether our FCI exerts any impact on the inflation rate and we therefore improve the analysis using the time-varying parameter VAR model (TVP-VAR) developed by Nakajima (2011) to capture the dynamic nature of the relationship between the FCI and the inflation rate.

The FCI is a tool that allows the monitoring of the dynamics of financial markets and asset prices with the aim to detect episodes of financial stress that pose a risk to the transmission of monetary policy. In developing countries, such as Mexico, this becomes particularly relevant when the economy is vulnerable to multiple external factors even in the presence of an inflation targeting monetary policy. We develop an FCI that fully internalise the possible causal relationship between multiple financial variables and monetary variables overcoming the limitation of other FCIs built for the Mexican economy (Armendáriz and Ramírez, 2015).

Since we are interested in the transmission of monetary policy, we first implement the VAR models, and then use the VAR's impulse-response functions to obtain the impact of the financial variables selected on aggregate demand. Finally, we calculate the weight of each variable based on the impact level. We follow the same operational procedure to calculate the FCI using an ARDL and the FAVAR model.

The interplay between inflation and the FCI depends on how the FCI is calculated. Our results show that while the FCI estimated by means of the VAR displays the same behaviour as the inflation rate over the entire interval range of our analysis, the FCI estimated through the ARDL shows a similar pattern to inflation only between 1995 and 2008. This result clearly suggests that the 2008 financial crisis heavily affected the Mexican financial system and that there was a misalignment between monetary variables and the financial system in the years following the crisis.

Interestingly, we also find evidence that an FCI shock has a significant and positive impact on the inflation rate over the short-medium term (10 months to one year). We also test for the robustness of our index by employing the empirical methodology developed by Nakajima (2011) within time-varying parameter VAR models with stochastic volatility. Our estimates confirm the time-varying nature of the dynamic relationships between inflation rate and financial conditions index.

Despite the differences in terms of usable observations and the nature of the structure of the index, the FCI built through the FAVAR confirms the main findings: a shock in the financial index can affect the inflation rate over a significant time interval.

In summary, our results show that financial conditions may significantly affect inflation to the extent that the stability of asset prices could be incorporated as an objective of a low and stable inflation rate.

The paper proceeds as follows. In the next section, we briefly review the literature on the issue. Section 3 discusses the theory about the role of FCIs in determining monetary policy. Section 4 describes the data and the empirical strategy, while section 5 presents the empirical results. Finally, section 6 draws some conclusions.

2. A Literature Review

There is evidence that inflation forecasts improve when the FCI is used as an informational variable. For instance, Chow (2013) finds that the FCI is a good predictor of inflation in Singapore for a forecast horizon of up to one year. Hatzius et al. (2010) incorporate quantitative credit measures in their FCI to trace the effects of the transmission of monetary policy through the economy. The idea is that in the presence of information asymmetries, uncertainty and other market imperfections, effective monetary policy actions need to consider financial variables such as measures of liquidity, risk and capacity to lend.

A well-built FCI has been proved to be able to predict other monetary variables such as the exchange rate. Molodtsova and Papell (2012) explore Taylor rule models using indicators of financial stress to forecast out-of-sample exchange rates and find that out-of-sample exchange rate predictability improves when financial stress indicators are included in an augmented model.

In practice, some central banks have explicitly targeted financial stability. Since 2010 the Central Bank of Turkey has adopted a new framework of monetary policy with a view to achieving both price stability and financial stability. Following this policy change, Bulut (2016) finds that in Turkey the FCI has a significant predictive power over inflation. Bulut's FCI includes financial variables, such as credit and liquidity measures, as well as monetary variables such as short-term interest rates, and proves to be effective in helping to design monetary policy interventions. Interestingly, upon employing an asymmetric causality test, Bulut finds that a negative shock in the financial conditions increases the inflation rate.

Alessandri and Mumtaz (2017) focus instead on volatility in financial markets and build a non-linear model so as to capture changes in aggregate volatility and structural breaks associated to financial crises. Using data for the United States, their analysis confirms that heteroscedasticity in a non-linear model improves the forecast of output and inflation.

The predictive power of the FCI, and how it behaves during the financial cycle, depends on how the index is built, which variables it encompasses and the features of the economy.

Hakkio and Keeton (2009) construct an index in order to trace the characteristics of financial stress in the USA. They consider financial stress a condition in which at least one of the following features is observed: increased uncertainty about fundamental asset values; increased uncertainty about investors' behaviour; increased information asymmetry; less willingness to hold risky assets (flight to quality); and less willingness to hold illiquid assets (flight to liquidity). They find that financial stress reduces economic activity through three channels: uncertainty, financing cost and standards of credit.

Angelopoulou, Balfoussia and Gibson (2014) build FCIs for the euro area including and excluding monetary policy variables to analyse the effect of financial crises on the transmission of monetary policy. They find that a complete index is able to detect the instability in financial markets and that monetary policy mitigates those effects. An additional FCI for the Euro Area was constructed by Moccero, Pariès and Maurin (2014). They assemble an index with 61 variables using the principal component analysis and incorporate the FCI into a monetary policy model identifying credit supply shocks.

More recently, some economists designed the FCI by employing factor-augmented vector autoregressive models with time-varying coefficients. By using a VAR model with stochastic volatility, Koop and Korobilis (2014) find that financial variables have a predictive power over different macroeconomic variables and that stochastic volatility is important in short-term forecasts.

Yet it is in more financially fragile economies where FCIs have a stronger predictive power about the effect of the transmission of monetary policy. Armendáriz and Ramírez (2015) estimate an FCI for Mexico to capture the influence of financial variables on the interest rate and external financial shocks, yet their work is quite different from ours. Since they are focused on financial instability, their FCI is built by means of a Principal Component Analysis. Armendáriz and Ramírez themselves recognize that their study could be extended in the direction of analysing in more details the relationship between economic activity and the financial conditions and to take into account the causality nexus between the two as well; and indeed they suggest that this could be done by employing the VAR and the SVAR models.

Álvarez Corrales and Mora Gómez (2016) use an index to evaluate financial stability in Costa Rica, especially following the 2008 financial crisis, the 2010 debt crisis in Europe and the capital inflows in 2012. Nivin and Pérez Forero (2019) build an index that serves as a guide in conducting monetary policy and measures the impact of financial markets on economic activity in Peru. Céspedes and Rodríguez (2011) propose an FCI for Bolivia to analyse the evolution of economic activity due to changes in the credit market. Finally, Gómez, Murcia and Zamudio (2011) evaluate the predictive capacity of the FCI in forecasting GDP growth and test the FCI's long-term ability to correctly anticipate periods of financial instability in the economy.

3. The FCI and inflation targeting

The role played by financial asset prices in formulating monetary policy has become the subject of considerable debate, especially since the 2008 crisis. The question surrounds whether asset prices should be included in the inflation target or if central banks should react to face movements in asset prices. The reason for including asset prices in the policy rule is to determine whether they provide a better forecast of the future path of the prices of goods and services than that offered by the current policy rule (Filardo, 2000).

The literature has long scrutinised which variables the FCI should include. On the one hand, the inclusion of several variables of a different nature allows us to detect changes in the cycle from several sources; on the other, it reduces its predictive power. Given that the FCI is a policy tool, Svensson (2010) puts forward the idea that the benefits of including financial variables in the FCI essentially depend on which policy one considers. Monetary policy and financial stability policy differ in their objectives, instruments and competent authorities. While monetary policy mainly targets the growth of the general level of prices, the objective of financial stability policy is to maintain and promote financial stability. This entails various policy instruments, as well as the need of different leading indicators to hint policy guidelines. Financial stability policy, for instance, normally requires non-monetary instruments such as supervision, regulation and financial-stability reports, and, during a crisis, actions such as lending of last resort, credit policies, government lending guarantees, government capital injections, etc. Yet Svensson (2010) himself recognizes that there is a relationship between monetary policy and financial stability policy. Since financial conditions affect the transmission of monetary policy, central banks must take financial indicators into account to adjust the policy instrument to their goals. In turn, financial stability is affected by monetary policy through its impact on asset prices and balance sheets. Such interaction between monetary and financial variables is a reason to include financial stability among the central bank's objectives.

Monetary policy can play a major role in aggravating leveraging cycles, especially in the presence of financial bubbles and inflated asset prices (Allen and Rogoff, 2011). When a significant fraction of individuals is credit-constrained, a sharp increase in house and financial asset prices significantly influences consumption and investment plans through wealth effects. Under such circumstances, a relaxed monetary policy can exacerbate the distortionary effects of price increments. Moreover, a burst in the price bubble will cause losses and, in turn, generalised bankruptcies and disruptions in the financial markets. For the above reasons, theory suggests that it is advisable for central banks to control asset price stability.

Although in recent years central banks have increasingly operated through inflation targeting which helps to promote financial stability, in the presence of excess demand, aggregate credit increases and so do asset prices. Hence inflationary pressures could influence financial markets much sooner than markets for goods and services. Therefore, sustained rapid credit growth and increasing asset prices are clear signals of increasingly dangerous financial imbalances.

In reality things are more complicated and monetary policy cannot easily address financial imbalances. Borio and Lowe (2011) identify three critical issues in the use of monetary policy with this objective. First, the authorities are unable to identify financial imbalances sufficiently in advance to implement a remedial action, and even if they anticipate such discrepancies, their action could increase the volatility in the economy. Second, the effect of policy response is unpredictable. While a small increase in the interest rate may not be sufficient to contain financial surpluses, a large increase in the interest rate would risk pushing the economy towards a recession. At the same time, any response whatsoever increases the central bank's credibility as a guarantor of price stability and fortifies market optimism. Third, central banks find it difficult to justify any action to the public.

If central banks were to take financial asset prices into account, they would be able to achieve inflation targets (Cecchetti, Genberg, and Wadhwani 2002). This is because the risk of boom-bust investment cycles is reduced when monetary policy reacts by tackling price bubbles. Moreover, since asset prices contain information about future inflation, a good inflation forecast requires that asset prices be considered as well.

Hence Cecchetti (2011) suggests that the inflation targeting framework be modified to consider financial stability and price stability. The suggested changes run in two directions: the policy horizon and the flexibility of monetary policy. Since financial misalignments tend to accumulate over time, central banks must allow inflation to deviate from its policy target horizon. On the other hand, to avoid a decrease in interest rates over time, monetary policy needs to respond aggressively during financial booms and to be loosened during subsequent busts. Following the 2008 financial crisis, low levels of interest rates may become incompatible with the control of price stability.

The 2008 crisis evidenced that financial factors deteriorate the transmission mechanism of monetary policy. For this reason, the use of the interest rate as the only tool could be less effective than expected. If central banks use price stability to achieve financial stability as well, they should adopt hybrid inflation targeting. As shown by Chow (2013) and Svensson (2010), an additional target of monetary policy requires new tools.

4. Data and methodology

We construct a financial conditions index for Mexico using monthly data spanning from 1990M1 to 2017M5. The dataset was obtained from the Inter-American Development Bank, the World Bank and the National Institute of Statistics and Geography of Mexico. To build the index we first need to estimate the weights of the financial variables. To this end we calculate the FCI weights by following two different econometric approaches: vector autoregression (VAR) with impulse response functions and the autoregressive distributed lag (ARDL) model. We apply a weighted-sum approach to assign the weight to each financial variable according to their role in the transmission mechanism of monetary policy[1]. Upon reviewing the literature, we found that indicators of financial conditions have mainly played two roles: that of measuring financial stress in the market and that of determining the transmission of monetary policy. With the exception of some basic variables, i.e. the interest rate and the exchange rate, there is no general consensus about the variables that should be included in such an indicator. Hence the composition of the financial condition index really depends on the objective for which it is built.

If one considers the transmission mechanism of monetary policy, the FCI simply encompasses fundamental variables such as the real interest rate, the real exchange rate and a stock market index. However, as already argued, these variables on their own might not be able to capture relevant features of the financial cycle in developing economies. For the above reasons we extend the basic model in the literature to incorporate other financial variables which are important for Latin American countries, as could be an index of private credit, the monetary aggregate M2, credit dollarization, the EMBI index, a risk spread, an agriculture raw material index, the commodities index and the crude average price.

The interest rate is included in the FCI because of its effect on investment and savings decisions. If, on the one hand, an increase in the interest rate reduces the current discounted value of future profits and, in turn, the value of current investment, on the other, an increase in interest rates lifts borrowing costs and the return on savings, and ultimately reduces consumption. Hence a rise in the interest rate reduces aggregate demand and the level of prices (Montagnoli and Napolitano, 2005; Chow, 2013). Yet in some contexts the Gibson Paradox still holds (see for instance Cogley et al., 2011) and the interest rate might be positively correlated to the level of prices and weakly correlated to the inflation rate. Moreover,

[1] To keep the exposition simple and compact we discuss the FAVAR model in the Appendix A2.

also the relationship between interest rate and investment may break down in the absence of diminishing returns (Mckenna and Zannoni, 1990).

The exchange rate can influence asset prices through the demand channel. For example, following strong appreciation of the exchange rate, national expenditure shifts away from domestic production towards foreign goods and services, and the trade balance deteriorates. Hence, appreciation of the domestic currency tends to reduce the level of expenditure and that of internal prices (Galindo and Ros, 2006; Chow, 2013;). The opposite occurs following depreciation of the exchange rate; in this case the cost of imported inputs increases, as does inflation, with the result that domestic producers have the chance to increase their margins while real wages may decrease, thereby worsening income distribution (Palley, 2001). Even if recent studies have found that Mexico's exchange rate pass-through to inflation was statistically significant but close to zero, González and Saucedo (2018) showed that pass-through depends on the economic sector[2] and the coefficient increases according to the selected period[3]. To detect these effects of the exchange rate, we include in our FCI the agriculture raw material index as an alternative to the commodity index. Moreover, in Mexico the relationship between the interest rate and the exchange rate appears to be non-linear, with the exchange rate influencing asymmetrically the interest rate (Capasso, Napolitano, and Viveros, 2019).

In emerging countries, the interest rate parity is often not established because of uncertainty in asset price expectations and the high volatility in the exchange rate. Hence, in such economies uncertainty plays an important role in determining monetary policy. This also means that to attract foreign investors the yield associated to the portfolio of financial assets in developing countries must be higher. From an empirical point of view, an important issue is how to measure financial instability and how central banks oversee financial instability. We take this uncertainty into account by including in our FCI an emerging markets bond index (EMBI) which tracks the total return performance of international government and corporate bonds issued by a selected group of emerging market economies.[4] We also introduce a risk spread given by the difference between the 3-Month Treasury Bill US rate and the CETES (*Certificados de la Tesoreria de la Federación*[5]) 91-day rate.

Following Goodhart and Hoffman (2001), we obtain the weights of the financial variables in the FCI by means of the reduced form of the aggregate demand equation. The simple formulation of the aggregate demand function augmented with financial variables is:

$$y_t = \beta_1 + \beta_2 y_{t-j} + \sum \beta_i x_{i,t-j} + \mu_t \tag{1}$$

where y_t is the gap between the effective and potential industrial production and where the potential industrial production is calculated using a Hodrick-Prescott filter; x_i represents the ith financial variable, where $i = 1, ..., n$ and t-j is the number of the lag. Since, we adopt a weighted sum approach, to construct our FCI for Mexican economy, the weight assigned to each component is derived from a monetary VAR model[6] (as in Goodhart and Hoffman, 2001) and determined by the magnitude of cumulative generalized impulses responses of inflation to an exogenous shock.

To identify the channels of transmission of monetary policy and detect the impact on the economy of the bank lending channel, the FCI should include variables related to credit. The transmission channel is well known: in the presence of insufficient liquidity, the central bank injects funds into the banking system which, in turn, increases credit supply, especially for smaller firms and households that, more than

[2] From 2011 to 2016, the elasticity of the pass-through for manufacturing sector was 0.36; for mining 0.55; for construction was 0.18 and for primary activities 0.17.

[3] The study shows that the coefficient of pass-through of underlying inflation went from 0.02 in the interval 2004-2016 to 0.12 in the years 2011-2016 as a consequence of a period of sustained depreciation.

[4]The EMBI we use is the bond prices index, a monthly average calculated by Bloomberg (Source: Inter-American Development Bank).

[5] These are the *Mexican Federal Treasury Certificates.*

[6] Among different approaches like the Principal Component Analysis, we choose this technique because VAR model allows us to get a weight according to how the theory predicts the transmission of shocks by the financial sector to the real economy.

others, depend on bank lending (Chow, 2013; Jimenez Polanco and Ramirez de Leon, 2016). Additionally, according to Kamin, Turner and Van't dack (1997), if the credit market is not particularly developed, the probability of monetary policy affecting aggregate demand through credit supply rather than credit price increases. We measure the liquidity in the market and the credit channel, respectively, by means of M2 and a private credit index.

Emerging economies often face the difficulty of borrowing abroad in local currency, which is why most have been forced through time to borrow in US dollars or in another strong currency. Hence, in this sense credit dollarization can be considered the "original sin" of developing countries (Eichengreen, Hausmann, and Panizza, 2004) with possible major effects on the economy and on monetary policy. Indeed, sizeable credit dollarization also means that these countries cannot afford to have autonomous monetary policies and a free-floating exchange rate. Moreover, in the presence of a sizeable level of credit dollarization, not only foreign investments but also remittances can significantly influence the banking system and the composition between deposit and loans in foreign and domestic currency (Capasso and Neanidis, 2019).

Dollarization is also related to high costs of internal financing, external debt securities and to a persistent dependency link with foreign suppliers. In particular for small economies, dollarization may involve a narrower access to international capital markets (Mántey, 2013; Morrone, 2016). According to Levy-Yeyati (2021), since 2000, Latin American countries have implemented successful strategies and policies to reduce dollarization but Mexico is an exception: the deposit dollarization ratio remained relatively stable and the share of public debt in foreign currency has not decreased up until 2019.

Changes in monetary policy alter the net worth of households and firms, and induce adjustments in consumption or in investment plans (Borio and Lowe, 2002; Chow, 2013). Hence, given the importance of asset prices in determining total wealth and given the balance-sheet effects that the latter has on demand, the FCI should also include asset prices.

An additional channel through which asset prices may affect aggregate demand is through stock market prices. "Investment is stimulated when capital is valued more highly in the market than it costs to produce it, and discouraged when its valuation is less than its replacement cost"; so reads the *q* theory of investment by Brainard and Tobin (1968) (p. 104). Yet a significant increase in asset prices creates the incentive for firms to issue shares beyond their real financing need and could ignite speculation resulting in a financial bubble. Finally, to take into account the wealth and the balance-sheet effect, we include the stock market index in constructing the FCI.

4.1 Constructing the financial conditions index for Mexico

In this section, we develop two FCIs for the Mexican economy. To determine the weights of the financial variables to be included in our FCIs, we employ both a vector autoregressive model and an autoregressive distributed lag model, and empirically measure the relevance of financial variables in the conduct of monetary policy. After deriving the weights of the financial variables, we standardize the data to reduce all the indicators to a common scale. The objective is to avoid distortions, given that we employ variables at different levels of aggregation[7]. The general expression of the index is:

$$FCI_t = \sum \lambda_t F_t \qquad with\ t = 1, \dots, n \tag{2}$$

where λ_t are the weights obtained from the econometric estimates and F_t, the set of the proposed variables. The weights are a function of the variables.

[7]Moreover, all series are checked for stationarity by means of different unit root tests: the Philips-Perron test, the augmented Dickey-Fuller test and the KPSS test; all the variables that exhibit unit roots are transformed before being included in the model.

Prior estimating the two models employed to calculate our FCIs, we need to establish the potential effects (if any) on these models of changes in the monetary policy regimes. At the end of 1999 the Central Bank of Mexico decided to switch to inflation targeting. This change may not have been "neutral" from a statistical point of view. To investigate this possibility, we employ in the VAR analysis the Wald test to detect a structural break, knowing *ex ante*, the date it occurred. The Wald test returns a χ^2 of 8.4585 with a P-value of [0.3900], which implies that we cannot reject the null hypothesis of no structural break in that period.

A different approach has been followed for the ARDL analysis. Following Brown et al. (1975), we attempt to establish the structural breaks in the ARDL model by means of recursive CUSUM and CUSUMSQ tests (see figures 6 and 7 in the Appendix A1). Both tests reject the presence of a structural break during the change in the monetary policy regime managed by the Central Bank of Mexico. As can be seen, the plot of CUSUM statistic crosses the critical value line indicating some instability in the coefficients. Yet the problem does not seem to be too serious because the instability that was observed in the late 1990s disappears over time. The temporary instability is also confirmed by the CUSUMSQ test which shows a substantial stability of the model. As a matter of fact, the two tests could produce contradictory findings depending on the nature of the break: if the break is in the intercept of the regression equation the CUSUM test displays higher power while, the opposite happens when the structural change involves a slope coefficient or the variance of the error term, then it is the CUSUMSQ test that shows higher power.

4.2 Vector autoregression model

We first estimate the weights of the financial variables by calculating the impulse response functions (IRFs) in a vector autoregression model (VAR). The IRF in a VAR is able to quantify the potential impact of financial shocks on the real economy (e.g. GDP growth, rate of employment, exports, and so on), and provides the advantage of incorporating the impact of the financial variables on all the other variables.

By construction, the VAR assumes that each relevant variable depends on all other variables in the system, and hence it allows the simultaneity between monetary policy variables and the real sector to be taken into account. Moreover, in a dynamic setting this model may express the current values of one or more variables as a function of their lagged values and the lagged values of others; as a result, it is able to detect the joint movements of the variables and their short-term interrelationships (Sims, 1980). The model can also be used for economic analysis through the impulse response function, variance decomposition, historical decomposition and prediction. More formally, let Y_t be a vector of $k\times1$ stationary variables. The autoregressive model of order p is

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{3}$$

where $A_i = (i = 1, \ldots, p)$ is a $k\times k$ parameter matrix, ε_t is a vector of non-autocorrelated disturbances with zero mean and contemporaneous covariance matrix $E[\varepsilon_t \varepsilon_t'] = \Omega$. The order of variables in a VAR model is important when the Cholesky decomposition is used. In our estimates, we impose the following order: exchange rate, interest rate, risk spread, credit dollarization, agriculture raw material index and stock market index, and obtain the weights on the financial variables by calculating the average impact of a one-unit shock to each financial variable on inflation over the following 36 months. The weights of our FCI obtained by VAR estimates are reported in Table 1.

Table 1: FCI weights by VAR

REER	Interest rate	Risk spread	Credit dollarization	Agr raw mat index	Stock market index
0.00751	-0.6490	0.74063	0.01943	-0.00020	0.00013

4.3 Autoregressive distributed lag model

The autoregressive distributed lag model (ARDL) is instead useful to analyse the long-run relationships between the determinants of the aggregate demand. We employ the ARDL to determine alternative weights of the financial variables to be included in our FCI. The estimated autoregressive distributed lag model (ARDL) with *p* lags of Y_t and *q* lags of X_t is given by

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \phi_i y_{t-i} + \beta' x_t + \sum_{i=0}^{q-1} \phi_i \beta_i^{*\prime} \Delta x_{t-i} + u_t \tag{4}$$

$$\Delta x_t = \omega_1 \Delta x_{t-1} + \omega_2 \Delta x_{t-2} + \cdots + \omega_s \Delta x_{t-s} + \varepsilon_t \tag{5}$$

where x_t is the k-dimensional I(1) variables that are not cointegrated among themselves, u_t and ε_t are serially uncorrelated disturbances with zero mean and constant variance-covariances, and ω_i are $k \times k$ coefficient matrices such that the vector autoregressive process in Δx_t is stable.

We obtain the weight of the financial variable *I* by dividing the value of the estimated coefficient ω by the sum of the value of the estimated coefficients of all other variables. More formally, the weight of each financial variable is

$$\lambda_t = \frac{\omega_i}{\sum(\omega_i)} \tag{6}$$

5. Empirical results

Following the Mexican crisis in 1994, the Central Bank of Mexico decided to abandon its policy of anchoring the exchange rate and, starting from the beginning of 2000, the monetary policy was based on inflation targeting (Schwartz and Torres García 2000). The new policy scheme consists in influencing the level of inflation through the real interest rate and by shaping market expectations rather than through the exchange rate manipulation. In accordance with conventional theory, the Central Bank of Mexico is committed to clearly communicating objectives and policy interventions to the public, it abides by the fulfilment of the uncovered interest rate parity and mainly reacts to inflation coming from demand pressures.

In 2003, the Central Bank of Mexico coupled the policy of pursuing a desired level of interest rate with implementing a neutral monetary policy. This kind of policy meant that the Central Bank would supply all the liquidity needed to maintain close to zero the average daily balance of the banks' accounts at the Central Bank. In this framework, a restrictive policy meant that the Central Bank would have charged higher interest rates to negative balance (the "*corto*"). An expansionary policy entailed, instead, a positive target for the daily balances. This is the reason why this policy targeting operational daily balances was known as the "*corto*". In February 2005 the Central Bank announced for the last time an operational target for the daily balances, and since then the monetary policy has been based on the announcement of a desired level of interest rate. Officially, the interest rate became the only operational target of the Central Bank of Mexico in January 2008.

To evaluate the effectiveness of monetary policy, we compare the two FCIs obtained in the previous section with the dynamics of the inflation rate. Our estimates using both methods to obtain the indexes (section 4.2 and 4.3) are shown in Figure 1. The latter also presents the inflation rate in Mexico from 1995 to May 2017. Most interestingly, while the FCI estimated by means of VAR (FCI_VAR) displays the same behaviour as the inflation rate over the entire interval range, the FCI estimated through the ARDL (FCI_ARDL) shows a similar pattern to inflation only between 1995 and 2008.

The Mexican currency crisis is clearly evident in the high inflation rates and FCIs during the latter half of the 1990s. During these years, the Mexican economy experienced sharp variations in the exchange rate, severe increases in the interest rate and, above all, large capital outflows which undermined the stability of the financial system.

In the following years the economy and the financial system slowly adjusted, with the result that the interest rates and the level of inflation have reached reasonable and sustainable levels. From 2002M1 to 2016M12, inflation averaged 4.08%, with a minimum of 2.14% in 2015M12. And yet, in this interval of time there have been other short episodes of stress in the Mexican financial and monetary markets. The most serious occurred between January and December 2008, following the US financial crisis, when inflation almost doubled, increasing from 3.7 to 6.53%, its highest since the implementation of inflation targeting. The consequences of the 2008 financial crisis were sharp and sudden, with major repercussions confined primarily within the financial market and with relatively short-term consequences. This explains the relatively small increase in the inflation rate in comparison with the larger jump in the FCI_VAR and the decrease in the FCI_ARDL. The 2008 crisis caused an increase in exchange rate volatility, contraction of the Mexican stock market and an increase in the risk premium, all variables influencing the FCI.

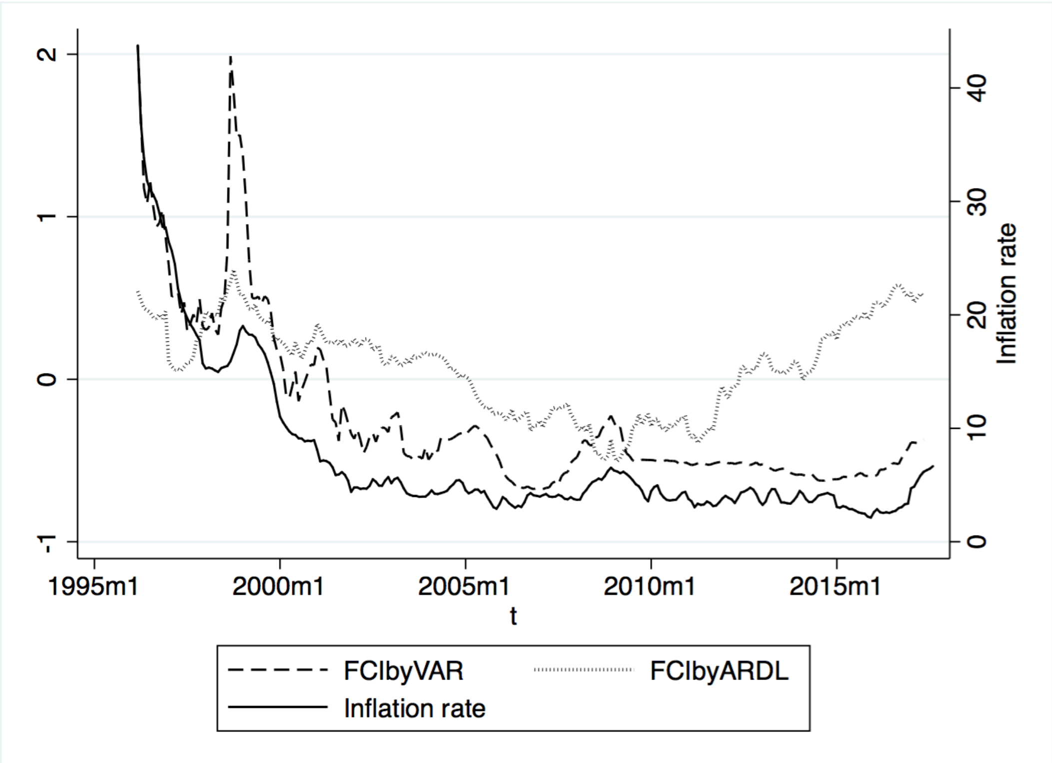


Figure 1: FCI and the inflation rate

Then, we estimate a new VAR model using a 12-month inflation rate and the FCI_VAR/FCI_ARDL to analyse the effects of monetary policy transmission through a random shock[8]. Figure 2 shows the impulse response of the inflation rate to FCI_VAR shocks over a 24-month horizon. The central solid line represents the response of the inflation rate and the shaded area is the confidence band at 90 percent. Our estimation confirms that an FCI shock has a significant and positive impact on the inflation rate, reaching the maximum effect in eight months. Thereafter the effect decreases toward zero in about two years.

[8] Residuals are reported in figure 8 and 9 in Appendix A1

Figure 3 shows instead the impulse responses of the inflation rate to FCI_ARDL shocks over a 24-month horizon. As in the figure above, the central solid line represents the response of the inflation rate and the shaded area is the confidence band at 90 percent. The estimation results show a similar path as in Figure 2 and signal a positive effect of a shock in the FCI_ARDL on the inflation rate. However, in Figure 3 the magnitude of the shock is less pronounced and its peak is around the 10th month.

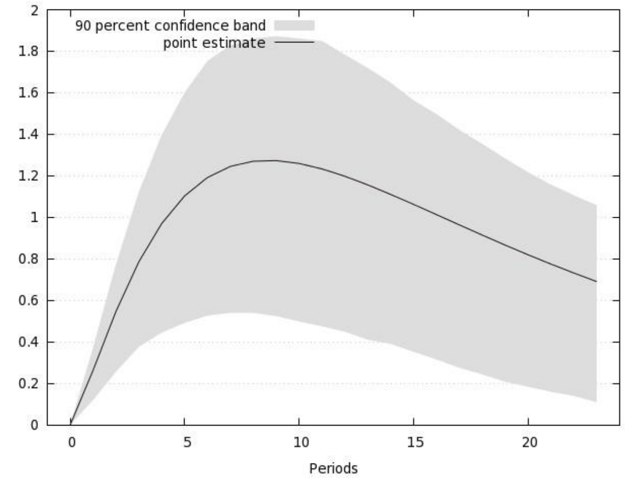


Figure 2: Response of inflation to a shock in FCI by VAR

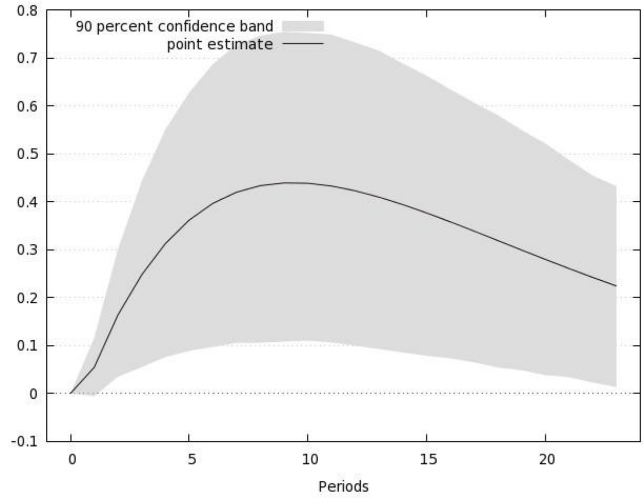


Figure 3: Response of inflation to a shock in FCI by ARDL

We are aware that despite finding a positive correlation between the FCIs and the inflation rate, the result does not imply causality. Hence, we perform a simple Granger causality test to determine in what sense these variables affect each other, and find out that the FCIs Granger-causes the inflation rate when using one lag at 5% level of significance. However, we can confirm this result even when we use twelve lags[9] (see tab. 5 in the Appendix A1).

To complete the analysis, we study the impulse response from a time-varying parameter VAR (TVP-VAR) model by employing the econometric procedure and the routine developed by Nakajima

[9] As the test is considered consistent if the result persists after applying for more than one lag, given the periodicity of our data, we check up to twelve lags.

(2011). The TVP-VAR model allows us to capture the dynamic nature of the economy in a flexible and robust manner. An additional advantage of this methodology is that it takes into account the role of stochastic volatility[10].

Since over the entire interval of time the FCI_VAR performs better when compared to the inflation rate, we implement the time-varying VAR just for this index. This estimation is used to examine the interactions between the FCI and inflation. We add the variable "change in oil price" as a control variable to consider the impact of external shocks on Mexican economy. We use normalized data to avoid problems of scale. As in the constant VAR, there are two lags for the TVP-VAR estimate; to compute the posterior estimates we draw 8,000 samples.

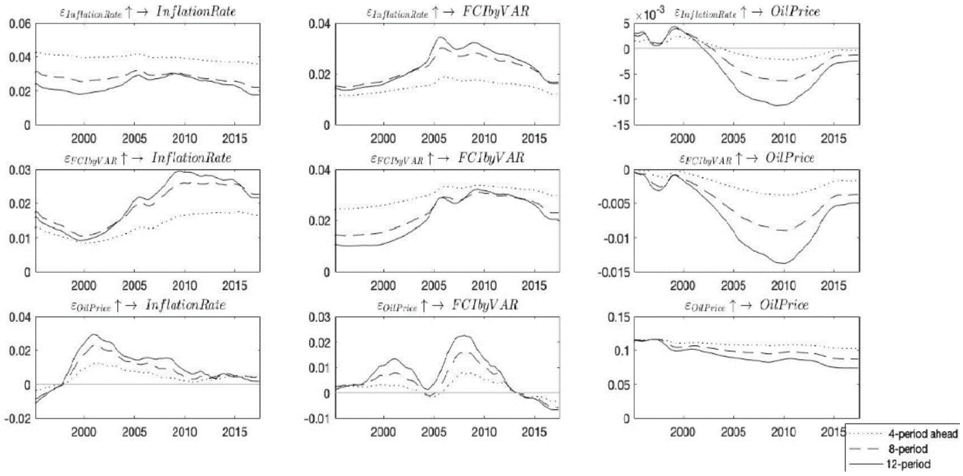
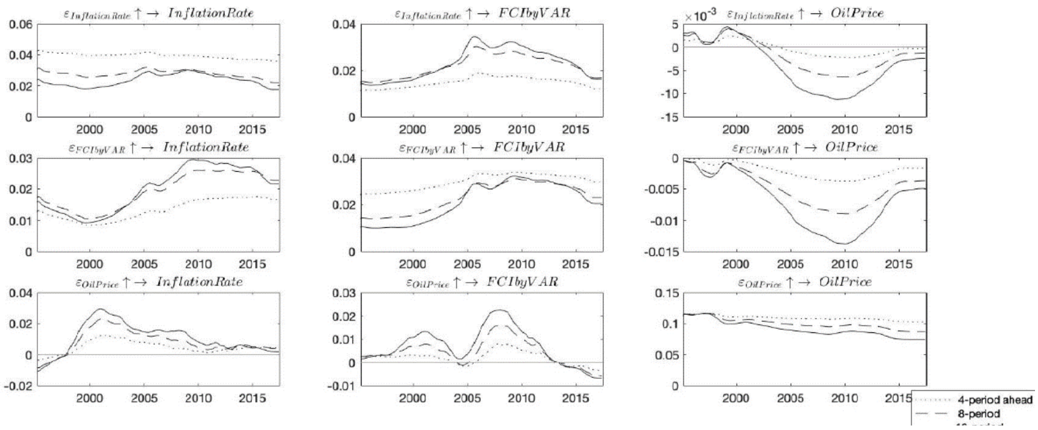


Figure 4: The impulse response function on the FCI_VAR using the TVP-VAR



[10] For all details of the estimation procedure please see Nakajima, 2011.

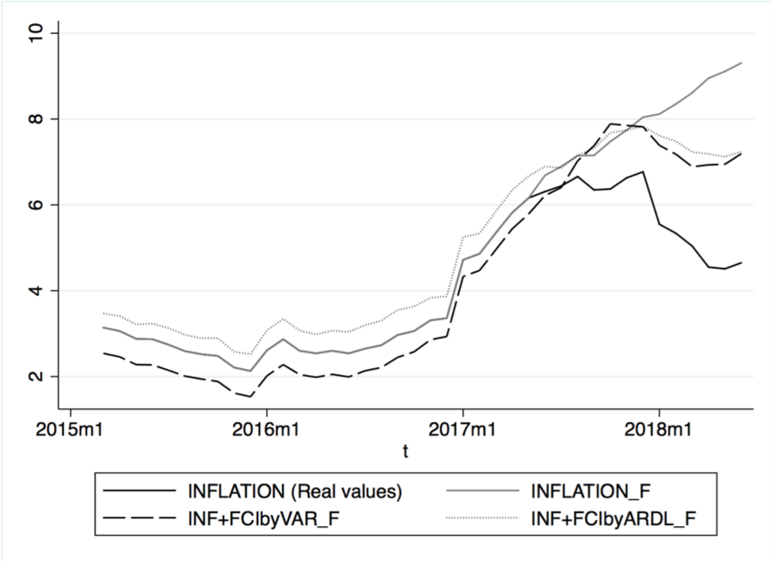


Figure 5: Forecast

Figure 4 shows the time-varying responses determined through the TVP-VAR model using the inflation rate, the FCI_VAR and, as a further variable, the oil price. The responses of each of these variables are determined in a time-series framework and show the size of the impulses for a one-, eight- and 12-month horizon following a shock on each of the variables in turn. Interestingly, the impulse responses of the inflation rate to a positive FCI_VAR shock remain positive over time. By contrast, the impulse responses of the inflation rate to a positive oil price shock remain negative from 1995 to 1999, approximately, thereafter becoming positive.

Since the FCI yields a synopsis of information from the financial markets and other relevant variables playing a role in the transmission of monetary policy, and since the FCI could represent an important tool to monitor and forecast inflation, it is useful to investigate the predictive power of our FCI indexes on the inflation rate. To perform the forecast estimates, we choose the period 2017M06 to 2018M06 as our evaluation sample (out-of-sample forecast). More specifically, we compare three autoregressive-moving-average (ARMA) models for inflation: a pure autoregressive specification (excluding financial indicators) and two models including, alternatively, the FCI_VAR and the FCI_ARDL. Figure 5 shows the results of the forecasts by employing these three models.

The forecast evaluation (see the Table 6 in Appendix A1) employs four different measures of forecast accuracy: the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE); and the Theil inequality coefficient. All of them indicate that the FCI_VAR is a good predictor of future inflation.

In summary, our results show that financial conditions may significantly affect inflation to the extent that the stability of asset prices could be incorporated as an objective of a low and stable inflation rate. Given that the FCI includes important information on the financial market, it becomes a useful tool for policy makers when, as a predictor, it sends signals of financial instability, and allows monetary authorities to react promptly through appropriate macroeconomic policies.

The effects of financial stability on the economic variables like GDP, unemployment and exports have been evident since the most recent crisis in 2008, showing that the Central Bank must take into account the role of financial markets in the design of monetary policy and include financial stability among the objectives to achieve.

6. Conclusions

Since the 2008 financial crisis the use of FCIs has gained strength as a tool to detect financial instability, or as an indicator to anticipate movements in the financial markets and in inflation. Like every index, each FCI has its own limitations and advantages which depend on the underlying variables and on the weights attributed to the variables in question. Despite their limitations, FCIs have generally proved to be good predictors of financial and monetary market conditions and are a good guide to efficient policy interventions. This is particularly true in developing countries where financial market crises are frequent and echo loudly on real and monetary aggregates.

We built an FCI for a developing country, Mexico, which in recent decades has undergone several severe financial crises due to relatively fragile internal financial markets and a weak exchange rate. We used our FCI in an inflation-targeting context to show that financial asset prices play an important role in the transmission of monetary policy which, in turn, implies that controlling inflation is not just about controlling price stability, but also controlling financial stability as well. Our results confirm the importance of financial variables to achieve inflation targets especially for a developing country such as Mexico, for which our FCI displayed strong predictive power for the inflation rate.

To test the robustness of our index, we used empirical methodology developed by Nakajima (2011) within time-varying parameter VAR models with stochastic volatility. The empirical results using Mexican data showed the time-varying nature of the dynamic relationships between inflation rate and the financial conditions index.

Clearly, our FCI allows for specific features of the Mexican economy and, as such, cannot be generalised in its current form. However, this indicator has the power to show that specific financial market conditions cannot generally be laid aside when designing reasonable guidelines to identifying and quantifying possible monetary policy objectives. The FCI allows information from financial assets to be used to predict the inflation rate. Hence it is not only an important tool to achieve price stability but it could become a new target for monetary policy within a hybrid inflation-targeting framework.

The FCI could be a very valuable tool to implement effective monetary policy aimed to control price stability. This is particularly true in a developing country, such as Mexico, where the Central Bank pursue a typical inflation targeting policy and the economy is very exposed to possible external shock to the financial and economic system.

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Appendix A1. Figures and Tables

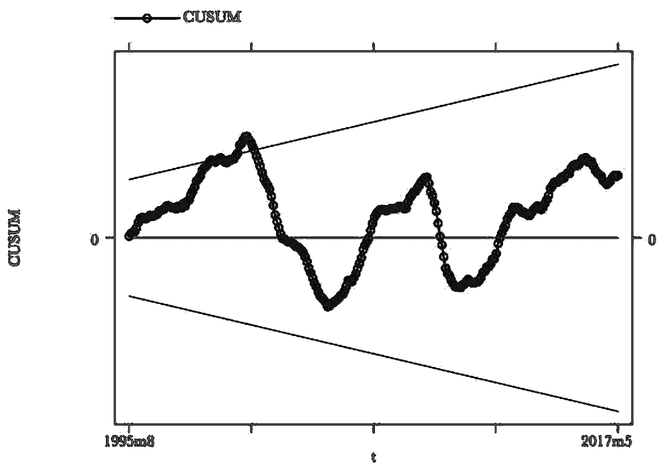

Figure 6: CUSUM test

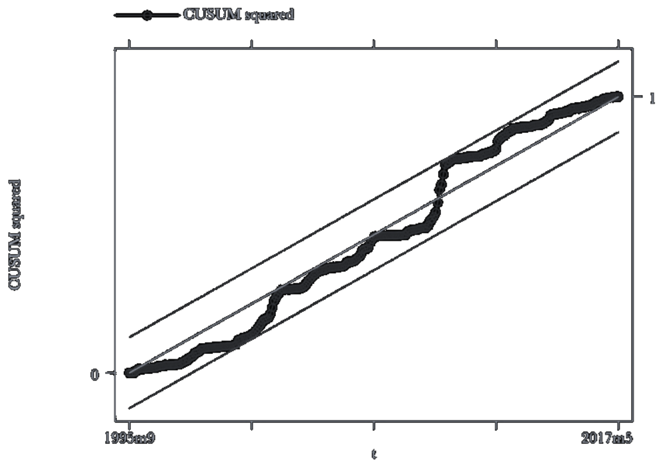

Figure 7: CUSUMSQ test

Table 2: ARDL Estimation

Conditional Error Correction Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.259691	0.082497	3.147874	0.0018
LY(-1)*	-0.09207	0.017681	-5.610826	0.0000
REER**	-0.0000602	0.0000741	-0.811651	0.4178
SPREAD(-1)	-0.001021	0.00078	1.309112	0.1917
RISKSPREAD**	-0.0000345	0.00015	-0.229775	0.8185
LCREDITDOLLARIZATION*	0.030082	0.00783	3.841988	0.0002
LAGRRAWMATINDEX**	-0.007222	0.005807	-1.243715	0.2148
LSTOCKMARKETINDEX**	0.028725	0.006168	4.656951	0.0000
CRISIS(-1)	-0.00754	0.004916	-1.533837	0.1263
D(LY(-1))	-0.155727	0.060311	-2.582069	0.0104
D(LY(-2))	0.026511	0.060418	0.438796	0.6612
D(LY(-3))	0.094939	0.057638	1.647146	0.1008
D(LY(-4))	0.100859	0.057488	1.7544251	0.0806
D(LY(-5))	0.138901	0.057481	2.416479	0.0164

D(SPREAD)	0.001471	0.000588	2.586845	0.0130
D(CRISIS)	0.010357	0.007256	1.427412	0.1547
D(CRISIS(-1))	0.007261	0.007482	0.970445	0.3328
D(CRISIS(-2))	0.010466	0.007458	1.40328	0.1618
D(CRISIS(-3))	0.016875	0.007395	2.281777	0.0233
D(CRISIS(-4))	0.015669	0.007511	2.086094	0.0380

* p-value incompatible with t-Bounds distribution. Dependent Variable: D(LY); Sample: 1990M01 2017M08

Table 3: ARDL Estimation

Levels Equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
REER	0.00606	0.000769	0.788992	0.4309
SPREAD	0.010293	0.008537	1.205709	0.2291
RISKSPREAD	−0.000348	0.001500	−0.232005	0.8167
LCREDITDOLLARIZATION	0.303229	0.072802	4.165139	0.0000
LAGRRAWMATINDEX	−0.072797	0.055564	−1.310160	0.1913
LSTOCKMARKETINDEX	0.289547	0.048945	5.915744	0.0000
CRISIS	−0.076005	0.054498	−1.394656	0.1644
C	2.617674	0.579778	4.514957	0.000

EC = LY - (-0.0006*REER + 0.0103*SPREAD -0.0003*RISKSPREAD + 0.3*LOG(CREDITDOLLARIZATION) -0.0728*LAGRRAWMATINDEX + 0.2460*LSTOCKMARKETINDEX -0.0760*CRISIS + 2.6177)

F-Bounds Test	Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
Asymptotic: n=1000				
F-statistic	6.28849	10%	1.92	2.89
k	7	5%	2.17	3.21
		2.50%	2.43	3.51
		1%	2.73	3.9
Actual Sample Size 270			Finite Sample: n=80	
10%			2.017	3.052
5%			2.336	3.458
1%			3.021	4.35

Case 2: Restricted Constant and No Trend

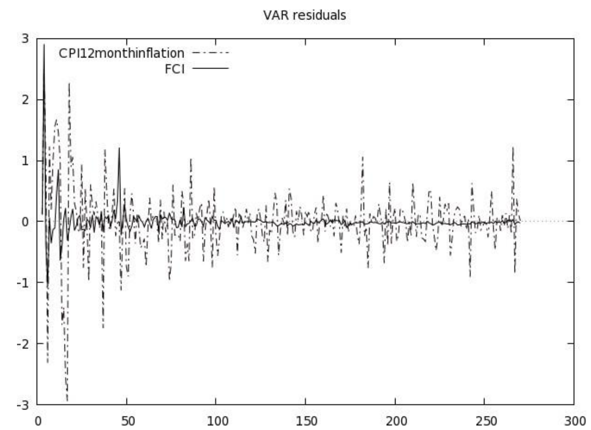

Figure 8: Residuals

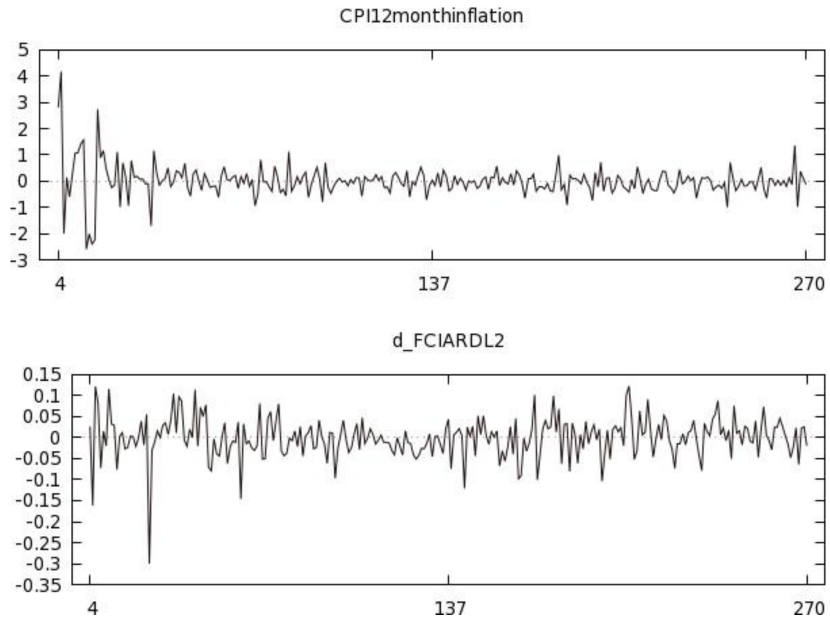

Figure 9: Residuals

Table 4: Unit root tests

Variables	ADF	Phillips-Perron	Zivot-Andrews
	Levels		
Inflation	-3.120	-3.143	-13.677
	(-0.104)	(-0.099)	(-0.010)
FCIbyVAR	-3.184	-3.579	-9.037
	(0.089)	(0.034)	(0.010)
FCIbyARDL	-0.785	-0.766	-2.263
	(0.964)	(0.966)	(0.953)
	First differences		
Inflation	-5.418	-4.078	-9.971
	(0.000)	(0.000)	(0.010)
FCIbyVAR	-14.871	-20.850	-19.263
	(0.000)	(0.000)	(0.010)
FCIbyARDL	-14.415	-14.418	-14.996
	(0.000)	(0.000)	(0.010)

p-value in parentheses

Table 5: Causality test

Pairwise Granger Causality Tests **Sample: 1994M12 2017M05**	Lags:1	Lags: 12
Null Hypothesis:		
FCI does not Granger Cause INFLATION	219.922	13.6308
	(1.E-36)	(3.E-21)
INFLATION does not Granger Cause FCI	0.00116	1.54875
	(0.9728)	(0.1080)
FCIARDL does not Granger Cause INFLATION	5.21140	2.55046
	(0.0232)	(0.0035)
INFLATION does not Granger Cause FCIARDL	0.69458	1.69687
	(0.4054)	(0.0683)

p-value in parentheses

Table 6: Forecast evaluation

Combination tests

Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
INFLATION_F	0.016177	0.984
INFMOREFCIbyVAR_F	46.81318	0.000
INFMOREFCIbyARDL_F	47.06327	0.000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
INFLATION_F	2.716307	2.185674	42.93822	31.80568	0.196067	8.497856
INFMOREFCIbyVAR_F	1.62547	1.399675	26.67111	22.35663	0.12483	4.889076
INFMOREFCIbyARDL_F	1.751775	1.552533	29.51899	24.53869	0.132879	5.250152
Simple mean	2.017272	1.705997	32.93827	26.40571	0.151197	6.186266
Simple median	1.747175	1.535708	29.25299	24.29171	0.132687	5.249757
Least-squares	2.716307	2.185674	42.93822	31.80568	0.196067	8.497856
Mean square error	2.716307	2.185674	42.93822	31.80568	0.196067	8.497856
MSE ranks	2.200485	1.840312	35.70171	28.03945	0.163239	6.789636

Sample: 2017M06 2018M06; Included observations: 13; Evaluation sample: 2017M06 2018M06;

Training sample: 2015M01 2017M05; Number of forecasts: 8

Appendix A2. An alternative model: the FAVAR

To enrich our analysis and to circumvent some limitations of the VAR and the ARDL models, we also estimate the FCI by means of a Factor-Augmented Vector Autoregression model (FAVAR). This methodology allows us to interconnect twelve financial/monetary variables (interbank interest rate, exchange rate, stock market index, raw materials index, EMBI index, M2, credit dollarization, crude price, private credit index, monetary base, commodities index and 28-cetes) and to reduce the demand variables (industrial production index, unemployment and inflation) to a limited number of common factors. The approach consists on estimating two equations: the first determines the latent factor from the financial variables; the second characterizes the movements and the interdependence of the financial with the macroeconomic variables such as the industrial production, the unemployment, etc., (Bernanke, Boivin, and Eliasz, 2005; Boivin, Giannoni and Mihov, 2009; Koop and Korobilis, 2014).

To estimate our FCI by FAVAR, we transform the data using the Hamilton Filter. Hamilton (2017) proposed an alternative to the Hodrick-Prescott filter to estimate a regression of the variable at date t+h on the four most recent values (in quarterly data) as of date t; this approach allows us to "isolate a stationary component from any I(4) series, to preserve the underlying dynamic relations and to consistently estimate well-defined population characteristics for a broad class of possible data-generating process" (p.20). Hence this approach allows to circumvent the Hodrick-Prescott filter's potential problems.

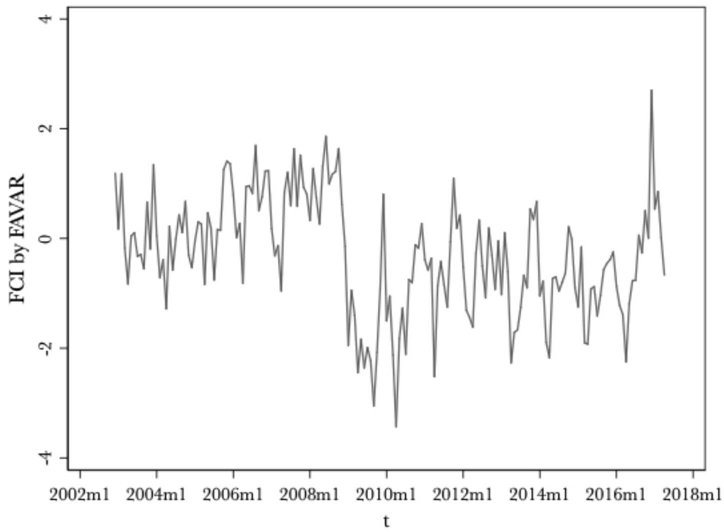

Figure 10: FCI by FAVAR

Figure 6 shows the FCI obtained by the FAVAR (FCI_FAVAR) while Figure 8 depicts the residuals from the VAR on Inflation and the FCI by FAVAR. In comparison to the estimations in section 5, the results here are more volatile since implementing this methodology requires a larger number of financial variables while the interval is restricted given that the Hamilton filter reduces the number of observations because of the Trend-Cycle decomposition. Despite these differences, the main result still holds: an FCI_FAVAR shock has a significant and positive impact on the inflation rate, reaching the peak after six months (Figure 7).

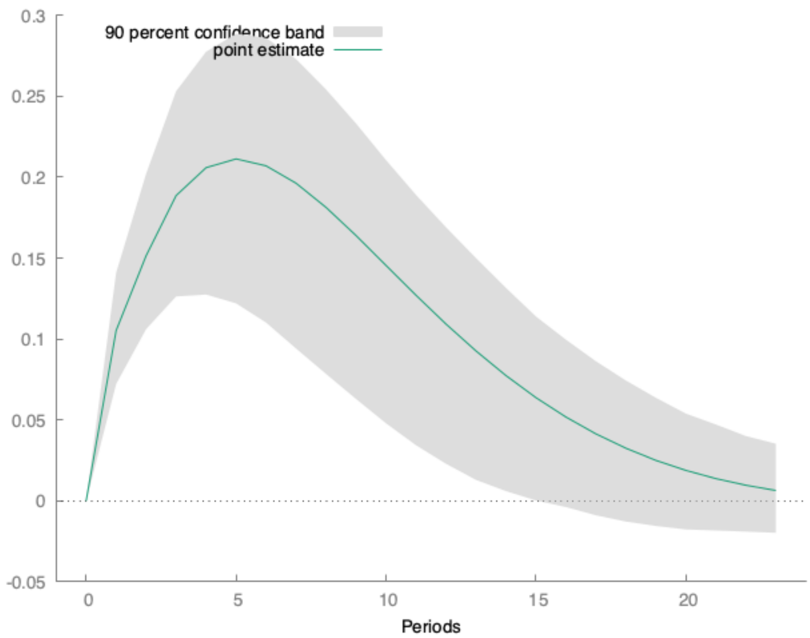

Figure 11: Response of inflation to a shock in FCI by FAVAR

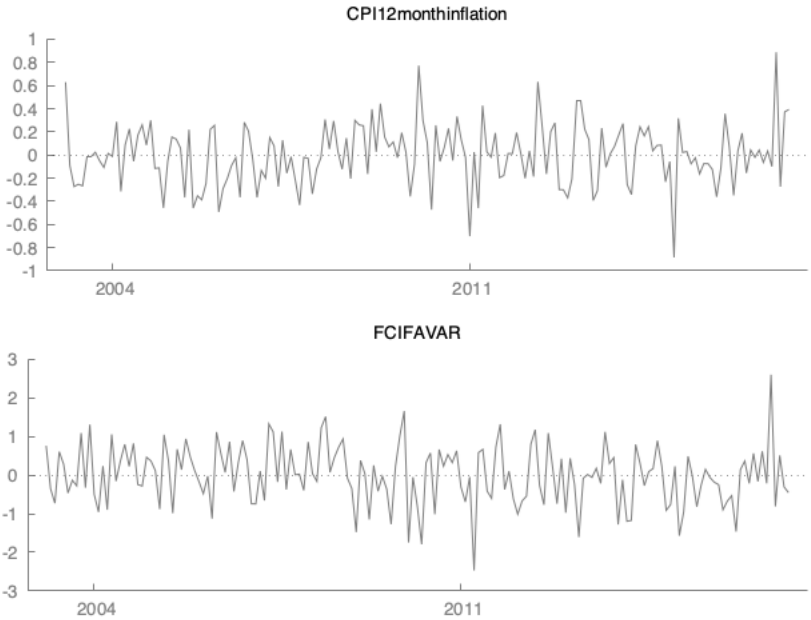

Figure 12: Residuals from VAR on Inflation and FCI by FAVAR