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Comment Mikhail V. Oet

Summary

Let me open by summarizing the main points of the chapter. The chapter describes a liquidity feedback model (hereafter, LFM) within a quantitative

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I would like thank the conference organizers, Andrew Lo and Joseph Haubrich, for inviting me. The chapter "Liquidity Risk, Cash Flow Constraints, and Systemic Feedbacks," by Sujit Kapadia, Matthias Drehmann, John Elliott, and Gabriel Sterne, is a very important and interesting study in the context of systemic feedbacks. I have followed several versions of this chapter to its current state with pleasure and am honored to be given an opportunity to comment.
The content represents the views of the author and is not to be considered as the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. For acknowledgments,

framework of systemic risk.[1] The LFM simulates balance sheets and funding interactions of a population of banks within a financial system[2] to assess shock-induced feedback effects on the individual banks and the represented financial system. The model represents the systemic interactions through five contagion channels and analyzes collapse mechanics in a financial system due to propagation of liquidity risk through bank balance sheets. The LFM offers a well-thought-out analysis of the mechanics of cash flow constraints and liquidity effects and institutional actions and reactions through a set of network relationships.

Model Framework

The liquidity feedback model can be described as a progressive simulation of the following three stages:

1. Institutional liquidity risk assessment
2. Feedback (systemic) effects
3. Retesting of system solvency

As a component of a quantitative framework of systemic risk, the LFM is complemented by modules that at a minimum allow (a) the application of shocks, (b) attribution of effects to institutional balance sheets and income statements, and (c) reinvestment to maintain solvency and to manage institutional assets and liabilities.[3]

In the initial stage, the LFM projects individual bank ratings[4] to determine future funding costs and whether the institution falls into a danger zone. The latter is determined via a separate model of deterioration of the bank credit ratings and their funding costs.

In the second stage, the LFM analyzes feedback systemic effects. Certain funding markets close to a bank when its danger zone score exceeds specified thresholds.[5] The bank fails when it is no longer able to meet its cash flow constraints or when its capital falls below the regulatory minimum. As funding markets close or as the bank fails, the remaining banks in the financial

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1. The LFMs originated as an important component of the Bank of England Risk Assessment Model for Systemic Institutions (RAMSI). Current development of the LFM allows for stand-alone modeling of liquidity feedbacks suitable for alternative quantitative approaches to systemic risk.

2. The specific analysis is performed on the RAMSI population of the ten largest UK banks as of 2007 year-end.

3. For example, RAMSI framework utilizes the following modules in addition to its LFM core: (a) macroeconomic BVAR model for macro/financial shocks, (b) credit risk model for bank PDs and LGDs, (c) institutional balance sheet and income statement model, and (d) reinvestment model.

4. In RAMSI, the LFM is supplied via modules (a) and (b). Outside of RAMSI, the inputs may be obtained through the supporting quantitative framework for systemic risk.

5. Long-term unsecured funding markets close when danger zone score reaches 25. Short-term funding markets close when danger zone score reaches 35.

network absorb the financial effects of the LFM systemic feedbacks, specifically: bankruptcy costs (through counterparty interbank lending losses), asset fire sales (through mark-to-market losses), general confidence slide (through increased funding costs for the remaining market participants), and snowballing and liquidity squeeze effects (through defensive actions by the distressed institution).

In the third stage, the LFM retests system solvency. If a particular bank fails, the model adjusts counterparty credit losses and mark-to-market available-for-sale (AFS) assets, updates danger zone scores, and retests individual banks for survival.

Model Evolution

It is important to note that the RAMSI framework is modular, and that the LFM is designed to fit a set of specific objectives within RAMSI. It is also instructive to view the LFM through its evolution within RAMSI. Originally, bank failure occurred when a bank was shut out of funding markets.[6] Therefore, the failure mode did not include the bank's flow constraint, and the contagion channels were "rational"; that is, they only operated after one or more banks had failed. The current LFM reflects the progressions of RAMSI from a stability model to a model of systemic conditions. In its original form as a funding liquidity model, the LFM looked at the effects stemming from a four-element mechanism: rating downgrades, solvency concerns, funding profile, and confidence. The current LFM extends the original mechanism by simulating additionally certain defensive actions by the banks, specifically (a) cash flows from defensive actions by banks, and (b) effects of the defensive actions on funding pressures. In both the original and the extended model, the combined effects of the feedback factors would trigger closure of markets to particular institutions. Therefore, through its extension to the present form, the model focus remains consistent. The main research question of the LFM remains as follows: is failure likely through a liquidity-based transmission mechanism?

Comparative Feedback

In this section I will offer some comparative feedback. The current version of the chapter identifies a number of pending modeling improvements. Therefore, this feedback would be conceptual and comparative in nature, raising some questions and offering some alternative approaches. Largely, this feedback expresses a perspective that I developed through work on an alternative quantitative framework of systemic risk at the Federal Reserve Bank of Cleveland.

6. Aikman et al. (2009, 3).

What Is the Systemic Motivation: Institutional Stability or Systemic Risk?

The motivation for this comparison is as follows. The chapter describes a model of liquidity feedbacks in a quantitative model of systemic risk (RAMSI). RAMSI's original motivation is a quantitative model of systemic stability. Thus, it is fair to recognize first, that the origins of the LFM lie within a stability model, and second, that stability is inherently a structural question. Why is this important?

RAMSI framework is taking balance sheet data for top UK financial institutions individually and then constructing a network model between these institutions based on *interbank exposures.*

The constructed network model then is considered to define the financial system. The model sends simulated shocks through the network to study feedback-induced collapse mechanisms of individual institutions and the resulting collapse path through the network. What is useful to note here is that the constructed network is just one example of the possible representations of the financial system, based on two assumptions:

Assumption I: Top banks are necessary and sufficient to represent all financial institutions in the system.

Assumption II: Aggregated interbank exposures are necessary and sufficient to represent the top banks.

Therefore, a violation of any of the previous two assumptions will prompt the need for the financial system to be described by more than one type of network. In the event that Assumption I is violated, the financial system may need to be represented by other types of participants in the financial services industry that contribute to systemic effects.[7] Violation of Assumption II will lead to representations that include a number of different asset classes. In general, it can be reasonably expected that due to concentrations within the financial system, the networks can vary quite widely by asset class and be dynamic in nature, both through attrition of the market players and through willful redistribution of assets by financial system participants to optimize returns.

Representing the financial system through the interbank lending network is only one possible representation of the financial system. A different set of institutions might be engaged and a different set of concentrations might be envisioned in networks represented by different asset classes. Since different representations could lead to the population change, the results of the simulated shocks might actually differ from the results based on the interbank

7. For example, thrift institutions, insurance firms, investment companies including hedge funds and mutual funds, pension funds, finance companies, securities brokers and dealers, mortgage companies, and real estate investment trusts. See Kroszner (1996).

lending-based network. Therefore, one possible direction to enhance the model would be to allow for collapse originating in an asset class. A second possible direction would be to enhance the model by extending the typological representation of the financial system from banks to a wider set of market participants. The 2007 crisis provides evidence that a propagation mechanism can initiate within a narrow set of asset class exposures with specific characteristics[8] and only later expand to the interbank market.[9]

Given the evolution of RAMSI and the LFM as a stability framework, it is not surprising to find that the stability is tested through simulation. Inherent within this simulation is an estimator for danger zones, that is, areas where probability of institutional instability is sufficiently high so that they can be hypothesized to represent likely or imminent failure states. Thus, running an effective systemic stability simulation would presuppose ability to effectively identify the institutional and systemic danger zones. A suggested refinement of the LFM therefore deals with the clarity and validity of this inherent identification. Thus, in order for the LFM and RAMSI to be successful in identifying systemic stability, the two must effectively embed an identification system, similar to an early warning system (EWS) that defines the variety of modes of failure. To the extent that these systemic failure modes stem from liquidity-induced feedbacks, the LFM should be able to accommodate the range of causal drivers effectively. In the LFM, the danger zones approach serves as the identification system with failure states defined a priori. Thus, support of the LFM identification system may be enhanced through further discussion of the parameterization and validation of the danger zone thresholds. One possible direction for clarifying the identification basis of a stability simulation is through the alternative methodology of an early warning system, for example, via empirical support for selection of danger zone thresholds.

In its present state, the LFM as part of RAMSI is clearly a simulation model that results in institutional and system distributions of assets and losses, so the resulting outcome may be considered to represent solvency. RAMSI exemplifies one type of quantitative framework of systemic risk (stability based) that benefits from the LFM. Alternative quantitative frameworks of systemic risk would similarly benefit from the LFM simulation model. As a stability framework, RAMSI asks two key questions: "Is an institution or system solvent?"; and "Is failure likely through a liquidity-based transmission mechanism?" An alternative key question that may be asked is: "Are there imbalances (potential expectations shocks) and network structural weaknesses that increase the probability of systemic stress?" This alternative question in fact arises within an early-warning system approach

8. For example, valuation uncertainty in mortgage-backed securities and structured finance exposures.

9. For example, through collateral assets tied to counterparty-risk exposures.

for systemic stress.[10] The shared technical challenge for both types of approaches is incorporation of uncertainty in the identification problem. In a simulation approach, the assessment depends on the success of capturing uncertainty in the simulated propagation mechanism. Omission of uncertainty will bias the correct estimation of placement within a danger zone. Similarly, a bias in estimating the effect of uncertainty will likely result in a biased estimation of EWS parameters.[11]

It is also useful to consider the formulation of shocks in the two alternate approaches. For the LFM and RAMSI, the only source of shocks is the Bayesian VAR module that captures the evolution of macroeconomic and financial variables. Therefore, a reasonable question might be: "Can the model allow for shocks originating within the financial system?" For example, in the SAFE approach, shocks can be triggered by imbalances, stemming from failure of expectations about return, risk, and liquidity in a wide variety of asset classes on- and off- institutional balance sheets.[12]

Another useful comparison is the causal framework behind the model. The LFM is fed and simulated through a clear schema: "systemic risks stem from the connectivity of bank balance sheets via interbank exposures (counterparty risk); the interaction between balance sheets and asset prices (fire sale effects); and confidence effects that may affect funding conditions."[13] In addition, effects of institutional defensive actions (hoarding and snowballing) are incorporated. This schema is essentially causal, feeding a simulation model of funding conditions that are affected by five factors: connectivity through interbank exposures, fire sale effects, confidence effects, liquidity hoarding, and snowballing. Thus, the research questions to extend the LFM can be formulated as follows:

- "Are the above factors sufficient to fully represent the possible liquidity-related propagation mechanism?"
- "Are there additional propagation mechanisms that can be tested using the LFM?"

10. Dependent variable in such an EWS can be a continuous measure calibrated to provide signals of probability and severity of systemic stress in the financial markets. The theoretical foundations for such an approach to identification are established in Borio and Drehmann (2009), Hanschel and Monnin (2005), and Illing and Liu (2003; 2006). An example of this approach can be seen in a model developed at the Federal Reserve Bank of Cleveland, dubbed SAFE for Systemic Assessment of Financial Environment (see Oet et al. 2011), that also asks if supervisory institutional data can help forecast the probability of a systemic stress in financial markets. The primary objective of such an early warning system is to serve as a supervisory monitoring tool enabling consideration of specific ex ante regulatory policy alternatives for systemic stress. SAFE EWS is implemented as a scenario-based optimal-lag regression model.

11. SAFE provides an alternative approach to accommodating "an uncertainty function" within a systemic stress early-warning system, where an uncertainty factor drives assessment scenarios.

12. The authors discuss that incorporation of shocks originating within financial institutions would be an interesting extension to the LFM. Presently, the LFM does not implement this extension.

13. Aikman et al. (2009, 3).

By extension, a larger quantitative framework of systemic risk might ask a broader question: "Are there additional propagation mechanisms that are relevant?" The LFM is a rich simulation environment for the analytical study of the path to collapse. However, in the event that additional propagation mechanisms are relevant, it is the responsibility of the feeder modules of a quantitative framework of systemic risk to test a variety of shocks. Hence, the LFM should be able to accommodate a variety of shock sources. Presently, the LFM primarily looks to liquidity-relevant "transactions," but leaves open by what factors the interbank exposures, asset prices, and confidence are motivated. Thus, relevant propagation mechanisms are "hidden" behind the transaction-based perspective of the LFM. For comparison, it is again useful to refer to the early warning system approach used in the Cleveland Fed's SAFE model. The EWS approach allows a variety of propagation mechanisms through several distinct classes of variables. For example, shocks in the model are allowed through three distinct types of asset-class imbalances in (1) return, (2) risk, and (3) liquidity. In addition, shocks are possible through structural weaknesses in the system. These structural weaknesses can stem from three types of structural imbalances: connectivity, concentration, and contagion.[14] Conceptually, this approach to structural factors largely parallels the theoretical precedent set by James Thomson (2009).

Path to Collapse

An important output of the Liquidity Feedback Model is path to collapse. This path is deterministic once the LFM establishes the BVAR shocks, their effects on the composition of the institutional balance sheet, and the interbank lending-based network. This leads to the following five questions:

1. Is there possibly a variety of failure modes affecting liquidity?
2. Is there a variety of propagation mechanisms?
3. If the structure is not static and underlying drivers have an irrational element, is a precise network important?
4. Are interbank exposures more representative of network effects than asset-class based associations?
5. How else can these networks be modeled?

Significantly, an alternative EWS-based quantitative framework may allow a systemic risk researcher to remain agnostic as to a particular precise path to collapse and particular institutions affected. The agnosticism stems from an ability of EWS to consider an aggregate systemic condition vis-à-vis the likelihood of systemic stress.[15] SAFE EWS, for example, allows a variety of failure modes through an approach that is less deterministic. SAFE failure modes originate in shocks through return, risk, and liquidity imbalances and act through a variety

14. Thomson (2009).
15. Gramlich et al. (2010); Ergundor and Thomson (2005).

of structural weaknesses (connectivity, concentration, contagion). Thus, the LFM may be complemented by a quantitative framework that, like an EWS, would accommodate a flexible set of propagation mechanisms.

It is worthwhile to detail this point further. Presently, the LFM simulation represents the systemic condition through stability, where stability of the system is the function of the stability of *discrete financial institutions.* However, within an EWS context, the LFM would support the representation of systemic condition through accumulations of systemic stress in *discrete asset classes.* The systemic stress in the EWS context is driven by the aggregated institutional imbalances and structural factors. Stated differently, the flexibility of the LFM may be increased by extending it from the present application in the bottom-up approach to simulate systemic stability from stability of individual institutions to a top-down approach to obtain early warning of stress in the financial system as a whole through accumulated imbalances in asset classes, including their structural characteristics.

Uncertainty: Rational, Irrational, and the Unobservable

Rational and irrational aspects present another interesting avenue of exploration. In the LFM, through the onset of shocks, banks make defensive choices at each quarterly period. The simulated results then serve as inputs for subsequent quarterly iteration. One possible shortcoming of this approach is that in practice failure is uncertain.[16] In the LFM, the failure state is deterministic. The mechanism of shocks and defensive actions by the banks is rational. There is a probability, however, presently not addressed in the LFM, that failure may be stochastic, the result of *random shocks,* or that network interactions become driven by *irrational* events.[17] Even more precariously, these factors may in fact be *rational from the perspective of the system as a whole,*[18] but remain opaque and *unobservable* to the individual institutions. Regardless of the precise nature of these factors—stochastic, irrational, or unobservable—the individual institutions may not anticipate precisely the timing, frequency, and severity of their impacts, but need to sustain them effectively in order to survive. Allowing these uncertain drivers (stochastic, irrational, or unobservable)[19] within a systemic model would enhance its usefulness. Therefore, if the irrational or unobservable drivers are allowed, then the natural question is, "Can they emerge spontaneously in the model?" If yes, then a systemic model will need to assess whether a healthy institution or system can withstand these drivers. Estimation of uncertainty in these driv-

16. For example, a particular source of uncertainty may be a regulatory action or inaction in the face of changing market or institutional conditions.

17. For example, some of these irrational events may be triggered by information asymmetry, perceptions of counterparty risk, or even fears—a whole variety of concerns.

18. For example, the system as whole may be driven by the aggregate market factors, asset-class characteristics, or structural attributes of a specific network.

19. Unobservable from the point of view of individual institutions.

ers then becomes a critical challenge for such a model. This is difficult and perhaps impossible to do well, since the uncertainty, particularly the irrational, are unknowable in the Knightian sense. Nevertheless, in order to deal effectively with this uncertainty, the model must find a way to estimate it.[20]

Suggestions

A number of the deterministic features of the LFM (e.g., BVAR, the defined interbank lending network, mechanics of credit rating migrations) and the lack of explicit stochastic elements and jump factors serve to limit the effective question of the LFM to whether liquidity-induced failure is likely. To the extent that the LFM seeks to expand its application within a systemic risk framework from the "likely" to the "possible," it needs to begin to incorporate some stochastic elements, jump conditions, and mechanisms that represent uncertainty of the market behavior and irrational market drivers.

The chapter already discusses a number of extensions that include similar elements. To this end, I would offer the following additional suggestions:

1. *Fire-sale model.* The LFM generates a relatively minor range in fire-sale haircuts from 2 percent to 5 percent. Recalibration of the fire-sale model factors θ and ε may be suggested.[21] In addition, the LFM can further emphasize the role of the market shock factor ε in the current LFM fire-sale model. Ideally, these model factors would capture a varying risk and some uncertainty.

2. *Asset-price model.* The Bayesian macroeconomic model (BVAR) does not strongly explain sample data on asset price shocks. Further, the LFM's asset price shocks occur in two parts, first from a decline in economic fundamentals and second from institutional liquidity feedback effects. The LFM can further explore the systemic stress condition that may be induced not by institutional effects but by asset-class effects, such as jump reversion to some long-term economic fundamentals (e.g., due to loss of confidence).

3. *PD / LGD correlations.* Discussion in a prior version of the study[22] reveals that PDs have limited and deteriorating power to explain debt in arrears during economic downturns. One possible explanation of this is due to an omitted variable that arises significantly during downturn conditions, for example, correlation between PD and LGD.

20. One possible method for dealing with uncertainty may be allowed by the application of the LFM within an EWS approach. In the SAFE EWS, the relative distances between crisis-driven valuations, stress-driven valuations, and normal valuations are monitored each period. Similar to the LFM, the stress and crisis valuations are amplified (Krishnamurthy 2009b) through liquidity feedback and asset fire sales. In SAFE, the crisis valuations are driven by "irrational" valuations in hypothetical immediate fire sales, whereas the stress valuations are driven by longer horizon asset sales, where "irrational" concerns are allowed to progressively subside.

21. See, for example, Board of Governors of the Federal Reserve System (2009); Basel Committee on Banking Supervision (2009); and Krishnamurthy (2009a).

22. Aikman et al. (2009).

Conclusion

In its current state, the LFM is essentially a simulation tool for institutional stability that looks at systemic stability from a particular propagation mechanism of macroeconomically-fed liquidity constraint. In addition, the LFM has limited ability to address uncertainty and asset-class effects. A useful extension of the LFM's application can be considered: from quantification of systemic risk from institutional stability to an EWS objective of monitoring systemic stress. It may therefore be highly desirable to extend the LFM to enable an analytical convergence that would incorporate a robust early warning system and a powerful LFM simulation engine.

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