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THE ROLE OF RISK PERCEPTION IN THE SYSTEMIC RISK GENERATION AND AMPLIFICATION: AGENT-BASED APPROACH

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Abstract: *In the paper we study how systemic risk, and in result stability of financial system, depends on the market participants' perception of risk and perception of risk attitudes of the remaining market participants. In our analysis we use both the general equilibrium approach and the complex systems approach to economic dynamics. Namely, we use insights from the social amplification of risk framework to build an agent-based model of financial system. The perception of risk has been widely studied, using both qualitative and quantitative methods, in psychology, sociology, communications theory, behavioral economics and finance. However, addressing the central problem in managing and mitigating systemic risk requires not only understanding of how and why people and institutions perceive risk but also how their perception of risk attitudes of the other market participants affects the distribution of risks in the financial system. We model dependence of the financial market risk distribution on the agents' perception of risk. We show that the perception of risk attitudes increases the vulnerability of the financial system to external shocks. Furthermore, the perception of risk attitudes can fasten the self-organization of the system and lead to emergence of new kinds of risks that would generate the systemic effects. As a result, the notion of systemic risk endogeneity seems to be redefined.*

Keywords: *systemic risk, non-equilibrium theory, complex systems, self-organized criticality, behavioral finance, social amplification of risk framework*

JEL Classification: C6; F3; G1;G2;

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Introduction

The perception of risk has been widely studied, using both qualitative and quantitative methods, in psychology (Gregory and Mendelsohn, (1993)), sociology (Wildavsky, Aaron and Dake (1990)), communications theory (Kasperson and Kasperson, (2005)), behavioral economics and finance (Tversky and Kahneman (1974)). Notwithstanding, remarkable little attention has been devoted in the literature to define the role of risk and uncertainty perception in the generation and amplification of systemic risk. However, addressing the central problem in managing and mitigating systemic risk requires not only understanding of how and why people and institutions perceive and estimate risk but also how their perception of risk attitudes of the remaining market participants affects the distribution of risks in the financial system.

We show that in accordance with the 'core approach' (Caballero (2010)) the perception of risk attitudes increases the vulnerability of the financial system to external shocks. Nonetheless, it does not allow us to explain the endogenous nature of systemic risk. To extend our understanding of systemic risk we applied 'periphery approaches' (Caballero (2010)) that allowed us to notice that in fact the perception of risk attitudes can fasten the self-organization of the system and lead to emergence of new kinds of risks that would generate the systemic effects. In that sense, the perception of risk and risk attitudes redefines the concept of systemic risk endogeneity. As a result, the effectiveness of financial regulation and macroprudential tools changes and it has a direct implications for policy-making (Hanson, Kashyap and Stein (2011)).

The endogenous nature of systemic risk

There is no commonly accepted definition of systemic risk at present. Hartmann (Financial Stability Review - ECB (2009)) points out that disputes concerning how to define systemic risk are directly related to the perception of its nature. In fact, there are two ways of approaching systemic risk. According to the first one, risk is related to the existence of external shocks (idiosyncratic or systematic) that trigger systemic effects. Alternatively, the event can emerge endogenously 'from within' the financial system or 'from within the economy at large' (Jakimowicz (2010)). The effects can be both types sequential or simultaneous. Moreover, we can distinguish between a 'horizontal' perspective of systemic risk and a 'vertical' one. The first one pays attention only to the financial sector. The second one includes feedback effects with the real economy. Most of theoretical and empirical studies on systemic risk published before the crisis emergence adopted a horizontal perspective. As a result, the modeling process has been significantly simplified, but the cost of simplification was rather high. The omission of important feedback effects and amplification mechanisms led to extraction of incomplete or incorrect conclusions (Hanson, Kashyap and Stein (2011), Korinek (2011)), which were then used for purpose of policy-making. Parting from the endogenous nature of systemic risk it is advisable to distinguish between:

- *'endogenous systemic risk generators'* – factors that generate systemic risks 'from within the system' and initiate the non-equilibrium intrinsic dynamics e.g. leverage and liquidity mismatches (Brunnermeier, Krishnamurthy and Gorton (2013)) or interconnectedness and interconnectivity (Drehmann and Tarashev (2011));
- *'amplificators' and 'amplification mechanisms'* – factors, mechanisms and channels that spread the adverse effects of external shocks to financial stability, mostly related to market failures (Korinek (2011)).

In fact, both groups of factors and mechanisms have played different roles in the origin, course and effects of the financial crisis. The quantification of their relative roles is relevant from the theoretical point of view as well as it would be useful in the 'governance and regulatory practice' (Schwarch (2011)).

New measurement and modeling techniques

Before the crisis, most public organizations have been using dynamic stochastic general equilibrium [DSGE] models. The broad consensus on how to construct econometric forecasting models existed despite of the knowledge of deficiencies of DSGE approach in financial sector modeling (Caballero (2010)). None of the models have been used to explain the systemic risks generation ‘from within the system’ or to describe amplification mechanisms nor were they useful in assessing potential effects of credit crunches. Since then, many alternative approaches have been developed as an alternative to the ‘core approach’ (Caballero (2010)): inter alia new studies in behavioral economics, econophysics (Abergel, Chakrabarti, Chakraborti and Ghosh (2013), Krapivsky, Redner and Ben-Naim (2010)), social network modeling (Armini and Minca (2013), Bak and Paczuski (1995)), agent-based modeling and simulations [ABMS] (Castellano, Fortunato and Loreto (2007), MacKay (2013), Thurner (2011)). Many of these models suffer from a relative lack of connection to the ‘real world’ societal behavior (Castellano, Fortunato and Loreto (2007), Sobkowicz (2009)). Moreover, not all of them are equally interesting from the perspective of systemic risk and perception of risk research. Among the most promising ones are: opinion and consensus models (Deffuant, Amblard, Weisbuch and Faure (2002), Deffuant, Neau, Amblard and Weisbuch (2000), Galam (2008)), models of homophily (Bala and Goyal (2000)), models of perception of similarity and popularity (Javarone and Armano (2013)), models of epidemics (MacKay (2013)), and contagion (Dodds and Watts (2005)). Even though the methodologies used in the aforementioned papers have not been directly applied to finance, they provide important insights which can be used in further empirical research. We show that on the example of the modeling procedure of perception of similarity adopted by Javarone and Armano (2013).

The authors analyze how basic properties of social networks appear to be deeply influenced by the individual perception of people. They map behaviors by considering similarity and popularity and ‘interpretations of similarity’. Considering that, we could assume that non-human agents, e.g. financial institutions, in risky situations are usually acting similarly to the other market participants. While in fact, their actions are rather based on their perception or interpretation of what other participants would do in a given situation. The ‘core approach’ provides an explanation of that fact in terms of asymmetric and/or incomplete information. Unfortunately, besides the game theory insights, little has been told on how to model such behavior; few existing general equilibrium contributions can be found in Barnhill and Schumacher (2011). In Javarone and Armano (2013), from a computational perspective similarity is calculated as a distance measure on top of a hyperbolic space. The simulations performed by the authors allowed them to analyze the relevant properties of community structures in the networks.

Another useful approach is the agent-based modeling and simulation [ABMS]. The ABMS approach allows for modeling the dynamics of complex systems and complex adaptive systems. The agent-based models are closely related to ‘theories of non-equilibrium behavior’. Additionally, in macrofinance, these kinds of models represent the group of ‘instability models of financial system’. The basic idea behind the complex systems approach is that “large dynamical systems naturally evolve, or self-organize, into highly interactive, critical state where a minor perturbation may lead to events, called avalanches, of all sizes” (Bak and Paczuski (1995)). The term “self-organized criticality” [SOC] was introduced to describe the dynamics of many-body systems that appear to reach critical state without fine-tuning their parameters (Janes (1998), MacKay (2013)). In reference to the macro finance modeling, the self-organized criticality refers to financial sector default or credit crunch that may occur spontaneously as a consequence of the system achieving a critical state. The crucial element is that system achieves it through its own intrinsic dynamic and critical nature (MacKay (2013)). The mathematical derivation of models presenting the self-organized criticality is included in Janes (1998) an in MacKay (2013).

The agent-based approach is useful in modeling specific human and non human behaviors as well as their interactions. In the ABMS approach, agents' behaviors are described by simple rules, and interactions with other agents, which in turn influence their behaviors."Patterns, structures, and behaviors emerge that were not explicitly programmed into the models, but arise through the agent interactions" (Macal and North (2010)). The most important defining characteristics of agents are their heterogeneity and capability to act autonomously, in response to new situations and actions of other agents in the neighborhood (in that sense, only local information is available to agents). The number of agent can change as simulation proceeds. Each agent has a state that represent the essential variables associated with its current situation and that varies over time. An agent's behaviors are conditioned on its state (Macal and North (2010)). The agent-based model's topology represents how agents are connected; typically it is a spatial grid or a network.

The most complete agent-based model of the EU economy is EURACE (Deissenberg, van der Hoog, Dawid (2008)). Although this model included the financial sector in the analysis, it has never been used in the context of systemic risk monitoring or as a management and mitigation tool. In fact, the problem of systemic risk generation and amplification is understudied, especially in the complex systems context. For exceptions and interesting contributions to the topic see: Thurner (2011), Klimek, Poledna, Farmer and Thurner (2014).

Perception of risk and risk attitudes in systemic risk research

Among many relevant findings in the area of 'perception of risk', the social amplification of risk framework [SARF] (Kasperson et al. (1988), (2005)) appears to be the most useful in the systemic risk research. Perception of risk 'per se' could be treated rather as the 'systemic risk generator' than 'amplificator'. However we do not want to narrow our analysis only to the 'generators', therefore we will also consider spreading risks across financial system.

In fact, spreading of risk across the system is related not only to the perception of risk but also to the perception of risk attitudes of the other market participants. It is mostly based on *making opinions* and *beliefs* about what the others' perception of risk is. In that sense, we are no longer only in the physical world of deterministic and/or stochastic rules. It is a creation of *interpretations* of risks and risk attitudes that plays a crucial role in the amplification mechanisms of financial system. For that reason, the social amplification of risk framework is so useful. According to the SARF, "the theoretical starting-point is the assumption that 'risk events' (…) will be largely irrelevant or localized in their impact unless human being observe and communicate them others (Luhmann, 1979). (…) SARF holds that, a key part of that communication process, risk, risk events and characteristics of both become portrayed through various risk signals, which in turn interact with a wide range of psychological, social, institutional, or cultural processes in ways that intensify or attenuate perceptions of risk and its manageability. The experience of risk therefore is not only an experience of *physical* harm but result of processes by which groups or individuals learn to acquire or create interpretations of risk (Kasperson et al. (1988))". As the authors continue, "these interpretations provide rules of how to select, order, and explain signals emanating from the physical world (Renn, Burns, Kasperson et al., 1992) (...). With this framework, risk experience can be properly assessed only through the interaction among the physical harms attached to risk event and the social and cultural processes that shape interactions of that events, secondary and tertiary consequences that emerge, and the actions taken by managers and publics (Kasperson et al. (1988))."

Risk and uncertainty

Finally, we seek to identify and quantify the role of risk perception and perception of risk attitudes in systemic risk generation and amplification. However, what risk actually is? Is an interpretation of risky or uncertain event a ‘true risk’ to financial stability? In many cases, it is rather a perception of attitudes and interpretation of event that trigger systemic effects. In that sense, from the regulatory and prudential policies perspective, it is not always useful to simply identify events as risks or uncertainties on a basis of potential quantification in probabilistic terms. On the other hand, to quantify systemic risk it is also necessary to analyze how much uncertainty there is in the amplification mechanisms related to perception of risk and risk attitudes. New modeling techniques could help us to understand how systemic risk is generated and amplified, but can we quantify the whole processes? A negative response to this question would put in doubt the effectiveness of ‘early-warning systems’. Further research on this topic is urgently needed.

The aim of this paper is to analyze the role of perception of risk and risk attitudes in the systemic risk generation and amplification using the agent-based techniques. Our simplified model is only a small ‘building-block’ of a greater model developed as a part of the research project funded by the National Science Centre [NCN]. It is not aimed to compete with ‘the core’ econometric forecasting and explanatory models. It is rather expected to provide a number of new insights that cannot be obtained using traditional tools, focusing on ‘emergence’ and ‘self-organized criticality’. In mathematical terms, we focus on the changes in the probabilistic distributions of risks in the system.

The remainder of the paper is organized as follows. In section 2, we review the analysis of perception of risks in the market performed by the Bank of England. Next, we outline the construction of some of our variables and develop our empirical model. In section 3, we present the main results and compare them to the GE models’ results. Section 4 concludes.

Empirical study on risk perception and attitudes

Evaluation of risk perception by Bank of England

The importance of analysis of risk perception in the systemic risk generation and amplification has already been noticed by the main central banks in the world. In July 2008, Bank of England introduced a formal ‘Systemic Risk Survey’ to “supplement its regular dialogue with market participants” and “to elicit market participants’ views about the prospects for financial stability in the United Kingdom” (Financial Stability Report - BoE (2014)). The objectives of research were “to ensure that the Bank is not missing risks that are of concern to survey respondents” and “to highlight risks that the Bank considers to be important but are not cited by market participants” (Financial Stability Report - BoE (2014)). This survey was a first (at least first published) attempt to quantify the perception of risks in the market, at least since the emergence of the crisis.

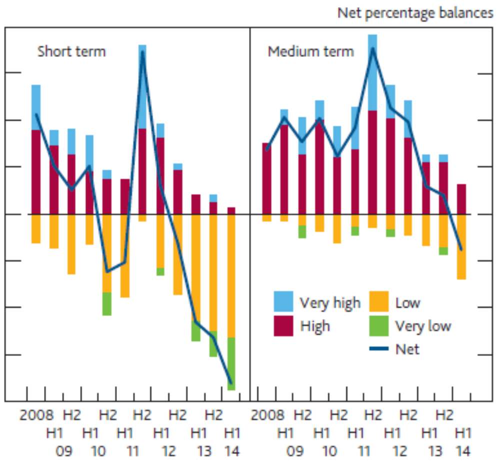

Figure 1: Perceived probability of a high-impact event in the UK financial system (Net percentage balances). (Source: Financial Stability Report, BoE, 06.2014).

It provides us many interesting conclusions about the main trends in the economy and financial markets. It is worth noticing that a peak of the perceived probability of high-impact event in the UK financial system was observed in 2011 as depicted in the [Fig.1]. Even if we assume that the United Kingdom economy could have been affected by the main financial shock with some delay with respect to other European countries (this statement may also generate some controversies, but assuming so), we clearly see that it was a *perception* of risk that played a special role in the amplification of shock from 2008. The same logic would apply to systemic risk 'generators' and 'amplificators'.

The main weakness of the methodology used by the Bank of England was that it was aimed to quantify the role of risk perception in ensuring financial stability, but it left unexplored (at least in the published form) the role of perception of *risk attitudes* in the systemic risk generation and amplification. One of the procedures that allows to capture how the market participants' behaviors and risk attitudes change is to analyze the differences between answers in the survey and so-called 'market measures of risk perception' results. What market participants indicate in the survey as a potential risk could be called an '*interpretation*' or '*social construction of event'* in the language of the social amplification of risk framework. The market measures provide real data on the result of '*interactions between different agents' perceptions of risks*'. We show that on the simplest example of liquidity on the interbank lending market. Although disaggregated data on risk perceptions did not indicate the lack of liquidity in the interbank lending market to be a main threat to financial stability, the market has frozen due to asymmetric information and liquidity hoarding. We return to this topic in the context of the publication of Alfonso, Kovner, Schoar (2011) and the comparison of market-based measures of risk perception and its modeling in terms of behavioral rules in the agent-based approach. It is crucial to compare market measures with the results of surveys carried out by the central banks (including the Bank of England). Additionally, such comparison should be supported by the inclusion of new modeling and quantification techniques of risk perception and perception of risk attitudes. In next subsection we present a tool that could help us to achieve such goal.

The role of risk perception and attitudes in systemic risk

Objectives, Methodology & Scenarios

We model dependence of the financial market risk distribution on the agents' perception of risk. To achieve this aim, we develop an agent based model of financial system with insights from the social amplification of risk framework. Then in '*Conclusions and Further research*', we compare results to ones obtained using the general equilibrium techniques (Barnhill and Schumacher (2011), Brunnermeier and Krishnamurthy (2014), Brunnermeier and Oehmke (2012)) and to empirical research conducted by Alfonso, Kovner and Schoar (2011) for U.S. interbank lending market. As previously mentioned, we show that the perception of risk attitudes increases the vulnerability of the financial system to external shocks (macroeconomic or financial external shocks). Furthermore, the perception of risk attitudes can fasten the self-organization of the system and lead to emergence of new kinds of risks that would generate the systemic effects. We focus on feedback effects and amplification mechanisms originating from different perception of risk attitudes. In this context, we analyze effectiveness of financial regulation and prudential policies in the systemic risk mitigation.

Scenario 0: Baseline

In the baseline scenario, we assume the state and characteristics of the Spanish economy and financial sector in 2007, before the emergence of the crisis (Economic Bulletin and Database of BdE (2007), (2014)). After a remarkable performance in terms of growth, employment and public finances over more than a decade in Spain, these favorable developments have been tempered by deterioration in several areas (OECD Economic Survey of Spain (2007)). First of all, the persistent high inflation differential harmed competitiveness. Secondly, there was an excessive domestic demand as a result of low real interest rates. Moreover, the external deficit remained unbalanced during years. The resilience of financial system was emphasized in the Financial Stability Report published by the Bank of Spain (2007). The main macroeconomic and financial indicators and values of variables were based on the Bank of Spain data. Then, as the simulation proceeds the values change according to the behavioral rules described below (see: *Behavioral rules*).

Scenario 1: Change in the official interest rate level (ΔOIR)

In the first scenario, we modify the official interest rate level. Evidence abounds that in the decade leading up to the 2008, banks expanded their loan portfolios. An inverse relation between the interest rate level and the expansion of loans seems to be a stylized fact, but it is not the only one effect. The low interest rate is also likely to be an important determinant of risky behavior (Dell, Laeven and Marquez (2014), Jimenéz, Ongena, Peydró and Saurina (2008)). Moreover, the 'sensibility of risky behavior' to changes in interest rate is not always the same. The empirical studies show that in period before the crisis the low interest rate determined the risky behavior while that risky behavior changes only gradually after the interest rate finally started to grow. Other studies emphasize that this conclusion does not apply to the period after the crisis emergence. In our model, the interest rate level determines the interbank lending behavior of financial institutions. We include the relations between the official interest rate and reference interest rates as well as interest rates charged for interbank lending and depositing of funds in the central bank. Although we assume in the model the behavioral measure of risk perception, we also analyzed the systemic risk measure that is based on the differential of the reference interest rate and official interest rate. In that terms, changes in interest rates have a direct impact on how the systemic risk perception was measured as well.

Scenario 2: Change in the interest rate (ΔOIR) & loans to banks that need to cover the reserve requirements (ΔIBP)

In the second scenario, we allow not only for modification of official interest rate, but we also take into account the possibility of obtaining a loan to cover the reserve requirements. In this scenario, the same logic as in the first one applies, but the counterfactual simulation of interest rate variations is supplemented by the analysis of changes in the interbank position. In this case, banks are not limited to exchanging funds in the interbank lending market or to depositing them in the central bank, but they are also allowed to obtain additional funds from the regulator. The aim of such policy is to ensure the adequate level of liquidity in the market and to reduce the risk of bankruptcy that could trigger the systemic risk effects. In our model, we assume that the *perception* of financial institution being on the edge of bankruptcy increases the systemic risk. The empirical studies show that loans to banks to cover the reserve requirements can reduce such perception and increase the liquidity in the market. At least in the theory, it should not have the same effect as the public 'back-up' or nationalization as it should not generate a moral hazard problem.

Scenario 3: Change in the interest rate (ΔOIR) & increase in reserve requirements (ΔRR)

In the third scenario, we analyze consequences of changes in the official interest rate and in the reserve requirements level. The logic of the first scenario applies, but additionally we study the effect of changes in reserves requirements. Reserve requirement sets the minimum fraction of customer deposits that each lending financial institution must hold as reserves. It is used as a supplementary tool in monetary policy. It changes the amount of funds available for banks to make loans. As the main 'building-block' of our model is the interbank-lending market it is necessary to study how the increase in reserve requirements changes behaviors of banks and what are the most common response to such policy in normal and stressed conditions in the market.

Structure of agent-based model

The model includes artificial financial system that allows us to study basic characteristics of financial markets. We model decisions taken by financial institutions in the financial market, taking into account their own characteristics (e.g. systemic risk perception, short-term and long-term deposits and loans, default rate) as well as external market conditions (e.g. interest rate, GDP growth or unemployment rate) and regulatory requirements (e.g. reserve requirements, changes in the official interest rate). Our model is a part of a bigger framework developed as a part of the research project funded by the National Science Centre [NCN]. In the project we develop a simulation for two economies: Spain and the United Kingdom in order to compare potential effects of the membership in the Euro Area and to assess the effectiveness of financial regulation and macro prudential tools in both cases. One of the most important 'building blocks' of the model is the simulation of interbank lending market. That part of the model includes the insights of simple model presented in the paper that is aimed to emphasize and quantify the role of risk perception and perception of risk attitudes in systemic risk generation and amplification.

Time and space

We use our approach to model in a simplified and stylized way, the Spanish financial sector (as an example of the EU financial system and a member of the Euro Area) including also the most important feedback effect with the real economy. To that end, we used economic data available from the Bank of Spain (Central bank of Spain) and Eurostat (the statistical office of the European Union). The temporal resolution of the model is a month. The activities undertaken by the agents take place at most on a month basis. Inflation was included in the model by using real interest rates.

Agents, variables, coefficients, parameters

In the model, agents are primarily financial institutions characterized by the following state (as a set of variables):

Table 1: Variables of the module of agent-based model. (Source: Own elaboration, 2014).

Variables	LTD	long-term deposits	
	STD	short-term deposits	
	LTL[HQ],[LQ]	long-term loans	Default rate for LTL[LQ]: it depends on unemployment rate.
	STL	short-term loans	
	RR	reserve requirement	RR sets the minimum fraction of customer deposits (SRD) that each commercial bank must hold as reserves; a bank can fix higher level than the obligatory one
	IBP	interbank position	In case of inability to cover the reserve requirements, a bank can borrow money paying interest rate (EONIA). Positive values indicate a lending position.
	Profits	profits in the last month	Profits are distributed among shareholders and they are derived from business activity of institution
	r(LTD)	long- term deposits interest rate	Interest rates: banks charge it to long-term loans and short-term loans; and they offer interest rate r(X) to long-term deposits and short-term deposits . r(X) – interest rate, where X is a type of loan or deposit (4 variables).
	r(STD)	short-term deposits interest rate	
	r(LTL)	long-term loans interest rate	
	r(STL)	short-term loans interest rate	
	SRP	systemic risk perception	It is the probability that an institution gives to at least one financial institution to bankrupt in the following month. There are other possible procedures of introducing SRP measure (see: commentary below).

Table 2: Parameters of the module of the agent-based model (Source: Own elaboration, 2014).

Parameters	RIR	reference interest rate	RIR: at the beginning constant and equal to 0.01. We then model how RIR changes according to financial risk (second stage modeling in the NCN model).
	OIR	official interest rate	Official interest rate (OIR): it increases (descreases) when the long-term loans increase (decrease) more than GDP. Lower bound is equal to 0. $OIR = \max[(0; OIR \cdot = \rho_{OIR}(GDP_t - GPD_{t-1})/GDP_{t-1} - ((LTLQL_t + LTHQL_t) - (LTLQL_{t-1} + LTHQL_{t-1}))/(LTLQL_{t-1} + LTHQL_{t-1})$
	Exp GDP_gr	expected GDP growth	
	Act GDP_gr	actual GDP growth	
	Unemp_rate	unemployment rate	It changes according to the Okun ley.
	HPI	house price index	$HPI = \alpha_{real\_estate} \cdot GDP$
	Default rate	default rate of loans	
	ar(LTD)	average interest rate LTD	
	ar(STD)	average interest rate STD	
	ar(LTL)	average interest rate LTL	
	ar(STL)	average interest rate STL	

Table 3: Coefficients of the module of agent-based model (Source: Own elaboration, 2014).

Coefficients	Avg_dur_LTL	average duration LTL	We compute the average.
	Avg_dur_STL	average duration STL	We compute the average.
	Avg_dur_STD	average duration STD	We compute the average.
	Avg_dur_LTD	average duration LTD	We compute the average.
	α_{real_estate}	relation between GDP and house price	
	α_{LTD}	relation between GDP and LTD	
	α_{STD}	relation between GDP and STD	
	α_{STL}	relation between GDP and STL	
	α_{LTL}	relation between GDP and LTL	

	$\beta_{r(STL)}$	effect of high interest rates on STL	
	$\beta_{r(LTL)}$	effect of high interest rates on LTL	
	$\rho_{r(LTD)}$	sensitivity of price competition on LTD	
	$\rho_{r(STD)}$	sensitivity of price competition on STD	
	$\rho_{r(STL)}$	sensitivity of price competition on STL	
	$\rho_{r(LTL)}$	sensitivity of price competition on LTL	
	ρ_{OIR}	sensitivity of GDP and LTL on OIR	

Initialization

We estimate the average duration of long-term loans (LTL) to 10 years. Although the average duration of the mortgage is more than twenty years, we assume that banks have other loans with shorter duration and that some of loans have already been partially paid, for that reason the average duration is approximately the half of the average duration of the mortgage. In case of short term loans (STL), the average duration of 18 months was assumed in the model as in the statistics most of short term loans are given for 12, 18 and 24 months.

Short-term deposits (STD) include the amounts of money deposited for no longer than 6 months. We estimate the average duration to 3 months. In case of long-term deposits (LTD), we consider deposits that are longer than 6 months and we estimate their average duration to 1,5 year. It is due to the large presence of deposits with duration of 12, 18 and 24 months (the proportion of deposits with longer duration is residual).

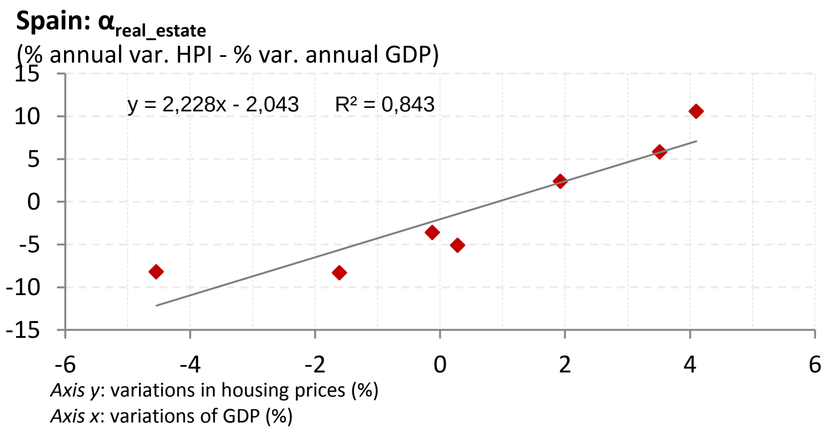

Figure 2: Relation between variations in housing prices (%) and variations of GDP (%). (Source: Own elaboration, 2014).

In order to compute the value of variable: 'α_{real_estate}' [Fig.2.], we use the following procedure: we take the statistics provided by the Ministry of Economy and Development (*Ministerio de Fomento*) and data on the evolution of GDP provided by Bank of Spain (*Banco de España*) to estimate the linear relation between them in the period between 2005 and 2012. There is no official data available for the period before 2005. In that case, we use a formula presented below [Fig.2.].

In the case of Spain there are no public disaggregated data on total deposits and loans according to their duration so in this case $\alpha_{LTD} = \alpha_{STD}$ [Fig. 3] and $\alpha_{STL} = \alpha_{LTL}$ [Fig. 4]. In the case of deposits for the period 1996-2012 we assume $\alpha_{LTD} = \alpha_{STD} = 0.9792$ while the loans are affected at a higher rate, for that reason: $\alpha_{STL} = \alpha_{LTL} = 1.0792$. These assumptions can be later relaxed.

To calculate the values of the parameters, we use Spanish data as well. We initiate the monthly change of GDP at value of approx. 0.166, as it gives us a 2% annual growth. Next, it follows bounded random walk, but we assume that it cannot change more than 0,05 % (small changes). During first six months the expected GDP is equal to 0.166, later it becomes the average of the last six periods.

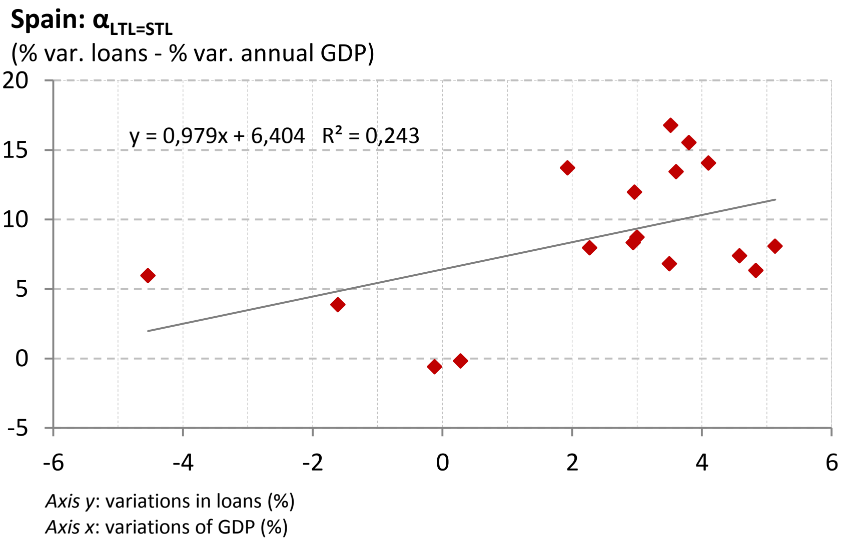

Figure 3: Relation between variations in loans (%) and variations of GDP (%). (Source: Own elaboration, 2014).

As well known, there is a direct relation between the unemployment rate and GDP [Fig. 5]. In case of Spain, a change of 1 percentage point of GDP represents a 8.07% change in the unemployment rate in the opposite direction, assuming 2,7% GDP growth as the basis values and the unemployment rate equal to 9,7% (the average rate of the period 2002-2008).

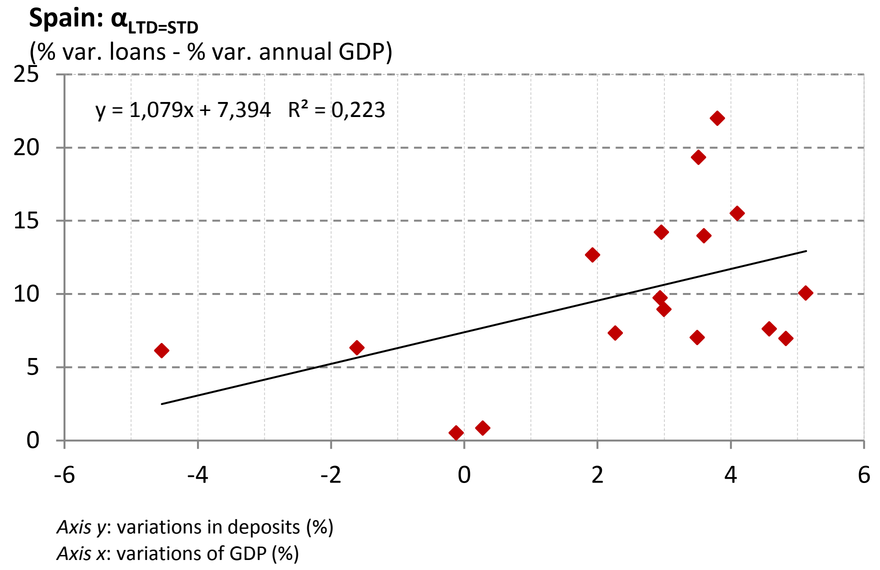

Figure 4: Relation between variations in deposits (%) and variations of GDP (%). (Source: Own elaboration, 2014).

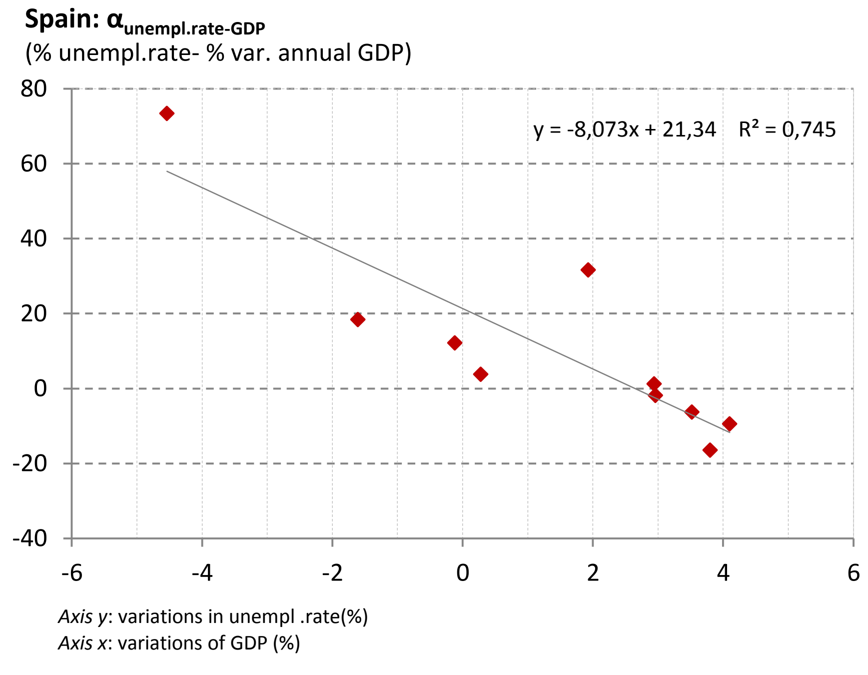

Figure 5: Relation between changes in unemployment rate (%) and variations of GDP (%). (Source: Own elaboration, 2014).

The default rate is the percentage of unpaid loans [Fig. 6]. The average default rate during the period 1999-2007 is 0.5686%. This value was used to initiate the simulation. The default growth rate is inversely proportional to GDP over the period 2000-2012, here we assume:

$$\Delta\%\text{ default rate} = -14.97\cdot\Delta\text{GDP}+4.193.$$

The minimum default rate is 0.5% regardless of GDP growth, because despite of high growth rate, as in the period before 2007 in Spain, default rate is never equal to zero.

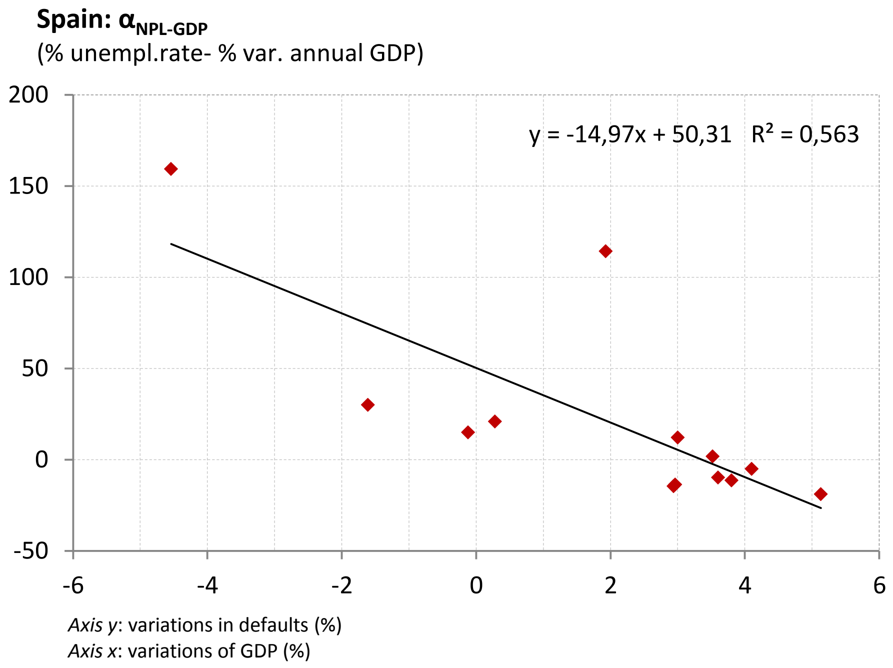

Figure 6: Relation between variations in NPL (%) and variations of GDP (%). (Source: Own elaboration, 2014).

We simulate a relation between the growth rate and non-performing loans in case of Spain (60 periods = 12x5 years) [Fig.7-9].
In the following that figures we can observe:

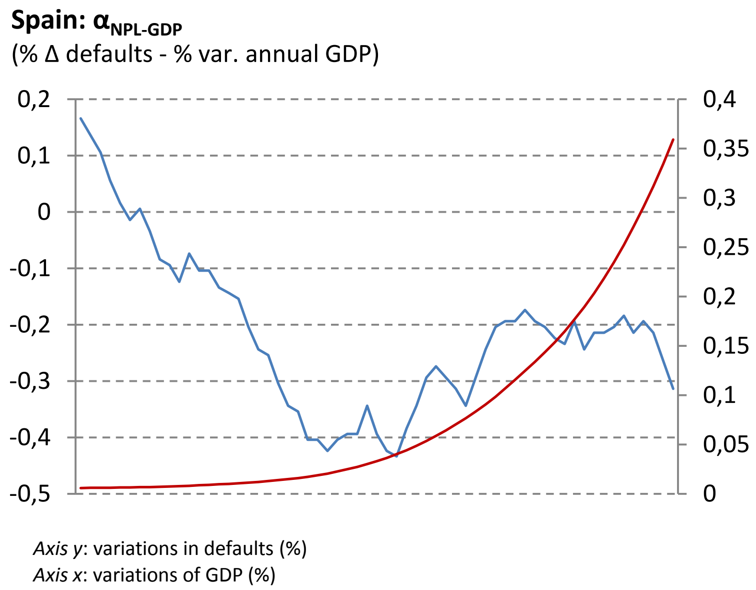

Figure 7: Relation between variations in NPL (%) and variations of GDP (%). (Source: Own elaboration, 2014).

that after 5 year of recession a default rate achieves the level of 35% [Fig. 7].

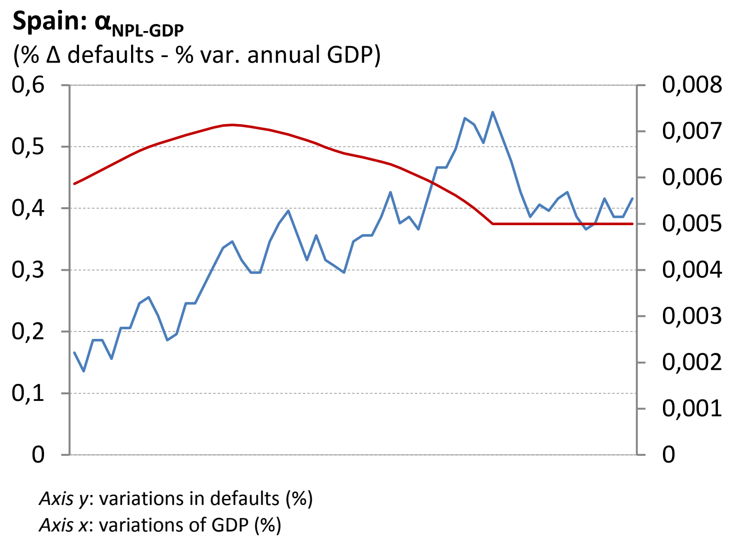

Figure 8: Relation between variation in NPL (%) and variations of GDP (%). Scenario 2. (Source: Own elaboration, 2014).

Alternatively, in the situation of very high growth rate, the NPL declines to minimum (average) level [Fig. 8].

In the situation of annual growth rate at the level of 2%, it hardly changes [Fig. 9]. As in other empirical research (Financial Stability Report - BdE (2007), Hernando and Villanueva (2010), Jimenéz, Ongena, Peydró and Saurina (2008), Nieto (2007)), in our model a direct relation between the annual growth rate and the non-performing loans was taken into account.

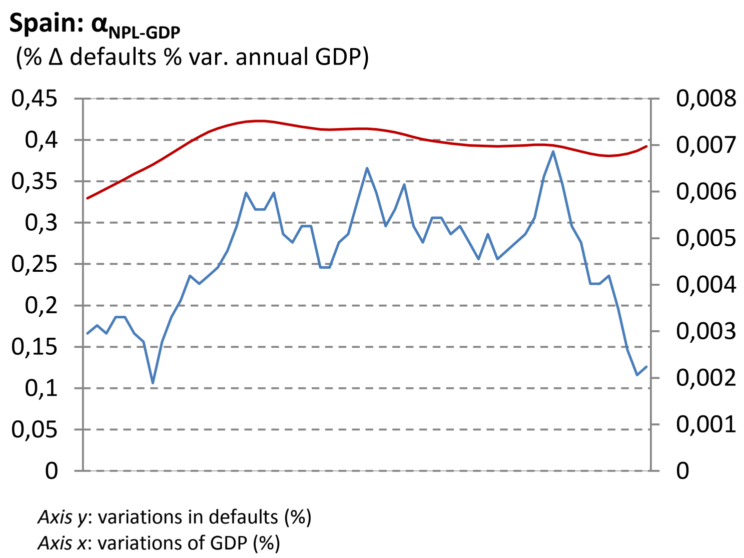

Figure 9: Relation between variations in NPL (%) and variations of GDP (%). Simulation 3. (Source: Own elaboration, 2014).

The official interest rate (OIR) [Fig. 10] is fixed by the ECB in order to keep the inflation low (below 2%). However, the correlation between the growth rate and interest rate is high as the ECB tends to reduce the official interest rate when the GDP is falling. For that reason, we can assume:

$$\Delta \text{ OIR}=0.198\cdot\Delta\text{GDP} -0.051$$

However, the regulator does not change the value of OIR each month, but rather each quarter or semester. For effects of dynamics in the model we can assume a smooth behavior in order to analyze consequences of the changes in the OIR. If due to reduction in the GDP values, we get to the value of 0.1, we assume that value as a minimum.

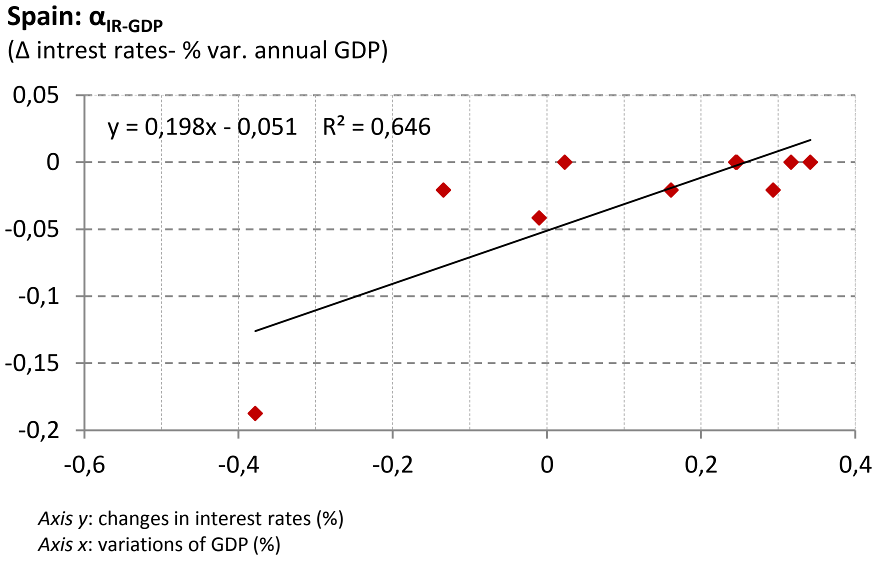

Figure 10: Relation between changes in official interest rate (p.p.) and variations of GDP (%). (Source: Own elaboration, 2014).

The simulation starts with RIR equal to OIR and later it depends on the performance of SRP. The levels of loans and deposits correspond to June 2007 in Spain. They change as the GDP increases or decreases (in amount predicted by the coefficients previously calculated). The initial values of the variables for each bank are provided at first by dividing loans and deposits equally (then we should study what is the disaggregated the effect of size of loans and deposits). The total of reserve requirements is equal to 'funds' financial institutions decide to leave apart.

Behavioral rules

Financial institutions as agents

Each agent in the model represents one financial institution in the artificial market. The main goal of the agent is to maximize its profits. The objective function is then the difference between the benefits obtained from lending funds (*interest rates [r(LTL),r(STL)] multiplied by the short-term and long-term loans[(LTL),(STL)]) and costs of borrowing funds (interest rates [r(LTD),r(STD)] multiplied by the short-term and long-term deposits[(LTD),(STD)]*), incremented by the interbank position multiplied by the reference interest rate, official interest rate multiplied by the reserve requirements and reduced by the cost of unpaid loans [*low quality long-term loans (LTLLQ) multiplied by the default rate*].

Objective function: Max(Profits)
Max[r(LTL)·(LTL)+r(STL)·STL-r(LTD)·LTD+r(STD)·STD+RIR·IBP+OIR·RR-default·LTLLQ]

In order to compute the values of profits for different values of variables and fixed parameters, we provide data on quantities of short-term and long-term loans, short-term and long-term deposits, interest rates and default rates.

Remark 1: we cannot modify radically quantities of long-term loans and deposits. Assuming an average term of loan (duration) to be 10 years, the maturity is 1/(12·10years) = 0.00833. The value of coefficient is rather low. The same applied to deposits: 1/(18 months) = 0.05555.

Remark 2: In the model, we assume that if financial institutions are unable to cover the reserve requirements, no more loans are created.

Remark 3: Cash and loans are distributed between the obligatory reserve requirements (RR) and interbank position (IBP). The positive interbank position equals the lending position in the market. At the same time, the reserve requirements shall be at least equal to the quantity that we obtain by multiplying short-term deposits by the reference interest rate [RR ≥ (RIR)·(STD)]

Interbank lending market

Depending on the interbank position (lending or borrowing position), each financial institution needs to decide whether to lend/borrow money on the interbank lending market or deposit/borrow extra funds in the central bank. It depends on at least two variables: systemic risk perception [(SRP)] and *Euribor* as a price of money. Notice, that the inclusion of systemic risk perception to model is direct and based on behavioral rule and it is not necessarily related to the existence of asymmetric or incomplete information as in the general equilibrium models and/or purely empirical research (for an interesting contribution about the importance of liquidity hoarding and counterparty risk in the U.S. overnight interbank market see: Alfonso, Kovner and Schoar (2011)). Additionally, we do not have to narrow our analysis only to the changes of interest rates as a result of variations in the systemic risk perception. It is not the only one procedure of inclusion of perception of risk in the behavioral rules of agents. Nonetheless, it is useful to emphasize the difference between quantification of systemic risk perception in terms of differential in interest rates and [(SRP)] as a *pure interpretation* of events ('subjective probability of at least one financial institution to be bankrupt in a month' in our case or 'perceived probability of a high-impact event in the UK financial system' as in the Bank of England research). This distinction has further implications for analyses of mutual relations (including network dynamics, the perception of similarity and popularity etc.) between agents in normal and adverse scenarios during crisis. Here we can also distinguish between the systemic risk generators and factors that threaten the financial stability due to being a consequence of external shocks. The bankruptcy of institutions can be treated as a factor that initiates the intrinsic dynamics of the system and forces changes 'from within' the system. Alternatively, a perceived probability of high-impact event is rather related to the systemic risk as a process exogenous in its nature and closely related to the interpretation of general equilibrium theory (the 'core approach'(Caballero (2010))).

If short-term and long-term deposits are lower than the sum of three components: reference interest rate multiplied by the short-term deposits, long-term high-quality and low-quality loans and short-term loans, agent can borrow money on the interbank lending market. In such situation, financial institution is in the borrower position [(IBP<0)]. Alternatively, if the sum of short-term and long-term deposits are higher than the aforementioned sum of components, financial institution is in the lending position [(IBP>0)]. Thus, it can deposit extra funds in the bank or in the interbank lending market as it has been already explained.

$$IBP=RIR \cdot STD+LTHQL+LTLQL+STL- STD+LTD$$

If we observe that

> *STD+LTD<RIR·STD+LTHQL+LTLQL+STL* (*financial institution can borrow money on the interbank lending market*),

Else

> *STD+LTD>RIR·STD+LTHQL+LTLQL+STL* (*financial institution can deposit extra funds in the central bank or in the interbank lending market*)

End if

If everything goes right:

> *IBP+=RIR·STD+LTHQL+LTLQL+STL-STD+LTD*

Else

> *(part is assigned to IBP) and (another part to RR)*

End if

In case of potential default of financial institution, central bank can lend money to the bank (see: *Scenarios 0-4 and rationale: Scenario 2*).

Additionally, the interest rate can change. There are many mechanisms and channels for interest rate to influence the quantity of loans and deposits. Moreover, the problem of quality of loans and deposits appears. We have 5 variables: interest rate of high quality long-term loans [r(LTLHQ)], interest rate of low-quality long term loans [r(LTLLQ)], interest rate of short-term loans [r(STL)], interest rates of long-term [r(LTD)] and short term deposits [r(STD)]. If interest rates are different from the average in the sector, then demand has to change. Additionally, in short periods of time, we can change only interest rates of short-term loans and deposits [r(STL)] and [r(STD)], because long-term deposits [(LTD)] are predefined. Long-term high quality and low quality loans are equal to the sum of three components: *Euribor*, reference interest rate and the coefficient that expresses the relation between perceptual variations in long-term loans and the perceptual changes in GDP growth: $\alpha_{LRL.}$ [$Euribor+RIR+\alpha_{LRL}$].

Finally, it is necessary to introduce the parameter of sensibility of demand of deposits and loans with respect to changes in the interest rates (the offered and average interest rates in the market). The corresponding rules are expressed as follow:

$$LTD{\cdot}{=}\alpha_{LTD}{\cdot}GDP\_growth{\cdot}\ \boldsymbol{\rho}_{r(LTD)}(r(LTD)-ar(LTD))/ar(LTD)$$

$$STD{\cdot}{=}\alpha_{STD}{\cdot}GDP\_growth{\cdot}\ \boldsymbol{\rho}_{r(STD)}(r(STD)-ar(STD))/ar(STD)$$

$$LTL{\cdot}{=}\alpha_{LTL}{\cdot}GDP\_growth{\cdot}\ \boldsymbol{\rho}_{r(LTL)}(r(LTL)-ar(LTL))/ar(LTL){\cdot}\boldsymbol{\beta}_{r(LTL)}{\cdot}(r(LTL)-OIR)$$

$$STL{\cdot}{=}\alpha_{STL}{\cdot}GDP\_growth{\cdot}\ \boldsymbol{\rho}_{r(STL)}(r(STL)-ar(STL))/ar(STL){\cdot}\boldsymbol{\beta}_{r(STL)}{\cdot}(r(STL)-OIR)$$

Additionally to GDP growth rate and difference between interest rate and average interest rate [r(x) and ar(x)], loans depend on a specific interest rate previously fixed for making a transaction. The same logic holds for deposits because one could choose between bonds or shares in the market, nonetheless, at that point of simulation we assume the most simplified version of the model. Systemic risk perception update was also considered in the model. It is an updating rule that depends on the value of default rate of LTLQL, on conditions in the interbank market and changes in profits.

SRM– interest-rate based measure of systemic risk

In our analyses, we have primarily focus on modeling behavioral rules and interpretive approach to measurement of systemic risk perception. Nonetheless, we can still study the 'interest-rate based' measures of systemic risk. In this case, we compute a measure of systemic risk that depends on a differential between the level of reference interest rate and the official interest rate as well as a differential between short-term interest rate and the official interest rate. It is computed as follows:

$$A = (RIR-OIR)/OIR$$

$$B=(SIR-OIR)/OIR$$

$$SRM=A/B$$

where RIR is a reference interest rate, OIR – official interest rate, SIR states for short-interest rate. The systemic risk measure values varies between 0 and 1 while 0 states for no systemic risk at all in the system and 1 expresses the maximum level of systemic risk in the market [Tab.4].

Table 4: Computation of interest-rate based systemic risk measure. (Source: Own elaboration, 2014).

Variables	Default rate (from 0 to 100)	Value	Results			Systemic Risk Measure	SRM
(RIR-OIR)/OIR			0,2	A	A/B	0,1	
(SIR-OIR)/OIR			2	B		This is a measure of systemic risk (from 0 to 1)	
	OIR	1					
	RIR	1,2				1 = max systemic risk	
	Short-term interest rate (SIR)	3				0 = min systemic risk	

The systemic risk measure/indicator is influenced by:

- changes in the defaults rates

(according to Bank of Spain nomenclature: '*tasa de morosidad'*)

- homogeneity or heterogeneity of banks
- different sizes of banks (small, medium and big ones)

In case of simulation of Spanish financial sector in 2007, the full heterogeneity of the system was assumed [Fig.13]

Methodology:

We develop a simple indicator SRM (systemic risk measure) that is useful in further simulations and we carry out Monte Carlo simulations assuming: different defaults rates, homogeneity or heterogeneity of banks, different sizes of banks.

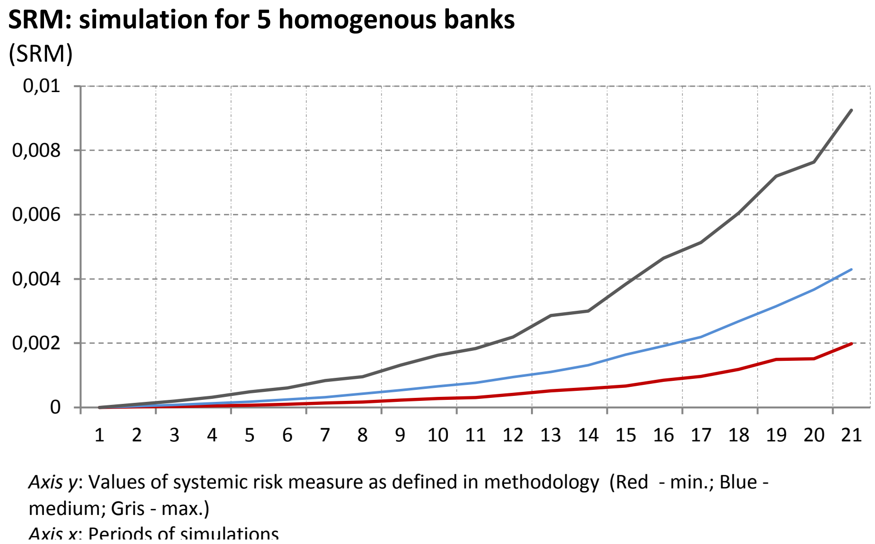

Figure 11: Simulation for 5 homogenous banks (Source: Own elaboration, 2014).

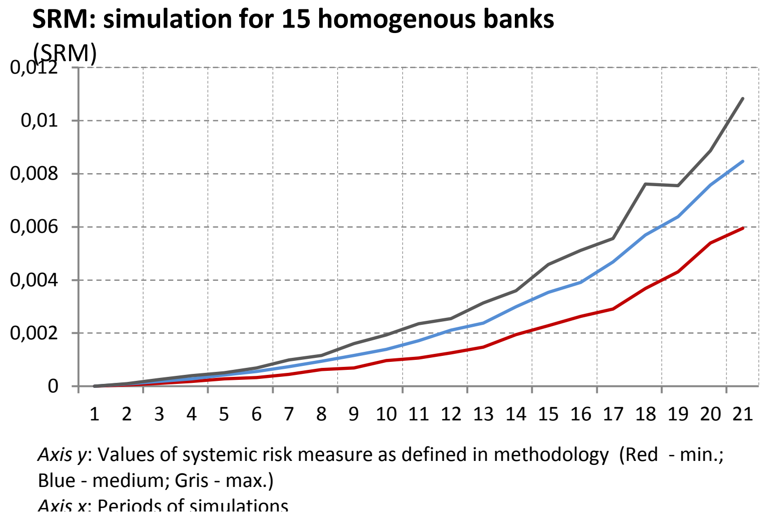

Figure 12: Simulation for 15 homogenous banks (Source: Own elaboration, 2014).

In all three cases we observe that as the simulation is taking place GDP and housing price decrease and heterogeneity of banks increases, the minimum, medium and maximum levels of systemic risk increase as well [Fig. 14]. When we start the market with fifteen homogeneous banks instead of five, the average systemic risk index is higher than in the scenario with only five banks. If we study the actual distribution in 2007 of the Spanish bank system, the level of systemic risk increases up to a 6% in five years. This value is not low because zero implies a null probability of default but the unit means banks have the same default risk of individuals and enterprises so they are charged the same interest rate.

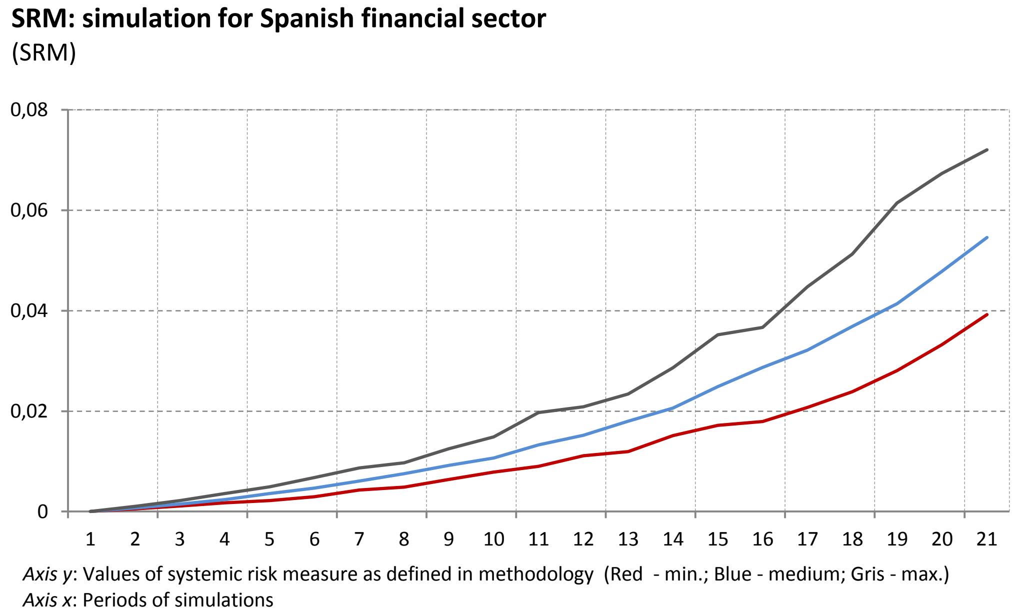

Figure 13: Simulation for Spanish financial sector (2007). (Source: Own elaboration, 2014).

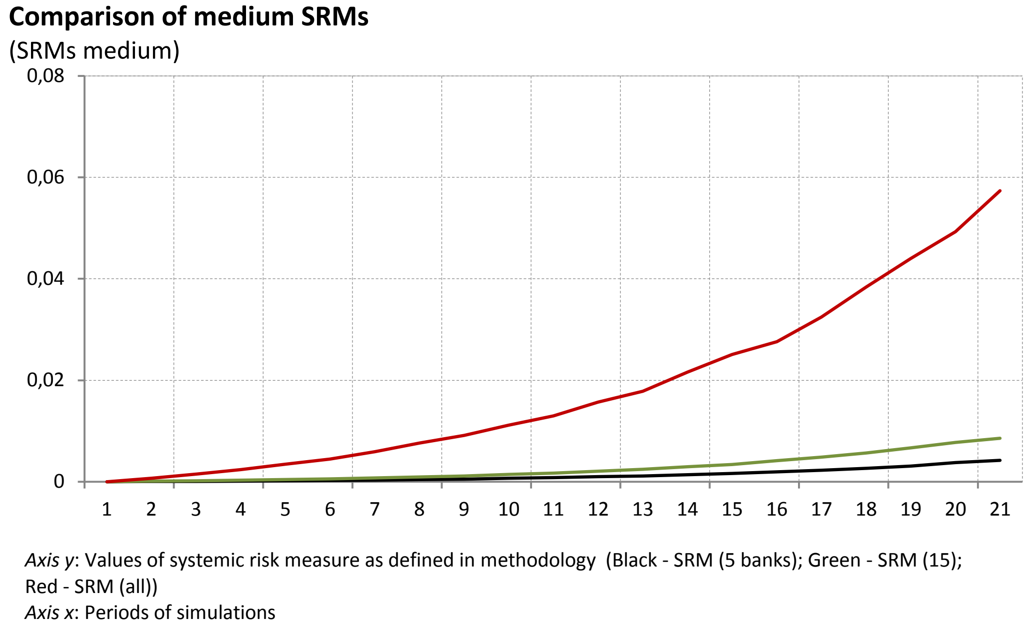

Figure 14: Comparison of simulation results. (Source: Own elaboration, 2014).

Conclusions and Further research

In the paper we studied how systemic risk depends on the market participants' perception of risk and perception of risk attitudes of the other market participants. We showed that the perception of risk has been studied in many fields of research. The insights from the social amplification of risk framework (SARF) together with the agent-based modeling (ABM) seem to be the most useful in the context of systemic risk measurement and modeling as well as from the regulatory perspective.

In the article, we explained the logic of one of the NCN framework for modeling systemic risk generation and amplification. The objective of our model was to show the role of risk perception and perception of risk attitudes in the systemic risk generation and amplification. The general equilibrium theory used to narrow the systemic risk research to analyses of adverse effects of external shocks. Nonetheless, the perception of risk and the perception of risk attitudes can fasten the self-organization of the system and can lead to emergence of new kinds of risks 'from within the economy or financial system' that would generate the systemic effects. Our analysis has direct implications for regulatory practice and macroprudential policies. In the broader context, the notion of systemic risk endogeneity is redefined as well. In the NCN framework we seek to use the agent-based approach to model different aspects and mechanisms of systemic risk generation and amplification. We also compare our results to the main econometric forecasting models (including dynamic stochastic general equilibrium models) that are currently being used in many public institutions.

The main objectives of this article were to emphasize the role of risk perception and risk attitudes in the systemic risk generation and amplification and to show the importance of new modeling techniques such as the agent-based approach. The results of simulations presented in the article ought to be compared to results of other empirical studies based on 'the core methodologies'. It is important to compare how systemic risk perception can be understood and included in the model. In the presented model, the systemic risk perception has been modeled as a behavioral rule. Nonetheless, a systemic risk measure based on the difference between interest rates has also been studied. That element of analysis can be easily compared to the quantification method used by Gara, Kovner and Schoar (2011). The authors examined "the importance of liquidity hoarding and counterparty risk in the US overnight interbank market during the financial crisis of 2008. Their findings suggest that counterparty risk plays a larger role than does liquidity hoarding: the day after Lehman Brothers' bankruptcy, loan terms become more sensitive to borrower characteristics. In particular, poorly performing large banks saw an increase in spreads of 25 basis points, but were borrowing 1 percent less, on average. Worse performing banks do not hoard liquidity. Worse performing banks did not freeze entirely, it did not seem to expand to meet latent demand (Gara, Kovner and Schoar (2011)) ".

The open question is whether the analysis of interest rates differentials presented in the paper can be treated as the 'true' systemic risk perception measure. Without doubts, the agent-based simulation techniques can help us to determine the role of counterparty risk and liquidity hoarding ex-post but they can also be a useful tool to carry out counterfactual simulations for the regulatory and governance practice. The 'periphery models' seem to be a great alternative to the 'core models'. Further research on measurement and modeling techniques as well as on the role of perception of risk attitudes is urgently needed.

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