Synchronization Patterns in the European Union

Guerini M., Luu D.T., Napoletano M.

OFCE Paris, 14 January, 2019

DRIC, OFCE-SciencesPo, France

Table of Contents

Motivation

We can be reasonably confident in the increasing integration of European countries, and in the fact that economic developments are becoming more and more correlated in the area. This has been highlighted, in the academic field, by several empirical investigations.

Moreover, EU countries' lower specialization compared to the United States or Canada reduces the risk of asymmetric shocks.

[Trichet, 2001]

Research Questions

What do we investigate?

- evolution of co-movements between EU economies in the past two decades
- comparison of synchronization and specialization
- origins behind co-movements

Why is it relevant?

- breakdown of one of the OCA conditions
- sub-optimality of common policies

$\Rightarrow$ might lower political support of the monetary union

Literature Review

Which data?

- Gross Domestic Product (GDP)
  - *pros*: low frequency, most inclusive
  - *cons*: too broad, misses high frequency variations
- Industrial Production (IP)
  - *pros*: high frequency and detail, high correlation with GDP
  - *cons*: only 25-30% of GDP, more volatile
- Final choice depends upon
  - data requirements of the employed method
  - time horizon of interest (long vs. short/medium)

Measuring Synchronization

Which measure?

- Bivariate correlations [Artis and Zhang, 1997]
- Concordance indexes [Harding and Pagan, 2002]
- Shock accounting [Centoni et al., 2007]
- Dynamic factor models [Del Negro and Otrok, 2008]
- Regime switching models [Leiva-Leon, 2014]

Synchronization patterns

How did synchronization evolve?

- Before and after 1979 European ERM creation debate:
  [Artis and Zhang, 1997] vs [Inklaar and de Haan, 2001]
- Pre-Euro period:
  increase synchronization in the 1990s according to
  [Camacho et al., 2006]
- Pre- and early-Euro periods:
  [Inklaar et al., 2008, De Haan et al., 2008] conclude for
  mixed evidence depending on data, measures, filters, ...

Synchronization origins

Why synchronization happens?

- Trade intensity hypothesis
  [Frankel and Rose, 1998, Baxter and Kouparitsas, 2005]
- Financial integration hypotheses
  [Imbs, 2004] vs. [Baxter and Kouparitsas, 2005]
- Common policy hypothesis
  [Rose, 2008] vs. [Barigozzi et al., 2014]
- Country vs. common foreign/internal shocks hypotheses
  [Clark and Shin, 1998, Centoni et al., 2007,
  Forni and Reichlin, 2001]

Methodology

Pre-processing

We begin from a row data matrix $\underset{N \times T}{\tilde{X}}$

We take a normalization for each row (i.e. for each country)

$$X_{i,t} = \frac{\tilde{X}_{i,t} - \mu(\tilde{X}_i)}{\sigma(\tilde{X}_i)} \tag{1}$$

We obtain a new data matrix $\underset{N \times T}{\mathsf{X}}$ with the two nice properties

- $\mu(X_i) = 0$
- $\sigma^2(X_i) = 1$

Correlation Matrices

Given the data in X, the correlation matrix between the different series is defined as:

$$\underset{N \times N}{\mathsf{C}} = \frac{1}{T}\mathsf{X}\mathsf{X}^T \tag{2}$$

with

- $C_{i,j} \in [-1, 1]$
- $C_{i,i} = 1$

Dividing the whole series in K rolling-windows of equal length T_w, we have K rectangular sub-matrices $\mathsf{X}(k)$ for $k = 1, \ldots, K$.

For each sub-matrix $\mathsf{X}(k)$ we compute the corresponding correlation matrix $\mathsf{C}(k)$

Similarity of correlation matrices

[Munnix et al., 2012] measured the similarity between the correlation at different time windows as

$$S(k,h) = 1 - E(|C(k) - C(h)|) \tag{3}$$

where k, h are two specific rolling windows.

A low level of S indicates a low similarity between two correlation matrices.

Random Matrix Theory - Empirical PDF

For a generic $\mathsf{C}(k)$ let $\{\lambda\}_N$ be the eigenvalues and $\{\mathsf{u}\}_N$ the associated eigenvectors.

We define the empirical PDF of the eigenvalues

$$\rho C(\lambda) = \frac{dn(\lambda)}{d\lambda} \tag{4}$$

We can then compare the empirical PDF of the eigenvalues with the theoretical PDF of the eigenvalues, generated by a null model.

This strategy has been applied to study asset co-movements and asset classes synchronization [Bouchaud and Potters, 2009, Stanley et al., 2011]

Random Matrix Theory - Null model PDF

Theorem (Marchenko-Pastur Law)

Let $\hat{X}_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2)$, for $N, T \to \infty$ and $Q = \frac{T}{N} \to a > 1$ then the PDF is equal to

$$\rho \hat{C}(\lambda) = \begin{cases} \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_{max}^{RMT} - \lambda)(\lambda - \lambda_{min}^{RMT})}}{\lambda} & \text{for } \lambda \in (\lambda_{min}^{RMT}, \lambda_{max}^{RMT}) \\ 0 & \text{else} \end{cases} \tag{5}$$

where $\lambda_{max/min}^{RMT} = \sigma^2(1 \pm \sqrt{1/Q})^2$ are the upper/lower bounds of the eigenvalues associated with a random matrix with the same variance and the same Q of our empirical data.

Example of PDF of the null model

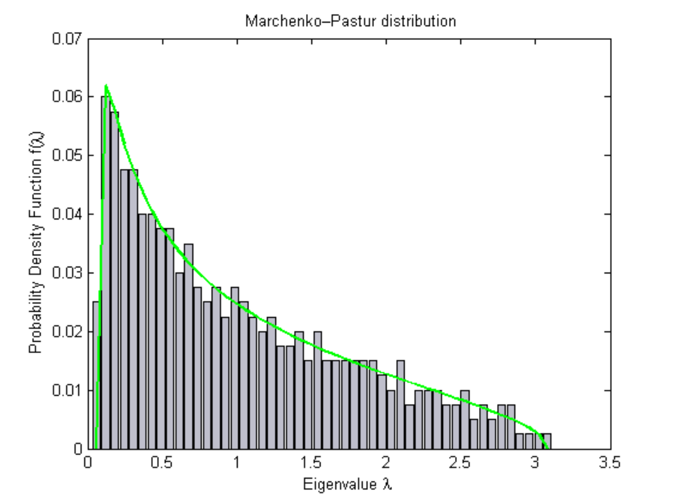

Figure 1: *Example of the Marchenko-Pastur distribution. Kenrnel density fit in green.*

Random Matrix Theory - Deviation from the null model

Now, suppose $\lambda_1 > \cdots > \lambda_M > \lambda_{max}^{RMT} > \cdots > \lambda_N$.

Hence the M eigenvectors associated to the largest M eigenvalues, contain information that allow one to explain deviations from a pure random correlation matrix.

We investigate dynamics of the eigen-values/vectors larger than λ_{max}^{RMT}.

We call these eigenvalues factors/components because of a strong link with PCA and DFM.
[Forni et al., 2000, Stanley et al., 2011]

Random Matrix Theory and PCA

We can diagonalize the correlation matrix $\mathsf{C}(k)$

$$\mathsf{C} = \mathsf{U}\Lambda\mathsf{U}^T = \sum_{i=1}^{N} \lambda_i u_i u_i^T \tag{6}$$

where u_i represents a column vector of U, Containing the eigenvectors associated with the eigenvalue λ_i.

We can then rewrite

$$\lambda_i = u_i^T \mathsf{C} u_i = u_i^T Cov(\mathsf{X}) u_i = Var(u_i^T X_t) \tag{7}$$

which according to PCA is the i-th principal component/factor.

Absorption Ratios

The total variance of the dataset X is given by

$$Var(\mathsf{X}_t) = \sum_{i=1}^{N} Var(X_{i,t}) = N = \sum_{i=1}^{N} \lambda_i = \sum_{i=1}^{N} Var(u_i^T X_t) \qquad (8)$$

Each eigenvalue λ_i describes therefore a portion of the total variance of the data (the fraction explained by the i-th factor).

Ordering the eigenvalues in descending order, means that λ_1 is the most important factor.

Inverse Participation Ratios

To understand the evolution of synchronization we can also use the information contained in the eigenvector associated to the most important factor.

$$IPR(1) = \sum_{j=1}^{N} u_1(j)^4 \tag{9}$$

We'll have that

$$IPR(1) = \begin{cases} \frac{1}{N} & \iff u_1(j) = \frac{1}{N} \quad \forall j \\ 1 & \iff u_1(j) = 0 \quad \forall j \text{ but one} \end{cases} \tag{10}$$

- 1^{st} Case: 1 factor explains N countries (perfect synch)
- 2^{nd} Case: 1 factor explains 1 country (no synch)

Data and Results

Dataset

Eurostat open datasets (R `eurostat` package)

- Manufacturing industrial production (SA)
- Monthly: from 2000-01 to 2017-12
- EU-28

OECD open datasets

- Total industrial production index (SA)
- Monthly: from 2000-01 to 2016-01
- EU-23 (no Bulgaria, Croatia, Cyprus, Latvia, Malta)

Dataset

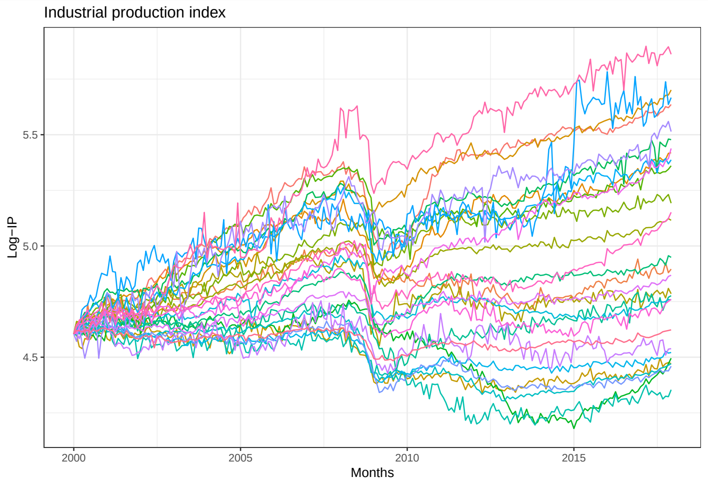

Figure 2: *Time series of the manufacturing industrial production index.*

Temporal similarity

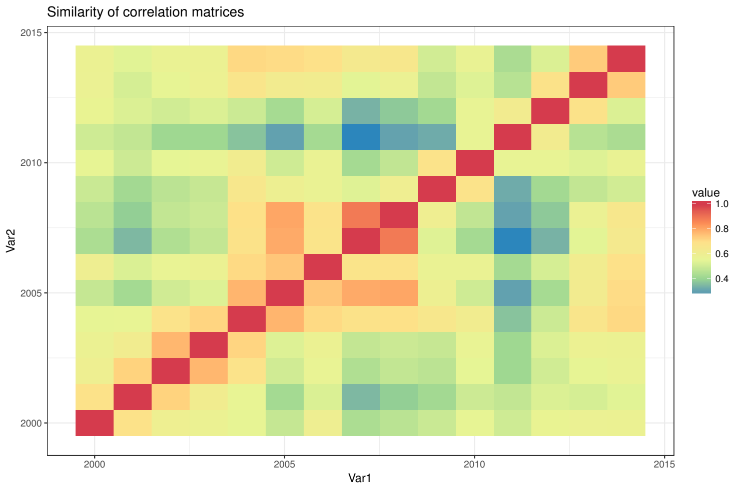

Figure 3: *Similarity of different correlation matrices over time.*

Eigenvalues evolution

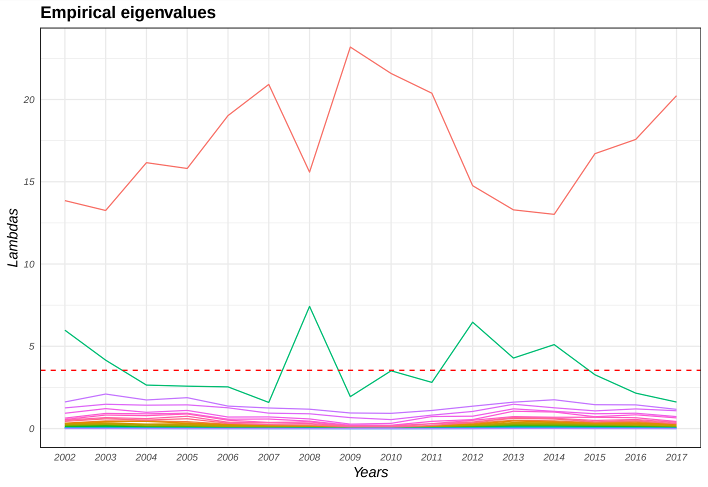

Figure 4: *Eigenvalues evolution vs. MP upper bound.*

Absorption ratio

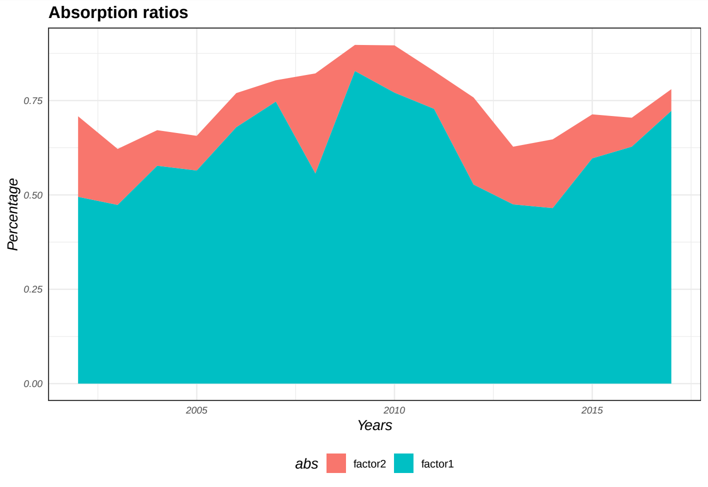

Figure 5: *Absorption ratios of the two largest eigenvalues.*

Inverse participation ratio

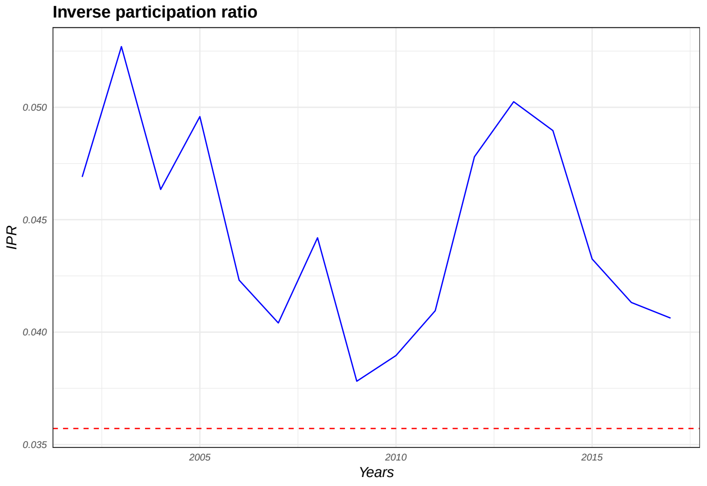

Figure 6: *Inverse participation ratio of the largest eigenvalue.*

Components of eigenvector associated to λ_1

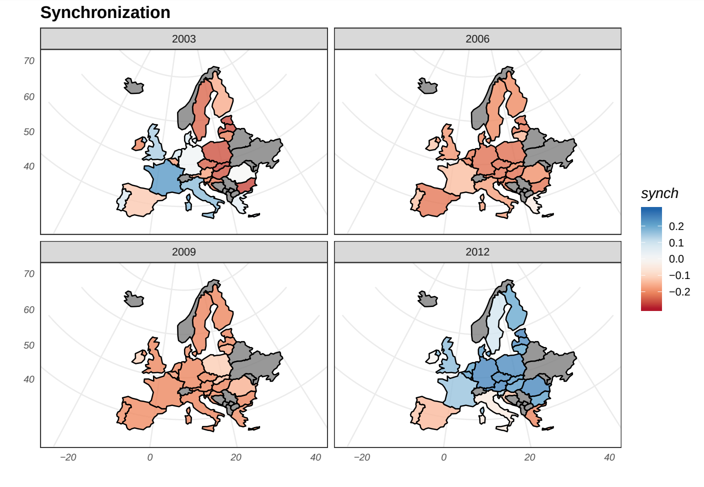

Figure 7: *Largest eigenvector components for different rolling windows.*

Wrap up

Four regimes in EU:

- the east-west divide period (2000-2005)
- the full synch period (2006-2009)
- the north-south divide period (2010-2014)
- the re-synch period (2015-2017)

Robustness Checks

Robustness check with Power law distribution

We have assumed that $\hat{X}_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2)$.

What if instead $\hat{X}_{i,t}$ has a heavy tail distribution with equal mean and variance as before but power law tail exponent γ?

[Biroli et al., 2007] proved that

$$\text{if } \; max(|X_{i,t}|) < (NT)^{1/4} \Rightarrow \lambda_{max} = \sigma^2(1+\sqrt{Q})^2 \tag{11}$$

We can use this new limit as a reference for our analysis.

Robustness check with Power Law Distribution

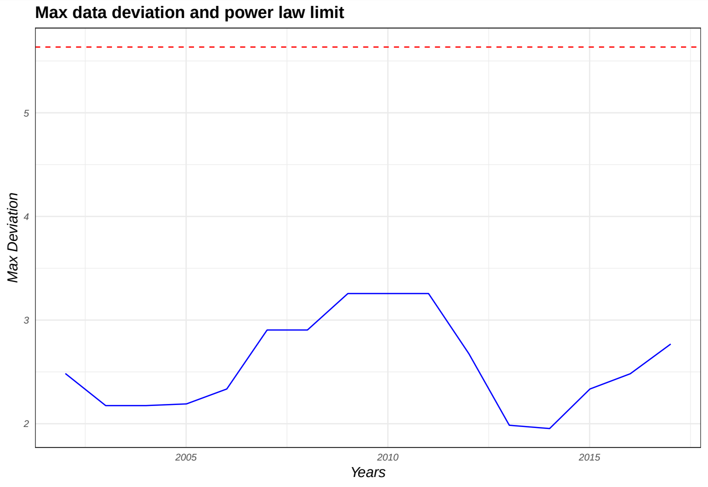

Figure 8: *Comparison between* $(NT)^{1/4}$ *and* $max(|X_{i,t}|)$

Robustness check with Power Law Distribution

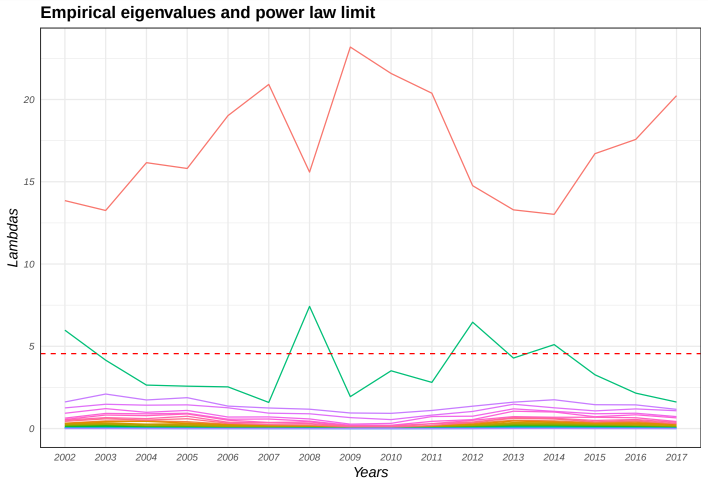

Figure 9: *Eigenvalues evolution vs. MP upper bound adjusted according to [Biroli et al., 2007].*

Other Robustness Checks

Additional robustness checks

- Eurostat data on mining sector
- Eurostat data on mining + manufactoring sectors
- Eurostat data on manufacturing consumption goods
- Eurostat data on manufacturing capital goods
- Eurostat data on 11 early EU adopters
- OECD Data on total industry production index
- BEA data and comparison with 8 US large-regions

Synchronization and Specialization

But is the EU more specialized?

We use Revealed Comparative Advantages [Balassa, 1965] to measure specialization and we look at pairwise similarities in specialization.

Data

- EU-KLEMS
- EU-26 (no data for Ireland and Malta)

Balassa Index

$$RCA_{i,s} = \frac{VA_{i,s} / \sum_s VA_{i,s}}{\sum_i VA_{i,s} / \sum_i \sum_s VA_{i,s}} \tag{12}$$

Cosine Similarity

$$cos_{i,j} = \frac{RCA_i \cdot RCA_j}{\|RCA_i\| \|RCA_j\|}, \qquad cos_{i,j} \in [0, 1]. \tag{13}$$

Specialization Similarities

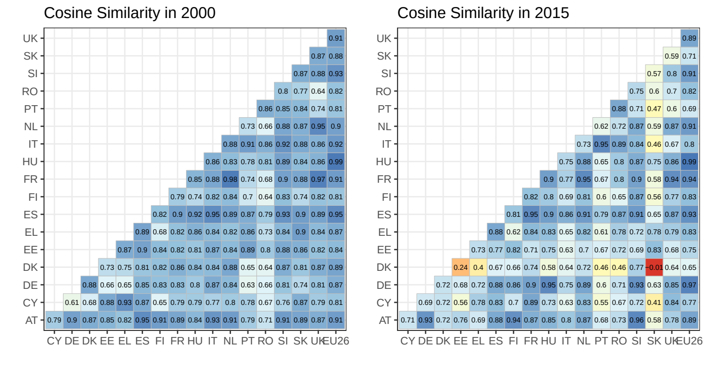

Figure 10: *Cosine similarity between RCA in 2000 and 2015*

Evolution of Specialization Similarities

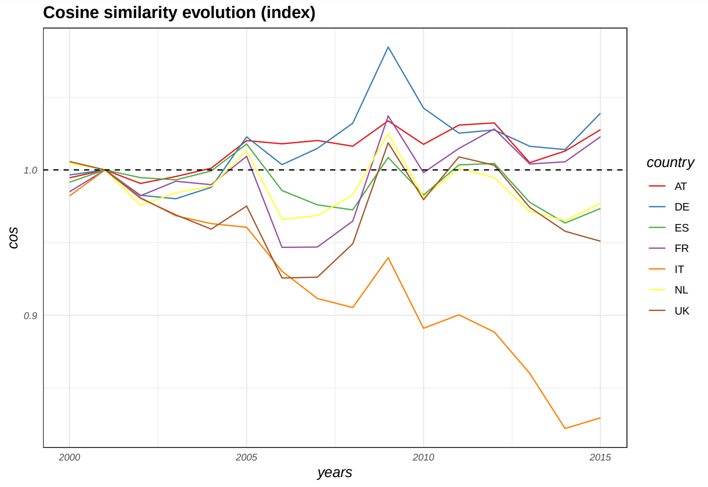

Figure 11: *Evolution of the cosine similarity between RCA for selected countries vs. average EU*

Conclusions and Future Research

Conclusions

We propose a new method for studying business cycle synchronization and we notice that:

- For a certain period the common policy seemed to work, improving convergence ...
- but in response to the crisis they did not work as expected increasing divergence.
- A possible explanation is the low degree of coordination in terms of fiscal policy ...
- another one is that the EU is becoming more specialized and shocks more asymmetric

Future Research

- Possible use of IO tables and integration with EU-KLEMS and other Eurostat aggregate data
- Possible use of firm level data from INSEE
- Econometric specifications to understand the origins of synchronization and to test hypotheses:
    - Trade intensity and trade relations?
    - Financial integration?
    - Common policies?
    - Debt and cost of debt dynamics?
    - The rise of superstar firms [Autor et al., 2017] and granularity [Gabaix, 2011]?

QUESTIONS?

References

Artis, M. and Zhang, W. (1997).
International business cycles and the erm: Is there a european business cycle?
International Journal of Finance and Economics, 2(1):1–16.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., Van Reenen, J., et al. (2017).
The fall of the labor share and the rise of superstar firms.

Balassa, B. (1965).
Trade liberalisation and revealed comparative advantage.
The manchester school, 33(2):99–123.

Barigozzi, M., Conti, A. M., and Luciani, M. (2014).
Do euro area countries respond asymmetrically to the common monetary policy?
Oxford Bulletin of Economics and Statistics, 76(5):693–714.

Baxter, M. and Kouparitsas, M. A. (2005).
Determinants of business cycle comovement: a robust analysis.
Journal of Monetary Economics, 52(1):113 – 157.

Biroli, G., Bouchaud, J.-P., and Potters, M. (2007).
Extreme value problems in random matrix theory and other disordered systems.
Journal of Statistical Mechanics: Theory and Experiment, 7:07019.

Bouchaud, J.-P. and Potters, M. (2009).
Financial Applications of Random Matrix Theory: a short review.
ArXiv e-prints.

Camacho, M., Perez-Quiros, G., and Saiz, L. (2006).
Are european business cycles close enough to be just one?
Journal of Economic Dynamics and Control, 30(9-10):1687–1706.

Centoni, M., Cubadda, G., and Hecq, A. (2007).
Common shocks, common dynamics, and the international business cycle.
Economic Modelling, 24(1):149 – 166.

Clark, T. and Shin, K. (1998).
The sources of fluctuations within and across countries.
Research Working Paper 98-04, Federal Reserve Bank of Kansas City.

De Haan, J., Inklaar, R., and Jong-A-Pin, R. (2008).
Will business cycles in the euro area converge? a critical survey of emprical research.
Journal of Economic Surveys, 22(2):234–273.

Del Negro, M. and Otrok, C. (2008).
Dynamic factor models with time-varying parameters: measuring changes in international business cycles.
Technical report.

Forni, M., Hallin, M., Lippi, M., and Reichlin, L. (2000).
The generalized dynamic-factor model: Identification and estimation.
The Review of Economics and Statistics, 82(4):540–554.

Forni, M. and Reichlin, L. (2001).
Federal policies and local economies: Europe and the us.
European Economic Review, 45(1):109–134.

- Frankel, J. A. and Rose, A. K. (1998).
  The endogeneity of the optimum currency area criteria.
  The Economic Journal, 108(449):1009–1025.
- Gabaix, X. (2011).
  The granular origins of aggregate fluctuations.
  Econometrica, 79(3):733–772.
- Harding, D. and Pagan, A. (2002).
  Dissecting the cycle: a methodological investigation.
  Journal of Monetary Economics, 49(2):365–381.

Imbs, J. (2004).
Trade, finance, specialization, and synchronization.
The Review of Economics and Statistics, 86(3):723–734.

Inklaar, R. and de Haan, J. (2001).
Is there really a european business cycle? a comment.
Oxford Economic Papers, 53(2):215–20.

Inklaar, R., Jong-A-Pin, R., and de Haan, J. (2008).
Trade and business cycle synchronization in OECD countries—a re-examination.
European Economic Review, 52(4):646 – 666.

Leiva-Leon, D. (2014).
Real vs. nominal cycles: a multistate markov-switching bi-factor approach.
Studies in Nonlinear Dynamics & Econometrics, 18(5):557–580.

Rose, A. (2008).
Is emu becoming an optimum currency area? the evidence on trade and business cycle synchronization.
Technical report.

Stanley, H. E., Wang, D., Podobnik, B., and Horvatić, D. (2011).
Quantifying and modeling long-range cross correlations in multiple time series with applications to world stock indices.
Physical Review E, 83:046121.

Trichet, J.-C. (2001).
The euro after two years.
Journal of Common Market Studies, 39(1):1–13.