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Assessing systemic risk due to fire sales spillover through maximum entropy network reconstruction☆

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ABSTRACT

Monitoring and assessing systemic risk in financial markets is of great importance but it often requires data that are unavailable or available at a very low frequency. For this reason, systemic risk assessment with partial information is potentially very useful for regulators and other stakeholders. In this paper we consider systemic risk due to fire sales spillovers and portfolio rebalancing by using the risk metrics defined by Greenwood et al. (2015). By using a method based on the constrained minimization of the Cross Entropy, we show that it is possible to assess aggregated and single bank's systemicness and vulnerability, using only the information on the size of each bank and the capitalization of each investment asset. We also compare our approach with an alternative widespread application of the Maximum Entropy principle allowing to derive graph probability distributions and generating scenarios and we use it to propose a statistical test for a change in banks' vulnerability to systemic events.

1. Introduction

After the recent troubled years for the global economy, in which two severe crises (the 2007 crisis of financial markets and the 2010 sovereign debt crisis) have put the whole economic system in dramatic distress, vulnerability of banks to systemic events is now the main focus of a growing number of investigations of the academic community. Simultaneously, many research efforts are devoted to understand the role of banks or, broadly speaking, of financial institutions in the creation and in the spreading of systemic risk. Given the prominent importance of the topic and its multifaceted nature, the literature on evaluation and anticipation of systemic events is huge (see Allen et al., 2012; Arnold et al., 2012; Barrell et al., 2010; Bisias et al., 2012; Demirgüç-Kunt and Detragiache, 1998; Duttagupta and Cashin, 2011; Harrington, 2009; Kaminsky and Reinhart, 1999; Kritzman et al., 2011; Merton et al., 2013; Oet et al., 2013; Scheffer et al., 2009; 2012, among many contributions).

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Several are the channels through which financial distress may propagate from one institution to another and, eventually, affect a vast portion of the global economy. Fire sales spillovers due to assets' illiquidity and common portfolio holdings are definitely one of the main drivers of systemic risk. Shared investments create a significant overlap of portfolios between couples of financial institutions. Such (indirect) financial interconnectedness is an important source of contagion, since partial liquidation of assets by a single market player is expected to affect all other market participants that share with it a large fraction of their own investments (see Caccioli et al., 2014; Corsi et al., 2016; Huang et al., 2013; Lillo and Pirino, 2015). Fire sales move prices due to the finite liquidity of assets and to market impact. In a perfectly liquid market there will be no fire sale contagion at all (see Adrian and Shin, 2008, for a review on the role of liquidity in financial contagion). Finally, leverage amplifies such feedbacks. In fact, as described in detail by Adrian and Shin (2010, 2014), levered institutions continuously rebalance their positions inflating positive and, most importantly, negative assets' price variations.

Assessing and monitoring systemic risk due to fire sales spillover is therefore of paramount importance for regulators, policy makers, and other participants to the financial markets. Greenwood et al. (2015) introduced recently a stylized model of fire sales, where illiquidity, target leverage, and portfolio overlap are the constituent bricks. They used the model to propose two systemic risk metrics: systemicness and vulnerability of a bank. Given a market shock, the first is the total percentage loss induced on the system by the distress of the bank, whereas the second is the total percentage loss experienced by the bank when the whole system is in distress. In order to compute these quantities, a full knowledge of the portfolio composition of all banks is needed, because the systemicness and vulnerability of a bank depends on the portfolio and leverage of the other banks.

Greenwood et al. (2015) applied their method to the European Banking Authority (EBA) data that resulted from the July 2011 European stress tests. These data provide detailed balance sheets for the 90 largest banks in the European Union. Duarte and Eisenbach (2013) exploited a publicly available dataset of balance sheets of US bank holding companies to apply the framework of Greenwood et al. (2015). They derive a measure of aggregate vulnerability that *[...] reaches a peak in the fall of 2008 but shows a notable increase starting in 2005, ahead of many other systemic risk indicators*.

In general, however, the detailed information set required to compute such systemic risk indicators might not be available. For example European stress test data are sporadic. Moreover the sampling frequency of balance sheet data is rarely higher than quarterly. Thus an important question is whether it is possible to estimate systemic risk due to fire sales spillovers in absence of data on portfolio composition of financial intermediaries.

Two possible approaches have been proposed in the literature. The first one (see, among others, Acharya et al., 2012; Adrian and Brunnermeier, 2011; Banulescu and Dumitrescu, 2015; Corsi et al., 2018) is purely econometric and it is typically based on publicly available data on price of assets and market equity value of publicly quoted financial institutions. Generically the method consists in estimating conditional variables, such as conditional Value-at-Risk or conditional Expected Shortfall. The econometric approach circumvents the unavailability of data on portfolio holdings, but pays this advantage with the introduction of a strong stationarity assumption: estimates based on the past information are assumed to be always good predictors of the future behavior of the system. Nevertheless, due to the nature of a global financial crisis, it is in the very moment of the onset of a period of distress that the stationarity assumption may fail to work properly. Moreover it is often restricted to publicly quoted institutions for which equity value are available at daily frequency.

A second possible approach[1], followed in the present paper, consists in inferring the matrix of portfolio holdings using only a reduced, but easily available, information set, and/or deriving a probability distribution for the portfolio weights according to some criterion. This is typically achieved summoning the *maximum entropy principle* which postulates that (Anand et al., 2013) *[...] subject to known constraints [...] the probability distribution that best represents our current knowledge and that is least biased is the one with maximal entropy*. The approach of Maximum Entropy, can be applied in at least two different ways that we distinguish clearly in the following, and is not new in systemic risk studies (Anand et al., 2013; Bargigli et al., 2015; Mistrulli, 2011; Musmeci et al., 2013; Squartini et al., 2013). It is widely used for inferring the structure of the interbank network when only data of total interbank lending and borrowing for each bank (plus possibly other information) are available (for a comparison of different methods, see Anand et al., 2017; Gandy and Veraart, 2016).

The seminal contribution by Mistrulli (2011), comparing the empirical Italian interbank network with that reconstructed via a Maximum Entropy optimization procedure, has shown that the latter is fully connected while the former is very sparse (see also Mastromatteo et al. (2012)) and, as a consequence of this misestimation, the reconstructed network underestimates the risk contagion[2]. Recently a comparison of network reconstructions techniques has been carried out also for bipartite networks (Ramadiah et al., 2017).

A part from network reconstruction, the use of entropic methods is widespread in economic sciences. For example, it is widely used in econometrics for the estimation of probability densities, as it is witnessed by a vast stream of contributions in this direction (see, among others, the contributions by Chen, 2015; Kouskoulas et al., 2004; Park and Bera, 2009; Ryu, 1993; Usta and Kantar, 2011; Wu, 2003; Zellner and Highfield, 1988). An interesting point of comparison for our paper is the

[1] There are, of course, many different approach to assess systemic risk in financial networks. For example, Amini et al. (2013) propose a rigorous asymptotic theory that allows to predict the spread of distress in interbank networks.

[2] A complementary method is proposed by Anand et al. (2015). Here the authors reconstruct the network of bilateral exposures for the German banking system via the matrix that, preserving some constraints, has the minimum density. Nevertheless, if cross entropy method underestimates systemic risk by overestimating the network density, Anand et al. (2015) show that, for a similar reason, minimum density returns positively biased estimates. Hence, the two approaches can be used jointly together to create a corridor in which the true systemic risk should lay.