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Dynamical macroprudential stress testing using network theory

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ABSTRACT

The increasing frequency and scope of financial crises have made global financial stability one of the major concerns of economic policy and decision makers. This has led to the understanding that financial and banking supervision has to be thought of as a systemic task, focusing on the interdependent relations among the institutions. Using network theory, we develop a dynamic model that uses a bipartite network of banks and their assets to analyze the system's sensitivity to external shocks in individual asset classes and to evaluate the presence of features underlying the system that could lead to contagion. As a case study, we apply the model to stress test the Venezuelan banking system from 1998 to 2013. The introduced model was able to capture monthly changes in the structure of the system and the sensitivity of bank portfolios to different external shock scenarios and to identify systemic vulnerabilities and their time evolution. The model provides new tools for policy makers and supervision agencies to use for macroprudential dynamical stress testing.

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1. Introduction

As the banking system of the world has become ever more complex and technological, there has been the need for more advanced supervision of the banking system as well. The financial crisis of 2007–09 made it more clear than ever before that the financial system is a complicated network and needs to be modeled as such by regulators. Most regulation standards still focus on microprudential factors, and although many advances have been made in modeling and stress testing bank networks. we are still far from a unified framework to confidently monitor systemic risk.

So far, most network-based models have focused on bank-to-bank networks, generally linking either via correlated exposures or direct interbank obligations. Such models can be useful when stress testing using individual bank failures as a starting point. However, financial crises often begin with toxic assets, as we saw with real estate-based assets in the 2007–09 financial crisis. A valuable tool to model such crises is a bipartite bank-asset network with banks and assets as elements of the system. We present such a tool and show how it may be used to monitor the whole system's sensitivity to shocks in various asset prices, as well as which banks are most likely to fail.

1.1. Basel regulation

The Bank of International Settlements (BIS) is a multilateral agency that has paid attention to financial crises since the 1980s. Guidelines on regulation and financial supervision have emerged out of BIS research (http://www.bis.org/forum/research.htm). Although BIS guidelines are not mandatory, the technical prestige and respectability of the institution attracts voluntary compliance.

In 1988 the Basel Committee on Banking Supervision, BCBS, posted the Basel Capital Accord (International Convergence of Capital Measurement and Capital Standards), better known as Basel I, which proposed banks should keep a minimum amount

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of equity, equivalent to 8 percent of their risk-weighted assets (Basel Committee on Banking Supervision (BCBS), 1998) in order to maintain global financial stability and a solid and adequately capitalized system.

In 2004, the BCBS published the New Capital Adequacy Framework, known as Basel II. While Basel I considered market and credit risks, Basel II substantially changed the treatment of credit risk and also required that banks should have enough capital to cover operational risks. Basel II also demanded greater transparency of information about credit risk and increased the documentation required to debtors, as well as diversification of balance through insurance activities (Basel Committee on Banking Supervision (BCBS), 2006).

In 2008, the BCBS introduced Basel III. Basel III introduces more stringent regulations to address liquidity risk and systemic risk, raises loan underwriting standards, and emphasizes the need for appropriate handling or removal of spaces with conflict of interest (Ito, 2011). Basel III also instituted some macroprudential measures to ensure banking operation even in times of systemic problems. During the 2010 G-20 Summit in Seoul, South Korea, Basel III standards were established to create greater banking stability through better microprudential supervision. Those standards will be implemented over the next decade.

However, Basel III is complex and opaque, a problem that should be addressed. Haldane and Madouros (2012) raised the general question of well-intentioned reforms, the tension between them, and transparency in simplicity, stating "Because complexity generates uncertainty, not risk, it requires a regulatory response grounded in simplicity, not complexity."

A key element of Basel III is addressing the financial system as a whole and not just focusing on the strength of individual institutions. The aim of macroprudential policy is systemic financial stability, which can be defined as exogenous (robustness to external shocks) or endogenous (resilience to endogenous shocks). In other words, the goal of Basel III macroprudential measures is to better deal with financial systemic risk. Addressing this issue has resulted in a growing interest in the application of network theory in finance and economics, because it has the ability to reduce the financial system to a set of nodes and relationships, deriving from them the systemic underlying structure and the complexities that arise from it.

1.2. Network science and its applications in finance and economics

Despite all the reforms and progress made, systemic monitoring standards continue to be rooted in microprudential supervision, focused on the strength of units of the system. This weakness remains a crucial issue that must be seriously addressed (Greenwood et al., 2012). Greater understanding of the externalities of economic and financial networks could help to design and adopt a framework of prudential financial supervision that considers the actors of the system (financial institutions) and the vulnerabilities that emerge from their interdependence in network. Such a framework would improve investment and corporate governance decisions and help prevent crises or minimize their negative impacts. Network modeling framework provides a systemic perspective with less complexity.

Network science has evolved significantly in the 21st century, and is currently a leading scientific field in the description of complex systems, which affects every aspect of our daily life (Newman, 2009; Jackson, 2010; Boccaletti et al., 2006; Cohen and Havlin, 2010; Havlin et al., 2012; May, 2013). Network theory provides the means to model the functional structure of different spheres of interest and understand more accurately the functioning of the network of relationships between the actors of the system, its dynamics, and the scope or degree of influence. In addition, network theory measures systemic qualities, e.g., the robustness of the system to specific scenarios or the impact of policy on system actions. The advantage offered by the network science approach is that, instead of assuming the behavior of the agents of the system, it rises empirically from the relationships they really hold. The resulting structures are not biased by theoretical perspectives or normative approaches imposed "by the eye of the researcher".

Modeling by network theory could validate behavioral assumptions of other economic theories, such as the relevance of diversity compared to traditional theory of diversification (Haldane and May, 2011a). Network theory can be of interest to various segments of the financial world: the description of systemic structure, analysis and evaluation of contagion effects, resilience of the financial system, flow of information, and the study of different policy and regulation scenarios, to name a few (Lillo, 2010; Summer, 2013; Tumminello et al., 2010; Kenett et al., 2010, 2012; Cont, 2013; Glasserman and Young, 2015; Li et al., 2014; Garas et al., 2010; Haldane and May, 2011b; Haldane, 2009; Cont et al., 2010; Amini et al., 2012; Chan-Lau et al., 2009; Majdandzic et al., 2014).

The interbank payment system can be seen as an example of a complex network, and thus, considered as a network, from which one can derive information on the system's stability, efficiency and resilience features (see for example Hüser, 2015). Analytical frameworks for the study of these structures are varied, and range from the identification of the type and properties of the network to the analysis of impact of simulated shocks, in order to quantify inherent risks and design policy proposals to mitigate them. For example, once the payment system can be mapped as a network, such as the recently introduced funding map (Aguiar et al., 2014), then the structure of the network can be used as input for models that simulate the dynamics of the system (Bookstaber et al., 2014b).

Recent studies by Inaoka et al. (2004), Soramäki et al. (2007), Cepeda (2008), Galbiati and Soramäki (2012), investigated the interbank payment system using network science. Considering the system as a network allows the design of scenarios and the visualization of specific effects, and these authors were able to uncover the structure of the system. Iori et al. (2008) analyzed the overnight money market. The authors developed networks with daily debt transactions and loans with the purpose of evaluating the topological transformation of the Italian system and its implications on systemic stability and efficiency of the interbank market.

The structure of interbank exposure networks also has been investigated (Boss et al., 2004, 2006; Elsinger, 2009). In an interbank exposure network, the nodes are banks. If banks have a debt exposure to another bank, there is a link between them. If information on the size of the exposure is included, these links can also be weighted by the value of the liabilities.

Considering the problem of contagion, Allen and Gale (1998) study how shocks can spread in the banking system when it is structured in the form of a network. Drehmann and Tarashev (2013) develop a measure that captures the importance of an institution in term of its systemic relevance in the propagation of a shock in the banking system.

Bearing in mind the size of the banks, the diversification and the concentration in the financial system, Arinaminpathy et al. (2012) develop a model combining three channels of transmission of contagion (liquidity hoarding, asset price and counterparty credit risk), adding a mechanism to capture changes in confidence contributing to instabilities. More recently, Acemoglu et al. (2013c,b,a) develop a model of a financial network through its liability structure (interbank loans) and conclude that complete networks guarantee efficiency and stability, but when negative shocks are larger than a certain threshold, contagion prevails, as does the systemic instability. The critical issue remains identifying such a threshold, and calibrating such models with real data. In this work, we will present a dynamic network based model to stress test a banking system, using publicly available information.

1.3. Bipartite bank-asset networks

Bipartite network models, in which the nodes of the network are banks and asset classes, can be used to model asset price contagion. Models such as those in Caccioli et al. (2012) and Chen et al. (2014) have been able to show the importance of effects such as diversification and bank leverage on the sensitivity of the system to shocks.

Recently, Huang et al. (2013) presented a model that focuses on real estate assets to examine banking network dependencies on real estate markets. The model captures the effect of the 2008 real estate market failure on the U.S. banking network. The model proposes a cascading failure algorithm to describe the risk propagation process during crises. This methodology was empirically tested with balance sheet data from U.S. commercial banks for the year 2007, and model predictions are compared with the actual failed banks in the United States after 2007, as reported by the Federal Deposit Insurance Corporation (FDIC). The model identifies a significant portion of the actual failed banks, and the results suggest that this methodology could be useful for systemic risk stress testing of financial systems.

There are two main channels of risk contagion in the banking system: (1) direct interbank liability linkages between financial institutions, and (2) contagion via changes in bank asset values. The former, which has been given extensive empirical and theoretical study (Wells, 2002; Furfine, 2003; Upper and Worms, 2004; Elsinger et al., 2006; Nier et al., 2007), focuses on the dynamics of loss propagation via the complex network of direct counterparty exposures following an initial default. However, data on the exact nature of these obligations are generally not publicly available. The most common practice is to take known data about given banks' total obligations to other banks and any other available data and use that information as a constraint on the possible structure of the complete network of obligations and then make an estimation assuming maximum entropy. This procedure results in an obligation network where all unknown obligations contribute equally to the known total obligations for each bank (Elsinger et al., 2006). Though the magnitude of the systematic error is not entirely clear because of this lack of data, consensus seems to be that the maximum entropy estimation underestimates contagion (Summer, 2013). Our network model avoids the need for this data by replacing the interbank network of obligations with a bipartite network of banks and assets. Though it may be seen as a limitation of the model that the direct network of obligations is not incorporated into the model, the benefit is that the model requires only more readily available balance sheet data and makes no assumptions about interbank obligations. More, most studies agree that contagion caused through interbank exposures is rare (Summer, 2013).

Studies of risk contagion using changes in bank asset values have received less attention. A financial shock that contributes to the bankruptcy of a bank in a complex network will cause the bank to sell its assets. If the financial market's ability to absorb these sales is less than perfect, the market prices of the assets that the bankrupted bank sells will decrease. Other banks that own similar assets could also fail because of loss in asset value and increased inability to meet liability obligations. This imposes further downward pressure on asset values and contributes to further asset devaluation in the market. Damage in the banking network continues to spread, and the result is a cascading of risk propagation throughout the system (Cifuentes et al., 2005; Tsatskis, 2012).

Using this coupled bank-asset network model, it is possible to test the influence of each particular asset or group of assets on the overall financial system. This model has been shown to provide critical information that can determine which banks are vulnerable to failure and offer policy suggestions, such as requiring mandatory reduction in exposure to a shocked asset or closely monitoring the exposed bank to prevent failure. The model shows that sharp transitions can occur in the coupled bank-asset system and that the network can switch between two distinct regions, stable and unstable, which means that the banking system can either survive and be healthy or collapse. Because it is important that policy makers keep the world economic system stable, we suggest that our model for systemic risk propagation might also be applicable to other complex financial systems, such as, for example, modeling how sovereign debt value deterioration affects the global banking system or how the depreciation or appreciation of certain currencies affect the world economy.

In this paper we present a dynamic version of the model in Huang et al. (2013). The model begins by collecting bank asset value data from balance sheets. All bank assets are grouped into some number of asset classes, so we have total value in the system for each bank and each asset. We begin by shocking an asset class which reduces the value of that asset on each bank's balance sheet. This reduces the total asset value of the bank. If that reduced value causes the insolvency of some number of banks, it triggers a fire sale of assets, which reduces the value of the assets being sold. This may once again trigger further insolvencies, and so on.

We study the banking system of Venezuela from 2005 to 2013 as a case study of the applicability of the model. Although in Huang et al. (2013), the model was applied using just the data from one moment at the end of 2007 and used to predict failures, our analysis is applied to over eight years of monthly data. We run stress tests on each data set over a range of parameters and can track how the system's sensitivity to these parameters changes on monthly basis. The dynamical bank-asset bipartite network model (DBNM-BA) provides a first tool of "Risk Management Version 3.0" (Bookstaber et al., 2014b), which allows one to rate the risk of different assets alongside the stability of financial institutions in a dynamical fashion.

We will first introduce the Venezuelan financial system (Section 2) and then the DBNM-BA in Section 3. In Section 4, we will apply the DBNM-BA to the Venezuelan financial system and demonstrate the capabilities of the model to monitor and track financial stability. Finally, in Section 5, we will discuss the implications and applications of the presented model and its potential as a new financial stability tool for policy and decision makers.

2. A case study: Venezuela

In this work, we use network theory to uncover the structural features of the Venezuela financial system. Venezuela is a medium-sized economy that during the past 15 years has had important regulatory changes to its banking system. Because most financial network analysis relies on large financial systems with many connections, focusing on Venezuela provides the means to demonstrate the relevance of these models for financial systems of all size. Venezuela showed economic growth until 1978, at which point its economy began a continuous phase of decline. However, it is worth noting that measures of the country's banking activity continued along a positive trend until 1982 (Levy-Carciente, 2006). An overview of the economy of Venezuela can be found in Appendix A.

We use of statistical information from the Superintendence of the Institutions of the Banking Sector, or SUDEBAN (http://www.sudeban.gob.ve/), its monthly statistics, publication,

Table 1
Asset and bank types.

Asset types	Bank types
Cash & Cash equivalents	Commercial banking
Credit	Universal banking
Commercial credit	Investment banking
Vehicle credit	Savings and loan institutions
Credit cards	Mortgage banking
Mortgage loans	Leasing institutions
Microcredit	Money market funds
Agriculture credit	Micro-finance banking
Tourism credit	Development banking
Manufacturing credit	
Securities	
Private securities	
Treasury notes	
Treasury bonds	
Public national debt	
BCV bonds	
(Central Bank of Venezuela bonds)	
Agriculture bonds	

newsletters and press releases, as well as its annual reports. The information is presented in national currency units, Bolivars, after the conversion process of 2008. Using the SUDEBAN information, we built bipartite networks for each month of the 16 years under study. We identified the banking subsectors in each period (commercial banking, universal banking, investment, savings and loan, mortgage, leasing, money market funds, microfinance and development banking) and based their systemic weight on asset levels. From the balance sheet of each bank we have identified the assets items (cash and equivalents, credit portfolio and securities), breaking each down to consider its systemic relevance. Later, we focus in detail on the loan portfolio by credit destination, namely: consumption (credit cards, vehicles), commercial, agricultural, micro-entrepreneurs, mortgage, tourism, and manufacturing. From that we derived the impact of the legal transformations in the credit portfolio composition.

For the period of 2005–2013, we also analyzed the securities held by the different banks, specified as: private securities, treasury bonds, treasury notes, bonds and obligations of the public national debt, bonds and obligations issued by the Central Bank of Venezuela (BCV) and agricultural bonds. The analysis was done with the interest of specifying the kinds of assets that warrant the intermediation's activity in the country. The credit and investment portfolio composition depicted the underlying structure of the system during the whole period, allowing us to show its evolution. A summary of the bank and asset types investigated in presented in Table 1, and detailed in Section A.2.

3. Dynamical Bipartite Network Model for Banks and Assets (DBNM-BA)

In bipartite networks, there are two types of nodes — in this case, banks and asset classes — and links can only exist between the two different types of nodes. So in this network, banks are linked to each type of asset that they hold on their balance sheet in a given month. Banks are never directly linked to other banks and assets are never directly to other assets.

The asset portfolios of banks contain such asset categories as commercial loans, residential mortgages, and short and long-term investments. We model banks according to how they construct their asset portfolios. For each bank, we make use of its balance sheet data to find its position on different nonoverlapping asset categories. For example, bank i owns amounts $B_{i,0}, B_{i,1}, \ldots, B_{i,N_{asset}}$ of each asset, respectively. The total asset value $B_i \equiv \sum B_{i,j}$ and total liability value L_i of a bank i are obtained from the investigated dataset. The weight of each asset m in the overall asset portfolio of a bank i is then defined as $w_{i,m} \equiv B_{i,m}/B_i$. From the perspective of the asset categories, we define the *total market value* of an asset m as $A_m \equiv \sum_i B_{i,m}$. Thus the market share of bank i in asset m is $s_{i,m} \equiv B_{i,m}/A_m$. We further define two additional parameters for the individual assets. We calculate the relative size of the asset, β, defined as:

$$\beta_m = \frac{A_m}{\sum_n A_n}, \tag{1}$$

and we define the level of concentration/distribution of a given asset, using the Herfindahl–Hirschman Index (HHI) (Rhoades, 1993). If A_m is the total value of asset class m and $B_{i,m}$ is the value of asset m on the balance sheet of bank i, then

$$\mathrm{HHI}_m = \sum_i \left(\frac{B_{i,m}}{A_m}\right)^2. \tag{2}$$

The HHI measures the degree to which a given asset class is distributed across the banks in the system. It reaches a maximum of 1 when the asset is entirely concentrated within one bank and a minimum of $1/N$ where the asset is evenly spread across all N banks in the system.

The model begins by selecting a month from which all balance sheet data is taken. For each bank, we use its balance sheet to find the value of its position in each of 16 asset classes, as well as its total liabilities. Let $B_{i,m,\tau}$ represent the value of asset m of bank i in iteration τ of the model. Initial values correspond to $\tau = 0$ so $B_{i,m,0}$ is the actual value of asset m on the balance sheet of bank i. The total asset value of bank i in iteration τ of the model is then $B_{i,\tau} \equiv \sum_m B_{i,m,\tau}$. Let $A_{m,\tau} \equiv \sum_i B_{i,m,\tau}$ be the total value of asset m across all banks in iteration τ of the model. The total liabilities of bank i, L_i, remains fixed over the iterations of the model.

Then we select one of the 16 asset classes to shock and values for $p \in [0,1]$, the fractional value of the asset class remaining after the shock, and $\alpha \in [0,1]$, the illiquidity parameter which determines the degree to which assets are devalued after the fire sales caused by bank failures. So p is an exogenous parameter to the banking system that cannot be controlled but α is an endogenous parameter related to the structure of the system.

If we begin by shocking asset class m' then the first step of the model will reduce the value of asset m' as follows,

$$A_{m',\tau=1} = pA_{m',\tau=0}. \tag{3}$$

So a value of p = 0.7, would mean that after the first step of the model, the total value of the specified asset across the system would be reduced to 70 percent of its original value, or in other words it is a 30 percent shock to the asset. A smaller p corresponds to a larger shock. Other asset nodes ($m \neq m'$) will have their values unaltered at this step in the model.

In the next step of the model, any bank that holds some of that shocked asset on its balance sheet will have that asset decreased by the same percentage. So, $B_{i,m'}$ is reduced similarly,

$$B_{i,m',1} = pB_{i,m',0} = B_{i,m',0}\frac{A_{m',1}}{A_{m',0}} \quad \forall i. \tag{4}$$

This will reduce the total value of assets of any bank i for which $B_{i,m',0} \neq 0$. If after the initial shock, $B_{i,1} > L_i$ for all banks i, then no bank has its equity reduced to zero or below and the algorithm stops. All banks survive the impact of the external shock. However, for all banks i for which $B_{i,1} \leqslant L_i$ then that bank node fails and the model continues to iterate. Any asset classes held on the balance sheet of a failed bank (i.e., that it is linked to in the network) will suffer a corresponding devaluation and the cascading failure algorithm will continue. This is where the illiquidity parameter α comes into play. If any bank fails then the total value each asset class is reduced as follows,

$$A_{m,\tau+1} = A_{m,\tau} - \alpha B_{i,m,\tau} \quad \forall m,\ i|B_{i,1} \leqslant L_i. \tag{5}$$

So if $\alpha = 0$, then the total value of an asset is not affected by the failure of a bank that owns that asset and there will be no cascading of failures. If $\alpha = 1$, then it is as if the assets of the defaulted bank have no value and the total value of those asset classes is reduced by the entire value on the defaulted bank's balance sheet. The α parameter quantifies the fire sale effect corresponding to the initial shock to a given asset. When a fire sale leads to a sharp reduction in an asset's price, similar assets held by other market participants decline in value as well, which might also bring them to financial distress and forced asset sales (see recent review by Shleifer and Vishny, 2011).

Cont and Wagalath (2013) propose a way to quantify the influence of fire sales on both prices and the risk factor distribution. Starting from assumed deleveraging schedules for banks, and assuming that in the course of deleveraging assets are sold proportionately, they show that realized correlations between returns of assets increase in bad scenarios due to deleveraging. Such an approach could be the basis of stress test procedures taking into account endogeneity of risk and feedback effects of market participants' reaction to adverse scenarios. They apply this approach to the analysis of fire sales and the quantification of their impact. Here the parameter α is introduced as a measure of illiquidity, or fire sale effect.

This reduction in the value of the asset classes will cause corresponding reduction in the values of those assets for each bank node as such,

$$B_{i,m,\tau} = B_{i,m,0}\frac{A_{m,\tau}}{A_{m,0}}. \tag{6}$$

This reduction in assets may again reduce a bank's equity to zero or below, thus triggering more bank failures, which will further devalue asset classes and so on. The process, which is visualized in Fig. 1 continues until the asset class devaluation no longer triggers any new bankruptcies. The primary observable at the end of the run is χ, the fraction of surviving banks. For a more technical description of the algorithm, see Appendix E.

As an example, let's assume a shock of $p = 0.7$ to credit cards, that reduces 30 percent of their value causes one bank, Bank A, to have its equity reduced below zero. Let's also assume that Bank A only has commercial credit, mortgage loans, Treasury notes and public national debt, in addition to credit cards, on its balance sheet. These asset classes will be reduced in value by α times the value of each of these asset classes on Bank A's balance sheet. So if $\alpha = 0.1$, then the total value of each of these five asset classes would be reduced by 10 percent of the respective values on Bank A's balance sheet. If more than one bank were to fail, then the reduction of each total asset class would be 10 percent of the sum of the respective assets on all the failed banks' balance sheets.

We observed the behavior of the model for various values of the parameters α and p, across all months and while separately performing the initial shock on each of the 16 asset classes. In addition to observing χ as an output of the model, noting that in most runs we see either most of the banks surviving or fewer than 20 percent surviving, we therefore set a critical threshold of $\chi = 0.2$ and for fixed α or p, found the corresponding p_{crit} or α_{crit} (varying each in 0.01 increments) that resulted in a χ just below the 0.2 threshold for initial shocks to each of asset classes. We performed this analysis for each month of data and observed the changes in α_{crit} and p_{crit} over time. The importance of these parameters is that they are intrinsically related to the asset distribution in the network structure of the system, given a surviving threshold. In the DBNM-BA, we focus on the month-by-month evolution of the critical parameters, p_{crit} and α_{crit}. Following the definitions above, the two parameters can be defined as following:

$$p_{crit}(\alpha) = p|(\chi(p,\alpha) \leqslant 0.20\ \&\ \chi(p+0.01,\alpha) > 0.20), \tag{7}$$

$$\alpha_{crit}(p) = \alpha|(\chi(p,\alpha) \leqslant 0.20\ \&\ \chi(p,\alpha-0.01) > 0.20), \tag{8}$$

where χ is calculated given an asset class to be initially shocked and a date from which the data is taken. The fraction of surviving banks may be greater than 20% for all values of α between 0 and 1, in which case α_{crit} is by definition set to 1.

A summary of the key parameters of the DBNM-BA is presented in Table 2. One of the most important features of the model is that it shows the differences of the impact of the shock of the assets in the system in different moments. So at a particular time a small shock of a particular asset is needed to generate a cascading failure while at another time it needs to be much larger to generate an impact. Another relevant feature of the model is that impacts of assets not only depends on its weight on the system but on their specific distribution among banking institutions in the different moments.

Given the topology of a banking system, the aim of this model is to evaluate its strength giving different stress scenarios. Usually it is done through a stress test, which is an analysis conducted under an unlikely but plausible worst-case scenario. This can be investigated at the level of a single firm, a financial system, or a country to assess resilience to adverse developments (market, credit or liquidity risks), to detect weak spots, or to create an early warning system for preventive action.

Alternatively, supervisory authorities can also use reverse stress tests, aiming to find exactly those scenarios that cause the bank or financial institution to cross the frontier between survival and default. Recently, Flood and Korenko (2015) reviewed the current state of stress testing for the financial system and differentiate between two classes of stress testing, as follows: In traditional stress testing, the tester (for example, the regulator) chooses one or more shocks and calculations reveal the response, for example, mark-to-model losses of the institution or portfolio. Note that the scenarios are posited ex ante, typically without detailed knowledge of the portfolio loss function. Careful choice of scenarios is important. Analyzing each scenario is typically expensive, both computationally and organizationally, so that a parsimonious scenario budget must be imposed. Moreover, an incautious choice of scenarios can lead to disputes over plausibility or reliability. A number of recent theoretical papers consider alternative approaches to stress testing, especially when considering the implementation of stress tests in an environment of limited or partial information (Breuer, 2007; Jandacka et al., 2009; Breuer and Csiszár, 2010; Glasserman et al., 2013; Pritsker, 2012). A leading alternative is reverse stress testing, which asks some variant of the inverse question: What is the most likely event that could create a response exceeding a given threshold, such as losses in excess of available capital? However, there is as yet no unified theory of stress testing. It is still a practical technique and must be engineered to address the requirements of each particular problem at hand (see also Bookstaber et al., 2014a).

Applying the model to balance sheet data of U.S. banks from 2007, Huang et al. (2013) have used information from the Federal Deposit Insurance Corporation (FDIC) list of bankruptcies to calibrate the parameters of the model. However, this represents one stress scenario, and as the system adapts and evolves, one must consider a wide spectrum of possible scenarios and states of the system. In this paper, we show the different possibilities of systemic impact given a shock to an asset and its cascading effect throughout the entire system. We use the asset value as a variable

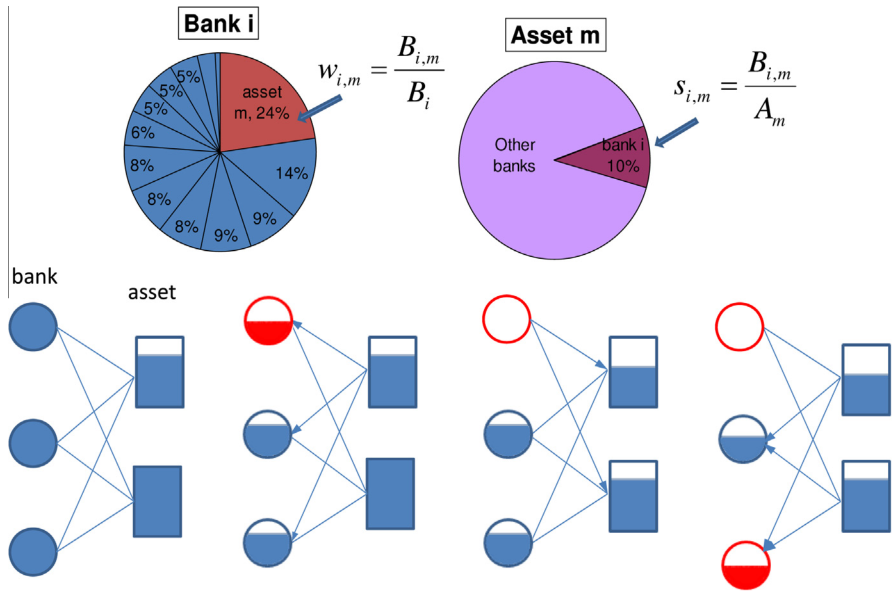


Fig. 1. Bank-asset coupled network model with banks as one node type and assets as the other node type. Link between a bank and an asset exists if the bank has the asset on its balance sheet. Upper panel: illustration of bank-node and asset-node. $B_{i,m}$ is the amount of asset m that bank i owns. A bank i with total asset value B_i has $w_{i,m}$ fraction of its total asset value in asset m. $s_{i,m}$ is the fraction of asset m that the bank holds out. Lower panel: illustration of the cascading failure process. The rectangles represent the assets and the circles represent the banks. From left to right, initially, an asset suffers loss in value which causes all the related banks' total assets to shrink. When a bank's remaining asset value is below certain threshold (that is, the bank's total liability), the bank fails. Failure of the bank elicits disposal of bank assets which further affects the market value of the assets and adversely affects other banks that hold this asset. The total value of their assets may drop below the threshold, which may result in more bank failures. This cascading failure process propagates back and forth between banks and assets until no more banks fail. Authors visualization, following model of Huang et al. (2013).

Table 2
List of model parameters and measurements.

Symbol	Description
$A_{m,\tau}$	Total value of asset m at iteration τ
B_i	Total value of all assets owned by bank i
$B_{i,m,\tau}$	Value of asset m owned by bank i at iteration τ
N	Number of banks
p	Parameter representing the shock level $(1 - p)$
α	Parameter representing the spreading effect of a shock to other asset values
χ	Fraction of banks surviving the cascading failure model
α_{crit}	Smallest α given a p for which $\chi < 0.20$
β_m	Relative size of asset m with respect to all assets
HHI_m	Diversification of asset m among banks

that summarizes the interaction of different types of risks, as market values are dependent of their risk factors (Grundke, 2011). Because the future is uncertain there are infinite case scenarios and a range of interactions to create financial effects from it. For our purposes, the result is a reduction of the assets values, and instead of defining the level of price reduction of the assets, we model the cascading failure for all the different levels and emphasize the analysis for a critical threshold of 20 percent of system survival. Our model provides the means to either focus on a critical shock or a critical contagion (fire sale) effect. The presented model provides the means to study both main approaches to stress testing.

4. Case study: Monitoring the stability of the Venezuelan financial system using DBNM-BA

As a first step, the Venezuelan financial system is represented using the bank-asset bipartite network. We began using the three types of aggregated assets (cash, credit, and securities) and created networks visualization for each month (see Fig. 2). These graphs made it easier to observe the relative significance of the different subsectors in the banking system during the period under study. They show clearly that the system shifted from a specialized one, with different types of institutions, to a system in which primarily universal banks and commercial banking remain (including those promoted by the public sector). We can also see the decrease in number of institutions in the system over the given period. Likewise the graphs showed the greater weight that credit assets have had in the system, although in the period 2003–2004, the weight of securities was higher. The networks visualization allows showing specific bank, type of institution, kind of asset and relative size of the asset, all in the same graph. Moreover, its periodic concatenation allows showing clearly transformations in time. As we use a bipartite network model, the lines that we see in these visualizations represent connections between banks and the asset types they hold in their portfolios. There are no direct connections among banks nor assets.

Next, the asset classes were separated into two categories, credit and securities, and created two respective sets of network visualizations. From either set of figures, it is clear that the assets tend to be concentrated in a few of the given asset classes. Credit networks showed the relevance of commercial credit during the whole period, even diminished since 2005, as credit disaggregation grew by legal requirements for mandatory credit to specified sectors. During the period 2005—2013, the securities networks showed the growing influence of national public debt instruments while the same time, the influence of private bonds and of those issued by the BCV diminished. Along with aggregated assets, these two groups of networks showed the transformations of the system month-by-month.

Having identified the structure transformation, the next step was to test the strength of the banking system by initiating a shock to each of the 16 asset classes and simulating the resulting aftershocks across the banking system. We did this from July 2005 through December 2013, the period for which we have complete credit and securities data for all the banks in the system at each moment. We tracked 9 different classes of credit and 7 different classes of securities over that time period for each bank.

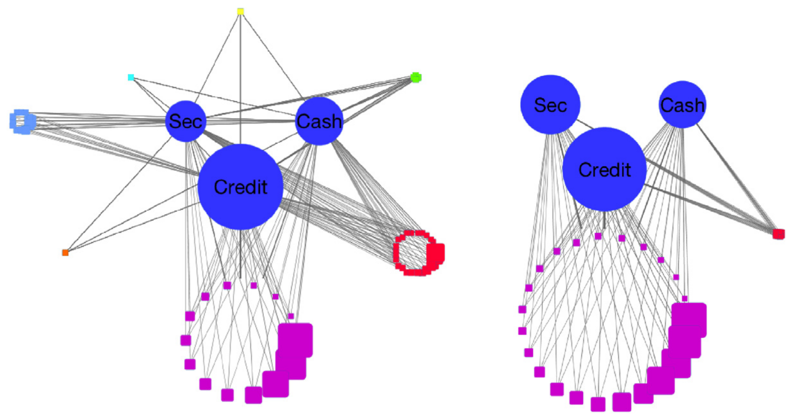


Fig. 2. Banking network structure for December 2000 and December 2013 with aggregate assets. Visualization made using Cytoscape®. Blue circles represent asset types (cash, credit and securities) and squares represent banks (Red = commercial banks; Green = investment banks; Aquamarine = leasing companies; Yellow = mortgage banks; Purple = universal banks; Light blue = savings and loan; Orange = money market funds). The plots show the two different structures of the system in the two moments. The first shows a specialized system with different kinds of institutions. The second plot shows a universal banking system with fewer banks. The lines connect different banks to the assets in their portfolios. In both moments, credit is the largest asset in the aggregated portfolios. In 2013, we can see an increase in the relative weight of securities in the aggregated portfolios of the banks. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.1. Surviving banks, shock level and contagion effect

The three main parameters of the model, as previously discussed, are p (external shock level), α (level of asset contagion), and χ (fraction of surviving banks). We begin the analysis by focusing on a given month and investigating the relationship between these three parameters for different individual assets. This comparison provides the means to identify how a shock to a given asset sets off the spreading of damage to the entire system (see also Duarte and Eisenbach, 2013).

In Fig. 3, we plot analysis of data from December 2005 and from December 2013 as 3-D surfaces that show the fraction of surviving banks for different levels of p and α for three types of assets: vehicle credit, commercial credit, and BCV bonds. These surfaces indicate the importance of both the relative size of the initial shock $(1-p)$ and the relative magnitude of the feedback aftershocks (α) for each type of asset in a given moment.

When the initial shocked asset class is one of the smaller asset classes, note that we often see flat surfaces with $\chi = 1$. This indicates no bank holds a position in that asset class greater than its equity. However, for most asset classes, particularly the larger ones, we see a great sensitivity to both p and α. We generally see two regimes in the p-α phase space: one where the fraction of survived banks at the end of the model is well over half and one where it is generally below 20 percent. Thus it appears that there are critical values of α as a function of p and vice versa which separate these two regimes and we will want to observe how these critical values change month-by-month over the time range of the data. In the case of BCV bonds, as seen in Fig. 3(c) and (f), we note that these critical values change quite drastically between 2005 and 2013.

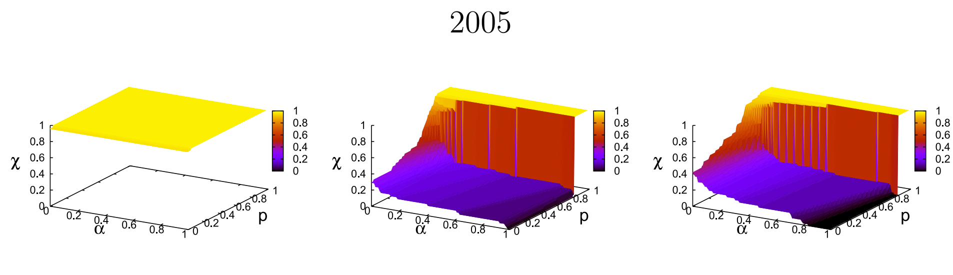
4.2. Asset size versus surviving banks

Following the recent financial crisis, one point of debate has been the issue of "too big to fail". The question arises whether the damage observed in the model is resulting from the size of the shocked asset. We investigated the relationship between the relative size of the shocked asset class, β, and the fraction of surviving banks, χ, for given α and p levels. In Fig. 4, we present an example for the case of $p = 0.60$ and $\alpha = 0.1$ (panels (a) and (c)) and $\alpha = 0.2$ (panels (b) and (d)). Points are plotted for each month and each type of asset class getting the initial shock. In Fig. 4(a) and (b), the points are color-coded by the year for which the model was run. We can see that for lower levels of α there is an approximate linear relationship between β and χ in the range $0.05 < \beta < 0.20$. Increasing α to 0.20, we see an abrupt change in χ around $\beta = 0.1$. There exists a wide range of β $(0.1 < \beta < 0.3)$ for which the system collapse independent of the value of β. This shows that not only the relative weight but also the way in which the asset is distributed through the structure of the system is relevant. The bank-assets network structure shows systemic risk based on details not shown or understood using traditional tools. For the model runs in which fewer than 20 percent of the banks survive, we see there was a tendency in earlier years for greater concentration of a given asset type. Simultaneously, we observe that for assets of the same weight in the system, the surviving percentage of banks was greater in the initial period of analysis. See Appendix C for more examples.

Fig. 4(c) and (d) presents the points color-coded by the asset initially shocked. We observe that different asset classes have different ranges of relative size. However, it is interesting to note, that different asset classes seem to show different critical values for β, though always within the range $0.1 < \beta < 0.2$. This further demonstrates the importance of α when the shock to the asset is on the order of 20 percent or greater. The smaller the shock to the asset, the more linear the relationship by χ and β. See Appendix D for more examples.

4.3. External shock and contagion sensitivity

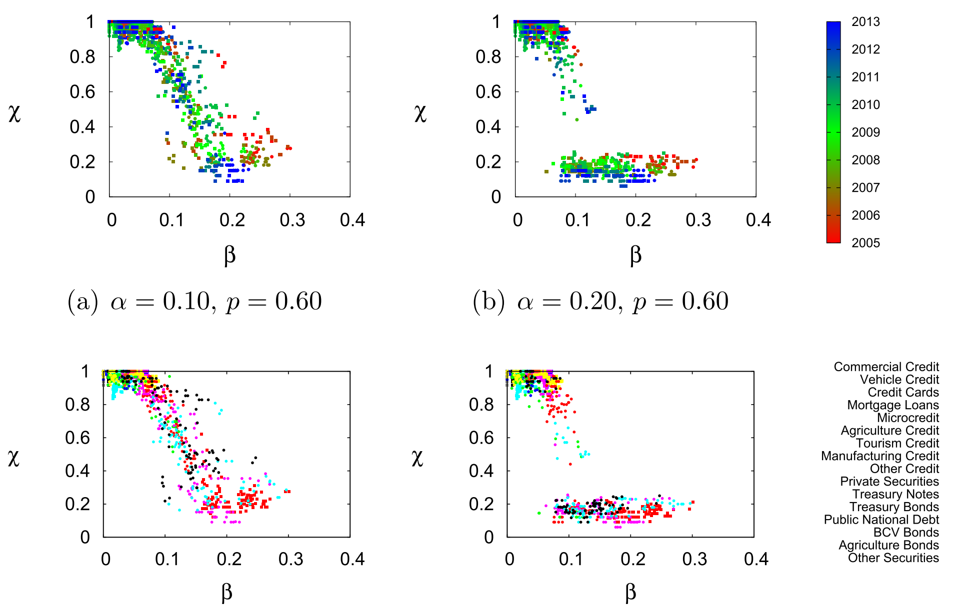
As we previously discussed, the DBNM-BA provides the means to rate the risk of the different assets held by the components of the financial system. Here, we focus on the α parameter, which measures the extent of contagion that results from a given asset. We set a critical threshold of $\chi = 0.2$ (20 percent of banks survive) and for a given p (or α) find the minimum α (or maximum p) that results in fewer than 20 percent of the banks surviving. Defined this way, we are able to simulate asset fire sales, and assign a value to each asset, according to the extent of damage it can cause to the system. Thus, throughout the rest of this section, we will focus on



(a) Vehicle credit (b) Commercial credit (c) BCV bonds

(d) Vehicle credit (e) Commercial credit (f) BCV bonds

Fig. 3. Fraction of surviving banks (χ) as a function of the fraction of shocked asset remaining (p) and the impact of bankruptcies on asset prices (α) for three different shocked assets, each for December 2005 and December 2013. (a/d) Vehicle credit is too small to cause bankruptcies for any value of p or α on the given dates. (b/e) Commercial credit is large enough that catastrophic bankruptcies occur for $p \leq 0.80$ for all but the smallest values of α. (c/f) In 2005, shocking BCV bonds causes systemic failure for all but the smallest values of α and $1 - p$. In 2013, only BCV bond shocks with the largest values of α and $1 - p$ cause the system to collapse. Color coded from black to yellow, with a range of [0,1], which represents the fraction of surviving banks under the shocks. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 2 and 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) $\alpha = 0.10,\ p = 0.60$ (b) $\alpha = 0.20,\ p = 0.60$

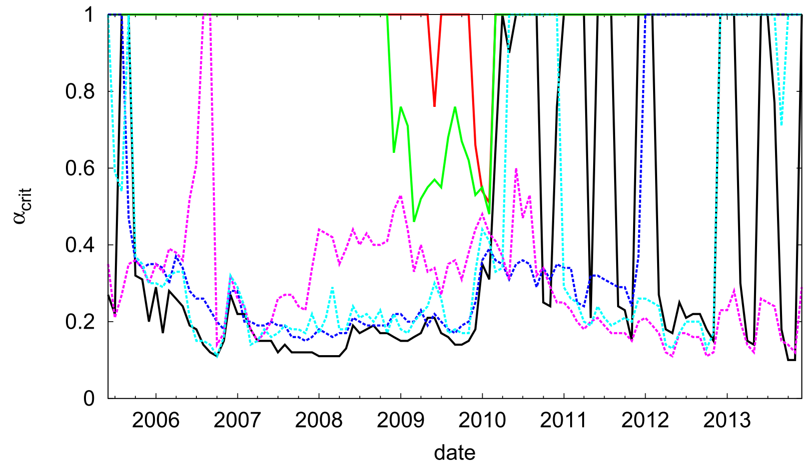
(c) $\alpha = 0.10,\ p = 0.60$ (d) $\alpha = 0.20,\ p = 0.60$

Fig. 4. The plots show the relationship between β and χ. (a) and (b) show points color-coded by the year for which the model was run. (c) and (d) show points color-coded by the asset which was initially shocked. (a) and (c) show the relationship for $\alpha = 0.10$ and $p = 0.60$, (b) and (d) for $\alpha = 0.20$ and $p = 0.60$. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 2 and 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

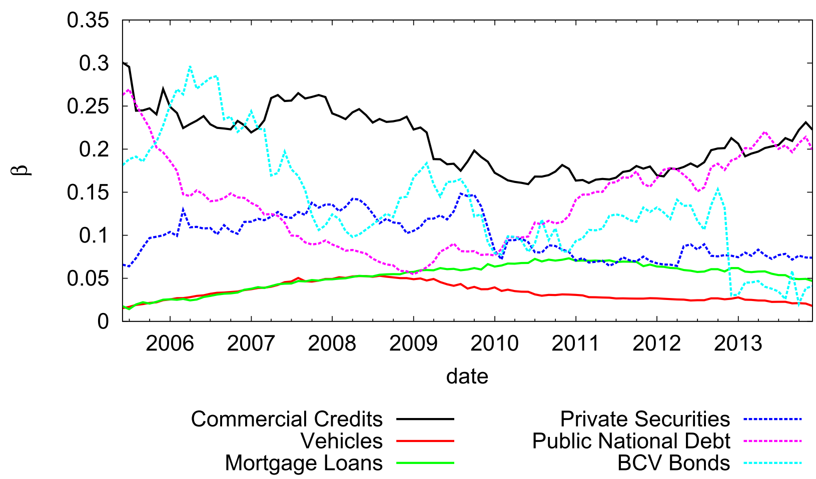
α_{crit}, however, the results presented below can alternatively be presented for the case of p_{crit}.

In Fig. 5(a) we present results obtained for the scenario of $p = 0.80$ (an initial shock of 20 percent to each of the respective assets) and track the critical value of α for which just under 20 percent of the banks survive the cascading failure algorithm for each month of data. The plot demonstrates that larger shocked assets, in general, show a lower α_{crit} than smaller shocked assets. It also reveals volatile behavior of α_{crit} over time. We see frequent large jumps in α_{crit} indicating that month-to-month changes within the system can result in drastically different levels of fragility from similar shock events. The value of α_{crit} reflects the macroprudential risk of the asset, and reflects the level of damage resulting from the network structure, and is thus a network effect.

In Fig. 5(b) we also tracked the systemic size of the assets (β) and in general, the higher β values correspond to lower α_{crit} values.



(a) α_{crit} vs. time for select asset classes with $p = 0.80$



(b) β vs. time for select asset classes

Fig. 5. (a) The behavior over time of α_{crit} for certain shocked asset classes. For $p = 0.80$ (an initial shock of 20 percent to each of the respective assets), we track the month-ny-month critical values of α for which just under 20 percent of the banks survive the cascading failure process. We see high volatility in α_{crit} indicating that monthly changes can produce different levels of fragility. (b) The size of the asset class relative to the entire system (β) over the same time period for the same asset classes. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 2 and 3.

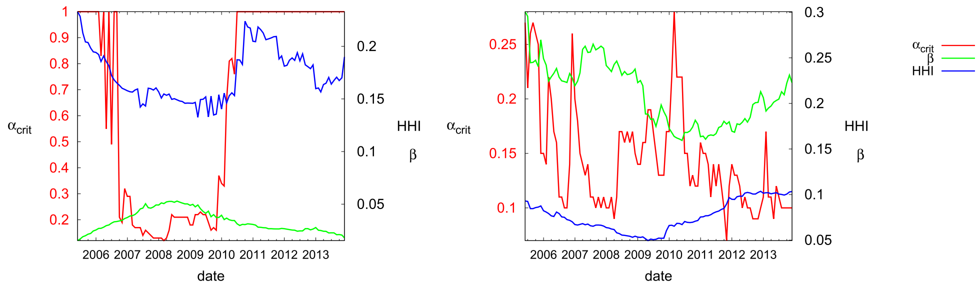
However we can see two small assets, mortgage loans and vehicle credits, that during 2009–2010 saw a significant drop in α_{crit} even though their systemic size had only a very small growth. Also at the beginning of 2009 there was a moment in which the size of public national debt was the same as that of vehicle credits though α_{crit} was higher for the latter. These details allow us to infer that the relative size of the asset is not the only factor to consider.

We are further interested in how α_{crit} may change in time with respect to the Herfindahl–Hirschman Index for the initial shocked asset and β. Both the HHI and β reflect characteristics of the individual asset embedded in system, and thus can be considered a macroprudential feature to assess risk factors. In Fig. 6(a) we present the case of an asset which has a low weight in the average portfolio of the banks. It is important to note that its HHI is low, mainly from 2007 to 2010, a period in which its α_{crit} was also very low, which means that a large negative shock–even in the value of a small asset which is distributed among institutions–can be easily disseminated in the system and generate a cascading failure. In this case, the model is able to uncover information that generally speaking we may not find with traditional measures, showing a weakness in the structure of system. On the other hand if we check another asset, such as commercial credit in Fig. 6(b), we see an example where α_{crit} and HHI tend to move against each other indicating that the more concentrated an asset is in a smaller number of banks, the smaller α_{crit} is, indicating that the system is more sensitive to cascading failures.

As presented in Fig. 6, we observed that for a given shock level, there is a different relationship between the size of the asset, β, and its α_{crit} value, over time, leading us to ask whether it is possible to quantify this relationship for all assets. To this end, we calculate the correlation between α_{crit} and the β across a range of shock sizes and for shocking each of the asset classes. In Fig. 7 we present these correlation values, using a heatmap graphic. We find that there is a strong tendency for α_{crit} and β to be anti-correlated for large shock levels. Only for the case of small shocks it is possible to observe a lack of correlation.

4.4. Non-surviving banks versus solvency index

In addition to studying the effect of the assets on the stability of the banking system, we also investigated the bank nodes of the network. To this end, we performed a series of tests to determine



(a) Vehicle credit, $p = 0.20$ (b) Commercial credit, $p = 0.70$

Fig. 6. (a) presents the case of vehicle credit, which has always had a small β. It is important to note that its HHI is lower from 2007 to 2010, and during that period the α_{crit} was also very low, which means that a large negative shock in the value of that asset, with a less homogeneous distribution among institutions, can be easily disseminated in the system and generate a cascading failure. (b), shows the case of shocked commercial credit (high β) whose α_{crit} and HHI tend to move against each other indicating that the more concentrated a shocked asset is, the more sensitive the system is to cascading failures. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 3.

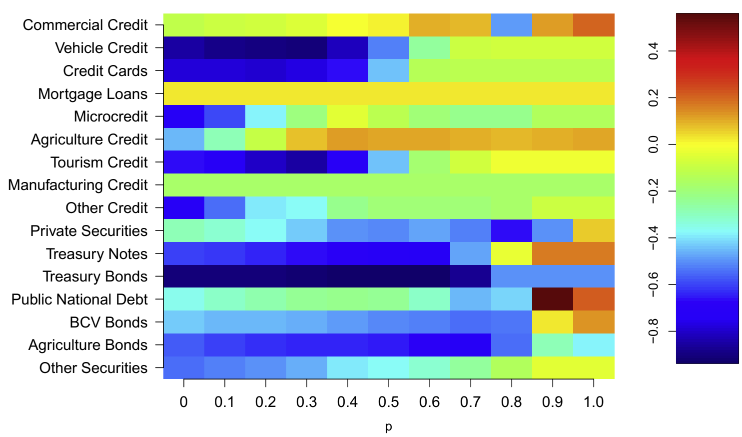


Fig. 7. Heat map of α_{crit} and the β correlation for each asset type and various shock levels. Color represents the strength of the correlation, ranging from red for positive values, to blue for negative values. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 2 and 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in what order banks underwent the simulated process of failure. We also considered its relationship with traditional measures to estimate bank's solvency, such as the debt-to- equity ratio (total liabilities/total equity), which is used to evaluate the long term robustness of a firm. It must be noted that the debt-to-equity ratio assesses the strength of a banking institution, while the DBNM-BA is aimed at assessing the strength of the banking system. However, both elements are relevant to elevate the fragility of the banking sector.

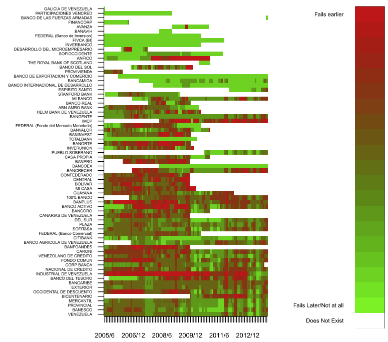
We find that the order of bank failures depends on the asset shocked, and that the model provides details of the strength beyond the state of the individual institution, which results from the whole network of institutions and assets of the system. The order of bank failure for all assets, given a shock level (p) and a spreading effect (α), is calculated. Next, these results are aggregated, representing the average failure order of each bank after a shock to its assets. We repeated this procedure for all the institutions and for each month of the period 2005–2013. Simultaneously, the debt-to-equity ratio was also calculated for all the institutions and for each month of the same period.

Fig. 8 shows the results of the average cascading failure steps for each institution in two states: (a) for $p = 0.70$ and $\alpha = 0.10$ and (c) for $p = 0.70$ and $\alpha = 0.20$. Fig. 8(b) shows the debt-equity ratio. We can see that Fig. 8(a) and (b) are more or less similar, while Fig. 8(c) shows a more fragile situation of the system. These results reinforce the capability of the model to show the sensitivity of the system due to the interdependence of the agents of the system. Traditional measures are able to capture important features of the units of the system. As soon as the connectivity is considered and the contagion effect is possible, traditional measures cannot assess the systemic effect, and so forth, underestimate the risk.

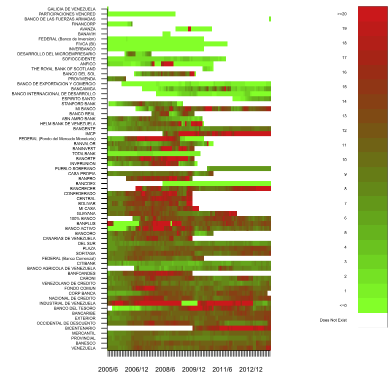
5. Summary and discussion

The increasing frequency and scope of financial crises have made global stability one of the major concerns in the economics field worldwide, because devastation spreads through a highly interdependent financial network via the contagion effect. During the last crisis, the world experienced the impact of the reduction of value of a specific kind of asset, which was included in many portfolios and generated a systemic contagion, ultimately resulting in a global recession. Big and small, solvent and highly leveraged institutions succumbed under the negative impact of the diminishing value of assets, which caused fire sales and ultimately a disruption of financial markets. Even though financial institutions are under supervision, the systemic impact was not foreseen by regulators.

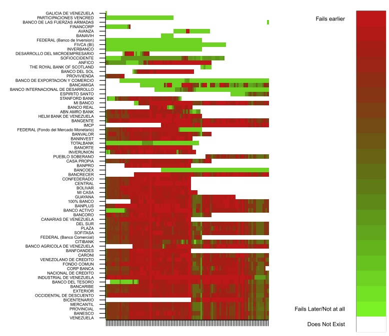
In this highly complex environment, financial and banking supervision has to be thought of as a systemic task, focusing on the health of the nodes (the banks and financial institutions involved) and on the connections among those nodes (different kind of links as flows of funds, loans, assets owned, etc.) to unravel the structure of the system under surveillance. This indicates the need to include the shadow banking institutions along with the traditional banking institutions because of their important role in the financial system and multiple links and connections.



(a) Bank failure order



(b) Debt-to-equity ratio



(c) Bank failure order

Fig. 8. (a) Heat map showing the average cascading failure steps for all system's banks, shocking all the assets with $p = 0.70$ and a contagion effect of $\alpha = 0.10$, from 2005 to 2013. (c) Heat map showing the average cascading failure steps for all system's banks, shocking all the assets with $p = 0.70$ and a contagion effect of $\alpha = 0.20$, from 2005 to 2013. The color code ranges from red to green. Red indicates a bank failing earlier in the model. Green indicates the bank survived the cascading failure process. White indicates the bank did not exist at that specific moment in time. (b) Heat map showing the debt-to-equity ratio for each bank, from 2005 to 2013. Heat map's color code ranges from red to green. Red indicates the higher debt equity ratio. Green indicates the lower debt-to-equity ratio. White indicates the bank did not exist at that specific moment in time. The comparison of the heat maps shows the capability of the model to show the systemic sensitivity due to the interdependence of the banks. Authors analysis of SUDEBAN data set, see Appendix A.2 dataset 2 and 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Simultaneously, we must remember the system is dynamic, so more than a one moment snapshot is required to follow up the evolution and transformation of the system and its strengths and weakness at different times.

With this in mind, this work proposes a modeling framework able to track systemic changes of a banking system. The model is applied to study empirical and publicly available data, avoiding as much as possible theoretical biases and data restrictions. Assessing the well-being of individual banks, and more importantly the banking system as a whole, heavily depends on the transparency of the banks with regards to their balance sheets and contractual obligations.

The proposed model focuses on the exposure network of banks, based on available information that is mandatory and transparent derived from the banks' balance sheets. In addition to this, there also exists the network of contractual obligations between the different banks. In terms of network science, this represents two different classes of networks. The first belongs to the class of functional networks, but the second to structural networks.

This work provides a novel macroprudential stress testing tool for the functional level, in the case where the exposure positions is the only available information. On the structural level, the contractual obligations would map out the network of claims and liabilities between institutions, and these types of networks have been extensively investigated in different countries (Boss et al., 2004; Cont et al., 2013; Craig and Von Peter, 2014; Langfield et al., 2012; Jaramillo et al., 2012; Elsinger et al., 2005). The ability of banks to fulfill these promises of course depends on the shocks to assets and asset classes. A general multi-level stress-testing framework would combine both functional and structural networks, and the dependencies between them. This would be made possible using the recently breakthroughs in the formalism of interdependent networks (Kenett et al., 2014), where only first steps have been made in its applications to the financial system (Bargigli et al., 2015; Bookstaber and Kenett, preprint).

As a case study we investigated the Venezuelan banking system from 1998 to 2013, because it is a period with several legal transformations that had impact on its structure. The DBNM-BA showed the impact of these legal transformations in the asset portfolio of all the units of the system in time. In this sense, the model yielded expected results.

To evaluate the stability of the system, we applied a series of shocks to the system to reveal intrinsic weaknesses at different times. It should be noted that the system displayed an important variation that did not appear to follow any specific trend. Quite the opposite the sensitivity of the system to initial conditions (structural distribution of the assets among banks) is important. It is also worth noting that some assets of insignificant systemic weight in some periods were able to cause important damage to the whole system even under small levels of shocks. The concentration of the assets in particular units of the system, as well as their distribution in it, were also elements of high relevance.

The proposed model provides a dynamical stress test modeling framework. Once the critical values are associated for each asset for a given month, we repeated the analysis for the next month. In this way, it is possible to define a dynamic, or time-evolving, model and track how the values of the different parameters, specifically the critical ones, are changing in time and evolving on a month by month basis. This provides the means of tracking changes in these critical values, which can be used as a signal in a decision support system or early warning system for regulators and policy makers.

In conclusion, the dynamical bipartite network model was able to reveal structural strengths and weakness of a banking system, giving supervisory agents and the banks themselves important new information about its stability. Although the DBNM model was demonstrated here using bank and asset data, it can be applied to additional financial instruments, and thus represents a general tool for policy and decision makers to monitor and regulate the financial system.

This work provides new tools to test and assess different economic scenarios and elaborate actions to be addressed by policy makers. The stress scenarios and insights resulting from this work further provide early alert signs of weakness of the economic and financial system, identifying vulnerabilities of the system as a whole. During or following a crisis, this model also provides the means to evaluate nodal points that promote the recovery of a system; for example, policy makers will have the capability to calculate to which nodes and to what extent actions should be applied to recover the system. Finally, this model can be complemented using the multilayer network approach when considering the banking system as part of a more complex system, including the global financial system and the real economy as a whole.

Acknowledgements

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Appendix A. Overview of Venezuelan economy and banking system

Many investigations have suggested that the economic performance of Venezuela is explained by the significant presence of natural resources, their exploitation and positioning in the international market. Venezuela is considered to be a rentier state due to having the main part of the national revenues originating from the rent of the oil exports (external sales and not taxes from domestic production). The rentier scheme, which is derived from the country's productive sphere, has had inevitable impacts on the rest of the social spheres. Other explanations emphasize the game of economic interests that are generated around a public sector that owns this resource and whose discretion generate economic distortions, weakens institutions and does not allow the growth of factor productivity, which, ultimately, is the economic objective evidence of the potential for growth. Also, one should note the conscious decision of the Venezuelan government during the 1970's to maintain a fixed exchange regime and capital controls in a flexible global context which strongly affected the Bolivar (Palma, 1985; Malavé-Mata, 1987; Naím and Piñango, 1988; Hausmann and Gavin, 1996; Mata, 2006).

Because of the unsustainable macroeconomic imbalances, a program of reforms was released in 1989 to correct all distortions the Venezuelan economy endured and to achieve a proper allocation of resources. But political instability and social unrest of the period ruined the onset of a macroeconomic recovery, as evidenced in 1991, and a timid stimulus to increase supply as a consequence of the floating exchange rate regime. The uncertainty raised costs, and interest rates reached a range between 50 and 80 percent. This environment unleashed a terrible banking crisis that affected a third of the population and whose resolution cost have been estimated as 18 percent of the country's 1994 gross domestic product (GDP). With Venezuela in this weakened economic condition and numerous institutions in the hand of the state, a phase of mergers and acquisitions by international consortia began (Hausmann and Gavin, 1996; Mata, 1996; Villar et al., 1997; Furlong, 1998; Berger, 1998; Krivoy, 2002).

During the 21st century, Venezuelan economic performance cannot be understood without taking into account that it is part of a specific, political ideological process called *Socialism of the 21st century*. The project has been showing different facets, dimensions, and scopes according to domestic and international circumstances that it has faced, but also due to the strategic decision of their planners to go gradually, showing their nature and further objectives (Levy-Carciente, 2013b; Levy-Carciente, 2013a). Driven ideologically, the economy is currently in a bad situation. with a dramatic decline in domestic production, high level of inflation and scarcity, an overvalued exchange rate controlled since 2002, low level of international reserves, important fiscal deficit, and international debt.

A.1. The Venezuelan banking sector 1998–2013

The financial sector throughout this period has been one of the few that has managed to take advantage of or to adapt to the new economic conditions of the country. The level of the sector's assets has increased 136 times, from Bs. 11 billion in 1998 to Bs. 1.5 trillion in 2013.[2] It has to be noted that if the analysis is made in terms of international currency, growth is lower, especially considering the year 2014 which ended the first quarter with three different mechanisms of evaluation of the exchange rate: the official rate (CENCOEX) 6.3Bs/U.S.$; SICAD I around 11Bs./U.S.$ and SICAD II around 50Bs./U.S.$.

During the period under study the structure of the system has had important changes, both in number and in subsectors. It should be noted that the growth in number and scope of the banking sector suffered a hard hit after the banking crisis of 1994, which consisted at the time of more than 100 institutions. By 2000, the number was reduced to 65. In addition, the traditionally predominant role of commercial banking turned to universal banks, while the financial investment and savings entities disappeared by 2013. In 1998, the commercial banks owned 37.4 percent of assets and universal banks 57.4 percent. By 2013 universal banks owned 80 percent of the assets of the banking sector. Both subsectors have represented more than 95 percent of the whole sector. This process further highlights the number of public entities involved in intermediation activities versus private ones.

[2] Using short scale terminology: 1 billion = 10^9, 1 trillion = 10^{12}.

With regard to the composition of the assets, the three main types are: cash and cash equivalents, credit portfolios, and securities. In 1998, the credit portfolio represented 60 percent of the banking assets; in 2004 it was 30 percent and at the end of 2013 was 45 percent. On the other hand, securities were 10 percent of the assets of the system by 1998, a figure that rose in 2004 to 50 percent but ended 2013 at 30 percent.

These changes cannot be well understood without noticing the numerous transformations of the regulatory system, which are causal determinants of these outcomes, in particular in the structure of the loan portfolio. Special mention should be given to the aliquots, or mandatory credit portfolios. Known colloquially as "gavetas", these portfolios have had preferential rates since 1999 and allow the government to channel lending activity to sectors and in amounts that are considered convenient. There are five sectors with this enforced credit: agriculture, tourism, microenterprise, manufacturing, and housing (see Table A.1).

Today they represent 60 percent of banking credit. It is also worth noting that the infringement on this obligation carries high fines, insofar as these are calculated considering the equity of the offender and not the prejudice of noncompliance (Muci, 2009).[3]

Table A.1
List of key changes in Venezuelan banking regulation laws.

Date	Title
Oct. 25,1999	República Bolivariana de Venezuela Gaceta Oficial #5395
Feb. 28, 2001	República Bolivariana de Venezuela Gaceta Oficial #37148
Nov. 09, 2001	República Bolivariana de Venezuela Gaceta Oficial #5551 Extraordinaria
Nov.13, 2001	República Bolivariana de Venezuela Gaceta Oficial #5555 Extraordinaria
Nov. 05, 2002	República Bolivariana de Venezuela Gaceta Oficial #37563
Jan. 03, 2005	República Bolivariana de Venezuela Gaceta Oficial #38098
Jun. 23, 2005	República Bolivariana de Venezuela Gaceta Oficial #38215
Aug. 28, 2007	República Bolivariana de Venezuela Gaceta Oficial #38756
Feb. 28, 2008	República Bolivariana de Venezuela Gaceta Oficial #3880
Apr. 29, 2008	República Bolivariana de Venezuela Gaceta Oficial #38920
Jul. 31, 2008	República Bolivariana de Venezuela Gaceta Oficial #5890 Extraordinaria
Jul. 31, 2008	República Bolivariana de Venezuela Gaceta Oficial #5892 Extraordinaria
Jan. 09, 2008	República Bolivariana de Venezuela Gaceta Oficial #38846
Dec. 30, 2008	República Bolivariana de Venezuela Gaceta Oficial #40260
Sep. 23, 2009	República Bolivariana de Venezuela Gaceta Oficial #5889 Extraordinaria
Sep. 23, 2009	República Bolivariana de Venezuela Gaceta Oficial #39270
Oct. 03, 2001	República Bolivariana de Venezuela Gaceta Oficial #37296

A.2. Detailed description of investigated data

We use of statistical information from the Superintendence of the Institutions of the Banking Sector, or SUDEBAN (http://www.sudeban.gob.ve/), its monthly statistics, publication, newsletters and press releases, as well as its annual reports. The information is presented in national currency units, Bolivars, after the conversion process of 2008. Using the SUDEBAN information, we built bipartite networks for each month of the 16 years under study. We identified the banking subsectors in each period (commercial banking, universal banking, investment, savings and loan, mortgage, leasing, money market funds, microfinance and development banking) and based their systemic weight on asset levels. From the balance sheet of each bank we have identified the assets items (cash and equivalents, credit portfolio and securities), breaking each down to consider its systemic relevance. Later, we focus in detail on the loan portfolio by credit destination, namely: consumption (credit cards, vehicles), commercial, agricultural, micro-entrepreneurs, mortgage, tourism, and manufacturing. From that we derived the impact of the legal transformations in the credit portfolio composition. For the period of 2005–2013, we also analyzed the securities held by the different banks, specified as: private securities, treasury bonds, treasury notes, bonds and obligations of the public national debt, bonds and obligations issued by the Central Bank of Venezuela (BCV) and agricultural bonds. The analysis was done with the interest of specifying the kinds of assets that warrant the intermediation's activity in the country. The credit and investment portfolio composition depicted the underlying structure of the system during the whole period, allowing us to show its evolution. A summary of the bank and asset types investigated in presented in Table 1. The data used was derived from three datasets provided by SUDEBAN:

(1) PUBLICATION BALANCE (Balance de Publicación, BP files, 1999–2013) Report Title: Banking System. Publication General Balance (Sistema Bancario. Balance General de PublicaciÓn) From here we extracted: Total Assets, total Liabilities and total Equity. Aggregates assets value (Cash, Total Credits, Total securities)
(2) PRESS REPORTS (Boletines de Prensa, BPR files, 2005–2013) Report Title: Investment in Securities by type by bank (inversiones en Ttulos Valores por tipo, segn banco) From here we extracted security details by bank: Treasury Notes, Treasury Bonds, Private Securities, National Debt Bonds
(3) MONTHLY BULLETIN (Boletines Mensuales, BM files, 1999–2013) Report Title: Credit Portfolio by Credit Destiny, by bank (Cartera de Crditos por Destino del Crdito, segn Banco) From here we extracted all the credit details by bank: Commercial Cr, Cr Cards, Vehicle Cr, agricultural Cr, tourism Cr, Manufacturing Cr, Mortgage Cr, Microfinance

A.3. Legal transformations in the Venezuelan banking system

In this appendix, we summarize the main legal transformations of the economic sectors with enforced credit and include some brief comments on their results, although such commentary is not the primary aim of this paper.

The Law of Agricultural Credit[4] of November 1999 was amended in 2001, 2002 and 2008 (RBV, Gaceta Oficial #5395; #37148; #5551; #37563; #38846 and #5890). Originally, the act established the obligation to direct credit to the sector by 30 percent of the total number of deposits, then it was changed to 30 percent of the total credit and is today in 24 percent of the total credit. This credit is granted at preferential rates of 5 percent and additional details of the final beneficiary are specified. Specifically, Article 8 of the Act determines in detail the characteristics of the agricultural portfolio, namely 5 percent to structured funds or Zamoranos; less than 15 percent for marketing and distribution; less than 15 percent on certificates of deposits, secured bonds, and distribution operations; less than 5 percent to the same company or corporate group; between 49 percent and 79 percent should be assigned to primary agricultural production of priority products; between 10.5 percent and 15 percent to finance infrastructure and the marketing of priority products or equivalents; and less than 4.5 percent for the commercial lending of nonpriority items.

The Special Protection Act to the Mortgagor of 2005, amended in 2007 (RBV Gaceta Oficial #38098 and #38756) and Resolution #114 of the Ministry of Housing and Habitat of Dec 30, 2008 (RBV Gaceta Oficial #40260) set out the guidelines in this type of credit. The weight of this portfolio was been increased from

[3] Normally the infringement of an obligation is related to the amount of that obligation; however, in this case it is related to the total equity of the institution.

[4] In 2008 the name of the Law was changed to Agrarian Sector Credit Law (Ley de Crédito para el Sector Agrario).

10 percent in 2009 to 15 percent in 2012 and reached 20 percent in 2013. These laws established monthly income characteristics to be fulfilled by the beneficiaries of loans for acquisition, construction, expansion, or renovation of main dwelling of this portfolio, 60 percent should go to people with incomes below 623 Bs/month ($100U.S./month[5]) 20 percent to people earning less 2800 Bs/month (445 U.S.$/month) and the rest to those who earn between 2800 and 7000 Bs/month (maximum 1060U.S.$/month). Credit is granted at a preferential rate of 5 percentage.

The obligatory portfolio to the tourism sector, regulated by the Organic Law of Tourism of 2005 (RBV Gaceta Oficial #38215) establishes an aliquot between 2.5 percent and 7 percent of the total credit portfolio on projects that qualify under tourist development, government policy, and the National Strategic Plan for Tourism. Later, in 2009, the aliquot was changed to 3 percent of the total credit (RBV Gaceta Oficial #5889 and Ext. #39270).). Likewise, in its Article 26, the law established that 40 percent of the credit has to be allocated to companies that billed less 20,000 UT[6]; 35 percent to companies that billed between 20,000 and 100,000 UT and 25 percent for the higher billing. Credit is granted at a preferential rate of 5 percent; but if they meet certain requirements companies can enjoy a further reduction of 3 percentage points.

To benefit the microcredit, the General Law on Banks and other Financial Institutions in 2001 (RBV Gaceta Oficial #5555 and #5892) in Article 24 sector imposes the granting of this credit by an amount equivalent to 3 percent of the loan portfolio of the preceding semester at a rate of 24 percent (this is the only rate of this mandatory credit not established at such a low preferential level). Encouraging microcredit has different objectives. On one hand, it stimulates entrepreneurship, and on the other hand, it is considered an instrument to alleviate poverty. Muhammad Yunus, winner of the 2006 Nobel Peace Prize, has highlighted the importance of financial institutions for these less advantaged sectors, which in turn are easy prey for unscrupulous financing schemes. However, studies on financing of street vending show that the limit is not the cost of capital but the associated costs to access it (Jaffé et al., 2007).

Finally, the mandatory credit for manufacturing activities, by resolution of the Central Bank of Venezuela, requires the banking sector (RBV Gaceta Oficial #3880 and # 38920) to make loans at 19 percent interest (Article 2). Article 3 establishes that entities may not decrease the subsector's participation after December 31, 2007, and that such participation should reach at least 10 percent of the total credit portfolio. Various legal professionals have pointed out the contradiction in Article 50 of the law of the Bank Central for this mandatory portfolio, which concerns maximum on loans, but no minimum, namely:

Article 50. *With the object of regulating the overall volume of bank credit and avoid getting inflationary trends, the Central Bank of Venezuela may fix the maximum percentages of growth of loans and investments for periods of time, as well as tops or limits for such loans and investment portfolio. These measures may be established, in a selective way, by sectors, areas, banks and financial institutions or by any other suitable selection criteria determined by the directory* (RBV Gaceta Oficial # 37296).[7]

[5] Using the official CENCOEX exchange rate.

[6] UT: Spanish acronyms for Tributary Units. These units were created in 1994 as value measures expressed in domestic currency that can be modified annually to compensate the inflation effects.

[7] Translation of: "Artículo 50. Con el objeto de regular el volumen general de crdito bancario y de evitar que se acentúen tendencias inflacionarias, el Banco Central de Venezuela podrá fijar los porcentajes máximos de crecimiento de los prstamos e inversiones para períodos determinados, así como topes o límites de cartera para tales prstamos e inversiones. Estas medidas podrán ser establecidas, en forma selectiva, por sectores, zonas, bancos e instituciones financieras o por cualquier otro criterio idóneo de selección que determine el Directorio."

Table B.1
List of interpolation of balance sheet data for banks, with dates of missing data.

Date	Bank
Dec. 1998	Banco Popular y de los Andes (BH), Confederado
Jul. 1999	Unido, Banesco (BH), Inverbanco, Venezolano, Corporacion Hipotecario, Union (EAF), Sofitasa (EAF), Sogecredito, Arrendaven, Fivca, Corpoindustria, La Venezolana, La Vivienda, Oriente, Casa Propia, Central, Del Centro, Mi Casa, La Primogenita, La Margarita, Valencia, Merenap, Corp Leasing, Prosperar, Del Sur, Provivienda, Caja Familia, Fondo Comun
Nov.–Dec. 1999	Arrendaven, Corpoindustria, Sofitasa (EAF), Sogecredito, Union (EAF)
Dec. 1999	Caja Familia, Casa Propia, Central, Del Centro, Del Sur, Fondo Comun, La Margarita, La Primera, La Primogenita, La Venezolana, Merenap, Mi Casa, Oriente, Prosperar, Provivienda, Valencia
Dec. 1999–Jan. 2000	Federal (BI)
Aug.-Nov. 2003	Anfico, Banesco (BH), Baninvest, Banplus, Banvalor, Casa Propia, Federal (BI), Federal (FMM), Financorp, Fivca (BI), Inverbanco, Mi Casa, Participaciones Vencred, Provivienda, Sofioccidente
Mar. 2004	Banplus, Casa Propia, Mi Casa
Nov. 2004	Banplus, Casa Propia, Mi Casa
Apr.–May 2005	Anfico, Arrendaven, Banesco (BH), Baninvest, Banplus, Banvalor, Casa Propia, Federal (BI), Federal (FMM), Financorp, Fivca (BI), Inverbanco, Mi Casa, Participaciones Vencred, Provivienda, Sofioccidente

It is not the aim of this paper to analyze the impact of these regulations. We can simply say that from figures of the BCV on gross domestic product by kind of economic activity, the effects of credit guidance in Venezuela do not offer signs of having achieved the objectives of sectorial development. This is because the availability of funds for the promotion of an economic activity is a necessary condition but not sufficient, because it so requires an economic environment conducive to production and that promotes productivity.

Agricultural activity has shown a downward trend since 2007, not associated with the lack of financing, but rather with the numerous price controls, which, in an inflationary environment, discourage production and favor imports. The latter even carried out by governmental entities within an international trade policy with regional partners.

Also in the case of tourism, one of the most important elements to encourage the sector is a secure personal environment, but the figures for the period are clearly troubling. In 2013 alone, violent deaths reached close to 25,000 people, as reported by the OVV,[8] that represents 79 of every 100,000 people. Violent crime caused the number of international arrivals between 2005 and 2011 to drop by more than 15 percent, while the departures abroad increased by more than 60 percent. These results are clear evidence of the failure of the policy.

Finally, it should be noted that the manufacturing sector has frequently expressed concern for importing bias of the economy that, in an inflationary environment, discourages all productive activity and reduces the possibility of job creation. The sector

[8] Acronym for Observatorio Venezolano de Violencia (www.observatoriodviolencia.org.ve).

had also denounced the weakening of property rights that discourage investment.

A.4. Stress scenarios for the Venezuelan economy

The Venezuelan economy relies heavily on oil exports. In 1998, oil exports represented 68.8 percent of total exports and in 2014, 96 percent. The increase in oil prices since 2004 stimulated the economy through fiscal expansion and a monetization of its deficit, regardless of the external constraints and the inflationary effects those policies generated. The sharp increase in monetary liquidity is one of the causes that have resulted in double-digit inflation rates during the last 15 years.

Since 2002, the Venezuelan economy has been under fixed-exchange control, which is increasingly overvalued (with a black market 29 times the official rate at the end of 2014) and favors imports to domestic production, deepening the external imbalances and reducing the level of international reserves (particularly the liquid reserves). By 2014, the country had a significant fiscal deficit, and it has been calculated that the economy needs an oil price of more than U.S. $100/barrel to operate. Oil income is the main collateral that backs public national debt bonds issued by Venezuela. But since 2007, the country's risk variations seem to be associated with other factors, such as an unfavorable business environment and a low degree of economic freedom in the Venezuelan economy.

With this synthetic macroeconomic description as the back drop, we conduct stress testing supposing a significant eduction of global oil prices, combined with a domestic recession with inflation and international credit restriction. Briefly, that scenario will negatively evolve as follows: For each U.S. dollar of oil price reduction, exports diminish nearly U.S.$1 billion (external vulnerability). This generates an important reduction in the country's income and heavy pressure on the fiscal budget, which is highly rigid (fiscal vulnerability). The high inflation limits freedom to apply a contracyclical monetary policy if fiscal policy has to control public expenses. Inflation and the degradation of the domestic currency value deviates liquidity to consumption of durable goods (price volatility), deepening external imbalances because internal production is suppressed. When a country is under high inflation and the currency is devaluating continuously, a rational decision is to get rid of the money (liquidity) and buy things (durable goods, not perishable, of course); and If domestic production is stagnant, imports will increase (deepening external imbalances) The deterioration increases the risk premium (country risk) for new debt with major losses for bondholders. Banks balance sheets deteriorate with the reduction of security assets values, lack of deposits, and delinquency credits.

Appendix B. Interpolated data

There were some months where credit data were missing for certain banks, so to maintain series continuity we interpolated. For example, in July 1999, we were missing credit data for all mortgage banks, savings and loans, and leasing companies. In each case of missing data where it was clear that the bank in question did exist in a given month i.e. we had data for the bank before and after the missing data points we used a geometric mean to fill in the missing points. For example, if Bank A was missing data for August 2005, then for each missing data point, we replaced the null

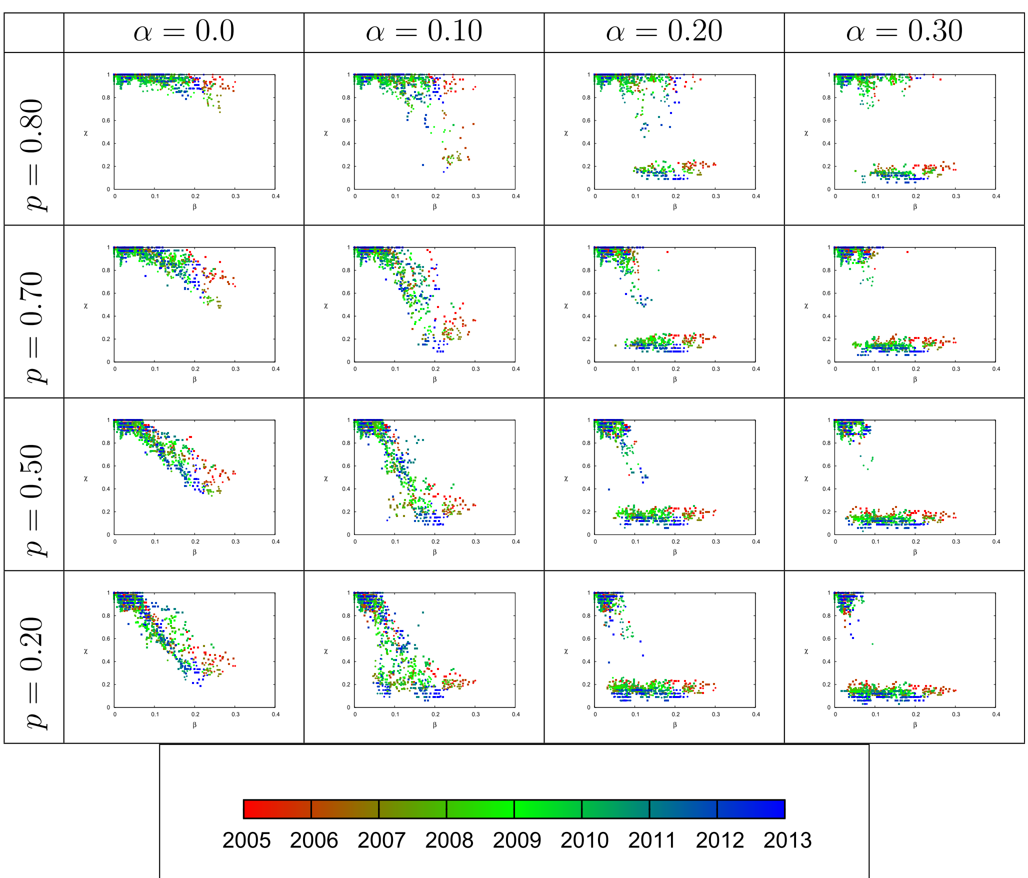

Fig. C.1. Relationship between share of assets (β) and fraction of surviving banks (χ) for different shock levels (p) and spreading effect (α). The points are color-coded by the year for which the model was run. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

value with the geometric mean of the July 2005 and September 2005 data for each data series. Table B.1 details the list of missing data that we interpolated. (see Table B.1).

Appendix C. Relationship between asset share and surviving banks colored by year

See Fig. C.1.

Appendix D. Relationship between asset share and surviving banks colored by shocked asset

See Fig. D.1.

Appendix E. Technical description of the algorithm

Step 1. Select data (see Table E.1)
Choose the month of the dataset to evaluate, which asset to shock (m') and values for $p \in [0,1]$ & $\alpha \in [0,1]$.

Step 2. $B_{i,m,0} \leftarrow$ value of asset m on balance sheet of bank $i \quad \forall i, m$
$L_i \leftarrow$ value of all liabilities on balance sheet of bank $i \quad \forall i$.
Record the value of each asset class and total liabilities on the balance sheet of each bank from our chosen dataset.

Step 3. $B_{i,0} \leftarrow \sum_m B_{i,m,0} \quad \forall i, A_{m,0} \leftarrow \sum_i B_{i,m,0} \quad \forall m$
Calculate both the value of all assets for each bank and the total value of each asset class across all banks.

Step 4. $A_{m',1} \leftarrow pA_{m',0}, B_{i,m',1} \leftarrow pB_{i,m',0} \quad \forall i$
Shock the chosen asset class (m') both at the bank level and the asset class itself.

Table E.1
List of model parameters and measurements.

Symbol	Description
$A_{m,\tau}$	Total value of asset class m at iteration τ
$B_{i,\tau}$	Total value of all assets owned by bank i at iteration τ
$B_{i,m,\tau}$	Value of asset class m owned by bank i at iteration τ
p	Parameter representing the shock level $(1-p)$
α	Parameter representing the spreading effect of a shock to other asset values

Step 5. $B_{i,1} \leftarrow \sum_m B_{i,m,1} \quad \forall i, \tau \leftarrow 1$
Recalculate the total assets of each bank after the shock to asset m'.

Step 6. If $B_{i,\tau} > L_i \quad \forall i$, then end, else proceed to Step 6.
If the assets of each bank are still greater than their liabilities, then there are no bankruptcies in the model and the algorithm stops. Otherwise, the algorithm continues.

Step 7. $A_{m,\tau+1} \leftarrow A_{m,\tau} - \alpha B_{i,m,\tau} \quad \forall m, i \mid B_{i,\tau} \leqslant L_i$
Each bank whose total assets dropped to or below the total liabilities is considered bankrupt and each asset class owned by those banks is devalued by an amount that scales both with the value owned by the failed bank and the parameter α.

Step 8. $B_{i,m,\tau+1} \leftarrow B_{i,m,0} \frac{A_{m,\tau+1}}{A_{m,0}} \quad \forall i, m, \tau \leftarrow \tau + 1$
Rescale the value of each asset class owned by each bank to the new total value of each asset class.

Step 9. Return to Step 5.
Once again recalculate the new total assets of each bank and then check for new bankruptcies.

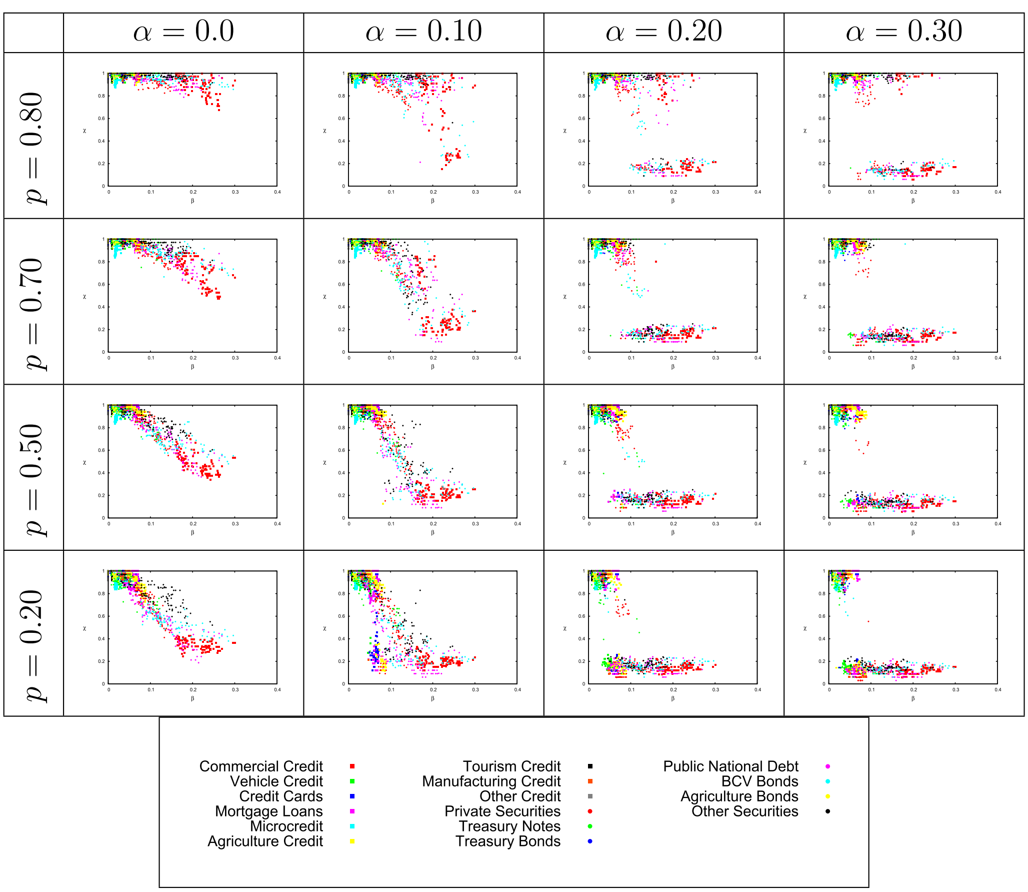

Fig. D.1. Relationship between share of assets (β) and fraction of surviving banks (χ) for different shock levels (p) and spreading effect (α). The points are color-coded by the asset which was shocked. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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