Financial Instability through the Eyes of the Federal Reserve Bank Supervisors*

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Abstract

Recent series of deep disturbances to the global financial system highlight the need for a systems approach to the analysis of financial instability. The latest financial crisis provided many examples of significantly destabilizing dynamic processes affecting the behavior of the financial system that clearly indicate that the fragility of the financial system is structural. Therefore, to understand financial fragility, it is critical to elicit the structure of the financial sector. A common practice in the field of economics is to create theoretical models without the practitioners input. Yet the professionals who work in the financial sector poses the deep knowledge of the system. The objective of this project is to contribute to the effort of constructing a unifying theoretical framework of systemic feedbacks within financial systems. This project constructs a shared mental model of the Federal Reserve Bank supervisors that captures their understanding of the financial instability. To the best of our knowledge, their views have never been explicitly documented before. This gives the voice to the expert group that is usually not part of the academic conversation about financial stability, although these experts possess the first-hand knowledge about the topic.

Keywords: financial fragility; financial instability; bank supervision; The Federal Reserve; mental models; structural debriefing; causal diagrams

Introduction

Recent series of deep disturbances to the global financial system highlight the need for a systems approach to the analysis of financial instability. The latest financial crisis provided many examples of significantly destabilizing dynamic processes affecting the behavior of the financial system that clearly indicate that the fragility of the financial system is structural. In particular, the most recent crisis was characterized by accelerated reactions and spillovers between different financial markets and the macro economy. This has been pointed out by many observers. As the financial crisis was gaining momentum in late 2007, Borio (2007: 10) noted that “given the presence of positive feedback mechanisms, the financial system has a number of natural procyclical elements” that turn the financial system “from being a shock absorber… into a shock

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amplifier."

In the crisis post-mortem, a number of authors study the destabilizing patterns of market dynamics empirically. For example, Gai and Kapadia (2010) consider how financial system interdependencies have created an environment in which feedback elements create amplified responses to shocks to the financial system. The 2009 Geneva Report on the World Economy provides evidence of the role plaid by certain amplifying spirals in the propagation of the crisis. Its authors state: "We believe that it is this internal, self-amplifying dynamic that has lain at the root of both the recent, and virtually all prior, financial crises" (Brunnermeier, et. al, 2009: 5).

Since it appears that the fragility of the financial system is structural (Calomiris and Haber 2014), to understand financial fragility, it is critical to learn the structure of the financial sector. A common practice in the field of economics is create theoretical models without the direct practitioners input. Yet the professionals who work in the financial sector poses the deep knowledge of the system.

The objective of this project is to contribute to the effort of constructing a unifying theoretical framework of systemic feedbacks within the financial system. This project constructs a shared mental model of the Federal Reserve Bank supervisors that captures their understanding of the financial instability. A shared mental model is a collectively organized knowledge structure that can be used to communicate the implicit knowledge shared by a group of experts. To elicit and document the shared mental model, we used the structural debriefing technique (Pavlov et al. 2015). To the best of our knowledge, their views have never been explicitly documented before. This gives the voice to the expert group that is usually not part of the academic conversation about financial stability, although these experts possess the first-hand knowledge about the topic.

The outcomes of this study can be useful to researchers and practitioners. Researchers can use the shared model as a starting point for theoretical model building, irrespective of the utilized methodology. The model can be a system dynamics model, agent based model or an equilibrium model. Practitioners, such as managers of financial institutions, can use this info for applied discussions of financial fragility within their teams. Better understanding of the feedback nature of the financial system is essential when exploring interventions aimed at stabilizing the system.

Theory construction

We understand the world by building models (Johnson-Laird 1983). Modern economists also understand the world by constructing models (Morgan 2012: 2-3). Models represent theories of the world. Our economic knowledge is expressed in terms of models. They are research objects that depict a schematic view of the world. Models are ubiquitous reasoning tools that are manipulated and experimented with during formal decision making in all modern organizations, including government and finance. However, it is not obvious how models are constructed.

Model construction is a complex and opaque process. Morgan and Morrison (1999) provide examples of how models in various disciplines have been created. A model can be theory based or based on practical observations. Some models are not theory based at all. In reality, models are mixes of various elements from disparate theories, data, analogies and even objects.

Theory construction is a creative process mixing, imagining, idealization, and recognition of similarities between distinct situations (Morgan 2012: 22-23). Model making involves integrating sufficient number of ingredients such as metaphors, empirical observations, ideas, intuitions and so on before they are deemed adequate (Boumans 1999; Morgan 2012: 21). According to Baumans (1999), model building is similar to baking a cake when the recipe is not known, yet we approximately know what final product should be. As in baking, the preparation of the model involves trial and error and once the cake is ready, you cannot distinguish the ingredients.
The final model is presented as a simplified, metaphorical image of some corner of economic reality.

This article does not create a finished model of the financial fragility. With this article, we contribute to the effort of theory building by providing a record of the mental model of the financial stability shared by a group of highly experienced bank examiners from the Federal Reserve. A comprehensive theory of financial feedbacks may capture information from various sources. Future work will involve synthesis of the findings presented in this article as well as elsewhere (Gramlich and Oet 2016).

Mental models

Mental models represent the perceived structures of external systems (Johnson-Laird 1983: 419; Doyle and Ford 1998). Mental models are stored in memory as patterns of constructs that include cause-and-effect relationships between objects and time delays (Cannon-Bowers et al. 1993; Jones et al. 2011). Mental models are cognitive structures that allow people to process essential information for functioning in the environment, to explain and predict behavior of systems, and ultimately use mental models for decision making (Jones et al. 2011). Mental models allow us generalize our experiences to many situations (Jones et al. 2011). People perform mental simulations with their mental models to test outcomes of future actions, different strategies and possibilities (Jones et al. 2011). Mental models can be incomplete or even inconsistent representations of reality because they are personally constructed based on the individual's experiences and the view of the world (Jones et al. 2011).

Mental models change over time as the person learns additional facts about the system. Johnson-Laird (1983: ch 11) discusses a high-level view of a procedure by which we construct mental models. The process is recursive and involved continuous addition of new elements to the existing related mental models, if they exist, validation of the model against reality and earlier mental models. This manipulation and evaluation of the mental model recognizes that there is a large set of possible models. As a result, mental models of a novice and experts are markedly different (Jones et al. 2011).

Elicitation of mental models

Because mental models are cognitive constructs, they are not available for direct observation and inspection (Jones et al. 2011). The development and changes of mental models is an active research topic (Ifenthaler et al. 2008). We cannot observe mental models directly; therefore, to be known, mental models must be externalized through communication (Ifenthaler 2008). Language communication reflects mental models that correspond to reality (Johnson-Laird 1983).

Researchers have used a number of techniques to elicit mental models and their changes over time (Ifenthaler 2008: 45). The direct elicitation techniques require participants to create a diagrammatic representation of the mental model (Jones et al. 2011). Participants can also arrange cards with existing concepts depicted on them (Jones et al. 2011). One of the cognitive mapping techniques that is commonly used in such fields as psychology, anthropology and education is free card-sorting (Kearney and Kaplan 1997). In free-card sorting, the participants organize pictures, concepts or objects into groups according to how they fit together. Open-ended interviews have been used to identify, for example, mental models of global warming

(Kearney and Kaplan 1997). The outcomes of interviews are descriptive or pictorial models (Kearney and Kaplan 1997). Each of the techniques has its own advantages and drawbacks. There is a number of semantic proximity techniques, which all require the participants to organize words into clusters or some associative structures, such as trees (Kearney and Kaplan 1997). Kearney and Kaplan (1997) implemented an open-ended 3CM technique, which includes first generating a list of relevant concepts by interviewing stakeholders and then asking participants to sort a number of cards with concept relevant to the topic into thematic clusters.

Özesmi and Özesmi (2004) used a two-stage approach to elicit mental models in the context of natural resource management. In their protocol, participants identified important variables that were then written on cards and arranged into causal maps. The causal maps were analyzed with a graph theory tool to explore the complexity of the derived network structure. Özesmi and Özesmi (2004) compile a fuzzy cognitive map, which is weighted directed graph, with weights in the range [-1,1]. However, the model constructed by Özesmi and Özesmi (2004) was not dynamic.

Causal maps

Natural, social and economic systems consist of parts that interact through complex causal networks of mutual causality, feedback loops and sequential causality (Grotzer, 2012). Causal relationships are fundamental blocks of our knowledge (Pearl 2009: 21). Yet, research shows that we typically underestimate the complexity of cause and effect relationships (e.g. Perkins and Grotzer, 2005).

In one study, when students were given information about the number of customers entering and leaving the store, they have underestimated the number of people in the store at any one time (Sterman, 2010). In another series of experiments, participants were repeatedly poor performance playing the game of beer distribution, a simple simulation of industrial production and distribution in a series of delays and evaluations (Sterman, 1989) incorporated. These cognitive deficits observed in experiments, which involved the management of natural resources (eg Moxnes, 2000; Perkins and Grotzer, 2005; Gudrat-Ullah, 2007). It has been suggested that people who generally are not concerned about climate change because they underestimate the delayed effects of the accumulation of CO2 in the environment (Sterman, 2008).

Our learning mechanisms are not well adapted for understanding the causal complexity of systems, especially when the event has several causes, or when feedback is involved (Grotzer, 2012). We tend to discover when we see results of an action. In addition, people often make decisions based on statistical correlations, rather than true causal relationships. Moreover, in the pursuit of genetically coded efficiency our minds ignore a lot of potentially useful information. Some things just do not grab our attention.

Representing our knowledge as causal networks is a reliable way to encode what we know (Pearl 2009: 22). A benefit of causal network representations is also their remodeling flexibility (Pearl 2009: 22). If an additional variable is discovered during the follow up discussion, then only that variable need to be added to the graph with edges corresponding to the relationships relevant to this particular variable with the rest of the structure left untouched. The flexibility of causal constructs is based on the assumption that each arc represents a stable and autonomous causal relationship (Pearl 2009: 22).

Several research teams have pursued the automated discovery of causal relationships from data (Pearl 2009, Ch. 2).

Bank supervision

Supervision of banking organizations is one of the tasks of the Federal Reserve (Federal Reserve 2005). The Fed supervises US state and national banks, bank holding companies, edge and agreement corporations, and US-branches of foreign banks. The Fed monitors, examines and inspects financial institutions in the US to ensure their compliance with laws and regulations. The aim is to maintain the safety and soundness of the banking organizations and the stability of the financial markets. Bank examiners within the Fed conduct on-site inspections of banks and they monitor them off-site. A typical periodicity of on-site visits is about once every year. The Fed also has the authority to examine information technology companies that provide services to banks.

The Fed currently follows the risk-focused approach to supervision, which assesses the bank's ability to identify and mitigate the greatest risks within the organization. The bank rating system is called CAMELS, which stands for: capital adequacy, asset quality, management and administration, earnings, liquidity, and sensitivity to market risk. The on-site inspection results are reported to the management of the bank or bank holding organization in the form of a confidential report that includes a rating of the financial condition of the bank. The report would outline areas that require bank's special attention.

The Federal Reserve staff rely on many sources of information during examinations such as reports filed by institutions, public information in the press and online as well as earlier inspection reports. Between bank visits, the Fed monitors bank financial ratios within The System to Estimate Examinations Ratings (SEER), which detects banks with deteriorating financial profiles. More supervisory attention is given to poorly performing institutions.

Banks would typically take prompt voluntary measures to resolve problems identified by the Fed examiners. The Federal Reserve may also resort to a set of formal enforcement actions. Such actions include an issuance of a cease-and-desist order against a banking institution, in imposition of a fine, or banning permanently an officer or a director from the banking industry.

Method

Participants

The participants were nine banks supervisors in the Cleveland Federal Reserve Bank, eight males and one female. They cover mid-tier banks ($1 billion-$10 billion in assets) within the 4th Federal Reserve District. Each of them had the banking and bank supervisory experience in the range of 15 to 25 years.

Data collection procedure

The authors conducted a workshop at the Federal Reserve Bank of Cleveland. We interviewed nine bank supervisors in a group setting. We elicited their shared mental model of the bank failure process. The authors facilitated the sessions.

The structural debriefing protocol used in this study (Table 1) is based on a more comprehensive structural debriefing protocol used in Pavlov et al. (2015). The protocol is based on the literature of systems thinking and system dynamics (e.g., Sterman 1994; Pavlov et al. 2014). It is a debriefing activity for documenting mental models of experts. The debriefing activity involved four steps needed to document the mental model of a dynamic system. The protocol allowed the participants to relate their knowledge of the financial system to the observed behavior of identified financial variables.

We used graphical notation to capture the mental model. A graph provides a clear depiction of the interrelated variables. Graphical notation has proven extremely useful for depicting causal and probabilistic systems of equations, such as Markov and Bayesian networks (Pearl 2009: 14). A similar graph structure is utilized in Social Network Analysis to capture the relationships between individuals (Wasserman and Faust 1999).

The structure was constructed based on the judgement of the experts of causal relationships between variables. In that sense, the created causal structure does not include any “paradoxical” dependencies that go against the intuitive knowledge of causation between variables.

Table 1. A structural debriefing activity for elicitation of a shared mental model

Step	**Description**
1. Problem identification	Participants discuss the problem.
2. List variables	Participants identify and list variables that make up the underlying structure.
3. Draw and discuss behavior-over-time graphs (BOTGs), also known as reference modes	Participants gain insight into the system’s behavior by drawing and discussing behavior-over-time graphs. Behavior-over-time graphs, commonly used in system dynamics modeling, are graphs that show behavior of variables over time (Richardson & Pugh, 1981).
4. Construct causal loop diagram	Participants represent the web of interactions between variables by drawing causal loop diagrams, including key variables and feedback loops. The causal diagram is a directed graph (a diagraph).

Structural debriefing (Pavlov et al. 2015) produces two artifacts: the causal loop diagram and behavior over time graph. The causal relationships are captured as a causal loop diagram. The behavior-over-time-graphs (BOTGs) show the dynamic nature of the system.

To make the captured rendition of the mental model more valid, to minimize omissions and to create an atmosphere conducive to sharing of knowledge, the process was conducted in a group setting. As facilitators, the authors encouraged a dialog and recorded information. The resulting record captured the shared mental model that incorporated the systemic feedback mechanisms.

Findings

Problem identification

Mental models are limited by their nature because they are functional, that is they serve a specific purpose (Doyle & Ford 1998). The mental construct that we were interested was specifically linked to financial instability. Hence, as a first step all the participants had to agree on the scope of the problem.

We wanted to document how bank supervisors viewed financial instability. Very quickly, it became clear that there are many facets to financial instability. We agreed to focus on mid-tier banks – the area this group was most familiar with. In the US, banks are commonly aggregated into three groups: big banks, mid-tier banks, and small banks. We limited our attention to mid-tier banks (MTBs) that is banks with assets in the range between $1 to $10 billion. Compared to MTBs, large banks are national and international in nature and offer more services. Small banks offer personalized attention to their customers. The participants agreed that that there are about 50 mid-tier banks in the US.

The group zoomed in on the following scope for the problem, "Under what conditions would a group of mid-tier banks create financial instability that may lead to a financial crisis at the national level?" The instability was understood as bank failures.

Variables

Once it became clear that we looked at the contribution of mid-tier banks to the financial instability, the group identified a list of variables that appeared to be relevant to bank performance. The variables are shown in Table 2. The list includes 47 variables. The facilitators then prompted participants to identify the most critical variables, which bank examiners would review particularly closely when auditing a bank. The 17 critical variables are marked with asterisks.

Table 2: Identified variables. Asterisks mark critical variables.

Regional economic conditions*	Liquidity*
Ability to recruit talent	Securitization
Technology*	Funding*
Competitive pressure*	Access to capital

Revenue	Correlated risk
Cost	Interconnectedness*
Operational risk*	Common exposure*
Legal risk*	Asset values*
Reputational risk*	Credit quality
Strategic risk*	Deposits
Counterparty risk	Financial stress
Capital*	Operating expenses
Capital planning	Defaults on payments
Asset prices*	Credit ratings*
Asset concentrations	Desired liquidity
Concentrations of assets*	Price of capital (spread)
Concentrations of liabilities	Capital requirements
Loan commitments	Asset sales
Derivatives	Losses*
Enterprise risk management (ERM)	Mid-tier bank capital
Stock price	Riskiness of activities
Spreads (for credit, CDS)	Supervisory ratings
Market risk	Credit risk

Behavior-over-time graphs

As the next step the group created behavior-over-time graphs (BOTGs) for several critical variables (Figure 1). Time horizon for the behavior-over-time graphs was set to three years (or about 1000 days). After the session, the BOTGs from the session were transcribed with the graphical software (Figure 2).

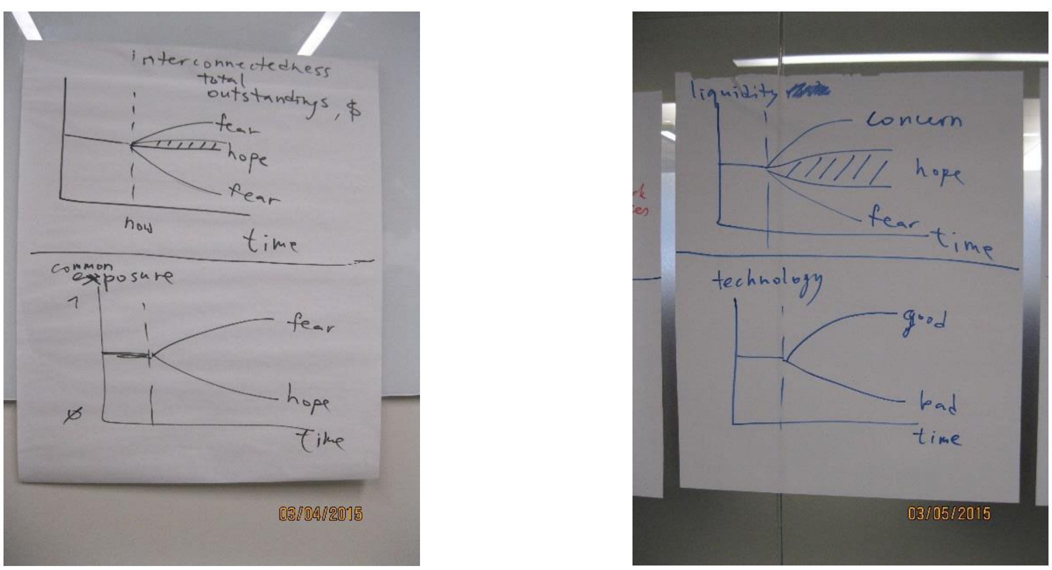
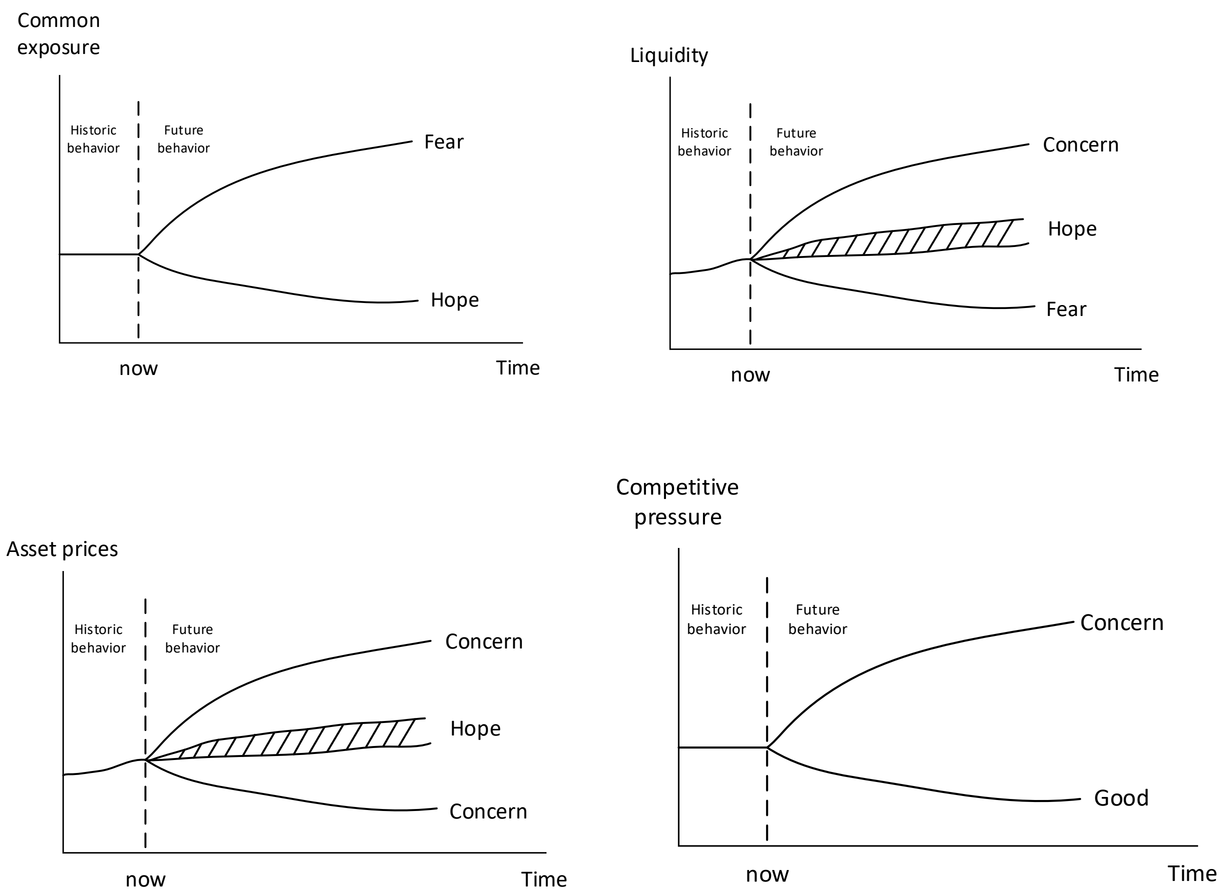


Figure 1: Samples of behavior-over-time graphs from a structural debriefing session

Figure 2 shows graphs for six variables. It is easily noticeable that behaviors of critical variables exhibit very similar patterns. The graphs consist of two periods: before "now" and after "now." The trajectory before "now" is the historical behavior. The variable behavior after "now" are the possible future scenarios. The trajectory called "Hope" depicts desirable scenarios, while "Fear" are the scenarios that mid-tier banks should avoid. Some trajectories, labeled "Concern," would lead to a closer examination of the banks by the supervisors because they indicate a deviation from the norm. For several variables participants felt that the normal behavior falls within a band.



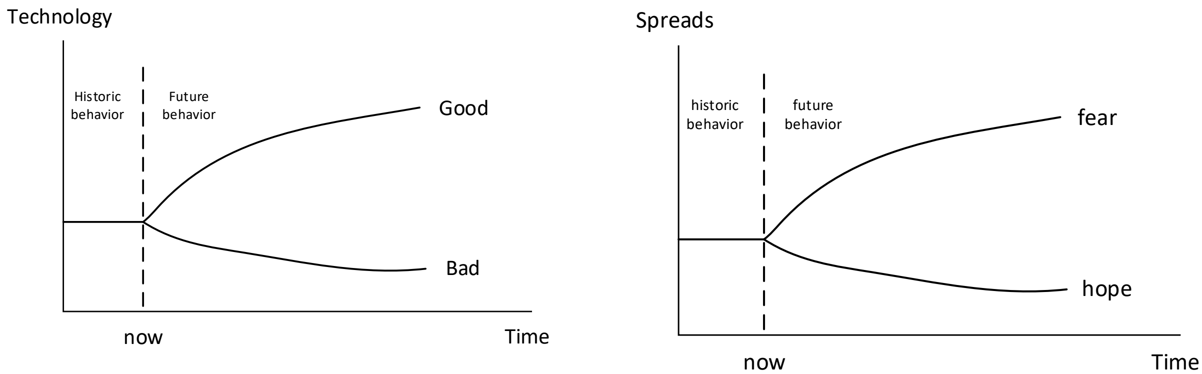


Figure 2: Behavior-over-time graphs for six variables

A causal loop diagram

By sharing their individual experiences as bank supervisors, the group created a causal loop diagram shown in Figure 3. The causal diagram represented their shared understanding of the interconnected web of influences affecting financial performance of a typical mid-tier bank.

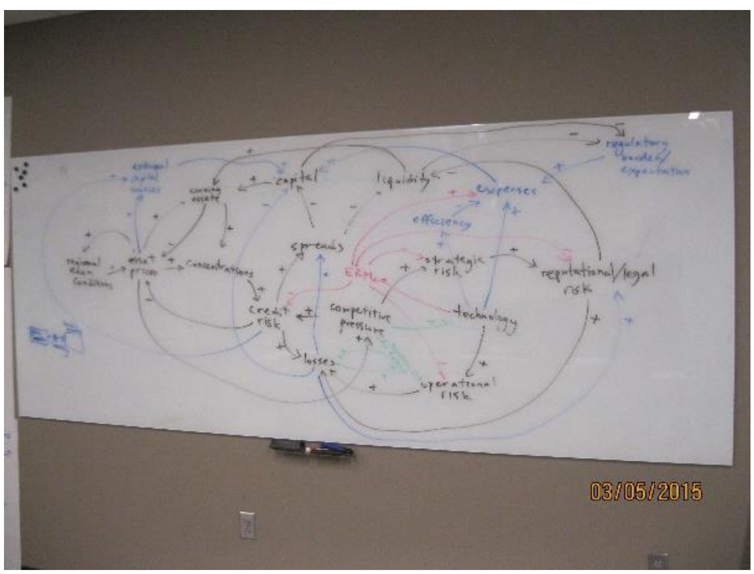


Figure 3: An influence diagram from a structural debriefing session

The diagram in Figure 3 was transferred into a software package called Vensim PLE, which is freely available online. The resulting graph is in Figure 4. The map contains 23 variables, only a subset of the variables that were identified in step 2. As with any mental map, the map in Figure 4 can be expanded further, but the group felt that this subset was sufficient to capture the critical structure of the system.

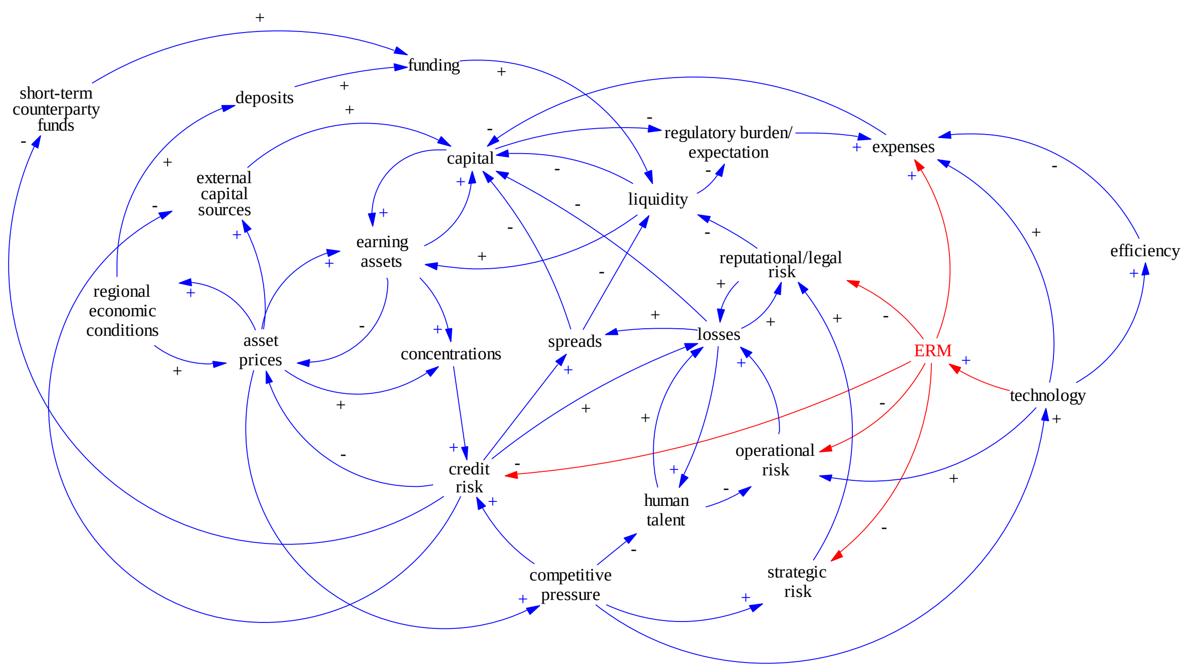


Figure 4: The causal loop diagram that captures the financial soundness of a mid-tier bank

Analysis of the causal loop diagram

The resulting structure in Figure 4 is a *directed graph* (or a *diagraph* for short) with 23 *nodes* (also called *vertices*) and 53 *arcs* (also called *arrows*) connecting them (see, for example, Foulds 1992 for the mathematical discussion about graphs). The nodes correspond to variables. It is a *labeled* diagraph because each node has a unique name. If there is a relationship between variables, the variables are connected with an arc. Two neighboring nodes that are connected with an arc are called *adjacent*. For example, deposits and funding are connected with an arc. In this connection, deposits is a predecessor and funding is a successor. The logical meaning of an arc (or an arrow, a link) is the relationship between a cause and effect.

Additionally, it is a *signed* diagraph. The arrows are coded with a “+” or a “-“. Positive links imply that the cause and effect move in the same direction. For example, deposits is connected with a positive arrow to funding; this implies that as the number of deposits increases, the funding available to the bank also increases. If deposits fall, funding also falls. Negative arrows suggest that two variables move in opposite directions. For example, if losses increase, capital decreases, which is shown as a negative arrow.

Table 3: Connectivity of variables

Variable	*Degree*		*Cycles*
	In	*out*	
Regional economic conditions*	0	2	7
Short-term counterparty funds	1	1	12
Technology*	1	4	87
Concentrations	2	1	97
Competitive pressure*	1	4	152
Losses*	4	4	129
Operational risk*	3	1	49
Reputational/legal risk*	3	2	85
Strategic risk*	2	1	32
Capital*	6	2	146
Asset prices*	3	5	180
Enterprise risk management (ERM)	1	5	67
Spreads (for credit, CDS)	2	2	88
Liquidity*	3	3	138
Funding*	2	1	18
Deposits	1	1	6
Human talent	2	2	34
Expenses	4	1	53
Efficiency	1	1	2
Credit risk	3	5	131
External capital sources	2	1	6
Earning assets	3	3	193
Regulatory burden/expectations	2	1	47

This diagraph shows high degree of *connectivity*. It is a *complete* diagraph since every two nodes are directly connected by an arc. Except for one node, regional economic conditions, every other node is *reachable* from any other node. When we can hop from one node to the next by following the arcs, we say there is a *walk* that joins these nodes. A walk with unique nodes is called a *path* and a walk with distinct arcs is called a *trail*. If by walking along a path in the direction of arrows you can return to the same node as you started, then this walk is called *closed*. A closed walk with at least three distinct nodes is called a *cycle*.

Table 3 shows the number of cycles that pass through the nodes. Earning assets has 193 distinct cycles passing through it. The complexity of the system and the iterative nature of the feedback effects can be appreciated if one considers that, for example, there are 180 causal feedback loops passing through the variable asset prices in the system that is depicted in Figure 4. Cycles shown in Table 3 were counted using the Vensim PLE software. Hence, the diagraph in Figure 4 is *cyclic*.

A circular chain of causal relationships forms a feedback loop. The sign of a cycle is determined as a product of the signs of the arcs in the cycle. If the chain contains only positive links or an even number of negative links, the loop is positive. A chain with an odd number of negative links forms a negative loop. Positive cycles are reinforcing. Negative loops are balancing. Table 3 does not differentiate positive and negative loops, though if desired it can be done after a considerable effort.

The *degree* of a node is the number of arcs connected to the node. The *indegree* of a node is the number of arcs directed towards the node. The *outdegree* is the number of arcs directed away from the node. Table 3 shows the indegree and outdegrees of the nodes in Figure 4. The sum of the indegree and outdegree of a node is equal to its degree. The smallest degree of a node in Figure 4 is two and the maximum is eight. Since all nodes have degrees greater than one, they are all called *internal*. One vertex, regional economic conditions, is a source that is all arcs are directed away from the node and none of the arcs direct towards the node. Of course, this an assumption that has been made by the group, which assumes that they take regional, economic conditions as external to the boundaries of their bank supervision. The group identified no *sinks*, that is there are no nodes that have no influence on other identified variables as would be depicted by arcs directed towards the node rather than away from it.

The higher the outdegree of a node the more influential the variable is.

Discussion

The mental model captured in Figure 4 shows variables and their interconnectedness deemed important by the bank examiners. The shared mental model produced in this project can be used to establish a consistent approach that allows subsequent merger with theoretical economic models. It can also contribute elements of structural typology of systemic feedback that improve analytical identification of feedbacks. Additionally, this study establishes systemic feedbacks at the level of mid-tier banks for subsequent economic policy research.

The causal diagram in Figure 4 can be used for policy intervention design and analysis. Earlier examples of policy analysis based on a causal loop diagram include the case of child protection services in England (Lane et al. 2016) and a study for the New Zealand Customs Service (Cavana and Mares 2004).

Researchers have noted that causal mental models thus constructed can be used to build computer simulation models for scenario analysis (Özesmi and Özesmi 2004; Jones et al. 2011). Researchers can use this information to build models irrespective the methodology used. For example, in the field of system dynamics, mental models are translated into computer simulation models, which are then used for computer experimentation with the objective of improving the original mental model (Vennix 1996).

The pictorial structure in Figure 4 can be viewed as a precursor to a true causal model. In its current form, it is not yet a model because it cannot be used for manipulations to test the behavior of the system it depicts. It is feasible to translate the graphic in Figure 4 into three different types of models. If one assigns equations linking the variables, then it can be translated into a mathematical model. Such a model can be used for traditional equilibrium and comparative static analysis. By assigning probability weights to arcs, the model can be converted into a causal Bayesian network. A system dynamics model is the third option. A system dynamics model is a computational model that would allow an out-of-equilibrium analysis of the system.

Conclusion

Bank examiners at the Federal Reserve have detailed knowledge of banks that they supervise. Having a visually articulated mental model that describes portions of this knowledge is desirable because the visual helps to share their knowledge with the outside research and practice community. This study makes this knowledge available for further economic theorizing that can be done in many different methods: mathematical economic models, causal Bayesian networks (Pearl 2009), and system dynamics model (Morecroft 2007), to name just a few.

The schema in Figure 4 confirms the interconnectedness and the feedback complexity of the financial system as has been hypothesized, for example, in Gramlich and Oet (2016). Once the map in Figure 4 was constructed, bank examiners were surprised by the high degree of interconnectedness of the system and the large number of feedbacks. This is not surprising considering that people misperceive feedback (Sterman 1989).

Because mental models are individually internalized knowledge constructs, they can potentially vary between bank examiners. Future studies can collect subjective mental models of the Federal Reserve supervisory staff and compare them to identify the degree of similarity between individual mental models (DeChurch and Mesmer-Magnus 2010). As examiners gain knowledge of the banking system and accumulate their experience, their mental models they rely on in bank supervision are likely to change. We can formally analyze the changing structure of the mental models, for example, similar to Al-Diban (2008). Training within the Federal Reserve can also be tailored using the mental model-centered instruction (Ifenthaler et al. 2008).

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