1 Informational contagion

1.1 Contagion between markets

Informational contagion refers to the process whereby information about one market has an impact on another market. The study of informational contagion did not originally require the use of an explicit network, but the concept of a network is a natural framework for the study of informational contagion. Two of the earliest studies, Kodres and Pritzker (2002) [KP] and Pavlova and Rigobon (2008) [PR], illustrate the network structure that is implicit in the study of informational contagion.

[KP] make use of the familiar rational expectations model of financial markets, in which private information is aggregated in asset prices. They consider a model consisting of two asset markets, A and B, and that traders in one market can observe the asset prices in both markets. The presence of noise traders prevents prices from revealing information perfectly. In fact, prices will reflect a combination of noise and fundamentals. The fundamental values of the assets in the two markets are affected by a combination of common and market-specific shocks. Traders in market A, observing changes in the prices of assets in market B, will try to infer information that is relevant to the valuation of assets in market A. In this way, an increase in prices in market B may cause prices to rise in market A if traders infer that the price increases in market B are due to a common shock that has raised fundamental values in both markets. Since prices do not reveal information perfectly, traders in market A may be fooled by price increases in market B that result either from noise trading or from fundamental shocks that are irrelevant to market A. Thus, the spillover from market B to market A may be unjustified by the information originally received by traders in market B.

Now suppose that there are three markets, A, B, and C, and that A and B have a common factor, B and C have a common factor, but that A and C have no factors in common. Contagion is possible between A and B and between B and C for the usual reasons explained above. What is more surprising is that portfolio rebalancing allows financial contagion between market A and market C. Even if there is no information asymmetry in market B and no market specific shock, a shock to market A will spillover to market B and affect prices there. These price changes will be interpreted as the result of a shock common to B and C and will thereby influence prices in market C.

In the simplest cases, the idea of a network structure is almost superfluous, but if one thinks of a larger number of markets, for example, capital markets in different countries, the network concept arises quite naturally. Suppose the markets are indexed by $i = 1, ..., m$ and the factors affecting asset values are indexed by $j = 1, ..., n$. Each market i is affected by a set of factors $J(i)$. A pair of markets i_A and i_B will share some common factors $J_{i_A} \cap J_{i_B}$ but each will also be affected by specific factors $J_{i_A} \backslash J_{i_B}$ and $J_{i_B} \backslash J_{i_A}$ that do not directly affect the other. Two markets i_A and i_B are directly connected if $J_{i_A} \cap J_{i_B}$ is non-empty. Of course, the "connection" between two markets is more complicated than the existence of an edge between two nodes in a graph, but the analogy is clear.

[PR], like [KP], use the rational expectations framework, but seek to show how informational contagion can affect economies that have no common shocks. They illustrate this idea with the Brazilian financial crisis that followed the Russian default of 1998. The link between the apparently unrelated crises in Russia and Brazil was the New York market, which was linked to both. The Russian default caused New York banks to adjust their portfolios because of institutional constraints designed to control risk exposures. This reallocation of wealth in turn caused changes in prices in the Brazilian market that signalled a bad shock. Here the network is salient: New York constitutes the **centre** of the network and Brazil and Russia represent two **peripheral** nodes.

These two papers also illustrate the difference between **pure information externalities** and **payoff externalities.** In [KP] there is a pure informational externality: the actions of traders in market B do not affect the payoffs of traders in market A. The only reason that traders in market A pay attention to the actions of traders (or prices) in market B is because of the information those actions (or prices) reveal. In [PR], on the other hand, the actions of the traders in New York have a direct affect on the traders in Brazil, through their effect on prices, in addition to the information revealed by the change in prices. Pure information externalities are somewhat unusual in economics, but they are characteristic of models of herd behavior (Banerjee, 1992; and Bikhchandani, Hirshleifer and Welsh, 1992). In those models, a sequence of agents chooses a discrete action after observing a private signal. One can think of the sequence of agents as forming a kind of network in which agent $N+1$ observes the actions of agents $n = 1, ..., N$, but not their private information. The discrete action chosen by preceding agents is a course signal of their private information and this makes possible informational cascades, in which agents ignore their private information and follow their predecessors, and herd behavior, in which agents choose the same action indefinitely. These ideas have also been applied in market settings. Avery and Zemsky (1998) have shown that the informational role of prices can prevent the occurrence of informational cascades and incorrect herds. Cipriani and Guarino (2008a, 2008b) have found conditions under which cascades can exist in financial markets (this requires transaction costs or gains from trade) and showed that contagion may occur between asset markets (information revealed by prices in one market may cause a cascade in another market).

In [KP] and [PR], traders are assumed to observe prices in all markets, but prices are not perfectly revealing because of the presence of noise. Other writers assume that agents in one location can only observe a subset of other locations. Examples include Gale and Kariv (2003), Acemoglu, Dahleh, Lobel and Ozdaglar (2011), and Mueller-Frank (2013). This literature is discussed in the chapter by Golub and Sandler, in this volume.

1.2 Contagion between banks

Informational contagion between banks has been explored in settings that do not call for an explicit network structure. One example is the paper by Ahnert and Georg (2012), in which the release of bad information about one bank provides information about other banks, because of common asset holdings and common counterparty exposures. The paper by Ahnert and Bertsch (2014) makes use of a different type of contagion, the "wake up call." Bad information about one bank causes depositors to obtain costly information about another bank, because the depositors suspect a common shock. Even if it transpires that the second bank was not subject to a common shock, the information revealed about the second bank may, coincidentally, provoke a run. Thus, even in the absence of a common shock, there is informational contagion.

These models, like those of [KP] and [PR] are interesting because they provide an account of informational contagion between banks, but they do not make use of an explicit network. It is easy to see how these informational contagion channels could be embedded in a network framework to give a richer account of financial contagion. Two examples of financial contagion in networks are described next.

Caballero and Simsek (2013) have exploited an explicit network formulation to show how informational contagion can amplify the mechanical contagion that results from counterparty exposures. Imagine a sequence of banks, indexed by $i = 1, ..., m$, arranged in a circular network. Bank i owes one unit to bank $(i-1) \bmod m$. Banks are funded by deposits and capital (equity) and the latter allows banks to suffer some losses without failing. If bank i fails completely (its assets become worthless), it cannot pay what it owes bank $i-1$. Then bank $i-1$ can pay bank $1-2$ the amount $\min\{1, e\}$, where e represents the bank's equity, bank $i-2$ will be able to pay bank $i-3$ the amount $\min\{\min\{1, e\} + e, 0\}$ and so on. If bank k is far enough away from bank i so that $(i-k+1)\, e \geq 1$,[1] it will receive the full amount and bank k will not fail. Thus, a complete failure of bank i only causes limited contagion within the network.

Now suppose that all banks know that some bank has failed completely but the identity of the failing bank is unknown. Then every bank will have a positive probability of being hit by the contagion and failing. In fact, if the probability distribution of any bank failing is unknown and depositors have an extreme form of uncertainty aversion, they may assume the worst case, i.e., that bank i is close to the failing bank and will also fail. In effect, uncertainty aversion collapses the network, making the failed bank every bank's neighbor.

Alvarez and Barlevy (2014) [AB] have undertaken a more complex and nuanced analysis of uncertainty about the location of bad banks. In their analysis, banks are randomly assigned to locations on a network. Some of the banks are bad banks, which have received a shock that makes it impossible for them to repay their debts in full. Other banks have not received such a shock but may have counterparty exposure, directly or indirectly, to one of the bad banks. As in [CS], bank i's exposure depends on the distance between bank i and the nearest bad bank. The complexity of the analysis derives partly from the generality of the networks considered and the difficulty of characterizing the distribution of good and bad banks. Each of the good banks has an investment option that can produce enough revenue to keep the bank solvent but it requires investment that has to be externally funded. The problem is that, because of the uncertainty of the location of good and bad banks, the debt overhang discourages investors from investing in the good banks. [AB] show that, under certain conditions, mandatory disclosure of banks' financial condition can permit some banks

[1] The contagion ends at bank k if bank $k-1$ can repay its debt in full and banks $k-2, ..., i$ cannot. In that case, bank $k-1$ can pay at most $(i-k+1)\, e$ and k will not fail if and only if $(i-k+1)\, e \geq 1$.

to obtain external funding and return to solvency, whereas non-disclosure ensures that none will receive the new investment they need to survive.

These two examples illustrate how financial contagion depends not only on the network structure but also on the banks' knowledge and beliefs about that structure. This suggests that providing information about or ensuring the transparency of the network structure, may be a useful regulatory tool.

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