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Systemic Financial Feedbacks – Conceptual Framework and Modeling Implications

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Abstract

Different approaches to model feedbacks in financial systems are assessed based on requirements for the conceptualization of the feedback dynamics. Given the non-linear, behavior driven, and interconnected characteristics of systemic financial feedbacks (SFFs), modeling concepts from System Dynamics (SD) theory provide appropriate and attractive features. Surprisingly, few SD models exist to explain systemic financial feedbacks. The scarcity of SD modeling for SFFs may be attributed to the lack of required economically-sound foundations for theoretical modeling. This paper considers a conceptual framework for SFFs that emerges from the synthesis of formal principles of economics and SD. In doing so, this study links existing SFF models to concepts of SD and provides suggestions for further modeling.

Keywords: Feedbacks, Modeling, System Dynamics, Simulation
JEL: B40, C15, C63, E47, G01, G17

1. Introduction

Analyses of the recent turmoil in global financial systems yield a major finding of the highly dynamic, interdependent, and non-linear character of crisis mechanisms (Allen and Carletti 2010, Brunnermeier 2009, FSA 2009). In the center of the crisis, the behavior of market players was determined from exaggerations, incomplete information, herding, and flight to quality, thereby incentivizing further rounds of contagion. In turn, financial systems' characteristics, such as credit spreads, stock prices, and foreign exchange (FX) rates (Adrian et al. 2010), experienced extreme acceleration effects to levels far-distanced from the historical norms, fed back on themselves and generated a series of critical tail events. During these phases, the central assumptions of efficient markets such as complete information and rational behavior appeared to fail. This particular type of dynamic spillovers on financial markets, further referred to as systemic financial feedbacks (SFFs), provided in-situ evidence of a structural breakdown in interactions between financial system agents. As a consequence, the agents' dependence on the macro-financial crisis factors (systemic risk) as a source of individual risk (micro-financial risk) has received a higher importance.

As it is mostly stated, models for systemic financial risk before the crisis have not been able to explain this behavioral pattern sufficiently (ECB 2010, p. 138). Particularly, the accelerating and self-feeding propagation mechanisms within the system have not been assessed adequately. A new class of models for systemic financial risk is therefore reclaimed, emphasizing particularly the SFFs. The necessity for improved understanding of SFFs is both recent and urgent. As recently as 2010, the European Central Bank (ECB 2010, p. 138) urged that “very significant further research efforts” in this area are needed. May and Arinaminpathy (2010, p. 823) state that attention towards financial dynamics has been focused only relatively recently and that “a super-exponential expansion of work” has occurred as a consequence of the financial crisis. As will be shown, most of these models approach the new dynamic non-linearities in an improved way, but still have insufficiencies. Increasingly, new models address the SFF dynamics through the techniques of discrete dynamic programming and iterative simulations. These approaches, however, still prove to be too functional and quasi-deterministic. They are missing the specific, stochastic, and highly interdependent characteristic of spillover effects.

By comparison, System Dynamics (SD) modeling approaches should be particularly well suited for the study of financial system non-linearities (An et al. 2009, Morecroft 2008, Radzicki 2011). The SD models offer explanatory power for self-feeding, exponential and interdependent processes and have a rich history in social science problems. Surprisingly, there are few SD models for SFFs. This scarcity may be attributed to the lack of required economically-sound foundations for theoretical modeling (Qudrat-Ullah 2011, p. 1). At first glance, simulation and feedback models based on experimental design do not provide full transparency about the effect causes and therefore are questioned by the researchers and public alike. On the other hand, the failure of mainstream economic models to address SFFs, leaves a functional void. Thus, SD models become attractive by virtue of their facility to test theories of SFFs and their dynamics. In summary, the conceptualization and probably integration of SD approaches with economically-sound theories seems to be highly beneficial. In the light of these considerations, the objectives of this study are:

- the assessment of concepts for the modeling of financial feedback and amplification effects and their discussion in the light of conceptual requirements for modeling financial system's dynamics,
- the analysis of specific conditions of appropriateness of SD modeling for the representation of financial feedbacks.

2. Concepts of Financial Feedbacks

2.1. Characteristics and Typology

The basic concept of feedbacks has mainly been developed within cybernetic theory as an approach to the dynamic behavior of complex systems (Wiener 1948). As a core element within cybernetics, the feedback concept has been applied to very different types of dynamic environments such as physical, social, biological and economic systems (Morecroft 2008, pp. 7-57). While definitions of feedbacks undergo some historical and interdisciplinary alterations, there are common characteristics. First, feedbacks reference to an underlying system[1] as the specific environment determining their origin, propagation and intensity. While cybernetics has been applied to almost all forms of dynamic systems, the relevant environment for

[1] Generally, a system is defined as a set of related elements, where the scope of the system, selected elements, and levels of connectivity can be applied flexibly.

this study is the financial system composed from the macrofinancial environment on the one hand (financial and real markets) and the microfinancial environment (financial institutions) on the other. A major challenge for this system is representational: that is the inclusion of appropriate system elements and their connectivity. For example, an economic system could be represented as comprising only firms and banks or be designed with a richer array of economic agents: firms, government, households, banks, and other financial intermediaries. Accordingly, connectivity among these agents could be considered via a number of channels where agent interactions arise from productivity, solvency, liquidity channels, etc. (spillover effects).

Irving Fisher (1932) provides an early example of feedbacks in the productive system of an economy describing the concept of debt deflation: When firms are highly leveraged, a small shock affecting their productivity can trigger a series of bankruptcies. This, in turn, generates a decline in investment, and thus in demand for intermediate goods, as a consequence in prices. Resulting decrease in asset value further aggravates the indebtedness of firms. In the next round, new failures may occur with cumulative effects on asset prices and the net value of firms. More recently, the emergence of bubbles (Dehnad 2010) and spillover effects on interbank funding markets may be considered as further examples for financial feedbacks.

Second, feedbacks are conceived as a response to some excitation of the system affecting the system’s level of activity. More specifically, the response may go back to the excitation itself (a procyclical or boomerang effect; “self-feeding” process, Korinek 2009, p. 3) thereby altering the level of excitation with further effects for the system. Third, and more generally, feedbacks are a driver of the system´s dynamic behavior. This includes impacts on the system’s activity or equilibrium level where the variation may have a positive (amplifying) or negative (attenuating) consequence or may have a complex mixed dynamic from alternating accelerating and dampening effects. Similarly, feedbacks are conceived as multi-round effects, that is a series of incentives and responses over time. In literature this is described as further-round, contagion, cascade or snowballing effect (Kapadia et al. 2012, p. 3).[2]

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[2] The pattern aspect of dynamic response can be the source of qualitative assessment of systemic feedback models. See Barlas and Kanar (2000).

Bernanke, Gertler and Gilchrist (1996) show that adverse shocks can propagate through economic systems with an amplifying effect, introducing the concepts of “financial accelerator” and “financial propagation mechanism.” In a study of agent behavior, Bikhchandani and Sharma (2001, p. 288) point out that propagation of effects through economic systems frequently follows “cascades” and is characterized by “positive feedback”, stating that “behavior in cascades is fragile with respect to small shocks.” Borio, Furfine and Lowe (2001) emphasize that a financial system’s amplification mechanisms result in “adverse feedback effects” and are prone to “contagion” and “procyclicality.” De Bandt and Hartmann (2000, p. 43) generalize various “propagation mechanisms”, “propagation chains”, and “contagion” as manifestations of feedback effects. The authors make a key connection of this concept to systemic risk: “At the heart of systemic risk are contagion effects, various forms of external effects. The concept also includes financial instabilities in response to aggregate shocks.” The authors distinguish that the systemic feedback effects may emerge either through narrow or wide shocks: “The second key element in systemic events in the narrow sense is the mechanism through which shocks propagate from one financial institution or market to the other. In our view, this is the very core of the systemic risk concept.”

Often the concepts of feedback, contagion, amplification and procyclicality are applied in parallel (Gai and Kapadia 2010, Korinek 2009, Tirole 2009). Mostly, feedbacks are referred to as processes leading subsequently from one state of systemic activity to another thereby spreading out from one element of the system to another (contagion). Accordingly, amplification gives some sense of the magnitude and speed of these dynamic processes – mostly in the sense of acceleration and magnification of already existing developments (procyclicality, Bijlsma et al. 2010, p. 39). Hence, whereas feedbacks can be related to the direction of dynamic effects and contagion to the series of elements involved, amplification and procyclicality reflect the intensity of these processes. While feedback, contagion, amplification, and procyclicality, therefore, may point to different dimensions of a system’s dynamics, they are often used in a similar way with amplification and procyclicality caused by feedbacks and contagion or feedbacks assumed to produce some variable (increasing or decreasing) effects via transmission across different elements.[3]

[3] E.g. Geršl and Jakubik (2010, p. 2) refer to multi-round feedbacks as a “magnification of swings” and as a major driver for procyclicality. See as well Gai and Kapadia (2010), p. 3.

It is useful to integrate the above aspects into a succinct statement: financial feedbacks are dynamic, ensuing responses to excitations of a financial system. They are time-dependent, generally non-linear and multi-step processes defining the relative stability of the system. Financial feedbacks may originate from endogenous or exogenous incentives to monetary markets and institutions, and are propagated via interactions within the system. The cumulative causal outcomes of feedback effects may range from amplification and procyclicality in positive-simple loop feedbacks, to dampening and countercyclicality in negative-simple loop feedbacks, to generally complex, asymmetric, time-dependent patterns in complex multi-loop feedback mechanisms. These outcomes are thus mainly determined by the structure and the behavior (May and Arinaminpathy 2010) of the system which in turn depends on the number of elements, their connectivity and sensitivity to excitations (see Fig. 1). This dependency on organizational and dynamic aspects of systems can be summarized by referring to financial feedbacks as “systemic financial feedbacks” (Korinek 2009, Brunnermeier et al. 2010).

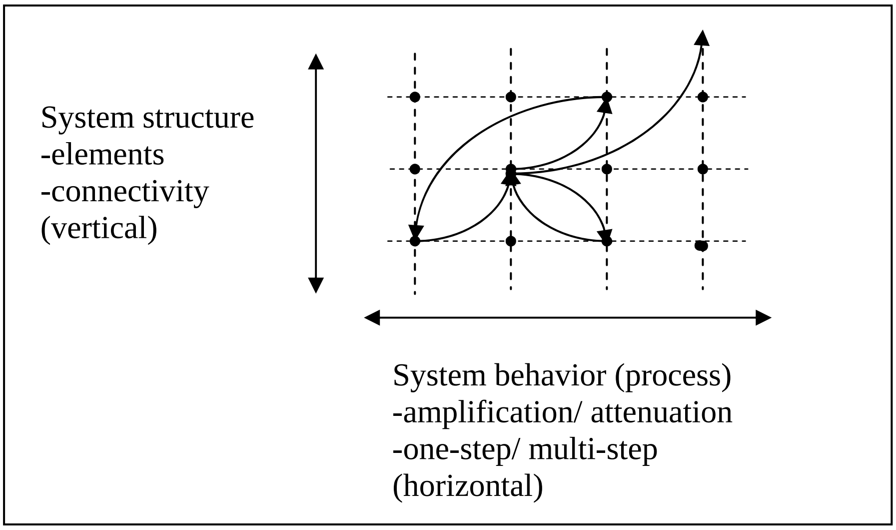

Fig. 1: Systemic feedbacks as multi-round, non-linear response processes – system structure and system behavior as drivers

Given the diversity of systemic structures and processes as drivers of feedbacks, a number of different types of feedbacks have to be considered and can be combined in multiple ways (Aikman et al. 2009; Gramlich and Oet 2011, pp. 280-282). In the context of economic-financial systems, Aikman et al. (2009, pp. 7, 9, 24) distinguish six aspects of financial feedbacks. These refer to:

- Intensity: 1) constant, increasing, decreasing,
  2) linear, non-linear,
  3) one-step, multiple (cumulative) steps,
- Direction: 4) direct, indirect (with at least one element between departing and ending point of the process),
- Origin: 5) starting from the macro-economy or the financial system with an emphasis on the asset-side (banks´ lending behavior) or the liability-side (banks´ funding behavior),
- Sensitivity: 6) active, latent (depending on attainment or lack of a critical threshold).

These aspects are particularly interesting from the perspective of financial system agents. Private agents may use this information to estimate the feedback effects for risk management. Supervisors are particularly interested in the feedbacks' sensitivity to change – a question that is particularly relevant as supervisors seek to maintain or to reestablish financial stability and to dampen undesirable feedback effects. The concept of "threshold breakpoints" (May and Arinaminpathy 2010, p. 823) becomes crucial for feedbacks, where a "seemingly minor happenstance" may initiate catastrophic changes. Consequently, May et al. (2008, p. 893) point out the specific need for ex ante policy. Kiyotaki and Moore (1997, pp. 213-214) emphasize the aspect of duration of feedbacks with timely limited or extended impact. Therefore, further aspects of feedbacks can be added that are more related to the effects from feedbacks:

- Duration 7) static (within 1 period), dynamic (intertemporal)
- Diffusion: 8) uni-directional, multi-directional (bifurcation)
- Impact: 9) positive (trend is increased), negative (trend is decreased).

2.2. Basic Modeling Requirements

Given the multiple patterns of systemic financial feedbacks, these processes have to be conceived as ambivalent dynamic phenomena. This dynamic ambivalence challenges the modeling of feedbacks based on past outcomes and makes forecasts of SFF's behavior very problematical. Propagation mechanisms from feedbacks and modeling approaches for feedbacks have to be judged in this context.

Feedbacks are not only important to explain the development of crises but may be considered for the treatment of crises as well. Their high impact on the financial system's dynamic condition requires careful modeling. Experience suggests that once processes of amplification and spillover have started, it becomes very difficult to control these mechanisms. A basic requirement, conventional for all modeling, is that financial feedback models have to be constructed in a way where the model architecture reflects both the characteristics of the modeling object and the objectives of the model user. As has been analyzed before, SFFs are mainly characterized by:

- distinct self-feeding mechanisms, where a particular feedback's effects influence the inputs and incentivize second round effects, creating a causal loop;
- inter-connectedness, where several feedbacks create spillover effects to system areas different from the feedbacks' origins;
- dynamic non-linearities, where the amplifying or dampening behavior of several feedbacks may largely be explained by the presence of thresholds, exceedance of which changes speed and direction of feedbacks.

A number of authors study interactions and construct combinations of individual feedbacks. FSA (2009, p. 6) suggested that a complex set of six interrelated feedbacks (see Fig. 2) has been responsible for the transatlantic financial crisis: "Very low yields, both real and nominal, on risk-free government securities created the macro-economic background which, combined with financial innovation, produced six interrelated effects that ultimately proved unsustainable."

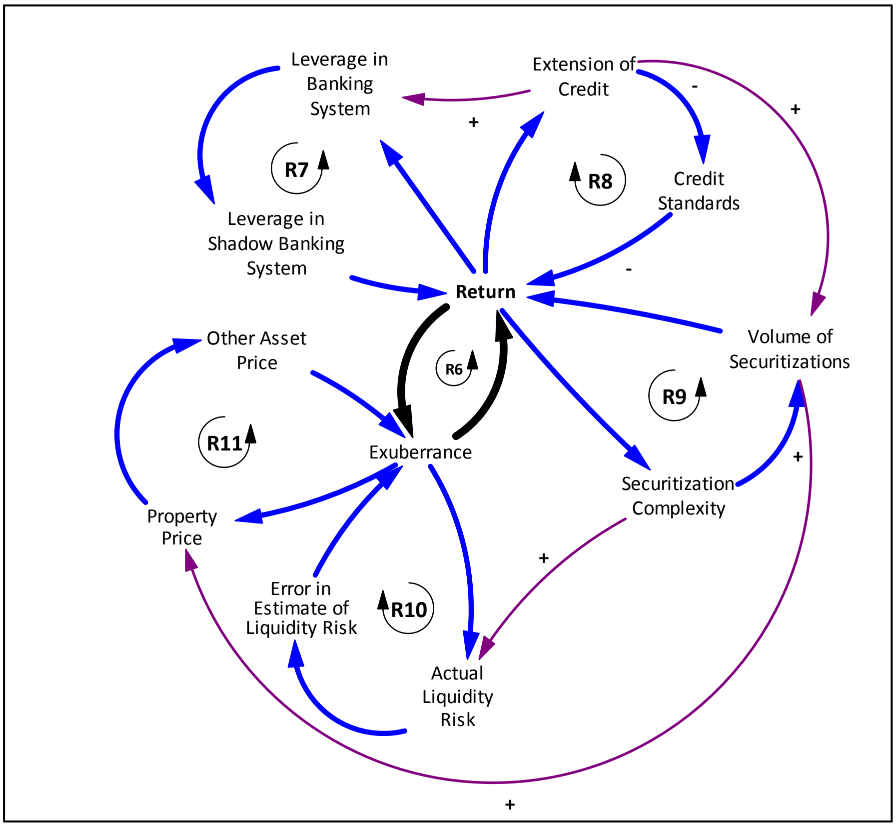

Fig. 2: Combined effects from feedbacks as causes of the financial crisis
Ref.: FSA – Financial Services Authority (2009, p. 6) (own representation)

With respect to their cross-sectional behavior, a main question is how the feedback relevant system is defined. Basically, there are multiple links between an economy's financial and real markets. Financial feedbacks and their effects are motivated from incentives within these two types of markets. As the ECB (2010, pp. 138-139) states, the financial system is already highly complex and displays a high degree of inter-connectivity between banks and other financial institutions. Feedback models have to capture both structural connectivity, reflecting the compositional complexity of the components or areas of the relevant system, and behavioral connectivity, reflecting effects coming from the interactions of the systems elements.

Modeling structural connectivity is mostly straightforward, since it refers to the interaction of observable and known components. For example, in a fair value based accounting system, losses of a financial institution from declining asset prices will result in write-downs in a first step (feedbacks from fair value accounting on systemic risk are assessed from ECB 2004 and IMF 2008). Consequently, these losses will reduce the institution's equity and therefore trigger regulatory constraints with further consequences for the volume and value of assets held. Ensuing downgrades from the rating agencies following the resultant balance sheet and equity ratios may cause the institution further rounds of deteriorating asset valuations and may extend its increasing troubles. In addition, asset losses together with problems in responding to regulatory requirements and signals from rating agencies may raise concern from the institution's shareholders and from its market counterparties. Depending on the intensity of problems and the overall state of the market, these concerns may exceed a critical level (threshold) and then get out of control often implying a herd behavior from other market participants as well. This example shows that non-linear dynamics can arise both from structural connectivity that accounts for the technical connections of the financial system agents and from behavioral connectivity arising from agent behaviors like irrational decision-making and herding.

1. Conceptual Aspects
   - definition of intended purpose
   - suitability of model philosophy
     -- adjustable to a dynamic and changing environment
     -- capturing non-linear effects and flexible dynamics
     -- adjustable to multiple time horizons

2. Model Architecture
   - adjustment to the modeling objectives
   - representation of structural and behavioral connectivity
   - modular design of systemic environment

3. Model Structure and Elements
   - consideration of the financial system and the real economy
   - integration of structural, behavioral and interconnective elements
   - optimization of the degree of heterogeneity (of abstractness)

4. Model Dynamics
   - positive and negative causal loops (self correcting mechanisms)
   - consideration of thresholds
   - integration of behavioral feedbacks, parallelism of actions

Table 1: Modeling requirements for systemic financial feedbacks

Modeling requirements for SFFs (see Table 1) comprise principles for the conceptual design of the model as well as for single components. Modeling objectives are initially aimed as simple analysis of SFF effects. Once the nature of feedbacks is sufficiently explained through simple models, this knowledge may be used for further purposes. Private institutions may use feedback models to estimate the patterns of feedbacks' dynamic outcomes and apply these estimates for risk/ return management.[4] Forecasting and prevention of crises associated with adverse systemic feedbacks is a central task for supervisors.[5] Subsequent to incorporation of SFF models into an early warning modeling framework, supervisors may seek to intelligently apply and/or modify specific feedbacks to achieve stabilizing counter-mechanisms within a

[4] E.g., Bijlsma et al. (2010, p. 9) suggest that in the context of systemic feedbacks individual institutions must extend their consideration of "the external effects of their own risk taking on other banks."

[5] E.g., the Banque de France (2001, p. 3) demands that prudential supervision target prevention of stress amplification beyond the normal degree. Haldane and May (2011, p. 354) suggest limiting the potential for risk spillovers to high capital standards for systemic banks. Allen and Carletti (2008, p. 11) refer to deposit assurance to prevent the possibility of panics.

crisis. In this, the mechanism features may contribute to balancing the situation in financial markets in a quasi-automatic way.

3. Feedback Modeling Approaches

3.1. Typology of Models

Modeling concepts for financial feedbacks first require causal foundations that are able to explain financial system's dynamics and second an algorithm to functionalize these dynamic mechanisms. Given the complex character of feedbacks, a variety of models exists. Overviews of modeling approaches for financial system's dynamic problems are given in Gertler (1988), Bernanke, Gertler and Gilchrist (1996), De Bandt and Hartmann (2000), Borio, Furfine and Lowe (2001), and Freixas and Rochet (2008, pp. 195-196). Feedbacks in the first generation of models are mainly related to macroeconomic dynamics that subsequently impact financial markets. Dynamic processes originate in the real economy, while the structure of the financial system mainly has been considered under the "working hypothesis" to be irrelevant (Gertler 1988, p. 559).

Among the first to analyze the macro-financial dynamics, Bernanke and Gertler (1989) develop an analytical framework to explain the effect of companies' net value on business fluctuations. A relation is set up between the soundness of entrepreneurs' balance sheets, the cost of monitoring from external lenders and the provision of outside funds. A main assumption is that the healthier an entrepreneur is and the higher his net value, the lesser are the costs of state verification (agency costs). Cyclical dynamics from a positive shock (e.g. higher productivity) are based on higher net worth of borrowers, subsequent reduced agency costs and, therefore, increased lending and higher investment. This applies vice versa for economic downturns. An asymmetric effect may occur, since in good times there is a high net value and some kind of over-collateralization while investing capacities cannot be further extended. In contrast, during economic downturns the above interactions may lead to a continuous reduction in investments.

Authors further address feedbacks from liquidity and interbank effects. Esser and Mönch (2003) develop an amplifying feedback mechanism driven by formal elements and narrowing its economic application on the topic of stochastic liquidity feedbacks. Aikman et al. (2009, p. 7) study interbank feedback in times of crisis, arguing that reducing credit lines and rising interest rates in times of crisis decrease the growth potential of the real economy, leading to adverse second round effects, such as higher default rates. This, in turn, may result in downgrades of financial intermediaries and reducing credit and liquidity extensions to the financial intermediaries in the interbank markets in further rounds. Amplification mechanisms during liquidity crises are further modeled in Krishnamurthy (2010). Two amplification channels are looked at, the first one generated by some market shock and the subsequent need for liquidity. Since the sale of assets leads to declining prices and less cash flow from sales, further disinvestment is needed and a balance sheet amplification mechanism is generated. The second mechanism is induced by the dynamic effects of rising market opacity and demand for liquidity.

More recent models are discussed by Allen and Carletti (2008), Freixas and Rochet (2008, pp. 195-203), Kida (2008),[6] Tirole (2009), Bijlsma et al. (2010), ECB (2010, Analytical), Sarkar and Shrader (2010), Gai et al. (2011), and the ECB (2011). The ECB (2010, Analytical) and Blake and Gondat-Larralde (2010) point out the results of workshops on macroeconomic modeling held at the European Central Bank and the Bank of England respectively, including also suggestions for further modeling of financial dynamics. Newer feedback models center more on the dynamics originating in the financial markets themselves.

Sarkar and Shrader (2010, pp. 2-4) see the decreasing net worth of institutions and collaterizable value for secured funding (balance sheet mechanism) as explanatory for first round of crisis. Further rounds are then triggered by asymmetric information and concerns about default risk of banks (adverse selection mechanism).[7] While this may imply assistance from monetary authorities, Meh and Moran (2010) argue differently in their study on interactions for banking feedbacks with monetary policy: They find that “moderate downturns associated with well-capitalized banks require less aggressive actions from monetary authorities.” Krishnamurthy (2010, p. 1) distinguishes two broad classes of feedback mechanisms: “balance sheet amplifiers (e.g., leverage, tight credit conditions, limited capital) and information

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6 Kida (2008, pp. 24-31) gives a concise summary of three different types of macro feedback models.

7 While this may imply assistance from monetary authorities, Meh and Moran (2010) argue that downturns associated with well-capitalized banks may imply less aggressive actions of central banks.

amplifiers (e.g., opacity, complexity, and uncertainty).” Geršl and Jakubik (2010, pp. 2-3) consider a wide range of interconnected factors such as “natural” factors (information asymmetry, over-optimism, herd behavior, fluctuations in balance-sheet quality, financial innovation) and “other” factors (regulation, accounting). Using this complex aggregation of feedbacks, they simulate effects for the Czech economy during the transatlantic financial crisis of 2007-2009. In their model declining asset values lead to decreases in bank equity. As credit standards rise due to bank defensive actions, credit extension decreases, resulting in a 1-2% reduction in the Czech GDP.

Gai and Kapadia (2010) model complex networks of direct loss and indirect write downs showing bank contagion and amplification effects. Their study applies evidence from central network theory to model dynamic contagion effects inside banking systems. In a balance sheet approach, banks hold illiquid external assets and interbank assets as well as liabilities from other banks. This makes the banks vulnerable to shocks from the default of other banks and from writing down the value of assets. Within this system, the intensity of shock propagation is particularly based on the degree of incoming and outgoing links between banks, the extent of the shock, and bank capital. For example, the default of a bank is modeled as a function of the loss from interbank claims, loss from assets, and the bank’s capital buffer. Based on a network with 1,000 banks and assumptions about banks balance sheet and capital buffer, numerical simulations are run. Main result of modifying the degree of interbank links is that as the connectivity within the system goes up the frequency of contagion is reduced while the extent of contagion losses is increased (“robust-yet-fragile”). In a similar approach, Kapadia et al. (2012) model feedback effects for the funding of banks arising from failures of other banks and liquidity hoarding and integrate this into a more comprehensive model for systemic financial risk (see Fig. 3).

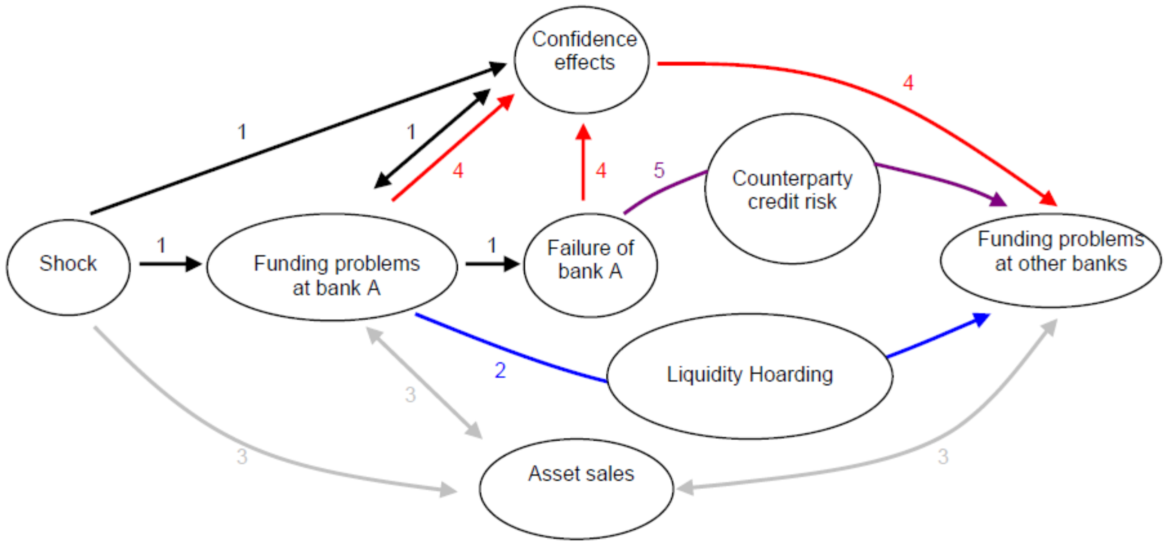

Fig. 3: Funding feedback model from Kapadia et al. (2012)
Ref.: Kapadia, Drehmann, Elliott and Sterne (2012), p. 4

An extended overview of models discussed in literature is presented in Table 2. The matrix groups the models according to their assumptions about sources of feedbacks originate (rows) and the chosen methodological framework for quantifying the effects (columns). As can be seen, existing models tend to focus on the transmissions between the real economy and financial markets. Models of the dynamics within financial markets are less frequent and tend to focus on the relationships between banks. There are only a few models considering the interactions between banking supervision and the financial system or between monetary policy and the financial markets.

	Network theory	Econometric approaches -regression based	General Equilibrium Models -formal equation	Further concepts
Macro-financial feedbacks/ amplifications	▪ Nier et al. 2007	▪ Bernanke and Gertler 1989 (shocks on borrowers net worth, effects on agency costs and outside funding) ▪ Chen 2001 (production shock with fb on collateral and capital) ▪ Kroszner et al. 2007 (crises, firm value, and financial market depth) ▪ Aikman et al. 2009 (fb from funding risk) ▪ Geršl and Jakubik 2010 (several rounds effects of credit crunch on GDP) ▪ White et al. 2011 (fb via quantile regressions)	▪ Aguiar and Drumond 2006 ▪ Liu et al. 2010 (am of macroeconomy through credit constraints)	▪ Shimizu 1997 (neural network) ▪ Kiyotaki and Moore 1997 (am from changing collateral value) ▪ Krishnamurthy 2003 (collateral am effects from incomplete hedging) ▪ Gallegati et al. 2003 (simulation of interacting bank and agent) ▪ Ozdenoren and Yuan 2008 (am via information effects and endogenously determined cash flows) ▪ Anderson et al. 2011 (SD model for testing financial and macro-financial stress factors)
Financial feedbacks/ amplifications, Financial markets, Banking supervision/ Monetary policy	▪ Gai and Kapadia 2010 (vulnerability from interlinkages and neighbours) ▪ Gai, Haldane and Kapadia 2011 (interbank lending, am from complexity)	▪ Esser and Mönch 2002 ▪ Sarr and Lybek 2002 ▪ Bliss and Kaufman 2003 (integrated capital and reserve constraints) ▪ Gertler and Kiyotaki 2010 (credit/ equity injections) ▪ Sarkar and Shrader 2010		▪ Kerry 2008 (liquidity indicator) ▪ May and Arinaminpathy 2010 (banking ecosystems, successive failures) ▪ Vayanos and Woolley 2010 (momentum, reversal via rational agents) ▪ Haldane and May 2011 (econophysics, instability from complexity) ▪ Neugebauer 2011 (SD model Taylor)
Combined macro-financial and financial feedbacks/ amplifications		▪ Bernanke et al. 1999 ▪ Kida 2008 (credit-interest rate risk, fb banks-real economy)	▪ Meh and Moran 2010 (simulations in a quantitative equilibrium model)	▪ An et al. 2009 (SD model of interactions among banking, housing and economic markets)

Table 2: Conceptual approaches of feedbacks and amplifications in macro-financial systems (am = amplification, fb = feedback)

3.2. Discussion of models

Financial feedbacks in a systemic context are complex phenomena that are difficult to assess and may probably not be captured with a singular approach. The validation of SFF models mainly is based on how appropriately the non-linear dynamics and the complexity of interactions are modeled. As has been shown, these primary characteristics may further be decomposed into behavior-related, partially irrational and stochastic components, and structure-related elements that reflect the multiplicity, complexity, and interaction of the financial system's components.

Existing models of SFF take account of these aspects. In most cases they are well-considered, sophisticated approaches emphasizing multiple perspectives of market dynamics. The degree up to which this dynamics is reflected is different, ranging from single basic functions to interacting loop structures. However, there are two prevalent modeling deficits that require recognition and that are crucial in the context of SFFs. First, modeling equations are mostly predefined, suggesting that SFF develop along determined processes and making SFFs calculable.[8] In the light of the recent financial turmoil this feature has to be considered too mechanical and limiting the model's degrees of freedom. Second, most authors center on specific aspects of financial markets dynamics in a rather isolated way, modeling the feedbacks in a manner too restricted to sufficiently account for interactions from connectivity (see Table 3). These restrictions in modeling seem comprehensible in the context of highly complex markets and the already achieved degree of model complexity. Further, an open model architecture would not be in line with formal clarity required for academic research. However, even if these limitations seem understandable from the model builder's point of view, current approaches do not yet satisfactorily represent the relevant characteristics of SFFs.

Given the design principles, feedback and simulation models on the basis of SD would suit the modeling requirements for SFFs particularly well. This review and discussion of current models reveals that there are surprisingly few existing approaches utilizing SD for mod-

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[8] E.g., Gai et al (2011) as a very recent and advanced modeling approach for feedbacks run simulations of systemic liquidity, whereby simulation is conceived as changing the parameters of the function but not the function itself. Similarly, Gai and Kapadia (2010, p. 10) model contagion in a "relatively mechanical fashion."

eling financial feedbacks (e.g. An et al. 2009, Anderson et al. 2011, Neugebauer 2011). One possible explanation for this is that SD approaches may be considered by economists to lack the formal clarity and replicability demanded for scientific research.[9] Particularly, simulation technique is considered to be critical, since it does not provide sufficient explanation “why the model does what it does” (Mojtahedzadeh 2011, p. 358). Further, while many SD models are set up and communicated via causal loop diagrams, these diagrams may be considered lacking in theoretical transparency, and precision in the description of variables, their links and behavior. Therefore, SD models may be considered lacking a sufficient basis for the rigorous deduction of behavior (Lane 2008, pp. 12-14).

Hence, a basic conflict has to be stated: where traditional models are limited by their principles of modeling to explain modern financial markets behavior, SD models would be able to capture non-linear dynamics and connectivity, but are criticized for their lacking formal exactness. This conflict appears similarly for all models and theories trying to integrate non-formal behavioral aspects into modern financial theory. Olsen (2008, p. 1), states that behavioral finance is a “thorn in the side of many finance traditionalists.” Yalamova and McKelvey (2011, p. 169) refer to the efficient market hypotheses as the basic paradigm and to fractal finance as some “competing schools of thought.” Smith (2008, p. 51) demands to move from an “Efficient to a Behavioral Market Hypothesis.” Szyszka (2011, p. 216) concludes that neoclassical theory lost its strength and “should be modified in line with dynamically changing financial environment.” The question is therefore, how these contradictory positions – formal clarity but modeling deficits on one hand versus modeling appropriateness yet formal deficits on the other – can be matched.

A further step is to develop basic principles guiding the integration of these two classes of models to achieve a new, combined, class of formal simulation models.

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[9] Gallegati and Richiardi (2011, p. 42) discuss a “common misunderstanding” between (agent based) simulations and mathematical models – different degree of abstractness, superiority in solution finding – and conclude that, in principle, simulation is mathematics.

	Causes/origins				Propagation factors															Effects	
	Macro		Finance		Structure 1 – System							Structure 2 - Instruments				Behavior					
	Economic shock	Other shock (1)	Asset price shock	Other shock (2)	Connectivity	Concentration	Complexity	Information asymmetry	Supervisory regulation	(Fair value) Accounting	Other (3)	Similar business model	Similar risk management	Leverage (derivatives)	Capital constraints	Procyclical behavior	Herd behavior	Short terminism	Overexuberance	Solvency	Liquidity
Bernanke and Gertler 1989	X							X												(X)	
Kiyotaki and Moore 1997	X		X					X							X					X	
Banque de France 2001									X	X		X	X			X	X	X			
Borio et al. 2001								X	X	X							X				
Gallegati et al. 2003	(X)				X			X							X					X	
Borio 2007				X	X						X										X
Allen and Carletti 2008					X						X						(X)				X
Persaud 2008			X						X	X			X							X	
Aikman et al. 2009	(X)		(X)		X			X													X
Hirano 2009	X										X			X						(X)	
Bijlsma et al. 2010								X	X	X							X		X		
Gai and Kapadia 2010			X		X		X													X	
Geršl and Jakubik 2010				X				X	X	X							X				
Krishnamurthy 2010			X					X													X
May and Arinaminpathy 2010			X		X	X															X
Sarkar and Shrader 2010	X							X							X						X
Gai, Haldane and Kapadia 2011			(X)	X	X	X	X										X				X
Haldane and May 2011	X	X	X					X				X		X					X		
Kapadia et al. 2012	(X)			X	X												X				X

(1) Political, environmental shocks (2) From innovation, technology (3) Market (in)completeness, financial development

Table 3: Causes, propagation and effects of feedbacks

4. Implications for Further Feedback Modeling

The operational deficits from SFF treatment by the traditional models of quantitative finance and the problem of lacking formal evidence by the SD models are discussed in critical literature. This literature also provides suggestions for handling the SFF modeling challenges. Radzicki (2011, p. 730) suggests three basic strategies for combining economic models and SD approaches. Klejnen (1995) refers to the integration of statistical methods, such as regression analysis and design of experiments, to optimize simulation-based models. Lane (2008, p. 21) requires that causal loop modeling should only be applied by those who are aware of and trained in simulation modeling. The different suggestions refer to (see Fig. 4)

- conceptual aspects for the modeling approach,
- model architecture,
- model implementation,
- model validation.

1. Model Concept	2. Model Architecture	3. Model Implementation	4. Model Validation
- philosophy - integration	- overall design - components	- application - interpretation	- testing - improving

Fig. 4: Relevant model dimensions for the integration of formal and simulation modeling

While looking for possibilities how to model increasing dynamics and complexity, traditional formal modeling and more recent simulation-based approaches should not be conceived as competing or opposite. They have a “separate-but-equal status” (Yalamova and McKelvey 2011, p. 169), and the question is not which one to replace by the other, but to what extent these concepts may be integrated thus accommodating situations with higher complexity and feedback dynamics. The strengths of both concepts are to be combined, making the resultant integrated approach both formally clear and sufficiently flexible. Different suggestions are provided to achieve this synthesis. While these suggestions mostly refer to operational aspects applied to different steps of the modeling process, a general condition for the estimation of these models is the acceptance of simulation techniques for modeling. This is a matter of consciousness, and there is an “impressive need for more Systems´ Thinking at universities” (Weber 2005, p. 3).

The combination of traditional and SD modeling should allow for a higher degree of heterogeneity and should be conceived as a two step process (Radzicki 2011, p. 730 suggests three principal ways). As a first step and in order to provide a sound theoretical foundation for the model and model outcome, modeling should be based on formal equations as far as possible (Yalamova and McKelvey 2011, p. 170), and the results from these equations should be made transparent. As a second step, iterative simulations should be viewed in aggregate, and the simulation effects should be compared to prior results.[10] The direct consequence of this approach is the avoidance of premature amalgamation of the formal modeling and partially random simulation results. The two-stage process also allows a more sound problem-specific approach, thus avoiding “canned” outcomes of application of pre-defined software tools to the modeling problem.[11] Although a dual step modeling is suggested, this does not mean that both modeling steps are independent. Rather, the modeling process takes into account the strengths and weaknesses of the two modeling approaches in every phase. The process is thus synthetic, rather than merely additive. This is conceptually similar to the Radzicki (2011, p. 730) proposed third or “hybrid” approach, where the advantages of economic and SD modeling are blended.

Higher heterogeneity of combined models can be achieved by a more detailed representation of structural components and from considering explicitly structural and behavioral connectivity. As the overall model thereby gets increasingly difficult to solve analytically, SD simulation and optimization approaches support the model solution. As problem scope extends, at some point of the relevant feedback system, the researcher has to confront and consider additional modeling choices. This would include choices for the heterogeneous agents from real and financial markets, and detailed factors or markets’ infrastructure and agent behavior such as liquidity, solvency, risk aversion, agent linkages, and the regulatory constraints of these factors. While running the model in SD environment, the algorithms used and the results obtained have to be kept as clear as possible. For example, Mojtahedzadeh (2011, p. 363) suggests using a metric of pathway participation to show the consistency of model com-

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[10] A good example for the integration of formal basic equations, simulation and validation is the SD model from Neugebauer (2011) investigating the Taylor rule for Brazil.

[11] Vice versa, in the context of “simplifications” for setting up formal equations, Moss (2011, p. 24) states that assumptions for simplifying the nature of an empirical problem makes the problem conform to the requirements of the mathematical technique.

ponents: Comparison of the effects from different loops in the model allows detection of feedbacks that remain dominant throughout the simulation. This helps to prevent phantom loops from engaging in the dominant structure of the model and helps to maintain mathematical consistency while allowing essential feedback complexity. To improve the modeling of connectivity of different variables, Klejnen (1995) suggests regression analysis to predefine the most efficient combinations and make the selection of combinations more objective. Critically, the research design and central results must be transparently stated —a principle emphasized in Lane's discussion (2008, pp. 17-20) of clear communication of links, equations and diagrams.

Finally, the validation (Barlas 1996, Coyle and Exelby 2000, Qudrat-Ullah 2011) of the hybrid models has to be adjusted to accommodate the more heterogeneous and opaque modeling approach. Where traditional models are primarily validated on the consistency between model assumptions and model equations (from "the left to the right" in Fig. 4), the adequacy of the dual models may be more difficult to assess in this way. Given the different approach of dual models to provide a more realistic framework for the complexity and dynamics of financial markets, validation may focus more on the model output, on its consistency with objectives, and on the empirical context to be explained (from "the right to the left").[12] Referring to the mentioned two step process for the combination of traditional and SD modeling, model validation integrates both validation of the model itself and the model building process (Qudrat-Ullah 2011, p. 2).

Overall, the dual approach to modeling based on formal equations and SD simulations seems appropriate to assess the effects from SFFs. Among its principal merits is a more realistic representation of the inherent heterogeneity and non-linearity of financial feedbacks. Critically, however, the higher complexity and opacity of this approach necessitates particular conceptual strength and technical quality. To advance the quality of SFF models, research may follow a rigorous dual process that starts with sound theoretical foundations. Methodologically, this process should incorporate explicit recognition of the strengths and weaknesses of the constituent modeling techniques, the analysis of stable and reliable components, clear communication of simulation results, and an empirical validation of the model quality.

[12] In this context, Moss (2011, p. 23) states that neoclassical economy has no empirically based micro foundation and its assumptions are not justified empirically.

References

Adrian, Tobias, Etula, Erkko and Groen, Jan J. J. 2010. Financial Amplification of Foreign Exchange Risk Premia. *Federal Reserve Bank of New York Staff Reports*, No. 461, New York, August.

Aguiar, Alvaro, Drumond, Inês 2006. Monetary Policy Amplification Effects through a Bank Capital Channel. *University of Porto Working Paper*, February.

Aikman, David, Alessandri, Piergiorgio, Eklund, Bruno, Gai, Prasanna, Kapadia, Sujit, Martin, Elizabeth, Mora, Nada, Sterne, Gabriel and Willison, Matthew 2009. Funding liquidity risk in a quantitative model of systemic stability. *Bank of England Working Paper,* No. 372, London, June.

Allen, Franklin and Carletti, Elena 2008. Financial system: shock absorber or amplifier? *BIS Working Papers*, No. 257, Basel, July.

Allen, Franklin and Carletti, Elena 2010. An Overview of the Crisis: Causes, Consequences, and Solutions. *International Review of Finance* **10** (1), pp. 1-26.

An, Lianjun, Subramanian, Dharmashankar and King, Alan 2009. On modeling some essential dynamics of the subprime mortgage crisis. *Proceedings of the 27^th^ International Conference of the System Dynamics Society*, Albuquerque.

Anderson, Stefanie, Long, Corbin, Jansen, Chip, Affeldt, Fred, Rust, JW and Seas, Bill 2011. Dynamically Stress Testing Financial Systems. *Proceedings of the 29^th^ International Conference of the System Dynamics Society*, Washington.

Banque de France 2001. The Financial Cycle: Factors of Amplification and Possible Policy Implications for Financial and Monetary Authorities. *Bulletin de la Banque de France* **95** (November), pp. 5-27.

Barlas, Yaman 1996. Formal aspects of model validity and validation in system dynamics. *System Dynamics Review* **12** (3), pp. 183-210.

Barlas, Yaman and Kanar, Korhan 2000. Structure-oriented Behavior Tests in Model Validation. *Proceedings of the 2000 International System Dynamics Conference*, Bergen.

Bernanke, Ben S. and Gertler, Mark 1989. Agency Costs, Net Worth, and Business Fluctuations. *American Economic Journal* **79** (1), pp. 14-31.

Bernanke, Ben S., Gertler, Mark and Gilchrist, Simon 1996. The financial accelerator and the flight to quality. *Review of Economics & Statistics* **78** (1), pp. 1-15.

Bernanke, Ben S., Gertler, Mark and Gilchrist, Simon 1999. The financial accelerator in a quantitative business cycle framework. In: Taylor, John B. and Woodford, Michael (Ed.), *Handbook of Macroeconomics*. Maryland Heights (Elsevier), Vol. 1, Part 6, Ch. 21, pp. 1341-1393.

Bijlsma, Michiel, Klomp, Jeroen and Duineveld, Sijmen 2010. Systemic risk in the financial sector – A review and synthesis. *CPB Netherlands Bureau for Economic Policy Analysis document*, No. 210, The Hague, July.

Bikhchandani, Sushil and Sharma, Sunil 2001. Herd Behavior in Financial Markets. *IMF Staff Papers* **47** (3), pp. 279-310.

Blake, Andy and Gondat-Larralde, Céline 2010. Chief Economists´ Workshop: state-of-the-art modelling for central banks. *BoE Bank of England Quarterly Bulletin* **50** (Q3), pp. 214-218.

Bliss, Robert R. and Kaufman, George G. 2003. Bank Procyclicality, Credit Crunches, and Asymmetric Monetary Policy Effects: A Unifying Model. *Journal of Applied Finance* **13** (2), pp. 23-31.

Borio, Claudio 2007. Change and constancy in the financial system: implications for financial distress and for policy. *BIS Working Paper,* No. 237, Basel, October.

Borio, Claudio, Furfine, Craig and Lowe, Philip 2001. Procyclicality of the financial system and financial stability: issues and policy options. *BIS Papers Monetary and Economic Department 1 – Marrying the macro- and microeconomic dimensions of financial stability,* Basel, pp. 1-57.

Brunnermeier, Markus K. 2009. Deciphering the Liquidity and Credit Crunch 2007-2008. *Journal of Economic Perspectives* **23** (1), pp. 77-100.

Brunnermeier, Markus, Gorton, Gary and Krishnamurthy, Arvind 2010. *Risk topography*, Mimeo, Princeton University.

Caballero, Ricardo J. and Simsek, Alp 2011. Fire Sales in a Model of Complexity. *NBER Working Paper*, No. 15479, Cambridge, April.

Chen, Nan-Kuang 2001. Bank net worth, asset prices and economic activity. *Journal of Monetary Economics* **48** (2), pp. 415-436.

Coyle, Geoff and Exelby, David 2000. The validation of commercial system dynamics models. *System Dynamics Review* **16** (1), pp. 27-41.

Craigie, Rebecca and Munro, Anella 2010. Financial sector amplification and credit cycles in New Zealand. *Reserve Bank of New Zealand Bulletin* **73** (2), pp. 15-34.

De Bandt, Olivier and Hartmann, Philipp 2000. Systemic Risk: A Survey. *European Central Bank Working Paper*, No. 35, Frankfurt, November.

Dehnad, Kosrow 2010. A Model of Formation of Asset Bubbles. *Journal of Financial Transformation* **29** (1), pp. 95-98.

ECB – European Central Bank 2004. The Impact of Fair Value Accounting on the European Banking Sector – A Financial Stability Perspective. *ECB Monthly Bulletin*, February, pp. 69-81.

ECB – European Central Bank 2010. Towards Macro-Financial Models with Realistic Characterisations of Financial Instability. *ECB Financial Stability Review*, December, pp. 138-146.

ECB – European Central Bank 2010, Analytical. Analytical Models and Tools for the Identification and Assessment of Systemic Stress. *ECB Financial Stability Review*, June, pp. 138-146.

ECB – European Central Bank 2011. Systemic Risk Methodologies. *ECB Financial Stability Review*, June, pp. 141-148.

Esser, Angelika and Mönch, Burkart 2003. Modeling Feedback Effects with Stochastic Liquidity. *Goethe University Frankfurt Working Paper*, Frankfurt, July.

Fisher, Irvine 1932. *Booms and Depressions*. New York (Adelphi).

Freixas, Xavier and Rochet, Jean-Charles 2008. *Microeconomics of Banking*. 2nd ed., Cambridge/ MA (MIT Press).

FSA – Financial Services Authority 2009. *Financial Risk Outlook 2009*, London.

Gai, Prasanna and Kapadia, Sujit 2010. Contagion in financial networks. *Bank of England Working Paper,* No. 383, London, March.

Gai, Prasanna, Haldane, Andrew and Kapadia, Sujit 2011. Complexity, Concentration and Contagion. *Journal of Monetary Economics* **58** (5), pp. 453-470.

Gallegati, Mauro and Giulioni, Gianfranco 2003. Complex Dynamics and Financial Fragility in an Agent-based Model. *Advances in Complex Systems* **6** (3), pp. 267-282.

Gallegati, Mauro and Richiardi, Matteo G. 2011. Agent Based Models in Economics and Complexity. In: Meyers, Robert A. (Ed.), *Complex Systems in Finance and Econometrics*. New York (Springer), pp. 30-53.

Gertler, Mark 1988. Financial Structure and Aggregate Economic Activity: An Overview. *Journal of Money, Credit, and Banking* **20** (3), pp. 559-588.

Gertler, Mark and Kiyotaki, Nobuhiro 2010. Financial Intermediation and Credit Policy in Business Cycle Analysis In: Friedman, Benjamin M. and Woodford, Michael (Ed.), *Handbook of Monetary Economics*, Vol. 3, San Diego (North-Holland), pp. 547-599.

Geršl, Adam and Jakubik, Petr 2010. Adverse Feedback Loop in the Bank-Based Financial Systems. *Paper presented at the Deutsche Bundesbank conference* “Beyond the Financial Crisis: Systemic Risk, Spillovers and Regulation”, Dresden, October.

Goodhart, Charles A.E., Sunirand, Pojanart and Tsomocos, Dimitrios P. 2006. A model to analyse financial fragility. *Economic Theory* **27** (1), pp. 107-142.

Gramlich, Dieter and Oet, Mikhail 2011. The structural fragility of financial systems: Analysis and modeling implications for early warning systems. *The Journal of Risk Finance* **12** (4), pp. 270-290.

Haldane, Andrew G. and May, Robert M. 2011. Systemic risk in banking ecosystems. *Nature* **469** (January), pp. 351-355.

Hirano, Tomohiro 2009. Financial Development and Amplification. *Munich Personal RePEc Archive Paper,* No. 16907, August.

IMF – International Monetary Fund 2007. Do Market Risk Management Techniques Amplify Systemic Risks?, *IMF Global Financial Stability Report*, September, pp. 52-76.

IMF – International Monetary Fund 2008. Fair Value Accounting and Procyclicality. *IMF Global Financial Stability Report*, October, pp. 105-130.

Kapadia, Sujit, Drehmann, Matthias, Elliott, John and Sterne, Gabriel 2012. Liquidity Risk, Cash Flow Constraints, and Systemic Feedbacks. Forthcoming in: Haubrich, Joe and Lo, Andrew (Eds.), *Quantifying Systemic Risk*. NBER conference volume, Cambridge.

Kerry, Will 2008. Measuring Financial Market Liquidity. *Journal of Risk Management in Financial Institutions* **1** (2), pp. 181-190.

Kida, Mizuho 2008. A macro stress testing model with feedback effects. *Reserve Bank of New Zealand Discussion Paper*, DP2008/08, Wellington, June.

Kiyotaki, Nobuhiro and Moore, John 1997. Credit Cycles. *Journal of Political Economy* **105** (2), pp. 211-248.

Kleijnen, Jack P.C. 1995. Sensitivity analysis and optimization of system dynamics models: Regression analysis and statistical design of experiments. *System Dynamics Review* **11** (4), pp. 275-288.

Korinek, Anton 2009. Systemic Risk-Taking: Amplification Effects, Externalities, and Regulatory Responses. *University of Maryland Working Paper*, December.

Korinek, Anton 2011. Systemic Risk-Taking: Amplification Effects, Externalities, and Regulatory Responses. *ECB – European Central Bank Working Paper*, No. 1345, Frankfurt, June.

Krishnamurthy, Arvind 2003. Collateral constraints and the amplification mechanism. *Journal of Economic Theory* **111** (2), pp. 277-292.

Krishnamurthy, Arvind 2010. Amplification Mechanisms in Liquidity Crises. *American Economic Journal: Macroeconomics* **2** (3), pp. 1-30.

Kroszner, Randall S., Laeven, Luc and Klingebiel, Daniela 2007. Banking crises, financial dependence, and growth. *Journal of Financial Economics* **84** (1), pp. 187-228.

Lane, David C. 2008. The Emergence and Use of Diagramming in System Dynamics: A Critical Account. *Systems Research and Behavioral Science* **25** (1), pp. 3-23.

Liu, Zheng, Wang, Pengfei and Zha, Tao 2010. Do Credit Constraints Amplify Macroeconomic Fluctuations?, *Federal Reserve Bank of Atlanta Working Paper*, No. 2010-1, Atlanta, February.

May, Robert M. and Arinaminpathy, Nimalan 2010. Systemic risk: the dynamics of model banking systems. *Journal of the Royal Society Interface* **7** (46), pp. 823-838.

May, Robert M., Levine, Simon A. and Sugihara, George 2008. Ecology for bankers. *Nature* **451** (February), pp. 893-895.

Meh, Césaire and Moran, Kevin 2010. The role of bank capital in the propagation of shocks. *Journal of Economic Dynamics & Control* **34** (3), pp. 555-576.

Mojtahedzadeh, Mohammad 2011. Consistency in explaining model behavior based on its feedback structure. *System Dynamics Review* **27** (4), pp. 358-373.

Morecroft, John 2008. *Strategic Modelling and Business Dynamics. A feedback systems approach*. Chichester (John Wiley).

Moss, Scott 2011. Agent Based Modeling and Neoclassical Economics: A Critical Perspective. In: Meyers, Robert A. (Ed.), *Complex Systems in Finance and Econometrics*, New York (Springer), pp. 22-29.

Neugebauer, Felix 2011. *Tayloring Brazil – A System Dynamics Model for Monetary Policy Feedback*. Dissertação apresentada à Escola de Administração de Empresas de São Paulo.

Nier, Erlend, Yang, Jing, Yorulmazer, Tanju and Alentorn, Amadeo 2007. Network models and financial stability. *Journal of Economic Dynamics & Control* **31** (6), pp. 2033-2060.

Olsen, Robert A. 2008. Cognitive Dissonance: The Problem Facing Behavioral Finance. *The Journal of Behavioral Finance* **9** (1), pp. 1-4.

Ozdenoren, Emre and Yuan, Kathy 2008. Feedback Effects and Asset Prices. *The Journal of Finance* **63** (4), pp. 1939-1975.

Persaud, Avinash D. 2008. Regulation, valuation and systemic liquidity. In: Banque de France (Ed.), *Financial Stability Review No. 12: Valuation and Financial Stability*. Paris, October, pp. 75-83.

Pesola, Jarmo 2011. Joint effect of financial fragility and macroeconomic shocks on bank loan losses: Evidence from Europe. *Journal of Banking & Finance* **35** (11), pp. 3134-3144.

Qudrat-Ullah, Hassan 2011. On the validation of system dynamics type simulation models. *Telecommunication Systems*, DOI: 10.1007/s11235-011-9425-4, pp. 1-8.

Radzicki, Michael 2011. System Dynamics and Its Contribution to Economics and Economic Modeling. In: Meyers, Robert A. (Ed.), Complex Systems in Finance and Econometrics. New York (Springer), pp. 727-738.

Sarkar, Asani and Shrader, Jeffrey 2010. Financial Amplification Mechanisms and the Federal Reserve's Supply of Liquidity during the Crisis. *Federal Reserve Bank of New York Staff Reports*, No. 431, February.

Sarr, Abdourahmane and Lybek, Tonny 2002. Measuring Liquidity in Financial Markets. *IMF Working Paper*, No. 02/232, Washington, December.

Schaffernicht, Martin 2010. Causal loop Diagrams Between Structure and Behaviour: A Critical Analysis of the Relationship Between Polarity, Behaviour and Events. *Systems Research and Behavioral Science* **27** (6), pp. 653-666.

Shimizu, Tokiko 1997. Dynamic macro stress exercise including feedback effect. *Bank of Japan Institute for Monetary and Economic Studies*, Tokio, pp. 163-191.

Smith, Donald J. 2008. Moving from an Efficient to a Behavioral Market Hypothesis. *The Journal of Behavioral Finance* **9** (2), pp. 51-52.

Szyszka, Adam 2011. The genesis of the 2008 global financial crisis and challenges to the neoclassical paradigm of finance. *Global Finance Journal* **22** (3), pp. 211-216.

Tirole, Jean 2009. Illiquidity and all its friends. *Paper prepared for the 8th BIS Annual Conference on "Financial Systems and Macroeconomic Resilience: Revisited,"* Basel.

Vayanos, Dimitri and Woolley, Paul 2010. An Institutional Theory of Momentum and Reversal. *LSE The Paul Woolley Centre Discussion Paper*, No. 621, August.

Vijverberg, Chu-Ping C. 2004. An emprirical financial accelerator model: Small firms´ investment and credit rationing. *Journal of Macroeconomics* **26** (1), pp. 101-130.

Watts, Duncan J. 2002. A simple model of global cascades on random networks. *PNAS – Proceedings of the National Academy of Sciences* **99** (9), pp. 5766-5771.

Weber, Lars 2005. A Contribution To Goodwin's Growth Cycle Model From A System Dynamics Perspective. *Proceedings of the 23rd International System Dynamics Conference*, Albany.

White, Halbert, Kim, Tae-Hwan and Manganelli, Simone 2011. VAR for VaR: measuring systemic risk using multivariate regression quantiles. *MPRA Paper*, No. 35372, December.

Wiener, Norbert 1948. *Cybernetics or Control and Communication in the Animal and the Machine*. Cambridge, MA. (MIT Press).

Yamalova, Rosita and McKelvey, Bill 2011. Explaining What Leads Up to Stock Market Crashes: A Phase Transition Model and Scalability Dynamics. *Journal of Behavioral Finance* **12** (3), pp. 169-182.