On the Interconnectedness of Financial Institutions: Emerging 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 sample of 23 emerging markets. We present a novel systemic risk score for each financial system by region. This score is a per-bank, size-weighted, and network-weighted credit risk measure that may be compared across geographical regions, 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 new stylized facts on systemic risk evolution based on emerging market experience and insights into the use of network models in policy-making for measuring, managing, and regulating systemic risk in the emerging market context. We find that the prediction of aggregate default risk in a region is greatly improved by using our systemic risk metric.

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Contents

1 Introduction

In this paper we undertake a large-scale empirical examination of systemic risk among major financial institutions in the emerging markets. There is limited prior literature on the evidence of systemic risk in emerging markets.[1] We provide analysis and 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,

[1]For e.g. Sensoy (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).

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 modification 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).

Our sample of emerging countries is obtained by combining the IMF's and MSCI's lists of emerging countries with firm-level data from two different sources: (1) stock return, financial and balance sheet data are extracted from Datastream, and (2) Probability of default data sourced from the Credit Risk Initiative (CRI), National University of Singapore (NUS). We employ active financial firms trading in a primary exchange in the local market, by matching the industry classification based on the Compustat Global Database. We exclude financial subsidiaries of non-financial corporations and specialized investment vehicles such as funds, REITs, and securitized assets. Our final quarterly data sample consists of 1048 financial firms comprised of 539 Banks, 389 Broker-Dealers, and 120 Insurers from 23 emerging market countries for the period 2004-2016. Our sample of 23 countries is clustered into five geographical regions: East Asia (China, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand), South Asia (India), Eastern Europe (Bulgaria, Czechoslovakia, Hungary, Poland, Russia, Ukraine), Southern Europe and Africa (Egypt, Greece, South Africa, Turkey) and South America (Argentina, Brazil, Chile, Columbia, Mexico).

We record four new key stylized facts on emerging market systemic risks in this paper:

1. We observe considerable heterogeneity in evolution of systemic risks across the emerging markets.

    - South Europe and Africa have the highest systemic risks compared to other regions over time mainly during the 2007-2009 crisis and 2010-12 post-crisis periods. East Asia registers highest systemic risk during 2013 Taper-tantrum period and again during the 2015-16 foreign exchange crisis period.
    - There is a high degree of concentration in systemic risks. The top 10 percentile contributors contribute 16% to 47% of the systemic variation. Eastern Europe and South America has the maximum concentration (over 46%) of systemic risk among the top 10 contributors. Most of the systemic risk for each geographic region is concentrated among fewer banks in the pre-crisis crisis periods compared to post-crisis period.
    - Using time series and panel data regressions, we examine to what extent emerging market systemic risks across geographic regions can be explained by different

risks. We find that credit and network risks together explain the majority of the variation in systemic risks i.e. between 88%-94% of the time-series variation, and 70%-80% across firms and over time. Firm-specific attributes (such as leverage, profitability, loans to assets, loans to deposits, and market to book ratios) add an additional 5%-20% explanatory power in panel data regressions.

2. Examining the correlations among systemic risks across different geographic regions, we find that information in systemic risks is quickly transmitted within the same quarter across emerging markets. Interestingly, India is relatively isolated from other country groups as its systemic risks are weakly correlated across other regions. Further univariate analysis shows that lead and lag effects in systemic risks are usually very short-term, at a quarterly level, and long-term effects fade out. Often the highest correlation in systemic risks across markets is contemporaneous, implying that markets co-move with respect to underlying systemic risks. Granger Causality tests show that the systemic risks have strong momentum within each market, while the spillover effects of systemic risks across markets is weak. Vector Auto Regression analysis confirms the earlier evidence that contemporaneous dependence of systemic risk across markets matters far more than lagged effects.

3. A principal components analysis (PCA) of region-wide systemic risk measures shows that the first PC explains 52% of the variation in systemic risk, while the next two components explain about 20% of the variation each. The first three (four) components together explain 92% (97%) of the variation. The first PC correlates highly with the default risk during the financial crisis. The second PC spikes in the post-financial crisis period (associated with Dodd-Frank regulatory phase-in), reflecting possible policy uncertainty; and again during the foreign exchange crisis event of 2015-16. The third PC (i.e., PC3) seems to capture the taper tantrum of 2013 and the 2015-16 foreign exchange crisis, episodes both associated with capital outflows from emerging markets to US. Further analysis shows that the first PC is significantly related to the US default factor. The second PC is weakly influenced by the contemporaneous funding (TED) and lagged risk aversion (VIX) factors at 5% level. The third PC is significant (at 1% level) affected by the contemporaneous funding cost (TED) factor.

4. Finally, we examine the information content of systemic risk in an out-of-sample setting. For all five geographic regions, we see that lagged changes in systemic risk are highly predictive of aggregate default risk (PD) in the following period. Interestingly, lagged PD is not. This suggests that our network measure of systemic risk provides explanatory power over and above the measure of credit risk levels in the economy. This suggests material ability to predict credit quality levels in economies using our new measure of systemic risk.

Systemic risk captures the conditional failure of the system at large, conditional on the failure of key financial institutions in an economy. Overall, in this project we undertake a large-scale study of systemic risk involving emerging market financial institutions in many countries and provide insights into policies for measuring, managing and regulating systemic risk. Our findings can be useful to academics, regulators, and financial practitioners.

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 and extant empirical literature. Next, Section 3 undertakes an exploration of the data we have for emerging markets, 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 estimated in Section 5. Section 6 conducts empirical analyses and section 7 concludes.

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. (2012)). 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)).

There are four possible 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 (Allen and Carletti (2013)). 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 and Pedersen (2009); Adrian and Shin (2010); Gorton and Metrick (2012); Acharya et al. (2013); Covitz et al. (2013)). 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); ChanLau et al. (2016); Bisias et al. (2012); Benoit et al. (2017); Silva et al. (2017); and Anand et al. (2018). 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. 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) introduce the Conditional Capital Shortfall index for Systemic Risk Measurement (or SRISK) to measure the systemic risk contribution of a financial firm. Engle (2018) examines the history and application of the SRISK measure. 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. (2012) use return correlations and Granger causality regressions on returns to construct network maps and develop network measures of systemic risk. Billio et al. (2012) apply several econometric measures of connectedness based on Granger-causality networks to the changes of sovereign risk of European countries. Diebold and Ylmaz (2014) provide several connectedness measures built from variance decompositions, which provide insightful measures of connectedness. Elliott et al. (2014) examine cascades in financial networks using a model of cross-holdings among organizations that allows for discontinuities in values. 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.

Other network based systemic risk papers include (a) Markose et al. (2012), who study the network among US CDS contracts to document the high concentration of exposures leading to a "too interconnected to fail" (TITF) phenomenon; (b) Poledna et al. (2015), who analyze systemic risk contributions jointly from four exposure layers (i.e., derivatives, security cross-holdings, foreign exchange and the interbank market of deposits and loans) of the interbank network; (c) Bluhm and Krahnen (2014), who study system wide value at risk (SVaR) measure 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; (d) Acemoglu et al. (2015), who provide a theoretical framework for the relationship between the structure of the financial network and systemic risk; (e) Brunetti et al. (2015), who study two network structures, a correlation network based on publicly traded bank returns, and a physical network based on interbank lending transactions; (f) Ahern (2013), who finds that industries that are more central in the network of intersectoral trade have greater market risk and earn higher stock returns than industries that are less central, confirming the results of Das and Sisk (2005); and (g) Donaldson and Micheler (2018), who uses a theoretical model to show that decreasing credit market frictions leads to an increase in borrowing via non-resaleable debt, such as repos; this in turn leads to credit chains, exacerbating systemic risk, as one banks default harms not only its creditors but also its creditors' creditors.[4]

[4]Other work includes Anand et al. (2013); Chan-Lau et al. (2009); Gabrieli and Georg (2014); and Colliard et al. (2017).

Complementing these network models, our model of systemic risk networks pro- vides 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).

2.2.3 Other Estimation Approaches

The methods 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. These include systemic risk based on Contingent Claims Analysis (Saldas (2013)); LASSO methods (Demirer et al. (2017)); copula-based dynamic model (Oh and Patton (2018)); multivariate credit risk model (Li and Zinna (2014)); Bayesian methods (Bianchiy et al. (2015)); tail event and extreme value driven models (Betz et al. (2016); Hrdle et al. (2016); Li and Perez-Saiz (2018)); principal component or factor models (Avramidis and Pasiouras (2015); Nucera et al. (2016)); and vulnerability to fire-sale spillovers (Duarte and Eisenbach (2015)).

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)).[5]

[5] The Dodd-Frank Act (201) 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).

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. Goodhart (2009), propose 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 SIFIs 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.

More recently, Abbass et al. (2016) find that market-based measures of interdependence can serve well as risk monitoring tools in the absence of disaggregated high-frequency bank fundamental data. Finally, Benoit et al. (2018) show that the current scoring methodology severely distorts identification and regulation of SIFIs, and the allocation of regulatory capital among banks; the authors then propose and implement a methodology that corrects for these shortcomings and increases incentives for banks to reduce their risk contributions.[6]

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.

[6]Other studies on systemic risk regulation include Lffler and Raupach (2018) and Roukny et al. (2018).

2.5 Empirical Studies on Systemic Risks

A plethora of empirical studies exist on systemic risk. These include[7] (a) Li and Zinna (2014), who show that systemic risks in the US and UK differ both in their evolution, and in their banks' systemic exposures; (b) Giglio et al. (2016), who study how systemic risk and financial market distress affect the distribution of shocks to real economic activity; (c) Sedunov (2016), who finds that CoVaR provides useful forecasts of future systemic risk exposures better compared to Systemic expected shortfall and Granger causality; (d) Laeven et al. (2016), who examine cross sectional variation of standalone and systemic risks of large banks during the global financial crisis; (e) Pagano and Sedunov (2016), who show that the aggregate systemic risk exposure of financial institutions is positively related to sovereign debt yields in European countries; (f) Bostandzic and Wei (2018), who show that compared to US banks, European banks appear to contribute more to global systemic risk, because of the lower quality of their loan portfolios and their higher relative interconnectedness with the rest of the global financial system; (g) Karolyi et al. (2016), who find that cross-border bank flows reduce systemic risk by improving banks asset quality, efficiency, and reliance on nontraditional revenue sources; and (h) Cai et al. (2018) who show that while loan syndication improves institution-level risk reduction through diversification, it can induce higher bank interconnectedness.

2.6 Systemic risks and Emerging markets

There is however a limited prior literature on the evidence of systemic risk in emerging markets. For example, Sensoy et al. (2017) find that the increased average correlation among emerging market sovereign bond returns is more likely caused by clusters of countries that exhibit high "within-cluster" co-movement rather than "between-cluster" co-movement. Sensoy (2017) finds that institutional ownership in Turkey leads to an enhanced systematic liquidity risk for mid-to-large cap firms by increasing the commonality in liquidity. Borri (2017) adopts the CoVaR risk measure to estimate the vulnerability of individual countries

[7] See also Tasca et al. (2014); Liu et al. (2015); Black et al. (2016); Varotto and Zhao (2018); Aparna Gupta et al. (2018); Adrian and Boyarchenko (2018); and Ellul et al. (2018).

to systemic risk in the market for local currency government debt. Fang et al. (2018) construct a tail risk network to present overall systemic risk of Chinese financial institutions, and show that firm's idiosyncratic risk is significantly affected by its connectedness with other institutions. Wang et al. (2018) investigate the interconnectedness and systemic risk of China's financial institutions and find that large commercial banks and insurers usually exhibit systemic importance, but some small firms are systemically important due to their high level of incoming (outgoing) connectedness.

3 Data

We first identify the list of 23 emerging countries by combining the IMF's & MSCI's lists of emerging countries and further intersecting with the CDS data available in the Markit database. Intersecting with CDS data helps us preserve only those firms where the public debt outstanding is sizeable and there is market wide exposure to the underlying credit risk. Using Datastream, we extract a comprehensive list of financial firms from these 23 markets. We require that our sample consists of active financial firms, and firms whose common equity are major securities trading on a primary exchange in the local market. We exclude (a) non-financial firms, (b) inactive (delisted) firms, (c) firms with only preferred stock, (d) foreign firms, and (e) firms trading exclusively in either a minor exchange in the local emerging market or a foreign exchange. We also drop 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 further match emerging market 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). Table 1 presents our final sample of emerging market financial firms. The final screened sample consists of 1048

Table 1: Sample count. The table presents the count of industry groups and the number of institutions with valid probability of default (PD) data by country.

Country	Bank	Broker-Dealer	Insurer	Total	Valid PD
Argentina	8	1	0	9	6
Brazil	7	4	6	17	15
Bulgaria	4	5	3	12	9
Chile	8	5	3	16	13
China	26	29	7	62	61
Columbia	8	3	0	11	11
Czech	2	0	0	2	2
Egypt	11	8	2	21	21
Greece	8	3	2	13	12
Hungary	2	3	1	6	5
India	193	191	3	387	356
Indonesia	58	14	14	86	82
Malaysia	15	7	9	31	31
Mexico	9	7	4	20	17
Philippines	28	5	1	34	31
Poland	27	28	5	60	47
Russia	19	2	1	22	16
South Africa	12	12	9	33	32
South Korea	16	24	13	53	52
Taiwan	23	15	12	50	34
Thailand	24	14	17	55	52
Turkey	22	9	6	37	37
Ukraine	9	0	2	11	6
	539	389	120	1,048	948

financial institutions, comprised of 539 Banks, 389 Broker-Dealers and 120 Insurers. Overall India has the highest proportion of the sample with 387 financial firms or 37% of the total sample, followed by Indonesia (8%) and China (6%). There is a high clustering of the sample among top five countries (i.e., India, Indonesia, China Poland and Thailand), which together account for 62% of the whole sample.

Using Datastream, we extract daily equity returns–dividend- and stock-split-adjusted consecutive (non-missing)–spanning a 13 year period from 2004 to 2016. We linearly interpolate any missing daily 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.

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. (2012). 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.

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.

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.

5.1 Network Metrics

There are several statistics that we compute from the adjacency matrix representing the bank network. These are as follows.

1. Eigenvalue centrality. A measure of the importance of any node or bank in the network in terms of its impact on other nodes or banks. This infinitely nested system of dependence results in an eigensystem. Solving the eigensystem reveals the principal eigenvector, denoted as "centrality" by Bonacich (1987), as described above.

2. Betweenness centrality. A measure of how central position a bank has in the network for a given bank. A node is said to be "between" other nodes when a large proportion of shortest paths in the network pass through the particular node.

3. The number of nodes. The larger the number of nodes the greater the connectivity and possibility of transmission of network risk, and hence higher the systemic risk.

4. 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. 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. Contagion travels further when diameter is low.

5. Degree: the number of connections of each node, which characterizes how interconnected the network is. The degree distribution also reveals how concentrated the network connections may be in a few nodes, as often occurs in hub and spoke networks.

6. Mean degree. We calculate $E(d)$, where d_i is number of connections of node i in the network. Mean degree depicts the average number of links each node in the network has.

7. Fragility. 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.

8. Herfindahl index of degree. 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 $NH = \frac{H-1/n}{1-1/n}$.

9. Clusters: we also examine how disconnected the network is by computing the number of connected groups, i.e., clusters, 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.

10. Herfindahl index of cluster sizes : This is a measure of the concentration in nodes, and measures if nodes are in one large cluster or are the clusters balanced in size.

Overall we have three firm-specific metrics: degree, eigenvalue centrality, betweenness centrality. We have seven network and cluster-specific metrics: number of nodes, mean degree, degree Herfindahl index, diameter, fragility, the number of clusters, and cluster Herfindahl index. These different network metrics can be calculated using the banks for a given country, or for a given region. We calculated these network statistics for all quarter end dates starting from Q3 2004 to Q4 2016, a total of 50 quarters.

We next examine the evolution of systemic risk across countries over time. Table 2 presents the network measures across geographic regions for three periods centered around the crisis, i.e., pre-crisis, crisis, and non-crisis periods that encompass the years 2004-2006, 2007-2009, and 2010-2016 respectively. We consider 23 countries clustered into five geographical regions: East Asia (China, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand), South Asia (India), Eastern Europe (Bulgaria, Czech, Hungary, Poland, Russia, Ukraine), Southern Europe and Africa (Egypt, Greece, South Africa, Turkey) and South America (Argentina, Brazil, Chile, Columbia, Mexico). We report average values of network measures aggregated at the country/regional level and the firm/regional level. Our sample of the banking networks is larger for Asia and smaller for Europe, Africa, and South America. Mean degree of a node in the network is also higher in Asia (~ 7.3) versus the other regions (ranging from $\sim 1.5 - 3.0$). Correspondingly, the betweenness centrality is much higher as well because it is not normalized. The diameter of the bigger networks is also greater as is to be expected. Because the Asian networks are bigger and more interconnected, the fragility is higher and the number of independent clusters is fewer.

Network connections are based on the Adjacency matrix populated using Granger regressions using p-values of 0.025, as discussed in Section 4. All average values reported are computed every quarter. Table 2 shows that network risks have increased during the crisis based on fragility and the Herfindahl index of degree for all the regions. Other metrics such as the Herfindahl index of clusters, number of nodes, and betweenness centrality indicate a higher network risk for the post-crisis period across regions.

Table 2: Network measures. The table presents the average values of eight network measures (three aggregate country-/regional-level metrics and five firm-level metrics) for country regional groups relative to crisis and non-crisis periods. The 23 emerging countries are grouped into five geographical regions. Pre-crisis, crisis, and non-crisis periods encompass years 2004-2006, 2007-2009, and 2010-2016, respectively. Aggregate-level network metrics include number of nodes, mean degree, and mean betweenness centrality between nodes; firm-level network metrics include diameter, fragility, degree concentration measured by HHI, number of distinct clusters, and HHI concentration between clusters. Network connections are based on Granger regressions using p-values of 0.025. All average values reported are computed every quarter.

		Aggregate-level metrics			Firm-level metrics				
Geographical region	Period	# of nodes	Mean Degree	Between centrality	Diameter	Fragility	HHI of of degree	# of clusters	HHI of clusters
East Asia	Full	217.6	7.38	535.6	12.38	11.53	0.0033	4.18	0.955
	Pre-crisis	151.5	4.53	351.4	15.60	6.97	0.0036	6.30	0.917
	Crisis	176.7	6.71	346.5	12.17	13.14	0.0051	5.25	0.941
	Post-crisis	245.5	8.24	636.9	11.32	12.47	0.0024	2.96	0.975
South Asia	Full	218.7	7.26	630.2	12.30	10.15	0.0022	2.96	0.969
	Pre-crisis	156.5	5.38	414.1	14.60	7.85	0.0036	5.00	0.924
	Crisis	210.7	7.82	558.2	11.67	11.49	0.0023	2.67	0.976
	Post-crisis	236.1	7.49	707.7	11.75	10.39	0.0017	2.36	0.982
Eastern Europe	Full	51.1	1.98	11.4	6.02	3.21	0.0299	11.58	0.410
	Pre-crisis	18.6	0.92	0.3	2.10	1.74	0.0742	9.90	0.087
	Crisis	33.9	1.72	1.5	4.00	3.64	0.0360	11.00	0.367
	Post-crisis	59.0	2.17	15.1	8.29	3.49	0.0131	12.43	0.544
South Europe & Africa	Full	82.9	3.08	42.2	10.28	5.43	0.0097	11.78	0.711
	Pre-crisis	67.9	2.35	17.9	9.30	4.54	0.0133	12.80	0.626
	Crisis	81.5	3.25	48.8	10.25	6.05	0.0103	9.67	0.757
	Post-crisis	87.7	3.22	46.3	10.64	5.48	0.0082	12.32	0.721
South America	Full	39.8	1.54	2.5	4.58	2.87	0.0262	14.06	0.301
	Pre-crisis	29.7	1.41	1.4	3.60	2.64	0.0312	12.40	0.217
	Crisis	32.1	1.57	1.8	3.75	3.01	0.0358	13.58	0.265
	Post-crisis	44.6	1.56	2.9	5.29	2.89	0.0204	14.86	0.346
Overall		174.9	5.94	426.1	9.11	6.65	0.0142	8.91	0.669

5.2 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. (2019). 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[8], 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:

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

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

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

6 Empirical Analyses

6.1 Distribution of the Probability of Default

We present the average quarterly values of probability of default, PD and systemic risk score measures for over time for five geographical regions. Network connections are based on Granger regressions using p-values of 0.025. 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. In order to create the vector C

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

Table 3: Risk measures. The table presents the average values of risk measures for country regional groups relative to crisis and non-crisis periods. The 23 emerging countries are grouped into five geographical regions. Pre-crisis, crisis, and non-crisis periods encompass years 2004-2006, 2007-2009, and 2010-2016, respectively. The risk measures include: probability of default, PD and systemic risk score. Network connections are based on Granger regressions using p-values of 0.025. All average values reported are computed every quarter.

Geographical region	Period	# of nodes	Probability of default, PD	Systemic risk score Network-level
East Asia	Full	217.6	0.0045	3.45
	Pre-crisis	151.5	0.0065	3.44
	Crisis	176.7	0.0062	3.83
	Post-crisis	245.5	0.0036	3.28
South Asia	Full	218.7	0.0094	3.59
	Pre-crisis	156.5	0.0068	3.62
	Crisis	210.7	0.0062	3.33
	Post-crisis	236.1	0.0112	3.69
Eastern Europe	Full	51.1	0.0066	4.45
	Pre-crisis	18.6	0.0028	5.65
	Crisis	33.9	0.0098	5.28
	Post-crisis	59.0	0.0062	3.66
South Europe & Africa	Full	82.9	0.0066	3.41
	Pre-crisis	67.9	0.0040	3.15
	Crisis	81.5	0.0073	3.55
	Post-crisis	87.7	0.0071	3.44
South America	Full	39.8	0.0040	4.74
	Pre-crisis	29.7	0.0056	5.40
	Crisis	32.1	0.0051	5.24
	Post-crisis	44.6	0.0032	4.29
Overall		174.9	0.0067	3.93

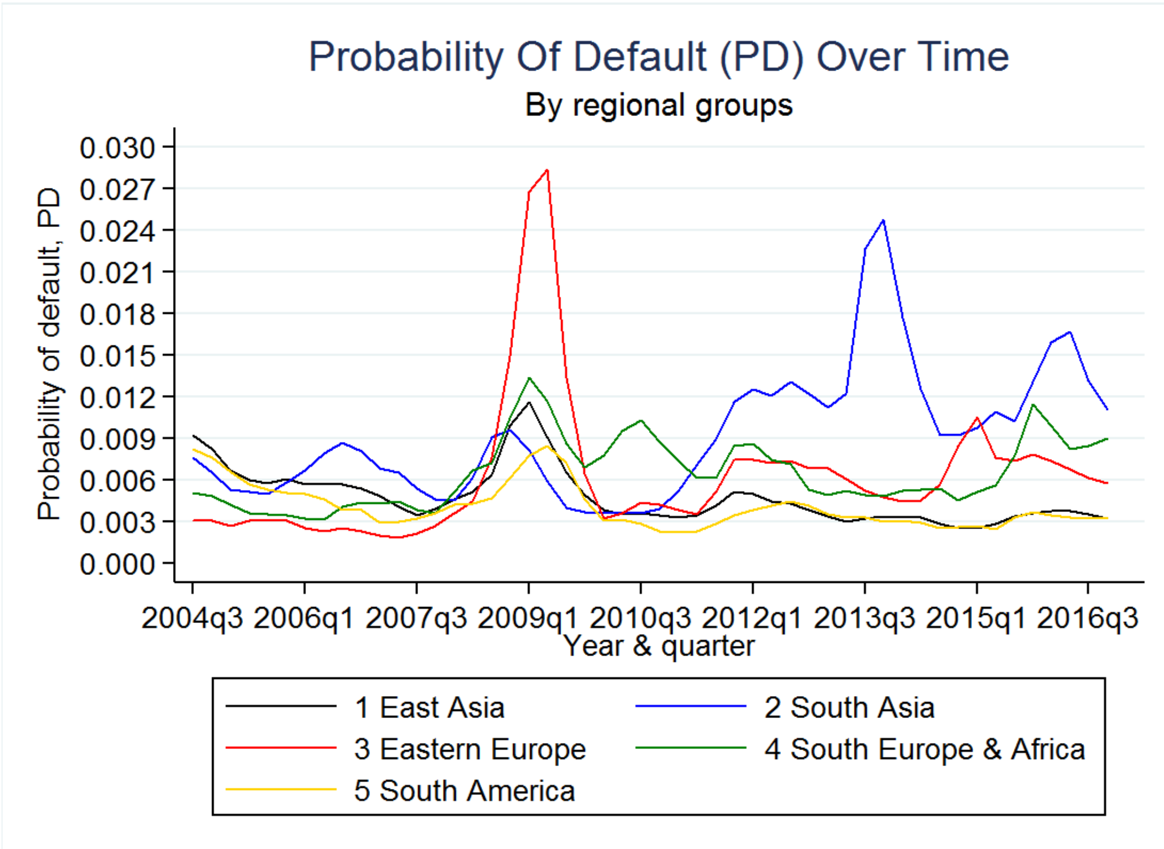

Figure 1: Times series of PD for the entire sample period from 2004 to 2016, for each of the five geographic regions.

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

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

Given, $PD \in (0, \gamma/100)$, where γ is the maximum PD for a country, 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 1 plots the the time series of PD for the entire sample period from 2004 to 2016, for each of the five geographic regions.

Table 3 presents the average quarterly values of probability of default, PD, over time for five geographical regions. We find that PD is higher for South Asia, Eastern Europe, and Southern Europe & Africa, more so during the crisis period. Systemic risk per bank is somewhat higher in Eastern Europe and South America relative to the other three regions.

The time series of systemic risk is shown in Figure 2. The systemic risk metric (equation (1)) is normalized for the number of banks, which has been increasing over time. In general, systemic risk spikes during the financial crisis period. South Europe & Africa have the highest systemic risks compared to other regions over time mainly during the 2009 crisis and 2010-12 period. East Asia registers highest systemic risk during the 2013 Taper tantrum period and again during the 2015-16 foreign exchange crisis period. Table 3 presents the average quarterly values of systemic risk score measures for over time for five geographical regions. Systemic risk is reported at the aggregate network-level. Network connections are based on Granger regressions using p-values of 0.025. Systemic risk is high at a network level during pre-crisis (crisis) period for Eastern Europe, and South America compared to East Asia, Southern Europe & Africa.

Does most of the systemic risk come from just a few banks? To investigate this, we apply equation (2) to compute the percentage of systemic risk contributed by the top 10 contributors in the full sample and each subperiod. This is shown in Table 4. Panel A reports the average contribution, as a percentage of total regional systemic risk, by the top 10 contributing institutions of each region using the data from 2004-Q1 to 2016-Q4. We observe that top 10 percentile contributors systemic risk explains 16% to 47% of the systemic variation. Eastern Europe and South America has the maximum concentration (over 46%) of systemic risk among the top 10 contributors. We also observe that the percentage contribution for each geographic region in general is much higher in the pre-crisis period. Panel B reports the average number of contributing institutions that account for the top 50 percentile (that is, contribute at least 50 percent) of total regional systemic risk. Eastern Europe and South America has the smallest number of banks (i.e. 12 and 11 respectively) in the top 50 percentile of the contributors of systemic risk. In general, most of the systemic risk for each geographic region is concentrated among fewer banks in the pre-crisis and crisis periods compared to post-crisis period. There is a clear bifurcation here: East Asia

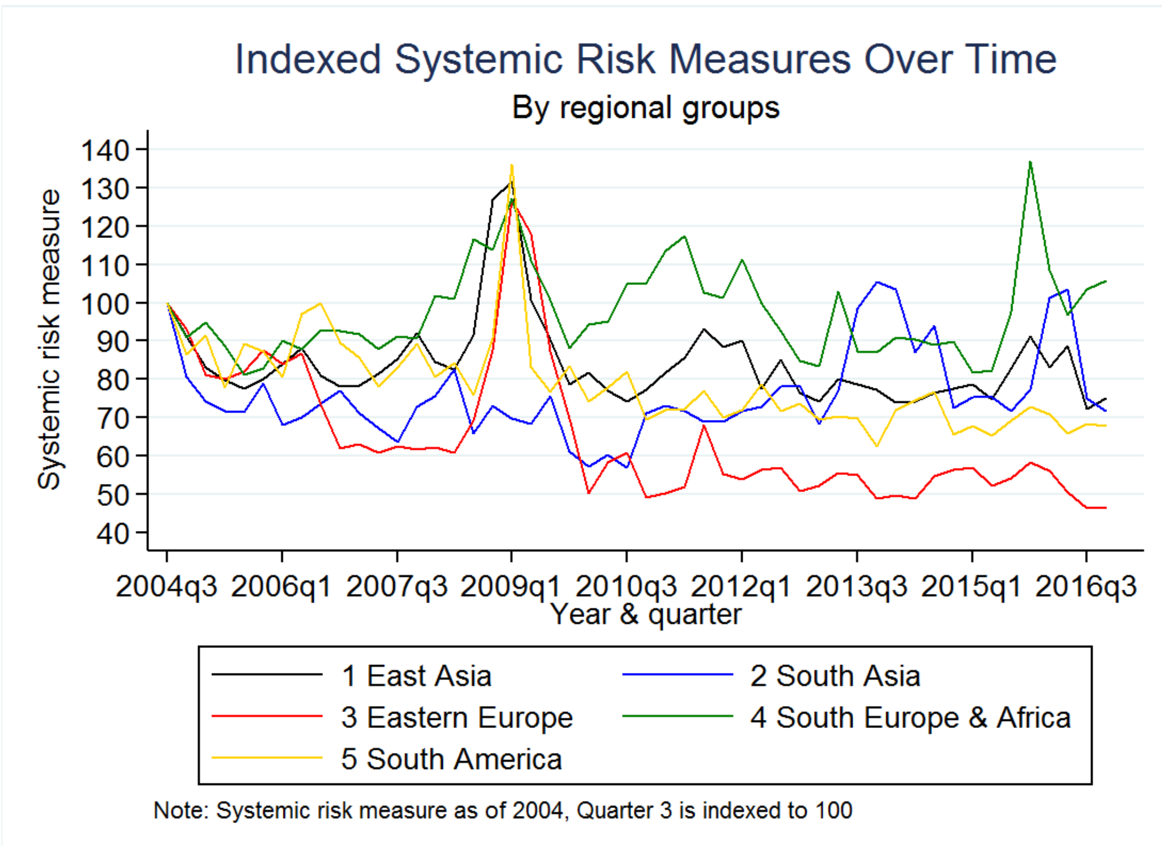

Figure 2: Times series of indexed systemic risk by region. Each series begins at an index value of 100.

Table 4: Systemic risk decomposition. The table presents the systemic risk decomposition by contributing institutions for country regional groups relative to crisis and non-crisis periods. The 23 emerging countries are grouped into five geographical regions. Pre-crisis, crisis, and non-crisis periods encompass years 2004-2006, 2007-2009, and 2010-2016, respectively. Panel A reports the average contribution, as a percentage of total regional systemic risk, by the top 10 contributing institutions of each region. Panel B reports the average number of contributing institutions that account for top 50 percentile (that is, contribute at least 50 percent) of total regional systemic risk. Network connections are based on Granger regressions using p-values of 0.025. All values reported denote averages computed every quarter.

Geographical	Period			
region	Full	Pre-crisis	Crisis	Post-crisis
Panel A: Percentage contribution of top 10 contributors				
East Asia	16.18	18.54	20.69	13.41
South Asia	20.09	21.50	17.94	20.51
Eastern Europe	47.11	72.89	52.83	35.45
South Europe & Africa	31.65	33.52	33.46	30.21
South America	46.72	55.79	51.48	41.45
Panel B: Number of contributors in top 50 percentile				
East Asia	54.9	42.1	41.6	65.1
South Asia	41.7	36.3	46.2	41.7
Eastern Europe	12.1	5.8	8.8	15.8
South Europe & Africa	20.2	18.3	18.7	21.6
South America	10.8	8.0	9.1	12.5

and South Asia have less concentration of systemic risk in their top 10 banks than do the other three regions. This is clearly an outcome of their bigger banking networks that enable greater spreading of systemic risk.

6.2 Time-series and cross-sectional regressions of quarterly regional systemic risk

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 several covariates: (a) aggregate credit risk (mean probability of default across firms), (b) various network parameters (mean degree across all nodes, degree concentration measured by HHI, mean centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters), and (c) 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); and (d) U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). All regressions include adjustments for heteroskedasticity.

Table 5 presents the time series regressions for the five geographic regions respectively in Panels A to E. For East Asia (Panel A) we find that the variables that quantify credit risk explains about 63% of the variation in systemic risk (regression 1). Adding network risk variables increases the explanatory power by 30% (regression 3). Prevailing firm-specific attributes in aggregate add another 3% and in general provide very little explanation of the evolution of systemic risk over time (regressions 4 and 5). Adding the US based default, term structure, and risk aversion factors increases the explanatory power additionally by 2% to a total of 98% (regressions 6 and 7). Taken together, we can explain almost 98% of the variation in systemic risk over time for East Asia. Table 7, Panel A summarizes the results from regressions for East Asia and other regions. We observe from Table 5 (Panels A to E) and Table 7, Panel A that overall across all five regions, credit risk explains a relatively lower portion of systemic risks in Eastern Europe (25%) and South America (38%); network risk at the same time explains the highest portion of systemic risks in Eastern Europe (68%) and South America (58%). In addition, the contribution of firm-specific attributes and US macro factors accounts for only about 3% to 4% of the explanatory power. 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.

Table 5: Time-series regressions of quarterly regional systemic risk. Panels A though E report the results for individual geographical regions. The dependent variable is network level systemic risk score. Explanatory variables include: credit risk (mean probability of default, PD); network attributes (mean degree across all nodes, degree concentration measured by HHI, mean centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters); 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); and U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). 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. All regressions include adjustments for heteroskedasticity.

Panel A: East Asia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.5499***	2.1402***	1.7998	5.0334	5.1091	3.7844	2.3368
	(17.15)	(9.96)	(0.64)	(2.00)	(1.91)	(1.38)	(0.93)
Mean PD	186.4082***		149.7606***	178.3409***	175.1190***	165.7276***	165.9726***
	(5.44)		(12.88)	(9.06)	(9.19)	(10.59)	(11.48)
Mean Degree		0.0807***	-0.0113	0.1021	0.0997	0.0676	0.0577
		(4.47)	(-0.17)	(1.70)	(1.69)	(1.43)	(1.25)
Degree HHI		225.2589***	-35.7732	-28.4602	-12.1804	-89.5361**	-91.3012**
		(5.69)	(-0.74)	(-0.67)	(-0.28)	(-2.95)	(-2.77)
Mean Bet. Centrality			-0.0009***	-0.0005*	-0.0006*	-0.0004*	-0.0004**
			(-3.61)	(-2.34)	(-2.71)	(-2.69)	(-2.81)
Diameter			-0.0120	-0.0007	0.0037	-0.0063	-0.0024
			(-1.05)	(-0.09)	(0.48)	(-0.99)	(-0.37)
Fragility			0.0571	0.0243	0.0226	0.0428	0.0493*
			(1.60)	(0.77)	(0.75)	(1.88)	(2.24)
Num. Clusters			-0.0069	-0.0171	-0.0471	0.0095	-0.0028
			(-0.22)	(-0.57)	(-1.44)	(0.30)	(-0.09)
Cluster HHI			1.1179	-1.2257	-3.8057	1.4954	0.2739
			(0.40)	(-0.48)	(-1.36)	(0.56)	(0.11)
Median Log(Assets)				-0.1127		-0.1686	
				(-1.07)		(-1.51)	
Median Log(Market Cap)					0.0400		-0.0693
					(0.53)		(-0.94)
Median Loans/Assets				0.3619	-0.2983	0.1730	-0.4089
				(0.51)	(-0.41)	(0.24)	(-0.59)
Median Loans/Deposits				-1.2890	-0.2566	-0.8507	-0.2226
				(-1.09)	(-0.21)	(-1.11)	(-0.29)
Median Debt/Assets				-7.7644**		-14.2486***	
				(-3.57)		(-4.29)	
Median Debt/Equity					-6.3058***		-11.0527***
					(-5.56)		(-6.52)
Median Debt/Capital				0.0360*	0.0239*	0.0477**	0.0353**
				(2.60)	(2.28)	(3.03)	(3.30)
Median ROA				0.0610***		0.0627***	
				(3.68)		(4.93)	
Median ROE					0.0328*		0.0433***
					(2.03)		(4.04)
Median Market/Book				0.0907	0.0224	-0.1356	-0.0315
				(0.57)	(0.13)	(-0.89)	(-0.24)
Default						0.0995*	0.1044
						(2.11)	(1.96)
Term (Level)						0.0552*	0.0696**
						(2.34)	(2.83)
Term (Slope)						-0.0466	-0.0395
						(-1.38)	(-1.25)
TED						0.1023**	0.1109**
						(3.20)	(3.30)
VIX						-0.0070***	-0.0062***
						(-3.94)	(-3.71)
Observations	50	50	50	50	50	50	50
R^2	0.635	0.697	0.947	0.974	0.972	0.989	0.988
Adjusted R^2	0.627	0.684	0.936	0.963	0.960	0.982	0.980

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

Panel B: South Asia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.8167***	2.7818***	7.9469	-0.5247	7.2282	-0.6660	7.0890
	(26.32)	(9.87)	(2.01)	(-0.08)	(1.61)	(-0.09)	(1.56)
Mean PD	83.7515***		111.9661***	104.3785***	109.2717***	95.4711***	101.5807***
	(7.96)		(12.31)	(7.63)	(7.85)	(6.00)	(6.87)
Mean Degree		0.0694*	0.2908***	0.1281	0.2749*	0.2084	0.2834*
		(2.31)	(3.66)	(1.53)	(2.41)	(1.93)	(2.26)
Degree HHI		142.6410***	140.9054***	103.3965**	150.7439***	123.8655**	156.7166**
		(3.78)	(3.92)	(3.00)	(3.94)	(3.11)	(3.16)
Mean Bet. Centrality			-0.0013**	-0.0011*	-0.0009*	-0.0006	-0.0006
			(-3.53)	(-2.35)	(-2.48)	(-1.04)	(-1.26)
Diameter			0.0068	0.0083	0.0011	0.0019	0.0003
			(0.76)	(0.83)	(0.09)	(0.17)	(0.02)
Fragility			-0.0933	0.0053	-0.0807	-0.0371	-0.0846
			(-1.86)	(0.10)	(-1.23)	(-0.59)	(-1.18)
Num. Clusters			-0.0898	-0.0428	-0.0889	-0.0311	-0.0681
			(-1.45)	(-0.65)	(-1.43)	(-0.43)	(-1.08)
Cluster HHI			-6.0311	-1.5621	-6.7113	-2.9004	-6.2261
			(-1.52)	(-0.36)	(-1.53)	(-0.56)	(-1.41)
Median Log(Assets)				0.1357		0.1677	
				(1.29)		(1.67)	
Median Log(Market Cap)					0.0891*		0.0471
					(2.19)		(1.29)
Median Loans/Assets				-0.0720	0.1386	0.3041	0.2752
				(-0.23)	(0.43)	(0.82)	(0.79)
Median Loans/Deposits				1.6824	-0.2143	0.9756	-1.3153
				(0.61)	(-0.12)	(0.32)	(-0.56)
Median Debt/Assets				2.0449		5.2440	
				(0.80)		(1.88)	
Median Debt/Equity					2.1044		2.8764
					(1.19)		(1.55)
Median Debt/Capital				0.0021	0.0090	0.0049	0.0117
				(0.24)	(1.62)	(0.54)	(1.94)
Median ROA				0.0202		-0.0078	
				(0.75)		(-0.20)	
Median ROE					-0.0135		-0.0281
					(-0.69)		(-1.01)
Median Market/Book				0.3164	0.0651	0.2719	0.1698
				(1.67)	(0.31)	(1.37)	(0.82)
Default						0.2054**	0.1535
						(2.96)	(1.96)
Term (Level)						0.1407	0.1031
						(1.96)	(1.32)
Term (Slope)						0.0403	0.0338
						(0.65)	(0.63)
TED						0.0143	0.0039
						(0.24)	(0.06)
VIX						-0.0080	-0.0067
						(-1.73)	(-1.33)
Observations	50	50	50	50	50	50	50
R^2	0.502	0.136	0.900	0.934	0.941	0.949	0.948
Adjusted R^2	0.492	0.099	0.881	0.905	0.915	0.914	0.913

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

Panel C: Eastern Europe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.6818***	3.3254***	7.0050***	10.3979***	10.1446***	12.2170***	9.9293***
	(13.50)	(5.51)	(13.59)	(3.87)	(5.54)	(5.55)	(4.06)
Mean PD	122.3535***		161.3706***	125.3098***	125.6804***	75.4128*	85.9349*
	(3.51)		(10.07)	(7.90)	(8.60)	(2.33)	(2.76)
Mean Degree		0.2786	0.0184	-0.1693	-0.3818	0.5513	0.4008
		(1.09)	(0.08)	(-0.53)	(-1.21)	(1.44)	(1.07)
Degree HHI		20.0728*	2.9416	-1.5056	-3.5269	0.3661	-1.0791
		(2.64)	(1.15)	(-0.54)	(-1.12)	(0.12)	(-0.30)
Mean Bet. Centrality			0.0147*	0.0149	0.0179*	0.0015	0.0050
			(2.17)	(1.37)	(2.24)	(0.16)	(0.63)
Diameter			-0.1214***	-0.0903	-0.0903*	-0.0401	-0.0441
			(-4.04)	(-1.94)	(-2.33)	(-1.10)	(-1.41)
Fragility			-0.0192	0.1359	0.1830	-0.0364	-0.0003
			(-0.17)	(1.05)	(1.28)	(-0.30)	(-0.00)
Num. Clusters			-0.1615***	-0.1493***	-0.1472***	-0.1216***	-0.1210***
			(-11.15)	(-7.13)	(-6.54)	(-5.25)	(-4.48)
Cluster HHI			-2.8163***	-2.8994***	-2.5388***	-3.6810***	-3.3756***
			(-5.63)	(-5.28)	(-4.42)	(-5.77)	(-4.94)
Median Log(Assets)				0.0007		-0.1175	
				(0.00)		(-1.17)	
Median Log(Market Cap)					0.1817		0.1770
					(1.04)		(1.03)
Median Loans/Assets				1.5716	3.1904	-1.8540	-1.7618
				(0.52)	(0.93)	(-0.68)	(-0.50)
Median Loans/Deposits				-6.2141	-7.8665*	-4.4511	-4.5282
				(-2.00)	(-2.26)	(-1.51)	(-1.36)
Median Debt/Assets				0.7244		-2.0730	
				(0.13)		(-0.41)	
Median Debt/Equity					0.3401		-2.0560
					(0.08)		(-0.49)
Median Debt/Capital				0.0408	0.0338*	0.0576*	0.0477*
				(1.88)	(2.05)	(2.72)	(2.61)
Median ROA				-0.0127		-0.0736*	
				(-0.51)		(-2.55)	
Median ROE					-0.0035		-0.0600*
					(-0.16)		(-2.54)
Median Market/Book				-0.1898	-0.3302	-0.4420*	-0.5826*
				(-1.27)	(-1.66)	(-2.54)	(-2.66)
Default						0.5284*	0.4187
						(2.09)	(1.84)
Term (Level)						0.2002	0.1760
						(2.03)	(1.56)
Term (Slope)						-0.2768	-0.3389*
						(-1.98)	(-2.69)
TED						0.1413	0.1415
						(0.95)	(1.15)
VIX						-0.0149	-0.0169
						(-1.20)	(-1.63)
Observations	50	49	49	49	49	49	49
R^2	0.264	0.240	0.942	0.966	0.967	0.978	0.979
Adjusted R^2	0.249	0.207	0.931	0.950	0.952	0.961	0.964

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

Panel D: South Europe & Africa

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.5729***	2.2172***	3.1014***	5.2187***	2.0291**	4.8778***	2.3184**
	(26.03)	(12.43)	(5.56)	(5.00)	(3.01)	(3.84)	(3.20)
Mean PD	127.8586***		109.1882***	122.6279***	121.7226***	119.7938***	111.5829***
	(7.93)		(14.34)	(15.25)	(9.91)	(7.03)	(5.84)
Mean Degree		0.3623***	0.4460**	0.5324***	0.4516***	0.4738***	0.4168***
		(7.32)	(3.42)	(7.54)	(5.21)	(5.64)	(4.11)
Degree HHI		8.7920	29.6124	13.7076	5.9344	8.4134	3.6177
		(0.93)	(1.70)	(1.55)	(0.52)	(0.84)	(0.30)
Mean Bet. Centrality			-0.0002	-0.0012	-0.0011	-0.0014	-0.0010
			(-0.26)	(-1.84)	(-1.69)	(-1.26)	(-0.93)
Diameter			-0.0031	0.0095	0.0073	0.0130	0.0089
			(-0.32)	(1.19)	(0.93)	(1.11)	(0.78)
Fragility			-0.0938	-0.0801	-0.0463	-0.0504	-0.0333
			(-1.26)	(-2.03)	(-0.94)	(-1.10)	(-0.59)
Num. Clusters			-0.0402**	0.0145	-0.0002	0.0089	0.0000
			(-3.26)	(1.19)	(-0.01)	(0.62)	(0.00)
Cluster HHI			-1.4493*	0.2304	-0.2892	0.0556	-0.2224
			(-2.67)	(0.48)	(-0.59)	(0.11)	(-0.40)
Median Log(Assets)				-0.2118**		-0.1854*	
				(-3.09)		(-2.05)	
Median Log(Market Cap)					0.0558		-0.0138
					(0.66)		(-0.13)
Median Loans/Assets				-0.9298	-0.3118	-0.8560	-0.4829
				(-1.47)	(-0.61)	(-1.24)	(-0.74)
Median Loans/Deposits				-0.4096	-1.2174	-0.3581	-1.0276
				(-0.59)	(-1.99)	(-0.41)	(-1.38)
Median Debt/Assets				1.2776		1.5473	
				(1.59)		(1.57)	
Median Debt/Equity					0.4680		0.8802
					(0.68)		(1.08)
Median Debt/Capital				-0.0081	0.0015	-0.0091	-0.0020
				(-1.33)	(0.29)	(-1.06)	(-0.26)
Median ROA				0.0263**		0.0269*	
				(3.15)		(2.21)	
Median ROE					0.0378*		0.0378
					(2.21)		(1.65)
Median Market/Book				-0.0201	-0.0298	-0.0617	-0.0265
				(-0.31)	(-0.28)	(-0.65)	(-0.21)
Default						0.0073	0.0689
						(0.13)	(0.99)
Term (Level)						0.0276	0.0375
						(0.82)	(0.86)
Term (Slope)						0.0033	0.0166
						(0.07)	(0.36)
TED						-0.0453	-0.0287
						(-0.91)	(-0.52)
VIX						0.0023	0.0010
						(0.53)	(0.20)
Observations	50	50	50	50	50	50	50
R^2	0.581	0.602	0.926	0.966	0.958	0.967	0.960
Adjusted R^2	0.572	0.585	0.911	0.951	0.940	0.945	0.933

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

Panel E: South America

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.5485***	2.2973***	3.8267***	-0.5697	1.4129	-2.0957	1.3150
	(11.23)	(6.22)	(13.34)	(-0.46)	(1.31)	(-0.87)	(0.69)
Mean PD	288.8971**		132.4928***	125.9416***	142.1782***	139.9259***	169.5208***
	(3.32)		(4.68)	(5.25)	(4.15)	(5.65)	(5.22)
Mean Degree		0.9625***	1.3003***	0.6854***	0.6616**	0.3755	0.6021*
		(9.67)	(5.87)	(4.44)	(3.35)	(1.68)	(2.28)
Degree HHI		36.7927***	32.8476***	7.6182	6.4924	-2.6615	1.1884
		(3.64)	(4.59)	(1.34)	(0.94)	(-0.36)	(0.15)
Mean Bet. Centrality			-0.0332	-0.0094	-0.0216	-0.0069	-0.0240
			(-1.28)	(-0.59)	(-1.04)	(-0.52)	(-1.50)
Diameter			0.0323	0.0061	0.0184	-0.0044	0.0280
			(1.05)	(0.22)	(0.66)	(-0.15)	(0.92)
Fragility			-0.3349*	0.0643	0.0944	0.2534	0.1405
			(-2.21)	(0.62)	(0.71)	(1.85)	(0.86)
Num. Clusters			-0.0807***	-0.0427***	-0.0608***	-0.0351**	-0.0382**
			(-8.66)	(-4.57)	(-5.75)	(-3.23)	(-2.84)
Cluster HHI			-1.5532***	-1.0174***	-1.4945***	-0.8828**	-1.0835***
			(-5.51)	(-3.80)	(-4.98)	(-3.02)	(-3.82)
Median Log(Assets)				0.2954***		0.3182*	
				(4.17)		(2.61)	
Median Log(Market Cap)					0.3067***		0.1640
					(4.61)		(1.95)
Median Loans/Assets				0.7871	0.3050	1.0725	0.2609
				(0.81)	(0.37)	(0.99)	(0.33)
Median Loans/Deposits				-1.6899**	-0.8065	-1.4398*	-0.3736
				(-3.13)	(-1.51)	(-2.07)	(-0.50)
Median Debt/Assets				-1.2264		-1.4432	
				(-0.39)		(-0.48)	
Median Debt/Equity					-0.7792		-0.7512
					(-0.51)		(-0.50)
Median Debt/Capital				0.0061	0.0032	0.0079	0.0032
				(0.92)	(0.48)	(1.12)	(0.43)
Median ROA				0.0377		0.0348	
				(1.21)		(0.96)	
Median ROE					0.0269		0.0298
					(1.26)		(1.25)
Median Market/Book				-0.3328*	-0.2344	-0.1822	-0.0821
				(-2.29)	(-1.22)	(-1.13)	(-0.48)
Default						0.1650	0.0338
						(1.75)	(0.29)
Term (Level)						0.0797	0.1190*
						(1.49)	(2.44)
Term (Slope)						0.0088	-0.0692
						(0.13)	(-1.19)
TED						0.0148	0.0028
						(0.22)	(0.04)
VIX						-0.0005	-0.0015
						(-0.11)	(-0.31)
Observations	50	50	50	50	50	50	50
R^2	0.387	0.630	0.943	0.978	0.972	0.981	0.980
Adjusted R^2	0.375	0.615	0.931	0.968	0.959	0.968	0.966

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

Next we consider panel regressions of quarterly systemic risk contributions of all emerging market banks. Panel A, Table 6 reports the results for all geographical regions considered jointly, and Panels B though F present the results for individual geographical regions. The dependent variable is each firm's contribution to network level systemic risk score. All regressions include controls for region-specific cluster effects and adjustments for heteroskedasticity. We find that the overall credit risk explains about 6% of the variation in individual firms' systemic risk (regression 1). Adding network risks increases the explanatory power substantially by 62%. Firm-specific attributes add another 3%. Table 6 (Panels B to F) and Table 7, Panel B show that across all five regions, credit risk explains a relatively lower portion of systemic risks in Eastern Europe (2%) and South America (14%). At the same time, network risk explains the highest portion of systemic risks in those regions: Eastern Europe (67%) and South America and East Asia (57%). In addition, the contribution of firm-specific attributes is highest for Eastern Europe (15%) and South America (20%) firms, while the US macro-factor contribution is negligible. Comparing the time series versus panel regressions based on Table 7, Panels A and B, we find that incremental explanatory power from network parameters is roughly similar across both sets of regressions. Cross-sectional variation of firm-specific attributes matters in explaining systemic risks as reflected in the panel regressions.

Table 6: Panel regressions of quarterly systemic risk contributions of firms. Panel A reports the results for all geographical regions considered jointly, and Panels B though F (shown in Appendix) present the results for individual geographical regions. The dependent variable is each firm's contribution to network level systemic risk score. Explanatory variables include: credit risk (probability of default, PD); network attributes (degree across all nodes, degree concentration measured by HHI, centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters); 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); and U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). Network connections are based on Granger regressions using p-values of 0.025. All regressions include controls for region-specific cluster effects and adjustments for heteroscedasticity.

Panel A: All Regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.7027	0.1822	3.6425**	2.6724*	3.0575*	2.4899*	2.9948*
	(2.58)	(0.99)	(5.34)	(4.01)	(3.90)	(3.64)	(3.99)
PD	23.0678		23.8721*	16.2903	17.8982	16.2030	17.6414*
	(2.64)		(2.93)	(2.40)	(2.68)	(2.62)	(2.82)
Degree		0.0363*	0.0762*	0.0783	0.0791	0.0784	0.0790
		(4.43)	(3.00)	(2.70)	(2.57)	(2.70)	(2.58)
Degree HHI		71.6447**	27.2748**	27.0671*	28.2436*	23.2694**	24.7328*
		(6.28)	(4.65)	(4.20)	(3.97)	(4.98)	(4.60)
Bet. Centrality			-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
			(-1.34)	(-1.23)	(-1.18)	(-1.16)	(-1.11)
Diameter			0.0017	-0.0093	-0.0108	-0.0183	-0.0186
			(0.14)	(-0.59)	(-0.66)	(-1.21)	(-1.21)
Fragility			-0.0560	-0.0763	-0.0771	-0.0809	-0.0819
			(-2.06)	(-1.97)	(-1.90)	(-2.15)	(-2.10)
Num. Clusters			-0.0550	-0.0542	-0.0502	-0.0550*	-0.0524
			(-2.50)	(-2.49)	(-2.25)	(-2.90)	(-2.58)
Cluster HHI			-3.1392**	-2.7987*	-2.7155*	-2.7942*	-2.7296*
			(-5.85)	(-3.90)	(-3.27)	(-4.00)	(-3.37)
Log(Assets)				0.0531		0.0565*	
				(2.69)		(2.80)	
Log(Market Cap)					0.0519*		0.0519*
					(2.90)		(2.88)
Loans/Assets				0.1761	0.2339	0.1671	0.2246
				(1.54)	(1.73)	(1.52)	(1.76)
Loans/Deposits				0.0030***	0.0030***	0.0030***	0.0031***
				(27.09)	(30.61)	(24.19)	(25.97)
Debt/Assets				0.0188		0.0795	
				(0.18)		(0.77)	
Debt/Equity					-0.0145		-0.0084
					(-1.36)		(-0.70)
Debt/Capital				0.0007	0.0015	0.0003	0.0014
				(0.89)	(1.31)	(0.42)	(1.22)
ROA				-0.0003		-0.0006	
				(-0.21)		(-0.30)	
ROE					-0.0010		-0.0011
					(-0.61)		(-0.63)
Market/Book				0.0035	-0.0041	0.0027	-0.0053
				(1.08)	(-0.53)	(0.86)	(-0.75)
Default						0.0574	0.0572
						(1.28)	(1.31)
Term (Level)						0.0591*	0.0471*
						(3.40)	(2.96)
Term (Slope)						0.0102	0.0083
						(0.63)	(0.61)
TED						0.0740	0.0913*
						(2.59)	(3.05)
VIX						-0.0006	-0.0008
						(-0.26)	(-0.33)
Observations	29158	29145	29145	19946	17866	19946	17866
R^2	0.064	0.415	0.639	0.675	0.674	0.681	0.679
Adjusted R^2	0.064	0.415	0.639	0.675	0.674	0.680	0.679

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

Panel B: East Asia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.3743***	0.0530***	2.7659***	3.1599***	3.1987***	2.0283***	2.3327***
	(74.56)	(4.45)	(9.02)	(11.26)	(11.06)	(5.51)	(6.05)
PD	24.1131***		20.7539***	19.3393***	20.6596***	19.6826***	21.0207***
	(20.20)		(24.55)	(25.11)	(26.62)	(25.14)	(26.59)
Degree		0.0371***	0.0457***	0.0455***	0.0453***	0.0454***	0.0452***
		(33.44)	(38.64)	(38.36)	(37.58)	(37.97)	(37.16)
Degree HHI		50.9535***	54.4897***	56.9087***	54.6123***	53.2832***	53.2088***
		(22.29)	(25.62)	(28.37)	(26.32)	(19.19)	(18.32)
Bet. Centrality			-0.0000	-0.0000	0.0000	0.0000	0.0000
			(-0.75)	(-0.05)	(0.31)	(0.08)	(0.42)
Diameter			0.0097***	0.0114***	0.0108***	0.0112***	0.0109***
			(6.96)	(9.01)	(8.25)	(8.96)	(8.41)
Fragility			-0.0318***	-0.0315***	-0.0310***	-0.0282***	-0.0276***
			(-34.96)	(-34.75)	(-33.54)	(-28.55)	(-27.44)
Num. Clusters			-0.0277***	-0.0391***	-0.0365***	-0.0261***	-0.0262***
			(-8.48)	(-13.37)	(-12.17)	(-6.77)	(-6.54)
Cluster HHI			-2.6094***	-3.6890***	-3.4526***	-2.6373***	-2.6649***
			(-8.67)	(-13.23)	(-12.04)	(-7.21)	(-6.96)
Log(Assets)				0.0323***		0.0322***	
				(44.89)		(44.45)	
Log(Market Cap)					0.0337***		0.0336***
					(40.11)		(39.86)
Loans/Assets				0.0306***	0.0664***	0.0315***	0.0667***
				(4.13)	(9.80)	(4.29)	(9.95)
Loans/Deposits				0.0009	0.0005	0.0008	0.0004
				(0.94)	(0.29)	(0.91)	(0.26)
Debt/Assets				0.0617***		0.0652***	
				(4.23)		(4.55)	
Debt/Equity					0.0058*		0.0066*
					(2.03)		(2.34)
Debt/Capital				-0.0007***	-0.0002**	-0.0007***	-0.0002**
				(-6.57)	(-2.63)	(-6.78)	(-2.72)
ROA				0.0006***		0.0006***	
				(3.83)		(3.83)	
ROE					0.0005***		0.0005**
					(3.30)		(3.25)
Market/Book				0.0083***	0.0053***	0.0081***	0.0052***
				(6.75)	(4.20)	(6.63)	(4.12)
Default						-0.0126	-0.0170*
						(-1.78)	(-2.29)
Term (Level)						0.0191***	0.0157***
						(6.16)	(4.91)
Term (Slope)						0.0078**	0.0099**
						(2.61)	(3.16)
TED						-0.0155*	-0.0191**
						(-2.42)	(-2.79)
VIX						-0.0002	-0.0002
						(-0.46)	(-0.50)
Observations	10335	10335	10335	8914	8557	8914	8557
R^2	0.167	0.433	0.744	0.820	0.818	0.822	0.821
Adjusted R^2	0.167	0.433	0.743	0.820	0.818	0.822	0.820

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

Panel C: South Asia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.2933***	-0.0562***	6.0451***	7.2992***	8.0887***	5.8428***	5.6822***
	(75.00)	(-3.62)	(16.91)	(9.26)	(9.22)	(6.81)	(6.01)
PD	19.0255***		17.4201***	14.7745***	15.5179***	15.5378***	16.5489***
	(45.05)		(52.90)	(28.62)	(31.18)	(29.83)	(32.63)
Degree		0.0480***	0.0571***	0.0617***	0.0677***	0.0604***	0.0665***
		(33.74)	(36.20)	(28.65)	(29.79)	(28.34)	(29.66)
Degree HHI		86.8167***	71.7714***	107.3961***	122.4916***	95.4837***	112.5733***
		(16.14)	(12.32)	(9.71)	(9.00)	(7.24)	(7.30)
Bet. Centrality			-0.0000***	-0.0000***	-0.0001***	-0.0000**	-0.0000***
			(-7.53)	(-4.27)	(-4.52)	(-3.29)	(-3.67)
Diameter			0.0022	-0.0045	-0.0033	-0.0023	-0.0001
			(1.44)	(-1.38)	(-0.94)	(-0.73)	(-0.02)
Fragility			-0.0351***	-0.0484***	-0.0572***	-0.0436***	-0.0513***
			(-26.63)	(-18.41)	(-18.10)	(-16.25)	(-16.02)
Num. Clusters			-0.0766***	-0.0982***	-0.1094***	-0.0850***	-0.0859***
			(-15.41)	(-9.80)	(-9.68)	(-7.82)	(-7.07)
Cluster HHI			-5.8770***	-7.3668***	-7.9472***	-6.2428***	-5.7487***
			(-16.66)	(-9.43)	(-9.19)	(-7.36)	(-6.17)
Log(Assets)				0.0224***		0.0304***	
				(8.48)		(11.55)	
Log(Market Cap)					0.0207***		0.0162***
					(7.19)		(5.80)
Loans/Assets				0.1474***	0.2516***	0.0884**	0.1603***
				(4.83)	(8.29)	(2.92)	(5.12)
Loans/Deposits				-0.0112	-0.0292**	-0.0159*	-0.0249**
				(-1.37)	(-3.28)	(-2.20)	(-3.19)
Debt/Assets				-0.1098***		-0.0515**	
				(-5.68)		(-2.58)	
Debt/Equity					-0.0106**		-0.0098*
					(-2.67)		(-2.42)
Debt/Capital				-0.0000	-0.0003	-0.0007***	-0.0003
				(-0.17)	(-1.43)	(-3.33)	(-1.51)
ROA				0.0006*		-0.0009**	
				(2.02)		(-2.77)	
ROE					0.0002		-0.0007
					(0.47)		(-1.93)
Market/Book				0.0033**	-0.0050***	0.0046***	-0.0046**
				(3.06)	(-3.32)	(4.20)	(-3.02)
Default						-0.0074	0.0109
						(-0.51)	(0.60)
Term (Level)						0.0551***	0.0710***
						(12.65)	(11.85)
Term (Slope)						-0.0325***	-0.0571***
						(-4.75)	(-6.88)
TED						-0.0427***	-0.0522***
						(-4.45)	(-3.67)
VIX						0.0037***	0.0034***
						(5.29)	(4.54)
Observations	10609	10609	10609	4329	3375	4329	3375
R^2	0.420	0.315	0.770	0.831	0.833	0.840	0.844
Adjusted R^2	0.420	0.315	0.770	0.830	0.832	0.839	0.843

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

Panel D: Eastern Europe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.0659***	0.5084***	6.1470***	2.9762***	4.7212***	3.3685***	5.4176***
	(34.78)	(8.25)	(22.41)	(11.65)	(15.21)	(6.06)	(8.93)
PD	33.4370***		55.2362***	44.3280***	48.5694***	59.9224***	63.5430***
	(4.71)		(10.07)	(10.10)	(7.35)	(10.60)	(7.15)
Degree		0.4158***	0.5394***	0.5159***	0.5031***	0.5182***	0.5047***
		(20.93)	(28.59)	(26.36)	(24.43)	(26.27)	(24.35)
Degree HHI		44.4022***	18.2005***	17.3309***	16.3616***	17.8790***	16.6659***
		(19.05)	(8.61)	(8.83)	(7.50)	(8.78)	(7.49)
Bet. Centrality			-0.0029***	-0.0027***	-0.0019**	-0.0033***	-0.0025***
			(-3.83)	(-4.04)	(-2.90)	(-4.91)	(-3.73)
Diameter			-0.0412***	-0.0354***	-0.0368***	-0.0450***	-0.0491***
			(-4.66)	(-5.12)	(-5.04)	(-5.77)	(-5.95)
Fragility			-0.4640***	-0.4420***	-0.4568***	-0.3822***	-0.3967***
			(-14.57)	(-15.61)	(-15.27)	(-15.11)	(-14.95)
Num. Clusters			-0.1564***	-0.1445***	-0.1415***	-0.1524***	-0.1570***
			(-15.47)	(-15.21)	(-13.27)	(-9.14)	(-8.80)
Cluster HHI			-3.9232***	-3.6174***	-3.5997***	-3.7777***	-3.9803***
			(-15.12)	(-14.85)	(-13.18)	(-9.35)	(-9.03)
Log(Assets)				0.1814***		0.1830***	
				(21.42)		(22.58)	
Log(Market Cap)					0.1536***		0.1561***
					(17.62)		(18.32)
Loans/Assets				-0.2043*	0.1263	-0.2092**	0.1478
				(-2.53)	(1.62)	(-2.70)	(1.96)
Loans/Deposits				0.0024***	0.0023***	0.0023***	0.0021***
				(13.45)	(10.70)	(11.37)	(8.80)
Debt/Assets				0.0552		0.0675	
				(0.39)		(0.51)	
Debt/Equity					-0.0273		-0.0166
					(-1.01)		(-0.68)
Debt/Capital				0.0009	0.0050***	0.0003	0.0043***
				(0.76)	(5.23)	(0.29)	(4.31)
ROA				0.0007		0.0015	
				(0.77)		(1.74)	
ROE					0.0010		0.0019*
					(1.16)		(2.19)
Market/Book				-0.0044	-0.0561***	-0.0041	-0.0523***
				(-0.51)	(-4.14)	(-0.48)	(-3.95)
Default						-0.4812***	-0.4238***
						(-6.62)	(-4.82)
Term (Level)						0.0003	-0.0474
						(0.01)	(-0.80)
Term (Slope)						0.0510	0.0722
						(1.07)	(1.37)
TED						0.0202	0.0436
						(0.31)	(0.55)
VIX						-0.0008	-0.0037
						(-0.24)	(-1.00)
Observations	2186	2173	2173	1733	1443	1733	1443
R^2	0.021	0.435	0.690	0.832	0.839	0.842	0.847
Adjusted R^2	0.021	0.435	0.689	0.831	0.838	0.840	0.845

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

Panel E: South Europe & Africa

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.8344***	0.4624***	3.0734***	2.2277***	2.5371***	0.9850***	1.8188***
	(48.62)	(11.54)	(13.26)	(10.51)	(10.93)	(4.44)	(7.54)
PD	57.6599***		58.7401***	55.8678***	62.7596***	58.4820***	65.6462***
	(23.65)		(28.60)	(22.40)	(27.73)	(24.38)	(28.53)
Degree		0.1972***	0.2249***	0.2167***	0.2218***	0.2160***	0.2209***
		(26.72)	(46.39)	(46.87)	(46.04)	(47.88)	(47.36)
Degree HHI		15.3984***	49.0400***	52.1203***	47.8313***	32.5306***	34.7253***
		(4.81)	(16.29)	(18.33)	(15.75)	(9.96)	(9.53)
Bet. Centrality			-0.0003**	-0.0001	-0.0001	-0.0001	-0.0001
			(-3.25)	(-0.78)	(-1.14)	(-0.66)	(-1.04)
Diameter			0.0157***	0.0142***	0.0152***	0.0059*	0.0063*
			(5.09)	(5.17)	(5.17)	(2.15)	(2.14)
Fragility			-0.1735***	-0.1686***	-0.1721***	-0.1389***	-0.1471***
			(-24.00)	(-23.71)	(-22.37)	(-18.40)	(-17.59)
Num. Clusters			-0.0677***	-0.0839***	-0.0702***	-0.0512***	-0.0483***
			(-12.93)	(-16.66)	(-13.16)	(-9.36)	(-8.11)
Cluster HHI			-2.5369***	-3.1479***	-2.7627***	-2.0969***	-2.0215***
			(-10.42)	(-13.66)	(-11.18)	(-9.18)	(-8.13)
Log(Assets)				0.0943***		0.0981***	
				(27.37)		(28.69)	
Log(Market Cap)					0.1026***		0.1016***
					(26.37)		(26.82)
Loans/Assets				-0.0636*	-0.0548	-0.0895**	-0.0578*
				(-2.15)	(-1.77)	(-3.23)	(-2.00)
Loans/Deposits				0.0012	-0.0015	0.0012	-0.0009
				(0.87)	(-0.94)	(0.85)	(-0.53)
Debt/Assets				-0.1569***		-0.1017*	
				(-3.32)		(-2.27)	
Debt/Equity					-0.0013		0.0014
					(-0.13)		(0.14)
Debt/Capital				0.0005	0.0020***	0.0000	0.0017***
				(1.30)	(6.28)	(0.03)	(5.77)
ROA				0.0010**		0.0008*	
				(2.85)		(2.39)	
ROE					0.0013***		0.0012***
					(4.27)		(4.17)
Market/Book				0.0083***	-0.0084***	0.0037	-0.0116***
				(3.30)	(-3.45)	(1.71)	(-4.69)
Default						-0.0838***	-0.1343***
						(-4.08)	(-5.87)
Term (Level)						0.1031***	0.0720***
						(15.11)	(10.04)
Term (Slope)						-0.0097	0.0007
						(-0.97)	(0.06)
TED						-0.0380*	-0.0323
						(-2.17)	(-1.60)
VIX						-0.0021*	-0.0026*
						(-1.96)	(-2.16)
Observations	4107	4107	4107	3226	2854	3226	2854
R^2	0.426	0.312	0.803	0.846	0.848	0.863	0.863
Adjusted R^2	0.426	0.312	0.803	0.845	0.847	0.862	0.862

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

Panel F: South America

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.1398***	0.2767***	2.7380***	-1.3574***	0.6411***	-2.3270***	-0.1103
	(50.02)	(3.56)	(13.92)	(-9.09)	(4.68)	(-11.30)	(-0.55)
PD	117.1526***		102.8414***	121.2928***	126.5029***	124.7151***	128.8793***
	(14.64)		(18.63)	(23.89)	(23.91)	(24.62)	(24.18)
Degree		0.7125***	0.7848***	0.7049***	0.6880***	0.7066***	0.6907***
		(27.95)	(32.63)	(36.10)	(36.54)	(37.07)	(37.17)
Degree HHI		49.3430***	42.4149***	40.5733***	39.7711***	26.2774***	27.3228***
		(17.66)	(16.19)	(21.71)	(20.00)	(9.51)	(9.09)
Bet. Centrality			-0.0044	-0.0026	-0.0006	-0.0026	-0.0008
			(-1.05)	(-0.85)	(-0.19)	(-0.90)	(-0.27)
Diameter			0.0323*	0.0254**	0.0294**	0.0251**	0.0247*
			(2.24)	(2.76)	(2.90)	(2.61)	(2.28)
Fragility			-0.5183***	-0.4708***	-0.4536***	-0.3850***	-0.3798***
			(-12.51)	(-13.88)	(-12.99)	(-11.18)	(-10.62)
Num. Clusters			-0.0762***	-0.0798***	-0.0719***	-0.0356***	-0.0350***
			(-10.33)	(-17.15)	(-14.91)	(-5.44)	(-5.07)
Cluster HHI			-1.2084***	-1.2534***	-1.0988***	-0.7805***	-0.7283***
			(-5.15)	(-8.41)	(-7.17)	(-4.82)	(-4.38)
Log(Assets)				0.2141***		0.2159***	
				(36.98)		(39.05)	
Log(Market Cap)					0.1678***		0.1685***
					(29.51)		(30.12)
Loans/Assets				0.1073	0.9196***	0.1300	0.8909***
				(1.32)	(9.61)	(1.74)	(9.55)
Loans/Deposits				-0.1205***	-0.3787***	-0.1419***	-0.3776***
				(-4.13)	(-9.28)	(-5.29)	(-9.53)
Debt/Assets				-0.1466		-0.0518	
				(-1.00)		(-0.37)	
Debt/Equity					-0.0685**		-0.0655*
					(-2.58)		(-2.50)
Debt/Capital				0.0005	0.0050***	0.0000	0.0050***
				(0.48)	(8.27)	(0.04)	(8.45)
ROA				-0.0001		0.0007	
				(-0.05)		(0.39)	
ROE					0.0004		0.0012
					(0.25)		(0.69)
Market/Book				0.0564***	-0.0042	0.0558***	-0.0071
				(7.11)	(-0.55)	(7.10)	(-0.94)
Default						-0.2413***	-0.2332***
						(-4.91)	(-4.52)
Term (Level)						0.1611***	0.1344***
						(7.77)	(5.77)
Term (Slope)						-0.1256***	-0.0943***
						(-5.18)	(-3.44)
TED						-0.0987**	-0.0442
						(-2.62)	(-1.05)
VIX						0.0122***	0.0107***
						(5.77)	(4.48)
Observations	1921	1921	1921	1744	1637	1744	1637
R^2	0.142	0.534	0.713	0.906	0.901	0.913	0.906
Adjusted R^2	0.141	0.533	0.712	0.905	0.900	0.912	0.905

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

Table 7: Summary of adjusted R^2s from time-series and panel regressions of systemic risk. Time-series regressions are conducted, analogous to the specifications in Table 5, for each regional group; the dependent variables are regional network level systemic risk score. Panel regressions are conducted, analogous to the specifications in Table 6, for each regional group; the dependent variables are region-specific firms' contribution to network level systemic risk score. Explanatory variables include: credit risk (probability of default, PD); network interconnectedness (degree across all nodes, degree concentration measured by HHI); network parameters (centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters); 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) and U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX).

	Regional Group					
Included explanatory variables	All	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America
Panel A: Adjusted R^2s from time-series regressions						
Credit risk (only)		63%	49%	25%	57%	38%
Network interconnectedness (only)		68%	10%	21%	59%	62%
Credit risk + network parameters		94%	88%	93%	91%	93%
Credit risk + network parameters + firm-specific attributes		96%	91-92%	95%	94-95%	96-97%
Credit risk + network parameters + firm-specific attributes + U.S. macro variables		98%	91-92%	96%	93-95%	97%
Panel B: Adjusted R^2s from panel regressions						
Credit risk (only)	6%	17%	42%	2%	43%	14%
Network interconnectedness (only)	42%	43%	32%	44%	31%	53%
Credit risk + network parameters	64%	74%	77%	69%	80%	71%
Credit risk + network parameters + firm-specific attributes	67-68%	82%	83%	83-84%	85%	90-91%
Credit risk + network parameters + firm-specific attributes + U.S. macro variables	68%	82%	84%	84-85%	86%	91%

6.3 Analyzing cross-information flows of systemic risks across regions

We next analyze how systemic risks are connected across regions. We employ cross-correlation and Granger causality tests to examine how systemic risks flow across regions. The objective is to better understand the nature of cross-market lead-lag relationships among systemic risks.

We measure correlations of systemic risk between regional groups, where systemic risk is obtained as the regional network level systemic risk score. Table 8, Panel A reports contemporaneous quarterly correlations, while Panel B reports one-quarter lagged correlations. Panel A shows that contemporaneous correlations are significantly high between East Asia and three non-Asian regional blocks (i.e. Eastern Europe, South Europe & Africa, and South America). Eastern Europe and South America show high contemporaneous correlation significance. Interestingly, South Asia (consisting of India) has no significant correlations with any other region and hence is relatively isolated. Panel B shows that significant lagged correlations exist across markets. Firstly, systemic risk in each region is significantly autocorrelated with its own lagged value. Secondly East Asia, Eastern Europe, South Europe/Africa, and South America all display significant lead-lag correlations. Overall, we find that both contemporaneous and lagged correlations matter in the evolution of systemic risks across regions. South Asia is again isolated from other country groups as lagged correlations are very small and trivial versus the other four groups. We also present these correlations in detail in Figure 3.

Table 8: Correlations of systemic risk between country regional groups. Systemic risk is the regional network level systemic risk score. Panel A reports contemporaneous quarterly correlations, Panel B reports one-quarter lagged correlations. Lagged values are on the columns and contemporaneous ones are on the rows. p-values are reported in parentheses.

	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America
Panel A: Contemporaneous correlations					
East Asia	1.0000				
South Asia	−0.0672	1.0000			
	(0.6430)				
Eastern Europe	0.6933	−0.1433	1.0000		
	(0.0000)	(0.3207)			
South Europe & Africa	0.5559	−0.1224	0.1637	1.0000	
	(0.0000)	(0.3971)	(0.2559)		
South America	0.6260	−0.1819	0.7864	0.1710	1.0000
	(0.0000)	(0.2061)	(0.0000)	(0.2352)	
Panel B: Lagged correlations					
East Asia	0.6827	−0.2073	0.3799	0.4923	0.3147
	(0.0000)	(0.1529)	(0.0071)	(0.0003)	(0.0276)
South Asia	−0.1159	0.6408	−0.2235	0.1037	−0.2660
	(0.4276)	(0.0000)	(0.1226)	(0.4783)	(0.0647)
Eastern Europe	0.7620	−0.1720	0.8354	0.2533	0.7089
	(0.0000)	(0.2372)	(0.0000)	(0.0791)	(0.0000)
South Europe & Africa	0.3998	−0.1996	−0.0317	0.5907	0.0351
	(0.0044)	(0.1692)	(0.8287)	(0.0000)	(0.8109)
South America	0.5623	−0.2444	0.5257	0.0942	0.4998
	(0.0000)	(0.0906)	(0.0001)	(0.5199)	(0.0003)

To better understand cross-market linkages, we present pairwise cross-correlograms across markets. Figure 3 presents the corresponding plots. We consider pairs of geographic regions and study lead and lag relationships between their respective systemic risks. In each plot, to the right of zero (x-axis ¿ 0), the first-named group leads the second-named group; to the left of zero (x-axis ¡ 0), the first-named group lags the second-named group. Specifcally, in the first plot, East Asia negatively leads South Asia (x-axis ¿ 0), and positively lags South Asia (x-axis ¡ 0). Similarly, East Asia positively leads and lags Eastern Europe and South America. East Asia positively (negatively) leads (lags) South Europe & Africa. Eastern Europe positively leads and lags South America. South Asia negatively lags Eastern Europe, South Europe & Africa, and South America. Overall we observe that lead and lag effects are usually very short-term. Long-term effects fade out. Often the highest correlation is contemporaneous (x-axis = 0)

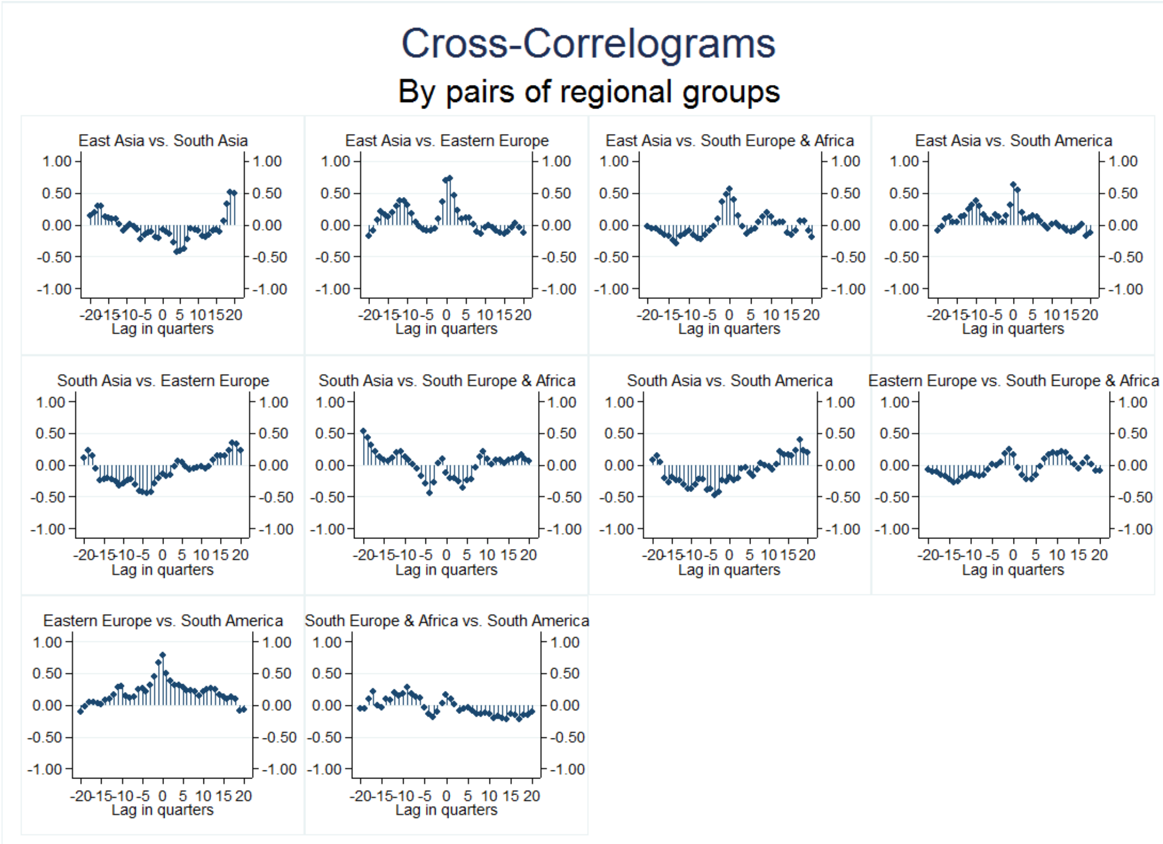

Figure 3: Pairwise cross-correlations between the five regions. There are 10 such plots.

Next, we present the Granger causality regressions. For each country regional group, the quarterly systemic risk measure is regressed on one-quarter lagged values of systemic risk measures of all five regional groups (including itself). Table 9, Panel A reports the univariate F-statistics of significance. Panel B reports the joint F-statistics of significance for the four other cross-regional groups considered together. We observe that dependence on self-lagged variables is usually strong (the diagonal terms) but dependence on cross-lagged variables is usually weak. We find cross-market evidence across three blocks: (a) East Asia significantly Granger causes the systemic risks in Eastern Europe, South Europe/Africa and South America. Similarly, (b) Eastern Europe significantly Granger causes the systemic risks in South Europe/Africa, and finally (c) South Europe/Africa significantly Granger causes the systemic risks in South Asia. Joint Granger causality tests from Panel B shows that systemic risks in East Asia, Eastern Europe and South America significantly depend on joint cross-lagged variables from other markets.

Table 9: Granger causality regressions. For each country regional group, quarterly values of systemic risk measure (regional network level systemic risk score) are regressed on one-quarter lagged values of systemic risk measures of all five regional groups (including itself). Panel A reports the univariate F-statistics of significance (and corresponding p-values in parentheses). Panel B reports the joint F-statistics of significance (and corresponding p-values in parentheses) for the four other cross regional groups considered together.

	Dependent variable: systemic risk corresponding to				
Explanatory variables: lagged systemic risk of	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America
Panel A: Univariate F-statistics of lagged variables					
East Asia	16.56	1.24	11.46	6.21	10.47
	(0.0002)	(0.2711)	(0.0015)	(0.0166)	(0.0023)
South Asia	2.84	33.33	0.78	2.85	3.35
	(0.0990)	(0.0000)	(0.3817)	(0.0987)	(0.0740)
Eastern Europe	0.14	0.07	14.29	4.94	0.02
	(0.7125)	(0.7897)	(0.0005)	(0.0316)	(0.8949)
South Europe & Africa	0.22	4.82	1.32	6.12	4.98
	(0.6421)	(0.0336)	(0.2564)	(0.0174)	(0.0309)
South America	0.86	0.35	0.17	0.03	0.22
	(0.3600)	(0.5591)	(0.6838)	(0.8739)	(0.6435)
Panel B: Joint F-statistic of all four lagged cross-variables					
All 4 lagged cross-variables	1.34	1.70	3.73	2.45	3.99
	(0.2709)	(0.1672)	(0.0108)	(0.0607)	(0.0077)

To better understand the linear time-series interdependencies between the systemic risks we implement the following Vector Auto-Regressions (VAR) model across the five country groups.

$$\begin{pmatrix} SysriskEastAsia \\ SysriskSouthAsia \\ SysriskEastEurope \\ SysriskEuropeandAfrica \\ SysriskSouthAmerica \end{pmatrix}_t = \text{intercept} + \begin{pmatrix} SysriskEastAsia \\ SysriskSouthAsia \\ SysriskEastEurope \\ SysriskEuropeandAfrica \\ SysriskSouthAmerica \end{pmatrix}_{t-1}$$

$$+ \ldots + \begin{pmatrix} SysriskEastAsia \\ SysriskSouthAsia \\ SysriskEastEurope \\ SysriskEuropeandAfrica \\ SysriskSouthAmerica \end{pmatrix}_{t-4} + error_t$$

The VAR model involves quarterly network level scores of systemic risks that are jointly regressed on four lagged (one through four quarters) values of systemic risk measures of the five regional groups. Both likelihood ratio (LR) and Akaike information criterion (AIC) identify that a maximum of four lags are material. Out of 100 explanatory variables (5 regressions $\times$ 5 systemic risk scores $\times$ 4 lags), only 7 coefficients are significant. This implies that consistent with all other results across country groups, contemporaneous dependence of systemic risk matters far more that lagged inter-dependence. Table 10 reports the summary of coefficients and t-statistics (corresponding p-values in parentheses) of seven such regressions. Out of the seven regressions, six regressions have significant 1-quarter lags and only one regression for South America that has a significant 3-quarter lag. Five (two) regressions have positive (negative) coefficients; three regressions have self-lag dependence and four others have significant cross-lag dependence.

Table 10: Vector autoregression, VAR (significant results only). Quarterly values of systemic risk measure (network level systemic risk score) of the five countries-groups are jointly regressed on four lagged (one through four quarters) values of systemic risk measure of the five countries-groups. Both likelihood ratio (LR) and Akaikae information criterion (AIC) identify that a maximum of four lags are material. Out of 100 explanatory variables (5 regressions * 5 systemic risk scores * 4 lags), only 7 are significant. The following summary reports the coefficients and t-statistics (corresponding p-values in parentheses) for these significant 7.

Dependent variable: systemic risk of	Explanatory variable: systemic risk of	Lag in quarters	Coefficient	t-statistic (p-value)
East Asia	East Asia	1	1.0208	4.27 (0.000)
East Asia	South Asia	1	-0.3928	-2.09 (0.047)
South Asia	South Asia	1	0.4753	2.25 (0.034)
Eastern Europe	East Asia	1	1.7500	4.33 (0.000)
Eastern Europe	Eastern Europe	1	0.7297	2.92 (0.007)
South America	East Asia	1	1.8488	5.08 (0.000)
South America	South Europe & Africa	3	-0.7605	-2.10 (0.046)

6.4 Analyzing Systemic risks using principal components

We further examine the key economic drivers behind systemic risks. We undertake a principal components analysis (PCA) of region-wide systemic risk measures. Table 11, Panel A presents the first five PCs and corresponding eigenvalues for the regional network level systemic risk score of the five regional country groups. We observe that the first PC explains 52% of the variation, while the next two components explain about 20% of the variation each. The first three (four) components together explain 92% (97%) of the joint variation in the regional time series of systemic risk.

Table 11: Principal component analysis, PCA. Panel A presents the first five principal components and corresponding eigenvalues for the systemic risk measure (regional network level systemic risk score) of the five regional country groups. Panel B reports the results of time-series regressions of quarterly values of the first three principal components on contemporaneous and one-quarter lagged values of U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX); regressions include adjustments for heteroskedasticity.

Panel A: Summary statistics of first 5 principal components

Component	Eigenvalue	Difference	Proportion	Cumulative
1	2.6124	1.6143	0.5225	0.5225
2	0.9981	0.0245	0.1996	0.7221
3	0.9737	0.7293	0.1947	0.9169
4	0.2443	0.0730	0.0489	0.9657
5	0.1714		0.0343	1.0000

Panel B: Regression of first 3 principal components on U.S. macroeconomic variables

Explanatory variables	Dependent variable					
	Component 1		Component 2		Component 3	
Constant	-4.8621***	-4.8670***	0.4301	0.3603	0.5716	0.3683
	(-6.64)	(-8.55)	(0.75)	(0.56)	(0.83)	(0.89)
Default	2.3307**	2.5376***	-0.1825	0.2230	0.6731	0.1805
	(3.19)	(3.62)	(-0.67)	(0.24)	(1.55)	(0.50)
Term (Level)	0.5828***	0.4719	-0.3566***	0.1914	-0.1793	-0.2397
	(5.63)	(1.16)	(-3.59)	(0.43)	(-1.40)	(-1.50)
Term (Slope)	0.0731	-0.7213	0.2260	-0.0950	0.3949	0.3707
	(0.40)	(-1.28)	(1.36)	(-0.18)	(1.62)	(1.99)
TED	0.4101	0.4438	0.5031**	0.5613*	0.8445***	-0.4052***
	(1.64)	(1.47)	(3.16)	(2.60)	(3.68)	(-3.78)
VIX	-0.0030	-0.0374	0.0228	0.0217	-0.0886*	-0.0099
	(-0.17)	(-1.59)	(1.44)	(0.96)	(-2.06)	(-0.66)
Lagged Default		-0.4711		-0.7633		-0.4735*
		(-1.49)		(-1.77)		(-2.56)
Lagged Term (Level)		0.0888		-0.5626		0.3019
		(0.21)		(-1.24)		(1.66)
Lagged Term (Slope)		0.9884		0.2460		-0.4229
		(1.55)		(0.40)		(-1.96)
Lagged TED		0.5969		-0.1371		0.2283
		(0.92)		(-0.20)		(0.94)
Lagged VIX		0.0196		0.0382*		0.0047
		(1.96)		(2.28)		(0.66)
Observations	50	49	50	49	50	49
R^2	0.729	0.827	0.357	0.422	0.239	0.364
Adjusted R^2	0.698	0.781	0.284	0.270	0.153	0.197

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4 plots the first three PCs. We observe that first PC (i.e. PC1) correlates highly with the default risk during the financial crisis. The second PC or PC2 spikes in the post-financial crisis period (associated with Dodd-Frank regulatory phase-in), reflecting possible policy uncertainty shock; and again during the foreign exchange crisis event of 2015-16. The third PC (i.e. PC3) seems to capture the taper tantrum of 2013 and the 2015-16 foreign exchange crisis, episodes both associated with capital outflows from emerging markets to US.

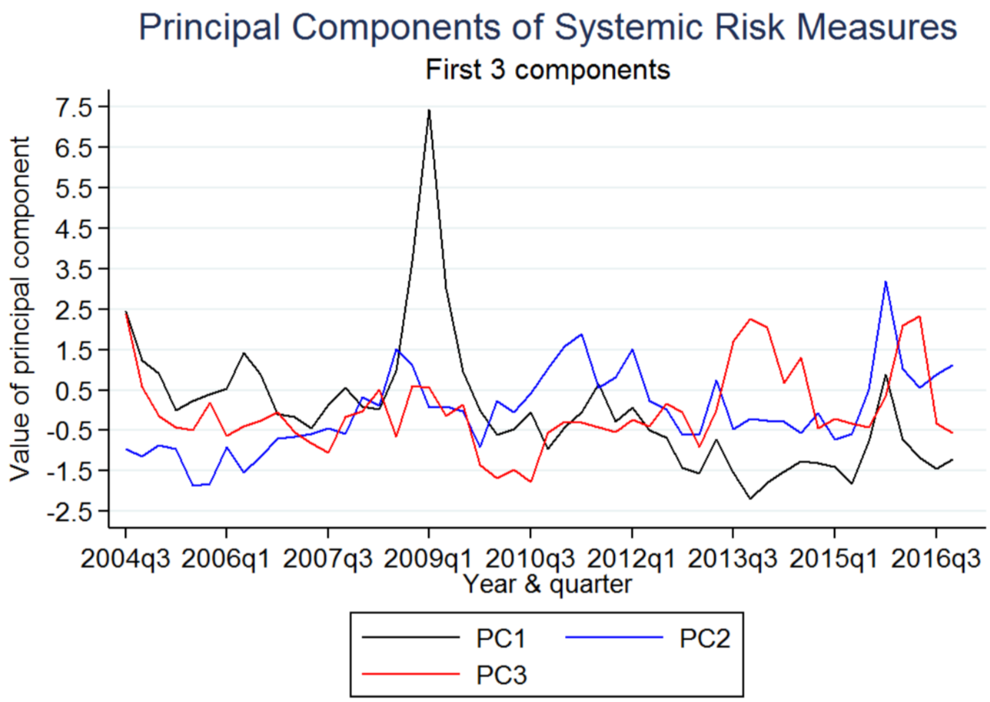

Figure 4: Principal components decomposition of the time series of systemic risk scores for the five regions.

We next study how the PCs are related to the underlying macro factors. Table 11, Panel B reports the results of quarterly time-series regressions of the first three principal components on contemporaneous and one-quarter lagged values of U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). Regressions include adjustments for heteroskedasticity. We observe that the first PC is significantly related to the US default factor. The second PC is not strongly related to any economic variables; its only weakly influenced by the contemporaneous funding (TED) and lagged risk aversion (VIX) factors at the 5% level. The third PC is significantly (at 1% level) affected by the contemporaneous TED factor, the sign switching from positive to negative once lagged factors are included.

6.5 Out-of-sample prediction of aggregate default risk

Finally we examine the information content of systemic risk in an out-of- sample setting. We consider the predictiveness of firm level default risks using lagged systemic risk measures. We consider predictive time-series regressions of quarterly changes in credit risk. Table 12, Panels A though E report the results for individual geographical regions. The dependent variable is the change in credit risk proxied by mean probability of default (PD) between quarters t and $t-1$. Explanatory variables include: quarterly changes in probability of default; quarterly changes in systemic risk (network level systemic risk score); quarterly changes in network attributes (mean degree across all nodes, degree concentration measured by HHI, mean centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters); quarterly changes in 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); and quarterly changes in U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). Mean PD, degree and centrality across firms, and market-wide median firm-specific attributes are computed every quarter. All regressions include adjustments for heteroskedasticity. The following observations hold. For all five regions, we see that lagged changes in systemic risk are highly predictive of aggregate default risk (PD) in the following period. Interestingly, lagged PD is not. This suggests that our network measure of systemic risk provides explanatory power over and above the measure of credit risk levels in the economy. In short, interconnectedness matters. Additional network risk measures and asset pricing factors also add explanatory power result in an appreciable increase in R^2 in the predictive regressions for all regions. This suggests material ability to predict credit quality levels in economies using our new measure of systemic risk. Table 13 summarizes the contribution to predictability from the various predictor variables.

Table 12: Predictive time-series regressions of quarterly changes in credit risk. Panels A though E report the results for individual geographical regions. The dependent variable is the difference in values of credit risk (mean probability of default, PD) between quarters t and $t-1$. Explanatory variables include: quarterly changes in probability of default; quarterly changes in systemic risk (network level systemic risk score); quarterly changes in network attributes (mean degree across all nodes, degree concentration measured by HHI, mean centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters); quarterly changes in 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); and quarterly changes in U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). Mean PD, degree and centrality across firms, and market-wide median firm-specific attributes are computed every quarter. All regressions include adjustments for heteroskedasticity.

Panel A: East Asia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0002	0.0002	0.0001	-0.0000	-0.0000	0.0000	0.0000
	(0.48)	(0.95)	(0.70)	(-0.14)	(-0.09)	(0.33)	(0.22)
Mean PD	-0.0517	-0.0355	-0.0237	0.0129	0.0119	-0.0174	-0.0139
	(-0.67)	(-0.80)	(-0.60)	(0.30)	(0.29)	(-0.64)	(-0.51)
Systemic Risk	0.0017^{***}	0.0038^{***}	0.0039^{***}	0.0044^{***}	0.0044^{***}	0.0029^{***}	0.0029^{***}
	(4.04)	(6.92)	(8.41)	(7.70)	(8.53)	(5.20)	(4.53)
Mean Degree		-0.0006^{***}	-0.0003	-0.0004	-0.0003	-0.0004	-0.0003
		(-4.89)	(-0.73)	(-1.72)	(-1.43)	(-1.94)	(-1.37)
Degree HHI		0.0461	0.3368	0.4065	0.4250^{*}	0.2897	0.3352^{*}
		(0.54)	(1.37)	(1.94)	(2.07)	(2.04)	(2.13)
Mean Bet. Centrality			0.0000	0.0000	0.0000	0.0000	0.0000
			(1.18)	(0.70)	(0.59)	(1.27)	(1.03)
Diameter			0.0000	0.0000	0.0000	0.0000	0.0000
			(1.31)	(1.21)	(1.16)	(0.56)	(0.72)
Fragility			-0.0002	-0.0002	-0.0002	-0.0000	-0.0001
			(-1.05)	(-1.28)	(-1.73)	(-0.33)	(-1.03)
Num. Clusters			0.0001	-0.0001	0.0000	-0.0001	-0.0001
			(0.71)	(-0.51)	(0.05)	(-1.54)	(-0.77)
Cluster HHI			0.0056	-0.0074	-0.0018	-0.0124	-0.0074
			(0.51)	(-0.79)	(-0.18)	(-1.72)	(-0.85)
Median Log(Assets)				0.0001		-0.0001	
				(0.23)		(-0.16)	
Median Log(Market Cap)					-0.0003		-0.0003
					(-0.67)		(-0.68)
Median Loans/Assets				-0.0057	-0.0030	-0.0044	-0.0026
				(-0.74)	(-0.41)	(-0.66)	(-0.39)
Median Loans/Deposits				0.0025	-0.0001	0.0040	0.0014
				(0.43)	(-0.02)	(0.94)	(0.32)
Median Debt/Assets				0.0328		0.0157	
				(1.76)		(0.93)	
Median Debt/Equity					0.0328^{*}		0.0217
					(2.33)		(1.44)
Median Debt/Capital				-0.0002^{*}	-0.0001^{*}	-0.0001	-0.0001
				(-2.37)	(-2.25)	(-1.39)	(-1.29)
Median ROA				-0.0003^{**}		-0.0003^{**}	
				(-2.99)		(-3.42)	
Median ROE					-0.0002		-0.0002^{*}
					(-1.87)		(-2.50)
Median Market/Book				-0.0004	0.0001	-0.0015	-0.0010
				(-0.54)	(0.09)	(-1.96)	(-1.12)
Default						0.0005^{*}	0.0005^{*}
						(2.31)	(2.08)
Term (Level)						-0.0004^{*}	-0.0004^{*}
						(-2.51)	(-2.25)
Term (Slope)						0.0002	0.0002
						(1.45)	(1.30)
TED						-0.0000	0.0000
						(-0.17)	(0.03)
VIX						0.0000	0.0000
						(0.19)	(0.42)
Observations	49	49	49	49	49	49	49
R^2	0.515	0.763	0.786	0.873	0.864	0.937	0.927
Adjusted R^2	0.494	0.741	0.736	0.810	0.795	0.887	0.870

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

Panel B: South Asia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0013	0.0009	0.0007	0.0004	0.0007	0.0007	0.0008
	(1.69)	(1.47)	(1.54)	(0.95)	(1.42)	(1.61)	(2.00)
Mean PD	-0.1287	-0.0797	-0.0559	-0.0148	-0.0288	-0.0238	-0.0365
	(-1.35)	(-1.01)	(-1.05)	(-0.31)	(-0.68)	(-0.53)	(-0.84)
Systemic Risk	0.0024*	0.0050***	0.0046***	0.0041***	0.0046***	0.0042**	0.0051***
	(2.39)	(4.90)	(5.82)	(3.63)	(3.82)	(3.45)	(3.69)
Mean Degree		-0.0009***	-0.0017**	-0.0016	-0.0014	-0.0012*	-0.0012*
		(-5.51)	(-2.73)	(-1.94)	(-1.84)	(-2.32)	(-2.22)
Degree HHI		-0.2604	-0.4926	-0.3177	-0.4348	-0.3212	-0.5298
		(-1.13)	(-1.70)	(-0.87)	(-1.22)	(-0.85)	(-1.29)
Mean Bet. Centrality			-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
			(-0.11)	(-0.22)	(-0.33)	(-0.61)	(-0.75)
Diameter			0.0000	0.0001	0.0000	0.0001	0.0001
			(0.32)	(0.76)	(0.72)	(1.26)	(1.32)
Fragility			0.0005	0.0005	0.0003	0.0003	0.0002
			(1.46)	(1.00)	(0.74)	(1.01)	(0.73)
Num. Clusters			0.0008*	0.0008	0.0006	0.0007	0.0004
			(2.12)	(1.82)	(1.46)	(1.59)	(0.78)
Cluster HHI			0.0435	0.0428	0.0305	0.0337	0.0156
			(1.80)	(1.32)	(0.99)	(0.99)	(0.42)
Median Log(Assets)				-0.0001		-0.0002	
				(-0.09)		(-0.27)	
Median Log(Market Cap)					0.0002		0.0000
					(0.74)		(0.12)
Median Loans/Assets				-0.0004	-0.0006	-0.0021	-0.0019
				(-0.17)	(-0.26)	(-0.86)	(-0.70)
Median Loans/Deposits				0.0121	0.0118	-0.0108	-0.0063
				(0.88)	(0.98)	(-0.60)	(-0.40)
Median Debt/Assets				-0.0701		-0.0929*	
				(-1.90)		(-2.52)	
Median Debt/Equity					-0.0509*		-0.0662*
					(-2.22)		(-2.53)
Median Debt/Capital				0.0003*	0.0002*	0.0003*	0.0002
				(2.12)	(2.11)	(2.05)	(1.93)
Median ROA				-0.0004		-0.0007*	
				(-1.58)		(-2.31)	
Median ROE					-0.0001		-0.0002
					(-0.48)		(-1.05)
Median Market/Book				0.0005	-0.0004	0.0015	0.0004
				(0.39)	(-0.34)	(0.93)	(0.31)
Default						0.0005	0.0002
						(0.58)	(0.18)
Term (Level)						0.0016	0.0012
						(1.78)	(1.51)
Term (Slope)						-0.0017*	-0.0015*
						(-2.56)	(-2.09)
TED						-0.0006	-0.0007
						(-1.35)	(-1.46)
VIX						0.0000	0.0000
						(0.74)	(0.69)
Observations	49	49	49	49	49	49	49
R^2	0.280	0.681	0.750	0.805	0.801	0.854	0.837
Adjusted R^2	0.248	0.652	0.693	0.707	0.701	0.740	0.710

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

Panel C: Eastern Europe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0009	0.0008	0.0009	0.0007	0.0006	0.0002	0.0002
	(1.30)	(1.43)	(1.66)	(1.10)	(0.97)	(0.32)	(0.26)
Mean PD	-0.0945	-0.0667	-0.0794	-0.0410	-0.0456	0.0288	0.0203
	(-0.73)	(-0.65)	(-0.83)	(-0.37)	(-0.39)	(0.28)	(0.18)
Systemic Risk	0.0036^{***}	0.0048^{***}	0.0048^{***}	0.0057^{***}	0.0054^{***}	0.0036^{***}	0.0037^{***}
	(5.79)	(9.80)	(9.93)	(7.69)	(6.59)	(4.11)	(3.81)
Mean Degree		-0.0019^{***}	0.0001	-0.0003	0.0003	-0.0011	-0.0012
		(-4.15)	(0.08)	(-0.18)	(0.17)	(-0.64)	(-0.72)
Degree HHI		0.0106^{*}	0.0184^{*}	0.0244	0.0245	0.0229	0.0221
		(2.05)	(2.41)	(2.03)	(1.96)	(1.97)	(1.93)
Mean Bet. Centrality			-0.0000	-0.0001	-0.0000	0.0000	0.0000
			(-1.54)	(-1.43)	(-1.31)	(0.43)	(1.29)
Diameter			0.0001	0.0002	0.0001	-0.0000	-0.0001
			(0.90)	(1.01)	(0.86)	(-0.07)	(-0.77)
Fragility			-0.0005	-0.0006	-0.0006	-0.0003	-0.0002
			(-1.07)	(-1.39)	(-1.10)	(-0.43)	(-0.37)
Num. Clusters			0.0001	0.0002	0.0002	-0.0001	-0.0000
			(0.86)	(1.16)	(1.16)	(-0.38)	(-0.13)
Cluster HHI			-0.0011	0.0008	0.0000	-0.0027	-0.0013
			(-0.27)	(0.18)	(0.01)	(-0.43)	(-0.23)
Median Log(Assets)				-0.0012		-0.0011	
				(-2.02)		(-1.83)	
Median Log(Market Cap)					-0.0007		-0.0012
					(-1.15)		(-1.82)
Median Loans/Assets				0.0263	0.0175	0.0131	0.0019
				(1.08)	(0.70)	(0.64)	(0.11)
Median Loans/Deposits				0.0124	0.0155	0.0026	0.0058
				(0.63)	(0.83)	(0.17)	(0.39)
Median Debt/Assets				-0.0253		0.0139	
				(-1.13)		(0.65)	
Median Debt/Equity					-0.0038		0.0328
					(-0.22)		(2.05)
Median Debt/Capital				0.0001	0.0000	-0.0000	-0.0002
				(0.88)	(0.14)	(-0.03)	(-1.32)
Median ROA				-0.0001		-0.0002	
				(-1.06)		(-0.92)	
Median ROE					-0.0001		-0.0001
					(-1.01)		(-0.46)
Median Market/Book				0.0009	0.0012	0.0011	0.0020^{*}
				(1.31)	(1.51)	(1.46)	(2.75)
Default						0.0040^{*}	0.0033^{*}
						(2.45)	(2.07)
Term (Level)						0.0009	0.0005
						(0.99)	(0.48)
Term (Slope)						-0.0011	-0.0003
						(-0.88)	(-0.27)
TED						0.0011	0.0009
						(1.49)	(1.26)
VIX						0.0000	0.0001
						(0.33)	(1.71)
Observations	49	47	47	47	47	47	47
R^2	0.664	0.807	0.821	0.857	0.843	0.907	0.903
Adjusted R^2	0.650	0.788	0.777	0.781	0.760	0.829	0.822

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

Panel D: South Europe & Africa

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0006	0.0005*	0.0005	0.0006**	0.0006**	0.0007**	0.0008**
	(1.61)	(2.07)	(1.91)	(3.04)	(2.75)	(3.15)	(2.92)
Mean PD	-0.0820	-0.0637	-0.0592	-0.0704*	-0.0772*	-0.0850*	-0.1068**
	(-1.26)	(-1.75)	(-1.63)	(-2.18)	(-2.42)	(-2.66)	(-2.93)
Systemic Risk	0.0020***	0.0057***	0.0060***	0.0057***	0.0054***	0.0050***	0.0047***
	(4.97)	(8.52)	(8.41)	(8.85)	(7.79)	(6.87)	(6.57)
Mean Degree		-0.0019***	-0.0025**	-0.0018	-0.0020*	-0.0009	-0.0007
		(-6.08)	(-3.11)	(-1.87)	(-2.18)	(-1.11)	(-0.89)
Degree HHI		-0.0081	-0.0236	-0.0134	-0.0391	0.0255	0.0256
		(-0.44)	(-0.23)	(-0.13)	(-0.41)	(0.32)	(0.33)
Mean Bet. Centrality			0.0000	0.0000	0.0000	0.0000	0.0000
			(1.39)	(1.92)	(1.29)	(0.46)	(0.70)
Diameter			-0.0000	-0.0001	-0.0000	-0.0000	-0.0000
			(-0.80)	(-1.32)	(-0.70)	(-0.62)	(-0.75)
Fragility			0.0001	-0.0001	0.0000	-0.0003	-0.0005
			(0.28)	(-0.24)	(0.01)	(-0.73)	(-1.01)
Num. Clusters			-0.0000	-0.0000	0.0000	0.0001	0.0001*
			(-0.50)	(-0.25)	(0.25)	(0.92)	(2.07)
Cluster HHI			0.0004	0.0002	0.0017	0.0020	0.0047
			(0.17)	(0.10)	(0.74)	(0.86)	(2.02)
Median Log(Assets)				-0.0012		-0.0016	
				(-1.08)		(-1.53)	
Median Log(Market Cap)					-0.0011*		-0.0013***
					(-2.46)		(-3.86)
Median Loans/Assets				0.0028	0.0004	0.0022	-0.0012
				(0.77)	(0.16)	(0.50)	(-0.43)
Median Loans/Deposits				-0.0064	-0.0044	-0.0084**	-0.0092
				(-1.56)	(-1.10)	(-2.78)	(-2.02)
Median Debt/Assets				-0.0108		-0.0036	
				(-1.58)		(-0.56)	
Median Debt/Equity					-0.0054		-0.0029
					(-1.09)		(-0.73)
Median Debt/Capital				0.0000	-0.0000	0.0000	0.0000
				(0.11)	(-0.01)	(0.73)	(0.68)
Median ROA				-0.0000		0.0000	
				(-0.12)		(0.47)	
Median ROE					-0.0000		0.0003
					(-0.03)		(1.53)
Median Market/Book				-0.0013*	-0.0008	-0.0008	-0.0001
				(-2.10)	(-1.39)	(-1.45)	(-0.31)
Default						0.0003	0.0007
						(1.20)	(2.01)
Term (Level)						-0.0008*	-0.0008*
						(-2.72)	(-2.46)
Term (Slope)						0.0003	0.0005
						(0.86)	(1.25)
TED						0.0002	0.0004*
						(0.78)	(2.09)
VIX						0.0000	-0.0000
						(0.06)	(-1.12)
Observations	49	49	49	49	49	49	49
R^2	0.373	0.755	0.780	0.844	0.864	0.895	0.919
Adjusted R^2	0.346	0.733	0.729	0.765	0.796	0.813	0.856

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

Panel E: South America

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004	0.0003
	(1.78)	(1.55)	(1.95)	(1.60)	(1.88)	(2.03)	(1.41)
Mean PD	-0.1511	-0.1013	-0.0980	-0.0934	-0.1013	-0.0965*	-0.0719
	(-1.75)	(-1.39)	(-1.80)	(-1.52)	(-1.68)	(-2.25)	(-1.55)
Systemic Risk	0.0001	0.0017**	0.0021**	0.0026***	0.0021***	0.0019***	0.0016**
	(0.41)	(2.92)	(3.55)	(4.25)	(3.65)	(3.70)	(3.17)
Mean Degree		-0.0012**	-0.0009	-0.0000	-0.0004	-0.0005	-0.0008
		(-2.72)	(-1.25)	(-0.02)	(-0.68)	(-1.07)	(-1.84)
Degree HHI		0.0034	0.0102	0.0442*	0.0304	0.0260	0.0214
		(0.53)	(0.63)	(2.66)	(1.53)	(2.01)	(1.62)
Mean Bet. Centrality			0.0001*	0.0000	0.0001	0.0000	0.0001
			(2.42)	(0.40)	(1.36)	(0.59)	(1.32)
Diameter			-0.0001	0.0001	-0.0000	-0.0000	-0.0001
			(-1.95)	(0.95)	(-0.42)	(-0.32)	(-1.02)
Fragility			-0.0004	-0.0013**	-0.0008	-0.0007*	-0.0005
			(-1.08)	(-3.17)	(-1.83)	(-2.34)	(-1.45)
Num. Clusters			0.0001*	0.0000	0.0000	0.0000	0.0000
			(2.26)	(1.32)	(0.67)	(0.88)	(0.56)
Cluster HHI			0.0016*	0.0011	0.0007	0.0010	0.0011
			(2.20)	(1.23)	(0.80)	(1.27)	(1.32)
Median Log(Assets)				-0.0013*		-0.0009*	
				(-2.73)		(-2.24)	
Median Log(Market Cap)					-0.0003		-0.0005
					(-1.17)		(-2.02)
Median Loans/Assets				-0.0041	-0.0014	-0.0029	-0.0018
				(-1.07)	(-0.28)	(-0.81)	(-0.46)
Median Loans/Deposits				-0.0029	-0.0058	-0.0029	-0.0031
				(-0.79)	(-1.46)	(-0.83)	(-0.94)
Median Debt/Assets				0.0105		-0.0013	
				(0.98)		(-0.13)	
Median Debt/Equity					0.0022		-0.0034
					(0.31)		(-0.55)
Median Debt/Capital				-0.0000	-0.0000	-0.0000	-0.0000
				(-1.81)	(-0.75)	(-1.66)	(-0.86)
Median ROA				0.0001		0.0001	
				(0.78)		(0.81)	
Median ROE					0.0001		0.0000
					(0.70)		(0.55)
Median Market/Book				0.0001	-0.0004	0.0003	0.0003
				(0.24)	(-0.71)	(0.62)	(0.67)
Default						0.0010*	0.0013***
						(2.58)	(4.03)
Term (Level)						-0.0002	-0.0001
						(-1.02)	(-0.71)
Term (Slope)						0.0006*	0.0005*
						(2.57)	(2.31)
TED						0.0002	0.0003
						(1.36)	(1.52)
VIX						-0.0000	-0.0000
						(-0.72)	(-0.67)
Observations	49	49	49	49	49	49	49
R^2	0.154	0.368	0.510	0.697	0.603	0.828	0.814
Adjusted R^2	0.117	0.311	0.397	0.546	0.405	0.694	0.669

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

Table 13: Summary of adjusted R^2s from predictive time-series regressions of quarterly changes in credit risk. Time-series regressions are conducted, analogous to the specifications in Table 12, for each regional group; the dependent variables are differences in values of credit risk (mean probability of default, PD) between quarters t and $t-1$. Explanatory variables include: quarterly changes in probability of default; quarterly changes in systemic risk (network level systemic risk score); quarterly changes in network attributes (mean degree across all nodes, degree concentration measured by HHI, mean centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters); quarterly changes in 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); and quarterly changes in U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX).

	Regional Group					
Included explanatory variables	All	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America
Systemic risk (only)		49%	25%	65%	35%	12%
Systemic risk + network parameters		74%	65-69%	78-79%	73%	31-40%
Systemic risk + network parameters + firm-specific attributes		80-81%	70-71%	76-78%	77-80%	41-55%
Systemic risk + network parameters + firm-specific attributes + U.S. macro variables		87-89%	71-74%	82-83%	81-86%	67-69%

7 Concluding Comments

Systemic risk implies quick propagation of illiquidity and insolvency risks, and financial losses across the financial system as a whole, impacting the connections and interactions among financial stakeholders (Billio, et al., 2012). In this project, we undertake a large-scale empirical examination of systemic risk among major financial institutions in the emerging markets. We extend the literature on network models by incorporating credit quality information in order to compute a single systemic risk score that summarizes the level of systemic risk across all emerging market financial entities. We provide computations of the dynamics of systemic risk evolution across emerging markets, and study the cross-sectional and time series determinants of systemic risk. We also examine the relationship of systemic risk to macroeconomic and market variables in order to assess if systemic risk and aggregate credit quality in emerging markets may be predicted. Indeed, we find that network measures of risk, including our systemic risk variable, enable prediction of credit risk levels on a quarterly horizon.

Taken together, our findings show that systemic risks for emerging market financial firms, determined jointly by underlying network and credit risks, are quickly transmitted across markets contemporaneously within the same quarter. This implies that regulators may perhaps have to initiate quick policy actions to manage and stabilize financial markets facing possible systemic risk events. The policy measures should target lowering network and default risks, perhaps through financial easing and short-term liquidity provision measures. Moreover, we find a factor structure among systemic risks across markets, where the first three principal components explain over 90% of the variance, and each factor is sensitive to a different type of systemic risk event. Accordingly, regulators could design specific strategies to control systemic risks based on which type of PC dominates that event. Moreover, our network measure of systemic risk can be used by regulators to predict financial sector credit quality changes in emerging markets.

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