Dynamical macro-prudential stress testing using network theory

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Abstract

The increasing frequency and scope of financial crises has made global financial stability one of the major concerns of economic policy and decision makers. Under this highly complex environment, financial and banking supervision has to be thought as a systemic task, focusing not only on the strength of the institutions but also on the interdependent relations among them, unraveling the structure and dynamic of the system under surveillance. Using network theory, we develope a dynamic model to reveal the systemic structure of a banking system, to analyze its sensibility to external shocks and to evaluate the presence of contagious underlying features of the system. As a case study, we make use of the Venezuelan banking system in the period of 1998–2013. The introduced model was able to capture, in a dynamic way, changes in the structure of the system and the sensibility of banks portfolio to external shocks. Results suggest the fruitfulness of this kind of approach to policy makers and supervision agencies to address macro-prudential dynamical stress testing and regulation.

Keywords: Financial Networks, Interdependence, Contagion, Banking System, Venezuela, Macro-prudential
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1. Introduction

Throughout the 20th century, most Nation-States accomplished their objectives on regulation and supervision of banking systems in highly cartelized and protected settings. Since the 1970s, the technological development, financial innovations and deregulation have de-centralized the system, and at the same time have made the assessment of banks risk/return profiles in many countries more complex. Besides competition, at least in the wholesale markets, the banking business is international, and as such domestic regulations becomes a competitive disadvantage. Hence, the interest of the banking sector is to develop a global normative set of unique characteristics, as established by the Basel Committee on Banking Supervision (BCBS) (Capie et al., 1995).

The aim of supervision is to ensure that depositors and the public have some guarantee and comfort, given the difficulty of understanding the information showing the level of solvency and liquidity and the risks that incur financial institutions, fostering confidence in the system. It is also important, to the average citizen, to achieve full access to information in a timely and periodically fashion in order to certify an adequate interpretation, promoting systemic transparency. On the other hand, the increasing frequency of financial and economic crises being of balance of payments, foreign exchange, banking system or the stock market - during the post Bretton Woods period, have spread due to the increasing global interdependence. These include crises that have lasted from 18 to 24 months, until they are considered to be under control; crises overlapping with the previous, as a result of the reactions of the actors of the market or consequence of the economic policy and strategies used to solve them; crises that keep the global economy on tenterhooks; and crises that ceased to be sporadic and exceptional and have become the norm, and not the exception, in the global economy.

A multilateral agency that has paid attention on financial crises since the 1980s has been the Bank of International Settlements (BIS), being that guidelines on regulation and financial supervision have emerged out of their research (http://www.bis.org/forum/research.htm). Although its guidelines do not have a mandatory character, the follow-up to their suggestions succeeds from technical prestige and respectability of the institution.

1.1. Basel regulation

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 that in order to maintain global financial stability and a solid and adequately capitalized system, it was required for banks to keep a minimum amount of equity, equivalent to 8% of their risk-weighted assets (Basel Committee on Banking Supervision (BCBS), 1998). From Basel I, the BCBS took a much more active role in the promotion of its standards of supervision worldwide, supporting this on existing collaboration with the authorities of national supervision and regional integration organizations. With this goal, in 1997 they developed the *Core Principles for Effective Banking Supervision*, which provide an efficient model for this activity. In addition, and with the purpose of facilitate the implementation of these principles, in 1999, provided the *Core Principles Methodology.*

In 2004 the BCBS published the *New Capital Adequacy Framework*, known as Basel II. While Basel I considered market and credit risks, Basel II changed substantially the treatment of credit risk and also required that banks should have enough capital to cover operational risks. It imposed quality requirements before the administration of all risks, as new disclosures of information. Also demanded greater transparency in the information about credit risk, increases the documentation required to debtors, as well as diversification of balance through insurance activities. Thus Basel II is based on three pillars: requirements of capital, discipline of market and prudential supervision carried out by the relevant entity (Basel Committee on Banking Supervision (BCBS), 2006).

Basel II seemed to be a robust scheme for the defense of banking systems to potential financial crisis. However, the crisis of 2007, proved its inadequacy. This resulted in the 2008 BCBS response of the Basel III agreement. This agreement increases the quality and quantity of equity depending on the cycle's phase in which the economy is, and can reach to 13% of the assets of the bank. The countercyclical cushion reflected in Basel III provides the national regulatory authorities the ability to define when credit growth is too high, and then to require higher levels of equity; and determines that such an increase is between 0 and 2.5% of the equity to achieve absorption of losses, which is worth noting and is impossible to calculate with accuracy in a crisis scenario. Similarly, 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. In this regard highlights the conflict of interests of the rating's agencies in its recommendations on structured values (Ito, 2011).

Considering the difficulties that many financial institutions went through in liquidity management, in September 2008, the Committee published the document *Principles for the Sound Liquidity Risk Management and Supervision*. Also established two financial liquidity standards: the *Liquidity Coverage Ratio* (LCR), which promotes resistance for short-term (30 days) of the risk profile of liquidity and the *Net Stable Funding Ratio* (NSFR), to promote resistance in a broader time horizon (one year) and create incentives to use sources of funding more stable for banking activities. Also, for a follow-up had been considered a variety of parameters, including: the gap of contractual maturities, the concentration of funding, the amount of free assets of loads that can be used as collateral, a liquidity analysis considering nomination badge; and finally a set of monitoring tools related to the market: data on prices and liquidity of assets, spreads on credit default swaps, stock price swaps and others (Basel Committee on Banking Supervision (BCBS), 2008).

During the G-20 Summit in Seoul of 2010, it was approved the establishment of standards of Basel III, which will be implemented during the next decade, seeking greater banking stability from the so-called micro-prudential. Also, Basel III instituted some macro-prudential measures to ensure banking operation even in times of systemic problems. It is the goal that by 2019 banks would have a liquidity coverage ratio of 100%, as well as a countercyclical fund for those institutions of systemic relevance that could be in problems.

1.2. Network science and its applications in finance and economics

Despite all the reforms and progress made, main monitoring standards still rest on the micro-prudential aspects and attend the strength of units of the system, leaving its systemic relationship as a simple consequence of the above. This is a weakness that remains a crucial issue that must be seriously addressed. In this regard, a greater understanding of the externalities of economic and financial networks could help to design and adopt a framework of prudential financial supervision in such a way of considering both the actors of the system (financial institutions) and the vulnerabilities that emerge from their interdependence in network and thus try to improve investment and corporate governance decisions and mainly, help prevent crises or minimize their negative impacts.

Network science has greatly evolved 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; Boccaletti et al., 2006; Newman et al., 2011; Cohen and Havlin, 2010; Havlin et al., 2012). Famous examples include the findings about sexual partners (Liljeros et al., 2001), Internet and WWW (Faloutsos et al., 1999; Barabási and Albert, 1999), epidemic spreading (Pastor-Satorras and Vespignani, 2001), immunization strategies (Cohen et al., 2003), citation networks (Radicchi et al., 2008), structure of financial markets (Bonanno et al., 2003), social percolation and opinion dynamics (Solomon et al., 2000; Shao et al., 2009), dynamics of physiological networks Bashan et al. (2012), structure of mobile communication network (Onnela et al., 2007), and many others. Among the phenomena that have been shown to fall in this conceptual framework are: cascading failures, blackouts, crashes, bubbles, crises, viral attacks and defense against them, introduction of new technologies, infrastructure, understanding measuring and predicting the emergence and evolution of networks and their stylized features, spreading phenomena and immunization strategies, as well as the stability and fragility of airline networks (Cohen and Havlin, 2010). Current and past research has shown that in real life systems, there is a strong feedback between the micro states and macro states of the system. This description of nature can be well represented by network science – in which the micro is represented by the nodes of the network and the links between them, and the macro by the network itself, its topology, dynamics and function. Thus, network science, present and future, is the leading framework to investigate real life systems. For example, as opposed to physical systems where the dynamics is usually bottom-up, in social and economic systems there are interplays on all levels with singular top-down feedbacks. Thus, in many practical realizations, in addition to the bottom-up contagion propagation mechanisms one finds that there is a global-to-local feedback: individuals, their interdependence and behaviors build up the system that finally affects back on individuals' choices. It has been proposed that the bottom/up – top/down feedback has the capability to change completely the character of a phase transition from continuous to discontinuous, thus explaining the severity of the economic crises in systems where the collective interacts as such with its own components (Cantono and Solomon, 2010)

Network theory provides the means to model the functional structure of different spheres of interest, and thus, understanding 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, it 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 that they really hold; hence, the resulting structures are not biased by theoretical perspectives or normative approaches imposed 'by the eye of the researcher'. On the contrary, the modeling by network theory could validate behavioral assumptions by economic theories and further, channeling the attention of policy instruments in quantity and quality highly focused. Network theory can be of interest to various edges of the financial world: the description of systemic structure, analysis and evaluation of the penetration or contagion effects (Lillo, 2010; Kenett et al., 2012b,c; Cont, 2013; Glasserman and Young, 2014; Li et al., 2014; Garas et al., 2010); studies that assess the impact of the insolvency of one or a particular group of actors in the system, depending on its relevance and connectivity within the structure (Jackson, 2010; Battiston et al., 2012); and those that allow to evaluate the impact of liquidity problems at specific times and initiated in different nodes of the system (Haldane and May, 2011; Haldane et al., 2009; Cont et al., 2010; Amini et al., 2012; Kenett et al., 2010, 2012a). In a nutshell, it becomes not only an alternative perspective, but provides tools allowing to compare and to contrast the structure of the systems in a static way and project different dynamic scenarios.

In this sense, the payment system can be seen as an example of complex network, and thus, considered as a network, derive its stability, efficiency and resilience features (see for example (Aguiar et al., 2014)). 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 the risks inherent in its operations to some extent 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., 2014).

Recent studies by Inaoka et al. (2004), Soramäki et al. (2007), Cepeda (2008), and Galbiati and Soramäki (2012), investigated the interbank payment system using network science. considering the system as a network, these authors were able to uncover the structure of the system and allowed the design of scenarios and the visualization of specific effects. Meanwhile, Iori et al. (2008) analyze 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.

Focusing on liquidity, Minoiu and Reyes (2011), explore the properties of the network of global banking using information from bilateral loans from 184 countries and their direct investment flows (quarterly). Coinciding with several papers on capital flows, they conclude that advanced economies are the major players in the global banking market with 10 times more flows between them than to developing or emerging countries, making up the core of the network with other countries in the periphery. After describing the topology of the network and evaluating its dynamics in the period 1978–2009, they found volatility in the network topological properties: the interconnection between nodes is unstable and connectivity tends to decrease during periods of crisis.

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. More recently, Acemoglu *et al.* (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 that when negative shocks are larger than a certain threshold, contagious prevails and so the systemic instability.

1.3. Bipartite bank-asset networks

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 US banking network. Between 2000 and 2007, 27 banks failed in the US, but between 2008 and early 2013 the number rose to over 470. 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 US commercial banks for the year 2007, and model predictions are compared with the actual failed banks in the US 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. The model also indicates that commercial rather than residential real estate markets were the major culprits for the failure of over 350 US commercial banks during the period 2008–2011.

There are two main channels of risk contagion in the banking system, (i) direct interbank liability linkages between financial institutions and (ii) 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 counterpart exposures following an initial default. The latter, based on bank financial statements and financial ratio analysis, has received scant 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 thus 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, e.g., requiring mandatory reduction in exposure to a shocked asset or closely monitoring the exposed bank, to prevent such 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 in the stable region, we suggest that our model for systemic risk propagation might also be applicable to other complex financial systems, e.g., to model how sovereign debt value deterioration affects the global banking system or how the depreciation or appreciation of certain currencies impact the world economy.

In this paper we present a dynamic version of the Huang et al. (2013) model. As a case study of the applicability of the model, we study the banking system of Venezuela, for the period of 2005–2013. As such, the dynamical bank-asset bipartite network model provides a first tool of 'Risk Management Version 3.0" (Bookstaber et al., 2014), which allows to rate the risk of different assets, alongside the stability of the banks of financial institutions, in a dynamical fashion. In the following, we will first introduce the Venezuelan financial system (Section 2), and then the dynamical bipartite network model (DBNM). We apply this model to a bipartite network of banks and assets (DBNM-BA, 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 have focused on the Venezuela financial system. Venezuela is medium size economy, that during the past 15 years has had important regulatory changes related to its banking system. Thus, the aim of this work is to make use of network theory to uncover the structural features of the system in a dynamical way. Furthermore, as most of the financial network analysis mainly 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.

2.1. General remarks on the Venezuelan economy

Soon after the declaration of Venezuela's independence, in the 19th century, important banks were established in its territory. The 20th century, especially the 1948–1978 period showed a strengthening of the banking sector and a deepening of the intermediation: bank penetration went from 10% to 43%; monetary creation allowed that the relationship between the powered money and liquidity went from 73% to 30%. Thus, the Venezuelan financial sector experienced a gradual growth of the funds mobilized with the participation of the public sector through sectorial financing. Venezuela has shown economic growth until 1978, at which point its economy initiated a continuous phase of decline; however, it is worth noting that measures of the banking activity continued its positive trend until 1982 (Levy-Carciente, 2006).

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, and the rentier scheme in which derived its productive sphere, with inevitable impacts on the rest of the social spheres. This phenomenon is known in the literature as the paradox of plenty or the resource curse, and is explained by models of Dutch disease, which points out that the discovery of vast natural resources or the unusual increase in its international price, generates a positive shock in the economy, re-evaluating the exchange rate because of the commodity rentability (but inconvenient for the rest of the activities), reducing the possibilities of investment and the competitiveness of its industrial sector. 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, it should be noted, the fatal neglect of Venezuela of the international transformations - the end of the Bretton Woods System - is what prevented the exploitation of potential in the financial sector and specific strengths that once influenced the Venezuela currency, the Bolivar (Palma, 1985; Malavé-Mata, 1987; Naím and Piñango, 1988; Hausmann and Gavin, 1996; Mata, 2006).

Between 1983 and 1988 the monetary liquidity fell from 49% to 33% of the GDP. At the end of the 1988, while the assets of the banking system were equivalent to 72% of GDP, bank credit had a secondary role in the economy. Commercial banks' credit granted to the private sector fell to less than a third of its value in current terms between 1982 and 1984, from US$36199 to US$11778 million and in 1986 was nearly a quarter, reaching the amount of US$9366 million. In this period the consumer prices index grew from 6% to 29% while the interest rates were controlled between 13% and 10%, being negative both to saving and to the banking sector. In 1989, due to the unsustainable macroeconomic imbalances, a program of reforms was released to correct all distortions that endured the Venezuelan economy and to achieve a proper allocation of resources. Since 1989 banking disintermediation deepens and their business tends to rely on investment activities, mainly State securities. In a first phase, the Central Bank of Venezuela, offered zero-coupon bonds, which then would be replaced by the Monetary

Stabilization bonds, TEM. With the emergence of the government securities, private banking changed the composition of their assets, emphasizing its dependence on fiscal behavior. While the rest of the economy was restructuring itself, the banking sector had no incentives to improve efficiency. At the end, this behavior progressively weakened the sector.

The political instability and social unrest of the period will ruin the onset of a macroeconomic recovery 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 raised to 50% and 80%. It is in this environment that unleashes a terrible banking crisis that affects a third of the population and whose resolution cost have been estimated as 18% of the 1994 GDP. With this weakness condition and with numerous institutions in the hand of the State[1], begins a phase of mergers and acquisitions by international consortia - highlights the participation of Spanish corporations-process that has been highly questioned (Hausmann and Gavin, 1996; Mata, 1996; Del 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 has had to face, but also due to the strategic decision of their planners to go gradually showing their nature and further objectives (Levy-Carciente, 2013b,a).

From a regulatory point of view, in 1983, 1984, 1987 and 1992 were enacted reforms to the Law of the Central Bank and in 1999 was passed a new one. In 1984, 1988, 1993 and 1996 were enacted reforms to the General Law on Banks, in what was called the General Reform of the Financial System, with the aim of strengthening the financial system and make it more competitive, productive and transparent.

2.2. The Venezuelan banking sector 1998–2013

The financial sector throughout this period has been one of the few who has managed to take advantage or to adapt to the new economic conditions of the country. The level of its assets has increased 136 times, from Bs.

[1] By mid-1995, 58 failed financial institutions and its associated companies were in the hands of the Venezuelan State

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/US$; SICAD I around 11Bs./US$ and SICAD II around 50Bs./US$.

During the period under study, the structure of the system has gone through important changes, both in number and in sub-sectors. 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, and from more than 100 institutions, by 2000 there were only 65 remaining. In addition, the traditionally predominant role of commercial banking turned to universal banks, while the financial investment and savings entities disappear by 2013. In 1998, the commercial banks owned 37.4% of assets and universal banks 57.4%, while by 2013 universal banks owned 80% of the assets of the banking sector. Both sub-sectors have represented more than 95% of the whole financial system. With regard to the composition of the assets, the three main types are: Cash & Equivalents, Credit Portfolio and Securities. While in 1998 the credit represented 60% of the banking assets, in 2004 it was 30% and ending 2013 was 45%. On the other hand, securities were 10% of the assets of the system by 1998, in 2004 raised to 50% and ending 2013 was of 30%.

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 (details in Appendix A). In this regard, special mention should be given to the aliquots, or mandatory credit portfolios–known colloquially as 'gavetas' (gavetas in Spanish means drawers)–at preferential rates, that since 1999 have been implemented 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, micro-enterprise, manufacturing and housing. Today they represent 60% of the banking credit. It is also worth noting that the infringement in this obligation has very high fines, insofar as these are calculated considering the equity of the offender and not the prejudice of non-compliance (Muci B., 2009).

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

2.3. Bank balance sheet data

We make use of statistical information from the Superintendence of the Institutions of the Banking Sector, SUDEBAN (`http://www.sudeban.gob.ve/`), through its monthly statistics Balance of Publication, Monthly 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 provided information we built bipartite networks for each month of the 16 years under study. We identified the banking sub sectors in each period (commercial banking, universal banking, investment, savings and loan, mortgage, leasing, money market funds, micro-finance and development banking) and their systemic weight was based on their respective asset level. From the balance sheet of each bank we have identified the assets items (cash and equivalents, credit portfolio and securities), breaking them down to consider its systemic relevance. Subsequently 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, analysis of the securities held by the different banks was also performed, specified as: private securities, treasury bonds, treasury notes, bonds and obligations of the public national debt, bonds and obligations issued by the BCV and agricultural bonds. The 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 to show its dynamic evolution. A summary of the bank and asset types investigated in presented in Table 1.

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 never 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

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	
Other credit	
Securities	
Private securities	
Treasury notes	
Treasury bonds	
Public national debt	
BCV bonds	
Agriculture bonds	

Table 1: Asset and Bank Types

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 non-overlapping asset categories, e.g., bank i owns amounts $B_{i,0}, B_{i,1}, ..., B_{i,N_{asset}}$ 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 $s_{i,m} \equiv B_{i,m}/A_m$.

Furthermore, we define two additional parameters for the individual assets. We calculate the relative size of the asset, β, defined as:

$$\beta_m = \frac{A_m}{\sum_m A_m}, \tag{1}$$

and we define the level of concentration/distribution of a given asset, using the Herfindahl-Hirsch 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 introducing a shock to one of the given asset classes within a given month. The parameter, p, determines the fraction of the asset class remaining after the shock. So $p \subset [0, 1]$ is an exogenous parameter to the banking system that cannot be controlled. If we begin by shocking asset class m and $A_{m,\tau=0}$ is its total value, where τ represents the iteration of the model, then the initial shock reduces its value 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% of its original value, or in other words it is a 30% shock to the asset. A smaller p corresponds to a larger shock.

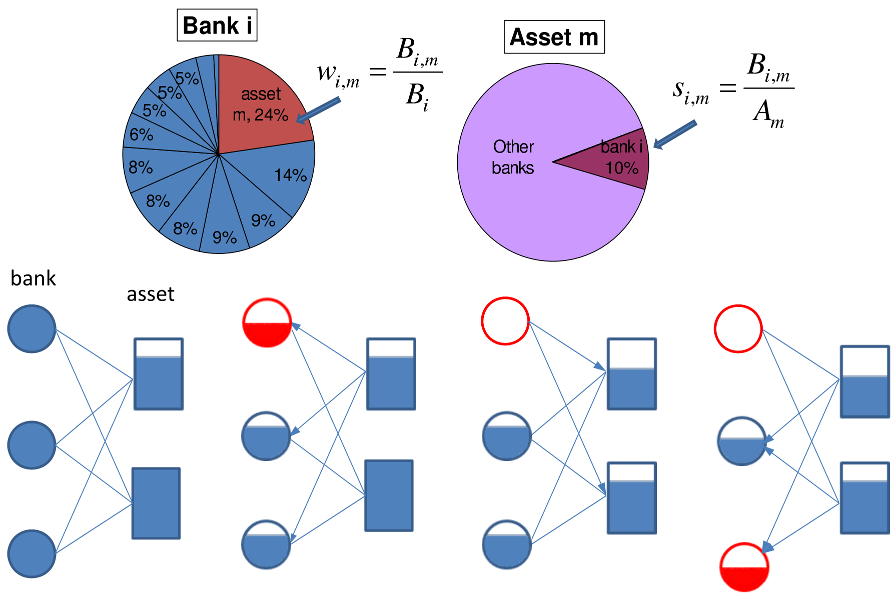


Figure 1: Bank-asset coupled network model with banks as one node type and assets as the other node type. Link between a bank and an asset exists if the bank has the asset on its balance sheet. Upper panel: illustration of bank-node and asset-node. $B_{i,m}$ is the amount of asset m that bank i owns. Thus, 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 (e.g. 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. This adversely affects other banks that hold this asset and the total value of their assets may drop below the threshold which may result in further bank failures. This cascading failure process propagates back and forth between banks and assets until no more banks fail. After Huang et al. (2013)

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 if $B_{i,m}$ represents the value of asset class m on the balance sheet of bank i, then the value of $B_{i,m}$ is reduced similarly,

$$B_{i,m,1} = pB_{i,m,0} = B_{i,m,0}\frac{A_{m,1}}{A_{m,0}}. \quad (4)$$

This reduction in assets for bank i reduces its equity accordingly. If after the initial shock, no bank has their equity reduced to zero or below, the algorithm stops and all banks survive the impact of the external shock. However, if any bank's equity is reduced to zero or below, then that bank node fails and any asset classes that it holds on its balance sheet (that it is linked to in the network) will suffer a corresponding devaluation and the cascading failure algorithm will continue. This is where the endogenous parameter, $\alpha \subset [0, 1]$, which is related to the structure of the system, comes into play. If bank i fails and has $B_{i,m}$ of asset m, then,

$$A_{m,\tau+1} = A_{m,\tau} - \alpha B_{i,m,\tau}. \quad (5)$$

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.

This reduction in the value of the asset classes will again cause the reduction at the bank level for any bank holding any of the devalued assets as such,

$$B_{i,m,\tau} = B_{i,m,0}\frac{A_{m,\tau}}{A_{m,0}}. \quad (6)$$

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.

As an example, let's assume a shock of p=0.7 to credit cards, that reduces 30% 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% 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% 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% 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 time evolution of the critical parameters, p_{crit} and α_{crit}. Following the definitions above, the two parameters can be defined as following:

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

and

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

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. Thus the model allow us to see systemic features not assessed by traditional measures, which is valuable for supervisory agencies.

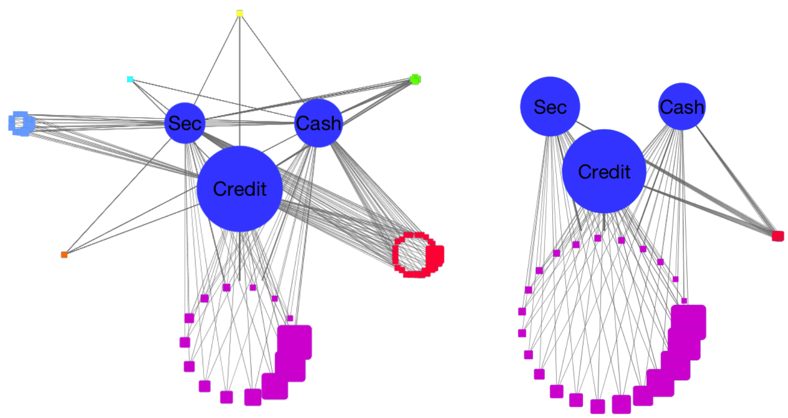
Symbol	Description
$A_{m,\tau}$	Total value of asset m at iteration τ
B_i	Total value of all assets owned by bank i
$B_{i,m,\tau}$	Value of asset m owned by bank i at iteration τ
N	Number of banks
p	Parameter representing the shock level $(1-p)$
α	Parameter representing the spreading effect of a shock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

Table 2: List of model parameters and measurements

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 sub-sectors 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 has 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. The securities networks showed, during the period 2005–2013, the growing influence of national public debt instruments while diminishing that of private bonds and of those issued by the BCV. As well as with aggregated assets, these two groups of networks showed the transformations of the system month by month.



(a) 2000 (b) 2013

Figure 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.

Having identified the structure transformation, the following 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, period in 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.

4.1. Surviving banks, shock level and contagion effect

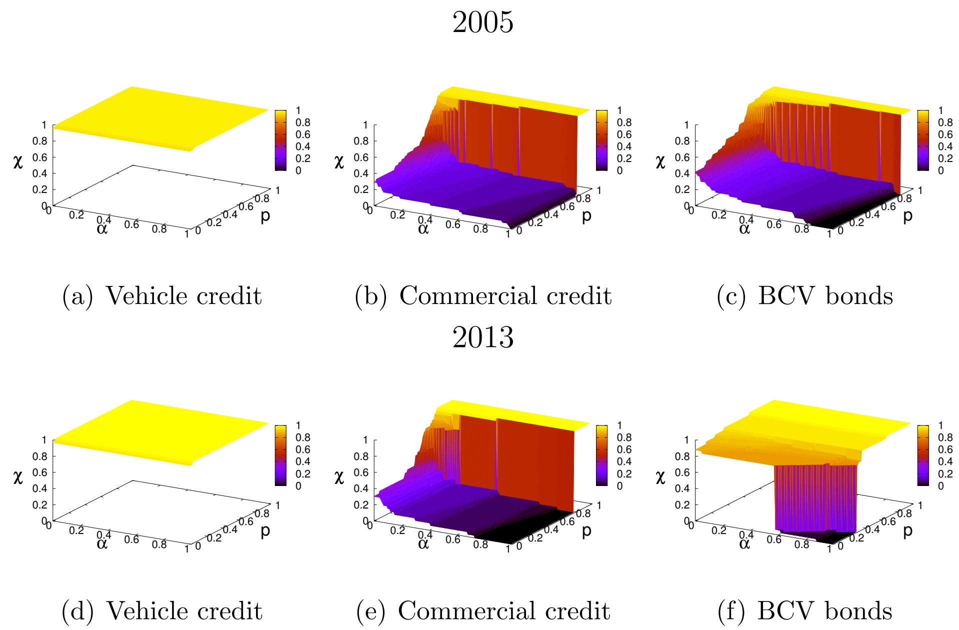
The three main parameters of the model, as discussed above, are p (external shock level), α (level of asset contagion), and χ (fraction of surviving banks). We thus begin the analysis by focusing on a given month, and investigating the relationship between these three parameters, for different individual assets.

In Fig. 3, we plot 3D 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. The analysis is done for data from December 2005 and from December 2013. 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%. 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 over time. In the case of BCV bonds, as seen in Figs. 3(c) and 3(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*. Thus, the question arises whether the damage observed in the model is resulting from the size of the shocked asset. Thus, 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 Figs. 4(a) and 4(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



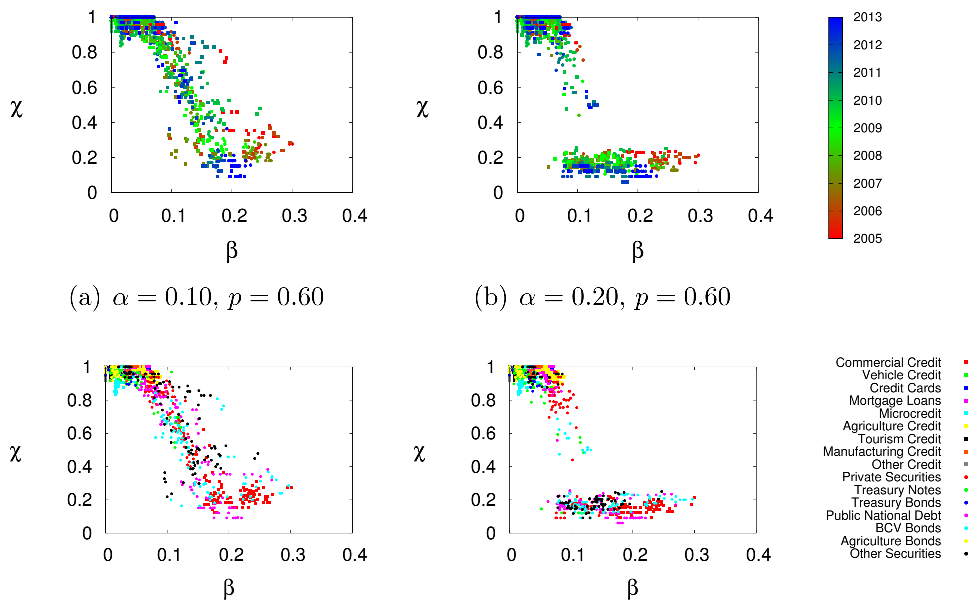
(a) Vehicle credit (b) Commercial credit (c) BCV bonds

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

Figure 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.

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 of the asset is relevant, but also the way in which it is distributed through the structure of the system. Thus, the bank-asseets network structure provides systemic risk based on details that are not captured or apprehended with traditional tools. For the model runs in which fewer than 20% of the banks survive, we see there was a tendency in the earlier years, for greater concentration of a given asset type. Simultaneously, it is possible to 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.

Figs. 4(c) and 4(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% or greater. The smaller the shock to the asset, the more linear the relationship by χ and β. See Appendix D for more examples.



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

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

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

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

Figure 4: The plots show the relationship between β and χ. Fig. 4(a) and Fig. 4(b) show points color-coded by the year for which the model was run. Fig. 4(c) and Fig. 4(d) show points color-coded by the asset which was initially shocked. Fig. 4(a) and Fig. 4(c) show the relationship for $\alpha = 0.10$ and $p = 0.60$, Fig. 4(b) and Fig. 4(d) for $\alpha = 0.20$ and $p = 0.60$.

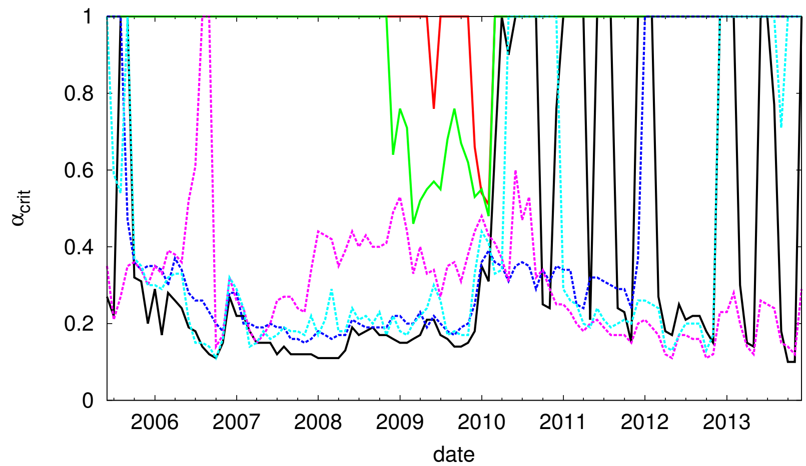
4.3. External Shock and Contagion sensitivity

As discussed above, 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% of banks survive) and for a given p (or α) find the minimum α (or maximum p) that results in fewer than 20% 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 α_{crit}, however, the results presented below can alternatively be presented for the case of p_{crit}.

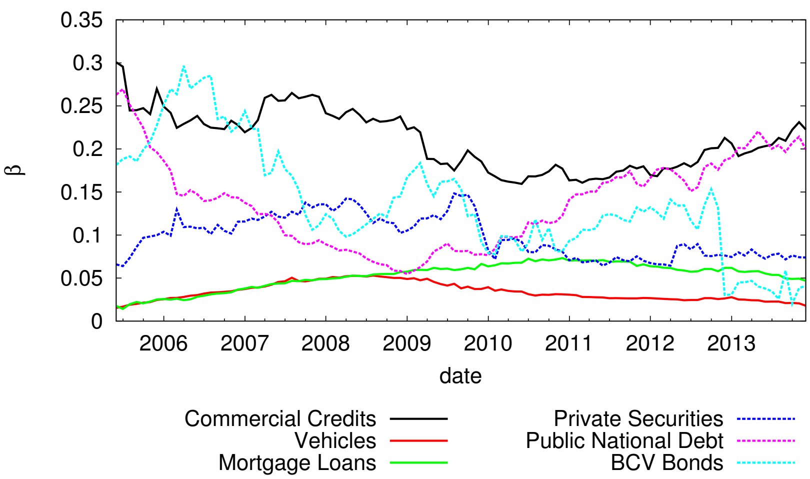
In Fig. 5(a) we present results obtained for the scenario of $p = 0.80$ (an initial shock of 20% to each of the respective assets) and track over time the critical value of α for which just under 20% of the banks survive the cascading failure algorithm. The plot shows that larger shocked assets, in general, show a lower α_{crit} than smaller shocked assets. It also reveals volatile behavior of α_{crit} in 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 to similar shock events. The value of α_{crit} reflects the macro-prudential 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. However we can see two small assets, mortgage loans and vehicle credits, that during 2009–2010 saw a significant drop in α_{crit} even their systemic size had only 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 HHI 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 macro-prudential 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 2007–2010, 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



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

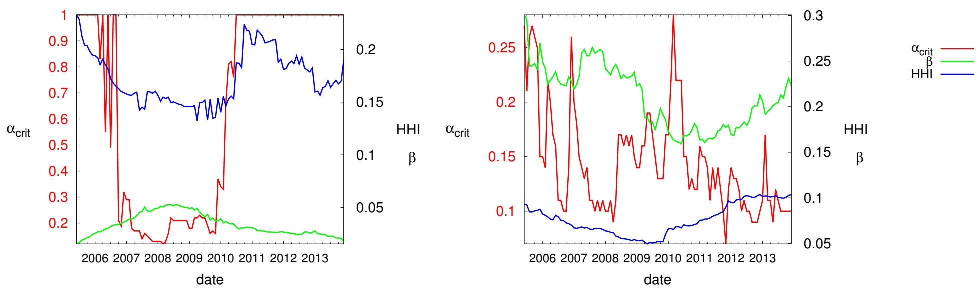


(b) β vs. time for select asset classes

Figure 5: (a) The behavior of α_{crit} in time for certain shocked asset classes. For $p = 0.80$ (an initial shock of 20% to each of the respective assets), we track over time the critical value of α for which just under 20% 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.

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 an asset is concentrated in a smaller number of banks, the smaller α_{crit} is, indicating that the system is more sensitive to cascading failures.



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

Figure 6: 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 2007–2010, 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. Fig. 6(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.

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, as a function of time. Thus, we 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 presentation. 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, a series of tests was performed to find the order in which banks participated in the simulated process of failure, and considered its relationship with traditional measures to estimate banks solvency, such as the debt-to-equity

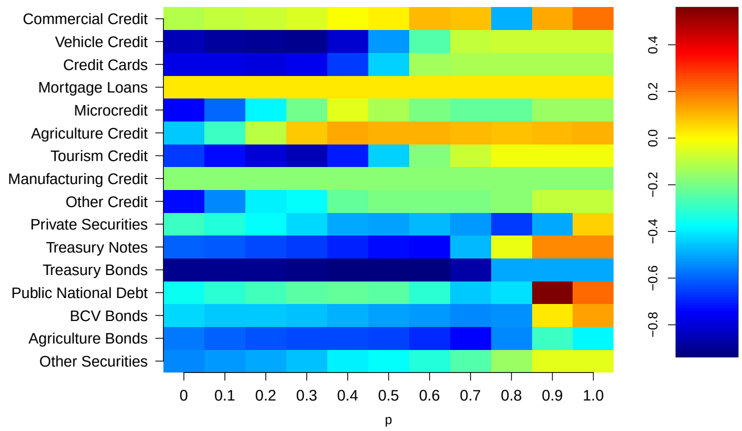
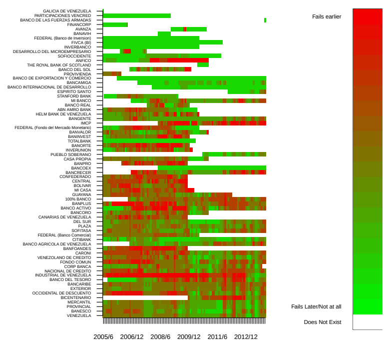


Figure 7: Heat map of α_{crit} and the β correlation for each asset type and various shock levels. Color represents the strength of the correlation, ranging from red for positive values, to blue for negative values.

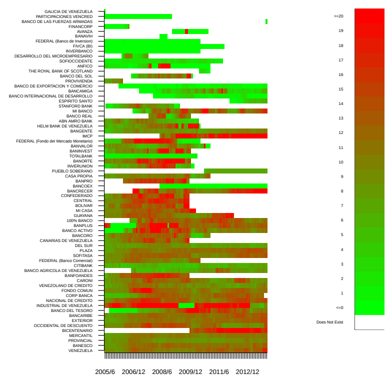
ratio (total liabilities/total equity), which is a long term ratio to evaluate the robustness of a firm. It must be noted that the debt-to-equity ratio assesses the strength of a banking institution, while the DBNM-BA is aimed at assessing the strength of the banking system. However, both elements are relevant to elevate the fragility of the banking sector.

We find that the order of banks failure 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 bank of 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. This procedure was performed 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.

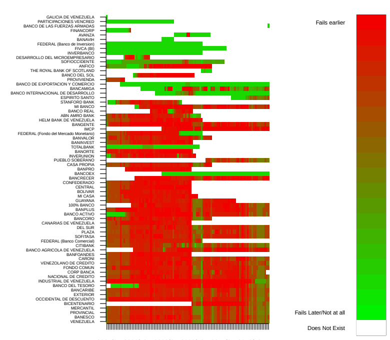
Fig. 8 shows the results of the average cascading failure steps for each institution in two states: (a) for $p = 0.70$ and $\alpha = 0.10$ and (c) for $p = 0.70$ and $\alpha = 0.20$. Fig. 8(b) shows the debt-equity ratio. We can see that Figs. 8(a) and 8(b) are more or less similar, while 8(c) shows 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



(a) Bank failure order



(b) Debt-to-equity ratio



(c) Bank failure order

Figure 8: Fig. 8(a) Heat map showing the average cascading failure steps for all systems banks, shocking all the assets with $p = 0.70$ and a contagion effect of $\alpha = 0.10$, from 2005–2013. Fig. 8(c) Heat map showing the average cascading failure steps for all systems banks, shocking all the assets with $p = 0.70$ and a contagion effect of $\alpha = 0.20$, from 2005–2013. These heat maps color code goes from red to green. Red indicates a bank failing earlier in the model. Green indicates that the bank survived the cascading failure process. White indicates that the bank did not exist at that specific moment in time. Fig. 8(b) Heat map showing the debt-to-equity ratio for each bank, from 2005–2013. Its heat maps color code goes from red to green. Red indicates the higher debt equity ratio. Green indicates the lower debt-to-equity ratio. White indicates that 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.

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 had made global stability one of the major concerns in the economics field worldwide, as they had spread their effect through a highly interdependent financial network, in the so-called 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, small, solvent as highly leveraged institutions succumbed under the negative impact of the diminishing value of assets, which caused fire sales and finally a disruption of financial markets. Even all financial institutions are under important supervision and albeit all the transformations in the regulating analyses, the systemic impact was not foreseen by regulatory institutions and resulted in a costly amount, which is still under siege.

Under this highly complex environment, financial and banking supervision has to be thought as a systemic task, focusing on the health of the nodes–the institutions involved: banks and financial institutions–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 implies that there exists the need to include the shadow banking institutions to the traditional banking institutions, in light of their important role in the financial system and their multiple links and connections. Simultaneously it has to be highlighted that the system is dynamic, so more than a one moment snapshot, a time dependent video is required, to follow up the evolution and transformation of the system and its strengths and weakness in different moments. With this in mind, this work proposes a modeling framework that is able to track structural 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.

As a case study we investigated the Venezuelan banking system from 1998–2013, as 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, a series of shocks were applied to the system, in order to reveal intrinsic weaknesses at different times. In this sense, it should be noted that the system displayed an important variation, which 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 very 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 element of high relevance.

As a proof of concept, the results emphasize the model's capability to assess the fragility of the system in a way that traditional measures are not able to. Traditional measures capture important information about the nodes of the banking network, but not the connections, direct or indirect, between them. Once the connectivity is considered and the contagion effect is made possible, traditional measures cannot assess the systemic effect, and so forth, underestimate the systemic risk.

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. While the DBNM model was demonstrated here using bank and asset data, it can be applied to additional financial instruments, and thus presents 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 thus 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 weaknesses and vulnerabilities of the system as a while. 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 which nodes, and to what extent, recovery should be applied in order to recover the system. Finally, this model can be complemented using the multilayer network approach, when considering as the banking system as part of a more complex system including the global financial system and the real economy as a while.

Acknowledgements

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Appendix A. Legal transformations of the Venezualan banking system

In what follows we summarize the main legal transformations of the economic sectors with enforced credit and, even it is not the aim of this paper, we include some brief comments on their results.

The Law of Agricultural Credit[3] 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% of the total number of deposits, then it was changed to 30% of the total credit and is today in 24% of the total credit. This credit is granted at preferential rates of 5% 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% to structured funds or Zamoranos; less than 15% for marketing and distribution, less than 15% on certificates of deposits, secured bonds and distribution operations; less than 5% to the same company or corporate group; between 49% and 79% should be assigned to primary agricultural production of priority products; between 10.5% and 15% to finance infrastructure and the marketing of priority products equivalent; and less than 4.5% for the commercial lending of non-priority 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 has been increased from 10% in 2009 to 15% in 2012 and reached 20% in 2013. It establish monthly income characteristics to be fulfilled by the beneficiaries of loans for acquisition, construction, expansion or renovation of main dwelling: 60% of this portfolio should go to people with incomes below 623 Bs/month ($100US/month[4]) 20% people earning less 2800 Bs/month (445 US$/month) and the rest to those who earn between 2800 and 7000Bs/month (max. 1060US$/month). Credit is granted at a preferential rate of 5%.

The obligatory portfolio to the tourism sector, regulated by the Organic Law of Tourism of 2005 (RBV Gaceta Oficial #38215) establishes an aliquot

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

[4]Using the official CENCOEX exchange rate

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

To benefit the so-called 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% of the loan portfolio of the preceding semester at a rate of 24% (this is the only one rate of this mandatory credit that was not established at such a low preferential level). Encouraging microcredit has different objectives, on one hand it seeks to entrepreneurial stimulation, and on the other hand has been considered an instrument to alleviate poverty. The 2006 Nobel Prize Muhammad Yunus 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. (Jaffe 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% of interest rate (Article 2) and in Article 3 establishes that entities may not decrease the participation having the sub-sector by December 31, 2007 and that such participation should reach at least 10% of the total credit portfolio. It has been highlighted by various legal professionals the contradiction with Article 50 of the law of the Bank Central for the purpose of this mandatory portfolio, which concerns maximum on loans, that 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*

[5]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.

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)[6].

It is not the aim of this paper to make an analysis of the impact of these transformations. 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 for what were created. This is because the availability of funds for the promotion of an economic activity is a necessary condition but not sufficient, as it is also required of an economic environment conducive to production and that promotes productivity.

[6]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."

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

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

Appendix B. Interpolated 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

Table B.1: List of banks and dates for which balance sheet data was interpolated.

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

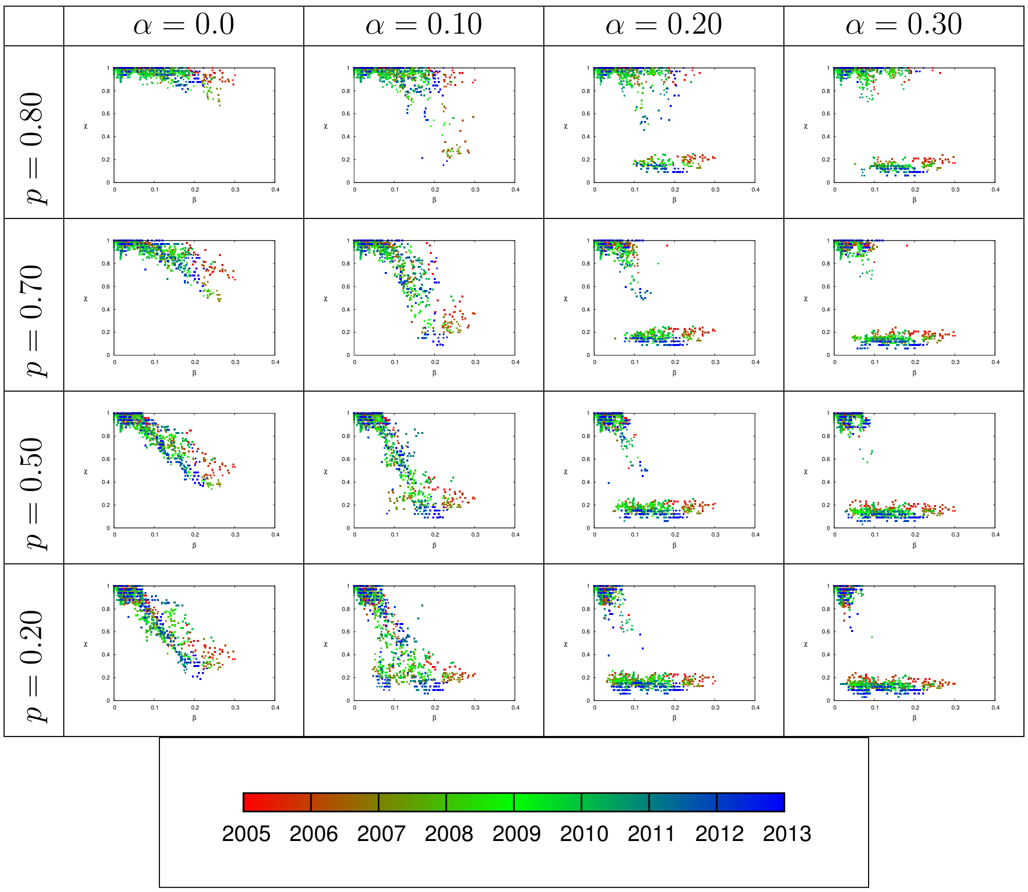

Figure C.1: Relationship between share of assets (β) and fraction of surviving banks (χ) for different shock levels (p) and spreading effect (α). The points are color-coded by the year for which the model was run.

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

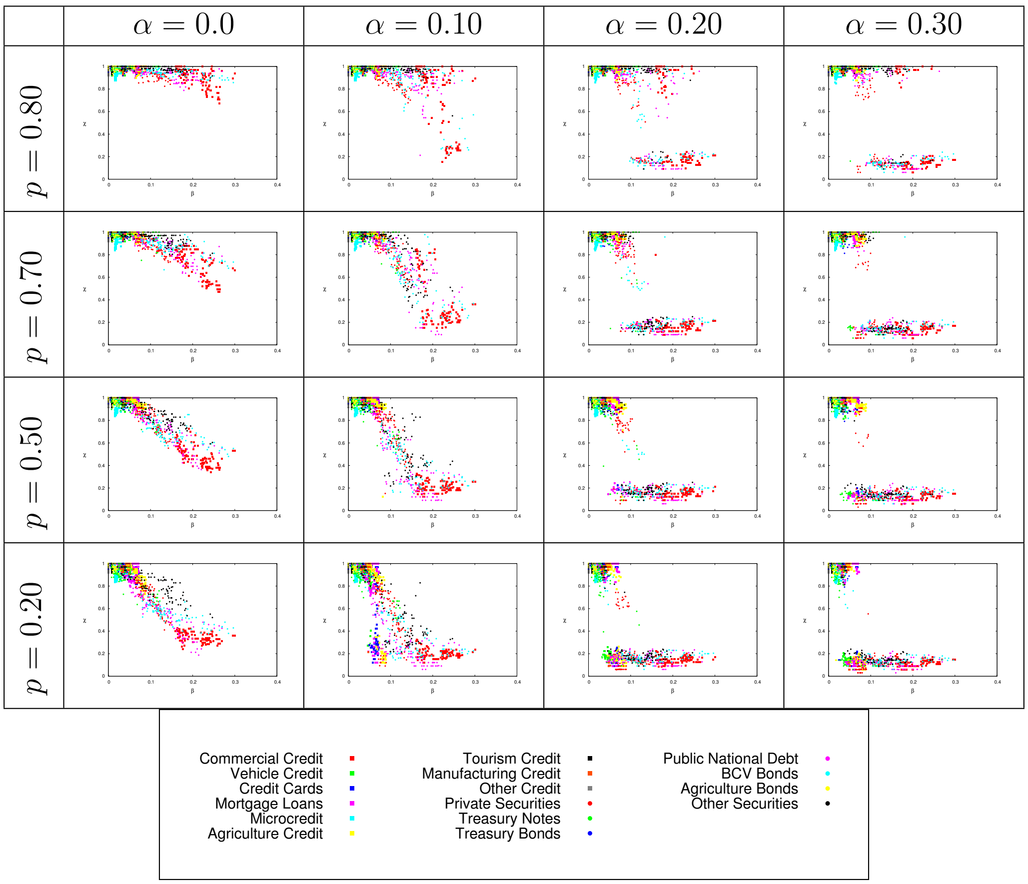

Figure D.1: Relationship between share of assets (β) and fraction of surviving banks (χ) for different shock levels (p) and spreading effect(α). The points are color-coded by the asset which was shocked.

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