Friends in Joy and Sorrow:
Analysis of 2007-2012 Global Financial Crisis via Bayesian Nonparametric
Dynamic Networks

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"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 [...]"

- **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

- "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

- **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 \( R_t = [r_{1,t}, \ldots, r_{V,t}]^T, \ t \in T \subset \mathbb{R}^+ \)

- **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 → 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 $Y_t$, $t \in T$, measuring similarities among national stock market indices.

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

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

Response Co-movement network $Y_t$
Including time-varying predictors using \textit{GDELT}

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

\textbf{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 $t$. 

\begin{align*}
\text{Material Cooperation} & \quad Z_{m,t} \\
\text{Verbal Cooperation} & \quad Z_{v,t}
\end{align*}
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.

\[
y_{ij,t} \mid \pi_{ij}(t) \sim \text{Bern}(\pi_{ij}(t)) \quad t \in \mathcal{T},
\]

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

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

- \( \mu(t) \): 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

\[ S(t) = \mu(t)1_{\nu}1_{\nu}^T + X(t)X(t)^T + \beta_m(t)Z_{m,t} + \beta_v(t)Z_{v,t} \]  \hspace{1cm} (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

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

\[ x_{ih}(\cdot) \sim \text{GP}(0, \tau_h^{-1} c_{X}), \quad \text{with} \quad c_{X}(t, t') = \exp(-\kappa_{X}||t - t'||^2_2), \]

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

\[ \tau_h = \prod_{k=1}^{h} \vartheta_k, \quad \vartheta_1 \sim \text{Ga}(a_1, 1), \quad \vartheta_k \sim \text{Ga}(a_2, 1), \quad k \geq 2. \]

\[ \beta_m(\cdot) \sim \text{GP}(0, c_m), \quad \text{with} \quad c_{m}(t, t') = \exp(-\kappa_{m}||t - t'||^2_2) \]
\[ \beta_v(\cdot) \sim \text{GP}(0, c_v), \quad \text{with} \quad c_{v}(t, t') = \exp(-\kappa_{v}||t - t'||^2_2) \]

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

Time-varying coefficients $\rightarrow$ 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?


