Friends in Joy and Sorrow:

Analysis of 2007-2012 Global Financial Crisis via Bayesian Nonparametric Dynamic Networks

Daniele Durante &
David B. Dunson
durante@stat.unipd.it,
dunson@duke.edu

University of Padua, Duke University

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Key facts behind financial crisis

"the crisis [...] was caused by: widespread failures in financial regulation, [...] dramatic breakdowns in corporate governance [...]; explosive mix of excessive borrowing risk [...]; key policy makers ill prepared for the crisis [...]"

2004	2005	2006	2007	2008	2009	2010	2011	2012

United States Housing Bubble

- Low Interest Rate: Fed "needs to create a housing bubble to replace the Nasdaq bubble"
- Saving Glut: growing demand for financial assets by foreign countries with high savings rates
- Originate and Distribute banking model: creation of securities of great complexity (CDO, RMBS)
- Inflation: underestimation of the risk of mortgage caused by optimistic forecasts

Global Financial Crisis

- "A housing crisis approaches": subprime borrowers unable to repay their mortgage
- Vicious Cycle: Owners holding negative equity motivated to default on their mortgages
- Financial Interconnection: "The U.S. economy has been spending too much and borrowing too much for years and the rest of the world depended on the U.S. consumer as a source of global demand."
- Contagion: development and spread of the crisis to the global recession, which affected the entire world economy and finance

European Debt Crisis

- Debt Pressure: transfer of private debts to the already high sovereign debt as a result of banking system bailouts
- Eurozone Monetary Union: impossibility for some countries to re-finance their government debt
- PIIGS: main difficulties for Greece, Ireland, Portugal, Spain, Italy
- Policy Responses: austerity measures and material bailout investments by the Eurozone institutions

Statistical answers to financial crisis

Available via multivariate time series analysis aimed at exploring co-variations and interconnection structures among financial markets.

Focus on $R_t = [r_{1,t}, \ldots, r_{V,t}]^T$, $t \in \mathcal{T} \subset \Re^+$

- **VAR models** (Longstaff, 2010)
- **VEC models** (Gentile and Giordano, 2012)
- **Bayesian Stochastic Volatility models** (Kastner et al., 2013)
- **LAF models** (Durante et al., 2013)
- **Dynamic Matrix Factorization** (Sandoval and De Paula, 2012)

Main Findings: useful overviews on the temporal and geo-economic changes in world financial markets, showing how high volatility phases are directly linked with increasing levels of interdependence.

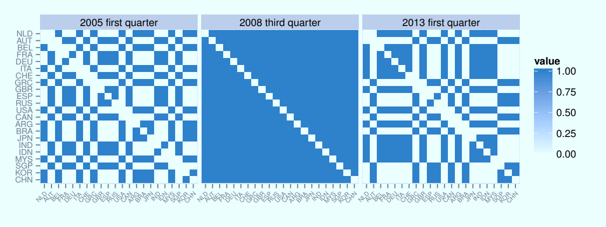
As friends moving together $\longrightarrow$ financial networks

Financial networks provide insight into the factors driving market behavior. Focus on the sequence of $V \times V$ (in our application $V = 22$) dynamic adjacency matrices Y_t, $t \in \mathcal{T}$, measuring similarities among national stock market indices.

Co-movement as relational data (using quarter log-returns from *Yahoo Finance*)

- $y_{ij,t} = y_{ji,t} = 1 \longrightarrow r_{i,t} > 0$ and $r_{j,t} > 0$, or $r_{i,t} < 0$ and $r_{j,t} < 0$
- $y_{ij,t} = y_{ji,t} = 0 \longrightarrow r_{i,t} > 0$ and $r_{j,t} < 0$, or $r_{i,t} < 0$ and $r_{j,t} > 0$

Responce Co-movement network Y_t



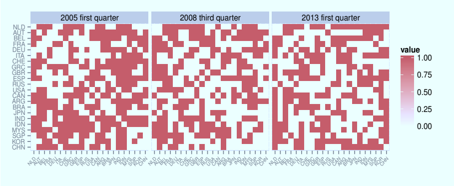
Including time-varying predictors using *GDELT*

Aim: Learn the effect of substantial increments in material and verbal cooperation on co-movements.

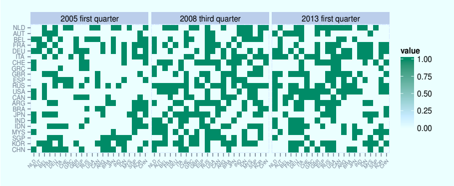
Definition of binary predictors:

1. Focus on the subset of important relations. (`IsRootEvent`)
2. Difference between number of cooperation and conflict events among each couple of countries and time. (`QuadClass`)
3. Compute standardized first differences.
4. ‘Substantial’: increment greater than the mean of all standardized first differences at time t.

Material Cooperation $Z_{m,t}$



Verbal Cooperation $Z_{v,t}$



Bayesian nonparametric longitudinal network model

Aim: provide a quantitative overview on the dependence structure among the main financial markets during the global financial crisis and estimate the effects of verbal and material cooperation efforts on such relationships.

$$y_{ij,t} \mid \pi_{ij}(t) \quad \sim \quad \text{Bern}(\pi_{ij}(t)) \quad t \in \mathcal{T}, \tag{1}$$

independently for each $i = 2, \ldots, V$ and $j = 1, \ldots, i-1$, with

$$\pi_{ij}(t) = \frac{1}{1 + e^{-s_{ij}(t)}}, \quad s_{ij}(t) = \mu(t) + x_i(t)^T x_j(t) + z_{ij,t}^T \beta(t), \tag{2}$$

- $\mu(t)$: baseline process quantifying the overall propensity to form links
- $x_i(t) = [x_{i1}(t), \ldots, x_{iH}(t)]^T$: vector of latent coordinates of $i - th$ unit
- $z_{ij,t} = [z_{ijm,t}, z_{ijv,t}]^T$: edge specific indicator vector for the presence of a substantial material and verbal cooperation among units i and j, respectively
- $\beta(t) = [\beta_m(t), \beta_v(t)]^T$: corresponding dynamic coefficients

Model interpretation

$$S(t) = \underbrace{\mu(t)1_V1_V^T}_{1} + \underbrace{X(t)X(t)^T}_{2} + \underbrace{\beta_m(t)Z_{m,t} + \beta_v(t)Z_{v,t}}_{3} \qquad (3)$$

1. Overall measure of denseness common to all units.
2. Measure of similarity in the latent space $\rightarrow$ units with latent coordinates in the same direction are more similar.
3. Allows the proximity between units i and j at time t to depend also on predictors in a manner that varies smoothly with time.

Interpretation

Latent coordinates may represent investors expectations and unexpected inflation, respectively, favoring indices of countries with features in the same directions to co-move, and countries with opposite features to move in different directions. We also allow the presence of a significant increment in verbal or material cooperation relations among pairs of countries to further increase or decrease the co-movement probability proportionally to its corresponding time-varying coefficient.

Prior specification

$$\mu(\cdot) \sim \mathrm{GP}(0, c_\mu), \quad \text{with } c_\mu(t,t') = \exp(-\kappa_\mu ||t - t'||_2^2)$$

$$x_{ih}(\cdot) \sim \mathrm{GP}(0, \tau_h^{-1} c_X), \quad \text{with } c_X(t,t') = \exp(-\kappa_X ||t - t'||_2^2),$$

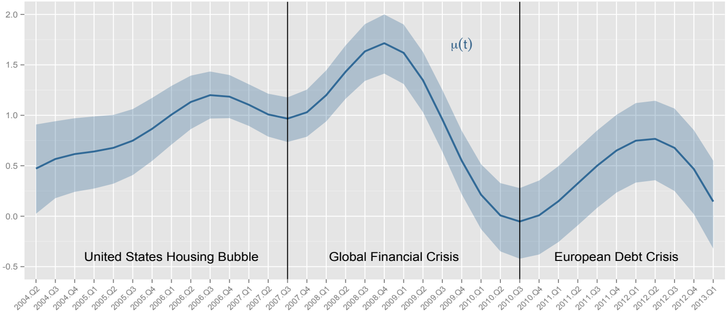
independently for $i = 1, \ldots, V$ and $h = 1, \ldots, H$, with τ_h^{-1} a shrinkage parameter

$$\tau_h = \prod_{k=1}^{h} \vartheta_k, \ \vartheta_1 \sim \mathrm{Ga}(a_1, 1), \ \vartheta_k \sim \ \mathrm{Ga}(a_2, 1), k \geq 2.$$

$$\begin{aligned} \beta_m(\cdot) &\sim \mathrm{GP}(0, c_m), \quad \text{with } c_m(t,t') = \exp(-\kappa_m ||t - t'||_2^2) \\ \beta_v(\cdot) &\sim \mathrm{GP}(0, c_v), \quad \text{with } c_v(t,t') = \exp(-\kappa_v ||t - t'||_2^2) \end{aligned}$$

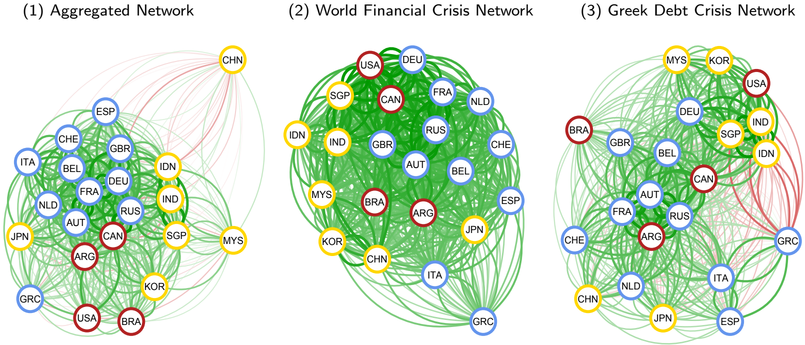
Posterior computation: simple Gibbs Sampler exploiting the recently developed Pòlya-gamma data augmentation scheme (Polson et al., 2013).

Baseline process → financial contagion effects



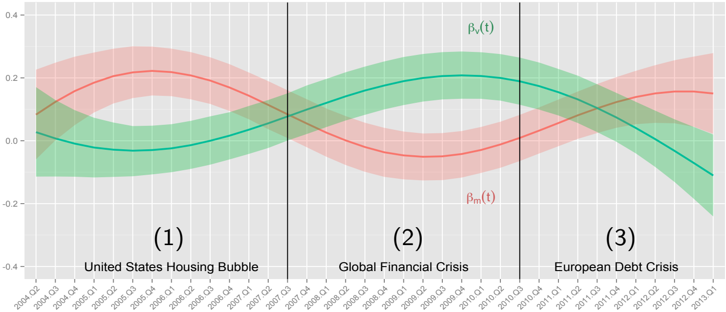
- Change of regime at the burst of the United States housing bubble
- Peaks of the overall co-movement propensity in correspondence to the global financial crisis and the European sovereign-debt crisis (financial contagion)

Some (fancy) estimated financial networks



1. Geo-economic proximity among countries manifested through tighter networks
2. Dense network during the global financial crisis → financial contagion effect
3. Greece shows low connection with all the other countries except Spain and Italy

Time-varying coefficients → new insights



1. $\beta_m(t) > \beta_v(t)$: in line with the "originate and distribute" banking model which stimulated large capital exchanges inflating the network of material relations
2. $\beta_m(t) < \beta_v(t)$: proliferation of meetings between governments and financial institutions, and the lack of material funds to invest in foreign markets
3. $\beta_m(t) \approx \beta_v(t)$: important material bailout investments by the Eurozone

Conclusion

The network lens

Developing statistical models to flexibly learn time-varying network structures, while inferring the effects of additional variables, is a key issue in many applied domains. It is increasingly common to have data available on dynamic networks and related node features. In addition, viewing data through a network lens can add substantial new insights, as we have illustrated in our finance application.

Future challenges we are working on (and *GDELT* represents a great data mine)

- Clustering and borrowing of information across different networks
- Structural equation models for network data
- Multivariate time series of networks
- Scalable methods for huge networks

Questions?

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