

Risk Topography

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Abstract

The aim of this paper is to conceptualize and design a risk topography that outlines a data acquisition and dissemination process that informs policy makers, researchers and market participants about systemic risk. Our approach emphasizes that systemic risk (i) typically builds up in the background before materializing in a crisis and (ii) is determined by market participants' response to various shocks. To this end we propose a two-step approach: First, regulators elicit from market participants their (partial equilibrium) risk as well as liquidity sensitivities with respect to major risk factors and liquidity scenarios. By doing so, one takes advantage of private sector internal risk models and over time an informative panel data set is obtained. Second, general equilibrium responses and economy-wide system effects are calibrated using this panel data set.

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1 Introduction

The recent economic crisis and financial innovation highlight the importance of an economy-wide risk topography across different sectors of the economy. Our approach is similar in spirit to the Federal Reserve’s Flow of Funds accounts, bank Call Reports and SEC filings, but are designed to highlight risk and liquidity exposures. Unlike two decades ago, in today’s world of derivatives entering a risky position is divorced from an initial flow of funds. Hence, current reports that are based on stocks and flows of cash securities are poor proxies for risk and liquidity exposures. Existing risk measures used by private banks suffer from other shortcomings. Notably, they focus on the risk of a firm in isolation, underemphasize important system-wide general equilibrium effect and as a consequence miss hot spots in the financial system.

Systemic risk builds up in the background typically in times of low volatility and only materializes when it becomes sufficiently apparent that accumulating imbalances are not sustainable. The subsequent fallout is characterized by significant spillover effects across the financial sector and the real economy. These spillovers can be direct due to contractual links or indirect through price and liquidity effects. To gauge the latter, it is not enough to simply look at current asset market measures, like current volatility, liquidity, spreads etc. Rather it is important to (i) measure and model how market participants endogenously *respond* (in a partial equilibrium sense) to negative shocks and (ii) how such responses feed back and produce system-wide or aggregate general equilibrium dislocations. The theoretical literature has suggested many channels for such endogenous amplifications, ranging from externalities, multiple equilibria, disequilibrium, and mutually inconsistent plans.

The aim of this paper is to conceptualize and design a risk topography that outlines a data acquisition and dissemination process that will inform policymakers, researchers, and private investors on systemic risks in the economy.

The data acquisition is intended to be comprehensive, informative and tractable. Like a map, our approach goes beyond simply depicting all details and position data and thereby reduces the information overload problem in addition to providing an aggregate general equilibrium picture. With regard to dissemination, the idea is that private market participants need to see the partial-equilibrium responses of other agents to avoid creating undesirable general equilibrium outcomes. Our approach can be split in two tasks. First, private market participants’ risk sensitivities with respect to certain factor and liquidity scenarios (of various degrees) are directly elicited from them. We take advantage of the data and knowledge of

private sector internal risk models. Individual market participants know best how they will react to certain scenarios. Truth-telling can be ensured by cross-checking the various internal risk models across all market participants. Second, the information submitted is aggregated, suitably anonymized, and then made public (e.g. on a web site) so it can be used in models to determine economy-wide system effects.

A simple example helps to illustrate our approach. Take real estate price changes as one relevant “risk scenario.” For a shock to real estate prices (as measured by the Case-Shiller Index, for example) of 20%, 30%, and 40% we ask market participants how much (a) the value of their enterprise will change and (b) the liquidity index, measured in “effective cash” will change. This is the first step outlined above. The partial reaction in value and liquidity index will allow us the model the market participants’ response to shocks in real estate. For example, a firm with a low liquidity index (e.g., funding that is short-maturity) will most likely try to reduce its risk exposure, while a firm with a high liquidity index (e.g., long-term funding) might hold on to these assets. In addition to price risk factors, we also include “liquidity scenarios,” like haircuts and margins double, triple or quadruple. Again, we elicit each market participants’ change in value and liquidity index. On top of eliciting partial effects, we also ask for risk and liquidity sensitivities along certain cross scenarios. The importance of these cross effects is best illustrated with an extreme example: suppose a firm specializes in selling derivatives that only pay out in the joint event that both real estate prices drop and haircuts double. As it does not suffer any losses if only real estate prices fall or haircuts double, the partial risk sensitivities along the factors are negligible. But what cross scenarios should we include? We propose to following selection procedure: In addition, to reporting risk and liquidity sensitivities each firm reports a vector in the factor space that points in the direction of factor movements the firm has the highest exposure too. If all firms’ reported vectors point in a similar direction, this particular cross-scenario has to be added in next quarter’s survey. The information should be kept simple and straightforward, and then continued on a regular basis such that over time, a rich panel of data will accumulate.

In the second step, the data allows regulators, academics and market participants to model different market participants’ responses to various shocks. These responses can be fed into a general equilibrium model where likelihood of aggregate dislocations is inferred. A typical model may say that dislocations occur and endogenously risk and illiquidity problems emerge when many agents react the same way. Returning to our previous example, suppose if the data reveal that a 5% drop in real estate prices would lead to a large sell off in mortgage backed securities with the consequence of an increase in mortgage rates, then one should conclude

that a 10% drop in real estate prices is more likely than a 5% drop. Overall, we envision that competing models will be developed and verified using the accumulated data.

Two literatures are related to the ideas in this paper. The first literature concerns measurement. As mentioned, in the U.S. the current measurement systems include the bank Call Reports of Condition and Income and the Federal Reserve Flow of Fund data. Both of these data sets were explicitly developed to aid bank regulators to monitor banks. The Call Reports were mandated by the National Bank Act (1863) (Sec. 5211) and have continued to this day. These reports are essentially fairly detailed balance sheet and income items of regulated banks. The Flow of Funds data was designed by Morris Copeland (1947, 1952) to characterize money flows in the economy. At first, economists did not see how to use the flow of funds and this took awhile to develop; see, e.g., Dawson (1958) and Taylor (1958).

The second related literature concerns bank stress testing. Bank stress testing is an evaluation of the impact on a firm of a particular scenario or event, usually a movement in financial variables. Stress testing is an adjunct to statistical models, such as value-at-risk models. There are many papers that provide a general introduction to stress testing. Examples include Blaschke et al. (2001), Jones, Hilbers, and Slack (2004), Cihák (2007), and Drehmann (2008). There are also collections of articles, e.g., Quagliarello (2009), that discuss stress testing. International organizations have developed stress testing procedures: the Bank for International Settlements (BIS (2009)), the Committee on the Global Financial System (2005), and the International Monetary Fund, which started the Financial Sector Assessment Program in May 1999. Other articles include Haldane, Hall, and Pezzini (2007) and Hoggarth and Whitley (2003). The recent financial crisis has clearly raised issues with current applications of stress tests (see, e.g., Alfaro and Drehmann (2009) and Haldane (2009)). Hirtle, Schuermann and Stiroh (2009) discuss the U.S. Supervisory Capital Assessment Program, i.e., the stress tests applied to largest U.S. bank holding companies from February to May 2009 (see Board of Governors of the Federal Reserve System (2009a,b)).

Our approach to measuring risk continues the tradition of the Call Reports; it is a kind of updated version of these reports. With regard to stress testing two main points distinguish this approach from ours, although they are clearly not mutually exclusive. We emphasize eliciting the same scenarios repeatedly and regularly to develop a risk map similar to the Call Report data. Over time it will become a large library of information that can be used to build and fine-tune models. Secondly, we emphasize that the data elicited (suitably anonymized) be made public so that private agents can see the condition of the financial system and adjust their exposures if they see fit. Also, by making data public, academics, regulators, and

industry participants will be in a position to build their own models of systemic risk.

The paper proceeds as follows. In Section 2 we present our approach more formally and discuss our conceptualization of systemic risk. Section 3 addresses more detailed issues on how scenarios will be chosen, which firms will be required to report, and how much will be required. In Section 4 we discuss the uses of the elicited data. Section 5 concludes.

2 Model

We explain our approach using a simple model. There are two dates, a date 0 ex-ante period in which assets and liabilities are chosen, and a date 1 with states $\omega \in \Omega$, when we may face a systemic crisis. Firm i chooses assets of A^i and liabilities of L^i . The assets A^i are a mix of cash, repo lending to other firms, derivative exposure, and outright asset purchase. Liabilities include short-term debt, long-term debt, secured debt, equity, etc.

The equity-value of the firm i is given by $\mathcal{E}_\omega^i = A_\omega^i - L_\omega^i$ with A_ω^i is the asset value in state ω and L_ω^i are total liabilities. The equity value \mathcal{E}^i measures how close firm i is to insolvency and can feed into how the firm is likely to behave given considerations such as capital constraints, the risk of bankruptcy, etc. In addition, to the total value of assets, A_s^i , and the equity value, \mathcal{E}_s^i , we are also interested in the liquidity position of each firm. For tractability, each asset/liability is assigned a liquidity index λ_ω^j for each state of the world. We index assets with positive j , while for liabilities j takes on a negative value. We normalize super-liquid monetary assets such as bank reserves and Treasuries to have a λ_ω^{money} of one across all states. For something like an MBS, we can imagine measuring λ_ω^{MBS} as one minus the repo haircut on that MBS in state ω . Alternatively λ_ω^{MBS} may measure the price discount that firm i has to accept if it immediately wanted to convert the asset into cash. The key point is that λ_ω^j measures, across states, the immediate-cash-equivalent value of asset j . Aggregating liquidity across the asset side, one obtains firm i 's market liquidity $\Lambda_\omega^{A,i}$ for the different states in the economy. We also measure the liquidity of the liabilities as $\lambda_\omega^{j<0} < 0$. Overnight debt has liquidity of -1 in all states, while longer-term debt has $-1 < \lambda_\omega^{LT} < 0$. Common equity is $\lambda_\omega^{equity} = 0$ for all states ω . Aggregating all liability positions gives the total funding liquidity of firm i , $\Lambda_\omega^{L,i}$.

Reporting. The dimensions of the Ω state space that describes a firms' asset, liability, and liquidity positions can be enormous. We propose to focus on states s within an S dimensional factor space, a subspace of Ω . Factors consist of certain prices (risk factors) or

liquidity/funding conditions (liquidity factors). For example a risk factor might be a change in real estate prices, while a liquidity factor could be a change in haircuts and margins. Individual market participants take these as given, but they are endogenously determined in the financial system. The selection of factors is discussed in more detail in Section 3. Along these dimensions, firms report a “value-liquidity” vector that consists of their estimated (i) total asset value, (ii) equity value as well as (iii) asset liquidity index, $\Lambda^{A,j}$, and (iv) funding liquidity index, $\Lambda^{L,j}$. For example, if there is only one risk factor (e.g. with N real estate price levels) and one liquidity factor (e.g. with M overall haircut levels), then the state space can be characterized by a $N \times M$ -matrix. Firms have to report their estimated values-liquidity indices in the first row and first column. From this one can derive the partial sensitivities of each firm along each single factor. In addition, firms will be asked to report their value and indices for some pre-specified cross scenarios, in n th column, m th row. Finally, firms report the four states in which they would experience the four highest losses in value and liquidity index, respectively. As long as all firms pick different (n, m) -combinations systemic risk seems contained. However, when many firms start picking similar (n, m) -combinations, this points to a systemic risk concentration. This suggests to make this scenario a specific cross-scenario in the future and follow it more closely.

Responses. The heart of our policy proposal to measure systemic risk is the focus on modeling the feedback behavior of the private sector. How will firm i alter assets and liabilities as a function of shocks that affect the firms’ value and liquidity? Systemic risk is driven by market participants’ responses to shift in prices and liquidity conditions. Instead of looking at the firm’s assets and liability choice, we rephrase the firm’s problem in terms of exposure choice along the factors. Exposure is defined as the change of the 4 value and liquidity indices as one moves within the S dimensional space. These exposures have to be modeled and verified using the above data. For models that focus only on incremental changes, the exposures are given by the first partial derivatives of the value-liquidity vector with respect to each other of the S factors. Using option-pricing terminology, we have Δ -exposure along each of factors. In this case, firm i ’s total exposure is fully described by a $S \times 4$ dimensional vector. More generally, one has to take non-incremental and non-linear effects into account, which reflect changes in Δ due to γ -risk. Let us denote the “exposure vector” of firm i by Δ^i .

How do we model and empirically verify a firm’s response in exposure due to a shift in the S dimensional factor space? Specifically, we are interested in estimating a function $f^i(\cdot)$:

$$\Delta^i = f^i(\text{future return and risk variables}, A^i, \mathcal{E}^i, \Lambda^{A,j}, \Lambda^{L,j}; \text{firm characteristics}). \quad (1)$$

The exposure, Δ^i , is akin to a portfolio choice: how much MBS to hold directly or through derivatives, and whether to fund it using short-term debt, long-term debt or equity. This choice is influenced by the expected return and risk profile (both fundamental and liquidity-driven) of MBS. The return and risk may be measured by financial variables such as spreads, volatility, and macro variables such as GDP growth and inflation. The portfolio choice is also driven by current value and liquidity of firm i . Finally, the choice is influenced by the type of business-model of the firm (i.e. is the firm a market-maker, a hedge fund, etc.)

We have expressed the model (1) in full generality. In most cases of interest, the objects on the left and right hand side of equation (1) can be simplified considerably. For example, if the firm is a real-estate investor, then its Δ^i s with respect to factors such as exchange rates and stock prices can be assumed to be zero. The return and risk variables will only be those that are relevant for investing in MBS. We might only be interested in asset value A^i and the net liquidity index, $\Lambda^{A,j} - \Lambda^{L,j}$.

Imagine repeating our date 0 data collection exercise every quarter for a number of years for many firms for some core set of states. Then over time, we will have data on the risk exposure choices, Δ^i , made by firm i (and other firms like i) for different value-liquidity vectors for firm i and in varying macro-state market conditions. As this panel accumulates, the data can be used to build and test models of how firm i makes its portfolio choice decision. That is, the data allows us to estimate equation (1). We view this as an important part of our approach, since a panel data set allows us to verify various future models using the whole history of data from time 0 onwards.

Why measure value and liquidity? Note that in writing the function $f_i(\cdot)$, we are assuming that firm i behavior can be summarized with the firm i state variables of value and liquidity. The assumption is not innocuous; indeed, it is the reason that the data collection process elicits information about the value and liquidity of firm i . If we find after several years that we have missed out on some key state variable describing firm i decisions, then the accumulated data will not be as helpful. We make this choice guided by our understanding of current theory. The two central variables that emerge in almost all theoretical analyses of crises are value and liquidity. For example, mechanisms involving capital constraints, funding constraints, fear of runs, fear of loss of liquidity, all describe a mapping between value and/or liquidity and a portfolio choice decision.

Finally, note that the modeling exercise here is a research endeavor and can be logically separated from the data collection exercise. We imagine that researchers at universities, the government, and the private sector will all work with the accumulated data to build better

models of macro-financial linkages. However, in the near term, the regulator's modeling of firm behavior will be guided heavily by theory. Existing models will have to confront whatever data is available and thus be quantified and calibrated.

General equilibrium. The heart of systemic risk measurement is computing a general equilibrium feedback from individual response behavior. In state s , firm i may be modeled to change risk and liquidity such that the firm's new exposure becomes Δ_s . But the modeler may also find that many firms are taking similar actions in that state so that equilibrium implies that the realized state is more likely s' worse than s . This further implies actions $\Delta_{s'}$, and likely states s'' , and so on. In equilibrium, a higher probability is assigned to s'' than to s .

Modeling these feedback loops requires specifying the market clearing conditions for the risky asset exposure and liquidity exposure. In addition, one needs to assume how the government and unmeasured agents (e.g., foreign investors) will behave in each state, supplying liquidity and risk-bearing capacity. Given individual response behavior and market clearing conditions, the equilibrium is a fixed point describing an inherently consistent joint probability distribution over all s states, where each state is characterized by firms' actions $\{\Delta_s\}_i^I$, endogenous price P_s and vector of endogenous liquidity weights $\{\lambda_s^j\}$. Section 4.1 discusses in more detail how general equilibrium analysis helps to detect systemic risk pockets in advance and for example alerts market participants that they are pursuing mutually inconsistent hedging plans.

Banking example. Suppose that there are $I - 1$ (where I is large) identical banks whose assets consist of interbank (short-term repo) lending, MBS holdings, and cash. The liabilities are equity and short-term debt to other banks and households.

Consider first a case in which $I - 1$ banks are well capitalized in all states. Order the states so that state s is worse than state $s - 1$. Suppose that bank I is insolvent and illiquid in states $s > \hat{s}$. Then most models will forecast that bank I will have to substantially reduce risk and increase liquidity in states $s > \hat{s}$, with other banks taking on the asset risk and providing the liquidity. There is no systemic feedback in this case. The result of a modeling exercise may be that the probability of illiquidity states is zero, while the probability of asset price states is determined purely by expectations of future cash-flows on the assets.

Next consider the case in which the $I - 1$ banks are illiquid in states $s > \hat{s}$, while bank I is solvent and liquid in all states. Then a model would tell us that a reduction in liquidity (to

state \hat{s}) will cause $I - 1$ banks to reduce risk exposure and scramble to increase liquidity. But given that there is only a single bank that is sound, we will likely see that the asset price and liquidity weights will fall. Thus the probability of a low asset price state occurring is not only determined by expectations of future cash-flows but also by the possibility that an illiquidity episode will trigger a fire sale. A calibrated model can be used to assess the probability of the low asset price/illiquidity states.

3 Specifying Factor Scenarios

The “s-states” described above are stress scenarios. The choice of scenarios is critical to the assessment of systemic risk. There are two considerations driving the choice. First, the propagation and amplification patterns share common features across various crises. Crises invariably involve capital and liquidity problems in important parts of the financial sector. Shocks interact with these capital and liquidity problems and lead to adverse general equilibrium feedback loops. To shed light on these feedback effects, we propose collecting data on a core set of factors held constant over time that form the panel data set on which to measure and calibrate the response functions of market participants.

Second, history suggests that the trigger for crises varies from event to event. Thus, at any time the regulator needs to choose factors that are informed by prevailing economic conditions. For example, the regulator may choose to focus on the effects of an internet shock in the late 90s, but such a shock may not have been relevant in 2007, where subprime mortgages were a more significant concern.

Third, in most cases, particular cross-scenarios are of special interest; i.e., a scenario involving say a simultaneous change in house prices, unemployment, and liquidity. This is the thinking behind the successful SCAP. From the standpoint of our analysis, what is missing in the SCAP is a modeling step that allows us to see the feedback/amplification that will arise if the scenario envisioned in the SCAP does occur. One approach to institutionalizing the stress-scenario is as follows. In each quarter, we ask each firm to submit a cross-scenario that the firm deems to be the “worst-case” for itself. The regulator then aggregates across firms to see if many firms have a similar worst case. The aggregate scenario is used to specify the cross-scenario which will be part of next quarters’ survey.

3.1 Example of scenarios

Scenarios can include events that have never happened before, that is events that are not in recorded experience. Broadly, stress scenarios fall into four groups. The first three are specified changes in market risks, idiosyncratic risks, and in liquidity factors. The scenarios in the first three categories are orthogonal stress scenarios. These correspond to partial derivatives of value and liquidity indices with respect to the factor. The last group asks for more complicated scenarios, e.g., what if house prices fall 20 percent and repo haircuts rise to 10 percent. We provide examples of scenarios.

3.1.1 Market risk scenarios

Market risk scenarios include specifications of changes in:

- Interest rates (yields) on major government bonds (e.g., US, UK, Germany, Japan, China) bond rates for different maturities; also swap rates in LIBOR, FIBOR (Frankfurt), PIBOR (Paris), HIBOR (Hong Kong), etc. at different maturities;
- Credit spreads: Changes in major credit derivative indices (CDX, CMBX, LCDX) at different maturities;
- Exchange rates of major currencies;
- Stock prices, measured by major indices;
- Commodity prices, measured by sector and aggregate indices;
- Commercial real estate prices, e.g., the NCREIF property index;
- Residential house prices, e.g., Case-Shiller index;

Many of the market risk scenarios are already the subject of risk management measures in financial firms. As we explain further below, the information we seek to solicit differs from risk management model information.

3.1.2 Liquidity risk scenarios

A liquidity risk scenario corresponds to a shock to liquidity as follows:

- Firms are unable to access the market to raise new cash for one month, three months, and six months.
- Repo haircuts on some asset classes rise.
- The syndicated loan market, or the securitization market, shuts down for some period.

The preceding risks can all be expressed as a change in particular λ 's. An alternative scenario is a market wide decline in liquidity. For this consider defining a new vector λ' of liquidity indices, where

$$\lambda' = \lambda + (1 - \lambda)\alpha,$$

and α is a scalar larger than one. In this example, the illiquidity of an asset, measured as $1 - \lambda$, is increased by the factor α . Thus, Treasuries which have a λ of one, and hence illiquidity of zero, are unaffected by a market-wide decline in liquidity. However, MBS which may have a λ of 0.90, will have a $\lambda' < 0.90$ in this scenario.

3.1.3 Idiosyncratic risk factors

Idiosyncratic risk refers to scenarios specific to the reporting firm. Such scenarios include:

- Default by the largest of the firm's counterparties, second largest counterparty, third largest;
- Default by largest supplier of bank lines;
- Default by a major clearing bank, or clearing system;
- Reputational event which prevents new security issuance for 6 months, 1 year;
- Inability to issue new securities for 1 month, 3 months, 6 months;
- Inability to clear for three days, 10 days;
- Rating downgrade of the senior unsecured debt of the company by 3 notches, 6 notches.

These idiosyncratic scenarios can shed some light on the network-linkage effects that play an important role in crises. For example, we envision that the first item on counterparty exposures will be measured for the largest financials. However, we should stress that our measures are not designed to inform a regulator on the dynamics *during* a crisis. That is, it

seems clear from recent experience that it would be useful for regulators to know in real-time the counterparty exposures to the default of AIG or the default on Lehman bonds. With such information, the regulator can make decisions on how or when to intervene during a crisis. For this, regulators would need data that is much more detailed (e.g., individual position data) than what we are suggesting here. Our coarser measures on the other hand shed light on the risk build-up and possibility of systemic risk in advance of a crisis. From this standpoint, what is important is to measure the extent of, for example, real estate risk held by major financial institutions including Lehman and AIG. These firms are in a market equilibrium with other financial firms, so that real-estate losses can be expected to affect other firms; whether the loss transmission is through a direct default, or through a firm unwinding a large risk position, lowering prices, and thus inflicting losses on other firms, is more detail than we think is necessary to understand systemic risk.

3.2 Discussion

Elicited information should include events that have never happened before, that is events that are not in recorded experience. The bulk of the elicited information should remain constant over time to develop a time series, as with the Call Reports. Elicited information will involve the use of models by firms. These models are not homogeneous across firms, so the elicited information will have different degrees of accuracy. Also, these models will evolve over time so that the accuracy of the responses will change over time, presumably it will improve.

3.3 Who reports?

One of the important aspects of the current crisis was that the amount of information supplied to regulators varied widely across different types of firms. Our view is that all firms significantly engaged in financial activities should report scenario responses. But, the amount supplied should vary by size. Larger firms should supply more, smaller firms less.

3.4 Cross-checks: Verification of the integrity of reported data

Several cross-checks need to be developed in order to verify the integrity of reported data. First, horizontal comparison across similar firms should provide some cross-check. Second, adding-up constraints and zero-sum conditions should be applied wherever possible in order to make it difficult for market participants to misreport their exposures.

4 Detecting Systemic Risk

The measures are useful to identifying systemic risk during a build-up phase and catalyzing actions that can forestall such risk. Here we discuss some specific ways in which the data can be used.

4.1 Risk and liquidity aggregates

The "delta" of asset value, A_i , with respect to a risk factor is a measure of risk exposure that naturally aggregates over firms. Denote this exposure for a particular risk factor (e.g., real estate prices) for firm i as $\Delta^{i,A}$. Consider the sum,

$$\sum_{i=1}^I \Delta^{i,A}.$$

This sum is the total exposure of all measured firms to real estate risk. We would expect that some firms are long exposure and others are short exposure. If we measured all important parts of the economy, the sum should equal the physical supply of risk. For risks in positive net supply such as real estate, we can arrive at what the sum should be considering how much real estate there exists in the economy. For risks in zero-net supply such as pure derivatives, the sum should be zero. In both cases, the risk measures have the feature that they can be aggregated into something meaningful. Even at less aggregated levels – say sectorally – the risk aggregates are likely to be informative. They will reveal pockets of risk concentration and can serve to diagnose systemic risk.

The liquidity measures can also be aggregated. An interbank loan that is a liquid asset for firm i is a drain on liquidity for the borrower, firm- j (i.e. negative liquidity weight). Consider the net liquidity index for firm i ,

$$\Lambda^i = \Lambda^{A,i} - \Lambda^{L,i}.$$

Again consider the sum,

$$\sum_{i=1}^I \Lambda^i.$$

Summed across all sectors, the liquidity aggregate should equal the supply of liquid assets: the λ -weighted sum across all relevant assets. The aggregates are more interesting in describing the liquidity position of particular sectors. We may expect to find, for example, that the banking sector always carries a negative liquidity position, while the corporate sector or asset

management firms carry a long liquidity position. The extent of liquidity transformation done by the banking sector may also be informative for diagnosing systemic risk.

4.2 Mutually inconsistent plans and information revelation

The data on risk and liquidity exposures can reduce systemic risk by allowing the private sector to improve its own risk management. Consider the problem of mutually inconsistent plans, which is a recurring theme in many financial crises. As Grossman (1988) argues, in the 1987 market crash, firms were following dynamic trading strategies to insure them against market downturns. These strategies involved firms selling stocks as prices fell, replicating a synthetic put option. In the crash, it became apparent that such strategies were mutually inconsistent: if everyone follows a portfolio insurance strategy, markets will not clear.

To go back to the model, suppose that firm i (and all other firms), carrying out its risk management, planned that in the event prices fell, so that the firm's liquidity and solvency were reduced, it would sell some of its assets to reduce risk and at the same time cut back on interbank repo lending to preserve liquidity. The regulator elicits information on all firms and makes such information public. Immediately, the firms recognize that their plans are mutually inconsistent. As a result all firms take decisions at date 0 to reduce risk exposure and enhance liquidity.

In addition to simply making public the exposure data, we can imagine that a regulator will additionally provide guidance for private risk management. It could reveal the results of its own analysis that private plans are mutually inconsistent. Or, it could survey firms on how they would behave in the low price scenario and then make public the result of this survey. Such a survey may be similar to the senior loan officer's survey of the Fed.

4.3 Externality regulation

There is a substantial literature which argues that private asset/liability choices do not adequately account for the risk of systemic breakdown. Since systemic breakdown involves externalities – firm i scrambling for liquidity and reducing risk-exposures, reduces liquidity in the market and causes prices to fall, reducing the solvency/liquidity of other firms, etc. – firm i 's private decisions will be socially inefficient. Since the data and modeling in our two-step approach is essentially about these feedback mechanisms, they allow a regulator to identify risks where there may be a difference between private and social incentives.

5 Comparisons

5.1 Collecting all position data

5.2 Repeated stress tests

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