

On The Resilience and Stability of Banks and Systems of Banks

A Quantitative Approach To Systemic Risks

This paper illustrates a new approach to systemic risks which naturally provides measures of their resilience, stability and, most importantly, allows one to better understand their dynamics and functioning. Applications to systems of Banks are illustrated

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In the era of globalized and interconnected economy, it is becoming clear that all corporations, banks and countries form part of a huge system of systems. As *turbulence* increases and the possibility of shocks and extreme events rises, the importance of a systems perspective of the economy becomes evident. In fact, due to turbulence, and because the global economy is increasingly fragile, in highly interconnected systems the propagation of stresses and traumas is very fast and can lead to a huge number of possible often surprising outcomes. This number increases with the complexity of the system. However, the idea and concept of “systemic risks”, even though it has become popular during the current economy meltdown, is very difficult to define. By “systemic” we refer of course to anything that can have repercussions (damage, consequences) at system level. For example, the so-called *Too-Big-To-Fail* companies are thought to be of systemic importance as their collapse could affect the economy severely. The TBTF concept, however, is becoming less significant and a new idea – *Too Complex To Survive* – is gaining popularity precisely because of what a systems approach can teach us. Since excessive complexity is a formidable source of vulnerability (exposure) and because the global economy is increasingly complex, a systems approach is mandatory. Conventional pre-crisis techniques of risk assessment, management and rating have been conceived in an almost turbulence-free world and are not applicable to the new situation as the current crisis so eloquently demonstrates. This paper illustrates a new approach – based on the quantification of complexity – which is not only applicable to systems as such, it naturally provides measures of their resilience, stability and, most importantly, allows one to better understand their dynamics and functioning. In particular, applications to banks and systems of banks shall be illustrated and discussed.

Systemic risks are not well-defined and are a generally poorly understood concept. This leaves the door open to regulatory discretion, which can compound these risks further. The idea, therefore, is to approach the problem from a totally different angle. Instead of trying to measure risks – a non-physical quantity which mandates the construction of a model - the idea is to measure the resilience of the system instead. Clearly, model uncertainty has a dramatic impact on the results and consequences of its usage. The advantage of measuring system resilience stems from two key issues. First of all resilience is a physical quantity which quantifies a system’s resistance to shocks and may be measured. Second, the computation may be performed without actually building a model via a model-free technique. In practice, all that is needed is periodically sampled data which reflects the functioning of a system. Good examples are cash flow, ratios or income statement-type data, which all corporations possess. The most important things in a model are those it doesn’t contain. When it comes to building models of complex systems the danger of leaving out important items increases rapidly with complexity. This is the main argument behind using model-free techniques.

As mentioned, a fundamental source of system fragility is excessive complexity. Corporations with excessively complex business models can be shown to be intrinsically fragile. It is for this reason that resilient businesses are generally simpler and leaner. It is intuitive that, with all things being equal, a simpler solution is preferred if it does the job. Clearly, complexity and resilience are intimately related hence complexity reduction is a means of increasing resilience. Recently developed Quantitative Complexity Management technology has shown how the complexity of a business is also a new and holistic Key Performance Indicator and how it can be used to not only measure its resilience but also to establish metrics of its governability (controllability) and stability. The present paper will concentrate on this particular issue.

A bank is as healthy as the ecosystem of its clients. This can range from hundreds of thousands to millions. Given the large numbers of clients it is highly probable that these clients themselves constitute a highly interconnected system. The clients of a bank provide it with two types of information:

1. Balance Sheet data (corporate clients)
2. Transaction-based data (corporate and retail clients)

Data in Balance Sheets is, generally speaking, subjective. In fact the same business may be reflected in a multitude of Balance Sheets compatible with the accepted accounting standards. Transactional data, on the other hand, is objective as it reflects real operations (deposit, withdrawal, purchase of stocks, loans, transfer of salaries, etc.). We shall show how both types of information may help a bank infer the state of health of its client base and, therefore, its own situation from a resilience, stability and sustainability standpoints.

Before getting to the heart of the matter, it is necessary to introduce some basic concepts. The computation of resilience for a given systems is based on the measure of complexity. Complexity is a fundamental physical characteristic of every system that may be found in Nature. Its importance is similar to that of energy. However, high complexity implies also an increase of management effort and energy. When taken to extremes, excessive complexity becomes a formidable source of exposure. This is why excessively complex systems are inherently fragile.

The complexity of a system described by a vector $\{x\}$ of N components is formally defined as a function of *Structure* and *Entropy*.

$$C = f(S \circ E)$$

Where S represents an $N \times N$ adjacency matrix, E is an $N \times N$ entropy matrix, \circ is the Hadamard matrix product operator and f is a norm operator. The adjacency matrix indicates the correlations between the components of $\{x\}$ (think, for example, how the entries of a Balance sheet are related to each other). The adjacency matrix is determined via a multi-dimensional algorithm which determines if entry S_{ij} is 0 or 1. This establishes the structure of the system. Structure is represented by means of graphs (maps) such as the one illustrated in Figure 1, which represents a business where the squares on the diagonal represent Balance Sheet entries and the dots reflect dependencies between them. The graph is known as a Business Structure Map and depicts the inter-dependencies between business parameters (black off-diagonal dots).

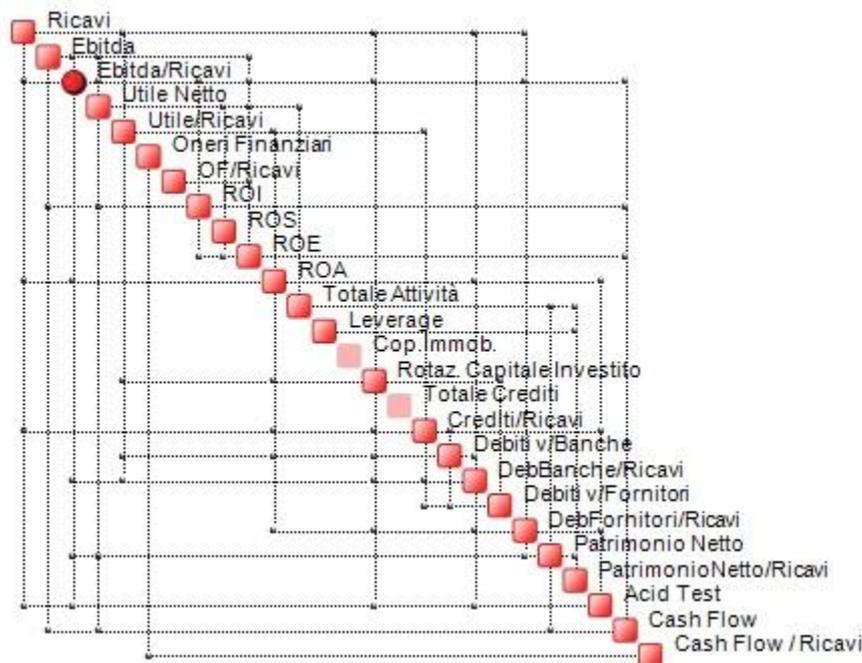


Figure 1. Example of a Business Structure Map based on Balance Sheet data.

The intensity of the dependencies, the so-called *generalized correlation*, is computed based on entropy. Entropy measures how crisp (or fuzzy) the dependencies between the elements of $\{x\}$ are. In essence, it quantifies the amount

of disorder within the system. The huge advantage of this *model-free* approach is that it is independent of numerical conditioning of the data and its ability to identify the existence of structures where conventional methods fail. Once the entropy matrix and the adjacency matrix have been obtained, one may compute the complexity of a given system as the following matrix norm:

$$C = \|S \circ E\|$$

A fundamental property of systems related to complexity is the so-called *critical complexity*, C_U , which corresponds to the upper bound of the complexity metric. Critical complexity may be defined formally using the above expression,

$$C_U = \|S \circ E_{\max}\|$$

where E_{\max} is the entropy matrix in which the entries correspond to a situation of *maximum sustainable disorder* within the system. In a similar fashion, the lower bound of complexity, C_L , may be computed as $C_L = \|S \circ E_{\min}\|$. In proximity of the lower complexity bound, a given system functions in a deterministic *structure-dominated* fashion. In proximity of the upper complexity bound the system in question is uncertainty-dominated and relationships between the various components of $\{x\}$ are fuzzy and therefore characterized by very low generalized correlations.

A measure of system resilience may now be defined as follows:

$$R = f(C_L; C; C_U)$$

where C_L , C and C_U represent, respectively, the lower complexity bound, the current system complexity and the upper complexity bound. The function f in the above equation is a second-order polynomial function such that:

$$\text{if } C = C_L \rightarrow R = 100\%, \text{ if } C = C_U \rightarrow R = 0\%$$

Let us now analyze the system composed of a certain bank together with a portfolio of its 220 largest corporate clients. The situation is illustrated in Figure 2, where only a few clients are shown for clarity.



Figure 2. Portion of Business Structure Map of a bank and its clients.

Each block of variables on the diagonal of the System Map (alternating red and blue is used to distinguish the clients) represents a client and the respective client-bank and client-client interactions. In the case in question, in which $Cl = 13.97$, $C = 36.68$ and $Cu = 48.02$, resilience is 74.5%.

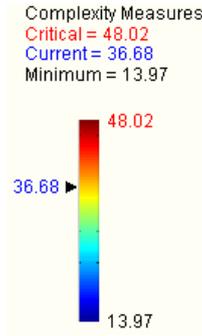


Figure 2. Illustration of minimum, current and critical (maximum) complexities of a system.

This means that the system (bank + 220 clients) is capable of withstanding a 75% increase in uncertainty (endogenous and/or exogenous) before it commences to lose structure and functionality.

As mentioned, the exchanged bank-client data can be either Balance Sheets, simple transactional data or both. In the case of transactional data, a simple example is illustrated in Figure 4.

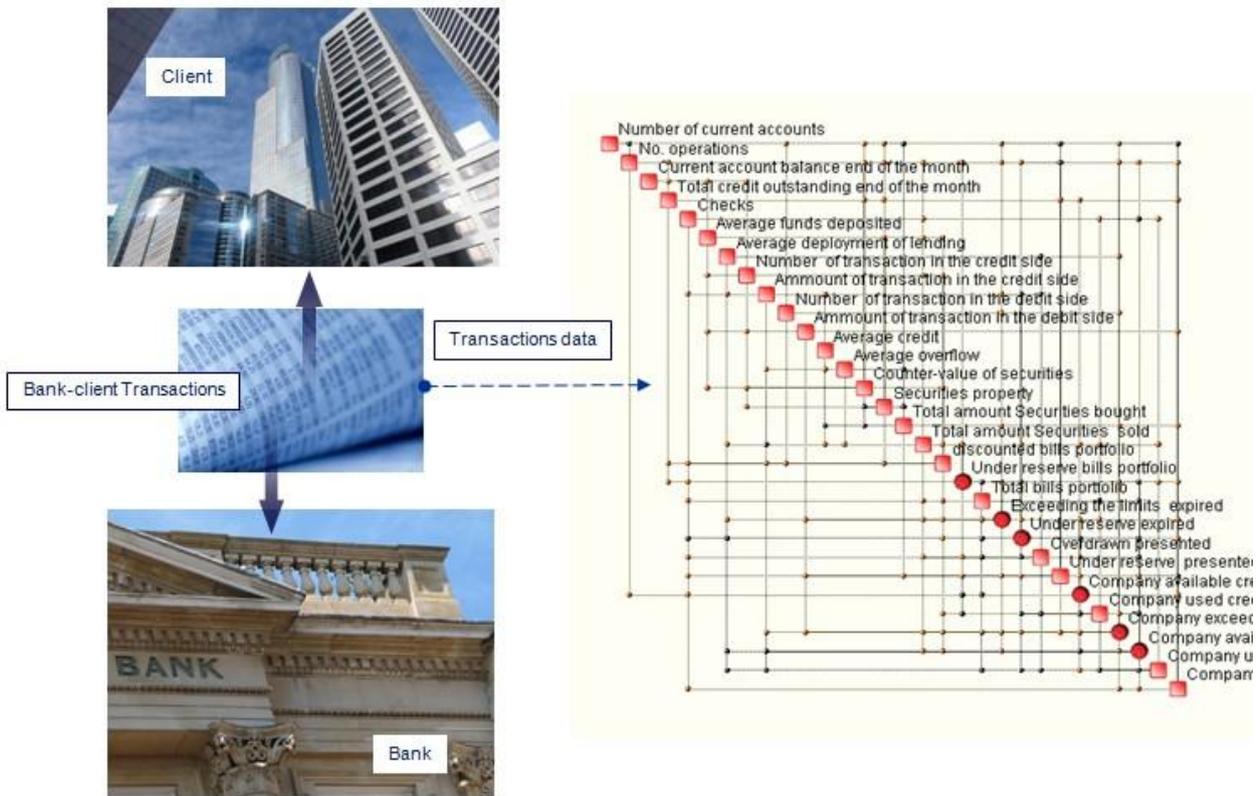


Figure 4. Business Structure Maps may be built based on client-bank transactions.

The map represents the structure of *bank-client interaction*. Clearly, large corporations work with more than one bank, therefore, information from Central Banks can be used to complete the picture. For each client the bank collects data on all his operations and computes the corresponding complexity. This is repeated on a monthly basis and

produces the corresponding complexity-time history. This delivers new insight into the dynamics of the bank-client relationship. In fact, based on how complexity varies over time it is possible to infer the general state-of-health of the said relationship:

- Case 1: Fast variations of complexity generally point to potentially unstable and critical situations.
- Case 2: Mild complexity variations generally point to stable situations.
- Transition from a Case 2 to a Case 1 scenario provides a formidable pre-alarm capability.

The rate of change of complexity defines the *stability* of a bank-client relationship and is defined formally as:

$$S=dC(t)/dt$$

The stability index ranges from 0% to 100%. Values close to 0% represent unstable situations while those close to 100% indicate highly stable conditions. It must be remarked that a highly stable situation does not necessarily represent a profitable one as stability and performance are generally independent quantities. Sudden changes in the stability of a business points to potential “traumas”. Independently of whether these changes are of endogenous or exogenous nature, they point to potential customer-retention problems: either a company is defaulting or it is changing banks. In both cases, the bank must be aware of the situation.

The Stability Profile of the example client portfolio is illustrated in Figure 5. The red vertical lines represent a critical stability limit, below which a particular client is investigated in greater detail.

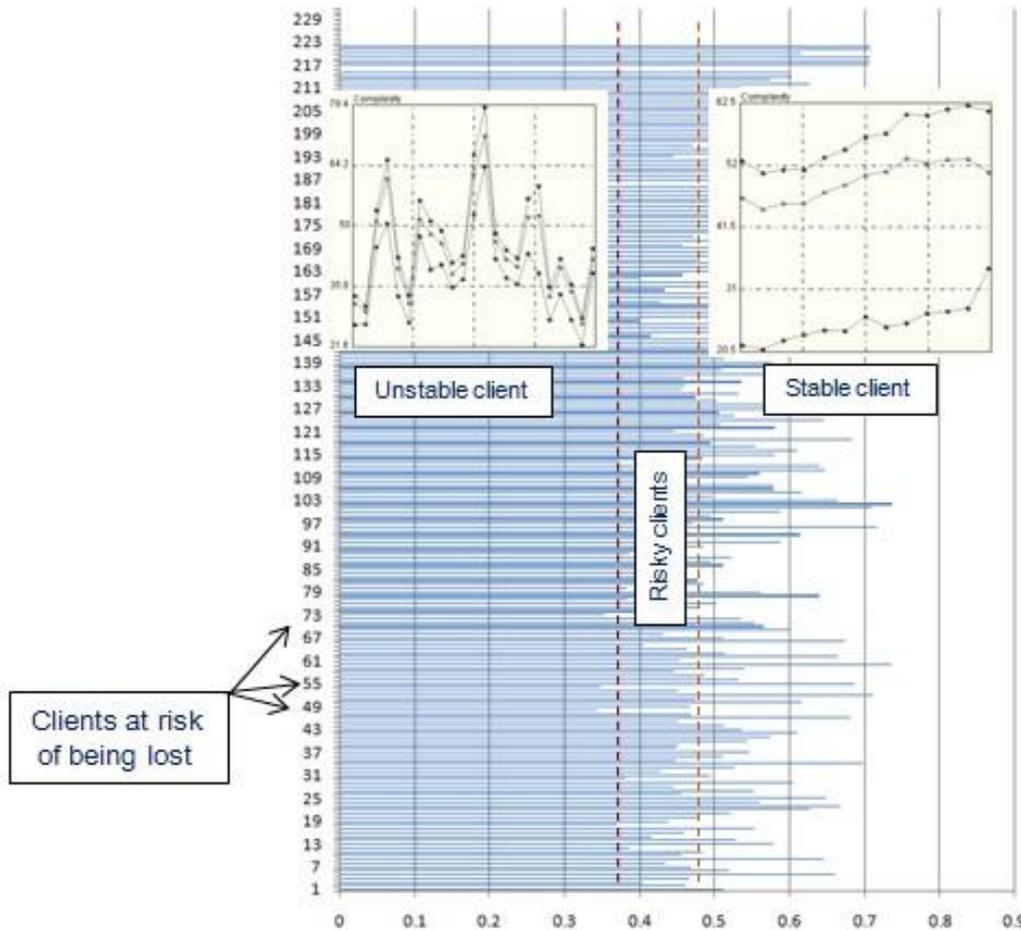


Figure 5. Stability profile of 220 corporate clients of a retail bank based on two years of monthly transaction data.

Once the stability of each client has been computed, one may proceed to compute the overall stability index of its client ecosystem as a simple average of all client stabilities:

$$SE = 1/N \sum Si$$

where the sum runs from 1 to N, total number of clients. In the case in question the overall stability of this portfolio is just over 55%. This means that making forecasts is not easy and reflects a significantly turbulent situation.

Example 1. System of ten EU banks. The system of ten largest European banks is illustrated in Figure 6. Reduced Balance Sheet data has been used to establish the combined Business Structure Map, offering a holistic perspective of a system. In the case in question, the system has an overall robustness (resilience) of almost 70%. The interesting information is provided by the so-called Complexity Profile which measures the contribution of each bank to the overall complexity, hence system resilience. Bank 2 carries the largest footprint in the system, of approximately 14% while that of Bank 9, 7 and 8 is around 12%. This means that the first 4 banks together account for approximately 50% of the system’s complexity and therefore they “drive” the resilience of the system.

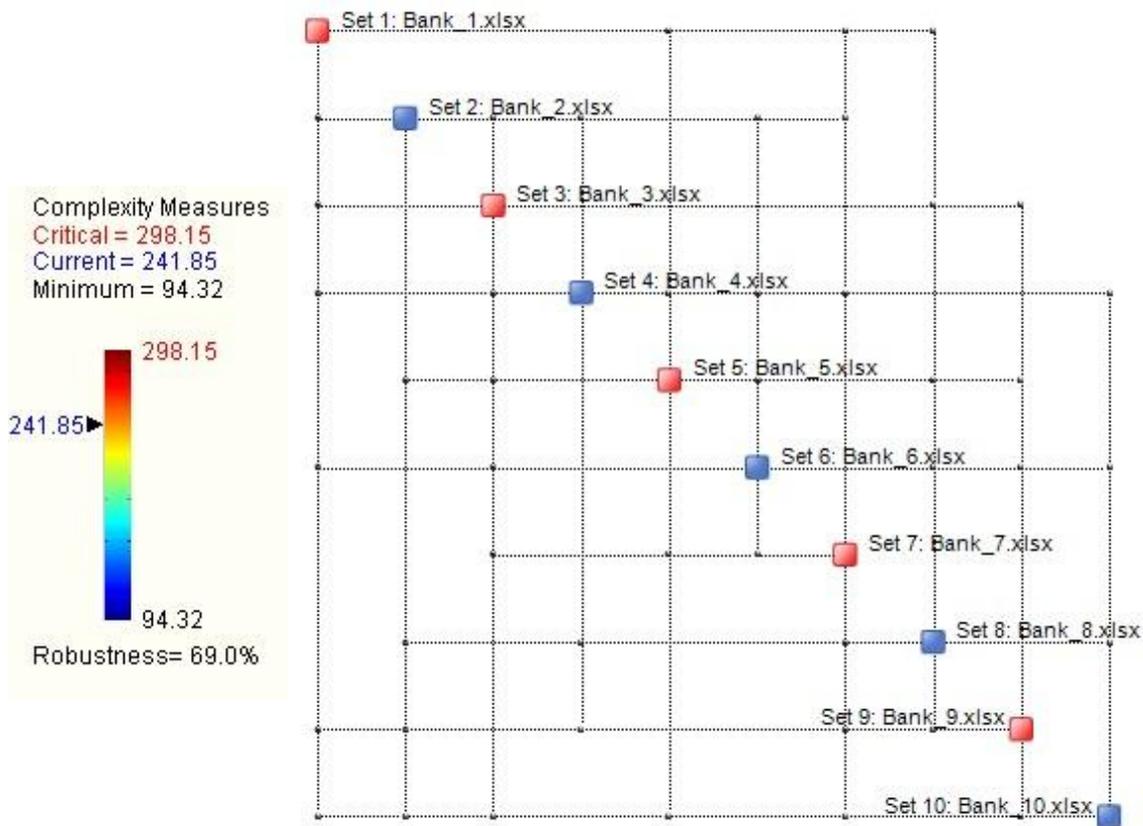


Figure 6. Business Structure Map of a system of ten EU banks computed based on reduced Balance Sheet data.

In the case of default, these banks would damage the system the most. The system Complexity Profile is indicated in Figure 7.

Example 2. Systems of top 115 US banks. In this case, Ratios have been used to analyze the system and synthesize the corresponding Business Structure Map. The system, depicted in Figure 8, has a similar resilience to that of the 5 EU banks, namely 70.2%. It is interesting to note that the density of the Business Structure Map is 29%, while that of the 10 EU banks is 49%. This indicates that the EU system is almost twice as interconnected (interdependent) as the US one. The consequences of such high interdependency can become evident in the case of default of one of the banks. In highly interconnected systems shocks and contagion spread much faster and can embrace wider portions of the system. However, the actual dynamics of a collapsing system depend greatly on its complexity. Higher complexity implies numerous failure modes and post-collapse “attractors” or states.

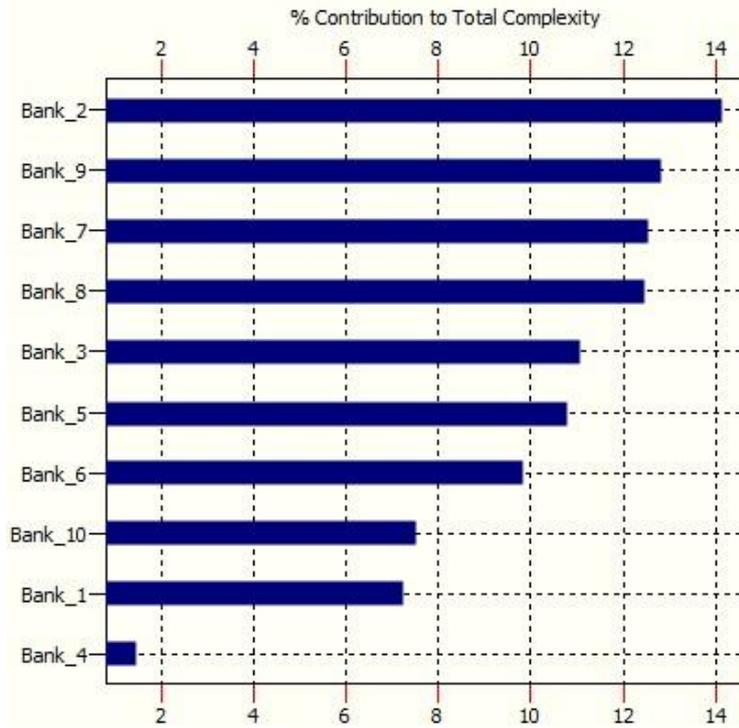


Figure 7. Complexity Profile of the system of ten EU banks illustrated in Figure 6.

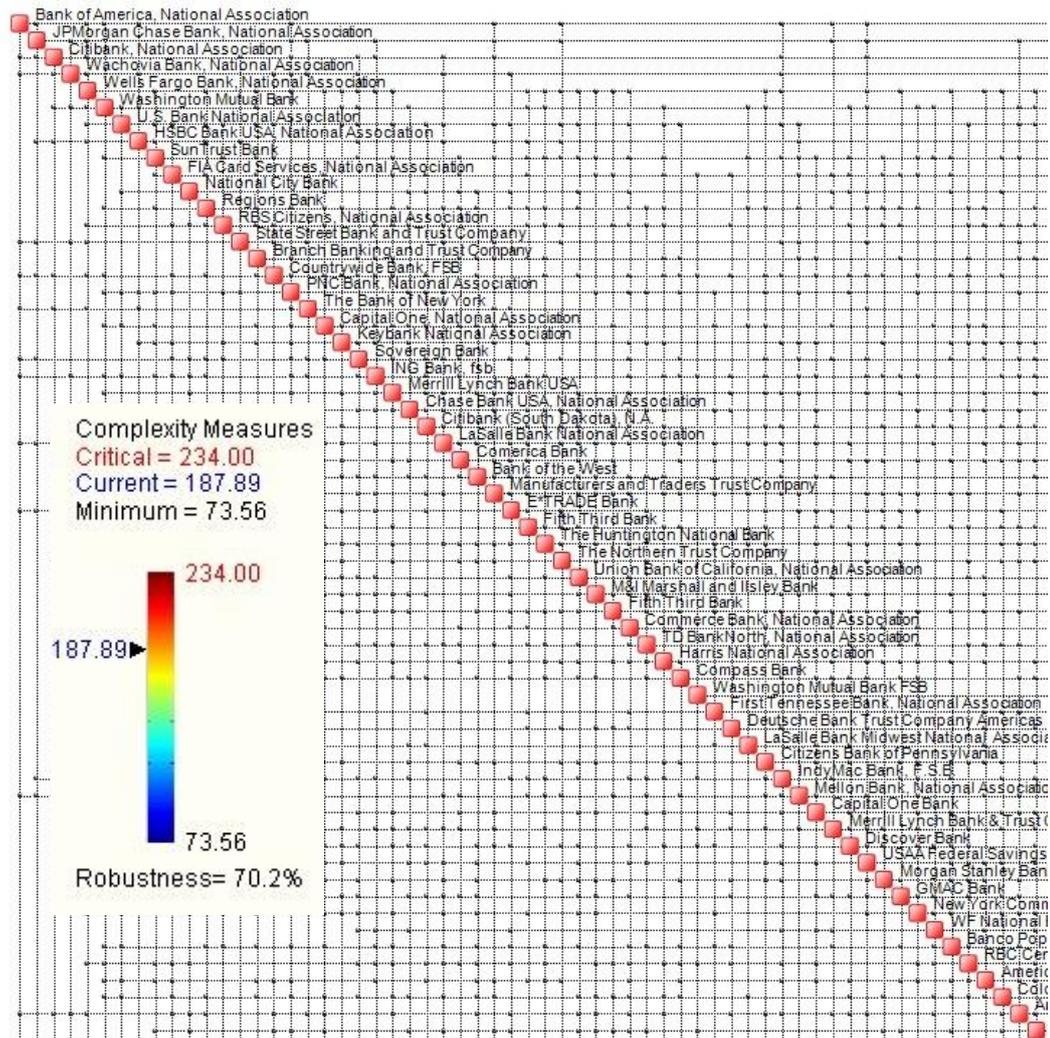


Figure 8. Portion of Business Structure Map of the system of top 115 US banks.

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In conclusion, a new approach to appreciating systemic aspects of risk is possible via the quantification of complexity and resilience. Systemic risk lacks an established formalism and little quantitative research on systemic risks is available. As systems grow in size and become more complex, the construction and adoption of mathematical models becomes an additional and important source of risk. Model-induced risk is rarely quantified. In the case of huge and complex systems such as those discussed in the present paper, quantification of model-induced risk would be very difficult to say the least. The methodology presented herein approaches the problem from an entirely different perspective. Instead of constructing a model of the system, a set of observable outputs (quarterly financial statements) obtained at each component (bank) of the system is used to measure the resilience of the system. This reflects the system's capability to resist shocks and extreme events. Most importantly, the computation of resilience is based on a model-free method which does away with modeling risk. Clearly the credibility of the analysis in this case hinges almost entirely on that of the data (financial statements).

Another important conclusion that stems from the above examples is that in order to reduce the impact of future crises or extreme events it is not necessary to split up huge companies into smaller ones, making them less dangerous for the economy, it is sufficient to render them less complex, reducing their footprint on the system. Size matters but not in this case.