On the Interconnectedness of Financial Institutions: Indian Markets Experience

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Abstract

The financial crisis of 2008 highlighted the absence of metrics for measuring, decomposing, managing, and predicting systemic risk. Systemic risk is interpreted as a risk that has (a) large impact, (b) is widespread, i.e., affects a large number of entities or institutions, and (c) has a ripple effect that endangers the existence of the financial system. Whereas there is now a wide-ranging literature on systemic risk in the US, there is little work on other financial systems, especially not in countries very different from the US. In this project, we undertake a large-scale empirical examination of systemic risk among major financial institutions in a large emerging market, namely India. We present a novel single systemic risk score for the entire financial system. This score is a per-bank, size-weighted, and network weighted credit risk measure that may be compared across countries, and across time. It is also additively decomposable and attributable to each financial institution, and may be used as an objective and quantifiable measure of whether a bank is a SIFI (systemically important financial institution). We provide an analysis of the Indian experience and insights into the use of network models in policy-making for measuring, managing and regulating systemic risk in the emerging market context. Network variables and credit variables explain systemic risk, with credit variables forming a greater portion of overall systemic risk.

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1 Introduction

In this project we undertake a large-scale empirical examination of systemic risk among major financial institutions in the emerging markets, starting with one country, India. There is limited prior literature on the evidence of systemic risk in emerging markets.[1] We provide an analysis of the Indian experience and offer metrics for measuring, managing, and regulating systemic risk in the emerging market context.

Why emerging markets? Starting in 2007, emerging economies accumulated significant external debt as non-financial corporations from emerging markets increased their external borrowing significantly through the offshore issuance of debt securities.[2] For example, emerging market corporate loans and debt rose from 73% of GDP at the end of 2007 to 107% of GDP by the end of 2014.[3] Although greater leverage can facilitate higher corporate investment and perhaps stimulate growth, the continued accumulation of corporate debt can be concerning because many financial crises in emerging markets have been preceded by rapid leverage growth. Emerging market credit in general is dominated by bank loans. Excessive corporate leverage can lead to increased risk exposure for local banks. If the high leverage though foreign debt is not adequately hedged by emerging market firms, it can further exacerbate the risks to domestic banks. Such increased risk exposure of banks can be critical in the face of commodity and currency market shocks and global monetary policy developments (e.g., the U.S. QE taper-tantrum).

Systemic risk is defined as the risk of substantial damage to, or failure of, the financial system in a country. This is different from systematic risk, characterized by correlation amongst assets in an economy induced by a set of common factors. Whereas systematic risk is driven by unconditional correlation, systemic risk is an artifact of conditional correlation, specifically the conditional failure of the system at large driven by (or conditional on) the failure of key financial institutions in an economy. Contagion is a symptom of systemic risk. In this paper, we model systemic risk by modeling a network among banks in a country. The network provides the mechanism for transmission of risk, and is the driving force of contagion. The interconnectedness of banks described by a network is augmented with information on the credit quality of banks. We combine network and credit information into a single measure of systemic risk for the entire financial system. This measure is a modifica-

[1] For e.g. Sensoya (2017) finds evidence from Turkey supporting the hypothesis that institutional ownership leads to an enhanced systematic liquidity risk by increasing the commonality in liquidity. Borri (2017) adopts the CoVaR risk-measure to estimate the vulnerability of individual countries to systemic risk in the market for local currency government debt.

[2] Committee on International Policy Reform: Corporate Debt in Emerging Economies: A Threat to Financial Stability? September, 2015; Avdjiev et al. (2014).

[3] Including the credit extended by shadow banks, there was even steeper rise and a higher total burden amounting to 127% of GDP (source: Economist, Nov 14, 2015). Overall the corporate debt of non-financial firms across major emerging market economies quadrupled between 2004 and 2014 (Corporate leverage in emerging markets – a concern? Global Financial Stability Report: Vulnerabilities, Legacies, and Policy, IMF, October, 2015).

tion of the model from Das (2016). We calculate the measure for each quarter from 2004 Q3 to 2016 Q4, a total of 50 quarters. This time series is then used for further analyses.

We calculate several metrics as part of this analysis. We compute various measures of the mathematical properties of the network each quarter such as the *diameter* of the network, because contagion travels further when diameter is low; average *degree* of the network, degree being the number of connection of each node, which characterizes how interconnected the network is; *fragility* or how susceptible the network is to a local problem becoming a global one; *degree HHI*, where the Herfindahl index of node degree describes the extent of concentration in the network (more concentrated networks support contagion because of their hub and spoke shape). We also report the number of *clusters*, and the cluster HHI, where a cluster is an independent group of nodes that is not connected to any other group of nodes. The greater the number of disconnected clusters, the less likely we might have economic contagion, but the more concentrated nodes are in a single cluster we have a greater chance of contagion and systemic risk.

For each quarter we also compute risk data by bank. We have the 12 month *probability of default* (PD) of each bank; banks with high PD and high interconnectedness pose a threat to the system, so we retain the *degree* of each bank. We also calculate *betweenness centrality* for each bank in the network, which is a measure of how central a position the bank has (this is defined formally later in the modeling section). Finally, we calculate the total systemic risk for each quarter, and decompose it into the risk contributed by each bank, which offers us a metric for how systemically important a bank is. This systemic risk decomposition may be used to identify SIFIs (designated systemically important financial institutions, stipulated by the Dodd-Frank Act, 2010).

We are able to explore how much systemic risk is explained by credit quality and how much is explained by interconnectedness. In the data from India, using regression analysis, we find that about 15% of systemic risk is explained by network components and about 50% by credit risk components (both statistically significant). Therefore, credit quality and network structure are important in determining systemic risk.

We may ask, is systemic risk spanned in India? In further analysis, we will proceed to examine how systemic risk is related to various macroeconomic variables. In other words, may we describe systemic risk as a projection of some combination of some macroeconomic variables (including market variables)?

Finally, in a continuation of this work, first, we will calculate the same metrics for a slew of other emerging markets, and then assess whether systemic risk is correlated across countries, i.e., is it possible to globally diversify this risk across emerging markets? Second, we may also extract the principal components of the time series of systemic risk of all emerging markets, and determine what the structure of global systemic risk looks like. Third, we will use the systemic risk series for all countries to build a network of country interconnectedness and determine a measure of *global* emerging markets systemic risk, and its various properties; in other words, we take our family of models for each country and build up a meta-model for all emerging markets.

The rest of the paper proceeds as follows. In Section 2 we survey the now vast literature on systemic risk and contagion in network models. We break this section down into looking at various aspects of this literature, such as the definition of systemic risk, the various ways in which researchers have measured systemic risk, how systemic risk has been managed, how it has been predicted, etc. Next, Section 3 undertakes an exploration of the data we have for India, and reports some basic descriptive statistics. Our specific network construction methodology is explained in Section 4, and the statistics of constructed networks is reported in Section 4. Various network metrics are derived and explained in Section 6. In Section 7, we describe our formula for systemic risk and its decomposition. This section also reports the time series properties of the metric and how it relates to credit and network features. We also show some sample percentage risk decompositions, highlighting the specific banks that may be deemed SIFIs by this metric. We examine if systemic risk is spanned in Section **??**. Section 8 offers concluding discussion and comments.

2 Literature Review

The overall objective of this research is to better understand the measurement, management, and prediction of systemic risk for emerging market financial institutions. Our research is built on different strands of literature briefly described below.

2.1 Systemic Risk and its Origins

Systemic risk involves the risks that affect many market participants simultaneously, leading to severe losses, which then spread through the system. Systemic risk entails quick propagation of illiquidity and insolvency risks, and financial losses through the financial system as a whole, impacting the connections and interactions among financial stakeholders, especially so during periods of financial distress (Billio et al. (012a)). Systemic risk arises when the intermediation capacity of the entire financial system is impaired, with potentially adverse consequences for the supply of credit to the real economy (Adrian and Brunnermeier (2016)).

Allen and Carletti (2013) identify four sources of systemic risks viz., (i) banking related panics; (ii) banking crises arising from falling asset prices; (iii) contagion; and (iv) foreign exchange mismatches in the banking system. Asset price declines can in turn arise from the following sources: business cycle fluctuations; bursting of real estate bubbles; mispricing due to inefficient liquidity provision and limits to arbitrage; sovereign default; and interest rate increases.

The recent financial crisis demonstrates that there are many channels through which seemingly small losses can become systemic and threaten financial stability. There exist multiple potential vulnerabilities, including weak financial firms, substantial interlinkages across these firms, complex financial products, and excessive leverage and maturity mismatches fueled by the shadow banking system (see Brunnermeier (2009); Adrian and Shin (2010); Acharya et al. (2013); Covitz et al. (2013); Gorton and Metrick (2012)). These vulnerabilities amplified the shock of subprime losses from a drop in real estate prices through direct counterparty losses. As financial intermediaries invested in increasingly risky assets funded using excessive short-term funding, there was an increased danger from systemic fire-sales. Systemically significant nonbank institutions such as Bear Stearns and Lehman Brothers became the epicenter of systemic risk.

2.2 Measuring Systemic risk

The extant literature presents several alternative approaches of measuring systemic risk. Surveys of systemic risk include De Bandt and Hartmann (2000); Gale and Kariv (2007); Schwarcz (2008); Chan-Lau et al. (2009); Bisias et al. (2012); Benoit et al. (2017); Silva et al. (2017). Broadly there exist two approaches (1) cross-sectional correlations, and (2) network based measures.

2.2.1 Cross-sectional Correlation Measures

In early work, Lehar (2005) uses a sample of international banks to estimate the dynamics and correlations between bank asset portfolios, where the asset portfolio for each bank is implied using the contingent claims model of Merton (1973). Huang et al. (2012) create the distressed insurance premium (DIP) measure, which captures systemic risk by calculating a hypothetical insurance premium against catastrophic losses in a portfolio of financial institutions. Adrian and Brunnermeier (2016) develop the conditional value at risk (CoVaR) model, which estimates the increase in the value at risk of the financial system conditional on a firms distress.

Acharya et al. (2016) present a model of systemic risk and show that each financial institution's susceptibility to systemic risk can be measured as its systemic expected shortfall (SES), i.e., its propensity to be undercapitalized when the system as a whole is undercapitalized. Notice that, while other measures of systemic risk measure the risk faced by the system as a whole, the SES metric measures the effect of systemic risk on an individual bank. Therefore, this raises the interesting question as to which direction of causality should be assumed when measuring systemic risk. In related work, Acharya et al. (2012) present the expected capital shortfall measure, which can be a useful tool or substitute for such stress tests. Brownlees and Engle (2015) introduced the Conditional Capital Shortfall index for Systemic Risk Measurement (or SRISK) to measure the systemic risk contribution of a financial firm. The above analyses all relied on stock data but did not exploit network relationships.

2.2.2 Network-Based Measures

Networks of banks are built from data on direct interconnections between firms and allows regulators to estimate how the distress of a given firm would directly affect the other firms in the network, and also to simulate follow-on effects, which can be very significant. For example, Nier et al. (2007) investigate how systemic risk is affected by the structure of the financial system, where they construct banking systems composed of a number of banks that are connected by interbank linkages. Billio et al. (012a) use return correlations and Granger causality regressions on returns to construct network maps and develop network measures of systemic risk. Billio et al. (012b) apply several econometric measures of connectedness based on Granger-causality networks to the changes of sovereign risk of European countries and credit risk of major European, U.S., and Japanese financial institutions in order to investigate the evolution of these connections. Anand et al. (2013) develop a general framework to gauge systemic stability in the presence of complex interlinkages and heterogeneous economic agents. Elliott et al. (2014) examine cascades in financial networks using a model of cross-holdings among organizations that allows discontinuities in values. Diebold and Ylmaz (2014) provide several connectedness measures built from variance decompositions, which provide insightful measures of connectedness.

Gabrieli and Georg (2014) study the liquidity allocation among European banks around the Lehman Brothers insolvency based on dataset of all interbank loans. Hautsch et al. (2015) propose realized systemic risk beta as a measure of financial companies contribution to systemic risk, given network interdependence between firms tail risk exposures. Kitwiwattanachai (2015) proposes a probabilistic graphical model relating the network structure to observable CDS spreads. Acemoglu et al. (2015) provide a tractable theoretical framework for the study of the economic forces shaping the relationship between the structure of the financial network and systemic risk. Markose et al. (2012) study the network among US CDS contracts to document the high concentration or localization of exposures that leads to a too interconnected to fail (TITF) phenomenon.

Poledna et al. (2015) analyze systemic risk contributions from four exposure layers of the interbank network (derivatives, security cross-holdings, foreign exchange and the interbank market of deposits and loans) and show that by relying on the single layer of deposits and loans–as done in previous studies–one drastically underestimates systemic risk in the system by over 90%. They demonstrate that the exposures related to the cross-holding of securities and the exposures arising from FX transactions are crucially important components of the systemic risk of a country. Bluhm and Krahnen (2014) analyze the emergence of systemic risk in a network model of interconnected bank balance sheets, incorporating multiple sources of systemic risk, including size of financial institutions, direct exposure from interbank landings, and asset fire sales. They suggest a new macro prudential risk management approach building on a system wide value at risk (SVaR).

Chan-Lau et al. (2009) build a network of banks following a methodology comprising three parts: (1) the use of the default correlation model of Duan and Miao (2016) to produce a forward-looking probability of default (PD) total correlation matrix and then transform it into a partial correlation matrix by applying the CONCORD algorithm; (2) the measurement of banks systemic importance hinging on six network centrality indicators based on the partial correlations, which represent the direct connections among banks; and (3) a graphical analysis of the global banking network which can then be partitioned into overlapping bank/group centric local communities. Their study is based on a global network with over one-thousand exchange-traded banks suggesting the Financial Stability Board rankings appear to be biased towards singling out large institutions as systemic, with connectivity playing a rather minor role. We find otherwise in our work on Indian data.

Brunetti et al. (2015) study two network structures, a correlation network based on publicly traded bank returns, and a physical network based on interbank lending transactions. While the two networks behave similarly pre-crisis, during the crisis the correlation network shows an increase in interconnectedness while the physical network highlights a marked decrease in interconnectedness. Moreover, these networks respond differently to monetary and macroeconomic shocks. Physical networks forecast liquidity problems while correlation networks forecast financial crises.

Ahern (2013) shows that industries that are more central in the network of intersectoral trade earn higher stock returns than industries that are less central, confirming the results of Das and Sisk (2005). He finds that stock returns of central industries covary more closely with market returns and future consumption growth, showing that stocks in more central industries have greater market risk. Increased risk stems from their greater exposure to sectoral shocks that transmit from one industry to another through inter-sectoral trade. In addition, the empirical evidence suggests that sectoral shocks that contribute to aggregate risk are more likely to pass through central industries than peripheral industries.

Complementing these network models, our model of systemic risk networks provides a measure of systemic risk for the entire financial system, and each institution's contribution to this risk, thereby providing an implementation pathway for measuring systemic risk, and the identification and monitoring of systemically important financial institutions (SIFIs).

2.2.3 Other Estimation Approaches

The methiods in this section focus on data features other than correlations and networks, and deal mostly with tail risk measurement and principal components analyses, applied to non-equity markets, such as debt and CDS markets. Saldías (2013) proposes a method to monitor systemic risk based on Contingent Claims Analysis to generate aggregated Distance-to-Default series using option prices information from systemically important banks and the Index of banking stocks.

Demirer et al. (2017) use LASSO methods to shrink, select, and estimate the high-dimensional network linking the publicly traded subset of the world's top 150 banks, using a sample from 2003-2014. They characterize static network connectedness using full-sample estimation and dynamic network connectedness using rolling-window estimation. Statically, they find that global bank equity connectedness has a strong geographic component, whereas country sovereign bond connectedness does not. Dynamically, they find that equity connectedness increases during crises, with clear peaks during the Great Financial Crisis and each wave of the subsequent European Debt Crisis, and with movements coming mostly from changes in cross-country as opposed to within-country bank linkages.

Oh and Patton (2016) propose a new class of copula-based dynamic models for high-dimensional conditional distributions, facilitating the estimation of a wide variety of measures of systemic risk. Based on sample of daily credit default swap (CDS) spreads on 100 U.S. firms over the period 2006 to 2012, they find that while the probability of distress for individual firms has greatly reduced since the financial crisis of 2008-09, the joint probability of distress (a measure of systemic risk) is substantially higher now than in the pre-crisis period.

Bianchiy et al. (2015) present a Bayesian based methodology to make robust system-wide inference on uncertain, time-varying, cross-firm financial linkages. They find that financial firms and sector features play a crucial role in systemic risk measurement, beyond their relative market values. Also, they find that companies more exposed to the overall risk of the system, i.e., those with higher weighted eigenvector centrality, are more likely to suffer significant losses when aggregate systemic risk is larger.

Betz et al. (2016) provide a measure of realized systemic risk referred to as marginal systemic relevance that takes into account both the individual riskiness of the bank as well as the degree of price co-movement with the left tail of the financial system return distribution. They find that at the height of the sovereign debt crisis, banks from countries participating in the EU-IMF program exhibit the greatest degree of systemic risk contributions. They document that marginal systemic relevance increases with size, leverage, and interconnectedness.

Härdle et al. (2016) propose TENET - Tail Event driven NETwork technique that allows ranking of the Systemic Risk Receivers and Systemic Risk Emitters in the US financial market. In particular TENET model brings tail event and CoVaR network dynamics together into one context and helps estimate systemic interconnectedness across financial institutions based on tail-driven spillover effects in a high dimensional framework.

Nucera et al. (2016) propose to pool alternative systemic risk rankings for financial institutions using the method of principal components. They find that the resulting overall ranking is less affected by estimation uncertainty and model risk.

Duarte and Eisenbach (2015) construct a new systemic risk measure that quantifies vulnerability to fire-sale spillovers using detailed repo market data for broker-dealers and regulatory balance sheet data for U.S. bank holding companies.

2.3 Managing Systemic risk

An effective systemic risk monitoring effort seeks to distinguish shocks, which are varied and difficult to predict, from vulnerabilities, which can amplify shocks and lead to instability (Liang (2013)). The regulatory framework in place prior to the global financial crisis was largely "microprudential" in nature, with a focus on individual banks and the risks on their balance sheets. The basic presumption was that if each bank could be prevented from taking large risks, there would not be a build-up of risk in the financial system. In the aftermath of the crisis, financial regulation shifted towards a "macroprudential" approach, which recognizes the importance of general equilibrium effects, and seeks to safeguard the financial system as a whole (Hanson et al. (2011)).

Brunnermeier and Pedersen (2009) emphasize the usefulness of a capital surcharge to reduce liquidity risk associated with maturity mismatches, while Perotti and Suarez (2009) propose a mandatory tax on wholesale funding that could be used to fund an insurance scheme. Others, such as Goodhart (2009), have proposed to limit systemic externalities through a liquidity insurance mechanism in which access to publicly provide contingent liquidity would be permitted if a premium, tax, or fee were paid in advance. Acharya et al. (2010) suggest that a risk-based deposit insurance premium should not only reflect the actuarial fair value but should also include an additional fee imposed on systemically important institutions to reflect their excessive risk taking and the disproportionate cost they impose on others in the system. Gobat et al. (2011) present three methodologies: Systemic Liquidity Risk Index (SLRI); Systemic Risk-adjusted Liquidity (SRL) Model; Stress-testing (ST) Systemic Liquidity Risk that measure systemic liquidity risk in a way that can be used to calculate a fee or surcharge.

The Dodd-Frank Act, enacted in 2010 in response to the financial crisis, designated the Fed as the primary supervisor for the largest bank holding companies as well as nonbank financial institutions designated as systemically important. The Act promoted a macroprudential approach to supervision and regulation. The Act suggested the designation of financial institutions as "systemically important" and such institutions are required to maintain additional regulatory risk buffers (about 1% additional capital). Our model of systemic risk networks provides a measure of systemic risk for the entire financial system, and each institutions contribution to this risk, thereby providing an implementation pathway for measuring systemic risk, and the identification and monitoring of systemically important financial institutions (SIFIs).

2.4 A Forward View of Systemic Risk

Most of the papers cited above in the discussion of measurement of systemic risk propose some forecast measure (e.g. Allen et al. (2012)). They do not however consider the dynamics in a way in which our network model can, by simulating changes in the network and changes in the credit quality of financial institutions. We will develop a state-variable based approach to generate dynamics, and use this to create an early warning program for detecting systemic risk.

2.5 Other Empirical Studies

Giglio et al. (2016) study how systemic risk and financial market distress affect the distribution of shocks to real economic activity. They analyze how changes in 19 different measures of systemic risk skew the distribution of subsequent shocks to industrial production and other macroeconomic variables in the US and Europe over several decades. They also propose dimension reduction estimators for constructing systemic risk indexes from the cross section of measures and demonstrate their success in predicting future macroeconomic shocks out of sample

Black et al. (2016) show that systemic risk measured as distress insurance premium (DIP) of European banks reached its height in late 2011 to around Euro 500 billion largely due to sovereign default risk. Although increased risk premia were a significant component of this increased systemic risk, the authors show that physical probabilities of default increased dramatically during this period. This suggests that the risk was not just due to changes in investor sentiment, but also due to real increases in the solvency risk of European banks. Avramidis and Pasiouras (2015) treat the banking system as a traded credit portfolio and calculate systemic risk capital as the amount of capital that insures the portfolios value against unexpected losses. Using data from the largest global financial institutions, they find evidence of extreme event dependence between banks during the recent financial crisis.

Pagano and Sedunov (2016) use Adapted Exposure CoVaR and Marginal Expected Shortfall (MES) measures to show that the aggregate systemic risk exposure of financial institutions is positively related to sovereign debt yields in European countries, varying positively with the intensity of the financial crisis facing a particular nation. They find evidence of a simultaneous relation between systemic risk exposure and sovereign debt yields suggesting that models of sovereign debt yields should also include the systemic risk of a countrys financial system in order to avoid potentially important mis-specification errors

Sedunov (2016) compares the performance of three measures of institution-level systemic risk exposure Exposure CoVaR (Adrian and Brunnermeier (2016)), systemic expected shortfall (Acharya et al. (2016)), and Granger causality (Billio et al. (012a)) and finds that Exposure CoVaR forecasts the within-crisis performance of financial institutions, and provides useful forecasts of future systemic risk exposures. Systemic expected shortfall and Granger causality do not forecast the performance of financial institutions reliably during crises.

Tasca et al. (2014) show for FIs depending on higher leverage there is a critical level of diversification that separates two regimes: (i) a safe regime in which a properly chosen diversification strategy offsets the higher systemic risk engendered by increased leverage and (ii) a risky regime in which an inadequate diversification strategy and/or adverse market conditions, such as market size, market volatility and time horizon, cannot compensate the same increase in leverage.

Abbass et al. (2016) analyze the relation between market-based credit risk interconnectedness among banks during the crisis and the associated balance sheet linkages via funding and securities holdings. They find that market-based measures of interdependence can serve well as risk monitoring tools in the absence of disaggregated high-frequency bank fundamental data.

Liu et al. (2015) examine the systemic credit risks across different states in US and find that macroeconomic variables have higher explanatory power for co-variations in state credit spreads and their systemic component than do financial market variables.

Laeven et al. (2016) examine cross sectional variation of standalone and systemic risk of large banks during the recent financial crisis to identify bank specific factors that determine risk. They find that systemic risk grows with bank size and is inversely related to bank capital, and this effect exists above and beyond the effect of bank size and capital on standalone bank risk. The authors further argue that the effects on systemic risk might underestimate the true systemic risk of large banks, because market values of bank equity during the crisis may be boosted by expectations of government support, and because they do not account for the social costs associated with large bank failures (e.g., output losses and unemployment).

Li and Zinna (2014) develop a multivariate credit risk model that accounts for joint defaults of banks and helps disentangle how much of banks' credit risk is systemic. They find that the US and UK differ not only in the evolution of systemic risk but, in particular, in their banks' systemic exposures. In both countries, however, systemic credit risk varies substantially, represents about half of total bank credit risk on average, and induces high risk premia. Their results suggest that sovereign and bank systemic risk are particularly interlinked in the UK.

Karolyi et al. (2016) examine the impact of cross-border bank flows on recipient countries systemic risk. Using data on bank flows from 26 source countries to 119 recipient countries, they find that bank flows are associated with improved financial stability (i.e. lower systemic risk) in the recipient country. In addition, they document that bank flows reduce systemic risk of large banks, with poor asset quality, more nontraditional banking activities, and more reliance on volatile sources of funds. Their evidence suggests that bank flows reduce systemic risk by improving banks asset quality, efficiency, and reliance on nontraditional revenue sources. Overall, their evidence supports the benign view of regulatory arbitrage in international bank flows.

Colliard et al. (2017) present a core-periphery model of trading in the overnight interbank market. They model periods of crises as an increase in the number of peripheral banks that lose access to core dealers, resulting in segmentation between core and peripheral markets. Their model implies that such an increase in segmentation raises (i) the market power of periphery banks connected to the core, (ii) the dispersion of rates in the interbank market, and (iii) inefficient recourse to the central bank standing facilities. The authors argue that these implications are consistent with stylized facts about the interbank market and propose new predictions about trading in a segmented OTC market.

3 Data

We collect a sample of 838 Indian firms from the Datastream Database that meet three criteria – are explicitly identified as financial firms, are active firms, and have common equity that are major securities trading in a primary exchange in the local (Indian) market. We reject (a) non-financial firms, (b) inactive (delisted) firms, (c) firms with only preferred stock, (d) foreign firms trading in Indian exchanges, and (e) Indian firms trading exclusively in either a minor exchange in India or a foreign exchange. We also reject firms with less than 125 active trading days (or six calendar months of exchange history).

Based on International Securities Identification Number (ISIN) and/or Stock Exchange Daily Official List (SEDOL) identifiers, we match the Indian financial firms to the Compustat Global Database and obtain the corresponding GVKEYs and Standard Industrial Classification (SIC) codes. Based on SIC codes, we categorize firms as (a) Banks (SIC: 6000-6199), (b) Broker-Dealers (SIC: 6200-6299), (c) Insurers (SIC: 6300-6499), and (d) Others (all other SICs). We eliminate firms with no SIC code and firms classified as others (which include financial subsidiaries of non-financial corporations and specialized investment vehicles such as funds, REITs and securitized assets). Our final screened sample consists of 387 Indian financial institutions – 193 Banks, 191 Broker-Dealers and 3 Insurers.

Datastream provides dividend- and stock-split-adjusted consecutive (non-missing) returns spanning a period of 13 years from 2nd January 2004 to 30th December 2016, comprising 3,391 consecutive daily observations. Based on GVKEYs, we obtain the Standard & Poor's ratings from Compustat Capital IQ and convert them into numerical values on an ordinal scale (with AAA rating assigned a value of 1). Discrete ratings are converted into daily time-series corresponding to returns. In addition, based on ISINs and/or SEDOLs, we obtain distances-to-default (DTD) and probabilities of default (PD) for 7 maturities: 1, 3, 6, 12, 24, 36 and 60 months, from the Credit Research Initiative (CRI) Database maintained at the Risk Management Institute (RMI) of the National University of Singapore (NUS). The database reports monthly DTD and PD values computed from Merton-type models using firm-specific values; these monthly values are converted into daily time-series corresponding to returns.

Table 1: Bank Identification Data. This table contains a sampling of the bank name, and various other identification information.

MNEMONIC	ISIN	SEDOL	NAME	INDUSTRY	GVKEY	SIC
IN:HFC	INE040A01026	B5Q3JZ5	HDFC BANK	Bank	144535	6020
IN:HDF	INE001A01036	6171900	HOUSING DEVELOPMENT FIN.	Bank	223055	6036
IN:SBK	INE062A01020	BSQCB24	STATE BANK OF INDIA	Bank	203666	6020
IN:ICG	INE090A01021	BSZ2BY7	ICICI BANK	Bank	223148	6020
IN:KOK	INE237A01028	6135661	KOTAK MAHINDRA BANK	Bank	223062	6020
IN:UTI	INE238A01034	BPFJHC7	AXIS BANK	Bank	252278	6020
IN:IBK	INE095A01012	6100454	INDUSIND BANK	Bank	273462	6020
IN:BJF	INE296A01024	BD2N0P2	BAJAJ FINANCE	Bank	284229	6141
IN:BFS	INE918I01018	B2QKWK1	BAJAJ FINSERV	Insurer	288902	6300
IN:YEB	INE528G01019	B06LL92	YES BANK	Bank	273436	6020
IN:IEZ	INE148I01020	B98CG57	INDIABULLS HOUSING FIN	Bank	315842	6162
IN:BBR	INE028A01039	BVF87C6	BANK OF BARODA	Bank	205654	6020
IN:LIC	INE115A01026	6101026	LIC HOUSING FINANCE	Bank	206322	6162
IN:FED	INE171A01029	BFT7KB7	FEDERAL BANK	Bank	204856	6020
IN:LFH	INE498L01015	B5KYHQ1	L&T FINANCE HOLDINGS	Bank	298645	6159

These FIs for India come from 3 industry groups and the counts are shown in Table 2. Banks and Broker-Dealers comprise a 50/50 split of the data.

Table 2: Industry groups, sample count.

	TOTAL	NUMBER WITH VALID			
INDUSTRY	NUMBER	RETURNS	RATINGS	DTD	PD
Bank	193	193	20	176	177
Broker-Dealer	191	191	0	177	177
Insurer	3	3	0	2	2
Total	387	387	20	355	356

The data for all FIs is not available for all dates, of course. For all dates on which returns are available for any FI, we calculated the percentage returns between consecutive days. Interestingly, given the large number of FIs and sub-periods, we get a range of pairwise correlations of returns: 68.9% of the pairs have positive correlation, 29.3% have negative correlation, and 1.8% do not overlap and there is no correlation available.

We also collect several balance sheet and income statement variables corresponding to the financial institutions from Datastream on a quarterly basis and compute the following firm-specific quarterly attributes:

1. Log(Assets) and Log(Market Cap) as measures of firm size in terms of book value of assets and market value of equity, respectively;
2. Loans/Assets and Loans/Deposits ratios to capture banks' focus on traditional lending activities and core financing activities (these ratios are set to zero for non-bank financial institutions);
3. Debt/Assets and Debt/Equity ratios to capture leverage;
4. Debt/Capital as a measure of the liquidity position of the financial firm;
5. ROA (return on assets) and ROE (return on equity) as measures of operating performance of the financial firm; and
6. Market/Book value of equity ratio of the financial institution as a measure of the stock price based performance.

4 Network Construction

We use the return data to construct networks using a novel modified Granger causality approach. Our approach is an extension of the method in Billio et al. (012a). In their original method, for any two banks i, j, we run the following regression:

$$r_{j,t} = a + b \cdot r_{j,t-1} + c \cdot r_{i,t-1} + e_{j,t}$$

where $r_{i,t}$ denotes return for bank i on day t. If coefficient c is significant (we use a p-value less than 0.025), then we assign a network link from bank i to bank j. This means that if bank i experiences a shock it will transmit the shock to bank j. Likewise, we can run the reverse regression to determine if a risk transmission link exists from bank j to bank i. We run pairwise regressions for all banks, i.e., for n banks we have $n(n-1)$ regressions. We store the network links in a network adjacency matrix denoted A of size $n \times n$. Here, $A(i,j) = 1$ if there is a risk spillover from bank i to j, else $A(i,j) = 0$.

This approach has been criticized as both banks may have co-movement on account of a joint factor, i.e., the returns on an overall index of FIs, see ChanLau et al. (2016) for a survey and critiques of network construction models. To exclude this effect and focus only on the pure linkage between two banks, we modify the regression above to include lagged values of the equal-weighted return ($r_{EW,t-1}$) of all banks used to construct the network. This variable soaks up any lagged co-movement, thereby isolating the idiosyncratic risk spillover between two banks. Our new specification is as follows.

$$r_{j,t} = a + b \cdot r_{j,t-1} + c \cdot r_{i,t-1} + d \cdot r_{EW,t-1} + e_{j,t}$$

where $R_{EW,t}$ is the equal-weighted return of all banks for day t. Again, to establish the link $A(i,j) = 1$, we require that the p-value of the coefficient c be small, i.e., $p \leq 0.025$, if $c > 0$. Note that if $c \leq 0$, then there is no risk spillover from i to j, in which case we also set $A(i,j) = 0$.

To construct the network matrix for any day t, we have to make choices about the look back period of returns, and which banks to include in the analysis. These choices are as follows.

1. The look back period is chosen to be $L = 130$ trading days, i.e., roughly a half-year.

2. For the chosen period, we extract all bank returns, and exclude any bank that does not exist through the entire period.

3. For the remaining banks, we find that many banks have stock prices that do not move much, and are illiquid. These are essentially very small banks that are not likely to have any systemic effects. If stock prices remain same from day to day, returns will be exactly zero on many days. We therefore exclude all such banks that have zero returns on more than 1/3 of the sample L days.

4. We then run the network construction model described above to create the adjacency matrix A. We do this for each quarter end starting with Q3 2004,

ending with Q4 2016. This provides a total of 50 quarters, and a network for each one. Recall that for each quarter end's network, we use data for the past $L = 130$ trading days.

A sample of the adjacency matrix is shown visually in Figure 1 for Q4 2016. A dot in row i and column j means that $A(i,j) = 1$. For this period, there are 214 banks that made it through the filters above. To construct this matrix we ran $n(n-1) = 45,582$ regressions. The number of cells in the adjacency matrix that are of value 1 is 1.83%. The diameter of the network (longest shortest path between any two nodes) is 9, and the average degree (incoming and outgoing links) per node is 7.79.

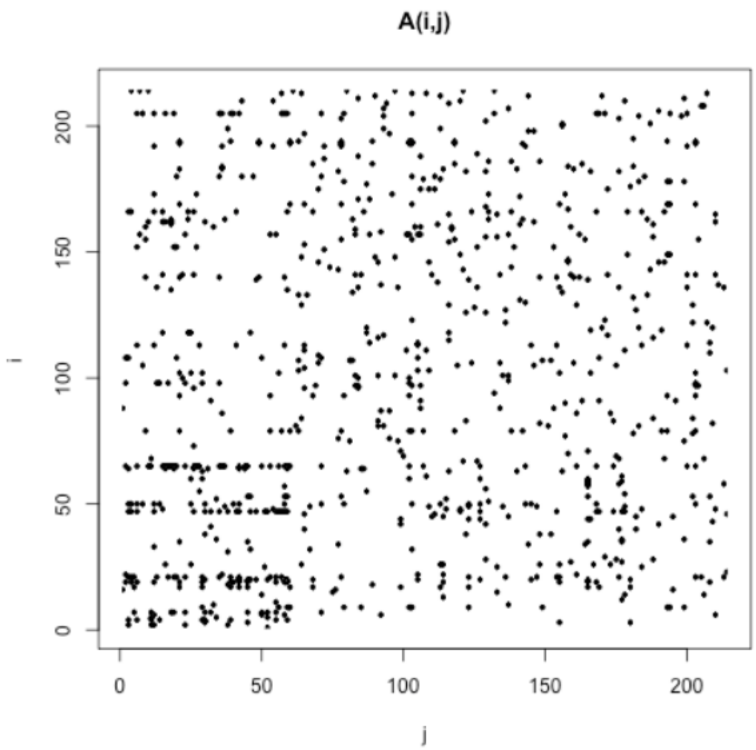

Figure 1: Visual representation of the network adjacency matrix for Q4 2016. There are a total of 214 FIs in the matrix. A dot in row i and column j means that $A(i,j) = 1$, i.e., j indexes the x-axis, and i indexes the y-axis. The threshold confidence level for network construction is 0.975, i.e., links are based on Granger regression coefficients with p value less than 0.025.

We also present the network in Figure 2. We see the full network with nodes of different sizes representing the number of connections they have, see the first plot in the figure. The second plot shows what happens when the threshold for setting a link in the network is loosened from a p value of 0.975 to 0.95, so we get more links in the network. By running the same analysis across a few other countries, for p values of

$\{0.01, 0.025, 0.05\}$, we settled on a value of 0.025. At the level the network is neither too sparse n or too dense.

5 Network Statistics

In order to detect which nodes are most influential in the network, we compute eigenvalue centrality and betweenness centrality from the adjacency matrix.

Eigenvalue centrality, originally defined in Bonacich (1987), and further discussed in Bonacich and Lloyd (2001), defines centrality of a node as being a function of the centrality of the nodes it is connected to. This leads to a circular system of simultaneous equations:

$$c_i = \sum_{j=1}^{n} A_{ij} c_j, \forall i$$

One solution to this system of equations is the principal eigenvector in an eigenvalue decomposition of matrix A, which Bonacich (1987) defined as "eigenvalue centrality". This vector contains n components $c_i, i = 1, 2, \ldots, n$.

The definition of betweenness centrality for node v is as follows, see Freeman (1977):

$$b_v = \sum_{\substack{i,j \\ i \neq j \\ i \neq v \\ j \neq v}} \left[\frac{g_{ivj}}{g_{ij}} \right]$$

where g_{ivj} is the number of shortest paths from i to j that pass through node v, and g_{ij} is the number of shortest paths from i to j. The distribution of centrality is shown in Figure 3.

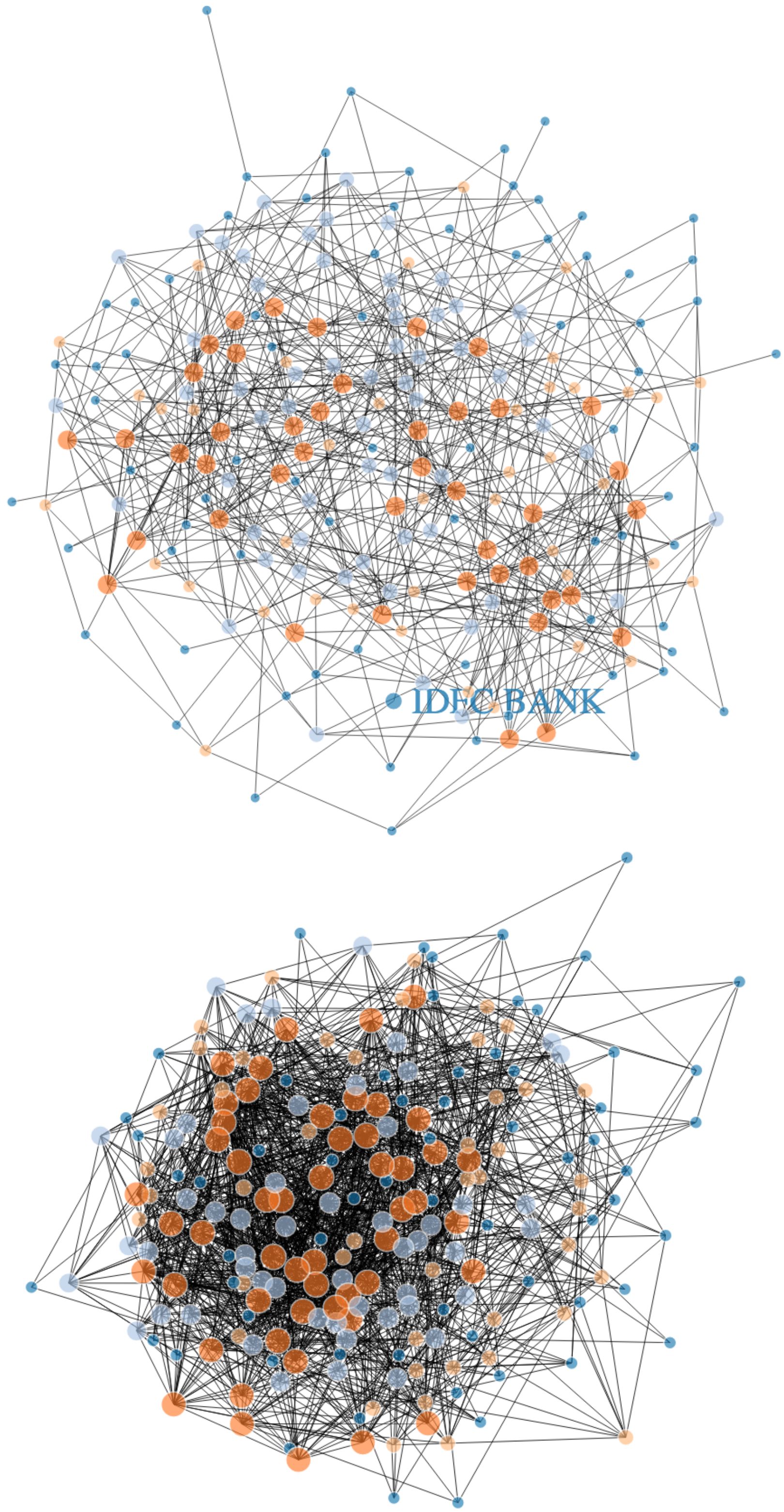

Figure 2: Visual representation of the network for Q4 2016. The plot shows the full network and one chosen bank, IDFC. Node size represents the number of connections a node has. The first plot is for link formation at a confidence level of 0.975, and the more dense plot is at a lower confidence level of 0.95, admitting many more links.

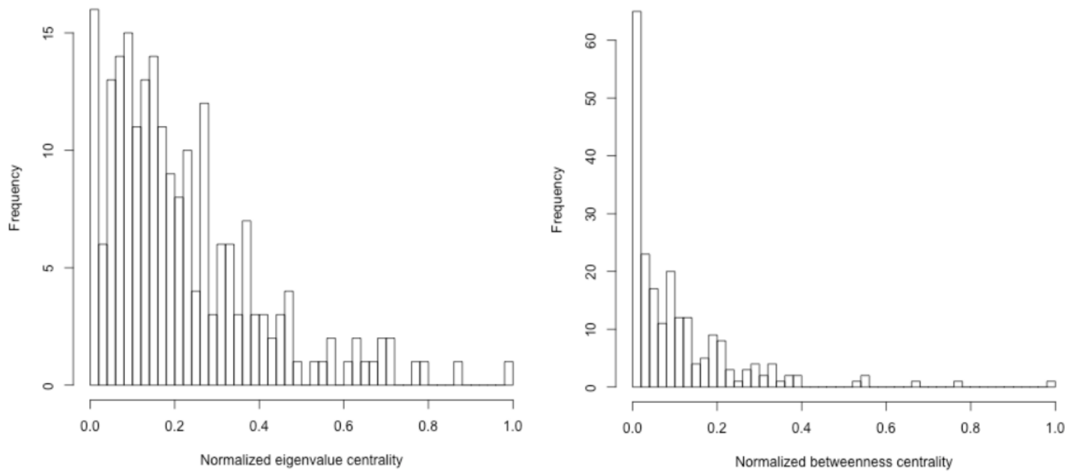

Figure 3: Distribution of Eigenvalue Centrality and Betweenness Centrality for all the nodes in the network, for Q4 2016. The centrality is normalized, so that it ranges from 0 to 1.

The top 20 banks by betweenness centrality are shown in Table 3. We see interestingly that the rankings are different depending on which centrality score is being used. We prefer to use betweenness centrality as it is more robust when there are many nodes in the network that are unconnected, in which case eigenvalue decomposition required for computing eigenvalue centrality becomes less stable. Further, betweenness centrality directly picks up the nodes through which risk passes fastest, since these nodes sit on the shortest paths between other nodes, and will facilitate transmission of risk spillovers. However, for a well connected network, eigenvalue centrality provides a better depiction of the importance of each node.

Table 3: Top 20 banks by eigenvalue centrality (EVCENT) and betweenness centrality (BCENT) for Q4 2016.

Bank	EVCENT	BCENT
PRITI MERCANTILE COMPANY	1.000000	0.217527
DHANLAXMI BANK	0.879521	0.289056
BANK OF MAHARASHTRA	0.797941	0.033656
INDIAN BANK	0.771766	0.033376
UCO BANK	0.710815	0.082385
UNITED BANK OF INDIA	0.708690	0.033280
RR FINL.CONSULTANTS	0.694695	0.135618
UNION BANK OF INDIA	0.687011	0.047011
CENTRAL BANK OF INDIA	0.675282	0.667370
IFCI	0.656577	0.053150
P N B GILTS	0.633888	0.248902
GLOBAL CAPITAL MARKETS	0.629967	0.375415
J M FINANCIAL	0.601884	0.132343
CORPORATION BANK	0.564888	0.000000
INTER GLOBE FINANCE	0.562848	0.533449
STATE BANK OF INDIA	0.548690	0.175723
BANK OF BARODA	0.539016	0.009665
S P CAPITAL FINANCING	0.497271	0.022460
SOUTH INDIAN BANK	0.476020	0.091634
TRANSWARRANTY FINANCE	0.472221	0.072575

6 Network Metrics

There are several statistics that we compute from the adjacency matrix representing the bank network. These are as follows, and for each metric, we report the value for Q4 2016 as an example. The network is shown in Figure 2.

1. The number of nodes, equal to 214.

2. The diameter of the largest cluster in the network. Diameter is the longest shortest path between any two nodes in the network, taken over all pairs of nodes. Here we calculate clusters, i.e., groups of connected nodes, and *diameter* is defined as the longest shortest path between any two nodes in the largest cluster in the network. For the network shown in Figure 2 for Q4 2016, the diameter is 9. There is a decent number of steps to go from one end of the network to the other.

3. We calculate *Mean degree* $E(d)$, where d_i is number of connections of node i in the network. Mean degree of all nodes in the network is 7.79.

4. We define the *fragility* score of the network as $E(d^2)/E(d)$. The numerator is the raw Herfindahl index of the degree distribution, and is higher if connections are concentrated in a few nodes. The denominator normalizes this score by dividing by mean degree. The higher the fragility or concentration in the network, the greater is the likelihood that a local problem in the banking network will spread across the network and become a global problem. High fragility is a property of

hub and spoke networks. Once a problem reaches and impacts a hub node, it then spreads rapidly through the network. We computed fragility for Q4 2016 and it's value is 12.30. Numbers larger than 2 represent a fragile network.

5. The Herfindahl index is calculated as $H = \sum_{i=1}^{n} \left(\frac{d_i}{\sum_{i=1}^{n} d_i} \right)^2$. We normalize it so as to get a value between 0 and 1, by computing $NH = \frac{H-1/n}{1-1/n}$. This score is 0.002722. Hence the network is not concentrated, and we see this from a visual inspection of Figure 2. There are not just a few nodes that contain all the connections.

6. We also examine how disconnected the network is by computing the number of connected groups, i.e., *clusters*. In this case there are 3, so the network is not very disconnected.

7. We also calculate the normalized Herfindahl index of cluster sizes, i.e., are all the nodes in one large cluster or are the clusters balanced in size? This score is 0.96, which suggests that there is one large cluster, and indeed the largest cluster has 211 of the 214 nodes in it. The remaining clusters are of size 1 and 2. For all practical purposes, the network is fully connected.

We calculated these network statistics for all quarter end dates starting from Q3 2004 to Q4 2016, a total of 50 quarters. The number of banks in the network is plotted in Figure 4. We see that the network has been growing steadily from 100 banks at the beginning of 2004 to 220 banks as of end 2016. The peak number of banks in the network are 274 in Q3 2014.

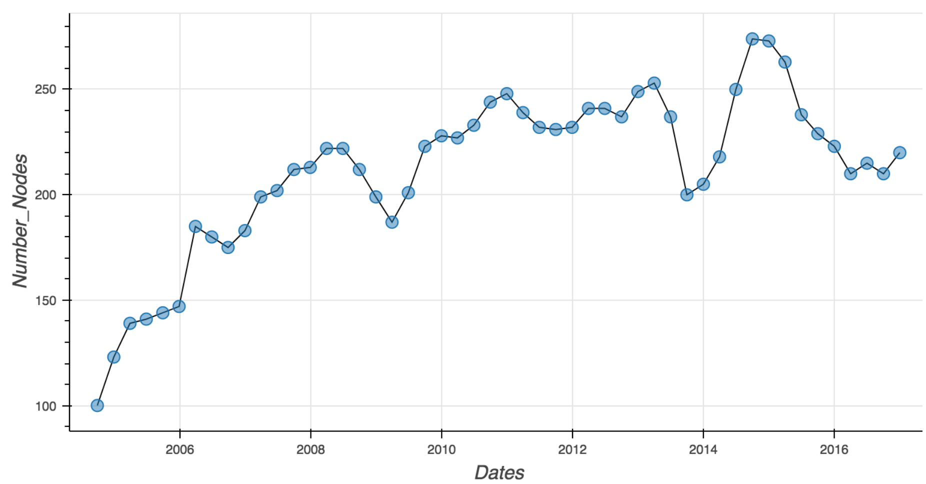

Figure 4: The number of banks in the network for all quarters between Q3 2004 and Q4 2016.

The diameter is a measure of how much time it would take for a problem at one side of the network to reach the opposite side. It is thus a measure of risk transmission.

Networks with a large diameter are less likely to experience system-wide problems. For India, Figure 5 shows that diameter of the banking network has remained more or less stable in the $10 - 15$ range.

Similarly, fragility measures how concentrated the network may be in a few nodes, with higher concentration being related to greater systemic risk. Figure 6 shops that fragility is usually quite low, but the system does experience sudden spikes when the fragility increases by a multiple of 4 to 5 times that of normal. A comparison of the time series for diameter and fragility should evidence an inverse relationship, and the figures support that assertion.

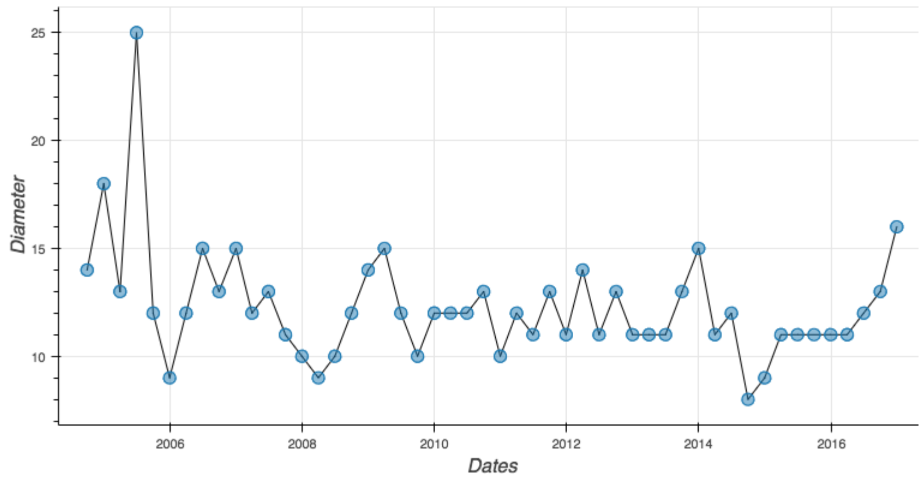

Figure 5: The diameter of the network for all quarters between Q3 2004 and Q4 2016. Diameter is the longest shortest path between any two nodes, taken over all node pairs.

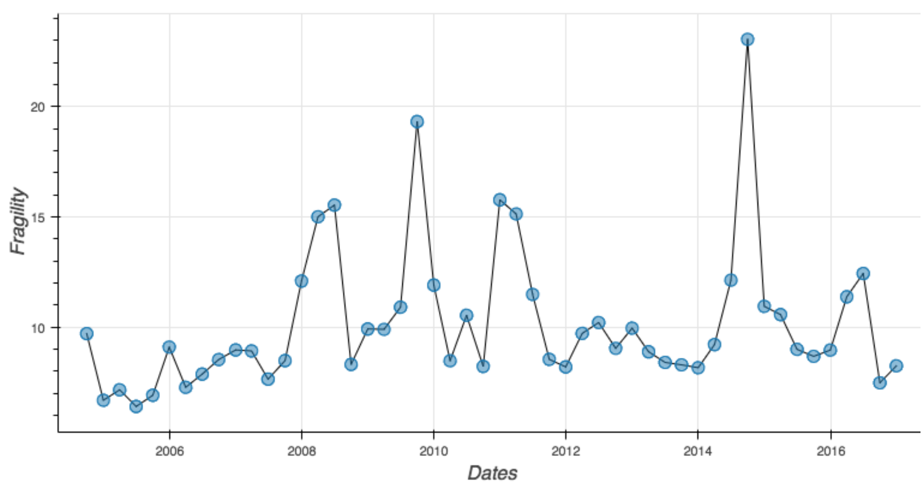

Figure 6: The fragility of the network for all quarters between Q3 2004 and Q4 2016. Fragility is a measure of the concentration in the network.

It is also interesting to see how connected each node is on average. The more connected each node is, the greater the extent to which problems will spread in the financial system. Figure 7 shows the average degree of the nodes in the network over time. We see that the number of connections a node has is usually around 6, but for some periods when these spike, such as in Q3 2014, when the network became the largest in the sample period. After being more or less flat in 2013, the Indian stock market started an aggressive pick up from 2014 onwards, and the increase in economic activity is possibly reflected in the size of the Indian banking network.

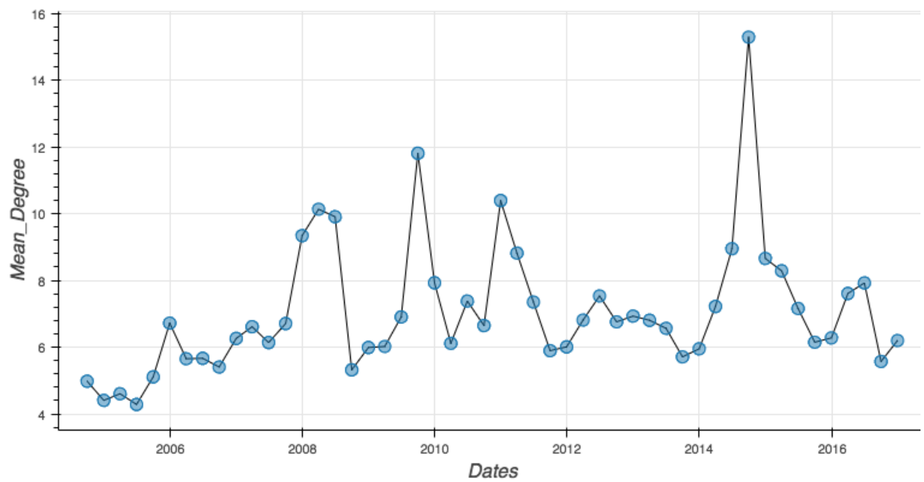

Figure 7: The degree of a node is the number of network links it has. We show the mean degree of the network for all quarters between Q3 2004 and Q4 2016.

We also explore how disconnected the network is. This is gauged by the number of clusters it has, each cluster being a set of connected nodes, and there are no connections between clusters. The more disconnected the network, the less susceptible it is to systemic risk. In Figure 8 we see the number of clusters dropping slowly from 2004 to 2016, suggesting that the network is becoming more prone to systemic risk. We do note however, that the number of clusters is not as critical a measurement as the concentration in the largest cluster, as most nodes tend to reside in one large cluster, with increasing concentration. This is assessed by the Herfindahl index, and is borne out by the increasing normalized Herfindal index of clusters, shown in Figure 9. A summary of all the network properties over time, showing how they relate to each other is portrayed in the correlogram in Figure 10.

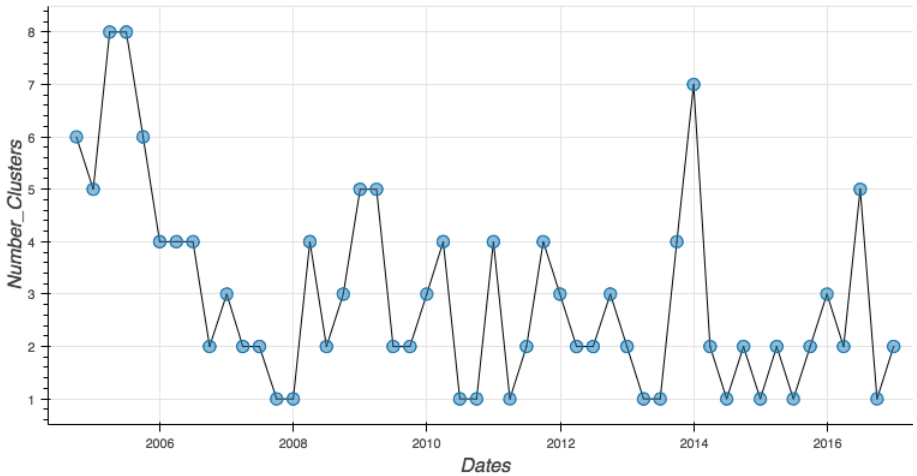

Figure 8: The number of clusters is the number of disconnected components (connected groups) it has. We show the number of clusters of the network for all quarters between Q3 2004 and Q4 2016.

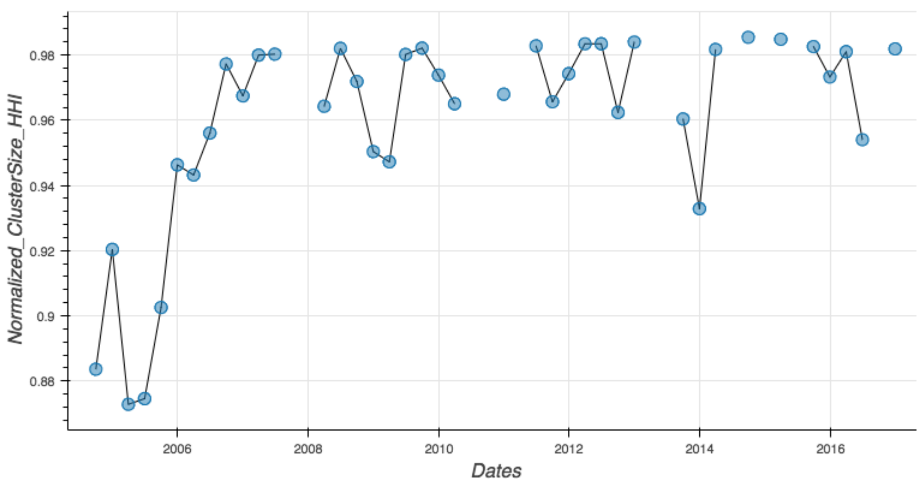

Figure 9: The normalized Herfindahl index of clusters is a measure of the concentration in the network. We show the normalized Herfindahl score of clusters of the network for all quarters between Q3 2004 and Q4 2016.

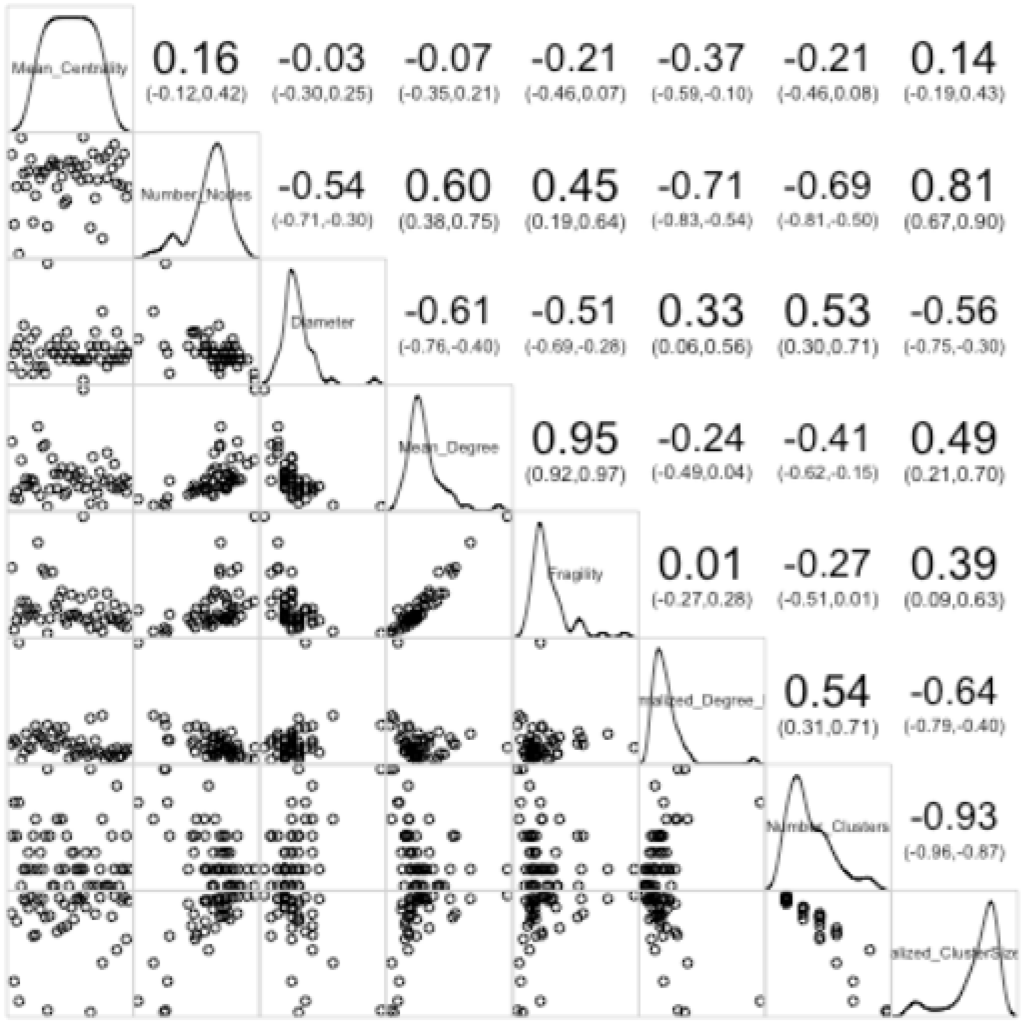

Figure 10: The correlation between all network metrics for all quarters between Q3 2004 and Q4 2016. Reading down the diagonal, the metrics are: Mean Centrality, Number of Nodes, Diameter, Mean Degree, Fragility, Normalized Degree Herfindahl, Number of Clusters, Normalized Cluster Size Herfindahl.

7 Risk Metrics

The network adjacency matrix A describes the structure of risk spillovers between banks. But the network does not account for the total potential impact of these risk spillovers on the system as a whole, i.e., systemic risk. We therefore, combine network information with credit information using the systemic risk score developed in Das (2016); Das et al. (2017). We deploy a modified version of the risk score in prior work by converting it into a risk score per bank instead. This normalizes the score so that we may proceed to use it for comparison of systemic risk across time, even as the number of banks changes. Our measure is as follows.

$$S = \frac{1}{n}\sqrt{C^\top \cdot A \cdot C} \tag{1}$$

where n, as before, is the number of banks, and $C = a \cdot \lambda$ is a n-vector of size-weighted credit risk scores of each bank where $a = \log(TotalAssets)$ and λ is a credit quality measure. We require that λ be increasing in credit risk. We make the following observations.

1. There are many conceivable ways to construct the λ vector. Examples are credit ratings converted into integer scores, with rating $AAA = 1$, $AA = 2$, etc. We may also use probability of default (PD), the reciprocal of distance-to-default, or a sparse scoring system where investment grade and below-investment grade are given a lower and higher chosen values.

2. Because we normalized the score by n, we may compare this score across countries, and across epochs for the same country. The S score represents a per-bank, dollar-weighted, and network-weighted credit risk measure for the entire financial system.

3. Noting that all elements of A are positive, i.e., $A_{i,j} \in \{0,1\}, \forall i,j$, and that $C_i \geq 0, \forall i$, systemic risk is non-negative, i.e., score $S \geq 0$.

4. An increase in any element of A (network effect) or C (individual risk effect) will result in an increase in S.

5. The function $S(C,A)$ is linear homogenous in C. Using this property, and applying Euler's homogeneous function theorem[4], we see that

$$S = \frac{\partial S}{\partial C_1}C_1 + \frac{\partial S}{\partial C_2}C_2 + \ldots + \frac{\partial S}{\partial C_n}C_n = \sum_{i=1}^{n} \frac{\partial S}{\partial C_i}C_i$$

   and each component $\frac{\partial S}{\partial C_i}C_i$ of this equation comprises the "Risk Contribution" of bank i to total systemic risk. This allows a regulator to apportion systemic risk to each bank such that it is additive across all banks.

6. The expression $\frac{\partial S}{\partial C_i}$ in closed-form is as follows:

$$\frac{\partial S}{\partial C} = \frac{1}{2n^2 S}[A \cdot C + A^\top \cdot C] \in \mathcal{R}^n$$

   which provides the entire vector in one matrix calculation making for efficient computation. Therefore, S may be written as the following scalar quantity:

$$S = \frac{1}{2n^2 S}\left([A \cdot C + A^\top \cdot C] \odot C\right)^\top \cdot \mathbf{1}$$

[4] http://mathworld.wolfram.com/EulersHomogeneousFunctionTheorem.html.

where $\odot$ stands for the Hadamard product of two vectors or matrices, and $\mathbf{1}$ is a n-vector of 1s, i.e., a unit n-vector. And clearly, the risk contribution of any bank i is

$$\frac{\partial S}{\partial C_i} \cdot C_i = \frac{1}{2n^2 S} \cdot [A \cdot C + A^\top \cdot C] \odot C \tag{2}$$

7.1 Distribution of the Probability of Default

Our data set also contains details on the probability of default (PD) of the banks in the sample. We use the one-year PDs in our analysis as is commonly done in the credit risk industry. For the entire sample period from 2004 to 2016, the mean PD for Indian FIs is 0.008095, i.e., slightly less than 1% (median PD is 0.0021, and the 75th percentile (0.0079) is close to the mean). In order to see the distribution better, we bifurcate the entire set of PDs across time for all FIs into two plots. The first is the histogram of PDs that lie in the interval $(0, 0.01)$, and the second in the interval $(0.01, 0.30)$. The highest PD in the sample is 0.2621. See Figure 11.

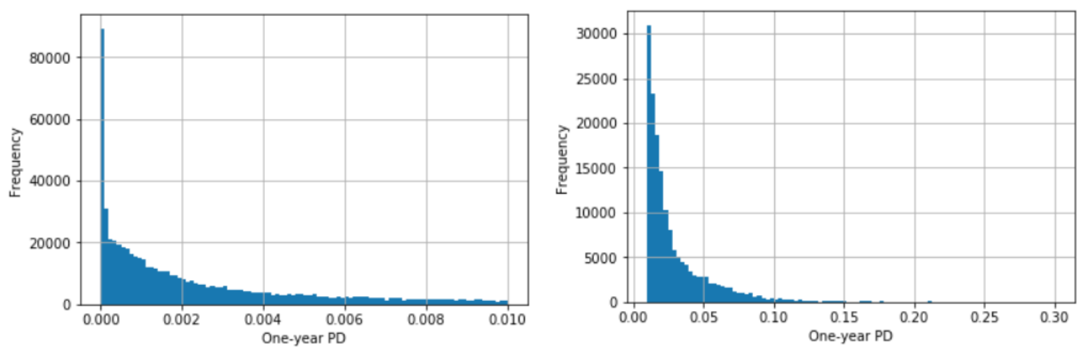

Figure 11: Distribution of PDs of all Indian FIs from 2004 to 2016. The first plot is the histogram of PDs that lie in the interval $(0, 0.01)$, and the second in the interval $(0.01, 0.30)$.

In order to create the vector C that we need to compute systemic risk, we map these PDs into a scale from 1 through 10, using a simple function, i.e.,

$$C = 1 + 30 \cdot PD$$

Since $PD \in (0, 0.30)$, this maps into $C \in (1, 10)$. For all the banks included in the data set each quarter, we calculated the systemic risk score S, using the C vector as noted earlier. For each quarter the element of the C vector is computed using the mean PD for each bank across the days in that quarter. If there a few days data of PD missing in the quarter, then the mean is calculated over the data on days for which it is available. In the rare case when a bank has no PD data for any days in the quarter, we ascribe the bank's C value is based on the mean PD across all the other banks in the sample for that quarter. Figure 12 shows the average PD over time for the sample period.

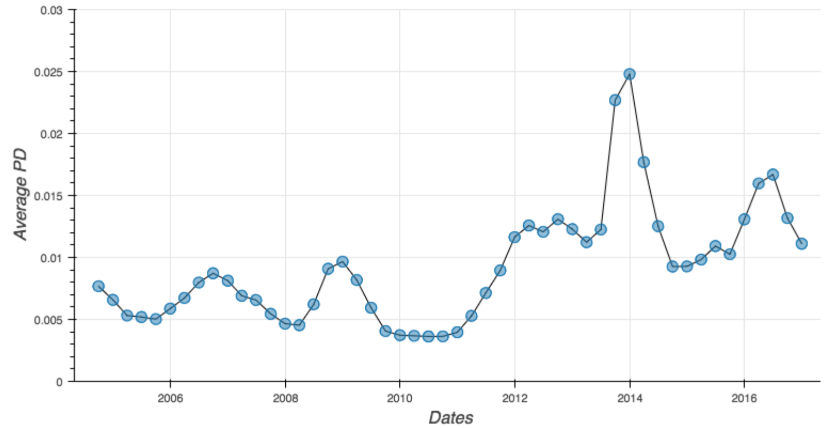

Figure 12: Time series of mean PDs across all Indian FIs from 2004 to 2016.

7.2 Systemic Risk over Time

The time series of systemic risk is shown in Figure 13. Remember this is normalized for the number of banks, which has been increasing over time, as shown in Figure 4. We may also compare the systemic risk score with the average probability of default over time, shown in Figure 12. The correlation between these two time series is significant and positive, with a value of 69.7%. The R^2 in a regression of systemic risk on mean PD over time is 0.48, which means that the level of PD only explains close to 50% of the variation in systemic risk, and the interconnectedness of banks must account for at least some of the remaining variation.

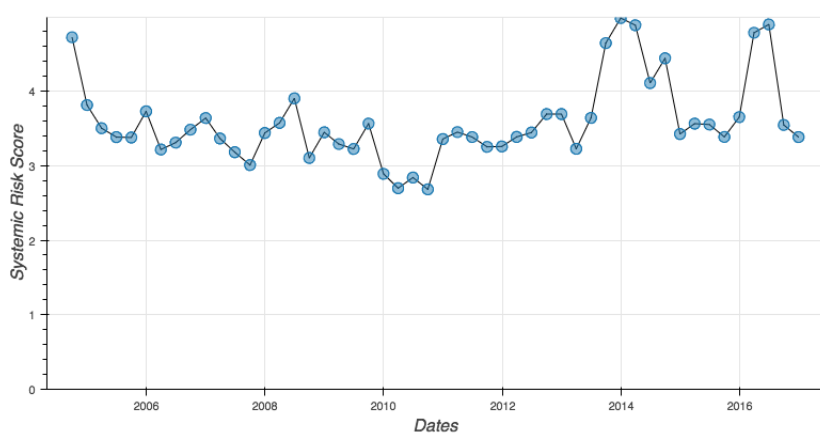

Figure 13: Time series of systemic risk for Indian FIs from 2004-Q3 to 2016-Q4.

Does most of the systemic risk come from just a few banks? To investigate this, we apply equation (2) to two quarters as an example, and compute the percentage of systemic risk contributed by the top 20 contributors in 2005-Q1 and 2016-Q4. This is shown in Table 4. We see that the top 20 banks contribute about 32% of the total systemic risk in 2005 (before the crisis) but only about 30% of the risk in 2016 (post crisis). This is not a very high level of risk concentration. We can therefore use this table to designate such banks as systemically important financial institutions (SIFIs), or even use another metric, such as a bank is a SIFI if it contributes more than 1% of the total of systemic risk. Based on this there would be fewer SIFIs in 2016 than 2005.

Table 4: Percentage of systemic risk contributed by the top 20 contributors in 2005-Q1 and 2016-Q1.

	2005-Q1		2016-Q1	
	Bank Name	Risk Decomp	Bank Name	Risk Decomp
1	STATE BANK OF INDIA	3.012025	BANK OF MAHARASHTRA	2.834978
2	PRIME SECURITIES	2.788330	UCO BANK	2.162268
3	UCO BANK	2.534994	STATE BANK OF INDIA	2.015743
4	CORPORATION BANK	1.962745	POWER FINANCE	1.924221
5	GIC HOUSING FINANCE	1.883520	STATE BK.OF BIN.& JAIPUR SUSP - SUSP.15/03/17	1.695611
6	UNION BANK OF INDIA	1.711946	INDIAN OVERSEAS BANK	1.695445
7	I N G VYSYA BANK SUSP - SUSP.15/04/15	1.644337	DENA BANK	1.632034
8	IFCI	1.545299	UNITED BANK OF INDIA	1.593664
9	P N B GILTS	1.508761	BANK OF BARODA	1.588961
10	SUNDARAM FINANCE	1.460714	BANK OF TRAVANCORE SUSP - SUSP.15/03/17	1.570695
11	JAMMU & KASHMIR BANK	1.380232	CIL SECURITIES	1.494462
12	ALMOND GLOBAL SECURITIES	1.248903	ANDHRA BANK	1.448089
13	MARGO FINANCE	1.218949	ORIENTAL BK.OF COMMERCE	1.254426
14	PUNJAB NATIONAL BANK	1.217674	CANARA BANK	1.095249
15	ANDHRA BANK	1.215547	JAGSONPAL FIN.& LSG.	1.047905
16	DEWAN HOUSING FINANCE	1.207646	DEWAN HOUSING FINANCE	1.042408
17	BANK OF BARODA	1.206728	ALLAHABAD BANK	1.019390
18	DENA BANK	1.187408	CUBICAL FINANCIAL SVS.	1.017735
19	DHANLAXMI BANK	1.174342	SYNDICATE BANK	1.015910
20	BANK OF INDIA	1.163571	SOUTH INDIAN BANK	0.986080
	TOTAL	32.27367		30.13527

In Table 5, we seek to explain the evolution of aggregate network-level systemic risk over time. To this end, we conduct time-series regressions (over 50 quarters from the third quarter of 2004 through the fourth quarter of 2016) of network systemic risk on (a) aggregate credit risk (mean probability of default across firms), (b) various network parameters (degree, centrality, diameter, fragility, number of clusters, and concentration across degrees and clusters), and (c) aggregate firm characteristics (market-wide median values of firm size, traditional operations and financing, leverage, liquidity, and operating and stock price performance). We find that the variables that quantify credit risk explain much more of the variation in systemic risk ($\tilde{5}0\%$), than network interconnectedness ($\tilde{1}4\%$). Prevailing firm-attributes in aggregate sense provide very little explanation of the evolution of systemic risk over time. Taken together, we can explain almost 95% of the variation in systemic risk over time. As a robustness check we also re-ran the entire network construction using Granger regressions where the confidence level for significance of the link coefficient is taken to be 0.99 instead of 0.975 (these results are omitted for brevity); we find that the structure and fit of the model is similar.

In Table 6, we strive to establish the determinants of individual entity-level systemic risk across the cross-section of financial firms. To this end, we decompose the aggregate systemic risk into risk contributed by each financial firm, and run panel regressions (262 firms over 50 quarters) of each firm's contribution to network systemic risk on its credit risk (probability of default), network attributes and its individual operational/financial attributes. We find that we can explain about 42% of firms' importance in the systemic risk network based on firm-level credit risk alone. Firm-level credit risk, network interconnectedness and other network parameters explain about 77% of the firm-level systemic risk. Firm-specific operational attributes, though largely significant, offer little incremental explanatory contribution. Taken together, we can explain 83% of the variation of systemic risk across financial firms in the network over time.

8 Concluding Comments

We develop a metric for the aggregate systemic risk of a country that combines for the interconnectedness of banks and the credit quality of each bank in the economy. The model constructs a bank network from the spillover risk of each bank on another, by first removing any relation from systematic risk and then using Granger causality regressions to determine the conditional impact of a drop in credit quality of one bank on another. We modify the measure from Das (2016) to quantify and decompose systemic risk into the risk contributed by each bank so as to rank order banks to designate them as SIFIs if necessary.

We find that systemic risk is explained by credit risk variables and network variables. Hence, we infer that the structure of the network does matter over and above individual credit risk of banks. We also examine the relationship of systemic risk to macroeconomic and market variables in order to assess if systemic risk may be spanned. This paper, using Indian data, serves as an exemplar of a model we intend to extend to many emerging market economies. Taken across all countries, we will gain an understanding of how systemic risk is correlated across economies and how diversifiable it might be. We should also be able to create a global network to quantify world systemic risk (at least for emerging market countries).

Table 5: Time series regressions of quarterly systemic risk against credit risk, network and firm-specific variables. The dependent variable is network level systemic risk score. Explanatory variables include: credit risk (mean probability of default PD), network attributes (mean network degree across all nodes in the network, degree concentration measured by HHI, mean centrality, network diameter, network fragility, number of distinct clusters, and concentration within clusters) and median firm-specific attributes (book value of assets, market value of equity, loans-to-assets and loans-to-deposits ratios of banks, debt-to-assets and debt-to-equity ratios, debt-to-capital ratio, returns on assets and equity, and market-to-book value of equity). Network connections are based on Granger regressions using p-values of 0.025. Mean PD, degree and centrality across firms, and market-wide median firm-specific attributes are computed every quarter.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.8167***	2.7818***	7.9469	-0.0022	-0.0022	7.3917	7.3917
	(22.68)	(8.15)	(1.71)	(-0.00)	(-0.00)	(1.59)	(1.59)
Mean PD	83.7515***		111.9661***	104.5427***	104.5427***	109.1854***	109.1854***
	(6.96)		(16.49)	(8.00)	(8.00)	(8.77)	(8.77)
Mean Degree		0.0694	0.2908**	0.1245	0.1245	0.2727*	0.2727*
		(1.77)	(3.18)	(1.25)	(1.25)	(2.35)	(2.35)
Degree HHI		142.6410*	140.9054*	102.4228	102.4228	149.4726**	149.4726**
		(2.44)	(2.57)	(1.94)	(1.94)	(2.90)	(2.90)
Mean Bet. Centrality			-0.0013**	-0.0012*	-0.0012*	-0.0009	-0.0009
			(-3.14)	(-2.32)	(-2.32)	(-1.87)	(-1.87)
Diameter			0.0068	0.0082	0.0082	0.0010	0.0010
			(0.46)	(0.57)	(0.57)	(0.07)	(0.07)
Fragility			-0.0933	0.0070	0.0070	-0.0791	-0.0791
			(-1.68)	(0.12)	(0.12)	(-1.19)	(-1.19)
Num. Clusters			-0.0898	-0.0462	-0.0462	-0.0894	-0.0894
			(-1.42)	(-0.69)	(-0.69)	(-1.48)	(-1.48)
Cluster HHI			-6.0311	-1.8428	-1.8428	-6.7961	-6.7961
			(-1.31)	(-0.36)	(-0.36)	(-1.48)	(-1.48)
Median Log(Assets)				0.1285	0.1285		
				(1.19)	(1.19)		
Median Log(Market Cap)						0.0890*	0.0890*
						(2.38)	(2.38)
Median Loans/Assets				-0.0837	-0.0837	0.1695	0.1695
				(-0.26)	(-0.26)	(0.54)	(0.54)
Median Loans/Deposits				1.5464	1.5464	-0.3376	-0.3376
				(0.66)	(0.66)	(-0.21)	(-0.21)
Median Debt/Assets				1.8750	1.8750		
				(0.93)	(0.93)		
Median Debt/Equity						2.1829	2.1829
						(1.56)	(1.56)
Median Debt/Capital				0.0022	0.0022	0.0084	0.0084
				(0.29)	(0.29)	(1.43)	(1.43)
Median ROA				0.0191	0.0191		
				(0.86)	(0.86)		
Median ROE						-0.0133	-0.0133
						(-0.64)	(-0.64)
Median Market/Book				0.3245	0.3245	0.0681	0.0681
				(1.70)	(1.70)	(0.31)	(0.31)
Observations	50	50	50	50	50	50	50
R^2	0.502	0.136	0.900	0.933	0.933	0.941	0.941
Adjusted R^2	0.492	0.099	0.881	0.904	0.904	0.914	0.914

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Panel regressions of quarterly systemic risk contributions of firms against credit risk, network and firm-specific variables. The dependent variable is each firms contribution to network level systemic risk score. Explanatory variables include: credit risk (probability of default PD), network attributes (network degree across all nodes in the network, degree concentration measured by HHI, centrality, network diameter, network fragility, number of distinct clusters, and concentration within clusters) and firm-specific attributes (book value of assets, market value of equity, loans-to-assets and loans-to-deposits ratios of banks, debt-to-assets and debt-to-equity ratios, debt-to-capital ratio, returns on assets and equity, and market-to-book value of equity). Network connections are based on Granger regressions using p-values of 0.025.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.2933***	-0.0562***	6.0451***	7.2741***	7.2741***	8.0971***	8.0971***
	(75.00)	(-3.62)	(16.91)	(9.21)	(9.21)	(9.23)	(9.23)
PD	19.0255***		17.4201***	14.7766***	14.7766***	15.4945***	15.4945***
	(45.05)		(52.90)	(28.63)	(28.63)	(30.92)	(30.92)
Degree		0.0480***	0.0571***	0.0617***	0.0617***	0.0676***	0.0676***
		(33.74)	(36.20)	(28.67)	(28.67)	(29.80)	(29.80)
Degree HHI		86.8167***	71.7714***	107.5495***	107.5495***	122.4065***	122.4065***
		(16.14)	(12.32)	(9.70)	(9.70)	(8.98)	(8.98)
Bet. Centrality			-0.0000***	-0.0000***	-0.0000***	-0.0001***	-0.0001***
			(-7.53)	(-4.27)	(-4.27)	(-4.54)	(-4.54)
Diameter			0.0022	-0.0045	-0.0045	-0.0032	-0.0032
			(1.44)	(-1.39)	(-1.39)	(-0.92)	(-0.92)
Fragility			-0.0351***	-0.0484***	-0.0484***	-0.0571***	-0.0571***
			(-26.63)	(-18.42)	(-18.42)	(-18.06)	(-18.06)
Num. Clusters			-0.0766***	-0.0975***	-0.0975***	-0.1093***	-0.1093***
			(-15.41)	(-9.72)	(-9.72)	(-9.68)	(-9.68)
Cluster HHI			-5.8770***	-7.3126***	-7.3126***	-7.9533***	-7.9533***
			(-16.66)	(-9.35)	(-9.35)	(-9.19)	(-9.19)
Log(Assets)				0.0201***	0.0201***		
				(7.76)	(7.76)		
Log(Market Cap)						0.0186***	0.0186***
						(6.60)	(6.60)
Loans/Assets				0.1883***	0.1883***	0.2901***	0.2901***
				(6.27)	(6.27)	(10.00)	(10.00)
Loans/Deposits				-0.0145	-0.0145	-0.0325***	-0.0325***
				(-1.75)	(-1.75)	(-3.65)	(-3.65)
Debt/Assets				-0.0749***	-0.0749***		
				(-4.57)	(-4.57)		
Debt/Equity						-0.0001	-0.0001
						(-1.46)	(-1.46)
Debt/Capital				-0.0002	-0.0002	-0.0005*	-0.0005*
				(-0.86)	(-0.86)	(-2.21)	(-2.21)
ROA				0.0007	0.0007		
				(1.85)	(1.85)		
ROE						0.0001	0.0001
						(0.32)	(0.32)
Market/Book				0.0019**	0.0019**	-0.0021*	-0.0021*
				(2.60)	(2.60)	(-2.13)	(-2.13)
Observations	10609	10609	10609	4329	4329	3375	3375
R^2	0.420	0.315	0.770	0.831	0.831	0.833	0.833
Adjusted R^2	0.420	0.315	0.770	0.830	0.830	0.832	0.832

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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