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The multi-layer network nature of systemic risk and its implications for the costs of financial crises

Sebastian Poledna[a,c], José Luis Molina-Borboa[d], Serafín Martínez-Jaramillo[d], Marco van der Leij[e,f,g], Stefan Thurner[a,b,c,*]

[a] Section for Science of Complex Systems, Medical University of Vienna, Spitalgasse 23, A-1090, Austria
[b] Santa Fe Institute, 1399 Hyde Park Road, Santa Fe NM 87501, USA
[c] IIASA, Schlossplatz 1, A-2361 Laxenburg, Austria
[d] Dirección General de Estabilidad Financiera, Banco de México, Ave. 5 de Mayo 2, Ciudad de México, Distrito Federal, Mexico
[e] CeNDEF, University of Amsterdam, Valckeniersstraat 65–67, 1018 XE Amsterdam, The Netherlands
[f] Research Department, De Nederlandsche Bank, Westeinde 1, 1017 ZN Amsterdam, The Netherlands
[g] Tinbergen Institute, Gustav Mahlerplein 117, 1082 MS Amsterdam, The Netherlands

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ABSTRACT

The inability to see and quantify systemic financial risk comes at an immense social cost. Systemic risk in the financial system arises to a large extent as a consequence of the interconnectedness of its institutions, which are linked through networks of different types of financial contracts, such as credit, derivatives, foreign exchange, and securities. The interplay of the various exposure networks can be represented as layers in a financial multi-layer network. In this work we quantify the daily contributions to systemic risk from four layers of the Mexican banking system from 2007 to 2013. We show that focusing on a single layer underestimates the total systemic risk by up to 90%. By assigning systemic risk levels to individual banks we study the systemic risk profile of the Mexican banking system on all market layers. This profile can be used to quantify systemic risk on a national level in terms of nation-wide expected systemic losses. We show that market-based systemic risk indicators systematically underestimate expected systemic losses. We find that expected systemic losses are up to a factor of four higher now than before the financial crisis of 2007–2008. We find that systemic risk contributions of individual transactions can be up to a factor of one thousand higher than the corresponding credit risk, which creates huge risks for the public. We find an intriguing non-linear effect whereby the sum of systemic risk of all layers underestimates the total risk. The method presented here is the first objective data-driven quantification of systemic risk on national scales that reveal its true levels.

1. Introduction

Systemic risk (SR) in financial markets is the risk that a significant fraction of the financial system can no longer perform its function as a credit provider and collapses. In a more narrow sense, SR is the notion of contagion or impact that starts from the failure of a financial institution (or a group of institutions) and propagates through the financial system, potentially to the real economy (De Bandt and Hartmann, 2000; Bank for International Settlements, 2010). Systemic risk in financial markets generally emerges through two mechanisms, either the synchronization of behavior of agents (fire sales, margin calls, herding), or the interconnectedness of agents. The former can be measured by a potential capital shortfall during periods of synchronized behavior, where many institutions are simultaneously distressed (Adrian and Brunnermeier, 2011; Acharya et al., 2012; Brownlees and Engle, 2012; Huang et al., 2012). The latter is a consequence of the network nature of financial claims and liabilities (Eisenberg and Noe, 2001; Boss et al., 2004). Network-based SR is potentially extremely harmful because of the possibility of cascading failure, meaning that the default of a financial agent may trigger defaults of others. Secondary defaults might cause avalanches of defaults percolating throughout the entire network and can potentially wipe out the financial system by a de-leveraging cascade (Minsky, 1992; Fostel

* Corresponding author at: Section for Science of Complex Systems, Medical University of Vienna, Spitalgasse 23, 1090 Vienna, Austria. Tel.: +43 14016036251.
E-mail addresses: sebastian.poledna@meduniwien.ac.at (S. Poledna), jmolina@banxico.org.mx (J.L. Molina-Borboa), smartin@banxico.org.mx (S. Martínez-Jaramillo), m.j.vanderLeij@uva.nl (M. van der Leij), stefan.thurner@meduniwien.ac.at (S. Thurner).

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and Geanakoplos, 2008; Geanakoplos, 2010; Adrian and Shin, 2008; Brunnermeier and Pedersen, 2009; Thurner et al., 2012; Caccioli et al., 2012; Poledna et al., 2014; Aymanns and Farmer, 2015). The fear of cascading failure is generally believed to be the reason why institutions under distress are often bailed out at tremendous public cost (Klimek et al., 2015). On the regulators' side, in response to the financial crisis of 2007–2008, broader attention is now directed to SR. A consensus is emerging on the need for a new financial regulatory system including a potential redesign of the financial sector (Aikman et al., 2013). In the regulatory framework of Basel III currently under discussion the importance of networks is recognized (Bank for International Settlements, 2010; Georg, 2011).

These developments have spurred research on SR and financial networks. It has been shown that the topology of financial networks can be associated with probabilities for systemic collapse (Haldane and May, 2011; Roukny et al., 2013). In particular, network centrality measures have been identified as appropriate measures for quantifying SR according to various groups (Boss et al., 2004; Puhr et al., 2012; Markose et al., 2012; Caballero, 2012; Billio et al., 2012; Minoiu et al., 2013; Thurner and Poledna, 2013). A disadvantage of centrality measures is that the SR value for a particular node has no clear interpretation as a measure for expected losses in the case of a cascading failure event. A variant of a centrality measure that solves this problem is the so-called *DebtRank*, which is a recursive method of quantifying the systemic relevance of financial nodes in terms of losses Battiston et al. (2012). This improvement, achieved by the DebtRank, has inspired recent work on financial SR, involving real data (Poledna and Thurner, 2014) and agent-based models (Thurner and Poledna, 2013).

Despite the tremendous importance of SR and the research efforts devoted to the topic, there are to date no reliable quantitative indices that quantify SR on a *national* and *temporal* basis. Indices that have sometimes been used to estimate SR in markets – such as volatility indices (like VIX), or spreads of credit default swaps (such as CDX) – are poor proxies because they are clearly incapable of taking cascading defaults into account. As a consequence these proxies greatly underestimate the true levels of SR in economies.

In this work we develop a number of potentially practical methods to quantify SR in financial multi-layer networks. First, we extend the notion of systemic importance in financial networks to multi-layer networks. This makes it possible to assess SR contributions from various layers of financial networks. Second, we develop a risk measure to quantify the expected loss due to SR, that takes cascading into account by explicit use of financial network topologies on a daily scale. This risk measure extends the notion of systemic importance to a national level and allows us to compare the SR levels of economies over time and to identify trends and historical events. In this sense the measure can be used as an indicator or an SR index. In particular it makes it possible to compare SR levels and their related potential costs before and after the recent crisis. Third, building on the work of Poledna and Thurner (2014), we use the risk measure to quantify the marginal contribution of individual exposures in financial networks to the overall SR. This allows us to extend the notion of systemic importance from financial institutions to individual exposures. In particular it allows us to quantify the expected loss due to SR associated with every individual exposure of financial institutions.

This work is based on a unique data set containing various types of daily exposures between the major Mexican financial intermediaries (banks) over the period 2004–2013 (for this work we use data from 2007 to 2013). Data were collected and are owned by the Banco de México and various aspects of the data have been extensively studied (Martínez-Jaramillo et al., 2010, 2014; López-Casta nón et al., 2012). Here we focus on banks that interact simultaneously in four different markets, generating four different types of exposures: (unsecured) interbank credit, securities, foreign exchange, and derivative markets. Hence, institutions are connected by four different types of contract. Different contract types can be seen as distinct network layers. A collection of various networks linking the same set of nodes is called a multi-layer or *multiplex network*. The interplay of the various exposure networks can be represented as layers in a financial multi-layer network. The data further contains the capitalization of banks for every month. With this data we quantify the SR contributions of the individual layers and estimate the mutual influence of one layer of exposures on the others.

We obtain a series of practically relevant results. First, we show that focusing on a single exposure layer individually underestimates the total SR by up to 90%. When focusing on all the layers, we find an intriguing non-linear effect that the sum of SR from all layers underestimates the total SR. Second, we show that market-based SR indicators systematically underestimate expected systemic losses. Third, we find that current expected systemic losses are up to a factor of four higher now than they were before the financial crisis of 2007–2008. Fourth, we find that SR contributions of individual transactions can be up to a hundred times higher than the corresponding credit risk, which creates huge risks for the public.

The method presented here is the first objective, data-driven quantification of SR on national scales that reveals its true levels on a temporal basis.

2. Related literature

Our work contributes to existing literature on SR and financial multi-layer networks. In recent years, several contributions to the statistical understanding of multi-layer networks and their dynamics have appeared in a broad and general context (Szell et al., 2010; Nicosia et al., 2013; Kim and Goh, 2013). Network similarity measures, node- and link correlations, and link-overlap measures have especially turned out to be useful tools for identifying and quantifying interactions between layers (Nicosia et al., 2013; Kim and Goh, 2013; Szell et al., 2010). The various layers of a financial multi-layer network comprise credit (borrowing-lending relationships consisting of counterparty exposures and implicit relationships, such as rollover of overnight loans), insurance (derivative) contracts, collateral obligations, and the market impact of overlapping asset portfolios and network of cross-holdings (holding of securities or stocks of other banks). Research on financial networks has mainly focused on a single layer: mostly, on direct lending networks between financial institutions (Upper and Worms, 2002; Boss et al., 2004, 2005; Soramäki et al., 2007; Iori et al., 2008, 2015; Cajueiro et al., 2009; Bech and Atalay, 2010; Fricke and Lux, 2014), but also on the network of derivative exposures (Markose et al., 2012; Markose, 2012), and on the network of common asset exposures (Greenwood et al., 2015).

Research on financial *multi-layer* networks has only appeared recently. León et al. (2014) study the interactions of financial institutions on different financial markets in Colombia. Bargigli et al. (2013) study the interaction in the Italian interbank market between financial network layers of short- and long-term bilateral lending, both secured and unsecured. Bargigli et al. (2013) and León et al. (2014) are however not directly concerned with measuring SR.

Bluhm et al. (2014) consider an agent-based model of a multi-layer interbank network, incorporating different contagion channels – i.e., from common asset exposure, direct lending exposures, and fire sales. They are not concerned with the interaction between the individual layers. On the other hand, Montagna and Kok (2013) do consider the contribution of individual contagion layers to SR. Their agent-based model consists of three layers: long-term direct lending exposures, short-term direct lending exposures, and common asset exposures. Calibrating the model