

Forecasting Financial Markets

Advances for exchange rates, interest rates and asset management

Marseille, 23, 24 and 25 May 2012

Forecasting Financial Crises and Recoveries

(ongoing research)

Sylvain Barthélémy

Executive Director

TAC Economic & Financial Research

Jean-Sébastien Pentecôte

Associate Professor

CREM, University of Rennes I

Outline

An empirical investigation to establish a typology and to identify some leading indicators of profiles of economic recoveries in the aftermath of financial crises.

Structure of the presentation

- Introduction
- Self Organizing Maps
- Database and crisis typology
- Profiles of recoveries
- Determinants of recoveries
- Conclusions

Introduction

- Since 2008, systemic banking crises and (subsequent) sovereign debt defaults (*Reinhart & Rogoff, 2011*) have led to several refinements of early warning systems:
 - **More flexible tools to improve forecasting accuracy**
Rules of thumb from Binary Recursive Trees (*Manasse & Roubini, 2009*), mapping financial instability with Self-Organizing Maps (*Sarlin, 2011; Sarlin & Peltonen, 2011*)
 - **Avoiding the post-crisis bias**
Still an open issue (*Bussière & Fratzscher, 2006 // Ciarlone & Trebeschi, 2005; Beckman, Menkhoff & Sawischlewski, 2006*)

Introduction

- Rising concern on the aftermath of financial crises, but no consensus about output recoveries:
 - **Only V-shape recoveries: Bounce-back effect or else?**
Gupta, Mishra & Sahay (2007); Howard, Martin & Wilson (2011); Kannan, Scott & Terrones (2009), Bussière, Saxena & Tovar (2012)
 - **Recovery paths crisis- and/or country-dependent?**
Rose & Spiegel (2011); Gourinchas & Obstfeld (2012)
 - **Creditless recovery and Phoenix miracle?**
Calvo, Izquierdo & Talvi (2006); Claessens, Kose & Terrones (2009)
 - **Full or incomplete recovery?**
Cerra & Saxena (2008) // Rancièrè, Tornell & Westermann (2008)
 - **Determinants of output recovery?**
Park & Lee (2003), Hong & Tornell (2005), Bordo & Haubrisch (2011)

Self Organizing Maps

General Description

- A special kind of neural networks created by Kohonen (1982).
- **Non-linear** projections of multidimensional spaces into a space of reduced dimension.
- A SOM is a grid where **units** are connected with a **neighbourhood relation**.
- Data that are “alike” are gathered in the same area (“near”).



Self Organizing Maps

Key Characteristics

- **Unsupervised** classification **with** data analysis
- Allows **incomplete** or **missing data**
- Able to capture **non-linearity**
- **Robust and flexible** tool
- **Not a “black box”** and easy to explain



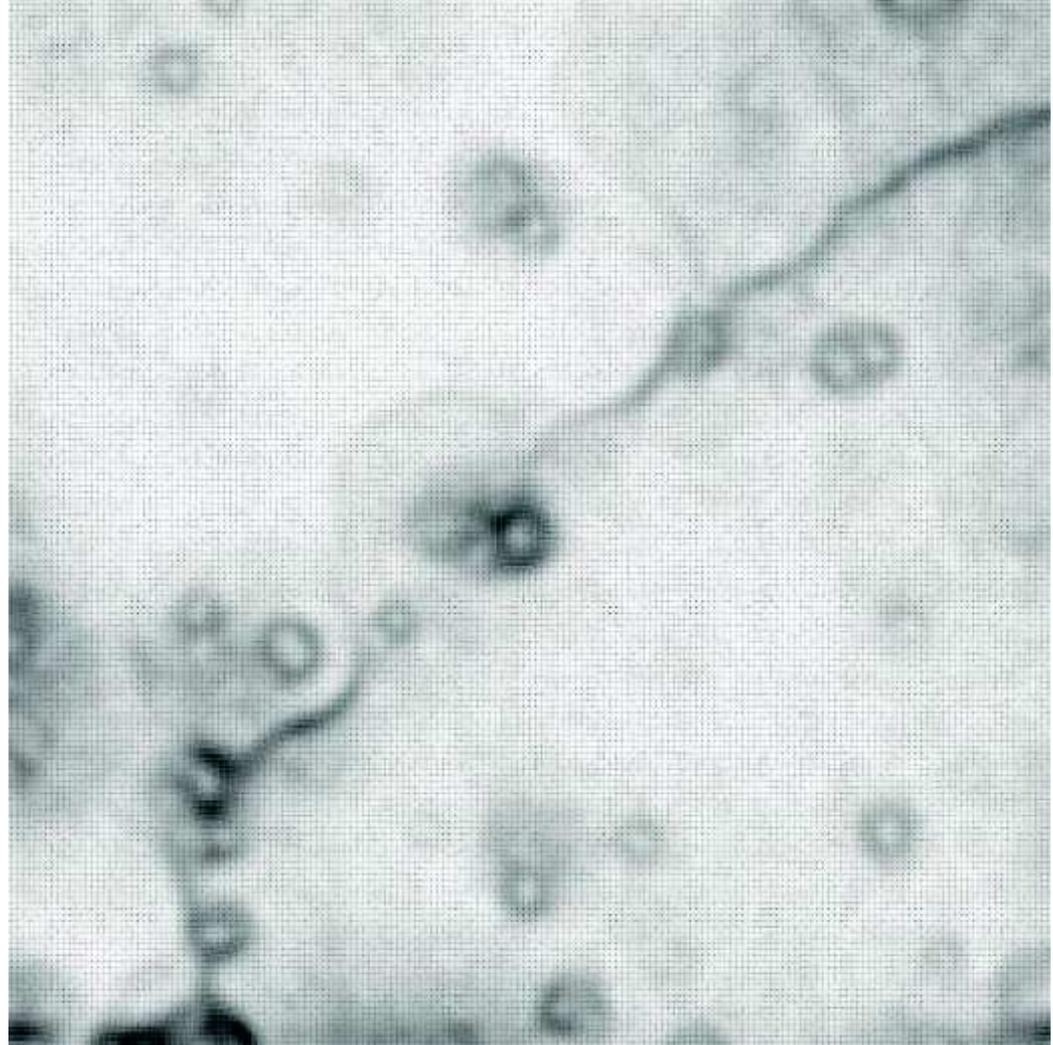
Self Organizing Maps

The algorithm

- *Initialization (step=0)*: Sequence of $w(1) \dots w(n)$ **randomly chosen weights** (n dimension of inputs, i.e. number of variables).
- *Sampling*: Choose **an input vector X**: a combination of macro patterns, a sequence of real GDP growth, ...
- *Competition or similarity matching phase (step t)*: Find **best matching unit (BMU)** to minimize distance $k(t) = \underset{i}{\operatorname{argmin}} \|x(i,t) - w(i,t)\|$
- *Self-organization through updating (step $t+1$)*: **Revise** BMU's neighbourhood according to : $w(k,t+1) = w(k,t) + a H(i,k) [x(k,t) - w(k,t)]$, a **learning rate**; H **neighbourhood function**
- *Reiterate process until "convergence"*

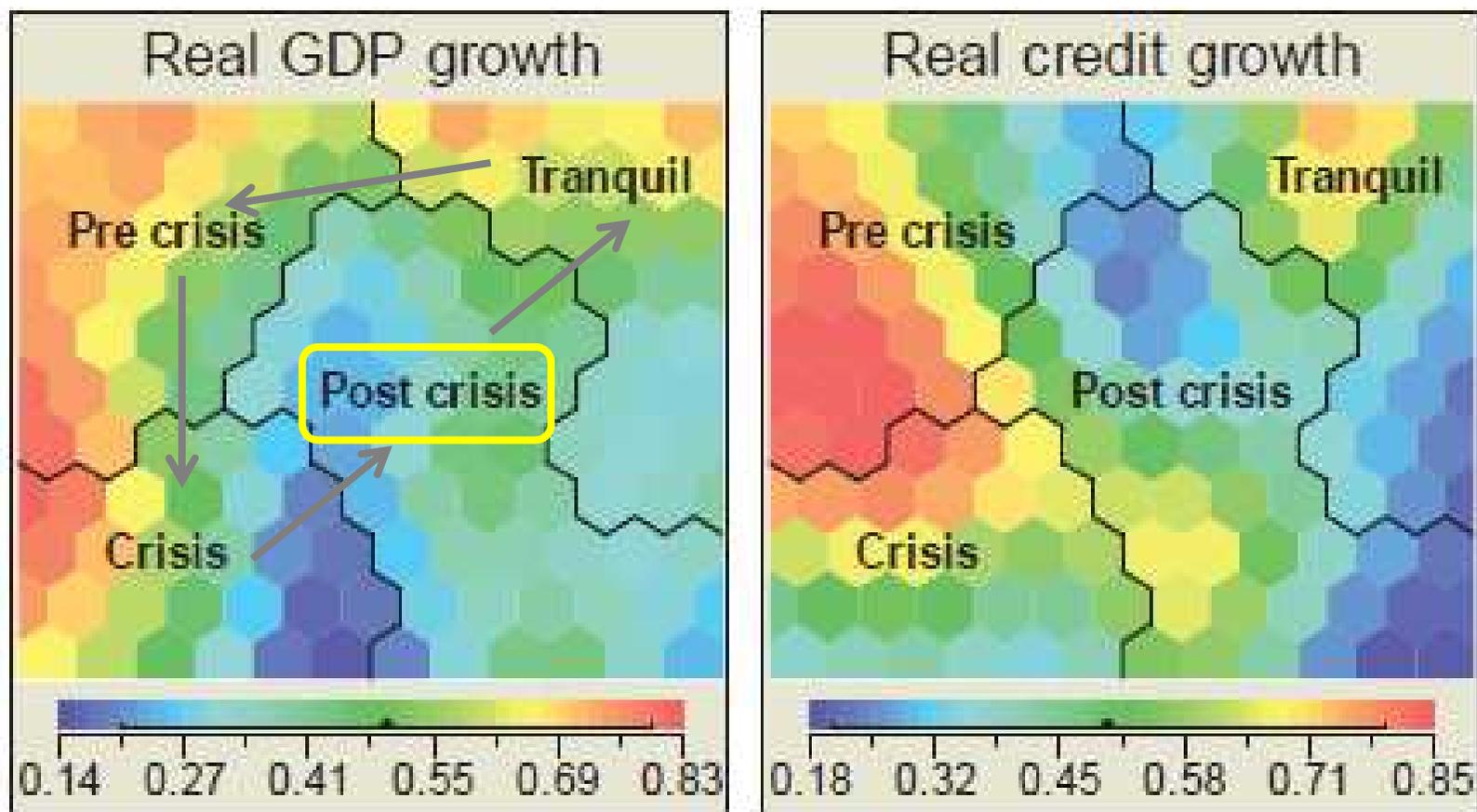
Self Organizing Maps

- Example of a SOM on 120,000 French companies.
- A “Typology of SMEs” for the French Ministry of Finance (2002).



Self Organizing Maps

Sarlin & Peltonen (2011): mapping financial (in-)stability



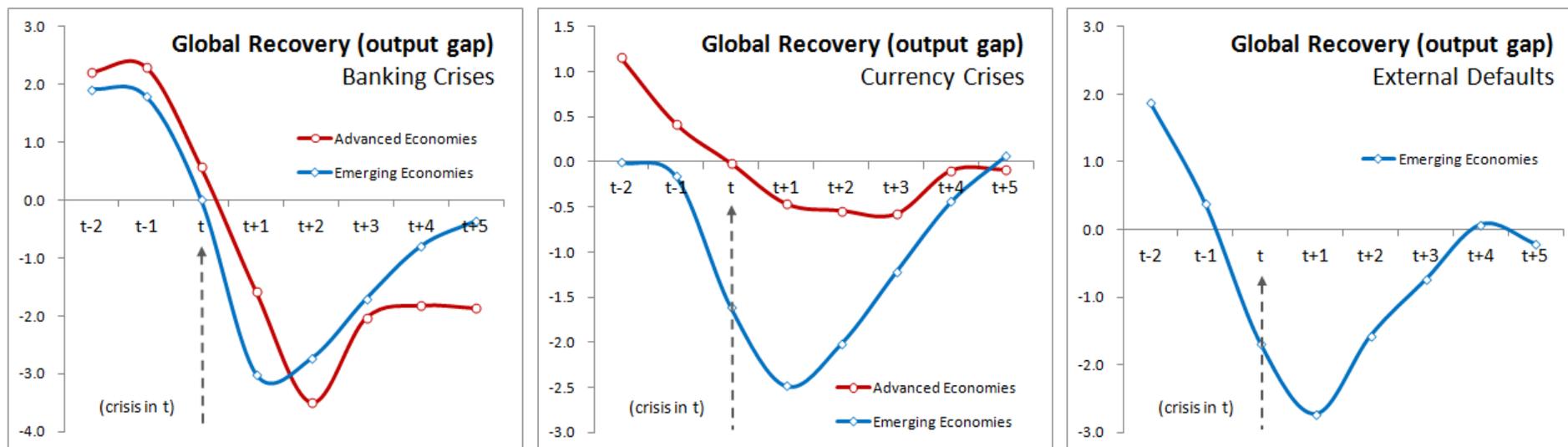
Database and list of crises

- **104 Emerging Markets and Advanced economies.**
- **Annual macroeconomic and financial indicators** from the IMF, World Bank, OECD, and BIS databases
- Sample period: **1973-2007.**
- **Crisis definitions** from *Gourinchas & Obstfeld (2012)* to replicate **dating** of events.
- **Crisis window**= $[t-2,t+5]$, if crisis in year t
- Economic recovery in terms of **output gap** (HP-filtered series)

Database and list of crises

- Following *Gourinchas & Obstfeld (2012)*, focus on:
 - Currency crises: **devaluation > 25% and y.t.y. change in depreciation rate >10%** (*Frankel & Rose, 1996*)
 - Banking Crises: **financial distress urging policy response** (*Caprio & Klingebiel, 2005; Laeven & Valencia, 2008*)
 - External (sovereign) Defaults: **arrears on principal/interests or debt rescheduling** (*Reinhart & Rogoff, 2011*)
- In sample: **244 crisis episodes** including **60** banking crises, **52** defaults,... **178** currency crises (?)
- Detection of “**multiple**” crises (*Kaminsky & Reinhart, 1999; Reinhart & Rogoff, 2011*)

Profiles of Recoveries

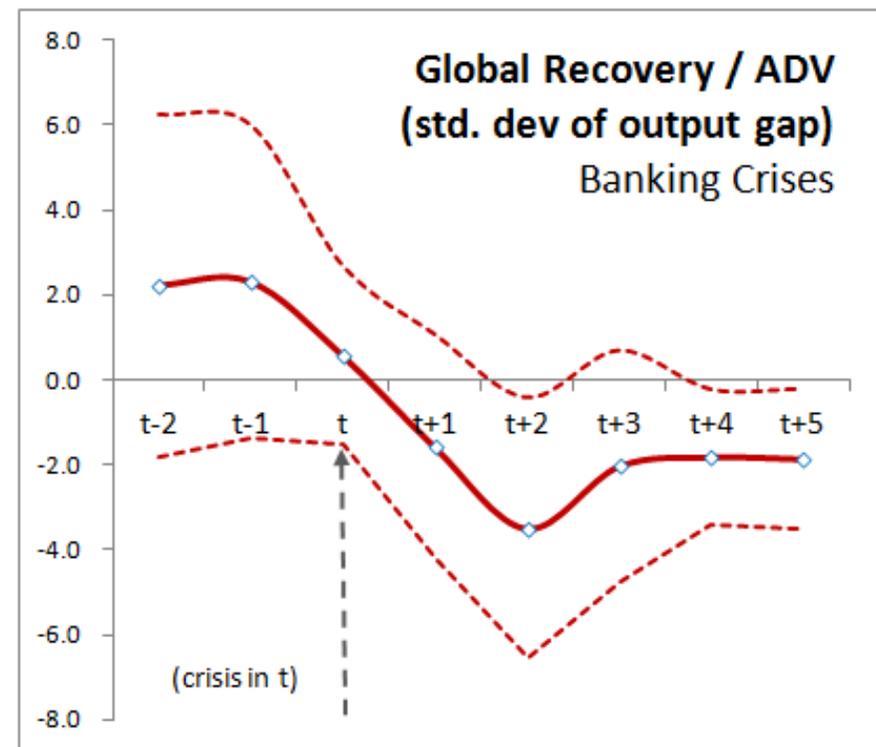
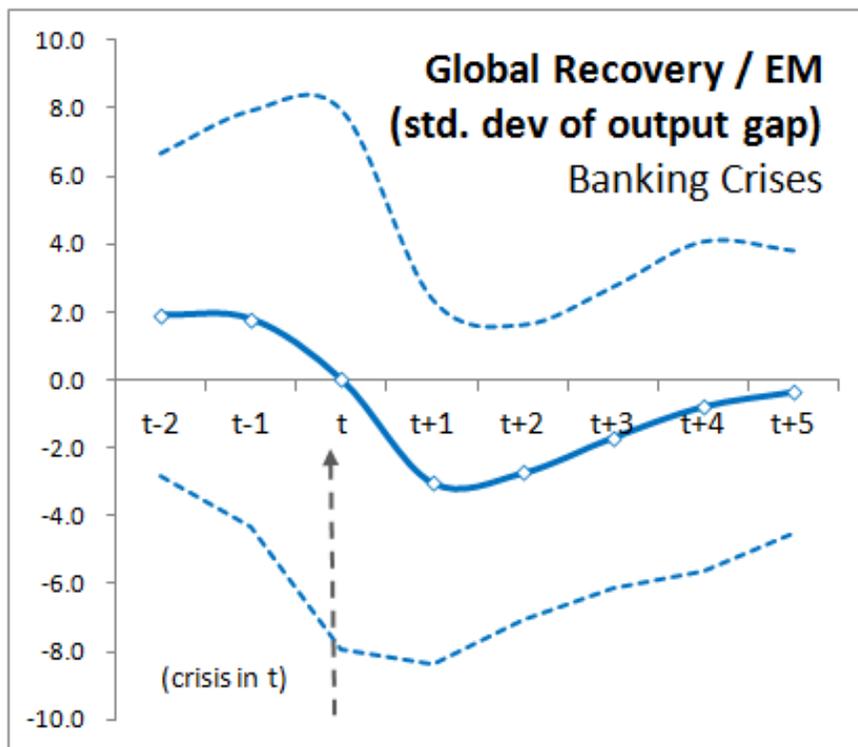


Global profiles of recoveries, by type of crisis and level of development...



Profiles of Recoveries

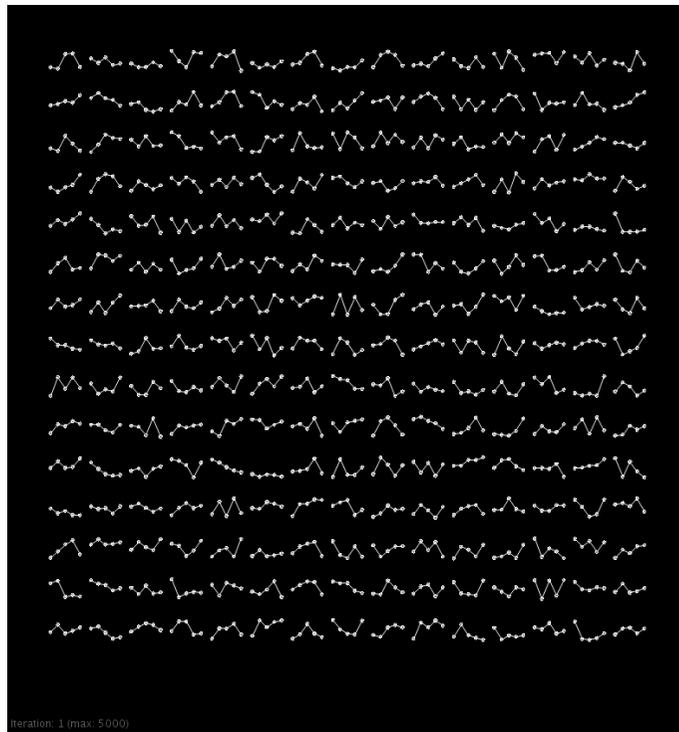
...but very large standard deviations (dashed lines), particularly for emerging economies.



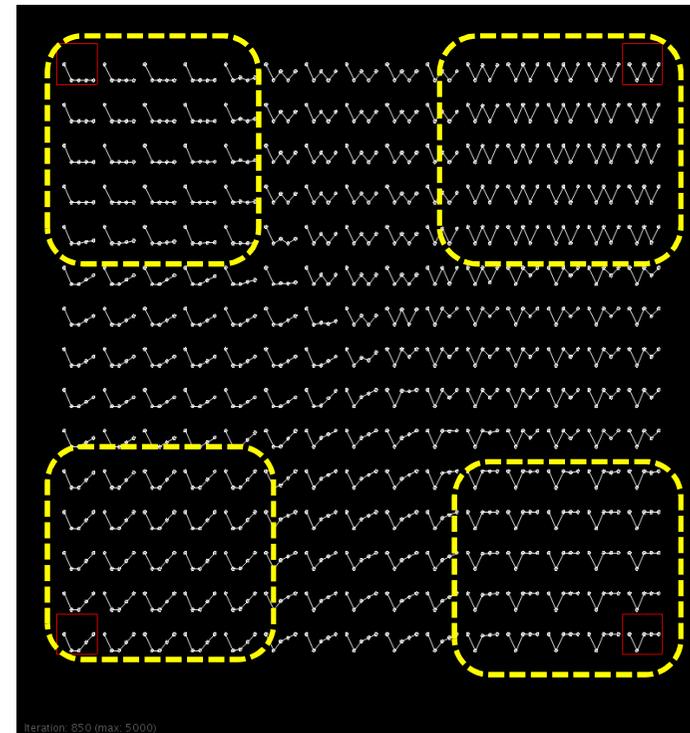
Profiles of Recoveries

Various SOM conducted on all recovery profiles

Start with random profiles...

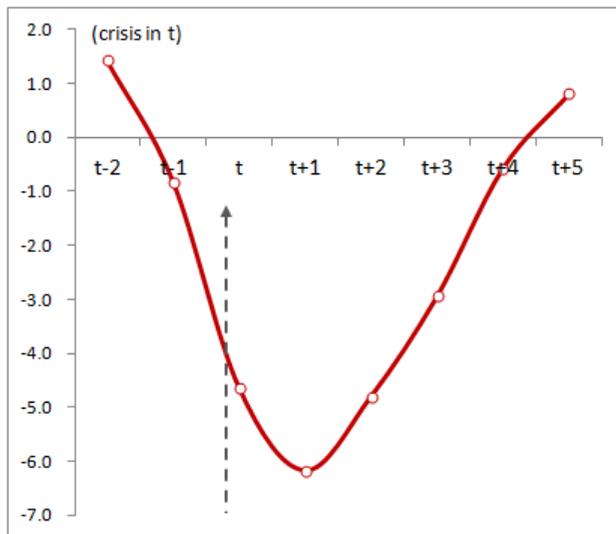


...after training we see the “main profiles”



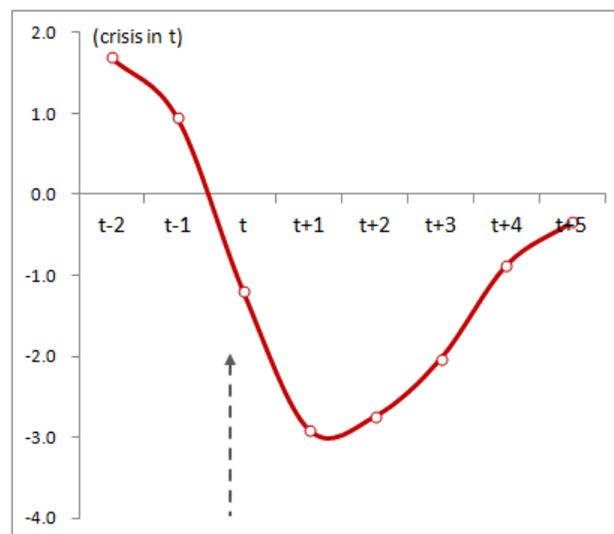
Profiles of Recoveries

- Beyond the standard “V-U-L” shapes, we identify a **couple of new profiles** (various sizes of SOM, but 5x5 lattice is preferred).
- Beyond the magnitude of crises, the **V** and **L** profiles are clearly identified, less clear for the **U** pattern :



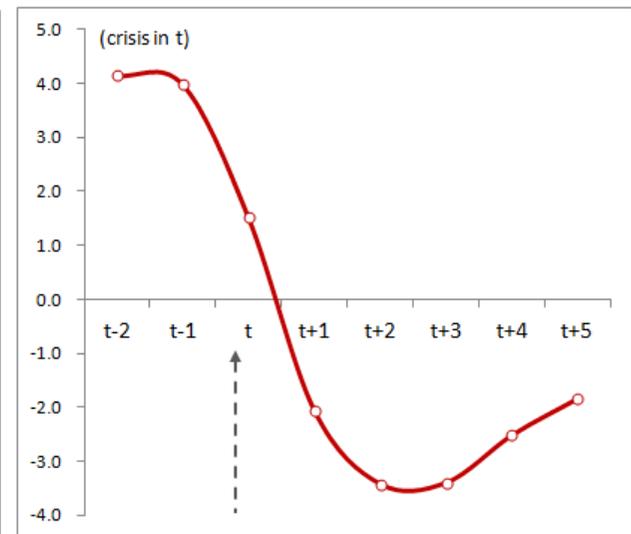
V

(≈30% of cases)



U

(≈ 5% of cases)



L

(≈ 25% of cases)

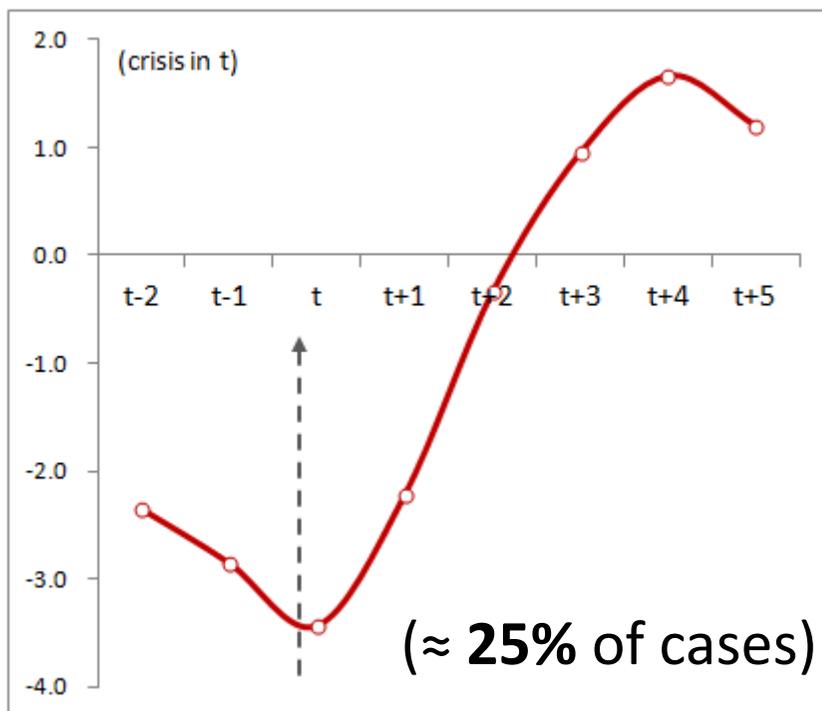
Profiles of Recoveries

2 other types of output recovery also identified:

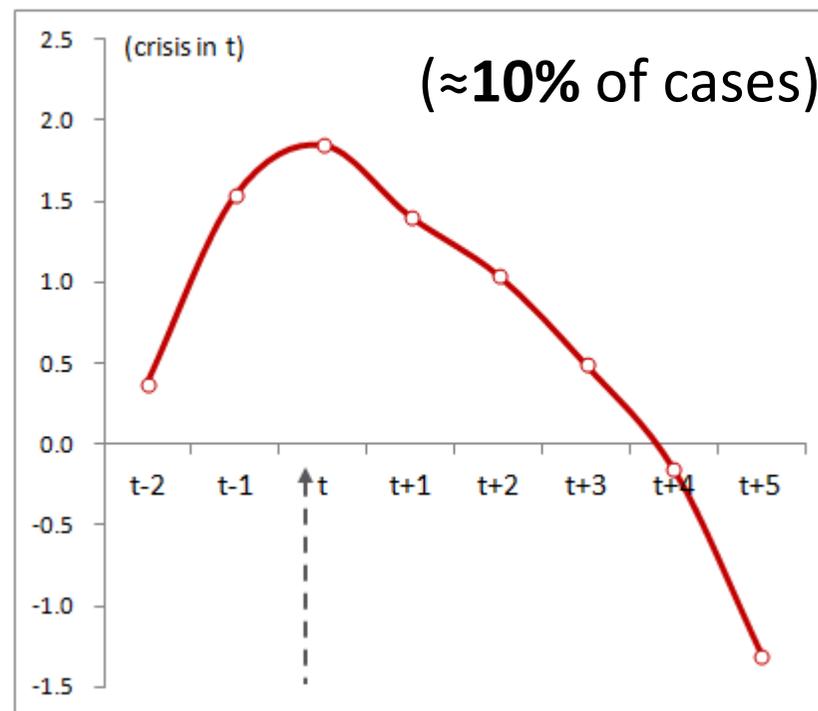
the “**S**”-shape

and

the “**D**”-profile



As in *Bussière, Saxena, Tovar (2012)*



« **DOOMED** »: full and quick recovery as a mirage

Profiles of Recoveries

Shape Crises	V	U	L	S	D	Other
Banking	31%	3%	37%	17%	9%	3%
Currency	35%	7%	19%	26%	7%	4%
Default	23%	0%	27%	31%	12%	8%
Multiple	25%	5%	30%	18%	15%	8%

Profiles of Recoveries

Examples of Identified Profiles

V	L	U	S	D
Argentina 89, Peru 90 , Uruguay 2002, ...	Bolivia 82, Chile 82, Indonesia 98 , Russia 91, Thailand 97, ...	Belarus 2000, Denmark 80 , Spain 82 , Peru 82, ...	Bolivia 89 , Cameroon 94, Kazakhstan 99, Nigeria 86, Ukraine 98, Un. King. 84 , ...	Algeria 88, Argentina 94, Brazil 86, China 94, Japan 79 , ...

Profiles of Recoveries

- Same analysis on **banking crises alone** yields same profiles, but sharper differences.
- **Currency crises:** S-shape *less* frequent and a new “**hyper-V**” profile (fast and huge recovery *above* pre-crisis level).
- **External defaults:** identification of shapes less obvious, partly because of small number of observations and strong differences in recoveries.

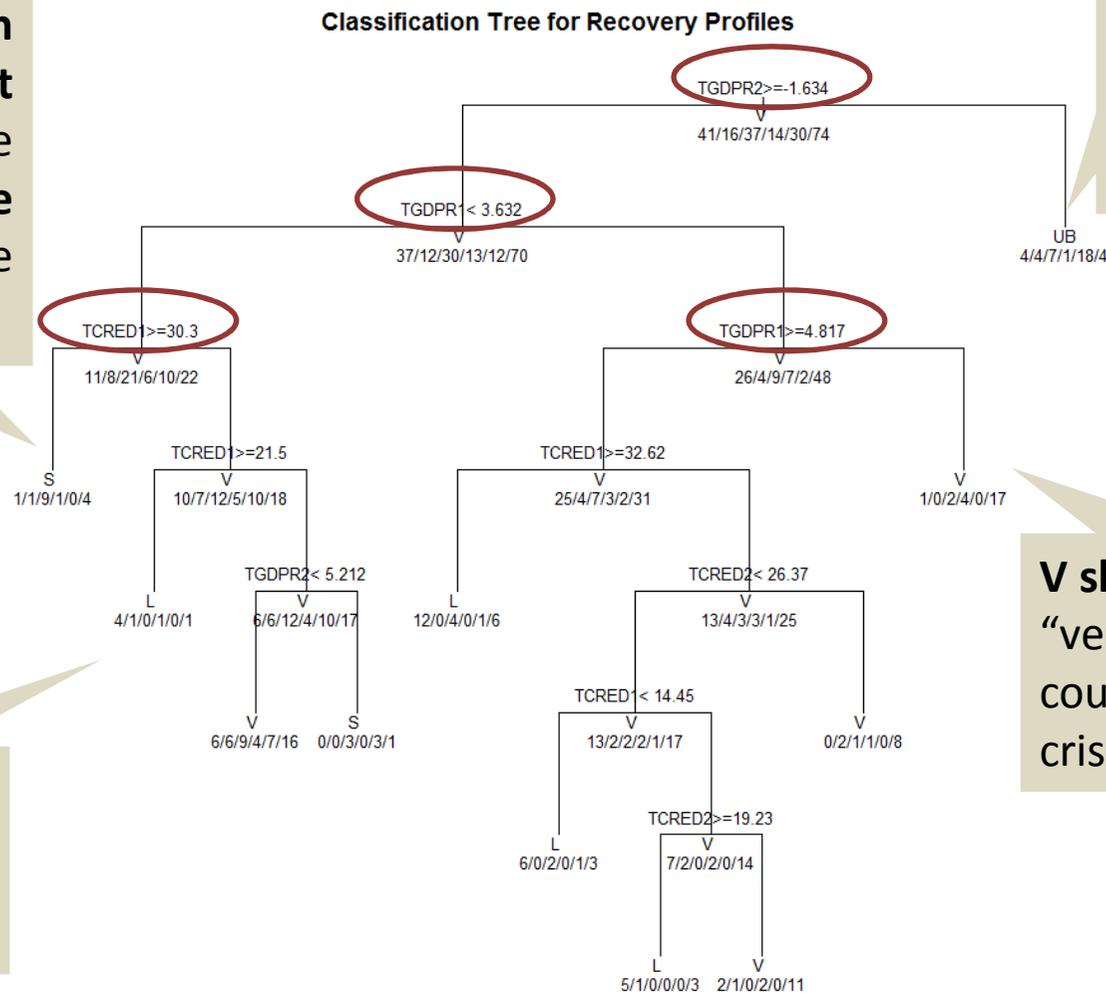
Macroeconomic patterns of recoveries

- What are the links between these recovery profiles, exchange rates, government debt, domestic credit and current account imbalances?
- We run recursive partitioning classification algorithms (*Breiman 1984, 1998*) on the VUL-SD profiles to identify key patterns.

Macroeconomic patterns of recoveries

Real GDP growth and domestic credit boom before the crisis explains more than 50% of the VUL-SUB profiles.

D-profile for countries already in recession prior to the crisis.



When growth is lower than 5%, credit is the key variable.

V shape expected for "very high growth" countries, before the crisis (>5%)

Macroeconomic patterns of recoveries

- Adding other macroeconomic variables for the two years preceding the crisis increase the reliability of the identification (current account, real exchange rate, public debt and output gap).
- With such an algorithm, 60% of all 9 profiles of taken from SOM 3x3 are correctly identified in advance, using domestic credit, real GDP growth and these variables.

Conclusion and Next Steps

- Self Organizing Map is a **flexible and visual tool** that provides interesting properties on unsupervised classification problems.
- Using a very large dataset, a **new typology of recoveries** after economic and financial crises is clearly identified: the **VUL-SD** profiles of recoveries.
- **Real GDP growth before** the crisis is clearly a key variable to explain the profile of recovery, and **the growth rate of domestic credit** is also critical for low growth country profiles (<5%).
- Dealing with crisis “**mutation**”? *Candelon, Demitrescu & Hurlin (2011)*

Thank you for your attention