

Stability analysis of financial contagion due to overlapping portfolios

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Extended abstract

The 2007–2009 financial crisis highlighted the complex interconnections between financial institutions and made it clear that we need a better understanding of how financial contagion propagates and the circumstances under which it is amplified [1, 2, 3, 4, 5, 6, 7, 8, 9]. Financial contagion comes through different channels, including *(i)* counterparty risk, *(ii)* roll-over risk, and *(iii)* common asset holdings, i.e. *overlapping portfolios*. Of these the first two have so far received the most attention, even though the primary problem is believed by many to have been due to the third. Our goal in this paper is to remedy this by gaining a better understanding of the problem of overlapping portfolios.

The idea behind financial contagion due to overlapping portfolios is very simple: Suppose two banks B_1 and B_2 invest in the same asset A and that B_1 is forced to liquidate its position on the common asset. Because of market impact, the liquidation process causes a devaluation of the asset A and therefore bank B_2 suffers a loss. If the loss experienced by B_2 is bigger than its equity, the bank defaults and is forced to liquidate its portfolio of investments. This liquidation will cause losses to other banks, and global cascades of failures may occur.

To study this contagion mechanism, we consider a model where the financial system is described in terms of a bipartite networks of banks and assets. Whenever a bank invests in an asset, we draw a link in the network connecting that bank to that asset. We then implement the simple contagion mechanism described above on this bipartite network.

The model we consider is purely mechanistic, i.e. we do not attempt to describe decision-making processes by banks. The underlying assumption is that, during the development of a crisis, banks do not have time to deleverage or rebalance their portfolios before failing. Thus we consider portfolios fixed until default occurs, and assume that they are fully

liquidated when it occurs. We then perform a macroprudential stress test by applying localized shocks affecting either a single bank or a single asset. After the initial shock is applied we test to see whether it causes any bank failures; if so we iterate the process as needed until either there are no more failures or all banks have failed. The only trades during the course of the dynamics are fire sales of the assets of insolvent banks.

The stability of the system is measured in terms of the probability of observing a global cascade of failures, and we are interested in understanding how this depends on parameters like average banks' diversification and leverage.

We find that as the diversification of the banks' portfolios increases, the system undergoes two phase transitions, with a region in between where global cascades occur. Below the first transition, banks are not interconnected enough for shocks to propagate in the network. Above the second transition, banks are robust to devaluations in a few of their assets. In between these two transitions, banks are both vulnerable to shocks in their asset prices, and interconnected enough for these shocks to spread. We also find that more leverage increases the overall instability of the network and that the system exhibits a "robust yet fragile" behavior, with regions of parameter space where contagion is rare but the whole system is brought down whenever it occurs.

In addition to present results of numerical simulations, using an analytical approach based on generalized branching processes on networks we are able to analytically estimate the region of parameter space where global cascades occur. This branching process is different from standard ones in the fact that the fate of a node depends on its degree and on the degree of all its neighbors. This greatly increases the difficulty of the problem. We are nonetheless able to solve it by generalizing existing methods.

The mechanistic model considered in this paper can be extended in several directions. First of all, it would be interesting to relax some of the specific assumptions considered in this paper (homogeneity of banks' balance sheets, Poisson degree distributions, market impact function) in order to understand how different choices for the network topology or the statistical properties of balance sheets impact the stability of the system. Although we do not expect different results from a qualitative point of view, it should nonetheless be possible to assess the relative stability of systems with different properties, similarly to what has been done for counterparty loss in [9]. In particular, it would be very useful to empirically characterize real systems and calibrate the model with real data. In fact, one advantage of this mechanistic approach is that it can in principle be calibrated against real data and used to perform stress tests on real financial systems. This could potentially make it possible to test the effectiveness of new policies aimed at reducing systemic risk.

A further direction we plan to pursue in the future is to go beyond the mechanistic model by considering a more realistic price dynamics and allowing banks to react to price fluctuations by rebalancing their portfolios. This should allow the system to develop endogenous crisis similar to the ones observed in [10], and to generate the systemic instabilities induced by leverage and mark-to-market accounting practices discussed in [11].

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