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Systemic risk, stress testing and financial contagion: Their interaction and measurement

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Systemic Risk, Stress Testing and Financial Contagion: Their Interaction and Measurement. *

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Abstract

Despite the acknowledgement of the relevance of *Systemic Risk*, there is a lack of consensus on its definition and more importantly, on the way it should be measured. Fortunately, there is a growing research agenda and more financial regulators, central bankers and academics are contributing to this field recently. In this work, we obtain a distribution of losses for the banking system as a whole. We are convinced that such distribution of losses is the key element that could be used to develop relevant measures for systemic risk.

Our model contemplates several aspects which we consider important in the concept of systemic risk: an initial macroeconomic shock which weakens some institutions (some of them to the point of failure), a contagion process by means of the interbank market and the resulting losses to the financial system as a whole. Finally, once the distribution is estimated, we can derive standard risk measures for the system as a whole, focussing on the tail of the distribution (where the *catastrophic* or *systemic* events are located).

By using this proposed framework, it is also possible to perform stress testing in a coherent way, including second round effects like contagion through the interbank market. Additionally, it is possible to follow the evolution of certain coherent risk measures like the CVaR in order to evaluate if the system is becoming more or less risky, in fact, more or less fragile. Additionally, we can decompose the distribution of losses of the whole banking system into the systemic and the contagion elements and we can determine if the system is more prone to experience contagious difficulties during a certain period of time.

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1 Introduction

Nowadays it is hardly disputable the importance of Systemic Risk. Furthermore, it is at the center of intense discussions for all regulators and financial authorities. Despite the relevance of systemic risk for the maintenance of financial stability and its recent popularity, it is still work in progress as we lack an universal definition and tools to measure it. Fortunately, due to the unfortunate recent events, there is a renewed and shared interest by the national and international financial authorities in developing such necessary tools. To add to the confusion on the field there are a few terms recently used, all of them associated with systemic risk: financial contagion, too-interconnected to fail, systemically important institutions, systemic losses, liquidity risk, financial networks, etc. Nevertheless, we argue that what is necessary is a common language to define systemic risk and simple yet robust ways of measuring it. We will adopt for practical reasons a definition which is shared in Márquez-Diez-Canedo et al. (2009) and Rochet (2009). Systemic Risk can be broadly defined as consisting of two components: an initial (macroeconomic) shock and a contagion mechanism. The initial shock weakens one or several financial institutions and then contagion might arise as a result of such shock. Regarding contagion, there can be different channels of transmission, for example the interbank market just to mention one of the most widely studied transmission channels in the literature.

Having defined systemic risk we can now focus on ways to measure it in order to manage it. In most standard risk models, there are risk measures like the expected loss, VaR, CVaR, etc. Such risk measures can provide us with an idea of the size of the loss and its likelihood in a systemic crisis or event. Having said so, in our opinion its very important to estimate in best possible and accurate form the distribution of losses for the system as a whole, instead of adding up individual risk measures for each bank. This approach is being promoted by the BIS on its Macroprudential working group. Moreover, there is a global concern on how to identify systemically important institutions in order to evaluate the impact on the system of such institutions. For example, the government of Sweden has created a financial stability fund which is constituted by charging some financial institutions a fee constituted by a fixed percentage of its liabilities. However, by the year 2011, such fee will be risk differentiated.

As it was previously stated, financial contagion is one of the key elements on the definition of systemic risk, it has been there from the beginning; in fact, both terms were used in an interchangeable way in the past. Nowadays, it is more clear that it is just one of the components of systemic risk, a very important one though. Moreover, the importance of financial contagion in systemic risk is beyond discussion in the aftermath of the fall of Lehman Brothers. However, it is not always easy to model or quantify financial contagion.

As in the case of systemic risk, there are many definitions for financial contagion due to the complex way in which financial institutions are related today. Additionally, it is difficult to verify empirically if financial difficulties are transmitted between financial institutions or if its something different, like common exposures, the cause of financial distress. Furthermore, it is necessary to distinguish between two different types of contagion: direct and indirect contagion. While direct financial contagion[1] has been studied widely by several central banks[2], indirect contagion[3] is in contrast difficult to estimate due to the inherent information problems faced by the financial authorities and researchers.

In this paper two institutions are said to be connected if there is an exposure between them in any direction. We have already expressed that complex derivatives (CDS) exposures and indirect connections may be problematic. Additionally we think it is important to mention that from our experience problematic connections in banking systems are those:

- That for the bank which is lending, such connection represents an important percentage of its Tier1 Capital. This is because if the borrowing bank fails, such failure would compromise the capacity of the lending bank to absorb further losses. Speaking in a more general way, banks which are lending in the interbank market enough to threaten their ability to absorb additional losses could transmit further problems to more banks in the system.

- When such "overexposed" banks have their lending highly concentrated (something which could be easily measured by using the Herfindahl-Hirschman Index) this could bring more distress to the banking system.

Regarding indirect connections, it is difficult to avoid being exposed to the same types of shocks, because many institutions have similar business models, and all strive to invest in those areas with the best returns. The extent to which a certain type of shock can hit the banking sector could be limited by a high degree of diversification of each financial institution, which would limit the extent to which it suffers from a shock.

Regulation could be enhanced to ensure a "higher degree" of diversification in the financial sector. However even this type of regulation may fall short form obtaining the desired results. For example, several very diverse companies may have foreign exchange debt and fail when the exchange rate changes abruptly rendering diversification regulation useless. Moreover, certain aspects of financial connections must be taken into account:

- Some activities are necessary and difficult to change. Banks which act like "hubs" in any network of the financial system are particularly important as a failure or disruption of any of such banks could threaten the stability of the system. It could be difficult and costly to find a bank (or a group of banks) which can substitute such hub-like banks.

- Banks' connectedness may depend on aspects such as: Relationship banking (preference), peer monitoring costs and TBTF moral hazard driven choices.

[1] Particularly in banking systems through the interbank market.

[2] See Upper (2007) for a good survey on the literature.

[3] Indirect contagion usually refers to similar business models or implicit correlations.

- It is commonly accepted that in normal times strong interbank linkages are fundamental for the well-functioning of the interbank market, for it is through these connections that liquidity travels across banking institutions. It is also accepted that in times of crisis these connections tend to dry up. There is a danger that any regulation that limits interbank connections may be costly in good times and not applicable in bad times.

In addition to the approaches on systemic risk measurement, contagion analysis and network models to study financial stability, there is another tool which is becoming increasingly important for the financial authorities: Stress testing. Stress tests have become very relevant in recent times and can be considered as an almost standard tool in risk management. Many commercial and central banks, insurers and regulators perform stress tests as part of the risk management strategy of their respective institutions. From the perspective of global financial regulators as from the perspective of central banks, stress tests are now an unavoidable tool for designing policies to preserve financial stability. Moreover, stress testing is a common part of the financial stability reports elaborated by central banks.

From a financial authority point of view, the methodologies for the design of stress tests can be divided in two approaches: the bottom up approach and the top down approach explained in Sorge (2004) and Čihák (2007). The top-down approach is commonly used by central banks. In this approach the purpose is to evaluate the impact of an scenario using aggregated data. Nevertheless, by using such an approach some relevant aspects could be ignored, for example the interconnections between banks and the inherent contagion. On the other hand, under the bottom-up approach the objective is to evaluate the impact of a particular scenario by using data from the individual portfolios of the relevant institutions. The bottom up approach should deliver more precise results; unfortunately, such and approach is limited by the lack of data and the complexity of the financial system.

In this work we employ the bottom up approach as we posses relatively good information on the individual banks, the interbank market and the size of the Mexican banking system permits to perform computer simulations to estimate the distribution of losses for the banking system as a whole. It is important from our point of view the relevance of performing coherent system wide stress test as it has been pointed out in Sorge and Virolainen (2006).

The design of scenarios is a relevant aspect in stress testing. It is important to point out that the result of the stress tests depends heavily on the design of such macroeconomic scenarios. For example, if a stress tests is performed under an scenario which is severe but it has a zero probability of happening,then the value of such exercise is null. On the other hand, if the scenario has a high probability of happening but is not severe enough to be considered as an stressful one, then the value of such exercise is also null. The real objective to design an stress scenario is that it must satisfy the conditions of being a severe event and its probability of occurrence is not zero. To this end, the aspects that generate the most vulnerability to the financial system must be identified and should be incorporated on the design of the stress scenario.

2 Related literature

There are different proposed methodologies to measure systemic risk and financial stability. For example, Goodhart et al. (2006) propose a general equilibrium model which includes heterogeneous agents, endogenous defaults and credit and deposit markets. In Segoviano and Goodhart (2009), the authors infer the multivariate density, which they use to derive relevant measures of distress for individual banks, groups of banks and the distress on the system due to an individual bank. In a different approach, in Boss et al. (2006) the authors use a simulation model which they use to estimate the distribution of losses for the system as a whole. We have common features with this approach and the differences are due to different levels of development or availability of the information. Another relevant work is Aikman et al. (2009), in which the authors put in place a complex simulation model to study financial stability.

Additionally, there some other works related to systemic risk which follow totally different approaches; for example, in Barnhill and Souto 2008 the authors propose to use portfolio simulation to study systemic risk in Brazil. In Bartram et al. 2007, the authors find that the probability of a breakdown of the international financial system is small; although, things have changed recently and their conclusions may not hold any more. In Lehar 2005, the author proposes a risk management methodology for assessing the risk in the regulators' portfolios (financial systems); however, the author discards contagion as an important element in systemic risk. Nevertheless, as we already said, things have changed a lot in recent times.

As it was mentioned on the previous section there are two types of contagion: direct and indirect. Regarding direct contagion, the empirical literature on contagion through the interbank market found little evidence of contagion on their respective banking systems (Blavarg and Nimander (2002), Boss et al. (2004a), Boss et al. (2006), Degryse and Nguyen (2004), Furfine (1999) Graf et al. (2005), Lehar (2005), Muller (2006), Sheldon and Maurer (1998), Toivanen (2009) Upper and Worms (2004), Wells (2002)). Nevertheless, it is important to mention that most of these studies were conducted before the global crisis began. In any case, during the global financial crisis contagion did materialize, though due to the lack of proper information we are unable to determine if contagion propagated through direct or indirect connections. As a result, it has become evident that measuring contagion through the interbank market alone is not enough, there are relationships not directly measured which were ignored in such studies (ie indirect contagion, similar business models, portfolios etc). Additionally, there are some instruments that are difficult to evaluate in times of crisis (complex products, credit default swaps, etc).

On a different line of research on financial contagion and systemic risk, there has been a recent furor for research on network theory (graph theory) and financial stability. Moreover, the term "too interconnected to fail" it is now part of the financial authorities language. It is common nowadays to see graphs and networks describing financial systems, trading networks, banking networks, interbank markets, etc. For example in Boss et al. (2004b) the authors describe the network topology of the Austrian interbank market, whereas in Iori et al. (2005) the authors study the Italian overnight market from the point of view of network theory and Markose et al. (2009) illustrates how to develop a network model of the credit default swaps market. Despite such a current fame there has been constant research in the past on network theory in finance and economics. However, there is now the general idea that such approach could be useful in understanding, measuring and managing systemic riskBattiston et al. (2009). In fact, bankers are fighting to stop recent proposals to implement policies to handle the Too Big To Fail (TBTF) problem; instead, they argue that such policies should be oriented to the too interconnected to fail issue[4].

A lively discussions is taking place in global forums regarding such too interconnected to fail issue. Nevertheless, we believe that is not clear if the network topology of the interbank market alone can be used to derive measures for financial stability or regulation purposes. Although the analytical models Allen and Gale (2000) and some simulation models Nier et al. (2006) might disagree on this. We believe that the initial shocks, their likelihood and the severity of the losses must be taken into account on the modelling of systemic risk. Otherwise, the conclusions extracted might be misleading.

In our simulation model we pretend to generate macroeconomic scenarios instead of generating "shocks" to the system as the risk factors are interrelated. For example, an increase on the interest rates would lead to a change on the market distribution of losses and would also lead to an increase on the defaults on the credit portfolio. Along this line, banks would be affected not only on its market portfolio but on its credit portfolio as well. Additionally, the second round effects like financial contagion could cause further losses to the banks.

We contribute to the field by proposing a practical and simple approach to estimate the distribution of losses for the banking system and we show some interesting measures which can be derived once such systemic distribution is estimated. Moreover, there is an important concern about how to measure the systemic importance of a financial institution, with our approach it is possible to estimate the individual contribution of a particular institution to the systemic risk. Finally, our approach allows to perform stress testing in a coherent way, even considering second round effects like contagion.

The remaining part of the paper is structured as follows: Section 3 explains the simulation model in detail, Section 4 presents the results of the execution of the simulation model for Mexico and finally, Section 5 draw some conclusions on the model and the results. Apendix A provides details on the macroeconomic model used.

[4]See the note on the Financial Times "Bankers to lobby for softer reforms" on the January 24th 2010

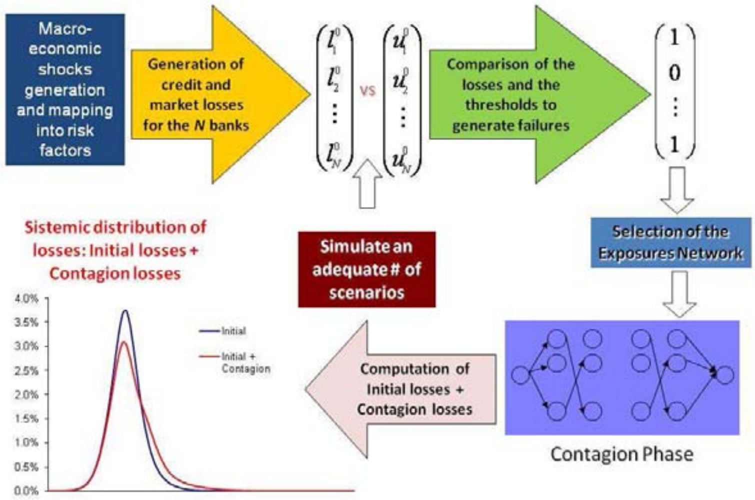


Figure 1: The simulation algorithm.

3 Simulation of joint losses for the banking system

Distributions of losses are a very important tool in risk management because such distributions allow the risk managers to compute several standard and well understood risk measures. Figure 1 illustrates schematically the simulation algorithm used to estimate the distributions of losses for the financial system.

In order for us to estimate the distribution of losses for the system we need to be able to generate joint losses. Joint losses are correlated by common or similar exposures and specially in times of financial hardship. We have developed a simulation model to allow the estimation of the distribution of losses of the system as a whole.

In previous works (Márquez-Diez-Canedo and Martínez-Jaramillo (2007) and Márquez-Diez-Canedo et al. (2009)) we have estimated the distribution of losses for the banking systems first using just the probabilities and secondly by using the individual distribution of losses for each bank.

While this approach has several advantages such as relying on detailed historical information and using this information to generate averse shocks to the financial system, it lacks a clear link between anyone of these shocks and real economic variables. It is not possible to know what kind of underlying events are causing the shocks being evaluated. It also faces technical and data challenges: to compute the joint distribution a copula to merge market and credit losses distributions is used. A very important part of the process is the calibration of the copula with banks' financial data, such as ROA, in order to capture the joint dependence structure. This information is not fully available for all the banks in the system, mainly because new banks haven't been reporting these indicators for long enough, hence previous studies were limited to a subset of the banks in the system.

Having a model linked to economic variables overcomes some of these difficulties. For instance, each shock can be mapped to the realization of variables and viceversa. This is very helpful for policy analysis. It also make the information requirements less demanding: banks' losses can be parsimoniously modelled as functions of the realizations of economic and financial variables, avoiding the calibration process as well as the computation of the copula, with the added advantage that, if properly modelled, market and credit losses are jointly determined hence capturing the interdependence between these kind of losses.

Once losses caused by the initial shock are determined, the contagion process takes place through the interbank market, and the final effect on the financial system as a whole depends on the magnitude of the effects caused by the initial losses combined with the interbank exposures and the interconnectedness of these exposed banks.

The interbank lending market plays a crucial role in liquidity transmission between banks. This market is the most recognized (or at least one of the most studied) channels for financial contagion. Moreover, there is a worldwide concern on characterizing the financial network of exposures in order to derive measures of financial fragility. However, such network changes constantly and some examples will be provided below.

3.1 Data

The data used to obtain the systemic distribution of losses for the Mexican banking system consists on the daily interbank exposures, the macro economic information used to build the macro models (GDP, interest rates, stock indexes, etc) which is going to affect the risk factors for market and credit risk and the market portfolio and Tier 1 capital.

Regarding the interbank market, the Mexican central bank has daily data that can be used to calculate the matrix of interbank exposures of the Mexican financial system, from January 2005 onwards[5]. The interbank exposures considered in this study comprise all the uncollaterized interbank lending, securities being hold which are issued by other banks, the credit component of derivative transactions and credit lines as part of the interbank market. This type of information is rarely available with such detail, so it is possible to perform analysis without making assumptions that might be unrealistic.

For example, a common approach along this line of research is making the assumption of maximum entropy on the distribution of the interbank exposures

[5]In fact, we have data from previous years but due to differences on the quality of such information we can only fully trust the data from January 2005.

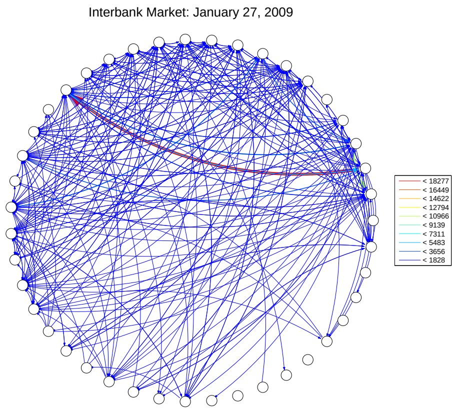


Figure 2: The Mexican interbank market (quantities are in millions of pesos).

but this is not a realistic one (as it is pointed out in Graf et al. 2005)[6], at least not in the Mexican case.

Figure 2 shows a typical network of exposures and in Figure 3 we can see only the largest exposures for such day. This is the network representing the interbank market that will be used during this work.

3.2 The link to economic variables

When the goal of the analysis goes beyond the day–to–day activity and is more policy oriented, it becomes more appealing having a shocks generation process that has a direct interpretation within the context of the real economy, that complies with minimal consistency requirements and that has the flexibility to explore different sets of conditions.

Depending on the scope of the work and the type of analysis to perform, there are several alternatives to establish the link between losses and the real economy. Some approaches are more theoretically sound or more robust than others, and options range from highly sophisticated dynamic GE models to relatively simple statistical models. Ultimately, considerations such as information availability, and the trade-off between tractability and predictive power, led us to opt to model the links between losses and economic variables using structural Vector Autoregressive (VAR) models.

Despite its limitations, we considered it was the most suited approach given the characteristics of the problem we were analyzing. We are modelling the short term effects of shocks in the credit and market portfolios of banks in order

[6]See Mistrulli (2007) for a comparison of contagion in a network built under the maximum entropy principle and without such assumption.

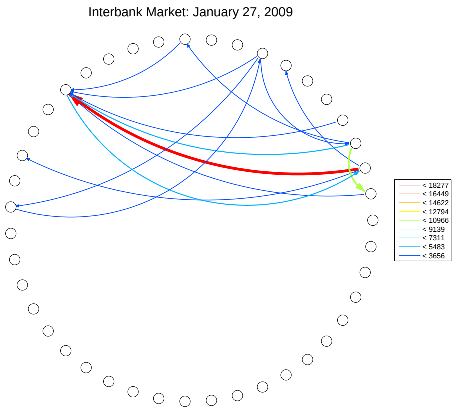


Figure 3: Large exposures at the Mexican interbank market (quantities are in millions of pesos).

to evaluate the possible contagion effects that these shocks can have. We have enough information to compute very accurately the impact of these shocks in the market portfolio, and to take full advantage of this information, projections on a bigger set of variables was necessary. In order to parsimoniously consider all these variables a relatively simpler model offered better alternatives. And as credit goes, this approach also considerably simplified the estimation of the joint distributions of market and credit. A little bit more detailed description of the model is covered in appendix A.

It also offers relatively simple yet powerful alternatives to evaluate extreme conditions[7]. It is highly likely that "brute force" simulation leads to no occurrence of shocks with a systemic impact; but it is still of interest knowing the possible effect of some events on the tails of the distribution. The parametric assumptions and the structure of the model allow to evaluate these events while assigning weights to their probability of occurrence. For example, if one is willing to explore what would happen if variable x increases in at least 4 standard deviations, a whole simulation process can be done conditional on x, and its probability can be determined.

Finally the point to emphasize here is that, for policy analysis, it is necessary

[7]The analysis of extreme condition or "stress scenarios" can be tricky using VAR models, especially when underlying the model there is a normal distribution of shocks. The normality assumption implies that extreme, or sometimes, not even so extreme, realizations occur with probability virtually zero. The problem with this situation is that experience tells that shocks tend to have heavier tails than those predicted by normal distributions and these "extreme", virtually impossible realizations occur much more often than the model predicts, hence it is highly relevant to assess, regardless of the projected probability of occurrence the effect of these scenarios.

to have a link between the distribution of losses and the real economy, but the way to do it is far from unique. In general, the more data intensive the evaluation process of systemic risk, the more beneficial a relatively simpler model is.

3.2.1 Scenarios generation

As described in appendix A, scenarios are generated following the impulse–response function construction methodology. Three sets of scenarios were generated (below there is a lengthier discussion about this): 4,000 "standard" scenarios, according to the underlying normal distribution; 1,000 "tail" scenarios, where the different variables were set to receive a severe shock (for example, a four standard deviations increase), and the rest of the random shocks were generated conditional on these realizations[8]. Finally, the third set of scenarios was through generating "extreme" impulse response functions, creating *caeteris paribus* shocks of increasing severity. 400 of these were generated.

4 Results

In this section we will present the results of the execution of the simulation using the model described in the previous section. We will present in first place the Systemic Distribution of Losses (SDL) originated from shocks to the macroeconomic model which are translated into market and credit losses. Second, we will show the effect on the distribution of losses of some stronger shocks and the derived contagion effects. After that we will present the impact of even stronger shocks which can be interpreted as stressful scenarios in which contagious defaults occur with higher frequency.

4.1 The systemic distribution of losses

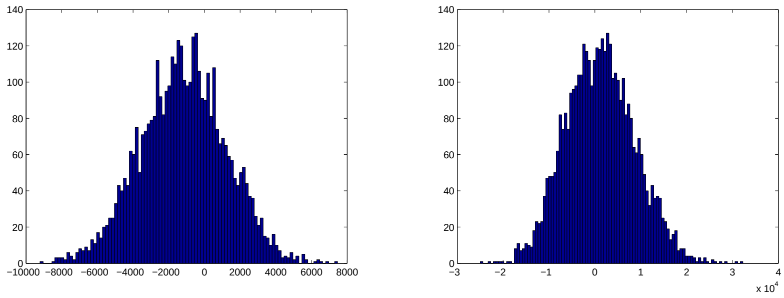
The first case described here is the estimation of the SDL by using 4000 random shocks originated from a parametric distribution.

Such a distribution can be seen in Figure 5 where it can be seen that behave very close to a normal distribution which is not surprising given that underlying the macroeconomic shocks was the assumption of a normal distribution. Given the levels of capitalization of the Mexican banks and the size of the generated shocks, there are no contagious defaults taking place under any of these 4000 generated scenarios.

This is precisely one of the main problems in measuring systemic risk, events which threaten the system (systemic) are located far in the tail of the SDL. One way to cope with such issue is to generate a huge number of simulations in order to populate properly the tail of the distribution. This is the way in which we proceed in the past[9]; nevertheless, under the current framework is not

[8]Notice that the white noise assumption considerably simplifies this exercise.

[9]In Márquez-Diez-Canedo et al. (2009) the number of randomly generated scenarios was five million.



(a) (b)

Figure 4: The systemic distribution of credit (a) and market (b) losses.

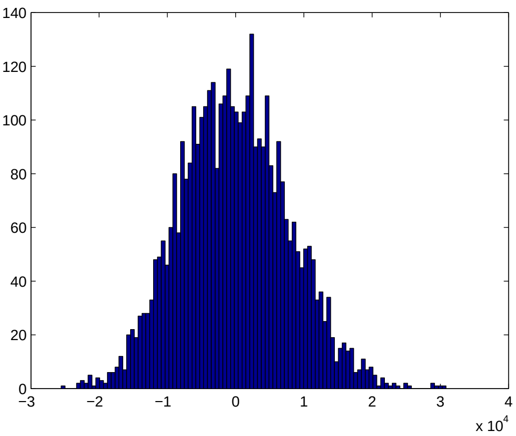
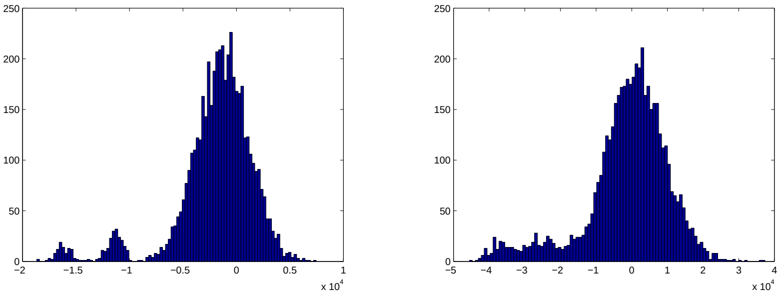


Figure 5: The systemic distribution of losses for the Mexican banking system.



(a)

(b)

Figure 6: The systemic distribution of credit (a) and market (b) losses 5000 scenarios including 1000 biased scenarios on the tail.

possible anymore as the valuation of the market portfolios for each bank takes a considerable computing effort.

Fortunately, given that we are able to generate the consistent scenarios from a normal random shock, it is possible to bias such generation process to more extreme regions and more importantly, it is possible to estimate the probability of such an event to happen. This characteristic of the simulation model is as important as the consistency aspect of the generation process as it is possible to bias the distribution of the generation process to focuss on the tail of the distribution without simulating a large number of scenarios and preserve the consistency (in terms of the generated model) of the scenarios. Having said so, we can generate scenarios that, although they are highly unlikely, at least they are in the region of possible things. We believe that this approach is more promising that the individual idiosyncratic defaults which found little evidence of contagion in previous studies.

Figures 6(a) and 6(b) show together the 4,000 "normal" scenarios next to the 1,000 "tail" scenarios. These figures illustrate in a stylized fashion the processes of biasing the scenario generation process to the tail of the distribution. A very important remark is that the tails of such distributions do not correspond to the same generation process, and the graphs are not actual histograms. However, we took such liberty for illustration purposes. In this distribution we can observe the amplified[10] losses which were generated by biasing the scenario generation process. Losses corresponding to such scenarios are derived from extreme movements in economic variables.

The resulting distribution from the merging of the above described distributions can be observed in Figure 7. From this figure we can infer.

Given the capitalization levels of banks in the Mexican financial system

[10]In an strict sense the probability of such extreme events is in a different order of magnitude.

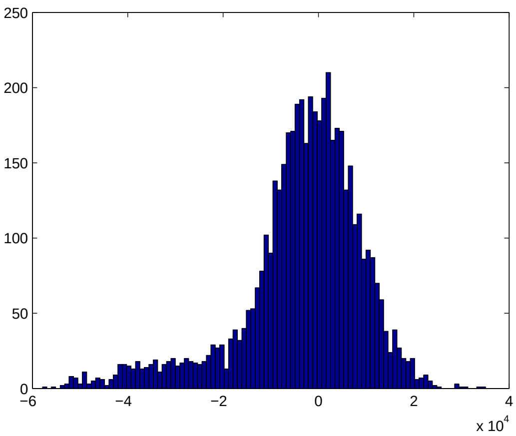


Figure 7: The systemic distribution of losses for the Mexican banking system 5000 scenarios including 1000 biased scenarios.

contagion under the 1000 ”extreme” scenarios did occur and the case is worth exploring in detail.

4.2 The contagion process

The Mexican financial system is very well capitalized. On average its capital ratio is of around 16%, with a minimum of 11.6% and a maximum of 424%. This explains to a great extent the lack of sensitivity to shocks because banks are able to absorb losses without risking individual solvency and avoiding triggering a contagion process.

Nevertheless, when considering the “tail” scenarios a very interesting case of study arose. After a very severe shock in the stock market index, and foreign and domestic interest rates a single bank regulatory capital went below the minimum requirement[11]. This bank was one of the small banks in the system. The composition of its portfolio made it practically immune to credit effects, so this was purely a market risk effect. If this were an idiosyncratic failing process it was likely that this failure would have gone unnoticed. The interesting part occurred through the contagion phase: the magnitude of the shock led to failure to only one bank, but the remaining banks were severely weakened by it, to the extent that the failure of this small bank to honor its interbank obligations caused the failure of a medium sized bank. This in turn led to the failure of a set of small and medium banks, which led to the failure of more banks, including a large one, and after that, everything went downhill and almost the entire financial system collapsed.

[11]In a slight abuse of terminology, we will refer to this kind of events as a “failure”.

The exercise with the most severe scenarios provided qualitatively similar outcomes (though are not reported here).

5 Conclusions and further work

The main conclusions we can extract from this work is that although in recent times the topic has received a well deserved importance into the regulatory arena, there are relevant aspects which we believe should not be ignored.

For some time the literature adhered to the belief that the topology of the network was enough to characterize the systemic riskiness of a particular financial system. Previous work (Márquez-Diez-Canedo et al. (2009)) shed some light about that issue and pointed at the fact that is not only the topology but also the size and concentration of the exposure.

This exercise brings to light one more issue, the relevance of the initial macroeconomic shock. It also carries one more argument against the idiosyncratic, one–by–one, evaluation of failures: it is impossible to dissociate banks from their economic environment. Pretending a "caeteris paribus" failure would be misleading.

Another important conclusion is that, to some extent, it could be the case that size doesn't matter. The focus has been traditionally on larger banks, and rightly so, but it shouldn't be at the cost of disregarding smaller banks. As evidenced by the case study, a sever enough shock can weaken the whole system to the extent that just a little push can drop the first dominoes.

There are still issues that need to be addressed. The first one is, these simulation exercise may be understating the systemic effect. After all, this is the one-month effect of a shock, especially misleading in credit, where losses usually take longer to take place. The issue here is how to deal with the implicit trade-off: a more accurate credit risk measurement requires a sacrifice in the market risk measurement accuracy and viceversa.

Another issue is the weight of the tails of the parametric distribution. To keep methodological consistency, the underlying assumption was that of normality in the shocks even though we know that extreme events tend to occur more often than predicted by the light-tailed normal distribution. Using a distribution with heavier tails is an alternative worth exploring that wouldn't require a change of paradigm.

Finally, one needs to acknowledge a limitation of this framework in terms of policy analysis: current infrastructure allows to obtain quite accurate market and credit risk measurement given the financial position of the participants of the system. But a more complete policy analysis requires the ability to analyzed "what if" cases, which necessary need to consider that financial positions are not exogenous, that are an endogenous element that can also impact the risk factors.

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A Generation of consistent scenarios

Previous versions of this work parted from joint losses distributions, considering market and credit losses. Once getting the joint distribution (using a copula) simulations were made to generate initial losses, which were used as starting point to analyze the contagion process.

Nevertheless, to make a more accurate assessment of systemic risk, it has to be established a link between the real sector and banks' losses. So as far as the previous work had gone, underlying the simulation process is the idea that "something" happens, but what is that "something"? To attain this goal a Vector Autoregressive Model (VAR) approach has been followed. It is widely known that VAR models allow to take into account multiple variables and their interactions in a parsimonious way so despite its limitations[12] this was the methodology followed to model the economic background underlying banks' losses.

Market losses are directly determined by some financial variables such as yield curves or stock indexes, but in their determination, these variables interact with other "real economy" variables, and they are also affected by external

[12]For instance, within the context of stress testing VAR models reportedly perform poorly near the tails of the distribution.

shocks either directly (exposition to a foreign stock index, for example) or indirectly by the effect that these external shocks may have in the domestic variables (for example, the domestic stock index follows closely movements of the Dow Jones index).

The availability of highly detailed data about banks' positions allows us to consider very specific conditions for each bank and to realistically assess the effect of each one of these shocks in the current[13] period. At any given time, given that time's financial positions and a relatively small set of variables and "risk factors"[14] the losses distribution is computed.

The scenarios generation process consists of three steps: the estimation of the VAR model, the estimation of other complementary models to complete the scenarios to make the valuation of the position, and finally the scenarios generation process.

A.1 The macroeconomic model

The macroeconomic model uses ten variables. In the choice of variables was also considered which variables have a direct impact in possible banks' losses. The variables used are[15] IGAE[16] (y), which is a close indicator of GDP, Cete interest rate (r^c), the consumer price index (π), exchange rate (e), the Mexican stock exchange index (ipc), the delinquency rate in bank loans (DR), treasury bill interest rate (r^{tb}), libor interest rate (r^L), the Dow Jones stock index (DJ), and the Brazilian stock index Bovespa[17] (bov).

The general form of the model is a customary VAR setting:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + \sum_{m=1}^{12} \delta_m D_{mt} + e_t, \tag{1}$$

which basically states that the set of variables in the 10×1 vector Y is jointly determined by p lagged values and dummy variables for each month. This model follows the spirit of structural VAR models, hence not all variables enter as explanatory variables (that is, some components of matrices A_i are zero).

The dependence of each variable was modeled according to the following

[13]In our case, the most recent available information.

[14]The market risk measuring infrastructure used by Banco de México was used to perform the valuation of the portfolio at each different scenario.

[15]All expressed in differences in logs.

[16] *"ndice General de Actividad Econmica"*, General Economic Activity Index.

[17]Experience in the Central Bank indicates that this variable can be important for modeling during stress scenarios.

equations:

$$
\begin{aligned}
y &= y(y, r^c, \pi, e, DR) && (2)\\
r^c &= r^c(y, r^c, \pi, e, ipc, r^{tb}, r^L) && (3)\\
\pi &= \pi(y, r^c, \pi, e) && (4)\\
e &= e(y, r^c, \pi, e, ipc, DR, r^{tb}, r^L, DJ) && (5)\\
ipc &= ipc(y, r^c, \pi, e, ipc, DR, r^{tb}, r^L, DJ, bov) && (6)\\
DR &= DR(y, r^c, \pi, e, DR) && (7)\\
r^{tb} &= r^{tb}(r^{tb}, r^L, DJ) && (8)\\
r^L &= r^L(r^{tb}, r^L) && (9)\\
DJ &= DJ(r^{tb}, r^L, DJ) && (10)\\
bov = &= bov(DJ, bov) && (11)
\end{aligned}
$$

Monthly data from January 1995 up to October 2009 was used, and $p = 3$, that is, the number of lags used was 3 months. For the estimation it was assumed that the errors were normally distributed, $e_t \sim N(\mathbf{0}, \Sigma)$, where Σ is the covariance matrix between the shocks. Coefficients were estimated using Maximum Likelihood[18].

[18] See Hamilton (1994).

Table 1: Estimation Results. Columns: Dependent Variables; Rows: independent variables.

	IGAE	**Cete**	π	e	**IPC**	**DR**	**TBill**	**Libor**	**Dow Jones**	**Bov**
L.IGAE	-0.4956	-0.5030	0.0485	-0.0572	-0.0640	0.1680				
	(0.0047)	(0.1925)	(0.0002)	(0.0071)	(0.0347)	(0.0404)				
L2.IGAE	-0.1179	-0.0937	0.0394	-0.1156	-0.0170	0.2624				
	(0.0055)	(0.2438)	(0.0003)	(0.0089)	(0.0434)	(0.0481)				
L3.IGAE	0.2341	0.0662	0.0305	0.0034	-0.2491	0.1363				
	(0.0046)	(0.1973)	(0.0002)	(0.0072)	(0.0353)	(0.0399)				
χ^2	104.2501	4.1954	4.8634	180.7991	20.1620	5.7631				
	[0.000]	[0.2411]	[0.1820]	[0.0000]	[0.0002]	[0.1237]				
L.Cete	0.0048	-0.0587	0.0039	-0.0603	0.0401	0.0227				
	(0.0002)	(0.0061)	(0.0000)	(0.0002)	(0.0011)	(0.0014)				
L2.Cete	-0.0009	-0.1376	0.0028	-0.0229	0.0530	0.0212				
	(0.0002)	(0.0071)	(0.0000)	(0.0003)	(0.0013)	(0.0014)				
L3.Cete	0.0235	-0.0355	-0.0035	-0.0574	0.0540	0.0047				
	(0.0001)	(0.0064)	(0.0000)	(0.0002)	(0.0011)	(0.0013)				
χ^2	29.8503	9.2403	4.1229	28.9509	3.2031	7.1465				
	[0.0000]	[0.0263]	[0.2485]	[0.0000]	[0.3613]	[0.0674]				
L.π	0.1773	2.0749	0.8476	-0.2652	-0.2856	1.8257				
	(0.0882)	(3.2711)	(0.0040)	(0.1357)	(0.6953)	(0.7648)				
L2.π	0.1659	-4.6778	-0.2670	1.0149	-0.8139	-3.0269				

(Standard Errors in Parenthesis.)
χ^2 refers to the joint significance test of the set of variables.
[p-values in square brackets.]

Continued on next page

	IGAE	**Cete**	π	e	**IPC**	**DR**	**TBill**	**Libor**	**Dow Jones**	**Bov**
	(0.1505)	(5.3510)	(0.0069)	(0.2008)	(1.0237)	(1.3049)				
L3.π	-0.0795	0.4150	0.2069	-0.5991	1.3761	1.9329				
	(0.0794)	(2.8644)	(0.0037)	(0.1067)	(0.5454)	(0.6887)				
χ^2	13.4182	1.4728	3.5030	7.7431	21.5347	5.0985				
	[0.0038]	[0.6886]	[0.3204]	[0.05163]	[0.0001]	[0.1647]				
L.e	0.0186	0.4672	0.0455	0.2233	0.3028	0.1858				
	(0.0027)	(0.1275)	(0.0001)	(0.0049)	(0.0257)	(0.0231)				
L2.e	-0.0600	0.5621	-0.0210	0.0241	-0.3166	-0.0641				
	(0.0028)	(0.1403)	(0.0001)	(0.0056)	(0.0287)	(0.0241)				
L3.e	-0.2115	0.4430	0.0526	0.0302	-0.0410	0.0948				
	(0.0020)	(0.0900)	(0.0001)	(0.0034)	(0.0178)	(0.0170)				
χ^2	27.3750	28.7384	1.7710	6.0917	4.0979	2.1713				
	[0.0000]	[0.0000]	[0.6213]	[0.1072]	[0.2511]	[0.5376]				
L.IPC	0.0000	-0.3272	0.0000	-0.0656	0.1081					
	(0.0000)	(0.0170)	(0.0000)	(0.0010)	(0.0054)					
L2.IPC	0.0000	0.2278	0.0000	0.0093	-0.1847					
	(0.0000)	(0.0183)	(0.0000)	(0.0009)	(0.0052)					
L3.IPC	0.0000	0.0583	0.0000	0.0016	-0.0622					
	(0.0000)	(0.0185)	(0.0000)	(0.0009)	(0.0051)					
χ^2		33.6664		12.6477	22.9358					
		[0.0000]		[0.0055]	[0.0000]					
L.DR	0.0053			0.0097	-0.0899	0.1697				

(Standard Errors in Parenthesis.)
χ^2 refers to the joint significance test of the set of variables.
[p-values in square brackets.]

Continued on next page

	IGAE	**Cete**	π	e	**IPC**	**DR**	**TBill**	**Libor**	**Dow Jones**	**Bov**
	(0.0006)			(0.0007)	(0.0036)	(0.0051)				
L2.DR	-0.0335			0.0178	-0.0366	0.0726				
	(0.0006)			(0.0007)	(0.0038)	(0.0053)				
L3.DR	-0.0122			-0.0017	-0.0367	0.2739				
	(0.0006)			(0.0007)	(0.0039)	(0.0053)				
χ^2	101.8799			18.3724	5.3384	18.3739				
	[0.0000]			[0.0004]	[0.1486]	[0.0004]				
L.TBill		0.0319		0.0053	-0.0099		-0.0371	0.3542	0.0019	
		(0.0011)		(0.0000)	(0.0002)		(0.0055)	(0.0006)	(0.0001)	
L2.TBill		-0.0011		-0.0209	0.0529		-0.6132	0.0411	0.0293	
		(0.0010)		(0.0000)	(0.0002)		(0.0052)	(0.0006)	(0.0001)	
L3.TBill		0.0297		-0.0093	0.0107		0.2604	0.1250	0.0265	
		(0.0015)		(0.0001)	(0.0003)		(0.0077)	(0.0009)	(0.0001)	
χ^2		13.5312		4.4223	20.1887		2.4314	9.7688	8.7547	
		[0.0036]		[0.2193]	[0.0002]		[0.4878]	[0.0206]	[0.0327]	
L.Libor		0.0794		0.0409	-0.1607		2.3446	0.1300	-0.0529	
		(0.0084)		(0.0003)	(0.0018)		(0.0422)	(0.0048)	(0.0006)	
L2.Libor		-0.0375		0.0016	0.0698		-2.3113	-0.4128	-0.0179	
		(0.0139)		(0.0005)	(0.0029)		(0.0736)	(0.0084)	(0.0011)	
L3.Libor		0.1392		0.0406	-0.0311		0.1956	0.4146	-0.0025	
		(0.0078)		(0.0003)	(0.0016)		(0.0373)	(0.0042)	(0.0006)	
χ^2		7.3611		10.4278	1.2495		0.6924	3.9115	12.2056	

(Standard Errors in Parenthesis.)
χ^2 refers to the joint significance test of the set of variables.
[p-values in square brackets.]

Continued on next page

	IGAE	**Cete**	π	e	**IPC**	**DR**	**TBill**	**Libor**	**Dow Jones**	**Bov**
		[0.0612]		[0.0153]	[0.7412]		[0.8750]	[0.2712]	[0.0067]	
L.DJ				-0.0117	0.1181		1.3079		0.2160	0.3338
				(0.0027)	(0.0201)		(0.2049)		(0.0051)	(0.0296)
L2.DJ				-0.0028	0.4137		0.7474		0.0310	0.1798
				(0.0028)	(0.0211)		(0.2256)		(0.0055)	(0.0297)
L3.DJ				-0.0945	-0.0195		-0.5674		0.1293	0.0084
				(0.0029)	(0.0210)		(0.2287)		(0.0056)	(0.0287)
χ^2				25.3815	6.4113		5.1410		3.9188	0.7579
				[0.0000]	[0.0932]		[0.1619]		[0.2704]	[0.8595]
L.Bov					0.0804					0.1744
					(0.0037)					(0.0042)
L2.Bov					-0.0527					-0.2737
					(0.0033)					(0.0039)
L3.Bov					0.1831					0.1385
					(0.0032)					(0.0037)
χ^2					0.4077					9.7237
					[0.9386]					[0.0211]

The impulse response functions were computed when a two standard deviations shock occurs.

A.2 Other variables that play a role as risk factors

To complete the valuation of the market portfolio, another set of variables is required to attain the goal. Interest rates yield curves, exchange rate, as well as some other stock indexes may have an impact in the bank's portfolio. A more accurate modeling of these variables would require a much more complex framework and more detailed information, and that also would be beyond the scope of this work. Nevertheless, to model changes in these variables the spreads and stock indexes were modeled independently using autoregressive processes, and to get the interest rate curves for Cete, Tbill and Libor, the variables used in the structural VAR were also used along with some nodes of the curve. Once these nodes were estimated, the curve was completed using a cubic Hermite polynomial.

A.3 Scenarios Generation

Once all the parameters were estimated, the generation of scenarios was done simulating random shocks and transferring the effects of the shocks using a Choleski-type decomposition of the covariance matrix estimated from the macro model.

Formally, the structural model is assumed to include a matrix of coefficients of contemporaneous effects,

$$\begin{aligned} BY_t &= \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \varepsilon_t \\ Y_t &= \sum_{i=1}^{p} B^{-1}\Gamma_i Y_{t-1} + B^{-1}\varepsilon_t \\ Y_t &= \sum_{i=1}^{p} A_i Y_{t-1} + e_t. \end{aligned}$$

The implication is that, considering contemporaneous effects, and if the model is rightly specified, the exogenous shocks are uncorrelated, that is $\varepsilon \sim N(\mathbf{0}, \mathbf{D})$ where $\mathbf{D}$ is a diagonal matrix. This allows to generate the scenarios to draw independent normally distributed random numbers, and using the matrix $\mathbf{B}^{-1}$ to contemporaneously "transfer" the error effect to the rest of the variables, in a similar fashion that the one used to build impulse–response functions.

The $\mathbf{B}$ matrix was obtained by a Choleski–type factorization of the estimated covariance matrix ($\mathbf{\Sigma}$). The ordering was $TBill \rightarrow Libor \rightarrow DJ \rightarrow Bov \rightarrow cete \rightarrow IGAE \rightarrow e \rightarrow DR \rightarrow \pi \rightarrow ipc$.[19]

[19] See Enders (2004).

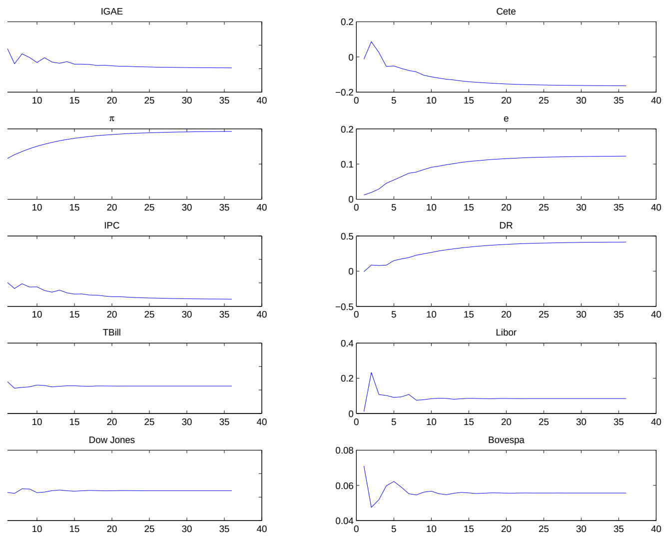

Figure 8: Impulse–response functions: change of other variables when IGAE changes by two standard deviations.

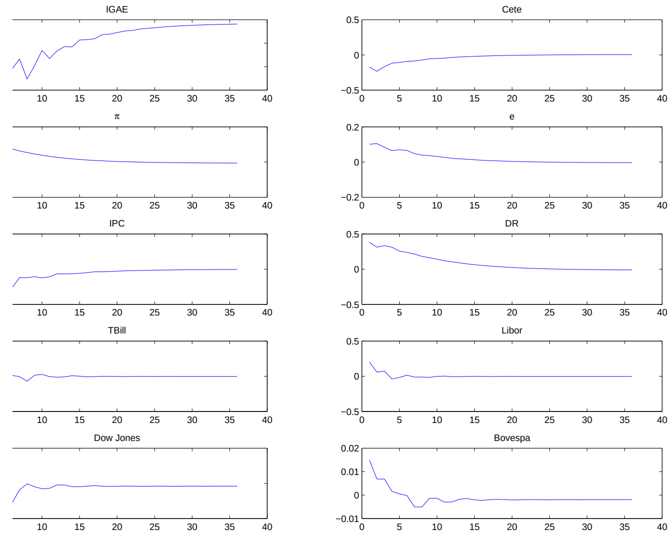

Figure 9: Impulse–response functions: change of other variables when Cete changes by two standard deviations.

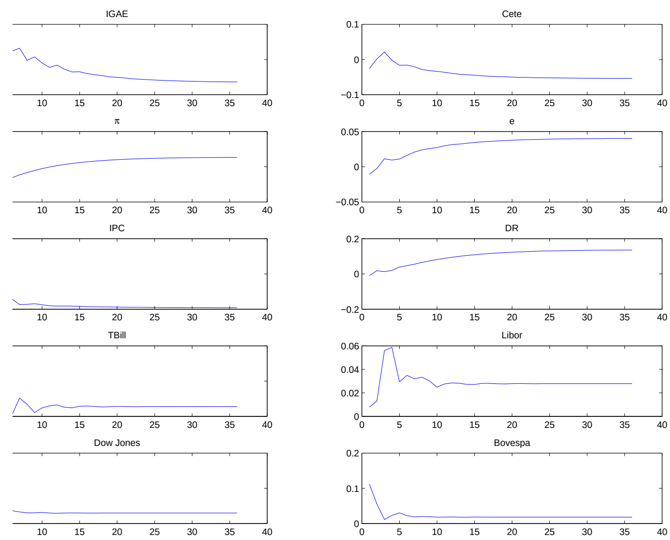

Figure 10: Impulse–response functions: change of other variables when INPC changes by two standard deviations.

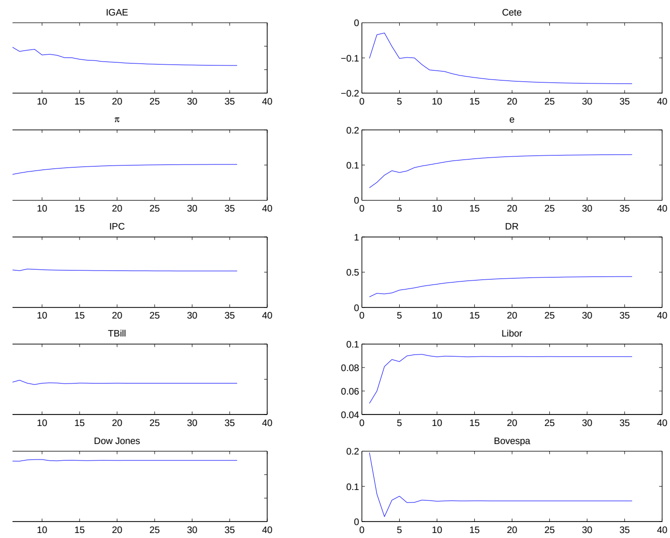

Figure 11: Impulse–response functions: change of other variables when e changes by two standard deviations.

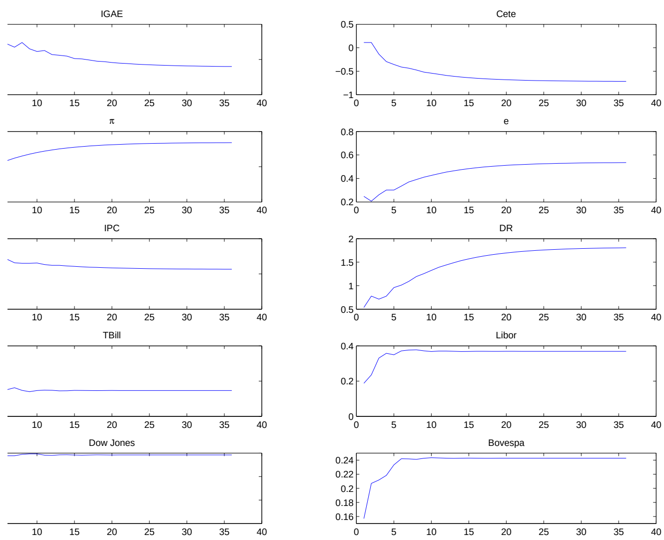

Figure 12: Impulse–response functions: change of other variables when IPC changes by two standard deviations.

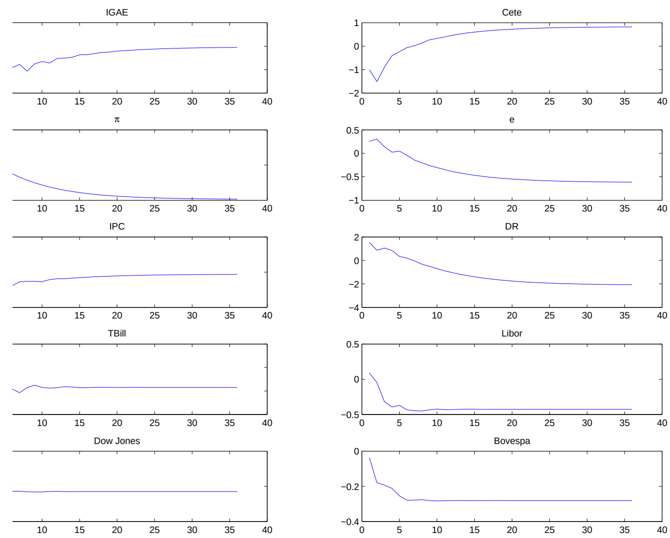

Figure 13: Impulse–response functions: change of other variables when DR changes by two standard deviations.

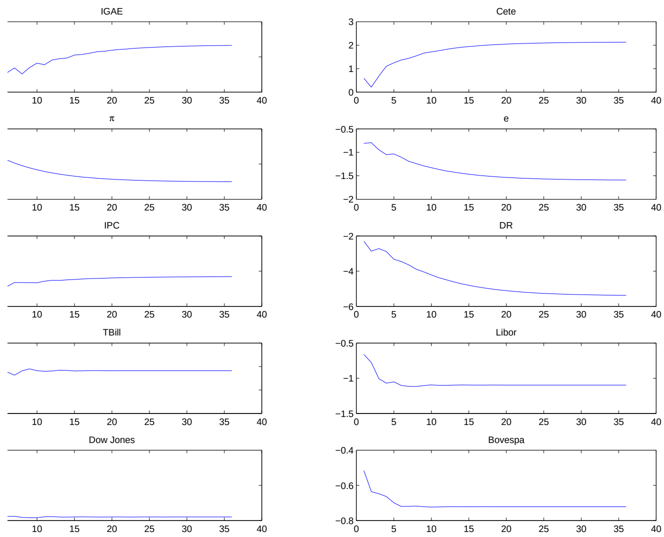

Figure 14: Impulse–response functions: change of other variables when TBill changes by two standard deviations.

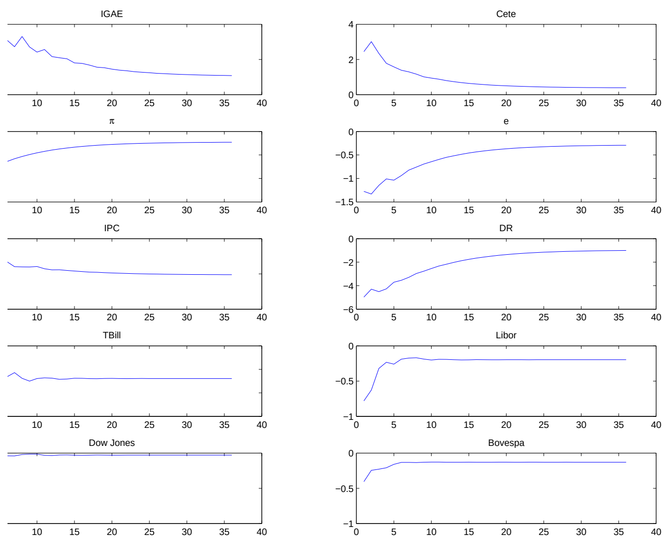

Figure 15: Impulse–response functions: change of other variables when Libor changes by two standard deviations.

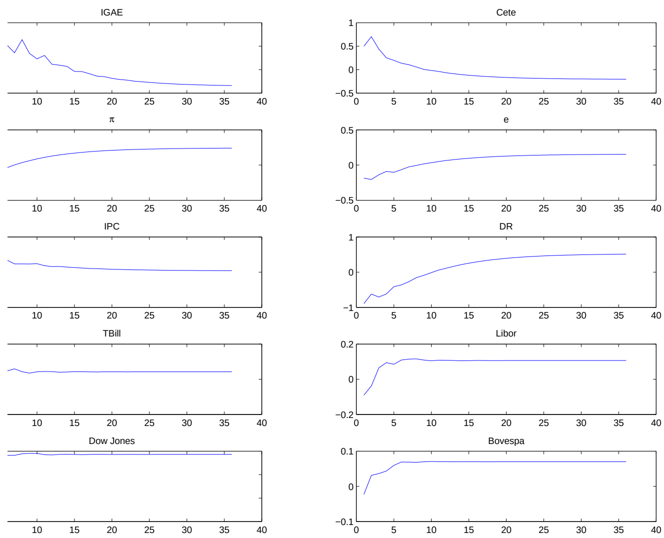

Figure 16: Impulse–response functions: change of other variables when Dow Jones changes by two standard deviations.

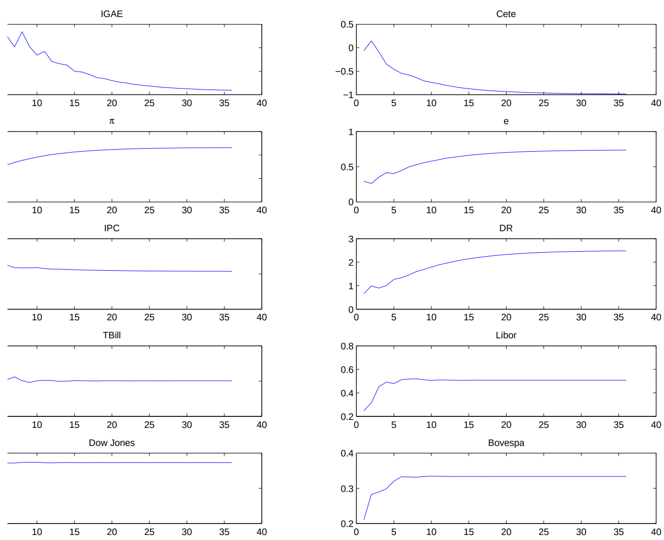

Figure 17: Impulse–response functions: change of other variables when Bovespa changes by two standard deviations.

Each realization of ε together with the estimated coefficients determines projected levels of the relevant variables in the model. To complete the scenario, the interest rate curves are also affected by the same shocks (for example, the TBill curve is affected by the same shock that affected the TBill in the VAR model) and the other variables are affected by autonomous shocks.

Credit deserves a lengthier discussion. It seems that a greater effort was exerted on the market side of the losses distribution, and to some extent it is right. The fundamental problem is the disparity of the risk horizon for both portfolios. While for market a one month horizon seems too long, for credit one month is hardly enough for marginal changes. This is the trade-off facing all those studying the joint distribution: to sacrifice accuracy in market position and to analyze a longer term to get significant credit effects or to get more accurate market losses but accepting that credit losses will be low and any significant credit effect will materialize in a few more months. We opted for the second option, and to determine the effect of shocks in credit losses the estimator for the change in delinquency rate was used as a proxy for credit losses weighted by current levels of delinquency rates by bank.