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Banking networks, systemic risk, and the credit cycle in emerging markets[☆]

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ABSTRACT

We study how globalization impacts systemic risk in emerging markets. We extend a large literature on systemic risk in the US, Europe, and other developed countries to emerging markets, which are relatively under-researched. Our findings are based on a large-scale empirical examination of systemic risk among 1048 financial institutions in a sample of 23 emerging markets, broken down into 5 regions, along with 369 U.S. financial institutions. Using an additively decomposable systemic risk score that combines banking system interconnectedness with default probabilities, systemic risk is quantified for each region, across time. The empirical analyses suggest that emerging markets' systemic risk is heterogeneous across regions, is strongly dependent on the interconnectedness of the banking system within each region, and drives the level of default risk in each region, while the regions are compartmentalized away from each other and insulated from the United States. The systemic risk score may be used as a policy variable in each emerging market region to manage the credit cycle. Our evidence is consistent with the notion that globalization engenders financial stability and does not lead to large systemic risk spillovers across emerging market regions.

1. Introduction

How does globalization impact financial stability in the emerging markets? In this paper, we shed light on this question by studying the evolution of systemic risk across emerging markets and over time. Extant literature shows that globalization is a double-edged sword for emerging markets. On one hand, globalization leads to enhanced market integration that in turn results in a lower cost of capital, increased investment opportunities, enhanced economic growth through diversification and international risk sharing, improved competition and better local corporate and public governance in emerging markets (Bekaert and Harvey, 2003; Carrieri et al., 2007; Kose et al., 2009; Karolyi et al., 2018). On the other hand, globalization can make the emerging markets more vulnerable to global shocks, as interconnected financial markets and cross-border lending activities help amplify and propagate the crisis across the global markets, especially during the stress periods, leading to financial instability (Bruno and Shin, 2015; Schnabl, 2012; Acharya et al., 2009). The effect of globalization on systemic risks is therefore an open empirical question, and depends upon the relative strength of the economic forces.

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In this paper, we study how globalization impacts systemic risk in emerging markets. We uncover how globalization influences systemic risk emergence and its evolution with respect to underlying credit risks. Using a network-based model of systemic risk, we provide new evidence on the interaction of credit cycles and systemic risk in emerging markets. Systemic risk is defined as the risk of substantial damage to, or failure of, the financial system in a country.[1] Network effects underlie systemic risk and impact the amplitude of the credit cycle, which we define as the levels of ex ante aggregate default risk in the financial sector, measured by credit spreads. There is limited prior literature on systemic risk and default in emerging markets (see Section 2), and our study contributes to the literature by presenting a comprehensive study of systemic risks of emerging markets.

Globalization has also led to a greater supply of credit financing to emerging markets. Starting in 2007, emerging economies accumulated significant external debt as non-financial corporations in these markets increased their external borrowing through the offshore issuance of debt securities.[2] Although greater corporate leverage financing from increased globalization and cross-market lending can facilitate higher corporate investment and perhaps stimulate growth, the continued accumulation of corporate debt can be concerning.[3]

Given that emerging local 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 through foreign debt is not adequately hedged by emerging market firms, it can further exacerbate the systemic risks within local 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 2013 U.S. Quantitative Easing (QE) related Taper-tantrum, Karolyi and McLaren (2017)).

Our key intent therefore is to describe bank network risk evolution across emerging markets over time and unpack its components. We implement the study by clustering the emerging market sample into 5 regions: (a) East Asia, (b) South Asia, (c) Eastern Europe, (d) Southern Europe and Africa, and (e) South America. For each emerging market region, using credit research techniques and graph-theoretic modeling, we construct a panel comprising (i) default risk and (ii) systemic risk levels by quarter at an aggregate level and for each bank. Our final quarterly data sample consists of 1048 financial firms comprised from 23 emerging market countries for the period 2004–2016. In addition, we also consider 369 U.S. financial institutions to benchmark the emerging market results.

We construct bank networks to quantify the interconnectedness of major financial institutions in five regions of emerging markets and the U.S., and therefrom compute a systemic risk measure and network metrics. 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.[4] We calculate the total systemic risk for each region-quarter, and decompose it into the risk contributed by each bank, which offers us a metric for the systemic importance of a bank.

Having constructed the network risk measure, we focus on studying the (a) evolution and (b) cross-market relationships of network risks in emerging economies, and on explaining (c) how such risks are driven by cross-sectional and time-series covariates and risk factors. Accordingly, our analysis follows three steps. (a) First, we compute and summarize various firm-level network measures, and systemic and default risk metrics for each geographic region, and inspect the market concentration of such risks. (b) Second, we examine contemporaneous and lagged correlations, auto- and cross-correlogram functions, and conduct a battery of tests (Granger Causality regressions, and Vector Auto regression (VAR), impulse reaction, variance decomposition and principal component analyses) to examine the intra- and cross-market information flows. (c) Finally, we implement robust time-series and joint cross-sectional and time-series quarterly regressions of systemic risks, and study the predictive ability of systemic risks in estimating future default risks. We ask several questions of interest and obtain results of interest to risk managers, credit risk participants, and policy makers, and enumerate our key findings below.

- *First*, we examine the time-series evolution of systemic risks. We observe considerable heterogeneity across the emerging markets. For example, Eastern Europe and South America have the highest systemic risks compared to other regions over time mainly during the 2004–2006 pre-crisis and 2007–2009 crisis periods. Southern Europe & Africa and East Asia experience systemic risk spikes during the 2010–12 Eurozone crisis as well as the 2015–16 China financial crisis. South Asia registers highest systemic risk during 2013 Taper-tantrum period and again during the 2016 India currency demonetization episode. These events impact specific regions despite globalization, and gives us an opportunity to assess spillover risks.
- *Second*, we examine the concentration of systemic risks. We observe there is a high degree of concentration in systemic risks among major banks in each region, consistent with the large-scale results for developed countries presented in Laeven et al. (2016). The top 10 percentile contributors contribute 16% to 47% of the systemic variation. Eastern Europe and South America have the maximum concentration (over 46%) of systemic risk among the top 10 contributors.

[1] Systemic risk refers to the conditional failure of the system at large driven by (or conditional on) the failure of key financial institutions in an economy (Li and Zinna, 2014). This is different from systematic risk, characterized by correlation amongst assets in an economy induced by a set of common factors.

[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. Including the credit extended by "shadow banks", there was even steeper rise and a higher total burden amounting to 127% of GDP (Economist, Nov 14, 2015; Committee on International Policy Reform: "Corporate Debt in Emerging Economies: A Threat to Financial Stability?" September, 2015; Avdjiev et al. (2014)). 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).

[3] Increases in corporate leverage in the post-crisis period significantly increased the default risks of emerging market firms (Dodd et al., 2021).

[4] This measure is a modification of the model from Das (2016).

- *Third*, the spillover effects of systemic risks across regions is weak, complementing similar findings for developed European countries in Sensoy et al. (2017) and Buch et al. (2019). Granger causality regressions show that cross-market lead–lags are generally absent in the majority (30 out of 36) market pairs. Vector Auto Regression analysis confirms that contemporaneous dependence of systemic risk across markets is stronger than lagged effects, while both effects are weak overall. Regions are reasonably insulated from each other in terms of systemic risk effects. Emerging market regions are also insulated from U.S. systemic risk. Even though the U.S. led all other regions in levels of default and systemic risk during the Global financial crisis (GFC), no other period showed a lead–lag effect. The relationship of systemic risk with the U.S. hence is not statistically significant, suggesting lower overall contagion in global systemic risk.
- *Fourth*, principal components extracted from the time series of systemic risk changes for each region shows no single component that would hint at a high level of global systemic risk across emerging markets. The first component accounts for 44% of common variation and is weakly related to U.S. default risk levels. The components are not strongly related to other measures of global macro risks such as level and slope of the U.S. term structure and aggregate volatility (VIX), though the TED spread, proxying U.S. market funding risk, is correlated with the third principal component.
- *Fifth*, time series and panel data regressions show that credit and network risks together explain the majority of the variation in systemic risks, i.e., between 81%–97% of the time-series variation, and 64%–82% 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%–15% explanatory power in panel data regressions. F-statistics confirm the strong significance of network risk variables. Overall, the results show that changes in systemic risk are driven more by changes in interconnectedness in each region's banking networks than by changes in default risk levels.
- *Finally*, changes in expected one-year ahead default risk levels in each region are explainable using lagged levels of default risk and current changes in systemic risk, and parallels a similar finding for developed European countries.[5] Except for South Asia, higher predictability comes from lagged changes in systemic risk, suggesting that structural changes in banking networks signal movements in the credit cycle.

Extant literature has documented that financial contagion can exacerbate systemic risks and have significant impact on credit and illiquidity risks. Bai et al. (2015) show that while explaining credit spreads, credit-event risk premia are dwarfed by the contagion premium. Helwege and Zhang (2016) examine troubled financial firms and find that both counterparty and information channels are significant factors in creating spillover effects. Azizpour et al. (2018) find strong evidence that contagion, through which the default by one firm has a direct impact on the health of other firms, is a significant source of corporate default clustering. The systemic risk metric in our paper may be used to provide information to policy makers about the credit cycles in each emerging market region.

Overall, our empirical analyses suggest that emerging markets' systemic risk is heterogeneous across regions, is strongly dependent on the interconnectedness of the banking system within each region, and explains the credit cycle in each region, while the regions are compartmentalized away from each other and insulated from the United States. Systemic risk may be used as a policy variable independently in each emerging market region to manage the credit cycle. Our evidence is consistent with the notion that globalization engenders financial stability by impacting the systemic risk spillovers *mainly* within each region rather than across emerging market regions.[6] The network risk measure extracted from traded financial institutions incorporates globalization shocks early on and can serve as a leading indicator for firm level default risks.

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. Next, Section 3 undertakes an exploration of the comprehensive emerging market data, and reports some basic descriptive statistics. Our specific network construction methodology is explained in Section 4. Various network metrics are derived and estimated in Section 5. Section 6 conducts empirical analyses and Section 7 concludes.

2. Literature

2.1. Definition and origins

Systemic risk affects many market participants simultaneously, characterized by large 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 during periods of financial distress (Billio et al., 2012b), with potentially adverse consequences for the supply of credit to the real economy (Adrian and Brunnermeier, 2016). A broad literature suggests 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; Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010; Gorton and Metrick, 2012; Acharya et al., 2013; Covitz et al., 2013). Keeping these ideas in mind we develop a measure of systemic risk that is based on a network model and allows decomposition by individual financial institution.[7]

[5] For example, Pagano and Sedunov (2016) find that a CoVaR-based measure of systemic risk is predictive of sovereign default levels in the 15 largest European countries.

[6] We note that we do not necessarily claim a causal relationship between globalization and systemic risk, but examine the nature of systemic risk in a time of increasing globalization.

[7] Extant surveys of systemic risk measurement include de Bandt and Hartmann (2000), Gale and Kariv (2007), Schwarcz (2008), Chan-Lau et al. (2016), Bisias et al. (2012), Benoit et al. (2017), Silva et al. (2017); and Anand et al. (2018).

2.2. Measuring systemic risk

The Dodd-Frank Act stipulates SIFIs as highly interconnected. Extant literature examines systemic risks based on interbank linkages (Nier et al., 2007), cross-holdings among organizations (Elliott et al., 2014), network interdependence between firms tail risk exposures (Hautsch et al., 2015), and networks among traded CDS contracts (Markose et al., 2012). Billio et al. (2012b) use return correlations and Granger causality regressions on returns to construct network maps and measures of systemic risk. Billio et al. (2012a) apply several econometric measures of connectedness based on Granger-causality networks to the changes of sovereign risk of European countries. Diebold and Yılmaz (2014) provide connectedness measures built from variance decompositions. Ahern (2013) 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).[8] Complementing these network models, our model of systemic risk networks provides a measure of systemic risk for the entire financial system, and each institution's contribution to this risk, thereby providing an implementation pathway for measuring systemic risk, the identification and monitoring of systemically important financial institutions (SIFIs), and the effect on the level of aggregate credit risk in emerging market regions.[9]

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 the basic presumption that if each bank could be prevented from taking large risks, there would not be a build-up of risk in the financial system. Post-crisis, 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).[10] Our paper examines the macroprudential linkages between potential future default levels in the economy and current systemic risk metrics, which would aid policy makers greatly in managing the credit cycle better.

Extant work shows that insurers exhibit similar levels of systemic risk as risky banks (Kaserer and Klein, 2019). Our analysis, therefore, includes insurance companies as well as broker-dealers. Government intervention through Troubled Assets Relief Program (TARP) to banks has been shown to reduce systemic risk contributions particularly for larger and safer banks, and those in better local economies, by increasing the value of common equity and increasing capital cushion (Berger et al., 2020). Moreover, there is support for a risk-based deposit insurance premium with an additional fee imposed on SIFIs to reflect their incremental costs (Acharya et al., 2010). Our analysis, which shows that systemic risk is concentrated in a small number of major banks,[11] and the primary principal component of systemic risk is default levels, supports similar policy prescriptions.[12]

Another principal component of systemic risk in our empirical analysis is liquidity risk. 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) proposes a liquidity insurance mechanism in which access to publicly provided contingent liquidity would be permitted if a premium, tax, or fee were paid in advance.

2.4. Systemic risks in developed countries

A plethora of empirical studies exist on systemic risk in developed economies. These studies[13] focus on (a) differences in systemic risks across US, UK, and European markets and in their banks' systemic exposures (Li and Zinna, 2014; Bostandzic and Weiß, 2018); (b) differences in systemic risks across banks during the global financial crisis (Laeven et al., 2016); (c) effects of systemic risks on real economic activity (Giglio et al., 2016); (d) relationships between aggregate systemic risk and sovereign European debt yields (Pagano and Sedunov, 2016); (e) effects of cross-border bank flows (Karolyi et al., 2018) and loan syndication (Cai et al., 2018) on bank interconnectedness and systemic risks; (f) the effects of incentive pay based on relative performance evaluation on systemic risk (Albuquerque et al., 2019); (g) how National Banking Acts (NBAs) of 1863–1864 changed the network structure and affected systemic risk (Anderson et al., 2019); and (h) how bank failures altered the network of financial institutions during the Great Depression (Das et al., 2018). More recently, Borri and Giorgio (2020) show that Covid-19 shock induced sovereign default risks significantly affected the systemic risk contribution of all European banks. We find parallels to many of these results in emerging markets.

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[8] Other network risk papers include Brunetti et al. (2015), Colliard et al. (2017), Donaldson and Micheler (2018), and Sensoy et al., 2019.

[9] Cross sectional systemic risk measures include DIP (Huang et al., 2012), CoVaR (Adrian and Brunnermeier, 2016), MES (Acharya et al., 2012), SRISK (Brownlees and Engle, 2017 and Engle, 2018), and SES (Acharya et al., 2016). Other methods focus on data features other than correlations and networks, and deal mostly with tail risk measurement and principal components analyses, applied to credit (i.e. debt and CDS) markets e.g. Contingent Claims Analysis (Saldías, 2013); LASSO methods (Demirer et al., 2017); copula-based dynamic models (Oh and Patton, 2018); multivariate credit risk models (Li and Zinna, 2014); and Bayesian methods (Bianchi et al., 2015).

[10] The Dodd-Frank Act (2010) 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).

[11] See the DebtRank model of Battiston et al. (2012), who show that in addition to the notion of "too big to fail" it is important to give consideration to the notion of "too central to fail", an issue that arises from risk being overly concentrated in a few banks.

[12] Other related work on systemic risk regulation includes Löffler and Raupach (2018), Roukny et al. (2018), Benoit et al. (2019), and Buch et al. (2019).

[13] See also Varotto and Zhao (2018), Gupta et al. (2018), Adrian and Boyarchenko (2018); and Ellul et al. (2018).

2.5. Systemic risks in emerging markets

There is 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. Borri (2018) adopts the CoVaR risk measure to estimate the vulnerability of emerging market countries to systemic risk in the market for local currency government debt. Brei et al. (2020) show that high growth in small and medium enterprise (SME) lending is associated with greater banking system stability in emerging market economies.

Other papers focus on select emerging country samples. Yun and Moon (2014) use CoVaR and MES measures to examine the time-varying systemic risk contributions of Korean banks and find both are qualitatively similar in explaining the cross-sectional differences in systemic risk contributions across banks. 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. Fang et al. (2020) present evidence from Peru that systemic risk changes can have adverse consequences on weaker, i.e., less profitable, less capitalized and less liquid banks facing high regulatory capital requirements. Pham et al. (2021) examine the domestic and regional systemically important banks in Asian emerging markets using cross-sectional tail based measures.

Some studies have examined the systemic risks among Chinese banks. Fang et al. (2018) show that idiosyncratic risk of Chinese financial institutions is significantly affected by prevalent risk networks. Wang et al. (2018) find that large Chinese commercial banks and insurers usually exhibit systemic importance, but some small firms are systemically important due to their high level of connectedness. Zhang et al. (2021) find that excessive liquidity creation in Chinese banks evidences systemic risk with a "U shape" relationship, and is exacerbated in the presence of higher network connectedness. Additional studies focus on a limited sample of banking firms and identify systemically risky banks in China (Xu et al., 2021; Huang et al., 2019), India (Verma et al., 2019) and Taiwan (Su and Wong, 2018).

The effect of globalization on systemic risk depends upon the relative strength of beneficial economic forces (Bekaert and Harvey, 2003; Carrieri et al., 2007; Kose et al., 2009; Karolyi et al., 2018) versus destabilizing ones (Bruno and Shin, 2015; Schnabl, 2012; Acharya et al., 2009), and hence is an open empirical question. In this paper, we examine how globalization impacts systemic risk in emerging markets. We use a comprehensive sample of 1048 FIs in 23 countries across 5 regions, and conduct a comprehensive study of systemic risk linkages across all emerging markets.

3. Data

We first identify the list of 23 emerging countries by combining the IMF's and MSCI's lists of emerging countries and further intersecting it with the corporate CDS data available in the Markit database. Intersecting with firm level CDS data helps us preserve only those firms where the public debt outstanding is sizable and there is market-wide exposure to the underlying credit risk. We consider the 23 emerging markets 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). The United States comprises the sixth region.

Using Datastream, we extracted 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 financial institutions, comprised of 539 Banks, 389 Broker-Dealers and 120 Insurers. Overall India accounts for the highest proportion of the sample with 387 financial firms or 37% of the total sample, followed by Indonesia (8%) and China (6%). India is treated as a stand alone country and not grouped with the rest of Asia to balance the sample and distribute the sample size. 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.

In addition to the data from emerging markets, for comparative purposes we also collect analogous data for 369 financial institutions in the United States, comprising of 177 banks, 48 broker-dealers, and 144 insurers. This complements the emerging markets data and increases the overall sample by a third.

For the emerging market financial firms, using Datastream, we extracted daily equity returns – both dividend- and stock-split-adjusted – spanning a 13-year period from 2004 to 2016. For U.S. financial firms, we collect the corresponding daily adjusted equity returns from CRSP. We linearly interpolate any missing daily returns. In addition, based on ISINs and/or SEDOLs, we obtain 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

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. We consider the 23 emerging markets 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). The United States comprises the sixth region.

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
Total	539	389	120	1048	948
United States	177	48	144	369	280

PD values computed from Merton-type models using firm-specific values; these monthly values are converted into daily time-series corresponding to returns.[14]

We also collect several balance sheet and income statement variables corresponding to the emerging financial institutions from Datastream (and Compustat in case of U.S. financial firms) on a quarterly basis and compute the following firm-specific quarterly attributes: (i) Log(Assets) and Log(Market Cap) as measures of firm size in terms of book value of assets and market value of equity, respectively; (ii) 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); (iii) Debt/Assets and Debt/Equity ratios to capture leverage; (iv) Debt/Capital as a measure of the liquidity position of the financial firm; (v) ROA (return on assets) and ROE (return on equity) as measures of operating performance of the financial firm; and (vi) Market/Book value of equity ratio of the financial institution as a measure of the stock price based performance. Extreme ratios are winsorized at the 1% level.

4. Network construction

We use the return data to construct networks using a modified Granger causality approach. Our approach is an extension of the method in Billio et al. (2012b). In their original method, for any two banks i, j, we run the following regression:

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

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 $A(i,j) = 0$; and $A(i,i) = 0$. The network links are unweighted and it is not possible to get transaction volumes or other data to be able to add link weights.

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 Chan-Lau 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

[14] CRI database provides forward default intensities, which are risk-neutral. We note that an alternative approach would be to use the physical probabilities of default from a change of measure. However, this may be ad-hoc and add to estimation error.

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.

$$r_{j,t} = a + b \cdot r_{j,t-1} + c \cdot r_{i,t-1} + d \cdot r_{EW,t-1} + e_{j,t} \tag{2}$$

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., $p \le 0.025$, if $c > 0$. Note that if $c \le 0$, 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 date 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. Therefore, we 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.

5. Network statistics

In order to detect which nodes are most influential in the network, we compute betweenness centrality from the adjacency matrix A.[15] The definition of betweenness centrality for node v is as follows, see (Freeman, 1977):

$$b_v = \sum_{\substack{i,j \\ i \neq j \\ i \neq v \\ j \neq v}} \left[\frac{g_{ivj}}{g_{ij}} \right] \tag{4}$$

where g_{ivj} is the number of shortest paths from node i to node j that pass through node v, and g_{ij} is the number of shortest paths from i to j. We preferred 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 may provide 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. First, we have two bank-level metrics:

1. 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.
2. Betweenness centrality. A measure of how central a bank's position in the network is. A node is said to be "between" other nodes when a large proportion of shortest paths in the network pass through that particular node.

In addition, we have seven aggregate network-level metrics, as follows:

1. The number of nodes. The larger the number of nodes the greater the possible connectivity and transmission of network risk, and possibly greater systemic risk.
2. Diameter. 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. It 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 one quantification of risk transmission. Networks with a small diameter are more likely to experience system-wide problems.

[15] An alternate measure is "eigenvalue centrality", originally defined in Bonacich (1987), and further discussed in Bonacich and Lloyd (2001), defines centrality of a node i to be a linear function of the connection strength A_{ij} with nodes j it is connected to, and the centrality of those nodes, c_j. This leads to a circular system of simultaneous equations:

$$c_i = \sum_{j=1}^{n} A_{ij} c_j, \qquad \forall i \tag{3}$$

One solution to this system of equations is the principal eigenvector in an eigenvalue decomposition of matrix A. This vector contains n components $c_i, i = 1, 2, \dots, n$.

3. 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.
4. 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 from there.
5. Herfindahl index of degree (Degree HHI). 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 $NH = \frac{H-1/n}{1-1/n}$. (NH stands for normalized Herfindahl.)
6. 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 more insulated the network is from economic contagion.
7. Herfindahl index of cluster sizes (Cluster HHI): This is a measure of the concentration in nodes, and measures if nodes are resident in one large cluster or if the clusters are balanced in size.

We calculate all the nine 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 report average values of network measures aggregated at the country/regional level and the firm/regional level. Both East Asia and South Asia, along with the United States, have the highest systemic risks based on nodal level (number of modes, mean degree, between centrality) and network level (fragility, number and Herfindahl index of clusters) risk measures. Most of the bank (aggregate) level risks are concentrated during crisis and pre- (post-) crisis periods. 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, depicting the average number of inter-bank connections, is also higher in Asia (> 7.3) versus the other regions (ranging from > 1.5–3.0). Correspondingly, the betweenness centrality that captures the relative importance of a given bank is much higher as well because it is not normalized. The diameter of the bigger networks is also greater. Because the Asian networks (and the U.S.) are bigger and more interconnected, the fragility is higher and the number of independent clusters is fewer. Furthermore, South America has high network level risks based on diameter and Herfindahl index of nodes measures.

Network connections are based on the Adjacency matrix populated using Granger regressions using p-values of 0.025, as discussed in Section 4 (the results are stable for p-values of 0.01 or 0.05). All average values reported are based on metrics computed every quarter. Table 2 shows that network risks have increased during the crisis based on higher fragility and the Herfindahl index of degree, which is higher for the crisis period than the full period for all regions other than the U.S. 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. The metrics appear consistent with and have the expected values based on network structure.

5.2. The systemic risk metric

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. Therefore, we combine network information with credit information using the systemic risk score developed in Das (2016) and Das et al. (2019). We deploy a modified version of the risk score in prior work by weighting credit risk by bank size, and 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 region-wide scalar measure, denoted S, is as follows:

$$S = \frac{1}{n}\sqrt{C^{\top} \cdot A \cdot C} \tag{5}$$

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. Before computing S, the adjacency matrix A is further updated to set the diagonal to be 1. In the special case where no bank is connected to another, i.e., $A = I$ (where I is the identity matrix), systemic risk is simply the L2 norm of credit risk vector C, i.e., $\frac{1}{n} \parallel C \parallel = \frac{1}{n}\sqrt{C \cdot C}$.
2. 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. In this paper, we employ PDs as a default proxy to obtained our default weighted systemic risk measure.

Table 2
Network measures. The table presents network 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. Network metrics include number of nodes, mean degree, and mean betweenness centrality between nodes, 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.

Geographical region	Period	Aggregate-level metrics			Firm-level metrics				
		# of nodes	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	198	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	Full	174.9	5.94	426.1	9.11	6.65	0.0142	8.91	0.669
	Pre-crisis	125.6	4.12	280.7	9.04	4.81	0.0242	9.28	0.554
	Crisis	157.9	5.99	342.1	8.37	7.46	0.0179	8.43	0.661
	Post-crisis	191.8	6.34	488.8	9.46	6.94	0.0092	8.99	0.714
United States	Full	220.1	9.18	304.9	11.38	23.13	0.0074	5.70	0.948
	Pre-crisis	239.5	7.59	505.5	11.30	14.22	0.0037	3.70	0.970
	Crisis	231.9	13.96	331.2	10.50	33.28	0.0066	3.00	0.977
	Post-crisis	206.3	7.55	209.1	11.79	21.96	0.0091	7.57	0.928

3. 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.
4. Note that all elements of A in Eq. (5) 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 $S \geq 0$.
5. An increase in any element of A (network effect) or C (individual risk effect) will result in an increase in S.
6. The function $S(C,A)$ is linear homogeneous in C. Using this property, and applying Euler's homogeneous function theorem,[16] we see that

$$S = \frac{\partial S}{\partial C_1} C_1 + \frac{\partial S}{\partial C_2} C_2 + \cdots + \frac{\partial S}{\partial C_n} C_n = \sum_{i=1}^{n} \frac{\partial S}{\partial C_i} C_i \tag{6}$$

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

$$\frac{\partial S}{\partial C} = \frac{1}{2n^2 S} [A \cdot C + A^\top \cdot C] \in \mathcal{R}^n \tag{7}$$

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

$$S = \frac{1}{2n^2 S} \left([A \cdot C + A^\top \cdot C] \odot C \right)^\top \cdot \mathbf{1} \tag{8}$$

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

where $\odot$ stands for the Hadamard product of two vectors or matrices, and $\mathbf{1}$ is a n-vector of 1s, i.e., a unit n-vector. Hence, the risk contribution of any bank i is a consequence of Eq. (6):

$$\frac{\partial S}{\partial C_i} \cdot C_i = \left\{ \frac{1}{2n^2 S} \cdot [A \cdot C + A^\top \cdot C] \odot C \right\}_i, \qquad \forall i. \tag{9}$$

Unlike metrics like SRISK and MES, our metric explicitly includes the network to model interconnectedness of banks. Moreover, the other metrics often examine the spillover of systemic risk on individual banks, whereas the metric here, through the decomposition described in Eq. (9) assesses how an individual bank's risk spills over to other banks, leading to systemic risk. We employ these various metrics in the following empirical analyses.

6. Empirical analyses

6.1. Probability of default

We compute the average quarterly values of probability of default (PD) and systemic risk score measures over time for six geographical regions (five emerging markets regional blocks, and United States for comparative purposes). 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 that we need to compute systemic risk, we map the PDs into C as follows:

$$C = \lambda \cdot \ln(A) \tag{10}$$

where A is total assets of the bank. $\lambda = (1 + 30PD)$ is a scaled value of PD, where the scaling is applied only to increase the size of the value of λ because PD values are numerically small. 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 to the mean PD across all the other banks in the sample for that quarter. Fig. 1 plots the time series of PD for the entire sample period from 2004 to 2016, for each of the six geographic regions. Panel A presents levels of PD while Panel B shows the changes in PD over consecutive quarters. Panel A shows a wide variation in regional PD levels over time. PDs from all regions went up during the financial crisis period. As is evident from both panels, the PD of the United States and, to some extent, Eastern Europe experiences the largest spikes during the crisis. Both the panels reveal that the spike in U.S. PD during the financial crisis leads the PDs of other five regions by one or two quarters. We also see an increase in PDs in the Southern Europe and Africa region during the 2010–2012 European debt crisis and the 2015–16 China financial turbulence. South Asian PD registers a large increase during the 2013 Taper-tantrum period, and also during the 2016 India currency demonetization episode. The Russian crisis of 2014–15 contributed to the increase in regional PD for the Eastern Europe.

6.2. Systemic risk

The time series evolution of systemic risk – in terms of both levels and changes – are shown in Fig. 2. The systemic risk metric (Eq. (5)) is normalized for the number of banks, which has been increasing over time. In general, systemic risk spikes during the financial crisis period. In terms of both levels and changes, the increase in systemic risk during the financial crisis is the highest for United States, and leads those of other five regions by one or two quarters. The three emerging regions East Asia, Eastern Europe, and South America, experience large increases in systemic risk compared to other two regions over time, mainly during the 2009 crisis. Southern Europe & Africa, Eastern Europe and East Asia experience systemic risk spikes during the 2010–12 Eurozone crisis as well as the 2015–16 China crisis. South Asia registers its highest systemic risk during the 2013 Taper tantrum and again during the 2016 demonetization period. Finally, increases in systemic risk for the Eastern Europe is observed during the Russian crisis of 2014–15. We also observe that the evolution of PD and systemic risk changes do not perfectly mirror each other.

6.3. Interaction of PDs and systemic risk

Table 3 presents the average quarterly values of PD and systemic risk over time for the five emerging geographical regions (and also the U.S. for comparative purposes). We find that, amongst the emerging markets blocks, South Asia has the highest mean PD; PD is also high for Eastern Europe and Southern Europe & Africa, more so during the crisis period. Systemic risk per bank (measured as number of nodes) is significantly higher in East Asia and South Asia relative to the other three regions. Systemic risk is also reported at the aggregate network-level. Systemic risk is high at the network level for the full sample and pre-crisis period for Eastern Europe and South America compared to other regions. For comparative purposes, United States exhibits (i) moderate mean PD overall (but very high PD during the crisis sub-period), (ii) highest systemic risk per bank, and (iii) lowest network level systemic risk. In summary, we see differences in regions that experience a rise in both firm- and network-level systemic risks. Systemic risk and PD movements do not always line up, suggesting that network risk based on the pattern of inter-connectedness also plays a key role, and is not just proportional to default risk levels.

We examine whether there is persistence in the time series of systemic risk, in levels or in changes, to better understand the implicit dynamics. The results are shown in Fig. 3. In the autocorrelation plot in levels, there is clear evidence of autocorrelation

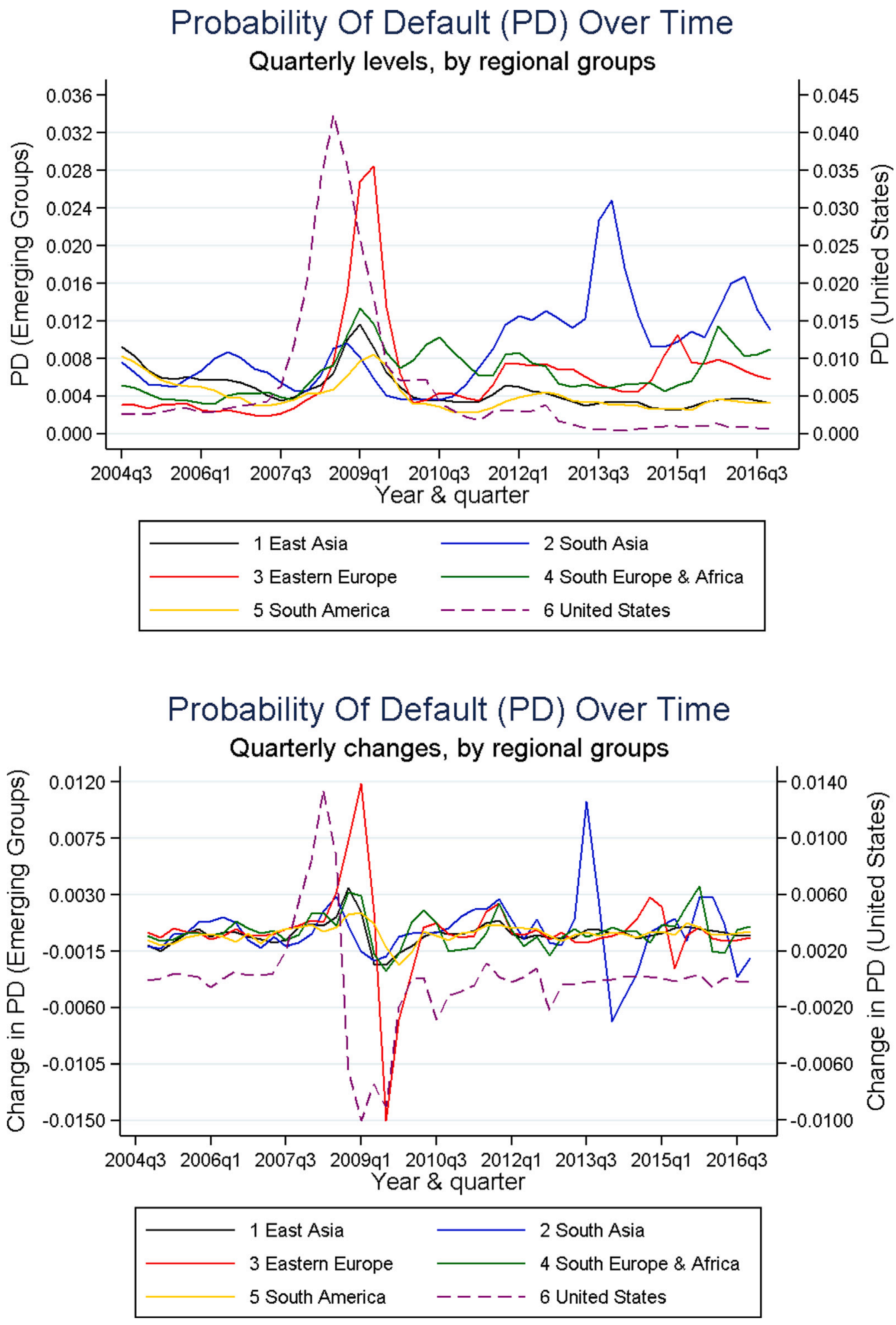


Fig. 1. Time-series trends of probability of default (PD) from 2004/Q3 to 2016/Q4 for each of the six geographic regions. The plots are shown in levels and changes.

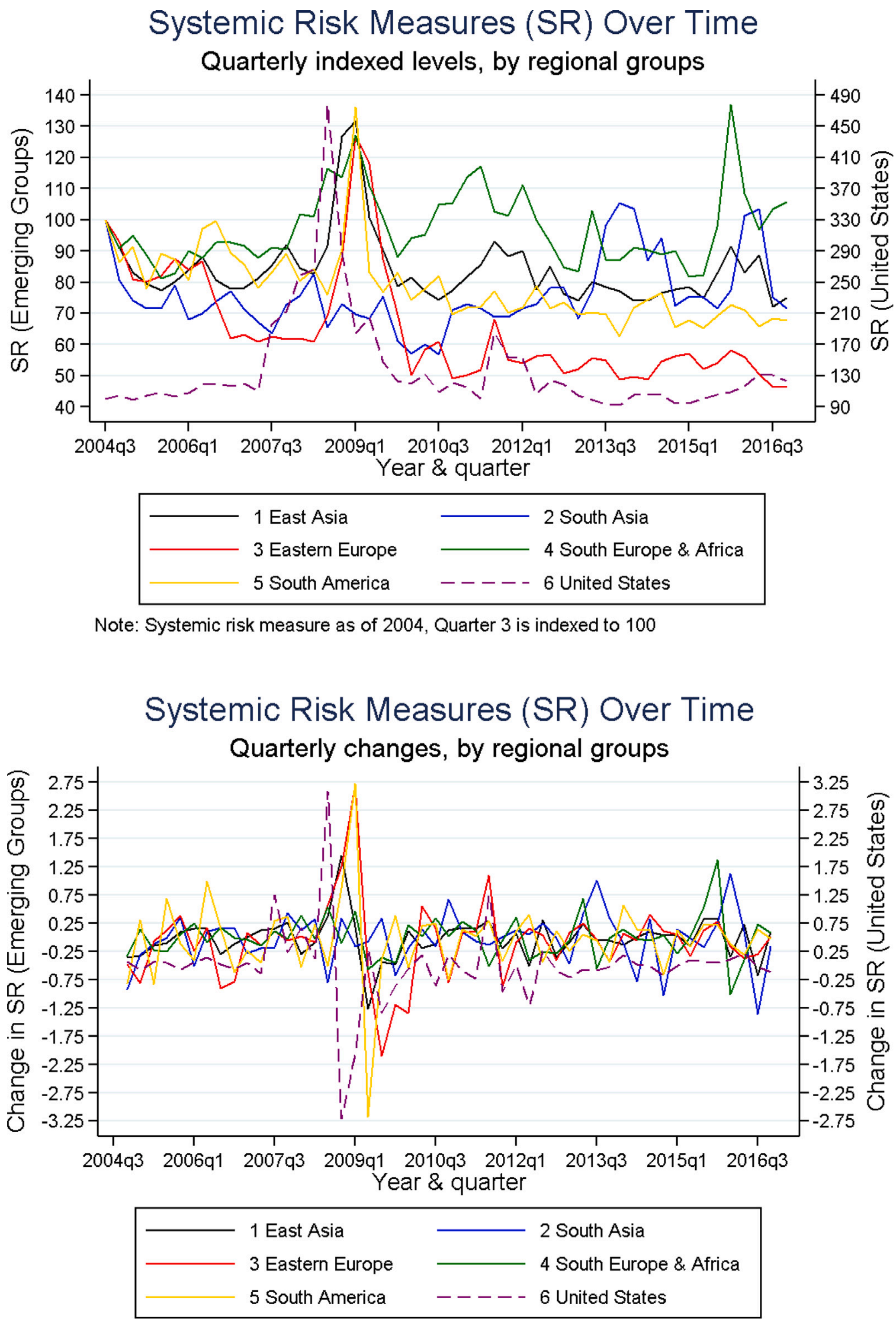


Fig. 2. Time-series trends of indexed systemic risk (SR) from 2004/Q3 to 2016/Q4 for each of the six geographic regions. Each series begins at an index value of 100 on 2004/Q3. The plots are shown in levels and changes.

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	Full	174.9	0.0067	3.93
	Pre-crisis	125.6	0.0060	4.25
	Crisis	157.9	0.0065	4.25
	Post-crisis	191.8	0.0069	3.67
United States	Full	220.1	0.0064	2.02
	Pre-crisis	239.5	0.0030	1.58
	Crisis	231.9	0.0182	3.15
	Post-crisis	206.3	0.0021	1.70

to at least one quarter lag in most regions, though in the case of three of the regions – Eastern Europe, South America and United States – there is greater persistence. The auto-correlograms for changes in systemic risk show much less persistence. Again, however, Eastern Europe shows some positive autocorrelation in changes at one lag whereas South America evidences negative autocorrelation at one lag. We also implement Augmented Dickey Fuller tests to test for non-stationarity (results available upon request). The results indicate that, by and large, level values of systemic risk and probability of default are non-stationary (or cannot reject the null of unit root) but quarterly changes in both systemic risk and probability of default are stationary. We will explore the use of these time series in predicting aggregate levels of default risk later in the paper.

6.4. Concentration of risks

Does most of the systemic risk come from just a few banks? To investigate this, we apply Eq. (9) to compute the percentage of systemic risk contributed by the top 10 contributors in the full sample and each sub-period. 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 the top 10 percentile contributors' systemic risk explains 16% to 47% of the systemic variation across periods (the U.S. average is 24%). Eastern Europe and South America have 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 (in contrast to East Asia and the U.S. where the percentage is the highest during crisis). 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 (again in contrast to East Asia and the U.S. where there are more contributors pre-crisis). There is a clear bifurcation here: East Asia and South Asia have less concentration of systemic risk in their top 10 banks than do the other three emerging regions. This is an outcome of their bigger banking networks that enable greater spreading of systemic risk.

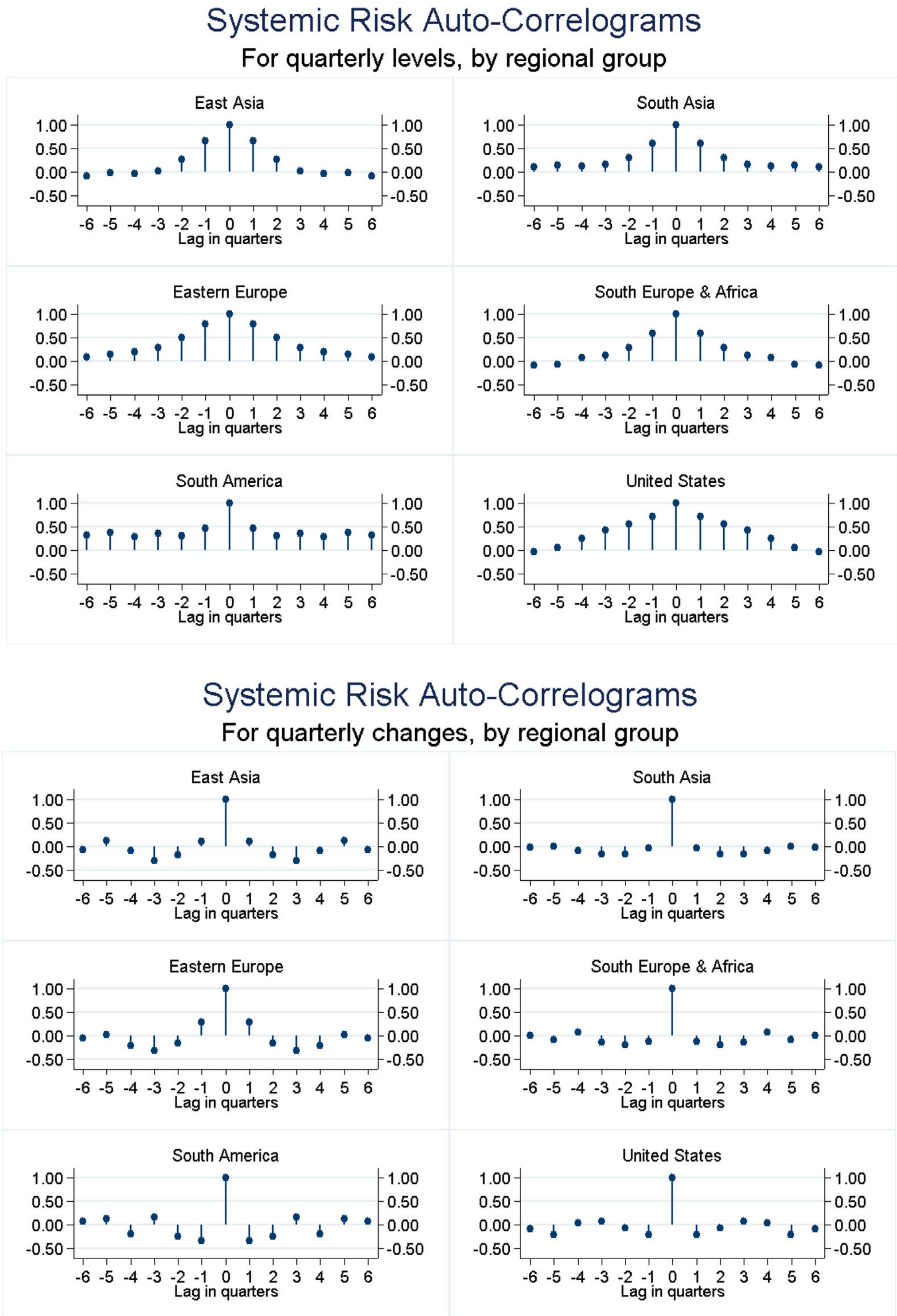


Fig. 3. Auto-correlations in systemic risk over 6 quarters lead/lag for the six geographic regions. The plots are shown in levels and changes.

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 region	Period			
	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
Overall	11.92	16.05	13.13	9.93
United States	23.66	17.27	29.14	23.60
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
Overall	88.3	60.3	75.2	103.9
United States	43.5	56.7	32.1	43.7

6.5. *Analyzing cross-market flows of systemic risks across regions*

We next analyze how systemic risks are connected across regions. We employ cross-correlations, Granger causality analysis, and VAR 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.

6.5.1. *Correlations across regions, contemporaneous and lagged*

We first measure correlations of systemic risk between regional groups, where systemic risk is obtained as the regional network level systemic risk score. Table 5, Panel A reports contemporaneous quarterly correlations, while Panel B reports one-quarter lagged correlations. Panel A shows that some contemporaneous correlations are significantly high between East Asia and three non-Asian regional blocks (i.e., Eastern Europe, Southern Europe & Africa, and South America). Eastern Europe and South America show strong contemporaneous correlation. Only South America depicts a significant contemporaneous correlation with the United States. Interestingly, South Asia (consisting of India), has no significant correlations with any other region, and hence, is relatively isolated. Panel B reveals that significant lagged correlations exist across markets. One quarter lagged systemic risk from East Asia significantly influences systemic risks in Eastern Europe and South America. Similarly, lagged systemic risk from Southern Europe & Africa significantly affects South Asian systemic risk. Lagged systemic risk of U.S. depicts significant correlation with systemic risks in East Asia. However, none of the lagged systemic risks is correlated with the systemic risk of the U.S., confirming the intuition that systemic risk of U.S. likely bears the leading impact on global systemic risk. South Asia is again isolated from other country groups as lagged correlations are very small and trivial versus the other four groups. In sum, we find that a limited number of contemporaneous and lagged correlations matter in the evolution of systemic risks across regions, but the overall linkages are weak across regions.

We next present pairwise cross-correlograms across markets. Fig. 4 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; similarly, to the left of zero (x-axis < 0), the first-named group lags the second-named group. Specifically, in the first plot, East Asia negatively leads South Asia (x-axis > 0) in the short-term over five quarters, and positively lags South Asia (x-axis < 0) in the long term over five years. Similarly, we find lead–lag effects across some markets.[17] Generally, 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). The second plot in Fig. 4 shows the cross-correlograms for quarterly changes in systemic risks across regions. Lead–lag effects are not noticeable in the systemic risk changes. Overall, our correlation results imply that globalization does not adversely impact financial stability, as systemic risk spillovers do not have long-term impact.

[17] East Asia positively leads and lags Eastern Europe and South America. East Asia positively (negatively) leads (lags) Southern Europe & Africa. Eastern Europe positively leads and lags South America. South Asia negatively lags Eastern Europe, Southern Europe & Africa, and South America.

Table 5
Correlations of quarterly changes in systemic risk between country regional groups. Systemic risk is the regional network level systemic risk score. Panel A reports contemporaneous correlations of changes in systemic risk, Panel B reports one-quarter lagged correlations of changes in systemic risk. 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	United States
Panel A: Contemporaneous correlations						
East Asia	1.0000					
South Asia	0.1744	1.0000				
	(0.2308)					
Eastern Europe	0.4970	−0.0001	1.0000			
	(0.0003)	(0.9997)				
South Europe & Africa	0.3394	−0.1972	0.2438	1.0000		
	(0.0170)	(0.1744)	(0.0915)			
South America	0.4422	0.0553	0.5573	0.2507	1.0000	
	(0.0015)	(0.7057)	(0.0000)	(0.0823)		
United States	−0.1539	−0.1796	−0.0884	0.0930	−0.3319	1.0000
	(0.2911)	(0.2168)	(0.5456)	(0.5250)	(0.0198)	
Panel B: Lagged correlations						
East Asia	0.1196	−0.1737	−0.0717	0.0652	−0.1732	0.4310
	(0.4180)	(0.2378)	(0.6284)	(0.6597)	(0.2392)	(0.0022)
South Asia	0.0504	−0.0266	0.1442	0.4079	−0.0350	0.1422
	(0.7336)	(0.8574)	(0.3280)	(0.0040)	(0.8135)	(0.3350)
Eastern Europe	0.6675	−0.0144	0.2901	0.2876	0.2407	−0.1272
	(0.0000)	(0.9226)	(0.0455)	(0.0475)	(0.0993)	(0.3890)
South Europe & Africa	0.1621	−0.0631	−0.0646	−0.1276	0.0293	−0.0201
	(0.2711)	(0.6703)	(0.6624)	(0.3873)	(0.8435)	(0.8923)
South America	0.3813	−0.0527	−0.2145	−0.0102	−0.3351	0.0291
	(0.0075)	(0.7219)	(0.1432)	(0.9452)	(0.0199)	(0.8444)
United States	−0.1434	0.1712	−0.1061	−0.0490	0.1436	−0.1986
	(0.3308)	(0.2447)	(0.4730)	(0.7409)	(0.3302)	(0.1761)

6.5.2. Granger regressions

Therefore, to better understand the auto- and cross-correlation relationships across regions, we implement 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 six regional groups (including itself). Table 6, Panel A reports the univariate F-statistics of significance. Panel B reports the joint F-statistics of significance for the five other cross-regional groups considered together. We observe that dependence on self-lagged variables (the diagonal terms) as well as cross-lagged variables are generally weak. Self-lagged variables are strong only for East Asia and South America. We find cross-market lead–lag evidence only across three emerging blocks: (a) East Asia significantly Granger causes the systemic risks in Eastern Europe, Southern Europe & Africa and South America; (b) Eastern Europe significantly Granger causes the systemic risks in South America; and (c) Southern Europe & Africa significantly Granger causes the systemic risks in South Asia. United States Granger causes the systemic risks in East Asia but is not impacted by the systemic risks of any of the five regional blocks. Overall, the results in Table 6, Panel A, show that lagged effects are significant in select markets. Joint Granger causality tests from Panel B show that systemic risks in East Asia, South Asia, Eastern Europe, and South America significantly depend on joint cross-lagged variables from other markets; only Southern Europe & Africa and United States appear to be immune from cross-lagged variables from other regional blocks. Overall, evidence from Granger causality regressions shows that cross-market lead–lags are generally absent in the majority (30 out of 36) market pairs, implying that systemic risks are compartmentalized within regions.

6.5.3. Vector auto-regressions

To better understand the linear time-series inter-dependencies between the systemic risks we implement the following Vector Auto-Regressions (VAR) model across the six regions.

$$\begin{pmatrix} SysriskEastAsia \\ SysriskSouthAsia \\ SysriskEastEurope \\ SysriskEuropeandAfrica \\ SysriskSouthAmerica \\ SysriskUnitedStates \end{pmatrix}_t = \text{intercept} + \begin{pmatrix} SysriskEastAsia \\ SysriskSouthAsia \\ SysriskEastEurope \\ SysriskEuropeandAfrica \\ SysriskSouthAmerica \\ SysriskUnitedStates \end{pmatrix}_{t-1} + \cdots + \begin{pmatrix} SysriskEastAsia \\ SysriskSouthAsia \\ SysriskEastEurope \\ SysriskEuropeandAfrica \\ SysriskSouthAmerica \\ SysriskUnitedStates \end{pmatrix}_{t-4} + error_t$$

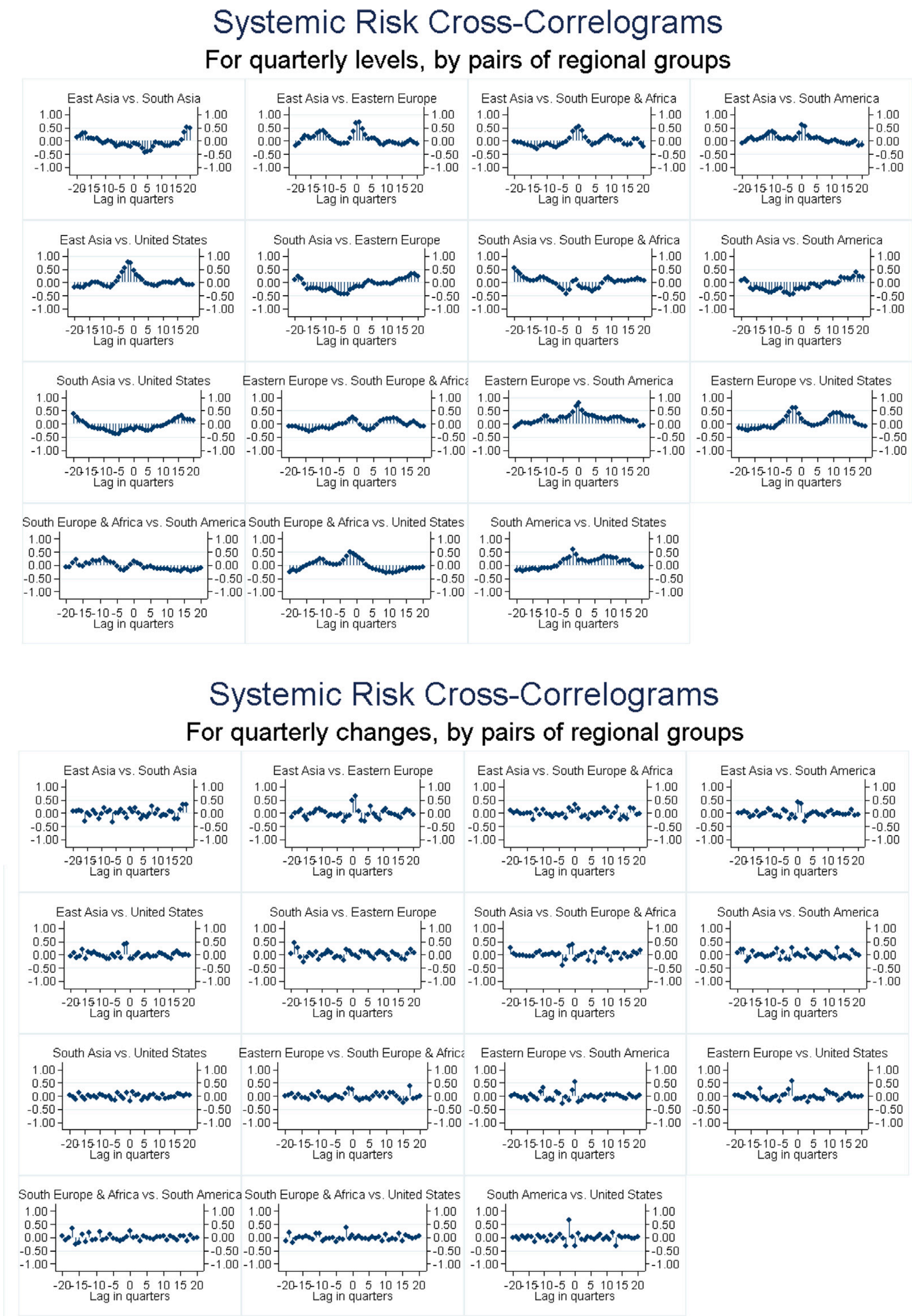


Fig. 4. Pairwise cross-correlations in systemic risk over 20 quarters lead/lag between 15 pairs arising out of the six regions. The plots are shown in levels and changes. In each plot, the positive (negative) quarterly scale on *x*-axis denotes the lead (lag) of the first-named region relative to the second-named region.

The VAR model involves quarterly changes in network level systemic risk scores of the six country regional groups being jointly regressed on four lagged (one through four quarters) values of systemic risk measures of all six regional groups. Both likelihood ratio (LR) and Akaike information criterion (AIC) identify that a maximum of three lags are material. Out of 144 explanatory variables

Table 6
Granger causality regressions. For each country regional group, quarterly changes in systemic risk measure (regional network level systemic risk score) are regressed on one-quarter lagged changes in systemic risk measures of all six 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 five other cross regional groups considered together.

Explanatory variables: lagged systemic risk of	Dependent variable: systemic risk corresponding to					
	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America	United States
Panel A: Univariate F-statistics of lagged variables						
East Asia	4.16 (0.0480)	0.64 (0.4295)	25.40 (0.0000)	3.76 (0.0595)	41.03 (0.0000)	2.07 (0.1576)
South Asia	1.38 (0.2474)	0.56 (0.4581)	1.35 (0.2520)	1.23 (0.2732)	3.56 (0.0663)	1.52 (0.2248)
Eastern Europe	0.70 (0.4065)	1.46 (0.2334)	0.07 (0.7953)	1.37 (0.2488)	5.92 (0.0195)	0.71 (0.4049)
South Europe & Africa	0.21 (0.6516)	9.19 (0.0042)	0.19 (0.6648)	2.32 (0.1357)	1.10 (0.3001)	0.13 (0.7251)
South America	0.20 (0.6598)	1.23 (0.2748)	0.36 (0.5534)	0.16 (0.6897)	13.61 (0.0007)	2.14 (0.1516)
United States	8.25 (0.0064)	0.11 (0.7468)	0.42 (0.5192)	0.04 (0.8373)	0.33 (0.5687)	0.69 (0.4121)
Panel B: Joint F-statistic of all five lagged cross-variables						
All 5 lagged cross-variables	2.89 (0.0253)	2.40 (0.0537)	6.13 (0.0002)	0.94 (0.4663)	8.56 (0.0000)	1.07 (0.3936)

Table 7
Vector autoregression, VAR (significant results only). Quarterly changes in systemic risk measure (regional network level systemic risk score) of the six country regional groups are jointly regressed on four lagged (one through four quarters) changes in systemic risk measure of the six regional groups. Both likelihood ratio (LR) and Akaikae information criterion (AIC) identify that a maximum of three lags are material. Out of 144 explanatory variables (6 regressions * 6 systemic risk scores * 4 lags), only 10 are significant at 5% level. The following summary reports the coefficients and t-statistics (corresponding p-values in parentheses) for these significant 10.

Dependent variable: systemic risk of	Explanatory variable: systemic risk of	Lag in quarters	Coefficient	t-statistic (p-value)
East Asia	South Europe & Africa	2	0.4575	2.46 (0.023)
East Asia	United States	2	0.2891	2.99 (0.007)
South Asia	South Europe & Africa	4	−0.7664	−2.61 (0.017)
Eastern Europe	United States	2	0.4822	2.94 (0.008)
Eastern Europe	United States	3	0.4591	2.39 (0.027)
South Europe & Africa	United States	2	0.3451	2.64 (0.016)
South America	South America	1	−0.7926	−3.37 (0.003)
South America	United States	2	0.5203	3.39 (0.003)
United States	East Asia	3	1.6770	2.38 (0.027)
United States	Eastern Europe	1	−0.9540	−2.18 (0.041)

(6 regressions × 6 systemic risk scores × 4 lags), only ten coefficients are significant. This implies that, consistent with previous results, contemporaneous dependence of systemic risk matters far more than lagged inter-dependence. Table 7 reports the summary of coefficients and t-statistics (corresponding p-values in parentheses) of the ten significant regressions. Out of the ten regressions, two regressions have significant 1-quarter lags, five have significant 2-quarter lags, two have significant 3-quarter lag, and one has significant 4-quarter lags. Out of the ten, only one has a significant self-lag dependence; other nine have significant cross-lag dependence. Overall, VAR tests show that systemic risk information flows across markets are mainly contemporaneous.[18]

[18] We additionally conduct VAR based Impulse response and Variance decomposition analyses. Results are not tabulated for brevity. Impulse response functions show that, in general, a shock in a given country leads to an immediate spike in systemic risk the current quarter and the effect dissipates in the next four quarters. Variance decomposition tests show that the shock to systemic risk in each region accounts for all of its variability next quarter, and that effect eventually fades away to 40% to 50% of the variance after four quarters.

Table 8
Principal component analysis. Panel A (Panel B) presents the first five principal components and corresponding eigenvalues for quarterly levels of (changes in) the systemic risk measure (network level systemic risk score) of the five regional emerging country groups. Panel C reports the results of time-series regressions of the quarterly changes in first three principal components corresponding to quarterly levels of systemic risk on quarterly changes in U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX) and quarterly changes in U.S. systemic risk measure (network level systemic risk score); all regressions include adjustments for heteroscedasticity, autocorrelation in residuals and year fixed-effects. t-statistics are reported in parentheses.

Panel A: First 5 principal components of levels of systemic risk

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: First 5 principal components of changes in systemic risk

Component	Eigenvalue	Difference	Proportion	Cumulative
1	2.1944	1.0355	0.4389	0.4389
2	1.1589	0.4112	0.2318	0.6707
3	0.7477	0.2512	0.1495	0.8202
4	0.4965	0.0941	0.0993	0.9195
5	0.4025		0.0805	1.0000

Panel C: Regression of changes in first 3 principal components of levels of systemic risk

Explanatory variables	Dependent variable								
	Component 1			Component 2			Component 3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	−1.2608***	−1.2330***	−1.3556***	0.0882	−0.0215	0.0944	−1.8312***	−1.8779***	−1.8161***
	(−3.65)	(−7.73)	(−4.08)	(0.25)	(−0.09)	(0.26)	(−8.03)	(−1.3.36)	(−7.47)
Default	2.3225*		1.9077	−0.1131		−0.0737	0.9731		1.1086
	(2.31)		(2.03)	(−0.27)		(−0.15)	(1.68)		(1.58)
Term (Level)	0.0449		0.2341	0.3639		0.3478	−0.1814		−0.2361
	(0.08)		(0.45)	(1.16)		(1.03)	(−0.49)		(−0.67)
Term (Slope)	−0.3728		−0.7794	−0.1903		−0.1654	0.4955		0.5949
	(−0.59)		(−0.94)	(−0.34)		(−0.29)	(1.21)		(1.47)
TED	0.6894		0.0782	−0.2168		−0.1659	0.8615***		1.0325**
	(1.52)		(0.10)	(−0.90)		(−0.42)	(4.29)		(3.02)
VIX	−0.0597		−0.0622	0.0064		0.0060	−0.0449		−0.0455
	(−1.43)		(−1.58)	(0.17)		(0.16)	(−1.61)		(−1.57)
U.S. Sys. Risk		−0.9811	−0.4971		0.1725	0.0439		−0.2863**	0.1411
		(−1.66)	(−1.01)		(1.43)	(0.20)		(−2.96)	(0.77)
Observations	49	49	49	49	49	49	49	49	49
R^2	0.519	0.494	0.543	0.354	0.326	0.354	0.458	0.308	0.470
Adjusted R^2	0.255	0.306	0.268	−0.000	0.075	−0.034	0.160	0.051	0.152

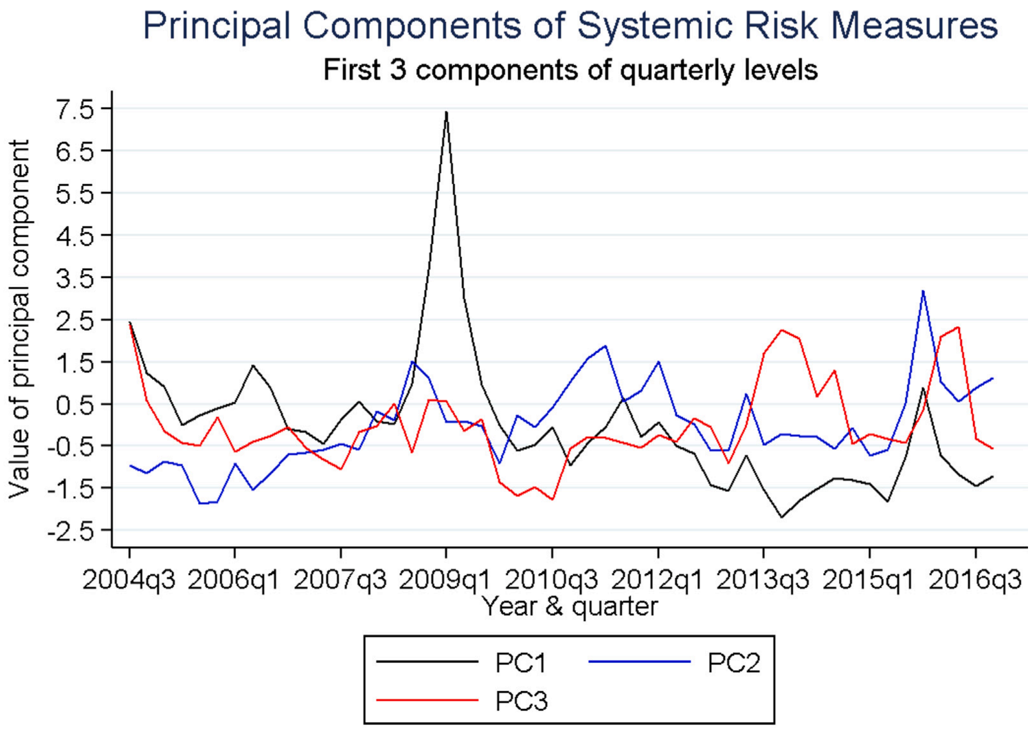
*Denote coefficient $p < 0.05$.
**Denote coefficient $p < 0.01$.
***Denote coefficient $p < 0.001$.

In summary, our findings in this section imply that systemic risk changes are autocorrelated within each region and to a lesser extent, contemporaneously correlated across regions. Spillover effects across regions show up in univariate tests, though tend to be less prominent in Granger causality and VAR regressions. Overall, the evidence is consistent with compartmentalized systemic risk across emerging market regions and that globalization does not create large spillovers across markets.

6.6. 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 8, 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 in levels, 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. Panel B further shows that first three (four) PC changes together account for 82% (92%) of the variation in systemic risk changes, with the main PC only accounting for 44% of the common variation. This further supports the fact that systemic risk tends to be compartmentalized within regions as there is no one large component accounting for much of the variation in systemic risk across regions.

Fig. 5 plots the first three PCs (levels as well as changes). We observe that the first PC (i.e., PC1) correlates highly with default risk during the financial crisis. PC2 spikes in the post-financial crisis period (associated with the Dodd-Frank regulatory phase-in),



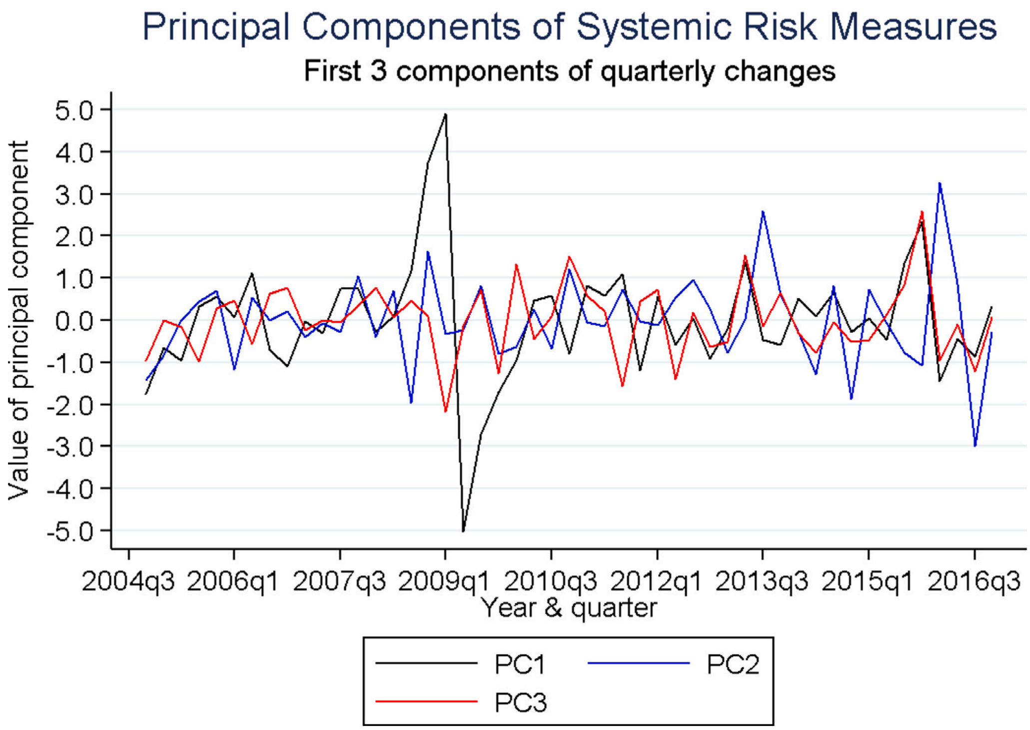


Fig. 5. Principal components decomposition of the time-series of systemic risk scores from 2004/Q3 to 2016/Q4 for the five emerging geographical regions. The plots are shown in levels and changes.

reflecting possible policy uncertainty shock; and it spiked again during the China market crisis of 2015–16. The third PC (i.e., PC3) seems to capture the Taper-tantrum of 2013 and the 2015 Chinese market crisis, episodes both associated with capital outflows from emerging markets to US. Fig. 5 also plots the PC changes extracted from regional-level systemic risks. The changes in the first PC captures the credit risk changes from the financial crisis. The second and third PCs, however, are less distinct and broadly capture the 2013 Taper-tantrum and 2015–2016 Chinese market crisis.

Panel C of Table 8 reports the results corresponding to the time-series regressions of quarterly changes in the first three PCs on quarterly changes in the U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX) and quarterly changes in U.S. network-level systemic risk. Regressions include adjustments for heteroskedasticity, autocorrelation in residuals, and year-fixed effects. Overall, we find that the PCs are only weakly related to the underlying macro factors, suggesting that global systemic risk sweeping across emerging market regions is less likely. Moreover, we observe that the first PC is significantly related to the US default factor. The third PC is influenced by the contemporaneous funding (TED) factor. The second PC does not appear to be related to any of the macroeconomic variables. The first two PCs bear no link with U.S. systemic risk. The third PC in strongly related to U.S. systemic risk in an univariate setup, but becomes insignificant once TED spread is included; this indicates that the relation between third PC and U.S. systemic risk is likely due to the funding channel.

6.7. Time-series and panel regressions of quarterly regional systemic risk

First, we seek to explain the evolution of aggregate network-level systemic risk in each region over time; the objective here is to examine the key drivers of quarterly changes in region-specific systemic risks. To this end, we conduct time-series regressions (over 50 quarters from the third quarter of 2004 through the fourth quarter of 2016) of quarterly changes in network systemic risk on several covariates: (a) one-quarter lagged network systemic risk, (b) aggregate credit risk (mean probability of default across firms), (c) 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), (d) 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 (e) U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX). The time-series model explains the average of systemic risk across firms for each quarter in a given region. All regressions are implemented in first-differences, include year fixed effects, and report robust standard errors adjusted for heteroskedasticity and autocorrelation in residuals. The regression equation for each region may be summarized as follows, where t indexes time:

$$\begin{aligned}\Delta Agg\_Sys\_Risk_t &= \alpha_0 + \alpha_1 \cdot \Delta Agg\_Sys\_Risk_{t-1} \\ &+ \alpha_2 \cdot \Delta Mean\_Credit\_Risk_t \\ &+ \gamma_0 \cdot \Delta Network\_Risk\_Variables_t \\ &+ \gamma_1 \cdot \Delta Firm\_Specific\_Attributes_t \\ &+ \gamma_2 \cdot \Delta US\_Market\_Risk\_Factors_t + \epsilon_t \end{aligned} \tag{11}$$

Table 9, upper panel, presents the summary of time-series regressions for the six geographic regions (detailed region specific results are presented in Table 11 in the electronic appendix). There is clear evidence that the addition of network variables enhances the models' adjusted R^2 substantially, indicating that network effects are important in explaining the evolution of systemic risk. The addition of network variables increases the R^2 from 61% to 94% (East Asia), 36% to 80% (South Asia), 75% to 92% (Eastern Europe), 44% to 96% (S. Europe & Africa), 46% to 97% (South America), and from 60% to 82% (U.S.), suggesting that network effects comprise a substantive portion of systemic risk. In addition, we consider the joint F-test of network variables (see Table 11, electronic appendix). We present three types of F-tests based on firm-level only, network-level only, and both firm- and network-level network variables. We find that the F-test for the improvement in R^2 is highly significant. We further observe that most of the significance largely comes from the network level metrics, with the exception of South Europe & Africa, where both firm- and network-level network variables matter. Overall, based on adjusted R^2 values as well as joint significance of the network coefficients, we observe that network metrics have significant incremental contribution to the time-series regressions.

Next we consider panel regressions of quarterly systemic risk contributions of all financial firms across the regions so as to explore the cross-sectional determinants of each financial firm's contribution to network level systemic risk score. For the panel model, the dependent variable is the systemic risk for each firm i for each quarter t in a given region. The covariates, as in model (11), include corresponding one-quarter lagged systemic risk, firm-level network risks and balance sheet attributes for that quarter, in addition to U.S. market risk factors. We include year fixed effects, and report robust standard errors adjusted for heteroskedasticity and region-specific cluster-effects. Specifically, we estimate the following panel regression model to understand the cross-sectional and time-series dynamics of systemic risks:

$$\begin{aligned}Sys\_Risk\_Contribution_{i,t} &= \alpha_{i0} + \alpha_{i1} \cdot Sys\_Risk\_Contribution_{i,t-1} \\ &+ \alpha_{i2} \cdot Credit\_Risk_{i,t} \\ &+ \gamma_{i0} \cdot Network\_Risk\_Variables_{i,t} \\ &+ \gamma_{i1} \cdot Firm\_Specific\_Attributes_{i,t} \\ &+ \gamma_{i2} \cdot US\_Market\_Risk\_Factors_{i,t} + \epsilon_{i,t} \end{aligned} \tag{12}$$

There are seven separate panel regressions — once for the aggregate sample of five emerging geographical regions considered jointly, and once each for the six geographical regions: five emerging blocks and the U.S. (results are not tabulated for brevity,

Table 9

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 11 (in E-Appendix), for each regional group; the dependent variables are quarterly changes in regional network level systemic risk score. Panel regressions are conducted, analogous to the specifications in Table 12 (in E-Appendix), for each regional group; the dependent variables are region-specific firms' contribution to network level systemic risk score. Primary explanatory variables include: one-quarter lagged systemic risk; credit risk (probability of default, PD); network interconnectedness (degree across all nodes, degree concentration measured by HHI); and network parameters (centrality between nodes, diameter, fragility, number of distinct clusters, and HHI concentration within clusters). Additional control variables include 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). Time-series regressions are conducted at network-level; firm-level variables are converted into network-level variables on a quarterly basis by using mean values (of pd, degree and centrality between nodes) and median values (of firm-specific attributes) across all firms constituting the network. Cross-sectional regressions are conducted at firm-level; network-level variables (degree concentration measured by HHI, diameter, fragility, number of clusters, HHI concentration within clusters and U.S. macroeconomic variables) are converted into firm-level variables on a quarterly basis by assigning the same network-level value to all firms constituting the network. All explanatory variables are in the form of quarterly changes for time-series regressions and in the form of quarterly level values for panel regressions.

Included explanatory variables	Regional group						
	All	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America	United States
Panel A: Adjusted R^2s from time-series regressions							
Lagged systemic risk (only)		43%	32%	42%	37%	49%	28%
Credit risk (only)		48%	40%	76%	32%	−0.01%	48%
Lagged systemic risk + credit risk		61%	36%	75%	44%	46%	60%
Network parameters (only)							
Firm-level		87%	57%	59%	76%	93%	36%
Network-level		86%	57%	57%	73%	90%	43%
Lagged systemic risk + credit risk + network parameters		94%	80%	92%	96%	97%	82%
Lagged systemic risk + credit risk + network parameters + firm-specific attributes		97%	90%–94%	93%–95%	96%–97%	99%	88%–94%
Lagged systemic risk + credit risk + network parameters + firm-specific attributes + U.S. macro variables		99%	97%	95%–97%	96%–97%	99%	90%–97%
Panel B: Adjusted R^2s from panel regressions							
Lagged systemic risk (only)	65%	31%	50%	62%	35%	42%	20%
Credit risk (only)	9%	21%	50%	48%	47%	21%	24%
Lagged systemic risk + credit risk	65%	35%	60%	63%	53%	44%	32%
Network parameters (only)							
Firm-level	4%	61%	38%	64%	35%	55%	43%
Network-level	47%	8%	4%	41%	1%	10%	0%
Lagged systemic risk + credit risk + network parameters	75%	78%	83%	81%	84%	82%	70%
Lagged systemic risk + credit risk + network parameters + firm-specific attributes	76%–77%	84%	86%	88%	87%–88%	91%–92%	73%
Lagged systemic risk + credit risk + network parameters + firm-specific attributes + U.S. macro variables	76%–77%	84%	86%	88%	88%	91%–92%	73%

and are reported in Table 12 in the electronic appendix). Table 9 summarizes the adjusted R^2s from regressions of systemic risk elaborated above. The systemic risk measure S is a combination of interconnectedness and default risk. From Table 9, lower panel, we again see that the models where network variables are included significantly better explain systemic risk than models with only credit risk variables. We note that the adjusted R^2 improves from 35% to 78% (East Asia), 60% to 83% (South Asia), 63% to 81% (Eastern Europe), 53% to 84% (S. Europe & Africa), 44% to 82% (South America), and from 32% to 70% (U.S.), suggesting that network effects comprise a substantive portion of systemic risk. The F-test for the improvement in R^2 is highly significant (See Table 12, electronic appendix). Based on their respective F-test values both firm-level and network variables are found to significantly contribute to the explanatory power. Taking all five emerging regions together also shows that the R^2 improves from 65% for a model with only lagged systemic risk and credit risk variables to 75% for a model with additional network variables. Because this is a panel regression at the firm level, we also see that firm-specific variables enhance the R^2 quite significantly, by only 3% for the South Asia and U.S. to 9%–10% for South America. The addition of U.S. macro variables does not appear to enhance explanatory power much.

Our empirical assessment of the role of each component in both time-series and panel regressions based on adjusted R^2 values as well as F-tests suggests that interconnectedness (network structure) plays an important role as it explains more of the changes in S than default risk. This provides empirical support for the tenet in the Dodd-Frank Act that SIFIs are characterized by their interconnectedness, which needs to be captured in systemic risk models.

Table 10
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 13 (in E-Appendix), for each regional group; the dependent variables are differences in values of credit risk (mean probability of default, PD) between quarters t and $t-1$. Primary explanatory variables include: value of probability of default in quarter $t-1$; quarterly changes in systemic risk (network level systemic risk score); and quarterly changes in network parameters (mean degree across all nodes, mean centrality between nodes, degree concentration measured by HHI, diameter, fragility, number of distinct clusters, and HHI concentration within clusters). Additional control variables include 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); U.S. macroeconomic variables (default factor, level and slope of term structure factor, TED spread, and VIX); and U.S. network level systemic risk. Time-series regressions are conducted at network-level; firm-level variables are converted into network level variables on a quarterly basis by using mean values (of pd, degree and centrality between nodes) and median values (of firm-specific attributes) across all firms constituting the network.

Included explanatory variables	Regional group					
	East Asia	South Asia	Eastern Europe	South Europe & Africa	South America	United States
Lagged credit risk (only)	71%	45%	40%	29%	24%	−2%
Systemic risk (only)	79%	3%	76%	40%	21%	10%
Lagged credit risk + systemic risk	78%	66%	76%	42%	24%	35%
Lagged credit risk + systemic risk + network parameters	85%–87%	78%–84%	87%	90%–92%	72%–91%	78%–85%
Lagged credit risk + systemic risk + network parameters + firm-specific attributes	89%–90%	89%–94%	88%–90%	93%–94%	94%–95%	48%–92%
Lagged credit risk + systemic risk + network parameters + firm-specific attributes + U.S. macro variables	99%	94%–97%	95%–96%	97%	97%	96%–99%
Lagged credit risk + systemic risk + network parameters + firm-specific attributes + U.S. systemic risk	90%	93%–96%	93%–94%	93%–94%	94%	

6.8. Information content of systemic risk

After establishing the key determinants in the evolution of aggregate network-level systemic risk, we, finally, examine the information content of systemic risk. Specifically, we study the relationship between systemic risk and expected default risks to understand how much variation in one-year probability of default – our proxy for default risk – can be explained by systemic risks. We accordingly conduct time-series regressions of quarterly changes in expected one-year credit risk on changes in network level systemic risk and various network parameters, after conditioning for lagged credit risk. Additional control variables include quarterly changes in median firm-specific attributes, U.S. macroeconomic variables and U.S. network level systemic risk. As in model (11), all regressions are implemented in first-differences, include year fixed effects, and report robust standard errors adjusted for heteroskedasticity and autocorrelation in residuals. There are six regressions corresponding to the six geographical regions. The regression equation for each region may be summarized as follows, where t indexes time:

$$\begin{aligned}\Delta Mean\_Credit\_Risk_t &= \alpha_0 + \alpha_1 \cdot Mean\_Credit\_Risk_{t-1} \\ &+ \alpha_2 \cdot \Delta Agg\_Sys\_Risk_t \\ &+ \gamma_0 \cdot \Delta Network\_Risk\_Variables_t \\ &+ \gamma_1 \cdot \Delta Firm\_Specific\_Attributes_t \\ &+ \gamma_2 \cdot \Delta US\_Market\_Risk\_Factors_t \\ &+ \gamma_3 \cdot \Delta US\_Agg\_Sys\_Risk_t + \epsilon_t \end{aligned} \tag{13}$$

The regression outputs, being comprehensive, are not tabulated for brevity (see Table 13 in the electronic appendix). However, Table 10 summarizes the contribution to aggregate default risk from the various explanatory variables.

We observe that lagged credit risk levels in each region offer good explanation of expected one-year ahead credit risk levels for all emerging market regions, with adjusted R^2s ranging from 24% in South America to 71% in East Asia. Adding in systemic risk increments the explanatory power, raising the R^2 for all regions from 71% to 78% (East Asia), 45% to 66% (South Asia), 40% to 76% (East Europe), 29% to 42% (Southern Europe & Africa), and −2% to 35% (U.S.), suggesting that systemic and credit risks are significantly related, i.e., systemic risk is intertwined with the credit cycle. The F-statistics for improvement in model fit (R^2) with the addition of contemporaneous changes in systemic risk are highly significant. Overall, we observe that the systemic risk variable has significant explanatory power for the expected probability of default, and together with lagged values of default and changes in network measures has pronounced effect on the overall default risk. Our network based model of systemic risk therefore offers policy makers early warnings about changes in the credit cycle.[19]

[19] Our sample period includes six major macro/financial events that impacted systemic risk levels (Section 6.7) and credit risk levels (Section 6.8) in one or more regions. The Euro Crisis at the end of 2010 impacted Southern Europe and Africa, the taper tantrum (2013–14) and demonetization (November 2016)

7. Summary and conclusions

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. In this paper, we examine how globalization impacts emerging market financial stability by undertaking 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. In particular, we focus on studying the (a) evolution and (b) cross-market relationships of network risks in emerging economies, and explaining (c) how such risks are driven by cross-sectional and time-series covariates and risk factors. Our study complements the large literature on systemic risk in developed markets.

Three main results emerge from our study. *First*, systemic risk evolution in emerging markets is heterogeneous across regions. Furthermore, we observe a high degree of concentration in systemic risks among major banks within each region, though the levels of concentration vary across regions. *Second*, the spillover effects of systemic risks across regions are weak. Systemic risk is strongly dependent on the interconnectedness of the banking system in each region, while the regions are compartmentalized away from each other and insulated from the United States. This implies that regulatory effort needs to be more focused on addressing the financial stability challenges locally within each region. *Third*, changes in systemic risk are driven more by changes in interconnectedness in each region's banking networks than by changes in default risk levels. Our systemic risk variable along with network measures of risk are significantly related to credit risk changes on a quarterly horizon. Our results imply that systemic risk may be hence used as a policy variable independently in each emerging market region to predict and manage the credit cycles.

Overall, our evidence is consistent with the notion that globalization engenders financial stability and does not lead to large systemic risk spillovers across emerging market regions. While we do not claim a causal relationship between globalization and systemic risk, we document effects of systemic risk in a time of increasing globalization. Network modeling approaches such as the one in this paper will be useful in the future to examine how financial stability was impacted by the Global Economic Compression following the Covid-19 pandemic, and whether the effects were different between the emerging and developed markets.

CRediT authorship contribution statement

Sanjiv R. Das: Conceptualization, Methodology, Software. **Madhu Kalimipalli:** Writing – review & editing, Writing – original draft. **Subhankar Nayak:** Formal analysis, Data curation, Visualization.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.intfin.2022.101633.

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impacted South Asia, the forex/Russia crisis (2014–15) impacted Eastern Europe, and the 2015–16 Chinese market turbulence impacted East Asia as well as Southern Europe & Africa. The biggest event, the GFC (2007–08) affected all regions except South Asia. The GFC was very much a global effect, but the other events affected only a couple of regions. This may also explain why we find that systemic risk spillovers are not large in the sample.

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