ANALYSIS

Prepared by

Tony Hughes
Tony.Hughes@moodys.com
Managing Director

Samuel W. Malone
Samuel.Malone@moodys.com
Director

Contact Us

Email
help@economy.com

U.S./Canada
+1.866.275.3266

EMEA
+44.20.7772.5454 (London)
+420.224.222.929 (Prague)

Asia/Pacific
+852.3551.3077

All Others
+1.610.235.5299

Web
www.economy.com
www.moodysanalytics.com

Systemic Risk Monitor 1.0:
A Network Approach

Introduction

In this paper, we introduce a new risk management tool focused on network connectivity between financial institutions. This tool will enable banks to better understand the counterparty risks faced by their counterparties and themselves. Additionally, our methodology cuts to the heart of the problem of systemic risk measurement and assessment. Our toolkit, which we call the Systemic Risk Monitor (SRM), will be indispensable for regulators seeking to fulfill their mandates to avoid banking crises.

Given a network scope defined by geography and a minimum asset size threshold, SRM delivers a rich set of system-wide and bank-specific counterparty and systemic risk analytics. For individual banks, outputs include measures of systemic risk contributions and exposures and counterparty credit risk sensitivities, including some highly useful measures that are new to the literature. We illustrate the framework with three case studies: U.S. financial institutions with a minimum size of $10 billion, Southeast Asian institutions with a minimum size of $1 billion, and a set of global mega-institutions. In econometric exercises focused on U.S. institutions, we document strong Granger causal relationships between SRM outputs and the Comprehensive Capital Analysis and Review variables used to formulate regulatory stress-test scenarios. In the cross section of U.S. institutions, SRM measures add significant forecasting power for future spikes in default probabilities during the Global Financial Crisis.

Systemic Risk Monitor 1.0: A Network Approach

BY TONY HUGHES AND SAMUEL W. MALONE

In this paper, we introduce a comprehensive set of tools designed to address the issue of network connectivity in the global financial sector. On a very basic level, our toolkit considers the transmission of shocks between institutions using accumulated financial market and balance sheet data. Employing this information, financial institutions will be better able to visualize and quantify risks associated with their exposures to various counterparties and, for the first time, will be able to quantify their counterparties' counterparty risks using widely available information.

In many ways, the concept of network connectivity is synonymous with that of systemic financial risk. Such risks are manifested when shocks to individual banks are transmitted to other sectors of the financial industry and the economy more broadly. In designing stress-test methodologies and other analytical tools to quantify systemic risk and safeguard the banking system, regulators must include measures of network connectivity as a central plank. Our methodology allows global or cross-country systemic risks to be considered as well as connectivity within specific jurisdictions. In that way, regulators can use our tool to identify systemically important institutions under their watch, find network-specific vulnerabilities, and locate conduits through which international shocks may be transmitted to their locale.

While the use case for regulators is compelling, our primary goal in developing this product is to help financial institutions manage risk more effectively. Ideally, stress-testing protocols will develop to the point where good stress testers gain a competitive advantage in the banking marketplace over bad stress testers. If this occurs, financial companies will adopt stress-testing tools voluntarily in their risk assessment procedures without the need for regulatory imposition. This ideal has guided our development of this toolkit. Though one can easily imagine regulators forcing banks to assess the network connectivity of their counterparties, our aim is to build a product that banks find indispensable in the operation of their businesses. In a world where bailouts are either uncertain or nonexistent, competitive advantages should accrue to institutions with a keen understanding of the network and their place therein. Our tool is designed to provide deep insight into the nature of these networks.

Section 1: Background discussion

Systemic risk is the most important problem in banking and finance. Despite this, financial institutions typically have no formal quantitative system in place for tracking the phenomenon or measuring their exposure or contribution to it. Although a bank can, with some difficulty, quantify its exposures to its various counterparties, it cannot easily gauge its counterparties' levels of exposure to third parties. If a bank is to take a holistic view of counterparty risk, these second- and higher-order relationships must be considered.

On their side, the Federal Reserve and other government regulatory agencies around the world take a conservative approach to capital adequacy, in part because they, too, do not have a standardized, formal system for quantifying systemic risk. Asset size is clearly an important component of systemic importance, but it is not the only component. Following recent guidance by regulators around the globe, issues such as an institution's leverage, geographic footprint, interconnectedness, complexity, and the degree of substitutability of operations also matter a great deal. In practice, however, regulators focus heavily on the use of financial institutions' book asset values as a proxy for their systemic importance, in part because book asset values are easily obtainable.

In contrast, measuring some other dimensions of systemic importance such as an institution's interconnectedness or the complexity of its operations is difficult. If the book size of an institution's assets were perfectly, or even very highly, correlated with these other dimensions of systemic importance, then measuring the latter would be unnecessary. Unfortunately, the empirical evidence we present in this paper suggests that, at least in the case of interconnectedness, this is not the case. Correlations between firm size and measures of market-

implied interconnectedness to other firms in the financial network are modest, even in times of significant market stress. Thus, it is necessary to track explicit quantitative measures of interconnectedness, since knowing institutional size alone is insufficient for understanding the nature of linkages between that firm and others in the system. Furthermore, although it is true that large firms typically have many counterparties and act as hubs for flows of capital through the system, they do not always drive the *default risk* of other financial institutions in the system. The tools we describe in this paper, which make up the Systemic Risk Monitor 1.0, are designed to provide reliable, market-implied metrics indicating which institutions do drive the default risk of other firms in the system as well as several key dimensions of systemic risk that arise from such interactions.

Our conversations with banks suggest that systemic risk tools are likely to be more widely adopted if they tie in directly to the credit risk and counterparty risk monitoring activities that banks already perform. Widespread adoption and use of such monitoring tools with carefully validated systemic risk properties would clearly serve the interests of regulators. Ironically, inconsistent feedback to financial institutions by regulators regarding best practices in stress-testing remains a nontrivial impediment to the adoption of next generation stress-testing tools, including those which may hold independent interest for the risk management function of banks. We hope that, by offering tools useful for both enhanced counterparty risk surveillance as well as for systemic risk monitoring, we can help banks and regulators more effectively achieve their respective mandates, as well as coordinate more effectively on the use of tools that are conducive to enhanced financial stability.

In this paper, we define systemic risk as the potential for a shock, endogenous or exogenous to the financial system, to cause broad-based financial system failure while inflicting collateral damage on other economic sectors. Since the Global Financial Crisis and the sovereign debt crisis in Europe, stress-testing has become one of the main

techniques for assessing the robustness of individual financial institutions and the financial system as a whole. Little emphasis has been placed on formal measurement of systemic vulnerabilities as an active part of stress-testing, even though it is officially part of stress-testing mandates such as the Federal Reserve's Comprehensive Capital Analysis and Review. This is not for a lack of core systemic risk research. Parallel to the development of stress-testing regimes, the academic literature on systemic risk measures has flourished (see Bisias et al., 2012 and Gray and Malone, 2012 for discussions of the leading systemic risk measures). Rather, we view the lack of widespread adoption of systemic risk analytics by financial institutions as the result of three temporary, but surmountable, barriers:

» Given the proliferation of systemic risk measures and inconsistent guidance by regulators, it is unclear which metrics risk managers should invest valuable resources in to operationalize and monitor in real time.

» Financial institutions do not understand how systemic risk analytics relate to their day-to-day risk management practices in terms of the risk and balance sheet variables they routinely monitor.

» It is still unclear empirically how systemic risk analytics relate to the macroeconomic variables used to operationalize the stress-testing scenarios issued by regulatory authorities such as the Fed.

The SRM toolkit that we describe in this paper is a solution for surmounting each of these three barriers. Our approach draws upon two strands of the academic literature on systemic risk: those that focus on structural credit risk models as the basis for systemic risk modeling (Gray and Malone, 2008; Gray, Jobst, and Malone, 2010; and Gray and Malone, 2012), and those that focus on network models as the basis for quantifying systemic risk (Billio et al., 2012; Merton et al., 2013). The structural credit risk model approach is often referred to as contingent claims analysis, or CCA-based ap-

proach to systemic risk, and that is how we will refer to it in this paper. Our work could be characterized as a "network CCA" approach, because it uses CCA inputs but links them together using network technology.

With respect to the first hurdle stated above, grounding our systemic risk suite in credit risk analytic concepts such as default probabilities, asset volatilities and leverage allows us to harness the power and versatility of Moody's proprietary CreditEdge database, which provides Expected Default Frequency metrics for publicly traded companies around the world. An obvious benefit of this approach is lowering the cost of adoption for existing CreditEdge customers. Further, both the CCA-based and network approaches to systemic risk drive thinking on the topic at major international institutions and regulatory bodies. Examples of the influence of these strands of thought include: contributions to country work and Financial Sector Assessment Program reports at the International Monetary Fund[1]; research by the Office of Financial Research in the U.S. Treasury Department[2], as well as research outputs of the Bank of International Settlements[3]; and emphasis by the Bank of England[4] on such approaches. In a recent speech, Fed Chair Janet Yellen emphasized the importance of research on interconnectedness and systemic risk for drawing the appropriate lessons and policy implications from the events of the Global Financial Crisis (Yellen, 2013).

More specific language from Fed regulatory communications suggests the utility of a network approach in particular. For the too-big-to-fail financial institutions subject to the Large Institution Supervision Coordi-

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1   See Jobst and Gray (2013) and IMF (2011) for example policy applications of the Systemic CCA approach at the IMF.
2   The Bisias et al. (2012) survey, a joint OFR-MIT collaboration, is one of many examples of research contributions by the OFR that emphasize CCA-based or network-based approaches to systemic risk.
3   For example, Huang, Zhou and Zhu (2010) compute systemic risk measures using publicly available data for 19 bank holding companies using methods described in Huang, Zhou and Zhu (2009), whereas a more recent Bank for International Settlements working paper by Blasques, Bräuning and van Lelyveld (2015) presents a dynamic network model of the unsecured interbank lending market.
4   The paper by Gai, Haldane, and Kapadia (2011) uses a network approach to analyzing vulnerabilities in interbank lending networks.

nating Committee framework, as well as the large domestic and foreign banking organizations with $50 billion or greater in assets, the Fed issued guidance in December 2012 stating that it would henceforth employ a variety of macroprudential supervisory approaches, including:

> *"Using comparative and aggregate analysis to monitor industry practices, common investment or funding strategies, changes in degree or form of financial interconnectedness, or other developments with implications for financial stability." (Board of Governors of the Federal Reserve System, December 17, 2012, emphasis ours.)*

Further, pursuant to this guidance, the Fed and the FDIC now require financial firms to have resolution plans, or "living wills," which they jointly review relative to supervisory requirements. Two points of the Fed's guidance with respect to resolution plans stand out and make clear the potential utility of a framework that combines network analysis with credit risk in a dynamic setting. The first point relates to the

> *"Analysis of potential impediments to resolution, and actions to make the firm more resolvable or otherwise reduce its complexity and interconnectivity." (ibid.)*

And the second is the

> *"Analysis of whether the failure of a major counterparty would likely result in the material financial distress or failure of the firm." (ibid.)*

By modeling credit risk spillovers directly, the SRM provides tools that would be useful for addressing the above two requirements for resolution planning on the part of large banking organizations in the U.S. and potentially abroad.

With respect to adoption hurdle (2), we believe that a systemic risk framework based on credit risk concepts dovetails naturally with the core credit risk and counterparty

risk monitoring activities already undertaken by financial institutions. The EDF networks that we construct help banks answer questions such as:

> » How will my default risk respond to a credit event at another institution in the network with whom I have few direct financial ties?
> » Who are my three biggest counterparties' main counterparties?
> » Am I nearer to the core or the periphery of the financial network?
> » What is the average probability of default for the most connected institutions in the financial system today?

We believe that a proactive risk management function will find such questions worth answering even in the absence of regulatory requirements to do so, although the potential utility of such tools in light of recent regulatory guidance is clear. In Section 5, we show that the novel bank-specific systemic risk measures we develop in Section 3 add additional forecasting power, after controlling for initial EDFs, for predicting high credit risk realizations of U.S. financial institutions during the worst period of the financial crisis (February 2008-January 2009).

To address barrier (3), we present additional econometric results in Section 5 demonstrating that, for the U.S. financial system, SRM analytics are related to numerous CCAR variables via the existence of highly statistically significant Granger causal relationships. We show that time series SRM analytics compare favorably with the leading systemic risk measures from the literature studied by Giglio, Kelly and Pruitt (forthcoming), in terms of the prevalence of such relationships with CCAR variables. This finding holds both for Granger causality running from systemic risk measures to CCAR variables and Granger causality running in the other direction.

The aforementioned findings, that bank-specific SRM measures aid in forecasting

future credit risk in a period of stress and that robust dynamic links exist between systemic risk analytics and CCAR variables, suggest that the proposal of Hughes and Malone (2015) to "put systemic stress into the stress-testing system" is indeed a feasible proposition.

While the CCA and network approaches do not provide a *comprehensive* set of systemic risk measures, they do provide what we believe is an *effective* set of tools to capture aspects of systemic risk that are of critical importance to banks and regulators. When used in conjunction with other judiciously selected systemic risk measures, including measures related to equity volatility, credit spreads, and market leverage that perform well in the tests of Giglio, Kelly and Pruitt (forthcoming), we believe that the network CCA approach underlying the SRM has the potential to address several of the directives in Fed regulatory guidance issued since the enactment of the Dodd-Frank Wall Street Reform and Consumer Protection Act into law.

The rest of this paper is organized as follows. Section 2 discusses the methods behind SRM. Section 3 discusses the core inventory of systemic risk analytics produced by SRM. Section 4 presents primarily graphical results for three case studies: large institutions in the U.S. financial sector ("U.S."), ASEAN-5 financial institutions with a minimum of $1 billion in book assets ("ASEAN-5"), and global financial institutions with at least $100 billion in book assets ("Global Megabanks"). Section 5 presents evidence on the predictive value of SRM analytics for credit events during the Global Financial Crisis, as well as on Granger causal relationships between SRM measures and CCAR variables for the U.S. Section 6 uses SRM to reveal more granular insights on credit risk spillovers between selected pairs of financial institutions in the Global Megabanks network. This provides one example of how SRM may be used as a counterparty risk surveillance tool. Section 7 concludes.

Section 2: Terminology and methods

The primary goal of SRM is to assess the prevalence and magnitude of dynamic spillovers in default probabilities, asset volatilities, or leverage ratios across financial institutions in the user-defined network. Network models use one variable at a time. Thus, we may refer to the EDF network, the volatility network, or the leverage network, depending on which of these variables forms the basis of analysis. The primary variable of interest in this article will be the EDF measure, which is an estimate of the real world default probability of the financial institution at the one-year horizon. In the CreditEdge database, the EDF™ measure of real-world default probability is coded as "edf", asset volatility is coded as "CSG", and our measure of market leverage is computed as default-point/AVL, where "defaultpoint" is the CreditEdge reported value for the default point and "AVL" is the reported estimate of the market value of assets, both measured in local currency. In CreditEdge, the default point refers to the adjusted net present value of the firm's promised debt payments or, more precisely, to the level of assets at which it is assumed the firm will incur a default. All of our examples use EDF9 version data.

The default point, as described by Crosbie and Bohn (2003), is the market value of assets at which the firm is assumed to default. Empirically, they note, this point lies between the book value of short-term liabilities and the book value of total liabilities. As described in Gray and Malone (2008), the default point is sometimes approximated as the value of short-term liabilities plus one-half of the value of long-term liabilities, where future bond cash flows are discounted at the risk-free rate.

In the Merton (1974) model, which forms the basis of the structural credit risk modeling literature, the risk-neutral default probability is a function of the firm's asset volatility and leverage. In this setup, given the firm-market asset return correlation, the market price of risk, and the firm's risk-

neutral default probability, it is straightforward to calculate the real-world probability of default for a given time horizon (Dwyer et al., 2010). In the setup where firm assets are assumed to follow a geometric Brownian motion whose drift equals the risk-free rate, the risk-neutral probability of default equals the cumulative normal distribution function evaluated at minus one times the distance-to-default measure.

Rather than translate the risk-neutral probability of default to the physical measure via use of the market price of risk, the CreditEdge methodology uses extensive historical data on firm defaults to map the distance-to-default directly to the EDF measure of real-world default probability via lookup tables (Crosbie and Bohn, 2003).

SRM outputs, which we will describe in detail in Section 3, take the form of bank- and industry-level measures of the extent to which statistically significant Granger causal connections can be identified between pairs of banks. The basic model will involve estimating bivariate vector auto-regression models of the form

$$Y_t = a^1 + \sum_{j=1}^{p} b_j^1 Y_{t-j} + \sum_{j=1}^{p} c_j^1 X_{t-j} + \varepsilon_t^1$$

$$X_t = a^2 + \sum_{j=1}^{p} b_j^2 Y_{t-j} + \sum_{j=1}^{p} c_j^2 X_{t-j} + \varepsilon_t^2$$

where Y_t and X_t contain the variable of interest (EDF, volatility or leverage) for a given pair of banks at time t and the off-diagonal coefficients (the c_j^1s and b_j^2s) measure the extent to which lagged observed outcomes for one bank are partially correlated with the outcomes for the other bank. If the relevant F-test of the c_j^1s is significant at the 5% level, we will say that X Granger-causes Y, whereas if the relevant F-test of the b_j^2s is significant at the 5% level, we will say that Y Granger-causes X.

If the estimated one-month lag coefficient in an equation is significant and positively signed, we say that a "forcing" Granger causal link exists. The implication here is that positive shocks to the default probability of one bank increase the default probability of the other bank in the future. This is one important channel through which systemic risk operates: The presence of significant credit risk spillovers creates the possibility for damaging credit risk cascades to occur, and analyses that focus on traditional measures of counterparty or credit risk exposures may miss this possibility.

Conversely, negative b and c coefficients in the VAR equations signify the existence of "damping" Granger causal connections. In such damping connections, one bank appears to benefit, via a lower future default probability, from the misfortune that befalls its competitor in the form of a positive shock to the competitor's current EDF level. This latter type of linkage, if highly prevalent, can act as an antidote to the normally insidious forms of systemic risk.

In general, the existence of a forcing or damping relationship of one bank's EDF on another bank's EDF can be established by observing the sign and statistical significance of the cumulative impulse-response coefficient at the horizon of interest. Since the impulse-response coefficient at the one-month time horizon is determined by the coefficient on the one-month lag of the impulse variable, we use the latter to determine the existence of forcing and damping relationships at the one-month horizon. We focus on the one-month horizon because we find that forcing relationships at this horizon are important empirically, but using another horizon would simply require using the cumulated impulse-response function coefficient in place of the one-month lag coefficient.

We will have more to say about forcing and damping relationships in our analysis of the U.S. financial sector in Section 4.

Section 3: Outputs

The key outputs of the framework fall into three categories. The first consists of classic network measures such as the degree of Granger causality; the In, Out, and In.plus.Out measures; and the Closeness measure defined in Billio et al. (2012). We provide equations for each of these measures below. Note that the DGC measure we report is different from that of Billio et al. (2012), as the latter is based on equity returns, whereas our setup focuses on the EDF measure of the probability of default.

The second category of measures consists of novel variations on classic network measures such as Out.plus, Out.minus, In.plus, In.minus and Net.degree.of.forcing. These measures are, to our knowledge, new to the literature.

The third category of measures involves weighted average CreditEdge variables, in particular weighted average EDF, volatility, and leverage measures, where weights are related to a measure of asset size, or to a measure of systemic influence. We report cross-sectional correlation measures, which illustrate how the relationship between selected pairs of measures in the cross section of banks varies over time. The two correlations we focus on are the EDF-Out rank correlation and the Volatility-Leverage rank correlation.

We also compute the time-varying beta sensitivities of individual bank EDFs to the weighted average EDF measures via the use of rolling regressions. We now elaborate on each of these categories of measures.

Classic network measures: DGC, In, Out, In.plus.Out, Closeness

To determine the strength of dynamic linkages between institutions over time, we compute the degree of Granger causality measure described in Billio et al. (2012) for each month of out-of-sample data. The procedure we use to compute the DGC measure, and the damping, forcing, and net forcing variations of that measure we will describe momentarily, is as follows.

First, for the set of $N(t)$ financial institutions in the system that exist and have sufficient data at a given point in time, we run the $\binom{N(t)}{2}$ bivariate vector autoregression models involving each unique pair of institutions, using a two-month lag length, $p=2$, and a 60-month rolling window of EDF data. We compute the adjacency matrix $A(t)$, defined as $[A(t)]_{ij} = 1$ if institution i Granger-causes institution j, and $[A(t)]_{ij} = 0$ otherwise. Granger causality of institution j by institution i occurs when the relevant F-test of the coefficients of the first and second lags of institution i's EDF in the equation for institution j's EDF is significant at the 5% level. The measure $DGC(t)$ is computed as

$$DGC(t) = \frac{1}{N(t)(N(t)-1)} \vec{1}^T A(t) \vec{1}$$

where $\vec{1}^T A(t) \vec{1}$ is the sum of the elements, or total number of active connections in the Granger causality network, at time t, and $N(t)(N(t)-1)$ is the total number of possible connections that could be active in the network at time t. Thus, the DGC measure lies between zero and 1 and gives the fraction of possible Granger causal linkages that are active in the system at a given time.

The Out measure captures the extent of downstream linkages for a given institution and is equal to the fraction of the other institutions in the network Granger-caused by the institution in question. The measure $Out(i,t)$ for institution i at time t is computed as

$$Out(i,t) = \frac{1}{N(t)-1} [A(t)\vec{1}]_i$$

The In measure captures the extent of upstream linkages and is equal to the fraction of other institutions in the network that Granger-cause the institution of interest. The measure $In(i,t)$ for institution i at time t is computed as

$$In(i,t) = \frac{1}{N(t)-1} [\vec{1}^T A(t)]_i$$

The In.plus.Out measure simply averages the In and Out measures for a particular institution:

$$In.plus.Out(i,t) = \frac{In(i,t) + Out(i,t)}{2}$$

The In.plus.Out measure is interpreted as the fraction of all possible upstream or downstream connections that are active for the institution in question.

The Closeness measure for an institution is the average length of the shortest path from that institution to each of the other institutions in the network. To compute Closeness, we first define the notion of weakly causal C-connection: node i is weakly causal C-connected to j if there exists a path of length C between i and j in the form of a sequence of nodes $k_1, \ldots, k_{C-1}$ such that

$$(i \xrightarrow{C} j) \equiv [A(t)]_{ik_1} \times [A(t)]_{k_1 k_2} \times \cdots \times [A(t)]_{k_{C-1}j} = 1$$

Define the matrix $C(t)$ by:

$$C_{ij} \equiv \min_C \left\{ C \in [1, N(t)-1] : \left(i \xrightarrow{C} j\right) = 1 \right\},$$

for $i \neq j$, where we set $C_{ij} = N(t) - 1$ if $\left(i \xrightarrow{C} j\right) = 0$ for all $C \in [1, N(t)-1]$. By convention we set $C_{ii} = 0$ for all i.

Then the Closeness measure for institution i at time t is defined as:

$$Closeness(i,t) \equiv \frac{1}{N(t)-1} [C(t)\vec{1}]_i$$

There are other potential conventional network measures we can compute given the adjacency matrix of a network graph such as betweenness, transitivity, eigenvector centrality and reciprocity, but we opt to defer discussion of these and other network analytics such as formal analysis of clusters and the similarity between any pair of bank nodes to later work.

Novel network measures: Forcing and damping Granger causality

We now introduce measures that are novel to the literature on financial networks

that we find to be especially useful in predicting credit events during periods of financial crisis. We construct our measures using information on the coefficient of the first lag of the other-bank endogenous variable in our bivariate VAR models from Section 2. In principle, we could focus on the impulse-response function at any horizon of interest, but we choose to focus only on the first lag coefficients (or equivalently, the one-month-ahead impulse-response coefficients) because the measures derived from these demonstrate very good empirical properties in the tests we present in Section 5.

In analogy to an oscillator in physics, the relationships between any pair of financial institutions in the network may be forcing or damping in nature. Forcing relationships are characterized by positively signed coefficients for the effect of institution X on institution Y in the next month. Such relationships propagate positive shocks to the endogenous variable of one institution downstream to all the other institutions that it affects. Conversely, damping relationships are characterized by negatively signed coefficients for the effect of institution X on institution Y in the next month. Damping relationships tend to reduce the downstream effect of the initial positive shock to an institution on the rest of the system. We find that most relationships are of the forcing kind, although the extent of both relationships goes up during crisis periods. Forcing- and damping-style measures can be constructed by specifying alternative definitions of the adjacency matrix that correspond to each concept, respectively.

For forcing relationships, we use the $A^+(t)$ matrix. Let the $A^+(t)$ matrix be defined as $[A^+(t)]_{ij} = 1$ if the positive one-sided t-test of the one-month lag coefficient for institution i in the model of institution j is significant at the 2.5% level, and $[A^+(t)]_{ij} = 0$ otherwise. That is,

$$[A^+(t)]_{ij} = 1 \text{ iff } c_1^1/se(c_1^1) > t^*_{p=.975, df=W-2p-1}$$

in the model of bank j=Y on bank i=X, where W is the size of the rolling window used for estimation. Analogously, for

damping relationships we define the matrix $A^-(t)$ as

$$[A^-(t)]_{ij} = 1 \text{ iff } c_1^1/se(c_1^1) < -t^*_{p=.975, df=W-2p-1}$$

in the model of institution j=Y on institution i=X. Having defined the $A^+(t)$ and $A^-(t)$ adjacency matrices, we may compute the following institution-specific, time-varying measures that serve as analogues to the Out and In measures encountered above:

Out.plus:

$$Out.plus(i,t) = \frac{1}{N(t)-1}[A^+(t)\vec{1}]_i$$

Out.minus:

$$Out.minus(i,t) = \frac{1}{N(t)-1}[A^-(t)\vec{1}]_i$$

In.plus:

$$In.plus(i,t) = \frac{1}{N(t)-1}[\vec{1}^T A^+(t)]_i$$

In.minus:

$$In.minus(i,t) = \frac{1}{N(t)-1}[\vec{1}^T A^-(t)]_i$$

Additionally, analogues to the DGC time series can be computed based on forcing and damping relationships, respectively:

DGC.forcing:

$$DGC.forcing(t) = \frac{1}{N(t)(N(t)-1)}\vec{1}^T A^+(t)\,\vec{1}$$

DGC.damping:

$$DGC.damping(t) = \frac{1}{N(t)(N(t)-1)}\vec{1}^T A^-(t)\,\vec{1}$$

The difference between these two measures gives the net degree of forcing relationships in the network at a given time.

Net.degree.of.forcing:

$$Net.Degree.of.Forcing(t)= DGC.forcing(t)-DGC.damping(t)$$

Weighted average measures, cross-sectional correlations, and betas

We compute weighted average EDF, volatility, and leverage measures using size and systemic importance weights. These provide system-wide, time-varying measures of the EDF and its drivers. As an example, if $BAusd(i,t)$ is the value of book assets for institution i at time t, then the size-weighted average EDF measure is computed as

$$EDF^{SizeWA}(t) = \frac{\sum_{i=1}^{N(t)} EDF(i,t)\,BAusd(i,t)}{\sum_{i=1}^{N(t)} BAusd(i,t)}$$

where the weight for institution i is equal to the value of its book assets measured in U.S. dollars as a fraction of the sum total of book assets measured in U.S. dollars of all the institutions in the network at time t. The Out-weighted average EDF measure is computed as

$$EDF^{OutWA}(t) = \frac{\sum_{i=1}^{N(t)} EDF(i,t)\,Out(i,t)}{\sum_{i=1}^{N(t)} Out(i,t)}$$

Equivalent weighted average measures for volatility and leverage are computed similarly. In Section 4, we display plots of size and systemic influence weighted average EDF, volatility, and leverage for different networks. Our systemic influence weighted average measure is defined as

$$EDF^{SysIWA}(t) = \frac{1}{3}\Big(EDF^{OutWA}(t) + EDF^{Out.plusWA}(t) + EDF^{InvClosenessWA}(t)\Big)$$

Here $EDF^{Out.plusWA}(t)$ is computed by replacing $Out(i,t)$ with $Out.plus(i,t)$ in the Out-weighted average EDF formula, and $EDF^{InvClosenessWA}(t)$ is computed by replacing $Out(i,t)$ with $1/Closeness(i,t)$ in the Out-weighted average EDF formula. The rationale behind the systemic influence-weighted EDF index is to take advantage of information in three types of measures for systemic risk. The Out measure was shown to have predictive properties for banks in the Global Financial Crisis by Billio et al. (2012). We show in Section 5 that the Out.plus measure appears to react more quickly

prior to adverse events and have better predictive power than the Out measure in the samples we consider, and the inverse closeness weights incorporate information on another dimension of systemic risk, namely the average closeness to the rest of the institutions in the network.

The primary cross-sectional correlations we track are the Spearman rank correlations between the EDF measure and the Out measure by bank, which we label *EDF-Out.spearman*, and the Spearman rank correlation between bank leverage and bank asset volatility, which we label *Leverage-Vol.spearman*.[5] The EDF-Out correlation tells us the extent to which default risk, measured by EDF, and systemic risk contribution, measured by Out, are aligned at a given point in time. When the correlation is positive, the interpretation is that firms that have higher credit risk are contribut-

ing disproportionately to systemic risk in the network compared with low credit-risk firms. The Leverage-Vol.spearman measure, on the other hand, allows us to track the relationship between bank leverage and asset volatility in the cross section of banks. If, as in the setup of Adrian and Shin (2014), banks follow an exact value-at-risk rule, where financial intermediaries keep their book equity matched with their VaR at some given confidence level, we should find that increases in asset volatility that raise the VaR are met by decreases in book leverage on the part of the bank. If book leverage is positively correlated with market leverage in the cross section, then we should find a negative cross-sectional correlation between bank asset volatility and bank market leverage. This is indeed what we find in the data for all three networks we examine. The time variation in the cross-sectional correlation between market leverage and volatility, however, is potentially informative about the state of the financial system. As the

correlation becomes weaker (moves toward zero), we can infer that there is likely more dispersion in the equity VaRs of different banks in the cross section.

Finally, the SRM computes rolling time series (elasticity) betas of bank-specific risk measures such as the (log) EDF with respect to selected systemic risk measures such as the (log) Out-weighted average EDF of the system. As in the asset-pricing literature, beta sensitivities in the cross section can be used to sort institutions at a given date and future outcomes for each institution related to its beta sensitivity or beta sensitivity rank on an initial date of interest. We apply this approach to forecasting future credit risk events, modeled as exceedances of high (10%) EDF thresholds during the next 12 months, for a cross section of U.S. banks in January 2008. Beta sensitivities have substantial forecasting power after controlling for initial EDFs. We report the results of this forecasting exercise for our leading bank-specific measures in Section 5.

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5   We also compute Pearson and Kendall correlations, but we do not report them here.

Section 4: Case studies

We divide our empirical results into case studies and econometric validation of SRM metrics, with this section devoted to the case studies. For all of our empirical analyses, we begin with a master dataset of financial institutions (institutions with a Standard Industrial Classification code between 6,000 and 6,799) from around the world. The particular network of interest is then determined by specifying the geographical location(s) and minimum book asset thresholds of the institutions to be included. Our data are sourced entirely from CreditEdge, and therefore the only requirement for an institution to be included in our dataset is that it must have traded equity and public financial statements with which to calculate EDF measures.

Although we can implement our methodology for all firms in the database globally, the three network-scopes we focus on are as follows: Dodd-Frank Act stress-testing-size financial institutions in the U.S. with book assets of $10 billion and above, ASEAN-5 region institutions with book assets of $1

billion and above, and the set of all global financial institutions with book assets exceeding $100 billion. The major crisis periods and events in all of these networks are the Asian crisis of 1997-1998, the Russian default and Long-Term Capital Management implosion in 1998, the bursting of the dot-com bubble in 2000, the Argentina default in late 2001, the Global Financial Crisis from 2007-2009, and the European sovereign debt crisis from late 2009-2012. Of all of these, the Asian crisis and the Global Financial Crisis stand out as particularly turbulent periods that had an outsize impact on global capital markets. The ASEAN-5 and U.S. network studies, respectively, allow us to focus on the regions of origins for these crises. The Global Mega-banks network study allows us to focus on the international set of financial institutions whose asset size almost automatically places them into the global systemically important financial institution category and assess the relative impact of different crisis events on the evolution of their systemic risk measures.

4.1 Case Study: U.S.

Table 1 displays the top 15 CCAR-size U.S. financial firms—firms with book assets exceeding $50 billion—as ranked by their Out measure as of October 2014. Discover Financial Services Inc. and the Intercontinental Exchange are of particular note since they have very high Out quantiles as well as being large and possessing EDF values at the 42nd and 54th percentiles, respectively, among all EDFs of institutions in the network. By the same token, Genworth Financial Inc. draws attention because its Out, EDF and size quantiles are all greater than or equal to 84%. When a moderate or high credit risk manifests itself in large, highly connected firms, it is a reasonable cause for increased scrutiny on the part of regulators, according to the guidance the Fed has offered to financial firms following the passage of Dodd-Frank (see Board of Governors of the Federal Reserve System, December 17, 2012).

The institutions shown in Table 1 are pre-screened by size. In the entire U.S. network

Table 1: Top 15 CCAR-size U.S. Firms Ranked by Out Measure as of October 2014: U.S. Network*

Financial Institution	Out		EDF		Book Assets	
	Value	Quantile	Value (%)	Quantile	Value ($ mil)	Quantile
Discover Financial Services Inc.	0.39	0.96	0.25	0.42	78,937	0.79
Chubb Corp.	0.37	0.95	0.18	0.21	51,440	0.72
Loews Corp.	0.36	0.93	0.11	0.05	82,894	0.80
Intercontinental Exchange	0.34	0.93	0.29	0.54	68,482	0.78
U.S. Bancorp	0.34	0.92	0.17	0.18	389,065	0.93
Northern Trust Corp.	0.32	0.91	0.23	0.36	105,761	0.83
BB&T Corp.	0.32	0.91	0.22	0.35	188,012	0.89
Allstate Corp.	0.31	0.90	0.16	0.16	110,233	0.84
Travelers Cos. Inc.	0.27	0.86	0.2	0.27	104,811	0.83
Genworth Financial Inc.	0.26	0.85	0.5	0.86	111,644	0.84
Annaly Capital Management	0.23	0.82	0.25	0.41	87,151	0.81
Protective Life Corp.	0.22	0.80	0.37	0.73	71,158	0.79
Cigna Corp.	0.21	0.78	0.16	0.15	55,929	0.74
Blackrock Inc.	0.20	0.78	0.54	0.88	231,693	0.90
UnitedHealth Group Inc.	0.20	0.77	0.11	0.06	85,466	0.80

*Ranking by Out value in U.S. network for the subset of institutions with book asset values exceeding $50 billion.
Source: Moody's Analytics

of institutions with $10 billion in assets and above, however, we find that as of October 2014, the Spearman correlation between book asset value and the Out measure across institutions was a mere 0.02. In January 2008, the correlation was also 0.02, and in January 2009, the correlation was 0.11. The correlations we obtain after replacing Out by Out.plus are nearly identical. Thus, book asset size and systemic influence do not appear to be strongly related in the cross section of firms, even in periods of significant market stress. We will see this result echoed in the case studies for Southeast Asia and the set of Global Megabanks. The robustness of this finding across time and geographic regions

provides strong evidence that regulating SIFIs based on their size alone is likely to be a flawed approach with a low chance of avoiding a spike in systemic risk during future crisis periods.

Chart 1 displays the weighted average EDF measures for the U.S. network over time. The two series shown are the size-weighted average EDF and the systemic influence-weighted average EDF.

Using 1% and 2% EDF thresholds as warning signals, a history of credit risk in DFAST-size U.S. banks emerges. The size-weighted average EDF barely breached the 1% threshold in January 1991, in the savings and loan crisis, before falling. It again

breached the 1% threshold in September 2000, following a sequence of capital market shocks that included the Asian crisis, LTCM's implosion, the Russian default, and the bursting of the dot-com bubble. The size-weighted average EDF breached the 2% threshold in September 2001 after the September 11 terrorist attacks and remained high until passing the 4% threshold in March 2008, following the onset of the Global Financial Crisis. From there, it spiked until reaching its apex of 14.3% in February 2009, from which point it has continued to fall, albeit with a recent uptick in late 2014. The systemic influence-weighted average EDF tracks the size-weighted EDF until 2000, is
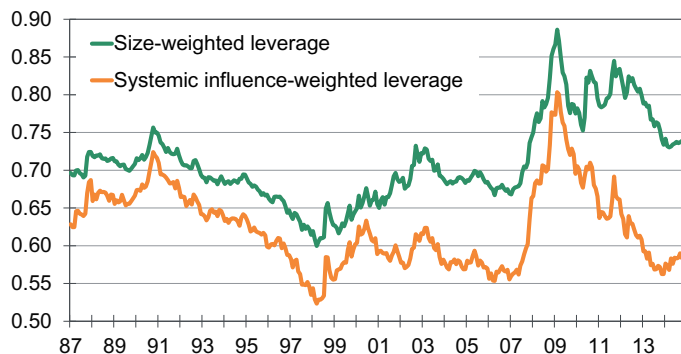
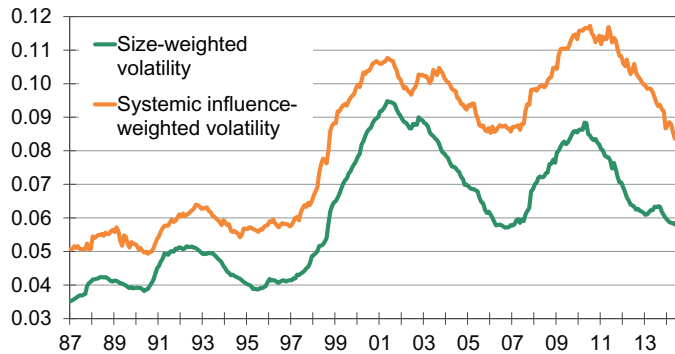## Chart 1: U.S. EDF Measures
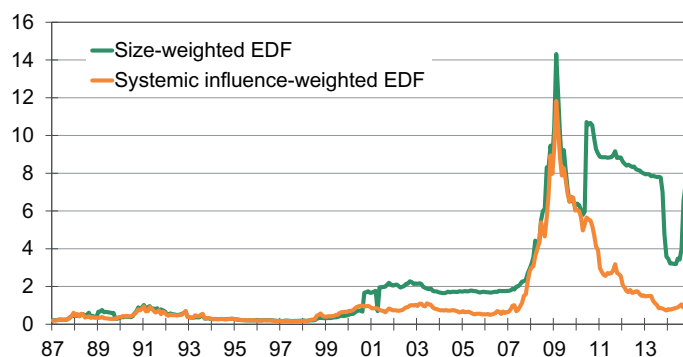
Source: Moody's Analytics

Chart 2: U.S. Degree of Granger Causality

Source: Moody's Analytics

Chart 3: Default Point/AVL in U.S. Network

Source: Moody's Analytics

Chart 4: Asset Volatility in the U.S. Network

Source: Moody's Analytics

substantially less than the latter series during the Great Moderation from 2000-2005 and the post-crisis period from 2010-present, and closely tracks the size-weighted series during the 2006-2009 period that includes the Global Financial Crisis.

To put the preceding results in context, Chart 2 shows the DGC of the EDF network for the U.S. over time. The spike in the first period of the sample, from 1987 to the early 1990s, corresponds with the savings and loan crisis in the U.S. and is very similar to the DGC for the Global Megabanks network during the same (and other) periods. Indeed, the remaining spikes and plateaus of the DGC measure for the U.S. correspond to major domestic and international crises. There is a brief spike for the Exchange Rate Mechanism crisis of 1993, a spike corresponding to the Tequila crisis in 1994, a major runup in the series from 1997-2000 that corresponds with the multiple shocks that occurred during that period, and a historically unprecedented trough-to-peak increase in the series from a nadir in early 2005 to a historical high of 0.35 in March 2009. The final spike in the series corresponded to the Taper Tantrum in 2013, and the DGC has since fallen to very modest levels.

Charts 3 and 4 display the evolution of weighted average leverage and asset volatility, respectively, in U.S. financial institutions over time. The measure of leverage we employ at the bank level is the default point divided by the estimated market value of bank assets. Both concepts are sourced from CreditEdge, as is the volatility measure, which captures the volatility of firm asset growth.

From Chart 3, we see that both size-weighted leverage and systemic influence-weighted leverage peaked at the height of the financial crisis. Since that time, size-weighted leverage has remained quite high by historical standards, while systemic influence-weighted leverage has fallen to low levels. The main systemically weighted leverage peaks in the series occurred in the early 1990s after the S&L crisis and in 2000, following the bursting of the dot-com bubble and the events of the Asian crisis, the LTCM implosion, and the Russian default.

Systemic influence-weighted average asset volatility, shown in Chart 4, is everywhere greater than size-weighted average asset volatility. Institutions that contribute the most to systemic risk tend to have more volatile assets on average than large institutions. Subject to this rule, the two weighted-average volatility measures are highly correlated over time, with peaks occurring at roughly the same points in time with minor differences in timing. The early 2000s and 2010 stand out as major historical peaks in bank asset volatility. The chief difference is that size-weighted average volatility achieved its historical high in the early 2000s, whereas systemically important institutions

achieved historically high volatility in 2010 after the conclusion of the Global Financial Crisis. In general, as we will see in the other case studies, volatility tends to build up over time as crisis events unfold, and peaks in volatility lag salient crisis events, whereas leverage tends to spike around the time that crisis events occur as firms' asset prices adjust more quickly than debt obligations in such situations.

Chart 5 displays the EDF-Out and Leverage-Volatility correlations over time for the U.S. network cross section. The correlations are Spearman rank correlations, computed at each time point using the cross section of values corresponding to the banks in the network in the month in question. A clear pattern emerges, in which the EDF-Out correlation rises above zero during periods of significant stress to the financial system. During these periods, including in particular the Global Financial Crisis, high-EDF firms

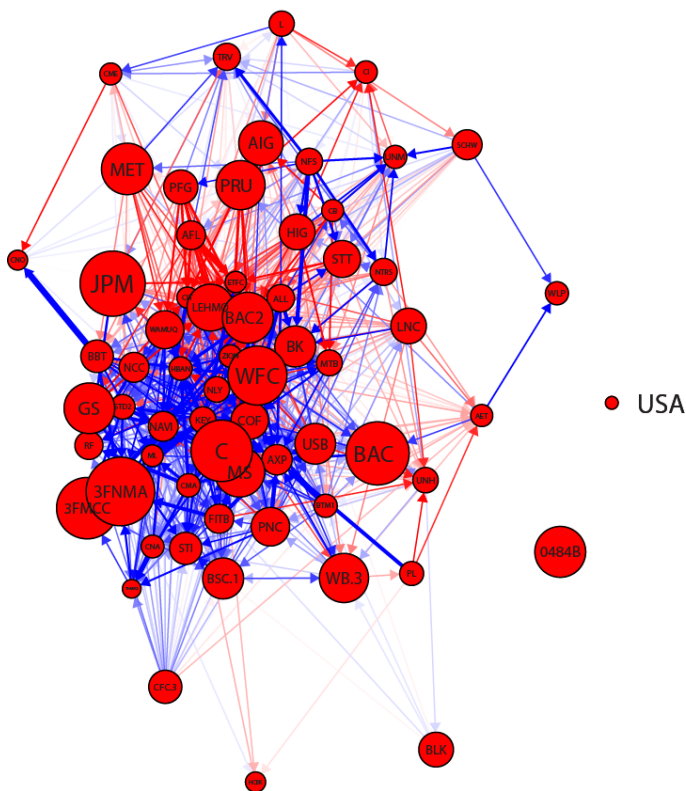## Chart 5: Cross-Sectional Correlations

Spearman correlation coefficients vs. time, U.S.
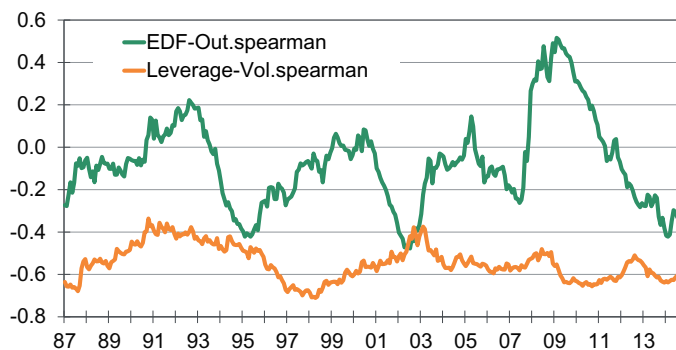
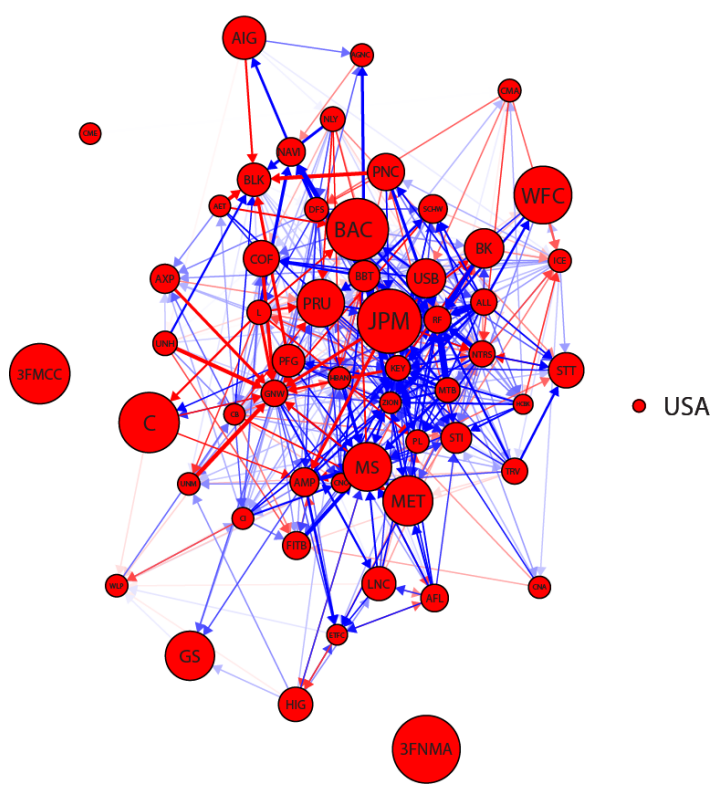Source: Moody's Analytics

Chart 6: U.S. Network
Financial institutions, EDF network VAR coefficients Jan 2008

Source: Moody's Analytics

Chart 7: U.S. Network
Financial institutions, EDF network VAR coefficients Oct 2014

Source: Moody's Analytics

drive the propagation of shocks to credit risk in the network.

Chart 6 displays the graph of the U.S. network in January 2008, with the same graph for October 2014 displayed in Chart 7 for comparison. The bubble size is proportional to the logarithm of the asset size of the corresponding bank. Blue arrows denote forcing relationships, whereas red arrows denote damping relationships, with arrows pointing to the institutions being Granger-caused (or more precisely in this case, whose EDF is the dependent variable in the model). We see that Bank of America and JP Morgan are very central in October 2014. This is not surprising since Bank of America acquired Countrywide Financial and Merrill Lynch in 2008, at the height of the financial crisis, and JP Morgan acquired Bear Stearns and Washington Mutual in the same year. Managing the legacy assets of the acquired firms, all of which were highly visible casualties of

the crisis, has presented challenges for both acquiring banks, which remain in the focus of markets for these reasons.

As Chart 6 makes clear, Lehman Brothers, Washington Mutual and Merrill Lynch were all very central in the network in January 2008. The number of forcing relationships was also very high at that time compared with the moderate level we observe in October 2014, a fact that is reflected in the relative density of the graph in Chart 6 versus the graph in Chart 7. Interestingly, as can be seen in the graph for January 2008, major insurance companies such as Prudential, MetLife, and Aflac exhibited multiple significant damping relationships toward several of the banks at the heart of the financial crisis. This finding is consistent with a buffer role for major insurers, in which increases in their credit risk signal transfer of risk or losses to their balance sheets off the balance sheets of insured counterparties. Finally, although

Wells Fargo acquired Wachovia in 2008, we see that it moved to the periphery of the network as of October 2014.

4.2 Case Study: ASEAN-5

In Southeast Asia, measuring and understanding the potential impact of systemic risk became an imperative after the Asian financial crisis of 1997-1998. The crisis began in Thailand in July 1997 and quickly spread to Malaysia, Indonesia, Korea and the Philippines. Singapore, a regional financial hub with an open economy, was affected as well. The crisis had a significant impact on these countries' economies. In one year, a decade of extremely strong economic growth—the East Asian Miracle—was in jeopardy. Between June 1997 and March 1998, GDP contracted by nearly 6% in Korea, 9% in Thailand, and 14% in Indonesia. Equity valuations plummeted by 50% or more in the affected countries (Berg, 1999). Assessing systemic

risk has been a key part of financial supervision in the region ever since.

In addition to regulators' and central banks' increased focus on systemic risk in the wake of the crisis (Kawai and Morgan, 2012), the International Monetary Fund and the World Bank jointly initiated the Financial Sector Assessment Program in 1999 to assess financial stability and perform stress-testing of countries' financial sectors. These initiatives have been credited with helping Southeast Asian countries weather the worst of the Global Financial Crisis and avoid a repeat of the economic devastation caused by the Asian financial crisis.

The analysis that follows presents our results on systemic risk in the Southeast Asian financial system during the last 20 years. We draw heavily on our exposition of these same results in Hamilton, Hughes and Malone (2015), our companion paper on the topic in *Moody's Analytics Risk Perspectives*.

The results of our empirical analysis are based on a dataset of financial institutions domiciled in the ASEAN-5 group of countries, which comprises Indonesia, Malaysia, the Philippines, Singapore and Thailand. We limit our dataset to financial institutions with at least $1 billion in book assets observed at some point over their available histories. Our sample begins in 1995, runs through October 2014, and includes 201 unique financial institutions in the ASEAN-5 countries: 36 in Indonesia, 49 in Malaysia, 30 in the Philippines, 46 in Singapore, and 40 in Thailand.

As a preview to our visual outputs, the main results of our ASEAN-5 analysis can be summarized as follows: (i) weighted-average default probabilities for highly connected institutions are consistently higher than those of large institutions as measured by asset size; (ii) both size and systemic influence weighted-average EDF measures spiked during the Asian financial crisis but displayed only a small uptick during the Global Financial Crisis; (iii) the overall level of connectedness in the ASEAN-5 network spiked during both crisis periods; (iv) the spike in default probabilities during the Asian financial crisis was primarily the result of a spike in leverage rather than a spike in asset volatility; (v) default risk and contributions to systemic risk are positively correlated across institutions in times of crisis; and (vi) the strongest mutually reinforcing relationships in the region currently appear to exist between Thailand and Singapore, and Thailand and Malaysia.

As a first piece of evidence, Table 2 shows the 10 financial institutions with the highest Out measures as of October 2014 and includes their Out measures, their EDF values, and the value of their book assets in U.S. dollars. TMB Bank Public Co. Limited, based in Thailand, exhibits the highest Out measure. The value of the Out measure indicates that the bank's EDF movements Granger-cause EDF movements in 30.6% of the other financial institutions in the network. Notably, the statistics shown in Table 2 suggest that systemic risk (measured by Out) bears little correlation with either the probability of default or with firm size, on average. The correlation between EDF and the Out measure across financial firms in the ASEAN-5 financial network was actually negative in October 2014, as we will see shortly in Chart 12.

The third and fourth columns show the firm's EDF quantile and book-asset quantile out of the 122 firms present in the network in October 2014. It is also notable that half of the 10 firms with the highest systemic risk measures as of October 2014 are based in Thailand and are about average with respect to their EDF levels as well as book-asset size. Most of the firms in the top 10 list are banks, but the rest are in the broker-dealer, real estate, infrastructure and insurance sectors.

The results shown in Charts 8 and 9 bring the impact of the 1997-1998 Asian Financial Crisis into sharp focus. Chart 8 shows the weighted average EDF level for the ASEAN-5 countries over time. We weight the historical EDF values using book assets (size) and by systemic influence (defined in Section 3). By either measure, the risk of default reached a historic peak during the Asian financial crisis. The average risk dropped sharply after 1998 but trended higher during the early 2000s

Table 2: Top 10 Firms Ranked by Out Measure as of October 2014, With EDF Level and Firm Size: ASEAN-5 Network

| Financial Institution	Country	Out		EDF		Book Assets	
		Value	Quantile	Value (%)	Quantile	Value ($ mil)	Quantile
TMB Bank Public Co. Limited	THA	0.306	1	0.28	0.34	24,568	0.8
OSK Holdings Berhad	MYS	0.281	0.99	0.09	0.03	880	0.07
Bank of the Philippine Islands	PHL	0.264	0.98	0.39	0.59	28,868	0.81
UOB-Kay Hian Holdings Limited	SGP	0.256	0.98	0.30	0.4	2,079	0.38
CIMB Thai Bank Public Co. Limited	THA	0.248	0.97	0.33	0.49	7,798	0.61
CitySpring Infrastructure Trust	SGP	0.24	0.96	0.11	0.09	1,513	0.24
Bangkok Land Public Co. Limited	THA	0.24	0.95	0.08	0.02	1,697	0.3
Hong Leong Capital Berhad	MYS	0.231	0.94	0.34	0.51	951	0.08
Bangkok Life Assurance PCL	THA	0.231	0.93	0.34	0.52	6,259	0.56
Bangkok Bank Public Co. Limited	THA	0.231	0.93	0.24	0.23	78,431	0.95

Source: Moody's Analytics

Chart 8: ASEAN-5 EDF Measures
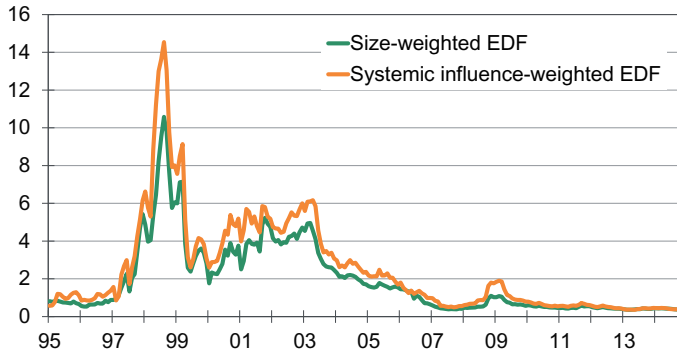
Source: Moody's Analytics

Chart 9: ASEAN-5 Degree of Granger Causality
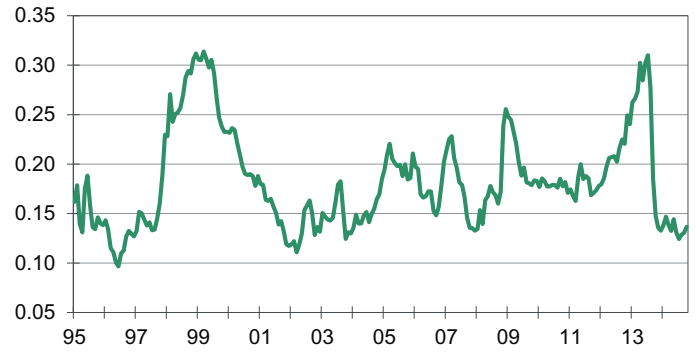
Source: Moody's Analytics

as the dot-com bubble burst, resulting in a recession in the U.S. and Argentina defaulting on its foreign debt. The Global Financial Crisis, as severe as it was in the West, is a relatively minor blip in the time series for the ASEAN-5 nations.

Chart 9 shows the DGC measure for the network at each point in time. In this one graph, we get a panoramic view of how systemic risk has evolved for ASEAN-5 financial institutions over the past 20 years. The strength of interconnectedness among financial institutions and the high risk of contagion that characterized the Asian financial crisis is captured by the peak 0.31 DGC measure. The graph also shows that it took at least four years for systemic risk to subside to levels that prevailed before the Asian financial crisis. Although economic growth in the countries most affected by the crisis bounced back strongly after 1998, our results on systemic risk corroborate other macro-

financial indicators showing that their financial systems and economies took a number of years to fully heal. The DGC time series in Chart 9 attests to the fact that the hazard of credit risk spillovers arising from the Global Financial Crisis was virtually a nonevent for the ASEAN-5 group. Although registering a brief spike, the DGC measure continued to fluctuate around the 0.18 average that prevailed after the Asian financial crisis. In contrast, the DGC measure for DFAST-size U.S. financial institutions reached a peak of 0.35 at the height of the Global Financial Crisis. Intriguingly, systemic risk as measured by the DGC reached its highest level since the Asian financial crisis in July 2013. However, systemic risk has subsided considerably since that date, falling to its lowest level in 20 years.

Chart 10 reinforces our historical understanding of the role of leverage as one of the key causes of the Asian financial crisis.

Here, leverage is defined as the ratio of a firm's default point to the market value of its assets. As in Charts 8 and 9, we calculate two weighted average measures of leverage: book asset (size)-weighted and systemic influence-weighted. Size-weighted leverage is nearly always higher than systemic influence-weighted leverage, in some time periods by a considerable margin. The implication is that larger financial institutions lever up more; this finding is consistent with data for U.S. financial institutions in the previous subsection as well as recent findings by Gandhi and Lustig (2015).

A second, and perhaps more important, implication is that a firm's size is not perfectly correlated with the spillover dimension of systemic risk contribution. Chart 11 shows size- and systemic influence-weighted average asset volatility over time. Unlike average EDF levels and leverage values, the weighted volatility measures rise throughout but peak

Chart 10: Default Point/AVL in ASEAN-5 Network
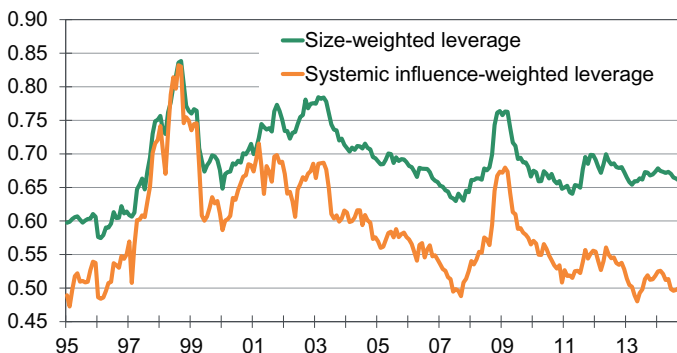
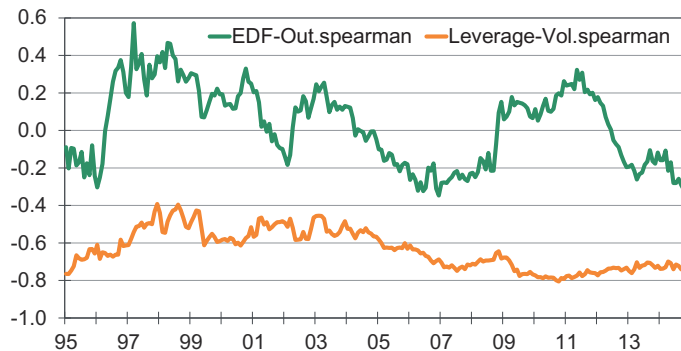Source: Moody's Analytics

Chart 11: Asset Volatility in ASEAN-5 Network
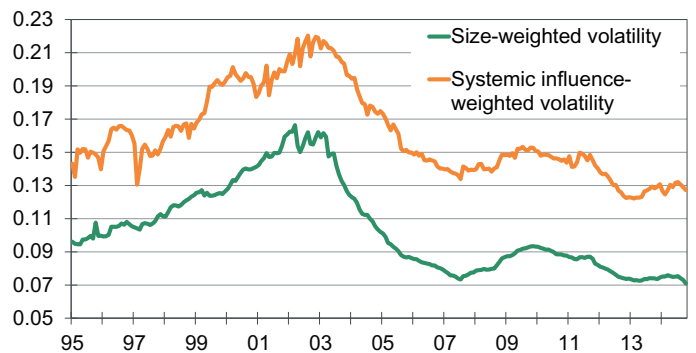
Source: Moody's Analytics
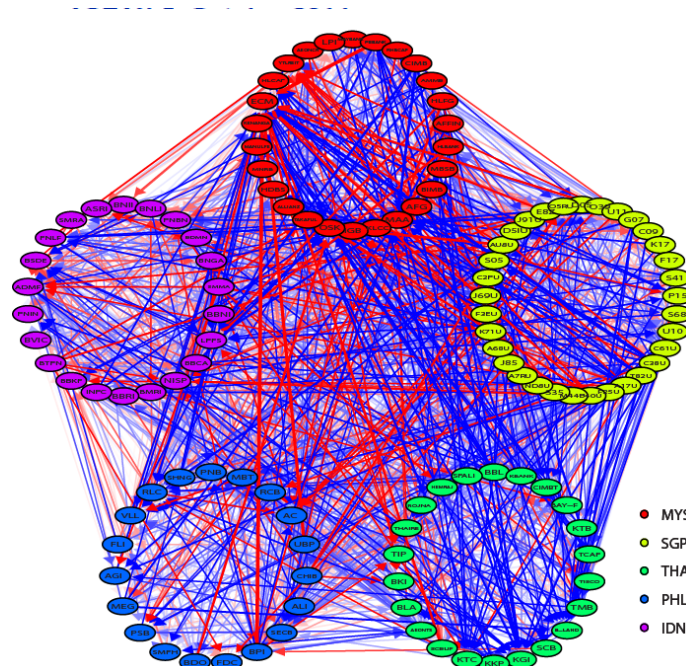
Chart 12: Cross-Sectional Correlations

Spearman correlation coefficients vs. time, ASEAN-5

Source: Moody's Analytics

Chart 13: ASEAN-5 Network

Financial institutions, EDF network VAR coefficients Oct 2014

Source: Moody's Analytics

well after the Asian financial crisis, around the time of Argentina's default. Systemic influence-weighted volatility is everywhere above size-weighted volatility: Firms that exhibit a relatively high Out ratio, and therefore have a high potential for contagion, also exhibit higher asset volatility. The Global Financial Crisis exerts a stronger effect on leverage than on volatility for ASEAN-5 financial institutions. Weighted volatility rises beginning with the Global Financial Crisis and through the European sovereign debt crisis, but the magnitude of the increase is relatively small. Weighted leverage spikes to levels attained during the early 2000s but then falls sharply to pre-Global Financial Crisis levels.

Tracking cross-sectional correlations over time can yield additional insights into system dynamics. In Chart 12, we display two Spearman (rank) correlations: the EDF-Out measure correlation and the leverage-volatility correlation. At each time point, the correlations shown are computed using only the cross section available at that time point for the system. It is immediately clear that the EDF-Out correlation tends to be negative during calm periods and positive during crisis periods. The interpretation is that riskier (that is, higher default probability) financial institutions increasingly drive the system during crises. Leverage and volatility correlations are always negative, but rise (become less negative) in the runup to crisis periods. Thus the negative relationship between leverage and volatility implied by the VaR targeting rule of Adrian and Shin (2014) appears

to become weaker in the cross section of financial firms during crises. Chart 12 also shows that the EDF-Out correlation tends to spike at the beginnings of crisis episodes, a pattern that is also apparent in data for U.S. financial institutions around 2007-2009.

Thailand was the epicenter of the Asian financial crisis in 1997, and the devaluation of the baht set off a cascade of financial distress throughout the ASEAN countries. Our study of Granger causal connections among EDF measures reveals that financial institutions in Thailand still represent a concentration of systemic risk in the ASEAN-5 network. Financial institutions in Singapore and Malaysia also have a high concentration of positive (that is, forcing) Granger causal relationships. Chart 13 shows the complete network map of Granger causal connections as of October 2014. Circles represent financial institutions and are color coded by country of domicile. This graph displays linkages based on the coefficients at lag 1 in the VAR models using EDF measures. Red lines correspond to negative coefficients (damping effects) and blue lines correspond to positive coefficients (forcing effects). The sets of lines connecting financial institutions in Thailand (green), Singapore (yellow) and Malaysia (red) are numerous, giving the graph a very dense appearance on the right side. The lines

connecting Thailand, Singapore and Malaysia also tend to be blue, meaning that the relationship between financial institutions in these countries is of the forcing variety: An increase in credit risk among financial institutions in one of these countries has a high propensity to cause an increase in credit risk in the others.

4.3 Case Study: Global Megabanks

The third and final case study we present pertains to the set of Global Megabanks, which includes international financial institutions with assets exceeding $100 billion. Table 3 displays the top 15 firms in the Global Megabanks network by Out measure as of October 2014 after an additional filter removed institutions with book asset values below $500 billion. Financial institutions in Germany, China and Canada are featured prominently. Of particular concern is the top entry on the list, Deutsche Bank Aktiengesellschaft, which also has an EDF at the 87th percentile of the EDF distribution and an asset size at the 95th percentile of the book asset size distribution within the network. Large, highly connected banks with

Table 3: Top 15 Financial Firms Ranked by Out Measure as of October 2014*: Global Megabanks

Financial Institution	Country	Out Value	Out Quantile	EDF Value (%)	EDF Quantile	Book Assets Value ($ mil)	Book Assets Quantile
Deutsche Bank Aktiengesellschaft	DEU	0.45	1.00	1.09	0.87	2,086,392.26	0.95
Bank of Nova Scotia	CAN	0.41	0.98	0.13	0.06	702,110.11	0.78
Toronto Dominion Bank	CAN	0.38	0.96	0.09	0.04	817,369.13	0.84
Commerzbank Aktiengesellschaft	DEU	0.28	0.91	1.78	0.93	729,857.07	0.79
Ping An Insurance (Group) Co. of China Limited	CHN	0.27	0.90	1.01	0.86	621,837.72	0.75
Bank of Montreal	CAN	0.25	0.86	0.11	0.05	520,377.94	0.7
Assicurazioni Generali S.p.A.	ITA	0.23	0.80	0.37	0.38	592,790.42	0.73
Bank of Communications Co. Limited	CHN	0.23	0.81	0.41	0.45	978,156.14	0.88
Mizuho Financial Group Inc.	JPN	0.22	0.79	0.56	0.64	1,568,381.90	0.91
Banco Santander S.A.	ESP	0.21	0.75	0.41	0.46	1,488,356.45	0.91
National Australia Bank Limited	AUS	0.20	0.73	0.35	0.36	743,533.04	0.8
Australia and New Zealand Banking Group Limited	AUS	0.20	0.72	0.27	0.27	648,440.61	0.77
Barclays PLC	GBR	0.19	0.70	0.66	0.69	2,178,844.41	0.96
Royal Bank of Canada	CAN	0.19	0.67	0.15	0.08	810,381.48	0.83
Nordea Bank AB	SWE	0.19	0.68	0.20	0.12	787,911.97	0.83

*This table reflects the filtering of the full list of Global Megabank firms to retain only those with assets exceeding $500 billion.
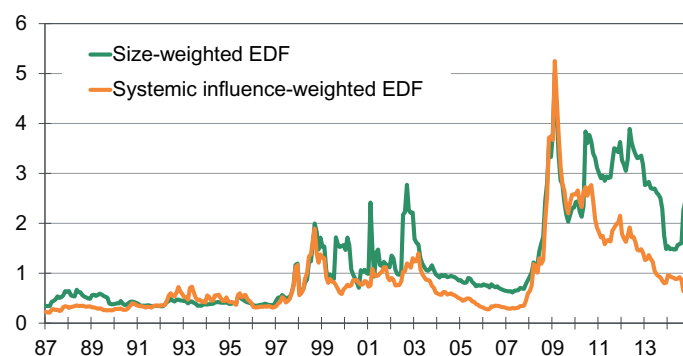Source: Moody's Analytics

nontrivial default probabilities should be a primary concern for global regulators. A second German bank, Commerzbank, also raises some concern because its EDF is in the 93rd percentile within the Global Megabank network, and its size is in the 79th percentile. Four Canadian banks make the list—more than any other country. These results should draw the attention of both European and Canadian regulators.

As we emphasized in the introduction, the correlation between the Out measure and the book size of assets in the cross section is low. In October 2014, for example, the Spearman rank correlation between Out measure and size in the Global Megabanks networks was a mere -0.02. If we look at the cross-sectional correlation in the Global Megabanks network in January 2008, a time of significantly higher market stress, we do find a higher Spearman rank correlation: 0.24. In January 2009, the correlation is 0.26. Thus, correlations in times of crisis are not strongly positive. On the whole, our results confirm the fact that the size and the degree of interconnectedness, at least for the market-based metrics we propose, have a modest relationship at best, even in times when regulatory intervention is most likely.

Chart 14 displays the weighted average EDF measures for the Global Megabank network over time. Using 1% and 2% EDF thresholds as warning signals, a history of credit risk in global SIFIs emerges. The size-weighted average EDF of Global Megabanks around the time of the Asian crisis first exceeded 1% in November 1997. It fell in early 1998, only to rise above the 1% threshold again in June 1998. It spiked to above 2% in February 2001 as the dot-com bubble burst, only to fall before spiking and remaining above 2% again from July-December 2002 following the Argentine default. The systemic influence-weighted EDF was below the size-weighted EDF for the 2000-2007 period but spiked along with the size-weighted measure to levels nearing 5% at the height of the Global Financial Crisis, only to fall significantly below the size-weighted EDF measure in the post-2010 period. Consistent with the results from the previous two case studies, it should not be surprising that the latter divergence in size-weighted and systemic importance-weighted measures occurs as the system reverts to a normal state following the crisis.

Chart 14: Global Megabanks EDF Measures

Source: Moody's Analytics

Chart 15: GMB Degree of Granger Causality

Global megabanks

Source: Moody's Analytics

To complement the preceding results, Chart 15 shows the DGC of the EDF network for Global Megabanks over time. The spike in the first period of the sample, from 1987 to the early 1990s, corresponds to the U.S. savings and loan crisis. From a nadir in mid-1996, the DGC rose steadily during the Asian crisis, Russian default, and LTCM debacle until reaching a peak in November 1999. From another low point in December 2002, the DGC then rose steadily during the Great Moderation, surpassing 0.3 again for the first time in December 2006, before falling slightly until soaring to a high point of 0.45 in March 2009, immediately following the tensest moments of the Global Financial Crisis. Together, Charts 14 and 15 tell a story that is consistent with familiar patterns from the last three decades of financial history.

EDFs are driven primarily by firm leverage and firm asset volatility. Charts 16 and 17

plot the evolution of weighted average measures of leverage and volatility, respectively, over time for the Global Megabanks network. A few insights emerge from these plots. Regarding leverage, we see that large banks are more highly leveraged than systemically important banks through the entire sample, although this gap narrows considerably during crises. As in the two previous case studies, we see that leverage increases dramatically during times of crisis, and especially in the case of the Global Financial Crisis. The sovereign debt crisis in Europe had a more marked impact on leverage in the Global Megabank network, which includes several major European banks, than it did in the U.S. network.

Turning to volatility, we see that systemic influence-weighted average volatility is consistently greater than size-weighted volatility, with the one exception to this rule being the S&L crisis in the late 1980s, when the latter was higher. Four distinct peaks are visible for both volatility series: one corresponding to the S&L crisis in the late 1980s, a second peak in July 1993 nestled between the ERM crisis in 1992 and the Tequila crisis in 1994, a third series of peaks that form

a historically high plateau stretching from mid-2001 until late 2002, and a final peak in December 2009 corresponding with the end of the Global Financial Crisis. Note that volatility tends to peak a few months later than leverage in each crisis episode and takes more time to build up as well as more time to revert to its historical mean. Conversely, we can characterize leverage as two distinct regimes, one pre- and the other post-Global Financial Crisis, with post-crisis mean leverage being much higher than pre-crisis mean leverage.

Although the late 1990s was a period of particularly high asset volatility for global SIFIs, the Global Financial Crisis was unique because the confluence of high leverage and high volatility together, which explains the dramatic increase in default probabilities for Global Megabanks during this period. Our systemic risk tools are useful because they show us further that, though systemically important banks tend to have higher asset volatilities even in calm periods, it is the particularly sharp increase in leverage during financial crises for connected firms that explains why highly systemic firms tend to coincide with high credit risk firms during such periods.

Chart 18 displays the EDF-Out and Leverage-Vol correlations over time for the Global Megabank cross section. The cyclical pattern of the EDF-Out relationship is noteworthy, as is the secular trend upward (from highly negative to modestly negative) of the Leverage-Vol correlation. These results suggest that Global Megabanks may
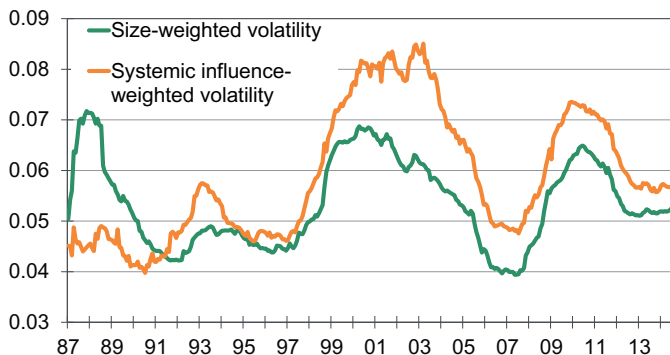
Chart 16: Default Point/AVL in GMB Network

Global megabanks
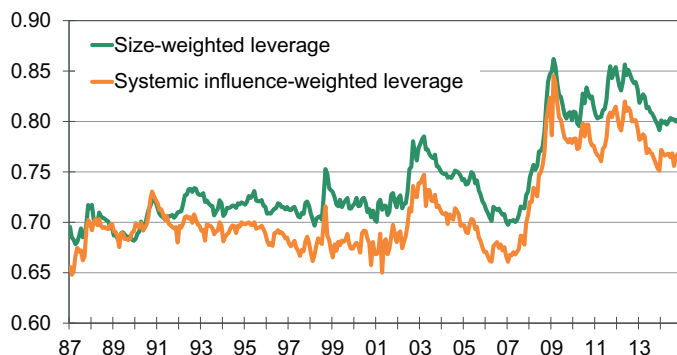
Source: Moody's Analytics

Chart 17: Asset Volatility in the GMB Network
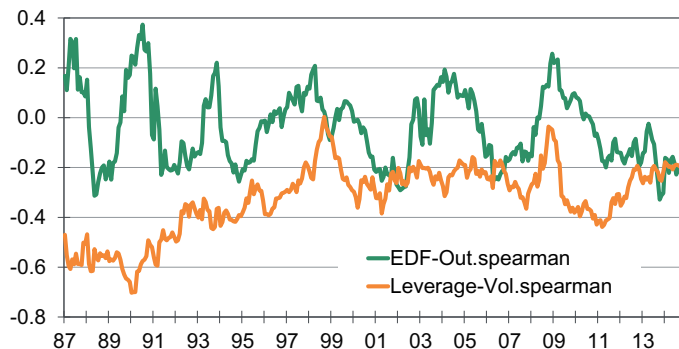
Global megabanks

Source: Moody's Analytics

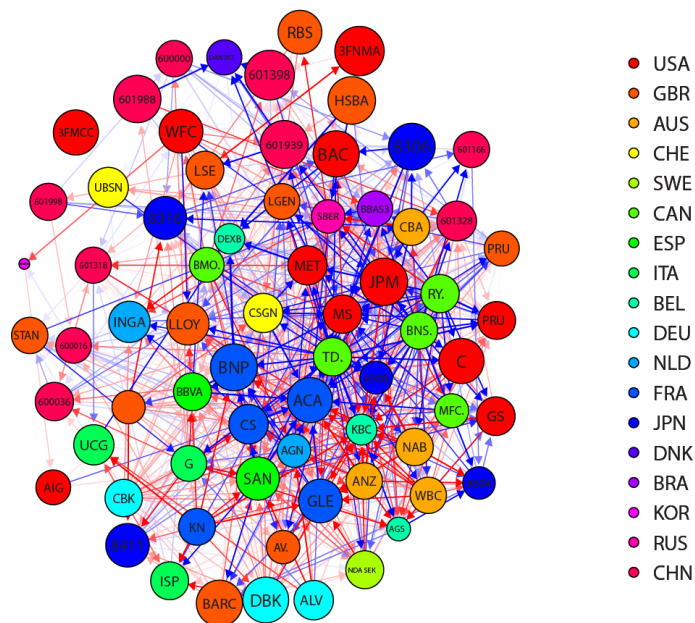## Chart 18: Cross-Sectional Correlations

Spearman correlation coefficients vs. time, Global Megabanks

Source: Moody's Analytics

Chart 19: Global Megabanks Network

Financial institutions, EDF network VAR coefficients Oct 2014

Source: Moody's Analytics

soon be in store for a period in which high credit-risk firms begin to drive the network for a few years, given that the EDF-Out correlation is near the historical minimum. Also, they suggest that financial innovation may be weakening the natural negative relationship between bank leverage and bank asset volatility in the cross section of major global financial institutions.

Finally, Chart 19 displays a snapshot of the Global Megabank network in October 2014. Only institutions with book asset values greater than $500 billion were included. We see that U.S. firms such as MetLife, Morgan Stanley, and JP Morgan

Chase are located near the center of the network and display numerous forcing relationships with other financial firms. This is also true for several foreign financial institutions such as Toronto Dominion Bank of Canada, Credit Suisse Group of Switzerland, and Credit Agricole of France. The centrality of MetLife is particularly noteworthy, given its recent lawsuit against the Financial Stability Oversight Council

protesting its designation as a Systemically Important Financial Institution.[6]

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6 The case reference is MetLife Inc. v. Financial Stability Oversight Council, U.S. District Court, District of Columbia, No. 15-00045.

Section 5: Econometric results

To complement the case study results of Section 4, this section presents findings from a few key empirical exercises designed to test the predictive power of our bank-specific SRM analytics for future credit events as well as validate the use of SRM time series analytics in conjunction with CCAR variables for stress-testing purposes.

5.1 Predictive value of SRM analytics for future credit risk events during the Global Financial Crisis

One of the major concerns of banks facing an economic contraction or adverse systemic event is the possibility of a spike in their credit risk, or a spike in the credit risk of one of their major counterparties, during a short- to medium-term time horizon. This

is also a major concern of regulators such as the Fed. As a simple measure of the predictive value of our leading bank-specific SRM analytics, we run a cross-sectional regression of the form

$$Y_i = \alpha + \phi EDFJan2008_i + \beta X_i + \varepsilon_i,$$

where Y_i is a dummy variable that is equal to 1 for banks whose EDF exceeded 10% during the February 2008-January 2009 period, and equal to zero for banks whose EDF did not exceed this threshold during that period. The variable $EDFJan2008_i$ contains the value, measured at the end of January 2008, of the initial EDF value for bank i. The variable X_i is a selected bank-specific SRM metric, also measured at the end of January 2008,

and ε_i is the mean-zero Gaussian error term. In Table 4, we report the results of running a baseline regression with the restriction $\beta = 0$ as well as five additional regressions, each corresponding to a different choice for the variable X_i. The five choices we consider for X_i are the Out measure, the Out.plus measure, the In measure, the In.plus measure, and a Beta measure. The specific Beta measure we use here is the coefficient of the log EDF of the bank on the log Out-weighted EDF of the system in a contemporaneous time series regression that uses the last 60 months of data, up to and including January 2008.

The results of Table 4 are clear. First, the initial EDF has significant predictive power for subsequent credit risk spikes in the cross section of banks and achieves an R-squared of

Table 4: EDF 10% Threshold Exceedance Regressions for the U.S. Network*

February 2008-January 2009

Variable	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat	Coeff	T-stat
Intercept	**0.24**	7.57	**0.14**	2.33	**0.16**	3.86	**0.12**	2.14	**0.13**	2.76	**0.17**	4.23
EDF-Jan-08	**0.03**	6.46	**0.03**	5.55	**0.03**	5.99	**0.03**	6.64	**0.03**	6.7	**0.02**	4.66
Out			0.48	1.85								
Out.plus					**1.13**	3.46						
In							**0.57**	2.92				
In.plus									**1.33**	3.31		
Beta											**0.21**	2.89
R-squared	0.18		0.194		0.228		0.215		0.218		0.214	

* Each regression is a linear probability model of the threshold exceedance dummy variable, which is equal to 1 for banks whose EDF exceeded 10% during the February 2008-January 2009 period and zero otherwise, against the explanatory variables indicated. The regression is estimated using the January 2008 cross section of the 194 publicly traded U.S. financial institutions available after applying book asset size and data availability filters. Coefficients in bold are statistically significant at the 1% level in a two-sided t-test against the null hypothesis of a zero coefficient.

Source: Moody's Analytics

18%. Second, four of the five SRM analytics we consider alongside the initial EDF value have coefficients that are statistically significant at the 1% level, and their associated regressions all possess R-squared values in excess of 21%. The strongest measure in this test is the Out. plus metric, whose regression has an R-squared value of 22.8%. Only the Out measure, whose coefficient has a p-value of 0.07, is not significant at the 1% level. These results are robust to reasonable variations in the 10% EDF threshold and the reference date (in this case January 2008) of the exercise.

Additionally, if we replace the exceedance dummy variable Y_i with the maximum value of the EDF attained during the February 2008-January 2009 period for each bank and rerun our regressions, the results are qualitatively similar to those shown in Table 4. The basic result holds: SRM analytics add robust, additional predictive sorting power to the initial EDF for subsequent credit risk spikes by U.S. banks during the worst period of the Global Financial Crisis.

5.2 Relationship of SRM analytics to CCAR variables: The macro-financial system

Having shown that our SRM analytics help to sort banks in the cross section with respect to future credit risk realizations, we now show that SRM analytics exhibit statistically significant, and in several cases bidirectional, Granger causal relationships with key CCAR variables. Furthermore, we show that the extent of such relationships is consistent with what we find for leading systemic risk measures from the literature.

Turning first to the results for the SRM analytics, we compute the F-statistics relevant for judging Granger causality for models run at the monthly frequency for each of a set of selected CCAR variables on four leading time series from the SRM. The four SRM time series analytics we consider are the Out.plus-weighted EDF, the Out. plus-weighted market value capital ratio, the Out.plus-weighted book value capital ratio, and the Degree of Granger Causality. The CCAR variables we consider are U.S. real GDP growth, the CPI inflation rate, the Dow Jones index (in log differences), the Chicago Board Options Exchange Market Volatility Index, the S&P Case Shiller Home Price Index (in log differences), the commercial real estate price index from the U.S. financial accounts (in log differences), the unemployment rate (in differences), the bank prime loan interest rate, the Merrill Lynch 10-year BBB corporate bond rate (in differences), and the three-month Treasury bond yield. The results of this exercise are displayed in Table 5.

We can draw several interesting conclusions from the results in Table 5. First, we see that the capital ratio measures, but not the EDF or DGC measures, drive and respond to real GDP growth. Second, we see that the EDF measure, but not the capital ratio or DGC measures, has a strong lead-lag relationship with inflation. Third, we see that of the SRM analytics, the EDF measure alone drives and is driven by the Dow Jones market return, the VIX, and the growth rate of both real estate price indexes. The EDF measure also drives changes in the unemployment rate, although not the other way around. Finally, we find that while the DGC measure appears only weakly related or unrelated to most of the CCAR variables, it strongly drives the bank prime loan rate, the 10-year BBB corporate bond interest rate, and the three-month Treasury bond yield. The latter yields in turn appear to drive both capital ratio measures.

When we test the Granger causality relationships of the SRM variables with one another (not shown), we find that the capital ratio and DGC measures all strongly Granger-cause each other, but that none of them Granger-causes or is Granger-caused by the EDF series. Putting this together with the results of Table 5, we can paint a picture of an economy with two distinct chains of im-

Table 5: Granger Causality Between CCAR and SRM Analytics*

Granger causality: CCAR causes SRM / SRM causes CCAR

	Out.pwEDF	Out.pwMVCR	Out.pwBVCR	DGC
Real GDP growth	NO/NO	**YES/YES**	**YES/YES**	YES(5%)/NO
Inflation	**YES/YES**	**YES**/NO	YES(5%)/NO	NO/NO
DJ (log diff.)	**YES/YES**	NO/NO	NO/NO	**YES**/NO
VIX	**YES**/YES(5%)	**YES**/NO	NO/NO	NO/NO
S&P Case Shiller index (Log diff.)	**YES/YES**	NO/NO	NO/NO	NO/NO
Commercial real estate index (Log diff.)	**YES/YES**	NO/NO	NO/NO	NO/NO
Unemployment rate (diff.)	NO/**YES**	NO/NO	**YES**/NO	NO/NO
Bank prime loan interest rate	NO/NO	**YES**/YES(5%)	**YES/YES**	NO/**YES**
Merrill Lynch 10-yr BBB corporate bond rate (diff.)	**YES**/NO	**YES**/NO	**YES**/NO	NO/**YES**
Three-mo Treasury yield	NO/NO	**YES/YES**	**YES/YES**	NO/**YES**

*This table reports whether the F-test of Granger causality was significant at the 1% or 5% level for models that use 12 monthly lags of the variables in the given row and column. Fields marked "YES" are significant at the 1% level. The number of observations for each row ranges from 162 to 463 months, depending upon the pair of time series variables being tested. CCAR variables were transformed to stationarity via first differencing (or log differencing) as necessary based on the results of an ADF test with a constant, a time trend, and automated lag selection based on SIC.

Source: Moody's Analytics

portant macro-financial relationships. In the first cluster of such relationships, the credit risk of systemically important financial firms drives and responds to innovations in goods, asset and real estate prices. In the second cluster of relationships, the degree of financial network connectivity (the DGC) drives capital ratios and key interest rates/yields in the economy, which in turn drive real GDP growth through standard macro channels. The two chains are connected via the response of asset prices to changes in yields.

The fact that the DGC is related to capital ratios and key yields suggests that it may be related as well to the asset growth lending channel described by Adrian, Estrella and Shin (2010), in which the term spread drives the net interest margin of banks, which in turn drives the size of bank balance sheets. They find that expansions of the quantity of assets on bank balance sheets, due to increased lending, in turn spur economic growth.

We test the hypothesis that the DGC Granger-causes the term spread directly using 12 monthly lags of both variables, where we construct the term spread as the difference between the 10-year and three-month Treasury yields following Adrian, Estrella and Shin (2010). Using a sample of 463 monthly observations, we find that we can reject the null hypothesis that the DGC does not Granger-cause the

term spread based on a p-value of 0.0001. In contrast, the F-test of the null hypothesis that the term spread does not Granger-cause the DGC has a p-value of 0.80.

Chart 20 displays the impulse-responses for the reduced-form VAR system comprising the term spread and the DGC measure to generalized one standard deviation innovations. Bands corresponding to two bootstrapped standard errors of the responses, computed using 500 Monte Carlo iterations, are shown in red.

Inspection of the impulse-response graph in Chart 20 indicates that increases in the DGC tend to lower the term spread at the three-month horizon, followed by an increase in the term-spread response that becomes positive and statistically significant at the nine-month horizon. One interpretation of this finding is that the uncoupling of credit risk linkages between many banks in the aftermath of the financial crisis—associated with a fall in the DGC—was the result of a significant decrease in the volume of repo/reverse repo transactions in the system. The decreased relative demand for long-term versus short-term credit resulting from the decreased repo activity led naturally to the immediate (one-

Chart 20: Impulse-Response Plots

Term spread and DGC measure from SRM for the U.S.
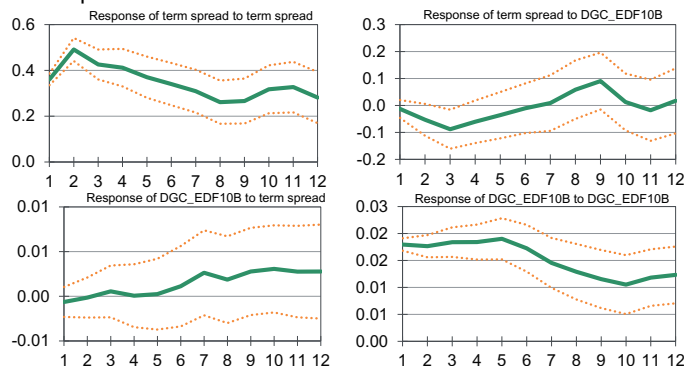
Source: Moody's Analytics

Table 6: Granger Causality Between CCAR Variables and Selected Systemic Risk Measures From Giglio, Kelly and Pruitt (Forthcoming)*

Granger causality: CCAR causes systemic risk / systemic risk causes CCAR

	Turbulence	Mkt. Lev.	GZ	CoVaR	MES-BE
Real GDP growth	NO/NO	**YES/YES**	NO/NO	NO/NO	NO/NO
Inflation	NO/**YES**	**YES**/NO	NO/**YES**	NO/NO	NO/NO
DJ (log diff.)	NO/**YES**	**YES/YES**	NO/NO	**YES**/NO	**YES**/NO
VIX	NO/**YES**	**YES**/NO	**YES/YES**	**YES**/NO	**YES**/NO
S&P Case Shiller index (Log diff.)	NO/**YES**	**YES/YES**	NO/YES(5%)	NO/**YES**	NO/NO
Commercial real estate index (Log diff.)	**YES/YES**	**YES/YES**	**YES/YES**	YES(5%)/**YES**	NO/**YES**
Unemployment rate (diff.)	NO/**YES**	**YES/YES**	NO/**YES**	NO/YES(5%)	NO/**YES**
Bank prime loan interest rate	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO
Merrill Lynch 10-yr BBB corporate bond rate (diff.)	NO/**YES**	**YES**/NO	NO/NO	YES(5%)/NO	NO/NO
Three-mo Treasury yield	NO/NO	NO/NO	NO/NO	NO/NO	NO/NO

*This table reports whether the F-test of Granger causality was significant at the 1% or 5% level for models that use 12 monthly lags of the variables in the given row and column. Fields marked "YES" are significant at the 1% level. The number of observations for each row ranges from 143 to 463 months, depending upon the pair of time series variables being tested. CCAR variables were transformed to stationarity via first differencing (or log differencing) as necessary based on the results of an ADF test with a constant, a time trend, and automated lag selection based on SIC.

Source: Moody's Analytics

quarter ahead) steepening of the yield curve that followed. Further research is necessary to understand the potential importance and prevalence of this channel.

To close this section, we compare the performance of our systemic risk analytics with leading systemic risk analytics from the academic literature. To that end, we repeat the Granger causality exercises of Table 5 using five selected systemic risk measures from the dataset of Giglio, Kelly, and Pruitt (forthcoming). Although those authors examine the predictive power of 18 measures from the literature for median and 20% quantiles of industrial output growth in addition to five systemic risk indexes of their own design, we focus on a subset of three measures that demonstrate very strong performance in their study (turbulence, market leverage, and the Gilchrist-Zakrajsek excess bond premium) as well as two measures that have received significant attention in policy discussions of systemic risk (CoVaR, MES-BE). The results of our Granger causality tests are displayed in Table 6.

The results of Table 6 can be summarized as follows. We take statistical significance at the 1% level or better as evidence of a Granger causal relationship. According to that standard, the turbulence measure of Kritzman and Li (2010) Granger-causes seven of the 10 CCAR variables considered—the most of any systemic risk measure—but is Granger-caused only by the commercial real estate index in log differences. Market leverage Granger-causes five CCAR variables, but is Granger-caused by eight CCAR variables, for 13 Granger causal connections in total. The GZ credit spread measure of Gilchrist and Zakrajsek (2012) exhibits a total of six Granger-causal connections with the CCAR variables, with the CoVaR measure of Adrian and Brunnermeier (2011) and the MES-BE measure of Brownlees and Engle (2011) attaining four connections each.

For purposes of comparison, the Out. plus-weighted average EDF measure from Table 5 displays 11 Granger causal connections with CCAR variables, with both Out.plus- weighted average capital ratio measures attaining eight total Granger causal connections with the CCAR variables. Thus, our measures are comparable in this respect with three of the best-performing measures (turbulence, market leverage, and GZ) from the study of Giglio, Kelly and Pruitt (forthcoming). Those authors employ quantile regressions and focus primarily on tail realizations of output growth proxies and interest rates. However, given the fact that linear regression coefficients can be estimated consistently using symmetric weighted combinations of quantile coefficient estimates, following Theorem 4.3 of Koenker and Bassett (1978), establishing linear dependence, or lack thereof, of CCAR variables on past realizations of systemic risk measures (and vice versa) is an empirical matter. By resolving this issue in the affirmative for many pairs of CCAR-systemic risk analytics, our results complement those of Giglio, Kelly and Pruitt (forthcoming). Furthermore, our findings strongly suggest that leading systemic risk measures, including the SRM analytics presented in this paper, have the potential for explicit use in regulatory stress-testing exercises, given the robust lead-lag relationships that exist between these variables and the set of core CCAR variables.
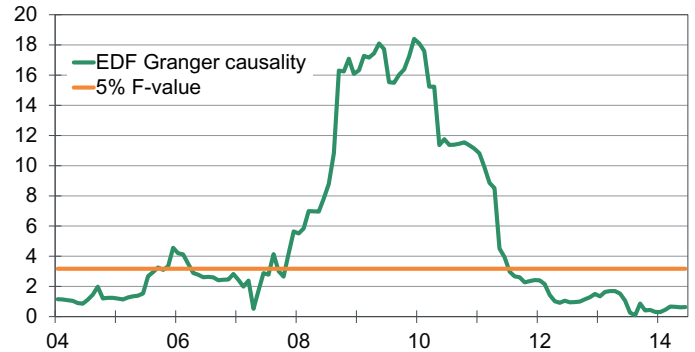
Chart 21: Global Megabanks Network

Bank of New York Mellon → Goldman Sachs
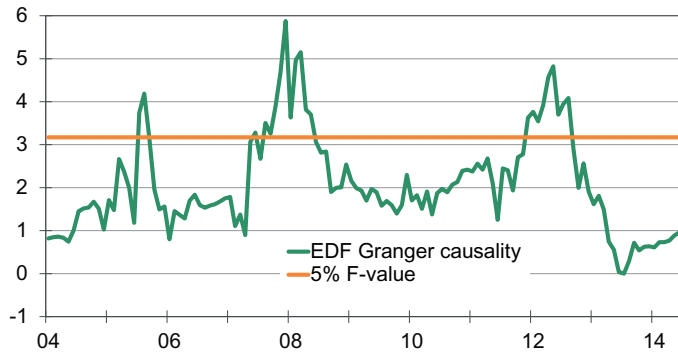
Source: Moody's Analytics

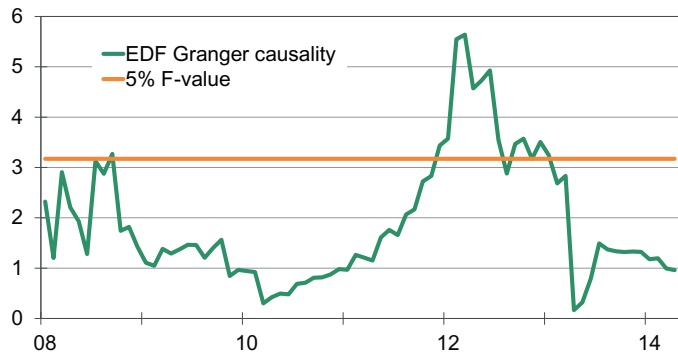**Chart 22: Global Megabanks Network**

Goldman Sachs → Bank of New York Mellon

Source: Moody's Analytics

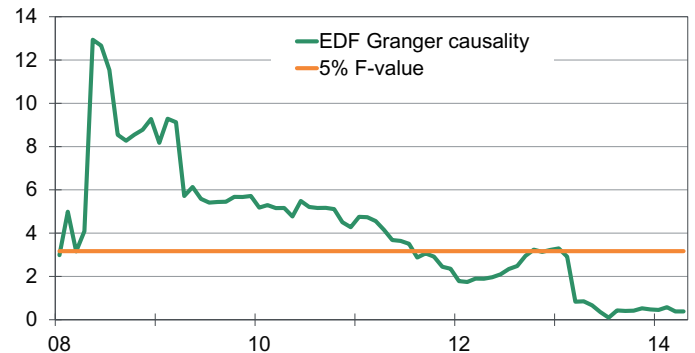**Chart 23: Global Megabanks Network**

Mizuho Financial Group → Goldman Sachs

Source: Moody's Analytics

Chart 24: Global Megabanks Network

Goldman Sachs → Mizuho Financial Group

Source: Moody's Analytics

Section 6: Bank-to-bank credit risk spillovers

In addition to generating informative systemic risk time series for a given financial network scope, and time series—such as Out and Out.plus—for individual financial institutions vis-à-vis the rest of the network, the SRM can be queried to generate time series of F-statistics, VAR model coefficients, and coefficient t-statistics for any pair of institutions in the network. The latter outputs are, in fact, the granular building blocks from which the systemic risk outputs are computed. These bank-to-bank outputs often, but not always, mirror larger trends in the systemic risk series. We focus on selected pairs of financial institutions in the Global Megabanks network for the purposes of illustration. The pairs are: Goldman Sachs/Bank of New York Mellon, Goldman

Sachs/Mizuho Financial Group, and BNP Paribas/Banco Santander. For all pairs, we plot the two F-statistics used to compute the relevant entries of the adjacency matrix relevant for computing the Out measures and the DGC. In each plot, the critical value corresponding to the 5% significance level of the relevant F distribution is plotted in red for comparison. Exceedances of this critical value in a given month are coded as 1 in the appropriate row and column of the adjacency matrix, and non-exceedances are coded as zero.

For the Goldman/BoNY Mellon pair, we see that BoNY Mellon's EDF Granger-caused the EDF of Goldman Sachs during 2008 and in late 2012-early 2013 (see Chart 21). These correspond to peak periods of market stress

during the Global Financial Crisis and the European Sovereign Debt Crisis, respectively. Goldman Sachs, in contrast, Granger-causes BoNY Mellon from 2008-2011 inclusive (see Chart 22), and the statistical significance of the latter Granger causal linkage was much higher.

The patterns exhibited in the Goldman/Mizuho FG relationship (see Charts 23 and 24) are quite similar to those we find in the Goldman/BoNY Mellon relationship, although slightly weaker. This is not surprising, as Goldman/BoNY are both based in the U.S., whereas Mizuho FG is based in Japan.

Finally, the pattern of credit risk spillovers between BNP Paribas and Banco Santander is somewhat similar to the Goldman/BoNY Mellon relationship, but with a much
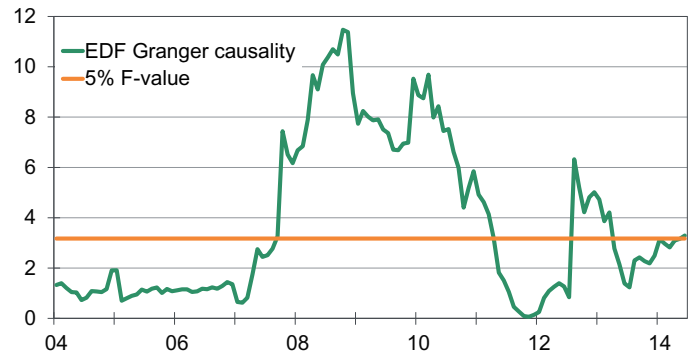
Chart 25: Global Megabanks Network

Banco Santander → BNP Paribas
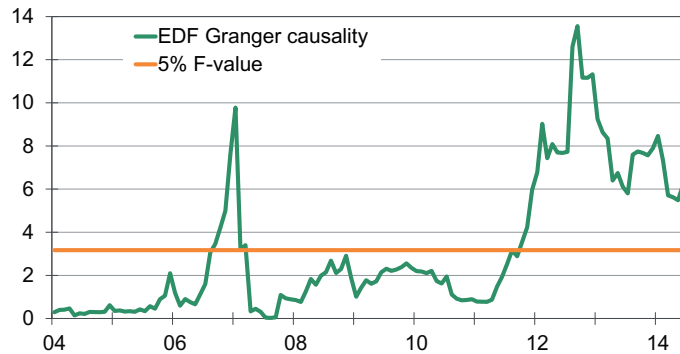
Source: Moody's Analytics

Chart 26: Global Megabanks Network

BNP Paribas → Banco Santander

Source: Moody's Analytics

greater degree of mutual Granger causality from early 2012 to October 2014, when our sample ends (see Charts 25 and 26). During the Global Financial Crisis, however, BNP Paribas played a role similar to Goldman in its relationship with BoNY Mellon, in that its EDF Granger-caused the EDF of Santander with a high degree of statistical significance during the 2008-2011 period, but not before. Banco Santander, on the other hand, exhib-

ited a spike in its F-statistic in 2007, Granger-causing BNP Paribas briefly before the worst part of the Global Financial Crisis in 2008. In the Goldman/BoNY Mellon relationship, BoNY Mellon exhibited a similar spike in its F-statistic in early 2006, briefly Granger-causing Goldman just prior to the onset of the Global Financial Crisis.

The above evidence is consistent with a pattern of bellwether-leader relationships,

in which "bellwether" banks such as BoNY Mellon or Santander provide early warning signals to "leader" banks such as Goldman Sachs and BNP Paribas, which then take the reins in driving credit risk spillovers to the former banks during the height of stress periods. If true more generally, this observation illustrates one way that systemic risk propagates on a more granular level throughout the financial network.

Conclusion

In this paper, we have described a new tool for counterparty and systemic risk analysis, which we call the Systemic Risk Monitor, and illustrated its outputs using three networks with distinct geographical footprints and institutional size thresholds: the U.S. DFAST-sized banks with assets of at least $10 billion, the ASEAN-5 country banks with assets of at least $1 billion, and a set of Global Megabanks with assets of at least $100 billion. We present results for dynamic network analyses of credit risk spillovers, based on the EDF measure of financial firm-specific default probabilities from Moody's CreditEdge.

As part of our approach, we develop novel measures of bank-specific systemic risk exposures and contributions such as systemic risk factor betas and the Out.plus measure, respectively. Our Out.plus and In.plus measures innovate on the Out and In measures

commonly used in the network literature. In analogy to forcing relationships in an oscillator, the Out.plus and In.plus measures extract signals more closely related to the forcing relationships in the network that are central to shock propagation at the monthly horizon. Our time series systemic risk measures track major events in financial markets in each of the three regions studied, with appropriate relative regional differences. In the ASEAN-5, for example, systemic risk measures peaked during the Asian crisis, whereas in the U.S. they peaked during the Global Financial Crisis, with Global Megabanks displaying an intermediate pattern that is slightly closer to that of the U.S.

Our econometric study of the cross-sectional and time-series properties of our systemic risk measures for the U.S. provides results that strongly support their potential utility for formal incorporation into stress-

testing efforts. In the cross section, our measures forecast future high credit risk events during 2008 after controlling for the initial value of firm EDF. In the time series, we find that our measures exhibit highly statistically significant Granger causal relationships with multiple CCAR variables and that their performance in this regard is similar to the most promising systemic risk analytics from the academic literature. Finally, a more granular analysis of bank-to-bank credit risk spillovers between individual bank pairs in the Global Megabanks network suggests the possibility of "bellwether-leader" patterns of credit risk transfer. In such patterns, pre-crisis periods during which bellwether banks briefly drive credit risk in leader banks are followed by longer periods that comprise the height of a crisis and its aftermath, in which leader banks drive credit risk of the bellwethers.

References

Tobias Adrian and Hyun Song Shin, "Procyclical Leverage and Value-at-Risk," *Review of Financial Studies* 27 (2) (2014): 373-403.

Tobias Adrian and M. Brunnermeier, "CoVaR," discussion paper, National Bureau of Economic Research (2011).

Tobias Adrian, Arturo Estrella, and Hyun Song Shin, "Monetary Cycles, Financial Cycles, and the Business Cycle," Federal Reserve Bank of New York Staff Report No. 421 (January 2010).

Andrew Berg, "The Asian Crisis: Causes, Policy Responses, Outcomes," IMF working paper, WP/99/138 (Washington: International Monetary Fund, 1999). http://www.imf.org/external/pubs/ft/wp/1999/wp99138.pdf.

M. Billio, M. Getmansky, A. Lo and L. Pelizzon, "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors," *Journal of Financial Economics* Vol. 104, No. 3 (June 2012): 535-559.

D. Bisias, M. Flood, A. Lo and S. Valavanis, "A Survey of Systemic Risk Analytics," *Annual Review of Financial Economics* 4 (2012): 255-296.

Francisco Blasques, Falk Bräuning, and Iman van Lelyveld, "A Dynamic Network Model of the Unsecured Interbank Lending Market," Bank for International Settlements working paper No. 491 (2015).

Board of Governors of the Federal Reserve System, "Consolidated Supervision Framework for Large Financial Institutions," Letter SR 12-17 / CA 12-14 (Washington, December 17, 2012). http://www.federalreserve.gov/bankinforeg/srletters/sr1217.htm

C. Brownlees and R. Engle, "Volatility, Correlation and Tails for Systemic Risk Measurement," working paper (NYU 2011).

Peter J. Crosbie and Jeffrey R. Bohn, "Modeling Default Risk," Moody's-KMV, mimeo (December 18, 2003).

Douglas Dwyer, Zan Li, Shisheng Qu, Heather Russell and Jing Zhang. "CDS-implied EDF™ Credit Measures and Fair-Value Spreads," Moody's-KMV, Modeling Methodology white paper, March 11, 2010.

P. Gai, A. Haldane and S. Kapadia, "Complexity, Concentration and Contagion," *Journal of Monetary Economics*, 58 (5) (2011): 453-470.

P. Gandhi and H. Lustig, "Size Anomalies in U.S. Bank Stock Returns," *The Journal of Finance* 70 doi: 10.1111/jofi.12235 (2015): 733-768.

S. Giglio, B. Kelly and S. Pruitt, "Systemic Risk and the Macroeconomy: An Empirical Evaluation," *Journal of Financial Economics*, forthcoming.

S. Gilchrist and E. Zakrajsek, "Credit Spreads and Business Cycle Fluctuations," *American Economic Review* 102(4) (2012): 1692-1720.

Dale Gray and Samuel W. Malone, "Sovereign and Financial Sector Risk: Measurement and Interactions," *Annual Review of Financial Economics* Vol. 4, No. 1 (2012): 297-312.

Dale Gray and Samuel W. Malone, *Macrofinancial Risk Analysis* (Chichester, England: John Wiley & Sons, 2008).

Dale Gray, Andreas Jobst and Samuel W. Malone, "Quantifying Systemic Risk and Re-conceptualizing the Role of Finance for Economic Growth," *Journal of Investment Management* Vol. 8, No. 2 (2010): 90-110.

David Hamilton, Tony Hughes and Samuel W. Malone, "Measuring Systemic Risk in the Southeast Asian Financial System," *Moody's Analytics Risk Perspectives* (2015).

X. Huang, H. Zhou and H. Zhu, "Systemic Risk Contributions," *Journal of Financial Services Research* (2010): 1-29.

X. Huang, H. Zhou and H. Zhu, "A Framework for Assessing the Systemic Risk of Major Financial Institutions," *Journal of Banking and Finance* Vol. 33, No. 11 (2009): 2036–2049.

Tony Hughes and Samuel W. Malone, "Putting Systemic Stress Into the Stress-Testing System," *GARP Risk Intelligence* (March 5, 2015).

International Monetary Fund, "United Kingdom: Stress-Testing the Banking Sector Technical Note," Country Report No. 11/222 (Washington: International Monetary Fund, July 1, 2011). http://www.imf.org/external/pubs/ft/scr/2011/cr11227.pdf.

A. A. Jobst and D. F. Gray, "Systemic Contingent Claims Analysis: Estimating Market-Implied Systemic Risk," IMF working paper No. 13/54 (Washington: International Monetary Fund, 2013).

Masahiro Kawai and Peter J. Morgan, Asian Development Bank Institute working paper No. 377, Central Banking for Financial Stability in Asia (August 2012).

Roger W. Koenker and Gilbert Bassett Jr., "Regression Quantiles," *Econometrica*, Econometric Society Vol. 46(1) (January 1978): 33-50.

Mark Kritzman and Yuanzhen Li, "Skulls, Financial Turbulence and Risk Management," *Financial Analysts Journal* Vol. 66, No. 5 (October 13, 2010).

Robert C. Merton, Monica Billio, Mila Getmansky, Dale Gray, Andrew W. Lo, and Loriana Pelizzon, "On a New Approach for Analyzing and Managing Macrofinancial Risks," *Financial Analysts Journal* 69 (2) (2013): 22-33.

R.C. Merton, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* Vol. 29, No. 2 (May 1974): 449-470.

Zhao Sun, David Munves, and David T. Hamilton, "Public Firm Expected Default Frequency (EDF™) Credit Measures: Methodology, Performance and Model Extensions," Moody's Analytics white paper (June 2012).

Janet L. Yellen, "Interconnectedness and Systemic Risk: Lessons from the Financial Crisis and Policy Implications," speech at the American Economic Association/American Finance Association Joint Luncheon, San Diego (January 4, 2013).

About the Authors

Tony Hughes is a managing director in the Economic & Consumer Credit group at Moody's Analytics. He is the head of a small group of high-caliber modelers, charged with identifying new business opportunities for the company. Prior to this appointment, he led the Consumer Credit Analytics team for eight years from its inception in 2007. His first role after joining the company in 2003 was as lead economist and head of the Sydney office of Moody's Economy.com.

Dr. Hughes helped develop a number of Moody's Analytics products. He proposed the methodology behind CreditCycle and CreditForecast 4.0, developed the pilot version of the Stressed EDF module for CreditEdge, and initiated the construction of the Default, Prepayment and Loss Curves product, which provides forecasts and stress scenarios of collateral performance for asset-backed securities and residential mortgage-backed securities deals worldwide. More recently, he championed the development of the Pre-Provision Net Revenue Factors Library, a tool that provides industry-level projections of key bank balance sheet line items. In the credit field, Dr. Hughes' research has covered all forms of retail lending, large corporate loans, commercial real estate, peer-to-peer, structured finance, and the full range of PPNR elements. He has conducted innovative research in deposit modeling and in the construction of macroeconomic scenarios for use in stress-testing.

Dr. Hughes has managed a wide variety of large projects for major banks and other lending institutions. In addition, he has published widely in industry publications such as American Banker, Nikkei, GARP, and the Journal of Structured Finance as well as papers in peer-reviewed academic journals. He obtained his PhD in econometrics from Monash University in Australia in 1997.

Sam Malone is director of economic research in the Specialized Modeling Group at Moody's Analytics. Dr. Malone has taught at and consulted for top institutions in Europe and the Americas, including Oxford, the University of Navarra, the European Commission, the Central Banks of Venezuela and Peru, and several large North American financial institutions. He is coauthor of the book Macrofinancial Risk Analysis, published in the Wiley Finance series with foreword by Nobel Laureate Robert Merton, as well as the author of numerous academic journal articles in economics and statistics. His articles have been published in outlets such as World Development, the Journal of Applied Econometrics, the Journal of Financial Econometrics, the International Journal of Forecasting, the Annual Review of Financial Economics, the Journal of Investment Management, and GARP Risk Intelligence. He holds undergraduate degrees in mathematics and economics from Duke University, where he studied as an A.B. Duke scholar and graduated with summa cum laude Latin honors, and masters and PhD degrees in economics from the University of Oxford, where he studied as a Rhodes scholar.

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