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An MS-VAR Approach

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Abstract[1]

This study analyzes the effects of "financial stress" on the Uruguayan macroeconomy in the 1998Q3-2016Q2 period with the underlying idea that financial shocks propagate differently during "normal times" than during times of "stress." This behavior is captured in a multivariate framework through a Markov-switching vector auto regressive (MS-VAR) model. The evidence found so far supports the idea that financial conditions affect the macroeconomy, as they not only change the private investment long-run average growth rate but also directly modify the behavior of monetary policy.

JEL classifications: C34, E27, E44, E62
Keywords: Switching-regression models, Investment, Financial markets and the macroeconomy, Uruguay

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1. Introduction

According to Modigliani-Miller (1958) theorem, the financial structure is both indeterminate and irrelevant to real economic outcomes. Nevertheless, the consensus now considers this assumption to be only a simplified tool in model designing and a good premise only when financial frictions are small.

Bernanke, Gertler and Gilchrist (1998: 1343) wisely point out:

> … However, as Gertler (1988) discusses, there is a long-standing altertantive tradition in macroeconomics, beginning with Fisher and Keynes if not earlier authors, that gives a more central role to credit market conditions in the propagation of cyclical fluctuations. In this alternative view, deteriorating credit-market conditions—sharp increases in insolvencies and bankruptcies, rising real debt burdens, collapsing asset prices, and bank failures—are not simply passive reflections of a declining real economy, but are in themselves a major factor depressing economic activity.

There is a vast literature characterized by asymetric information and agency problems where the Modigliani-Miller irrelevance theorem no longer applies. For instance, credit-markets malfunctions may increase the real cost of new credit and reduce the efficiency of matching potencial borrowers and lenders, which may negatively affect real output and employment. As a result, nowadays it is widely accepted that there are important links between the financial sector and the macroeconomy. Work along this line includes, among others, Bernanke and Blinder (1988), Kashyap, Stein and Wilcox (1993), Kashyap and Stein (1994), Hubbard (1998), Bernanke, Gertler and Gilchrist (1999), and Céspedes, Chang and Velasco (2000).

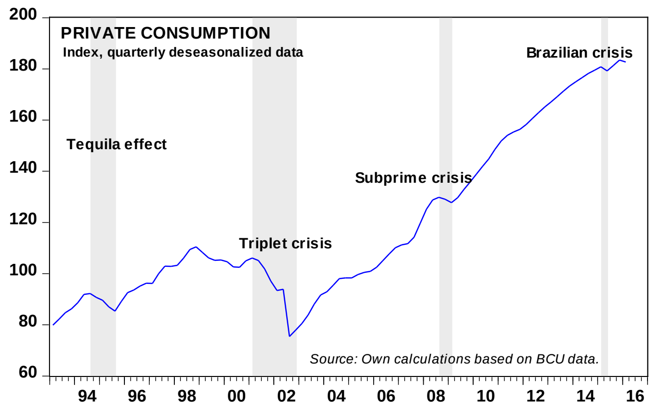
More recently, after the occurrence of the subprime mortgage crises in 2008, it has become evident that stress in financial markets may affect economic activity. Many central banks and financial agencies began to collect and analyze different kinds of information in the hope of understanding the phenomenon and creating tools with predictive value. Still, there is no consensus on how to define or measure financial stress.

Hubrich and Tetlow (2014) point out that it is hard to find evidence of the link between the financial sector and the macroeconomy during normal times once monetary and other factors are accounted for. According to their view, one reason why statistically significant and macroeconomically important linkages have been elusive is because the importance of financial factors has tended to be *episodic* in nature. They argue that financial frictions become more important when the financial system is not operating normally. They conclude that it seems reasonable to examine the interdependency of the financial sector and the macroeconomy in a nonlinear multivariate framework. They use a richly parameterized Markov-switching VAR (MS-VAR) model estimated using Bayesian methods.

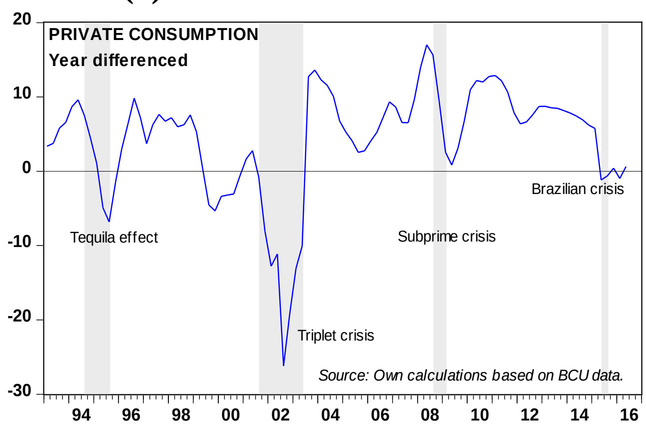
That approach seems appealing and appropriate for explaining the Uruguayan performance. Almost since its independence in the second half of the nineteenth century, Uruguay has experienced stop-and-go episodes closely related to an adverse financial event (banking crisis, exchange rate crisis, external debt crisis, etc.).[2]

Figure 1. Uruguayan Private Consumption

Panel (a) Index



Panel (b) Year differenced

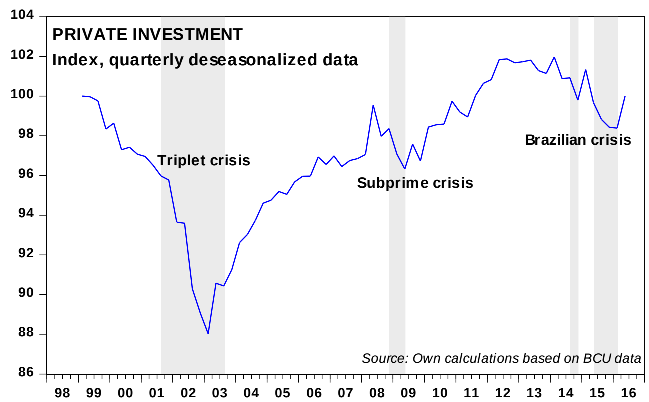


[2] For a more comprehensive analysis, see Barrán and Nahun (1967-1978) and Vaz (1999).

Figure 1 depicts the evolution of Uruguayan private consumption. It shows a rising pattern for most of the 1993-2016 period, excepting some specific episodes which can be related to some kind of financial turbulence. We can identify a few main events. In 1994-5, the *Tequila effect*, a sudden devaluation in the Mexican peso, caused other currencies in the region (mainly Southern Cone and Brazil) to decline, leading to an income fall given the important level of dollarization of the Uruguayan economy.[3] In 2001-2 there was a *triple crisis* in Uruguay[4] (balance of payments, banking and fiscal crisis). Third were the domestic consequences of the 2008 *subprime crisis.* Finally, a drop toward the end of the sample was probably related to the deterioration of the political and economic situation in Brazil.[5] Although they are only coincidences, they are indicative of some correlation between the financial markets and the macroeconomy. Figure 2 presents almost the same evidence for the evolution of private investment.[6]

Figure 2. Uruguayan Private Investment

Panel (a) Index



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[3] Since both the Uruguayan Government and firms had high levels of U.S. dollar-denominated debt, the devaluation reduced disposable income and made it increasingly difficult to pay back tdebts.

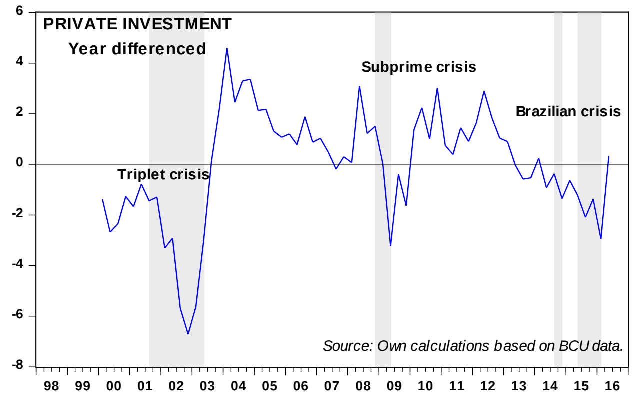
[4] A more detailed explanation is found in Section 3.2.

[5] The influence of Brazil, one of Uruguay's main trade partners, is reflected in the weight of Brazilian currency in the effective Uruguayan real exchange rate: 30 percent.

[6] Measured as gross fixed capital formation by the private sector, including buildings and machinery and equipment.

Figure 2, continued

Panel (b) Year differenced



In this study, it is asssumed that stress events are episodic in nature. It is also assumed that their exact occurrence is unknown beforehand but that they have a non-negligible probability of appearance. There is an underlying idea that shocks propagate differently during "normal times" than during times of "stress," which is captured in a nonlinear multivariate framework through a Markov-switching vector auto regressive (MS-VAR) model. Following Hubrich and Tetlow (2014), a "stress event" is defined as a period where the latent Markov states for both shock variances and model coefficients are adverse[7].

The rest of the paper is organized as follows. Section 2 explains and justifies the methodology used, presents the data and gives details of an estimated coincident FCI to be incorporated into the MS-VAR. Section 3 estimates the MS-VAR model and identifies the transmission mechanisms. Section 4 concludes.

2. Methodology

This section deals with methodological issues. First of all, statistical indicators to measure financial stability are explained and a financial conditions index (FCI) is constructed. Next, Markov-switching models are analyzed. Then, an MS-VAR model for Uruguayan data is presented.

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[7] The present document does not allow for changing parameters; that approach is left for future research.

2.1 Stress Indicator

The survey by Kliesen, Owyang and Verman (2012) notes the existence of an array of statistical indicators designed to measure financial instability, named either “financial stress indexes” (FSIs) or “financial conditions indexes”(FCIs) depending on the variables that are used to construct them. Although there is considerable overlap between FCIs and FSIs, the former tend to contain quantitites, prices and economic indicators, whereas the latter generally use only prices. As the authors point out (page 370), “…These indexes show latent conditions and are constructed from other economic and/or financial data using sophisticated statistical techniques long in use by economists and statisticians.”

The Central Bank of Uruguay has also conducted this line of research, concentrating mainly on housing prices because they are the most important asset of Uruguayan households’ wealth.[8] Both excess price volatility and deviations from market fundamentals may lead to instability in the financial market and may have real effects on the value of households’ wealth, and even on their ability to access credit because houses act as collateral. Relevant work in this regard includes Ponce (2012), Ponce and Tubio (2013) and Landaberry and Tubio (2015).

Ponce (2012) and Ponce and Tubio (2013) discuss a methodological approach, and Landaberry and Tubio (2015) use it to propose a set of price indexes to monitor the housing market in Uruguay, including the use of a hedonic model. The use of this methodology helps to improve the set of housing price indicators and provides a framework to evaluate the deviation of current housing prices from market fundamentals.

Finally, Landaberry (2015) calculates a synthetic indicator of financial stability (SIFS) for Uruguay using a methodology that provides an image of the macroeconomic, external and financial environment in order to identify potential risks to financial system stability. The indicator, which is derived using principal component techniques and a proper weighting of the different dimensions, is evaluated in the context of the last financial crisis.

Nevetheless, the SIFS is not available for a large sample size. In effect, many of its time series begin in December 2002, and it finishes in December 2014. For this reason, it has been necessary to calculate a financial conditions index specifically for this study.

[8] According to official records, 59 percent of Uruguayan households are homeowners, and their homes represent almost 60 percent of their wealth.

2.2 Financial Conditions Indicator

Uruguay is an open, small and dollarized economy with a rather shallow financial market. Previous empirical works[9] support the idea that external financial shocks do not hit the Uruguayan economy directly, but rather through a "cascade" of effects. First, the financial variable changes. Second, commodity prices react. Third, developed countries are affected, followed by our relevant region[10] and, finally, Uruguay. For this reason, it is a challenge to get an aggregate index which could incorporate all these topics.

A financial conditions indicator (FCI) was calculated specifically for this study instead of using the systemic risk indicator elaborated by the Banco Central del Uruguay (BCU) because of its short time span.[11] Our FCI is composed of 32 time series that are listed in Table 1 in the Annex and include variables both in UY pesos and in US dollars.[12] They are composed of: (a) financial price measures that influence the user cost of capital (including the interest rates that firms pay to borrow), (b) consumer interest rates that affect the tradeoff between consumption today and consumption tomorrow, (c) measures of borrower risk (percentage of nonperforming loans), (d) quantitative indicators (such as the number of transactions), (e) commodity prices (oil, food, soybean, wheat), (f) some ratios related to Argentinian risks (total credit to GDP, total reserves except gold to GDP), (g) measures of Uruguayan risk (embi, nominal and real depreciation) and (h) uncertainty (nominal exchange rate volatility, VIX[13]).

First, raw (deseasonalized) time series are put on a common scale by standardization. The usual way is to substract the sample mean from the raw score and divide this difference by the sample standard deviation. Another way is to allow for extreme events to have more weight in this standardization process because as most of the raw variables may not be normally distributed, the results obtained from the use of standardized variables are sensitive to aberrant observations (Holló, Kremer and Lo Duca, 2012). The authors propose a transformation of raw

[9] See Masoller (1998), Sosa (2010), and Bucacos (2015).
[10] Argentina, Brazil and recently China.
[11] Some series begin in December 2002; all of them end in December 2014.
[12] Uruguay is a highly dollarized economy: almost 80 percent of total deposits and more than 50 percent of total credit in the banking system are foreign-currency denominated (mainly US dollars). The main problem, though, is currency mismatches. According to Licandro and Mello (2012), 87 percent of Uruguayan firms report having liabilities denominated in currencies (mainly U.S. dollars) different from those of their incomes (mainly Uruguayan pesos).
[13] VIX is a a popular measure of the implied volatility of S&P 500 index options. Often referred to as the *fear index* or the *fear gauge*, the VIX represents one measure of the market's expectation of stock market volatility over the next 30-day period.

stress indicators based on their empirical cumulative distribution function (CDF) involving the computation of order statistics.

Following Holló et al, let us denote a particular data set of a raw stress indicator x_t as $x = (x_1, x_2, \dots, x_n)$ with *n* the total number of observations in the sample. The ordered sample is denoted $(x_{[1]}, x_{[2]}, \dots, x_{[n]})$ where $x_{[1]} \leq x_{[2]} \leq \cdots \leq x_{[n]}$ and *[r]* refers to the ranking number assigned to a particular realisation of x_t. All values of the original data set are arranged in ascending order such that the order statistic $x_{[n]}$ represents the sample maximum, i.e., the highest level of a stress indicator in a given sample, and $x_{[1]}$ accordingly the sample minimum. The transformed stress indicators z_t are now computed from the raw stress indicators x_t on the basis of the empirical CDF F_n (x_t):

$$z_t = F_n(x_t) = \begin{cases} \dfrac{r}{n} & for \;\; x_{[r]} \leq x_{[t]} < x_{[r+1]} \quad r = 1,2,\dots,n-1 \\ 1 & for \;\; x_{[t]} \geq x_{[n]} \end{cases}$$

The transformation thus projects raw stress indicators into variables which are unit-free and measured on an ordinal scale with range (0, 1].

Next, all variables are controlled for past GDP growth and inflation,[14] concentrating on the predictive power of financial conditions for future economic activity (Hatzius et al., 2010):

$$z_t = a_0 + a_1 \Delta gdp_{t-1} + a_2\, \Delta gdp_{t-2} + a_3 \Delta p_{t-1} + a_4 \Delta p_{t-2} + \varepsilon_t$$

This depuration was undertaken on the basis of the belief that, ideally, an FCI should measure *financial shocks*, that is, exogenous shifts in financial conditions that influence or otherwise predict future economic activity. As Hatzius et al. (2010: 1) point out:

> "… True financial shocks should be distinguished from the endogenous reflection or embodiment in financial variables of past economic activity that itself predict future activity. If the only information contained in financial variables about future economic activity were of this endogenous variety, there would be no reason to construct an FCI: Past economic activity itself would contain all the relevant predictive information."

[14] Two lags on each one. Inflation is computed as GDP deflator growth.

Then, once the data have been deseasonalized, standardized and purged, there are two main approaches in the literature for constructing FCIs: the weighted-sum approach and the principal components approach. In the former, the weights on each financial variable generally come from estimates of the relative impacts of changes in the variables on real GDP. These weights could come from large-scale macroeconomic models, vector autoregression (VAR) models, or reduced-form demand equations. In the principal component approach (PCA), a common factor is extracted from a large group of financial variables. This common factor captures the greatest common variation in the variables.[15] We followed the latter approach.

Composition of the Financial Conditions Indicator (F)

Table 1.

	Loadings
Quantitative indicators	2.276358
Financial price measures	-1.086143
Uncertainty	-0.205693
Uruguayan risk	-0.222078
Borrower risk	0.104453
Consumer interest rates	0.054044
Argentinian risks	0.054002
Commodity prices	-0.046187

Source: Author's calculations.

Figure 3.

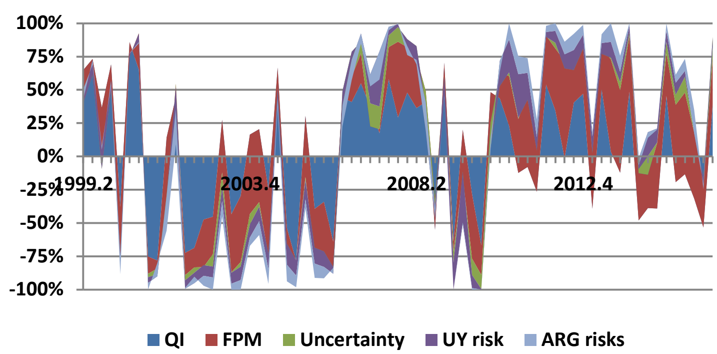
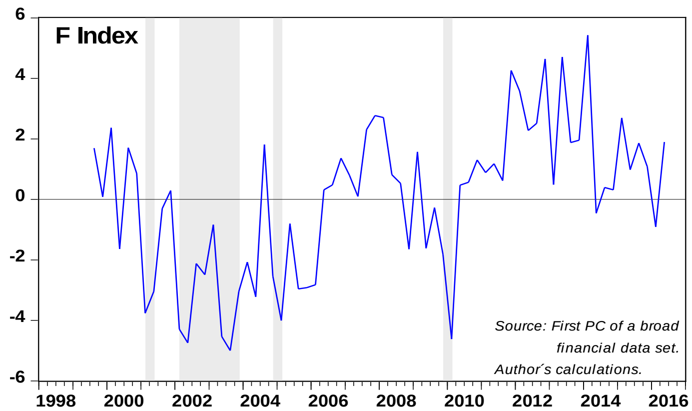


Table 1 and Figure 3 show the loadings of the 32 time series used in the first principal component, grouped by broad items. Accordingly, increases in the number of new loans—to firms and/or to families—have beneficial effects, because more credit not only helps many agents to make ends meet but also may leverage economic activity. Thus the positive loading of

[15] In a previous version, I used factor analysis approach (FA) instead of principal components approach (PCA) to calculate the FCI. FA and PCA are similar because both create variables that are linear combinations of the original ones. But they differ in thatk while PCA accounts a maximal amount of variance for observed variables, FA accounts for common variance in the data. That is one of the reasons why FA is generally used when the research purpose is to detect data structure (i.e., latent constructs or factors) or causal modeling, while PCA is generally preferred for purposes of data reduction (i.e., translating variable space into optimal factor space), but not when the goal is to detect the latent factors. As one of the main objectives here is to obtain an aggregate index that reflects rare financial events that may not be generalized through the whole financial system, it sounds plausible to extract the maximal variance and not the common one. Besides, when applying FA, some series are discarded because of sample adequacy and goodness-of-fit criteria while the whole data set is used when PCA is applied.

2.28 indicates better financial conditions. On the other hand, higher spreads point out to riskier circumstances in the market that made the borrower require a higher premium in order to be willing to participate and this variable has a negative loading in the FCI of 1.09. The same is true for those variables that measure uncertainty and risk. For the Argentinian variables, one of them has a negative loading (reserves-excluding-gold to GDP ratio) and the other one, positive (total credit to GDP ratio), making positive the average between the two of them.

Figure 4. Financial Conditions Indicator



The main goal of using stress indices is to measure the current level of frictions, stresses and strains (or the absence of them) in the financial system and to summarize them in a single statistic. As such, a negative value in F should be seen as a deterioration of the financial situation and a negative event; conversely, a postive value in F should be understood as a better climate for economic activity and so a positive event. Besides, F may also help delineating historical episodes of "financial crises," which might then be better compared and studied empirically in the context of early warning signal models, for instance.

The 2001-2002 triplet crisis is clearly recognized. There is an important credit reduction in that period that created frictions in the financial markets. As the crisis was unfolding during 2002, the drastic and sustained deposit withdrawals[16] translated into a system-wide credit crunch as banks—both private and public—scrambled to find any available liquidity by suspending new loans as well as by requesting early repayment in existing loans. Thus, credit to the non-financial sector shrunk by 37 percent during 2002 alone. Then, in 2003 there were important increases in

[16] By the end of July 2002, 38 percent of total deposits had been withdrawn from the system.

spreads, making it more expensive to get credit, increasing both non-performing loans ratings and country risk. All together pull F down. There are two more episodes of “unrest,” both related to a new governmental period: in 2005Q1, perhaps related to the expectation and uncertainty surrounding the Vázquez presidency, and in 2010Q1, perhaps related to the Mujica presidency.[17] The F index also accounts for the negative collateral effects of two other episodes: the 2008 subprime crisis and the 2014 Brazilian crisis.

2.3 MS Models

Models are simplified descriptions of reality. Among other features, they need stability in the relationship between its variables in order to describe a system in a reliable way, to be capable of making credible inferences and even to analyze counterfactual situations. But structural breaks are a fact of reality and econometricians deal with them in different ways.

The simplest way to discover the break is simply to plot the time series and, adjusting a segmented intercept, use an autoregressive model. On the other hand, more sophisticated techniques allow a model to determine the different regimes and use econometric tools to estimate the breaks. For instance, Bai and Perron (2003) develop a procedure that estimates the breaks, while Castle, Doornik and Hendry (2008) apply impulse-indicator saturation to perform the same task.

Regime-switching models allow some part of the model to depend on the state of the economy (the “regime” or “state”) while simultaneously estimating it when there is a transition from one state to another (only rarely are the exact dates known). In that way, the model is able to estimate different mean growth rates of the dependent variable, one for each state.[18] But different means may not be enough; we may also need different dynamic behavior in the two regimes. Or perhaps three regimes are needed for a satisfactory description (Doornik, 2013).

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[17] Frente Amplio, a leftist coalition, won the National Elections in 2004 for the first time in Uruguay. During the campaign and just before the election, Presidential candidate Tabaré Vázquez and prospective Finance Minister Danilo Astori went to Washington and assured IMF and World Bank authorities of their commitment to macroeconomic stability and international payments. Five years later, Frente Amplio again won the national elections. This time the president-elect was José Mujica, a former Tupamaros guerrilla, who was supported by Vázquez but had not been his first choice. Finally, the econometric estimation treated both points as outliers that did not indicate any structural change.

[18] Several types of models implement this feature, such as Self-exciting Thresholds Autoregressions (SETAR, Tong, 1990), Smooth-transition models (LSTAR, Terasvirta, 1994) and Markov-switching models (Hamilton, 1989).

Hamilton (1989) introduced a random variable S_t that represents the unobserved regime or state of the economy:

$$(1) \quad y_t = \nu(S_t) + \epsilon_t, \qquad \epsilon_t \sim IIN(0, \sigma^2)$$

for $S_t \in \{0,1,2, \ldots, S-1\}$

The objective of his model is to estimate the probabilities of being in a regime, together with the other model parameters. The unobserved random variable S_t follows a Markov chain, defined by transition probabilities between the S states:

$$(2) \quad p_{i/j} = P[S_{t+1} = i / S_t = j], \quad i, j = 0, 1, \ldots, S-1$$

The probability of being in a regime, given available data and past regimes, only depends on the previous regime (and available data); there is no benefit from knowing the whole history of the model. Then, the probabilities of moving from one regime to another ("transition probabilities") have a Markovian structure:

$$(3) \quad P[S_{t+1} = i \,/\, S_t = j, S_{t-1}, S_{t-2}, \ldots] = P[S_{t+1} = i / S_t = j], \quad i, j = 0, 1, \ldots, S-1$$

Because the system has to be in one of the S states:

$$(4) \quad \sum_{0}^{S-1} p_{i/j} = 1$$

the extension to the multivariate framework is straightforward.[19] A conventional VAR(1) can be written as:

$$(5) \qquad y_t = \nu + \pi_1 y_{t-1} + \varepsilon_{t,} \qquad \varepsilon_t \sim IN_n(0, \Sigma)$$

where y_t, ν, ε_t are nx1 vectors and π_1, Σ are nxn matrices.

The MS-VAR model allows for a great variety of specifications. Krolzig (1997) has established a unique notation for each model, adding to the general MS term the regime-dependent parameters; if exogenous regressors are included into de system, it is denoted as MS-VARX. See Table 2.

[19] This closely follows Chapter 14 of Doornik (2013).

Table 2. MS-VAR Notation

M	Markov-switching *mean*	MSM-VAR
I	Markov-switching *intercept*	MSI-VAR
A	Markov-switching *autoregressive parameters*	MSA-VAR
H	Markov-switching *heteroskedasticity*	MSH-VAR

Source: Krolzig (1997).

For instance, a VAR(1) with Markov-switching in intercept and variances, MSIH(S)-VAR(1), can be written as:

$$(6) \qquad y_t(S_t) = \nu(S_t) + \pi_1 y_{t-1} + \varepsilon_{t,} \qquad \varepsilon_t \sim IN_n\big(0, \Sigma\,(S_t)\big)$$

Within each S regime, the specification is a conventional VAR. The density of y_t conditional on the state $S_t = j$, is a multivariate normal:

$$(7) \qquad f(y_t(S_t)|S_t) = [(2\pi)^n|\Sigma(S_t)|]^{-\frac{1}{2}} \;\; exp\left\{-\frac{1}{2}v_t(S_t)'\,\Sigma(S_t)^{-1}\,v_t(S_t)\right\}$$

where $v_t(S_t) = y_t(S_t) - \nu(S_t) - \pi_1 y_{t-1}$ and $|\Sigma|$ is the determinant of Σ. Then, the procedure consists in maximizing the loglikelihood as usual.

In order to solve the identification problem,[20] a convenient way is to apply Choleski decomposition:

$$(8) \quad \Sigma = PP'$$

where P is lower diagonal with positive diagonal elements. This can be written as:

$$(9) \quad \Sigma = B\,S^2 B'$$

where B is lower diagonal with ones on the diagonal and S is diagonal. This has the advantage of making it easier to get the determinant and inverse of Σ.

In this investigation three different specifications are tried, as presented in Table 3.

Table 3. MS-VAR: Different types of variance

Type of variance	**Specification**	**Parameters**	
		in scale	**in B**
Fixed	$\Sigma = \mathrm{B}\,\mathrm{S}^2\mathrm{B}'$	n	n(n-1)/2
Switching scale	$\Sigma(S_t) = \mathrm{BS}^2(S_t)\mathrm{B}'$	Sn	n(n-1)/2
Switching variance	$\Sigma(S_t) = \mathrm{B}(S_t)\mathrm{S}^2(S_t)\mathrm{B}'(S_t)$	Sn	Sn(n-1)/2

Note: Σ is nxn variance-covariance matrix, B is lower diagonal with ones in the diagonal and S is diagonal; S_t denotes the unknown states or regimes.

[20] The *identification problem* deals with the fact that $\frac{(n^2-n)}{2}$ restrictions between the regression residuals and the structural shocks are required in order to recover deep parameters from the reduced-form parameters in a VAR.

2.4 Discussion

A structural break is clearly recognized when there is an unexpected shift in a time series. When there are too many unknown breaks it is assumed that the parameters are time-varying. This is not the way the Uruguayan financial situation seems to be characterized in the time period analyzed here, because it shows a picture of relative stability interrupted by a few episodes of roughness (Figure 3). In addition, both private consumption (see Figure 1) and private investment (Figure 2) evolve in a similar way.

In a globalized economy, financial frictions may appear without previous notice from different places, disturbing a previously normal scenario. But those disturbances are rare. As a result, it is reasonable to assume that the economy works coherently well in each state of nature as if they were worlds apart. When a sudden and unexpected particular event occurs—e.g., a financial shock—the economy may move from one state to the other with a positive probability.

Switching models allow to estimate both the relationships between the variables in each state and also the probabilities of moving from one state to the other. Besides, stochastic shocks may vary over states.

2.5 Model Specification

A four-variable MS-VAR (Markov switching vector autoregressive) model is implemented. In particular,[21]

$$(5) \quad y_t = [\mathrm{F} \;\; \mathrm{I} \;\; \mathrm{r} \;\; \mathrm{P}\,]$$

where *F* is the financial conditions index (FCI)[22] calculated in Section 2.1, *I* is the private investment[23] growth rate, *r* is the nominal 1-day interbank interest rate (call rate) and *P* is CPI inflation excluding fruits and vegetables, Government-fixed prices and maid services (hereinafter, *core inflation*). All variables are quarterly, seasonally adjusted, standardized[24] and expressed at annual rates. The data span from 1998Q3 to 2016Q2.

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[21] In earlier versions, private consumption and unemployment were used as proxies for real activity. By choosing private investment, the model was reduced to a four-variable VAR.

[22] It would have been unwise to use the stress condition index (SCI) elaborated by BCU because of its short sample size (some series begin in December 2002). As a result, we calculate our own FCI from 1998Q3.

[23] As a measure of activity; sensitivity analyses were performed using private consumption as a measure of wellbeing. It was decided not to use real GDP because it had been used to purge the variables included in *F*.

[24] Standardization is crucial in order to assure a better measure of the relative loadings of each variable in the factors and to improve the reading of IRFs.

For identification purposes,[25] I use the well-known Choleski decomposition, which imposes a recursive causal structure from the top variables to the bottom variables but not the other way around. The first variable is *F* because, by construction, the financial conditions index is independent of the business cycle variables and should just reflect pure financial shocks. The Uruguayan inflation data-generating process has proved to be a rather complex one and, at least in the short run, inflation does not seem to be exclusively a monetary phenomenon.[26] Rather, inflation seems to be contemporaneously influenced by different factors stemming from financial, real and monetary markets. Then, *P* goes in the fourth place. Although the call rate has been the monetary policy instrument in Uruguay for only a short time (2007Q3-2013Q2) it is still the most reliable variable for monetary policy analysis. As such, monetary decision making does not seem to react contemporaneously to changes in private investment or current inflation rate;[27] instead, the call rate seems to react contemporaneously to financial shocks and to real activity changes (through changes in private investment). Private investment is only affected contemporaneously by financial conditions and not by monetary policy decisions; a change in the 1-day interbank nominal interest rate does not reach the public immediately but with a lag, once interest rate arbitrages have been made and investment plans redefined. So, *I* goes in the second place and *r* goes in the third place. As a result, the chosen ordering is [F, I, r, P].

Following Hubrich and Tetlow (2014), there are some questions that are intended to be answered by this model. The first is whether whether there are periods of financial turbulence that appear randomly in the middle of normal times. Second, if such periods exist, which kind of regime switching better describes the data, that is, differences in long-run average growth rates (switching mean) and/or differences in the economic environment (switching variance). A third question is whether regime switching appears only in a specific equation—the stress equation alone or the monetary policy response to the financial stress—or in more than one equation of the VAR.

[25] Impulse-response analysis must be done with the structural shocks; the ones recovered from the reduced form VAR are a weighted average of pure shocks.
[26] See Bucacos and Licandro (2003).
[27] It reacts to expected inflation deviations from the target.

3. Estimation

This section presents the estimated model and discusses the results achieved, analyzing critically the performance of the estimated model in explaining the interelationship between some financial events and the Uruguayan economy.

3.1 Main Results

The model presented is

$$(6) \qquad y_t(S_t) = \nu(S_t) + \pi_1 y_{t-1} + \varepsilon_{t,} \qquad \varepsilon_t \sim IN_n\big(0, \Sigma\,(S_t)\big)$$

and

$$(5) \quad y_t = [F \;\; I \;\; r \;\; P\,]$$

It is estimated maximizing the multivariate log-likelihood function. The optimal lag length is 1. Different combinations of change of regime were estimated: only in the mean, only in the variance, only in the variance with switching scale, only in the variance with switching variance, and the combinations among them.[28] Information criteria, mainly Schwartz criteria—and maximization of loglikelihood function are the goodness-of-fit selectors. The main results are displayed in Table 4, I and II.

Table 4-I. Main results of MS-VAR Estimation

Model	Log L	AIC	SC	N obs.	N par.
FAVAR(1)	-375.56600	11.6342	12.2871	68	34
MSI(2)-VAR(1)[1]	-373.186927	12.0349	13.2099	68	36
MSIH(2)-VAR(1)[2]	-306.691667	10.1968	11.5024	68	40
MSIH(2)-VAR(1)[3]	-285.571681*	9.7510*	11.2535*	68	46

Notes:

1: Markov-switching in intercept term with fixed variance

2: Markov-switching in intercept term with heteroskedasticiy (switching scale in variance)

3: Markov-switching in intercept term with heteroskedasticity (switching variance)

Log L = log likelihood value, AIC = Akaike Information Criteria, SC = Schwartz Criteria

N Obs = number of observarions, N par = number of parameters, (*) indicates the chosen model.

[28] MS models with changing parameters, MSA-VAR, are left for a future investigation.

The chosen model[29] distinguishes two regimes: R_0 = “turbulence” and R_1 = “normal times,” both in the long-run mean and in the variance (switching variance). According to Krolzig’s (1997) notation, that model can be named MSIH(2)-VAR(1).

Table 4-II. Main Results of MS-VAR Estimation

ML estimates of the MSIH(2)-VAR(1) model, with SV (1998Q3 to 2016Q2)

	F	**I**	**r**	**P**
Intercepts				
R_0: Turbulence	-0.94703	-0.66874	0.79574	0.03181
R_1: Normal times	0.21019	0.12339	-0.18264	0.03634
Long-run mean				
R_0: Turbulence	-1.52220	-1.88306	1.74438	0.39051
R_1: Nomal times	0.33785	0.34745	-0.40037	0.44606
Coefficients				
F_{-1}	0.37785	-0.19216	0.01747	0.04884
I_{-1}	0.00861	0.64487	-0.02504	0.01089
r_{-1}	-0.13221	-0.40303	0.54383	0.23829
P_{-1}	-0.07700	0.03340	-0.03065	0.91854
Standard errors				
R_0: Turbulence	1.59358	1.31053	0.96623	3.06060
R_1: Normal times	2.14411	1.17388	0.10091	0.51492

Source: Author’s calculations.

Table 5. Transition probabilities

MSIH(2)-VAR(1) model, with SV (1998Q3 to 2016Q2)

	Regime 0,t	**Regime 1,t**
Regime 0,t+1	0.6107	0.0760
Regime 1,t+1	0.3893	0.9240

Source: Author’s estimates.

3.2 Discussion

The time series are plotted together with their fit in Figure 5. Based on the MSIH model, the contribution of the Markov chain to the series is apparent for the inferred regimes clearly describe two distinctly different financial environments inside which economic activity has taken

[29] According to the maximum log likelihood value and information criteria.

place in Uruguay in recent times. TRegime 0, called R_0, tracks turbulence in financial markets and dates recessions of the Uruguayan economy quite well, while Regime 1, called R_1, refers to normal times.

Figure 5. Time Series and Their Fit

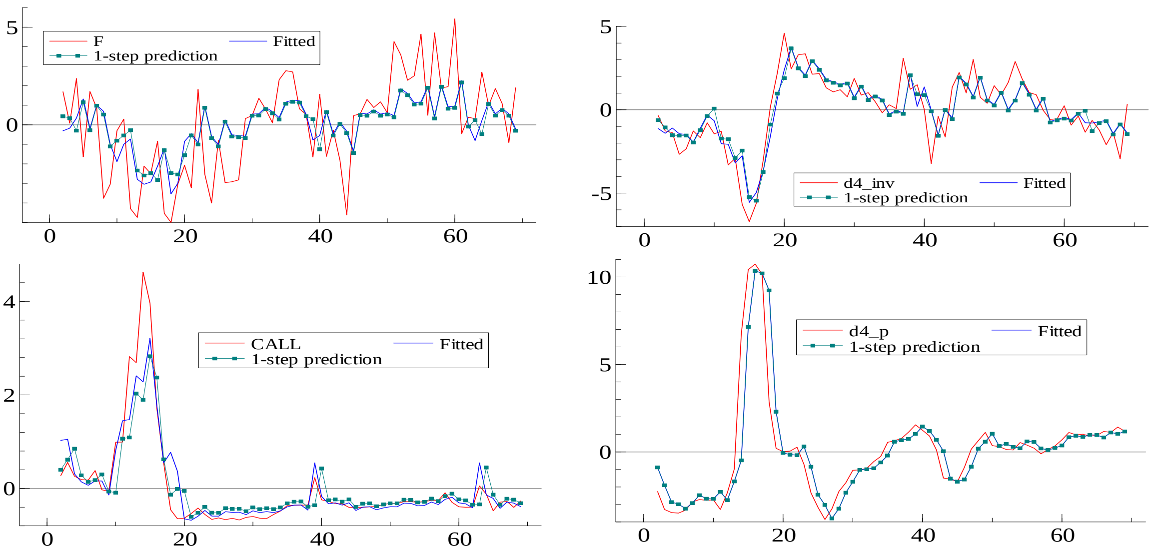

Figure 6 diplays the regime probabilities of the two regimes in the MSIH model. According to Table 5, both regimes are persistent: in normal times, there is a 92 percent probability of stability next period, but if something unexpected disturbs that tranquility there is a 60 percent chance for that financial unrest to continue.

Figure 6. Regime Probabilities in MSIH(2)-VAR(1)

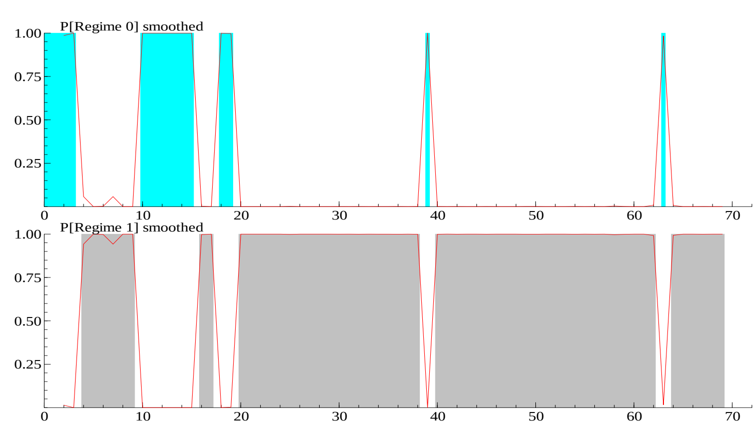

Table 6 diplays the regime classification based on smoothed regime probabilities. We can recongnize several events as instances of turbulence in financial markets (in R_0): the Brazilian financial crisis in 1999, Argentina's devaluation in 2001 and its financial and political crisis afterwards, Uruguay's triplet crisis in 2002-2003 (balance of payments, banking and fiscal crisis), the subprime crisis in 2008 and the declining commodity prices that led to the Russian financial crisis together with the Brazilian crisis in 2014. A description of those events is presented next.

Table 6. Regime Classification Based on Smoothed Probabilities[30]

Regime	Period	Quarters	Average probability
R_0 = "Turbulence"			
	1999Q3-1999Q4	2	0.993
	2001Q3-2002Q4	6	1.000
	2003Q3-2003Q4	2	1.000
	2008Q4	1	1.000
	2014Q4	1	0.984
Total: 12 quarters (3 years, 17,65%) with average duration of 2.40 quarters (around a semester)			
R_1 = "Normal times"			
	2000Q1-2001Q2	6	0.980
	2003Q1-2003Q2	2	0.999
	2004Q1-2008Q3	19	1.000
	2009Q1-2014Q3	23	0.999
	2015Q1-2016Q2	6	0.999
Total: 56 quarters (14 years, 82.35%) with average duration of 11.2 quarters (almost 3 years)			

Source: Author's estimates.

In 1994 Brazil put into practice a stabilization plan named after its new currency, the *real*. Despite the Real Plan's success in controlling inflation,[31] the new currency was overvalued, which negatively affected Brazilian external accounts. To make matters worse, Brazil began to suffer from financial contagion from the Asian crisis in 1997 and the Russian crisis in 1998. In

[30] Smoothed probabilites take into account all the sample information.
[31] In 1994, the year the Real Plan was implemented, Brazil's annual inflation rate exceeded 900 percent; by the end of 1998, price increases were negative.

order to stop investors from withdrawing their investments from Brazil, the authorities raised interest rates, but that measure increased the fiscal deficit to 8 percent of GDP. Finally, in January 1999 Brazil devalued its currency and abandoned its pegged exchange rate that was implemented together with other measures in 1994 in order to attack hyperinflation. By that time, the Brazilian economy was already in recession.

After 1999, Argentinian exports were negatively affected by Brazilian real devaluation and a considerable international revalorization of the British pound, which led to a revaluation of the Argentinian peso against its main trade partner, Brazil (30 per cent of total commercial flows) and the dollar zone (23 per cent of commercial flows). Fernando de la Rúa took office as President in Argentina on December 10, 1999, when the recession was already underway;[32] the economic stability achieved by the Convertibility Plan[33] had turned into economic stagnation. The possible solution, abandonment of the fixed exchange rate with a voluntary devaluation of peso, was considered political suicide at the time, and "quasi-currencies" appeared in order to fill a liquidity gap.[34] Under those circumstances, Argentina quickly lost investors' confidence and capital outflows increased. In 2001, people fearing the worst began to withdraw large amounts of money from their bank accounts, exchanging pesos for American dollars and sending them abroad, which caused a bank run. Then, the Argentine government imposed capital controls and deposit freezes on Argentinean nationals' time accounts, current accounts and saving accounts, a set of measures popularly known as the "*Corralito.*" Those measures turned out to be highly unpopular, resulting in the *Cacerolazo*,[35] followed by a government-declared state of siege; still, protests turned violent and fatalities occurred. iolence and fatalities eventually resulted. the climate got worse and turned violent and violent and even people died in the protests. Finally, the government collapsed, and on December 20, 2001 the President had to leave the Pink House by helicopter. The Convertibility Law was abolished on January 6, 2002.

As many analysts have pointed out,[36] it is fair to say that the 2002 banking crisis in Uruguay might not have occurred had Argentina not collapsed first. But this exogenous

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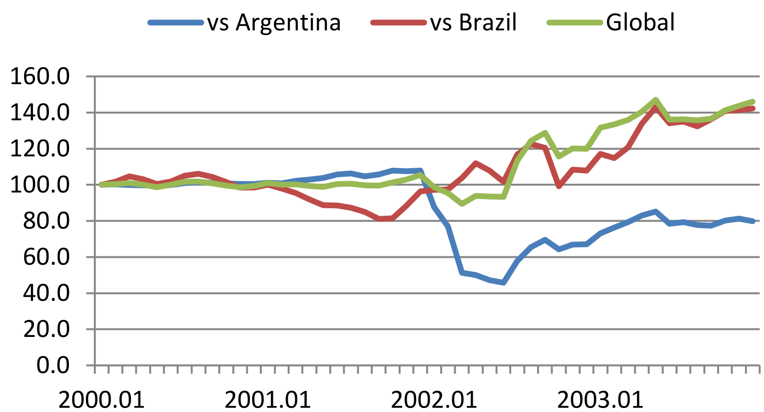
[32] In 1999, Argentinian GDP fell by 4 per cent.
[33] The Convertibility Law, Nº 23.928, was sanctioned on March 27, 1991 and established a fixed parity of 1 US dollar = 10,000 Australes (convertible Peso).
[34] Such as Bono Patacón and Bono Lecop.
[35] It refers to the beating of "cacerolas" (*saucepans*) by the people at predetermined hours as a sign of protest against the government.
[36] De la Plaza and Sirtane (2005) and Paolillo (2004), among others.

contagion to the Uruguayan financial sector was magnified by inherent weaknesses of the Uruguayan economy and its banking sector. In effect, by the end of 2001, the Uruguayan economy was characterized by weaknesses in public banks,[37] a high level of foreign indebtedness—both private and public[38]—and economic stagnation resulting from the appreciated real exchange rate of the Uruguayan peso in relation to its major trade partners[39] (Figure 7).

Figure 7. Uruguayan Real Exchange Rate



The crisis in Uruguay[40] began in December 2001 when the Argentine government imposed the "*Corralito*" and then that spark was quickly spread to the Uruguayan economy through the financial links between the two countries. Banco Galicia Uruguay and Banco Comercial, which combined represented approximately 20 percent of total deposits within the Uruguayan system, were both owned by Argentinian financial groups. At the begining, there were only instances of limited non-resident deposits runs related to those financial institutions, but as the crisis in Argentina was developing, deposits withdrawals gradually increased in

[37] As of December of 2001, the level of non-performinge loans of the two main public banks, BROU and BHU, was greater than that of the rest of the system (39.1 versus 5.6); while after-tax return on equity was minus 4.5 for the public banks versus minus 0.9 for the private banks. In addition, BHU, the country's almost only provider of mortgage lending, was vulnerable to external shocks owing to substantial currency and maturity mismatches in its balance sheets: 77 percent of deposits were US dollar-denominated and were at short maturities, while 94 percent of its loans were long-term peso-denominated. BHU had almost 10 percent of total deposits within the system.
[38] Total Government debt was 58 percent of GDP in 2001, of which 83 percent was denominated in foreign currencies.
[39] According to BCU figures, the Uruguayan real exchange rate index (base 2010=100) reached a value of 109.8 by December 2001.
[40] See De la Plaza and Sirtane (2005) for a more detailed description of the Uruguayan banking crisis.

Uruguay and by March 2002, 12 per cent of bank deposits, mainly by non-residents, had left the country. Although Uruguayan authorities diligently provided liquidity support to the affected banks, negative public perceptions of the situation led to a widening the crawling exchange rate band from 6 to 12 per cent. Meanwhile, the Argentinian crisis worsened and deposit freezes were tightened (popularly known as the "*Corralón*"), which led to a second wave of deposits withdrawals in April 2002, followed by Uruguay's downgrade from investment grade status.

The situation steadily worsened in the following months. First, withdrawals from the public banks began. Subsequently, Banco de Montevideo-Caja Obrera, the third largest private bank, run into severe liquidity shortages and had to be taken over by Uruguayan authorities. Finally, the run on dollar deposits extended local currency deposits as well. As a result, the level of available international reserves reached US$ 650 million (an 80 percent decline with respect to December 2001), which was clearly insufficient to both service the external debt and continue backing the large proportion of foreign currency-denominated deposits still present within the system (US$ 8.7 billion as of July 2002). Uruguayan authorities had to let the peso freely float—whereupon it immediately depreciated by 27 percent—and declared a five-day bank holiday on July 30, 2002. Just after the lifting of the bank holiday on August 5, 2002, a new legislative framework (Ley 17.523) was designed that included a series of measures aimed at finally putting an end to the crisis.[41] During the second half of 2002 and in 2003 another series of additional legal and regulatory measures was undertaken in order to restructure the banking system, strengthen the financial sector's both regulatory and supervisory frameworks and resolve the imminent crisis of government finances and the increasingly large foreign deficit. In particular, in May 2003 Uruguay successfully re-scheduled a large proportion of its foreign currency-

[41] They were: 1- it created the Fondo de Estabilización del Sistema Bancario, US$ 1.4 billion stabilization fund, sufficient to fully back the entire book of US dollar sight and savings deposits at public and intervened banks; 2 – the US dollar time deposits of the public banks (BROU and BHU) were reprogrammed and their maturities stretched over a three-year period; 3 – no restrictions were imposed on foreign banks' operations, as long as they were to rely on their own resources to provide liquidity support; 4 – the BROU absorbed all foreign currency and timed deposits of the BHU, which, although it remained in operation, was no longer allowed to received deposits; 5 – the operations of the three intervened banks (Banco Comercial, Banco de Montevideo-Caja Obrera and Banco de Crédito) were permanently suspended and actions were initiated towards their eventual restructuring and/or liquidation.

denominated debt.[42] The return of the deposits to the system validated this debt exchange, with the total level of deposits of the system growing by 3 percent during May 2003 alone.

The cost of the crisis was extremely important. By the end of 2002, the Uruguayan banking system had lost 46 percent of total deposits and the level of non-resident deposits had decreased by 65 percent. As a result of this massive deposit run, one bank had to be closed and three additional banks had to be taken over and restructured by the government, which, by the end of 2002, controlled approximately 70 percent of total deposits in the system. In total, liquidity support provided by the government during 2002 amounted to US$ 2.4 billion, approximately 20 percent of that year's GDP, while GDP contracted by was approximately 11 percent.

As De la Plaza and Sirtane (2005) point out:

> "The very manner in which the authorities behave themselves during and after the crisis may have been a crucial element in stopping and recovering from the crisis. A key element of the government's strategy that contributed to its effectiveness was their willingness to relatively quickly and publicly intervene troubled banks to both prevent systemic contagion and assure the worrying public about the solidity of the financial system. Furthermore, not only has Uruguay been capable of simultaneously counteracting concurrent banking and public debt crisis, but it has been able to do so by preserving the necessary trust in banking contracts, achieveing a high level of social stability and political cohesion, and maintaining a fluid dialogue with multilateral financial institutions and all the affected parties."

Table 6 points out another event in the bad or turbulent regime: the United States subprime mortage crisis, a natiowide banking emergency, that contributed to the U.S. recession of December 2007-June 2009, which our MSIH model depicts in 2008Q4. That crisis was triggered by a large decline in home prices after the collapse of a housing bubble. The expansion of household debt was financed with mortgage-backed securities (MBS) and collateralized debt obligations (CDO), which initially offered attractive rates of return due to the higher interest

[42] The participation of the debt exchange was unusually high: US$ 5 billion worth of principal amount was rendered for exchange, approximately 93 percent of eligible bonds. Domestic participation was extremely high, with 100 percent participation by domestic financial institutions and 98 percent by domestic retail investors.

rates on the mortgages; however, the lower credit quality ultimately caused massive defaults.[43] While elements of the crisis first became visible in 2007, several major financial institutions collapsed in September 2008, with significant disruption in the flow of credit to businesses and consumers and enormous losses to Wall Street firms and hedge funds. It was the onset of a severe global recession.

Finally, the last event that can be identified from the smoothed regime probabilities (Table 6) in the turbulent regime is related to the commodity prices fall of 2014, with its effects on the Russian financial crisis and on Brazil. In mid-2014 the Russian ruble collapsed rapidly in the global foreign exchange market and Russian companies found it increasingly difficult to repay foreign-denominated debts, such as U.S. dollar-denominated debts.[44] Foreign capital began to flow out of Russia. In addition, crude oil prices fell, cutting deep into the country's largest source of revenue.[45] To make matters worse, Russia's decision to invade Ukraine in mid-2014 resulted in a series of economic sanctions on the country by the United States and its allies. According to Russian Prime Minister Dmitry Medvedev, Western sanctions had cost the country $26.7 billion in 2014. Those factors have resulted in a steep drop in the country's GDP, rising inflation, and a sharply lower currency valuation that spiraled out of control.[46] The main channel through which lower oil prices could affect Brazilian GDP was likely to be investment, rather than purely the terms of trade, as is the case for net oil exporting countries like Russia, because Brazil is still a net oil importer. Total investment has thus declined by 6 percent on average since early 2014, partly due to developments at Petrobras, the public oil producer, which accounts for 10 percent of total Brazilian investment and almost 2 percent of GDP. The company had to cut investment by 33 percent in both 2014 and 2015 to adjust to lower oil prices and also in response to a widespread corruption case, triggering confidence effects throughout the economy. The direct and indirect effects of the decline in investment by Petrobras have been estimated by Brazil's Ministry of Finance to have subtracted around 2 percentage points from GDP growth in

[43] A *subprime* mortgage is a type of mortgage that is normally issued by a lending institution to borrowers with low credit ratings. As a result of the borrower's lower credit rating, a conventional mortgage is not offered because the lender views the borrower as having a larger-than-average risk of defaulting on the loan. Lending institutions often charge interest on subprime mortgages at a rate that is higher than a conventional mortgage in order to compensate themselves for carrying more risk.
[44] Encouraged by the U.S. Federal Reserve's low interest rates, Russia's debt had increased from $325 to $502 billon between 2007 and mid-2014.
[45] Oil prices fell 7.5 percent in 2014 (9.9 in real terms), while non-fuel commodity prices fell 4.0 percent in 2014 (6.4 in real terms), according to IMF figures.
[46] In 2014, the ruble devalued 41 percent against the US dollar and 34 per cent against the euro.

2015. The economic recession was also coupled with a political crisis in Brazil that has resulted in the impeachment of president Dilma Rousseff and widespread dissatisfaction with the current political system.

Uruguay has benefitted a great deal from stabilization in the Region,[47] and it has suffered from recession in its MERCOSUR partners as well. In effect, during the 1990s the Uruguayan economy grew first with the introudciton of the Austral and Real Plans and later with the introduction of the Convertibility Plan. By the same, difficulties in Argentina and/or Brazil had negative effects on the economy of Uruguay, although the latter country has tried to change its trade linkages. While Argentina had been Uruguay's second largest export destination and its largest source of imports, following the collapse of the Convertibility Plan and Uruguay's own crisis its exports to Argentina dropped by 10 percent between 2001 and 2002. Likewise, at the beginning of the period under consideration the Region accounted for around 40 percent of Uruguayan exports (including Brazil at 22 percent and Argentina at 15 percent), while China's share was only 5 percent. Both Brazil and Argentina, however, gradually lost ground to China, which by 2016 had become Uruguay's main trade partner at 21 percent of exports, compared to 17 percent for Brazil and 6 percent for Argentina.

In sum, it has been possible to identify five events of frictions, stresses and strains in the financial markets, representing around 18 percent of the full sample considered (1998Q3-2016Q2). Those episodes could be captured mainly by increases in spreads, falls in the number of new loans and higher uncertainty both locally and from Argentina.

The results obtained so far point to the existence of a link between the macroeconomy and the financial sector in Uruguay that can be characterized by a nonlinear relationship. The nonlinearities in our model come from the fact that the long-run mean and variance of the process are state-dependent. However, all regimes share the same autoregressive parameters.

Financial shocks may affect the behavior of the variables considered: financial index (*F*), investment growth rate (*I*), nominal interest rate (*r*), and inflation rate (*P*). This presumption is confirmed, except for *P*, by a likelihood ratio test of the null hypothesis that $\nu_{j0} = \nu_{j1}$, where j = F, I, r, P. The results are presented in Table 7.

[47] The so-called "Region" is composed of: Argentina and Brazil; recently China has also been included.

Table 7. LR Test for Shifts in the Intercept H$_0$: $\boldsymbol{\nu_{j0} = \nu_{j1}}$

	MSIH(2)-VAR(1)
F	$\chi^2(1) = 3.16993$ [0.0750]
I	$\chi^2(1) = 3.18198$ [0.0745]
r	$\chi^2(2) = 11.4085$ [0.0007]
P	$\chi^2(2) = 2.5787e-005$ [0.9959]

[...] Marginal *p* value

Therefore, I shall expect that all the variables but core inflation are significantly affected in their long-run mean by regime shifts (recall Table 4.II). That is, during normal times, average investment growth rate is positive and monetary policy is more contractive. During financial rough times, investment growth falls and monetary policy is more expansive, reducing interest rates. But there is no significant difference in core inflation.

Although the autoregressive coefficients are regime-invariant in the MSIH(2)-VAR(1), the long-run means are different as well as the variance-covariance matrices, so the VAR matrices are regime-dependent and the impulse response functions[48] become regime-dependent as well. During turbulent times, financial shocks are less volatile (2.54 compared to 4.60 in normal times) and are negatively correlated with investment growth and call rate while those correlations change sign when the economy sails through quiet waters, as shown in Table 8. This different behavior between the variables depending on the regime translates into different patterns of transmission of financial shocks.

[48] An impulse response function (IRF) reproduces the impact of any variable on others in the system. It is sensitive to variable ordening and it omitting important variables may lead to major distortions in IRF and make the empirical results worthless. Unlike the traditional impulse response analysis, the "generalized" impulse response analysis (Pesaran and Shin, 1997) does not require orthogonalization of shocks and is invariant to the ordering of the variables in the VAR. The orthogonalized and the generalized impulse responses coincide only in the case of the impulse responses of the shocks to the first equation in the VAR. That is the case analyzed here.

Table 8. Variance-Covariance Matrices, Depending on the Regime

Regime 0 (unrest)

	F	**I**	**r**	**P**
F	2.53950			
I	-0.18276	1.71750		
r	-0.29450	-1.1869	0.99336	
P	0.80522	-3.3775	2.64449	9.36730

Regime 1 (normal times)

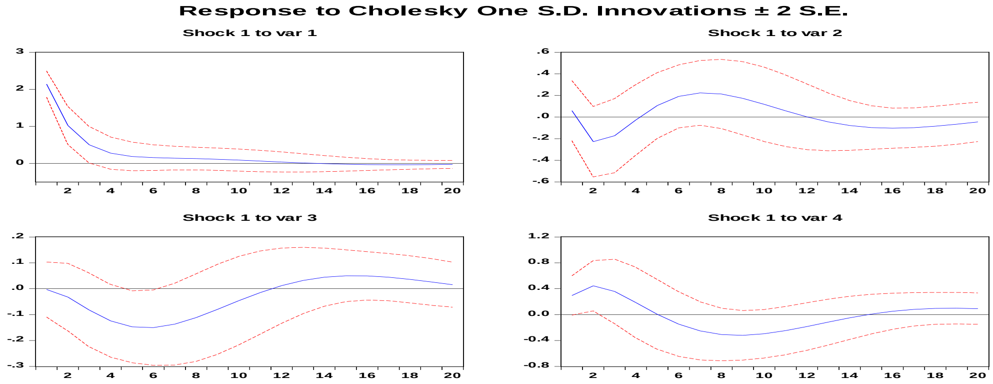
	F	**I**	**r**	**P**
F	4,5972			
I	0.26700	1.37800		
r	0,007398	0.003797	0.010183	
P	0,27926	0.046865	0.000875	0,26514

Source: Author´s calculations.

When comparing to a model with only one regime, a linear FAVAR for instance, the impulse response results are quite different. In effect, in the FAVAR model shown in Figure 8, the effect of a pure financial shock on private investment (var 2) is uncertain: an increase of one SD in *F* seems to either raise private investment by 3.5 or reduce it by 2, and that pattern is not clarified in the projection horizon. In the MSIH(2)-VAR(1) model, however, the response is conditional on the regime. During turbulent times, an unforeseen increase in financial distress reduces private investment growth by 0.4, and it remains negative for more than a year; in normal times, that same shock impulses private investment growth at the beginning, but as the financial shock becomes more and more understood, the negative effect appears. The ambiguous response seen in the FAVAR model can be unmasked in the MSHI model in accordance with the assertion that financial unrest is needed for the interconnection between the financial environment and the macroeconomy to be actually uncovered. Besides, it can be seen that the monetary policy reaction to financial shocks is quite different depending on the regime the economy is in when the shock hits it. It can be seen that, an increase of one SD in *F* reduces the call rate by 0.2 if the economy is in financial distress while it increases it by 0.04 if the economy is in normal times. That supports the observation that monetary policy has tended to be more expansive during financial unrest.

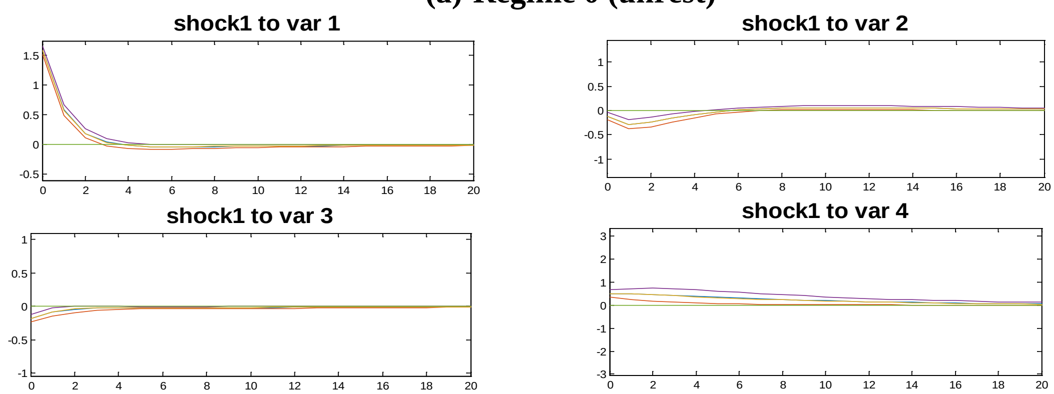
Figure 8. Impulse Response Functions

8.1 Only one regime (Linear FAVAR)

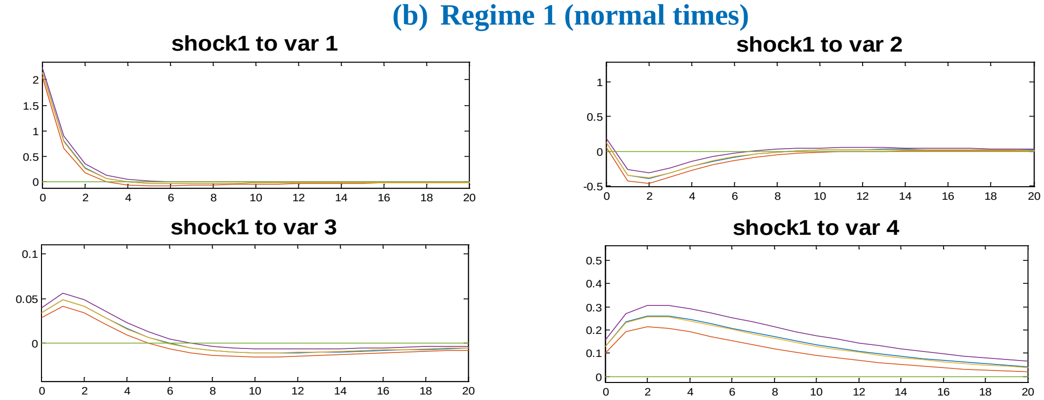


8.2 Markov switching regimes[49]

(a) Regime 0 (unrest)



(b) Regime 1 (normal times)



[49] I am grateful to P. Zagaglia (2011) for sharing his code and to S. Frache for his help in adaptating it to this investigation.

3.3 Accountability

So far, this model has given some answers. First, there are periods of financial turbulence that appear randomly in the middle of normal times. Second, the kind of regime switching that better describes the data is the one that combines differences in long-run average growth rates (switching mean) together with differences in the economic environment (switching variance); third, regime switching appears in more than one equation of the VAR, revealing different responses to the financial stress depending on the regime.

4. Conclusions

This paper considers the effects of financial stress on the macroeconomy with the underlying idea that financial shocks affect the macroeconomy differently during "normal times" than during "stress." The evidence supports the hypothesis that stress events are episodic in nature, their exact occurrence is unknown beforehand and they have a non-negligible probability of appareance. This behavior is captured in a multivariate framework through a Markov-switching vector autoregressive (MS-VAR) model.

The comovements of a wide range of financial variables were summarized in one factor as a measure of financial instability. More precisely, F was calculated as an indicator of frictions, stresses and strains that occur in the financial system as a whole.

There is evidence that a single-regime model is inadequate to describe the dynamics of the Uruguayan economy during the period of 1998Q3-2016Q2: there seem to be shifts in the stochastic shocks and the switching appears in all equations but those in price formation. Most of the sample corresponds to normal times, but around 17.65 percent of the sample corresponds to stress episodes, specifically in 2001Q3-2002Q4, 2003Q3-2003Q4, 2008Q4 and possibly in 1999Q3-Q4 and 2014Q4, with almost three quarters of average duration. During the "bad" regime (R_0), together with financial stress a negative pattern can be observed in the rest of the variables: a great swing in private investment and less stringent monetary policy.[50] During the

[50]Also, according to sensitivity analysis done, a great swing in private consumption and higher unemployment is found during stress. Then, in normal times, private consumption stabilizes and unemployment falls. However, recovery from the crisis began before the actual crises ended. As a result, the long-run mean growth rate of consumption is higher during the "bad" regime than during the "good" one. In effect, efforts to overcome the 2001-2003 crisis began in the middle of it and by 2003Q2 the consumption growth rate had just offset the previous fall and all subsequent positive growth led to a positive average consumption growth rate for the 2001Q3-2003Q4 period.

"good" regime (R_1), however, the financial sector moves smoothly, private investment stabilizes and monetary policy tightens.

Both situations (or states) seem to be quite persistent, for once the economy is there the probability to remain in the same state is high. For instance, if there was financial turbulence in the current period there is a 61 percent probability of financial stress in next period, and if the present period was a normal one, the probability of remaining in tranquility is 92 percent. During the bad regime, all shocks have larger variance than in the normal regime but the (pure) financial one. Besides, there is evidence of changes in the magnitude of the covariances among the variables.[51] That is to say, during a stressful period, financial shocks have a negative mean and are more concentrated and are negatively linked to the other variables in the system. As a result, there are different patterns for the transmission of financial shocks. In effect, during financial stress, a pure financial shock reduces investment growth rate for four months while its effect is positive and almost unnoticeable during normal times. So far, the evidence supports the idea pointed out by Hubrich and Tetlow (2014) that financial unrest is necessary to reveal the linkages between the financial world and the macroeconomy.

Financial stress seems to have some effects on the Uruguayan macroeconomy. Monetary policy is directly affected by financial conditions and becomes more contractionary; besides, the policy rate reacts more aggressively in the presence of financial stress than during normal times. Although stress events do not seem to have a significant impact on inflation rates, both private investment and private consumption (not reported here) react as expected. As a result, the evidence points out that macroeconomic stability seems to improve wellbeing.

The results achieved so far are exciting and promising, but they should be taken with caution. In particular, we believe that this line of research may be improved by incorporating a wider group of financial variables into the data set—such as variables related to the banking industry—in order to design a better measure of financial instability. But trying to expand the time period does not seem to be an easy task. Next, the availability of lower frequency macroeconomic data (monthly to begin with) would allow a more realistic analysis of the dynamic relationships between the financial conditions and the macroeconomy. Then, the model could include parameters affected by different regimes which could allow for a changing

[51] Sensitivity analysis show that the covariance between financial stress and consumption is almost inexistent (-0.0042) during tranquility while it jumps to almost 500 times during financial stress (-2.0131).

response pattern depending on the state in order to investigate whether there are shifts in the dynamic propagation of shocks. And last but not least, the use of Bayesian methods would be recommended in order to mitigate the small sample limitations we have encountered.

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Annex 1. Data

Mnemonics	Description	Source	log	dif	Seas
i_a_agro_30	Nominal interest rate offered to agro firms up to 30 days in UY pesos	Banco Central del Uruguay	N	N	N
i_a_com_30	Nominal interest rate offered to commercial firms up to 30 days in UY pesos	Banco Central del Uruguay	N	N	N
i_a_ind_30	Nominal interest rate offered to industrial firms up to 30 days in UY pesos	Banco Central del Uruguay	N	N	N
i_a_agro_30m	Nominal interest rate offered to agro firms for more than 30 days in UY pesos	Banco Central del Uruguay	N	N	N
i_a_com_30m	Nominal interest rate offered to commercial firms for more than 30 days in UY pesos	Banco Central del Uruguay	N	N	N
i_a_ind_30m	Nominal interest rate offered to industrial firms for more than 30 days in UY pesos	Banco Central del Uruguay	N	N	N
itlup	30-days Uruguayan T- bills	Banco Central del Uruguay	N	N	N
10T	10-year US Treasury Bills rate	FRED	N	N	N
FFR	Federal Funds rate	FRED	N	N	N
n_a_agro	Number of loans in UY pesos to agro firms	Banco Central del Uruguay	N	N	N
n_a_com	Number of loans in UY pesos to commercial firms	Banco Central del Uruguay	N	N	N
n_a_ind	Number of loans in UY pesos to industrial firms	Banco Central del Uruguay	N	N	N
n_a_30m	Number of loans (more than 30 days) in UY pesos to firms	Banco Central del Uruguay	N	N	N
n_a_30	Number of loans (less than 30 days) in UY pesos to firms	Banco Central del Uruguay	N	N	N
n_f_30m	Number of loans (more than 30 days) in UY pesos to families	Banco Central del Uruguay	N	N	N
n_f_30	Number of loans (less than 30 days) in UY pesos to families	Banco Central del Uruguay	N	N	N
n_a_d_agro	Number of loans in US dollars to agro firms	Banco Central del Uruguay	N	N	N
n_a_d_com	Number of loans in US dollars to commercial firms	Banco Central del Uruguay	N	N	N
n_a_d_ind	Number of loans in US dollars to industrial firms	Banco Central del Uruguay	N	N	N
n_a_d_30	Number of loans (less than 30 days) in US dollars to firms	Banco Central del Uruguay	N	N	N
n_a_d_30m	Number of loans (more than 30 days) in US dollars to firms	Banco Central del Uruguay	N	N	N

Mnemonics	Description	Source	log	dif	Seas
n_f_d_30m	Number of loans (more than 30 days) in US dollars to families	Banco Central del Uruguay	N	N	N
n_f_d_cd	Number of loans in US dollars to families on credit card usage	Banco Central del Uruguay	N	N	N
mor_d_pdo	Change in overdue accounts in US dollars, private sector with banking system	Author´s own calculations on Banco Central del Uruguay data	N	Y	N
PWheat	Commodity Price of wheat in US dollars; deflated by US CPI and deseasonalized	International Monetary Fund	Y	Y	Y
PSoybean	Commodity Price of soybean in US dollars; deflated by US CPI and deseasonalized	International Monetary Fund	Y	Y	Y
PFood	Commodity Price of food in US dollars; deflated by US CPI and deseasonalized	The World Bank	Y	Y	Y
POil	Commodity Price of oil in US dollars; deflated by US CPI and deseasonalized	International Monetary Fund	Y	Y	Y
EMBI_URU	Uruguayan country risk indicator	República AFAP	N	N,Y	N
D_TCN	Nominal depreciation	Author`s own calculation on Banco Central del Uruguay data	Y	Y	Y
D_2_TCN	Nominal volatility	Author`s own calculation on Banco Central del Uruguay data	Y	Y	Y
D_TCR	Real effective depreciation	Author`s own calculation on Banco Central del Uruguay data	Y	Y	Y
VIX	Chicago Board Options Exchange index volatility	FRED			
res_to_gdp_ar	Total reserves (excluding gold) to GDP ratio, for Argentina	FRED	N	N	N
cr_to_gdp_ar	Total credit (to non financial sector) to GDP ratio, for Argentina	FRED	N	N	N
i	1-day interbank nominal interest rate	Banco Central del Uruguay	N	N	N
C	Private consumption	Banco Central del Uruguay	Y	Y	Y
μ	Unemployment rate	Instituto Nacional de Estadística	N	Y	Y
P	Core inflation	Banco Central del Uruguay	Y	Y	Y
gdp	Uruguayan Gross domestic product	Banco Central del Uruguay	Y	Y	Y
P	Uruguayan Gross domestic product deflactor	Banco Central del Uruguay	Y	Y	Y

Annex 2. Recent Monetary Policy Regimes in Uruguay

Monetary regime	***Date***	***Operative Target***	***Inter-mediate Target***	***Final Target***	***Exchange rate Inter-vention***	***Reserves require-ments***
Endogenous	1991- June 2002	Exchange rate bands	Deprecia tion Expecta tions	Inflation	Yes	Yes
Monetary aggregates control	July 2002- August 2007	Monetary base	M1	Inflation	Yes	Yes
Inflation target	Sept 2007-June 2013	Interest rate	Inflation Expecta tions	Inflation	Yes	Yes
Inflation target with monetary aggregates control	July 2013- today	M1 prime (cash in the hands of the public, demand deposits and current account deposits)	Inflation Expecta tions	Inflation	Yes	Yes

Source: Author's compilation

Annex 3. Previous Related Literature on This Topic

Bernanke and Blinder (1988) developed several models of aggregate demand which allow roles for both money and "credit" (bank loans). They found that money-demand shocks became relatively more important than credit-demand shocks in the 1980s in the US and thought that it was perfectly conceivable that the relative sizes of money-demand and credit-demand shocks would revert once again to what they were earlier.

Kashyap, Stein and Wilcox (1993) pointed out that monetary policy affected the economy through a lending channel because shifts in monetary policy seemed to alter the mix of loans and commercial paper, and the induced shifts in this mix seemed to affect investment (even controlling for interest rates).

In an extensive survey, Kashyap and Stein (1994) analyzed the work done so far related to the "lending" view of the monetary policy transmission and outlined the microeconomic conditions needed to generate a lending channel. In particular, they asserted that open-market operations affected the supply of bank loans and that these loan supply shifts affected both the magnitude of supply output and its composition. The key issue that guaranteed this mechanism was the imperfect subsititutability of bank loans and publicly issued bonds, both as corporate liabilities and bank assets. They concluded that, despite the strong evidence found in favor of the existence of a lending channel, its exact impact across different sectors remained uncertain.

Hubbard (1998) reviewed developments and challenges in the role of financial constraints in determining investment and his findings suggested the significance of capital-market imperfections for firm decisions. He concluded that more research was needed to understand the source of the capital-market imperfections that affected firm decisions.

In that respect, Bernanke, Gertler and Gilchrist (1998) developed a dynamic general equilibrium model trying to clarify the role of credit market frictions in business fluctuations, both from a qualitative and quantitative standpoint. This pioneering model introduced the concept of the "financial accelerator"—the fact that endogenous developments in credit markets amplify and propagate shocks to the macroeconomy—and incorporated both money and price stickiness and heterogeneity among firms.

Although there has been some research on the monetary transmission mechanisms for Uruguay, such as Chiesa, Garda and Zerbino (2004), Ferreira (2007), Capurro et al. (2010) and Borraz and Gianelli (2010) who looked at the inflation expectation channel, there are only a few studies that have taken into account the link between the financial world and the real one. I can cite Licandro and Mello (2012) and Bucacos (2015) in that respect.

Licandro and Mello (2012) observe the credit channel within the banking system for the period 2007.01-2012.06. They distinguish between credit in domestic and foreign currency, finding evidence of a financial accelerator and a nonlinear relationship between external financial premium (EFP) and the monetary policy rate. During "normal" times, they find that the EFP works as a financial accelerator just as in the case of nondollarized economies. This financial accelerator operates both in domestic and foreign currency-denominated credit, though it is stronger in the former. During "crisis" periods the balance sheet channel works like a financial break. Overall, they conclude that this transmission channel seems to play a larger role than previously believed.

Chiesa, Garda and Zerbino (2004) use VAR models for the 1983-2004 period to analyze the effects of non-anticipated interest rate shocks on aggregate variables. They find that an interest rate shock impacts on the level of economic activity but has no effect on inflation.

Ferreira (2007) studies a different time period—1998-2007—and points out that the best monetary policy indicator is the nominal exchange rate (1998-2002, while the exchange rate bands were used) and then she argues that the one-day (overnight) interest rate has been the best monetary policy indicator since 2002 (when money aggegates were used). She finds a traditional interest rate channel of monetary policy to both activity and prices for the whole period.

Capurro et al. (2010) focus on the 1998-2009 period and show the existence of an interest rate pass-through from the policy interest rate to several bank rates, both passive and active ones. They also found long-run relationships in pairs between the call rate and each bank interest rate pointing to the existence of underlying common tendencies in the long run between them. Specifically, the average active interest bank rate in UY pesos not only has the more stable correlation with the call rate but also has a pass-through of "one" indicating a complete transfer from the monetary policy to that bank interest rate. In addition, they find a relatively rapid adjustment for any deviation from that long-run equilibrium relationship: it adjusts 24 percent the following month, and the total disalignment is absorbed in 20 months. These results are robust to more than one monetary regime, encompassing the exchange rate bands of 1998-2002, the money aggregates of 2002-2007 and the short-run interest rate of 2007-2009. Besides, Capurro at al. (2010) tried to incorporate dollarization explicitly into their analysis, introducing real exchange rate as a dependent variable in the estimated SVAR and SVEC models. They found that an expansive monetary shock creates a short-run rise in both GDP and inflation and a fall in RER.

Bucacos (2015) analyzes the vulnerability of the Uruguayan economy to changes in US monetary policy by describing its linkages with other relevant variables in the last twenty years. When trying to unveil the channels through which those shocks finally affect relevant Uruguayan variables, a Factor-Augmented Vector Autoregressive (FAVAR) model was implemented for the first time on a quarterly balanced Uruguayan data sets that span from 1996Q2 to 2014Q4. In the first stage, the impact of foreign monetary policy was assessed on commodity prices (calculated by factor analysis techniques), foreign output, and regional output. In the second, the effects on real exchange rate, domestic assets (as housing prices) and on domestic output were analyzed. The outcome of IRFs suggest that Uruguay, a small open dollarized economy with a relatively less sophisticated assets market, seemed to be reachable.