On the Epidemic of Financial Crises

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Outline of this talk

- Introduction to Financial Contagion
- Modelling Framework: Stochastic Epidemics
- Likelihood and Inference
- Application to Currency Crises
- Policy Implications
- Extensions
- Conclusion

Financial Crises Literature

- A financial crisis originating in one country can travel within and beyond its original neighbourhood spreading among countries like a contagious disease.
- Contagion by definition can only occur if there are interactions among subjects. Interactions can materialise at different levels and via numerous channels.
- Literature broadly distinguishes between
  - Fundamentals-based contagion (transmission of a crisis through real and financial linkages, spillovers)
  - Pure contagion (a crisis might trigger additional crises elsewhere for reasons unexplained by fundamentals)
- Any discussion of the appropriate policy response must be based on an analytical understanding of the contagion mechanism given by a model of that phenomenon.
- Literature is replete with theoretical models highlighting the motives for and dynamics of crises and potential channels of contagion

Empirical research on contagion

- Identifying existence of contagion: Bulk of literature suggests that there is evidence of contagion.
- Studies that focus on the propogation mechanism of crises:
  - Cross country (probit/logit) regressions of a crisis index on variables representing trade or financial links, economic situation
  - Regressions of the change in some crisis indicator on the average crisis in all other countries as well as weighted crisis elsewhere
  - Some hidden Markov Modelling on continuous responses (e.g. log-returns)
- Potentially important transmission channels:
  - Trade links
  - Financial links
  - Neighborhood effects
  - Macro similarities

Empirical research on contagion

- Common to the above studies:
  - Absence of direct modelling of the inherent dependencies in the transmission mechanism
  - No canonical measure of the crisis severity
  - No naturally implied control mechanism

- This work:
  - Propose a novel modelling framework to analyse contagion
  - Approach based on a stochastic epidemic process where the population of countries is explicitly structured
  - Model explicitly regional and global contagious contacts and infer the rate of their transmission
  - Directly quantify the severity of the crisis episode
  - Allow for 'cascading effects', Glick and Rose (1999)
  - Naturally accounts for an increase in the likelihood of a crisis in a specific country given a crisis elsewhere (definition of contagion in Eichengreen et al 1996, Kaminsky and Reinhart, 2000)

Two-level mixing models (Small-world, Metapopulations)

- Real-life populations do not mix homogeneously
- Population size N partitioned into 'local contact' groups (eg geographical regions, sectors...)
- Close contacts locally (globally) with rate λ_L ($\frac{\lambda_G}{N}$)
- A threshold parameter R_* can be derived by considering a branching process in which 'individuals = groups'
- Then $R_* = \lambda_G E(I) v(\lambda_L)$ and the process may explode if and only if $R_* > 1$. $v(\lambda_L) = \frac{\sum_s s\mu_s\pi_s}{\nu}$ is the average local final size if only local infections permitted, s : size of each region, μ_s : local final size (within a group of size s), π_s : proportion of groups with size s

Data and likelihood

- We have a model with parameters λ_L, λ_G
- The data are $\mathbf{x} = \{x_{ij}\}$ where x_{ij} denotes the number of regions within which i out of j countries suffered the crisis in question
- Posterior density: $\pi(\lambda_L, \lambda_G | \mathbf{x}) \propto \pi(\mathbf{x} | \lambda_L, \lambda_G) \pi(\lambda_L, \lambda_G)$
- The likelihood $\pi(x|\lambda_L, \lambda_G)$ is computationally intractable
- Data augmentation (D & O'Neill 2005): work with $\pi(\lambda_L, \lambda_G, G|x) \propto \pi(x|\lambda_L, \lambda_G, G)\pi(G|\lambda_L, \lambda_G)\pi(\lambda_L, \lambda_G)$ s.t. $\pi(x|\lambda_L, \lambda_G, G)$ and $\pi(G|\lambda_L, \lambda_G)$ are both tractable.
- What is G?

Random Graphs

- Focus only on the *final outcome*, i.e. 'who gets infected'
- Consider a directed graph in which vertices $\leftrightarrow$ individuals, vertex j has (independent) links with probability $1 - \exp(-\lambda_L I_j); 1 - \exp(-\lambda_G I_j / N)$
- Then $\pi(GC) = \pi(\mathbf{x})$ where GC is the 'giant component'.
- MCMC:
  - Updating λ_L, λ_G is standard, update the I_j's in small blocks
  - Update G by proposing to add/delete edges.
  - G offers 'convergence-diagnostic'

Application to Currency Crises

- Cross-sectional binary final outcome data of Glick and Rose (1999).
- Group the countries into regions based on UN classification.
- ($\leq$)160 countries for five different currency episodes:
  - 1971: Breakdown of the Bretton Woods System
  - 1973: Collapse of the Smithsonian Agreement
  - 1992: EMS crisis
  - 1994: Mexican Meltdown and Tequila Effect
  - 1997: Asian Flu

Posterior Summaries from 2LM Model using the RG method

individuals	$\leftrightarrow$	countries
groups	$\leftrightarrow$	regions

	Parameters		
Episode	λ_L	λ_G	$\frac{\lambda_G}{N\lambda_L+\lambda_G}$
1971	0.445(0.239,0.738)	0.297(0.093,0.618)	0.005(0.001,0.013)
1973	0.349(0.164,0.574)	0.446(0.169,0.868)	0.010(0.003,0.027)
1992	0.018(0.000,0.066)	1.019(0.487,1.731)	0.381(0.073,0.932)
1994	0.013(0.000,0.047)	1.043(0.516,1.777)	0.456(0.102,0.955)
1997	0.011(0.000,0.041)	1.068(0.617,1.616)	0.491(0.127,0.958)

where Ratio $= \frac{\lambda_G/N}{\lambda_L+\lambda_G/N}$ is the ratio of global/(local+global) rate.

- Shift from local to global spread
- Knowledge of initial 'infective' not crucial
- 1m MCMC iterations $\sim$ 2 minutes

Policy Implications

- Vaccination coverage: Number of countries (for World Bank, IMF) to support for 'herd immunity' ($P(R_* < 1) \geq 0.95$).

- Threshold without support: $R_* = \frac{\lambda_G E(I)}{v} \sum_s s\mu_s \pi_s$
- With support: $R_* = \frac{\lambda_G E(I)}{v} \sum_s s\mu_s \sum_{r \leq s} \pi_r \binom{r}{s} (1-v)^s v^{r-s}$

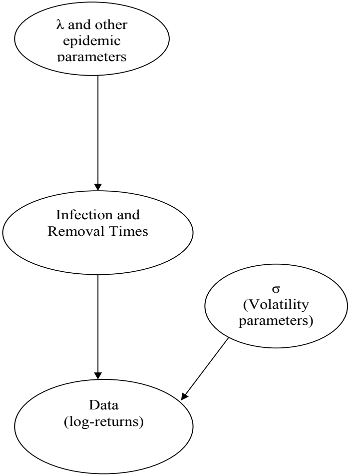
	Parameters		
Crisis Episode	R^*	$P(R^* < 1)$	p_v
1971	2.186(0.674,4.610)	0.094	0.291(0.034,0.523)
1973	2.046(0.602,3.632)	0.115	0.265(0.029,0.513)
1992	1.242(0.525,2.425)	0.325	0.240(0.016,0.508)
1994	1.194(0.568,2.170)	0.356	0.230(0.015,0.504)
1997	1.200(0.665,1.938)	0.293	0.210(0.011,0.443)

- The $R_* > 1$ assumption (common in classical inference) not appropriate

Extensions

- Extension to categorical covariates (developed/developing countries):
  - There are important differences between developed and developing countries.
  - R_* and control measures still available, but more involved.
  - Identifiability restrictions in global (and sometimes local) rates.
- Can construct the population network based on information regarding financial links/trade links/macroeconomic similarities (Gai and Kapadia 2010 use exposure to construct a banking network and then propose a percolation model).
- More generally, use covariates ($\lambda = \lambda_0 \exp(\alpha x)$): preliminary results suggest that trade links are important
- Consider temporal data, how?

A Hidden Epidemic Model



Future Work

- We use geographical location to partition countries within groups, other partitionings could be explored.
- Alternative support policies / partial coverage $\rightarrow$ optimisation problem
- Non-independent 'infectious periods'. Does it matter? $\left(\frac{dI}{dt} = \lambda S(t)I(t) - \gamma I(t) - \delta I(t)R(t)\right)$