# Modeling Financial Crises Mutations

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# Introduction

→ **Importance of financial crises** (Latin America, in Asia, Scandinavia, ERM, Russia, Asian, Lehman brothers, Greece, Ireland, Portugal...

→ **Modeling crisis is a crucial issue** for the analysis of the crisis, Optimal policy set up, Early Warning Systems,...

# Introduction - Modeling Methods

**How to model a financial crisis?**

→ **Static models** - rich literature (Kaminski et al.,1998; Berg and Patillo,1999; Kumar et al.,2003 Bussiere and Fratzscher, 2006; etc.)

→ **Dynamic models**

- Duration model; (Tudela, 2005)
- Markov Switching model; (Abiad et al. 2003).

Recently, Dynamic probit model:

"Currency crises early warning systems: why they should be dynamic" (2010) B.Candelon, E. Dumitrescu and C. Hurlin.

# Introduction - Economics 1

**What is a financial crisis?**

Frederic Mishkin: *Nonlinear disruption,..., so that financial markets are unable to channel funds to those with the most productive investment opportunities*.

- Currency crisis.
- Banking crisis.
- Sovereign debt crisis.

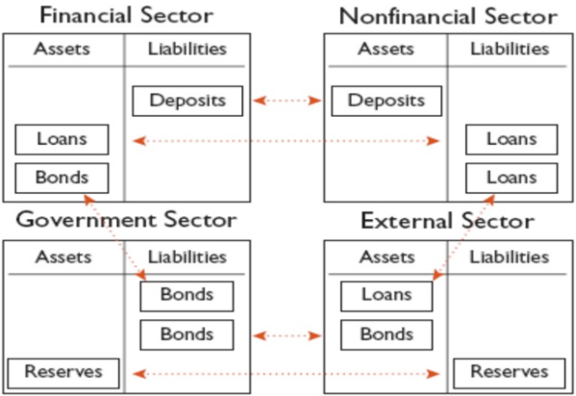
# Introduction - Economics 2

**From one crisis to another one, examples..**

- Banking to sovereign debt in Europe. (Candelon and Palm, 2010)
- Banking to currency (twin crisis), Ecuador 1999,... (Glick and Hutchinson, 1999, Reinhart and Rogoff, 2010)

# Introduction - Economics 3

## ... and Economic theory (Balance sheet approach)



# Originality

**Dynamic EWS models**

$\rightarrow$ Dynamic model with binary crisis variables.

$\rightarrow$ Multivariate to take into account for the potential crisis mutation

# Sketch of the presentation

1. Methodology:
   - The Model.
   - Exact Maximum Likelihood Estimation.

2. Empirical Application:
   - Data.
   - Defining the crisis periods.
   - Bivariate vs multivariate model.
   - The Ecuador example: conditional probability and IRF.

# Take Aways

1. MDP is a much more parcimonious model.
2. MDP shows better in-sample properties as it takes into account crisis mutation.

$\rightarrow$ It should be implemented as often as possible.

# Methodology- The Model 1

$$y^*_{m,t} = \pi_{m,t} + \epsilon_{m,t}, \tag{1}$$

and

$$y_{m,t} = \mathbb{1}(y^*_{m,t} > 0), \tag{2}$$

with $m \in \{c, b, s\}$, $\pi_{m,t}$ being the expected value of $y_{m,t}$ that may depend on covariates which vary across markets, country and time and with $E(\epsilon_{m,t}|\pi_{m,t}) = 0$, $Var(\epsilon_{m,t}|\pi_{m,t}) = \Gamma$, $Cov(\epsilon_{m,t}, \epsilon_{m',t}|\pi'_{m,t}, \pi_{m',t'}) = \omega_{mm'}$ when $i = i'$, $t = t'$ and zero whenever $i \neq i'$ and $t \neq t'$.

# Methodology- The Model 2

$$y^*_{m,t} = \alpha_m + x'_{m,t-1}\beta_m + \sum_{m'} y_{m',t-1}\Delta_{m,m'} + \sum_{m'} \Gamma_{m,m'}\pi_{m',t-1} + \varepsilon_{m,t}$$
$$y_{m,t} = \mathbb{1}(y^*_{m,t} > 0). \tag{3}$$

**Interpretation for persistence and causality:**

→ Persistence: diagonal terms Δ (non-linear) and Γ (linear).

→ Causality (Granger): off-diagonal terms of Δ and Γ.

# Methodology- the Model 3

Finally, the disturbances $\varepsilon_t = [\varepsilon_{c,t}\ \varepsilon_{b.t}\ \varepsilon_{s,t}]'$ are trivariate normally distributed with a $3 \times 3$ symmetric matrix $\tilde{\Omega}$:

$$\tilde{\Omega} = \begin{pmatrix} \sigma_c^2 & \rho_{bc}\sigma_b\sigma_c & \rho_{sc}\sigma_c\sigma_s \\ \rho_{bc}\sigma_b\sigma_c & \sigma_b^2 & \rho_{sb}\sigma_b\sigma_s \\ \rho_{sc}\sigma_c\sigma_s & \rho_{sb}\sigma_b\sigma_s & \sigma_s^2 \end{pmatrix}, \quad (4)$$

where $\rho_{m,m-1}$ represents the correlation coefficients. It is also assumed that $\tilde{\varepsilon}_t$ is *i.i.d* so that the covariance matrix for all $T$ observations is given by $V(\tilde{\varepsilon}) = I_N \otimes \tilde{\Omega}$, $\tilde{\Omega}$ being a flexible covariance matrix.

# Methodology- the Model 4

1. $$\pi_t = \alpha + x'_{t-1}\beta + y'_{t-1}\Delta + \Gamma'\pi_{t-1}. \quad (5)$$
2. $$\pi_t = \alpha + x'_{t-1}\beta, \quad (6)$$
3. $$\pi_t = \alpha + x'_{t-1}\beta + y'_{t-1}\Delta, \quad (7)$$
4. $$\pi_t = \alpha + x'_{t-1}\beta + \Gamma'\pi_{t-1}, \quad (8)$$

# Methodology- Exact ML 1

The FIML estimates are obtained by maximizing the log-likelihood:

$$\text{LogL}(y|z,\theta;\Omega) = \sum_{t}^{T} \text{Log}\Phi_{3,\varepsilon}(w_t; Q_t\Omega Q_t) \tag{9}$$

where $Q_t$ is a diagonal matrix whose main diagonal elements are $q_{m,t} = 2y_{m,t} - 1$ and thus depends on the realization or not of the events ($q_{m,t} = 1$ if $y_{m,t} = 1$ and $q_{m,t} = -1$ if $y_{m,t} = 0$, $\forall$ $m \in \{c, b, s\}$). Besides, the elements of the vector $w_t = [w_{1,t}, ..., w_{3,t}]$ are given by $w_{m,t} = q_{m,t}\pi_{m,t}$.

# Methodology- Exact ML 2

**Ideas for the empirical procedure:**

→ Huguenin, Pelgrin and Holly (2009) show in a static probit framework that simulated methods lead to bias So Exact ML.

→ $\Phi_{3,\varepsilon}(w_t; Q_t \Omega Q_t)$ is some a simple, double and triple integrals. Triple integrale can be decompose in a non-unique way into double integrals.

→ Integrals are numerically evaluated using Gauss-Legendre Quadrature rule over bounded intervals.

# Application- Data

TABLE 1 – Database

| Country | Bivariate model | Trivariate model |
|---|---|---|
| Argentina | February 1988 - May 2010 | December 1997 - May 2010 |
| Brazil | September 1990 - May 2010 | December 1997 - May 2010 |
| Chile | January 1989 - May 2009 | May 1999 - May 2010 |
| Colombia | February 1986 - August 2009 | December 1997 - August 2009 |
| Ecuador | January 1994 - November 2007 | December 1997 - November 2007 |
| Egypt | February 1986 - June 2009 | July 2001 - June 2009 |
| El Salvador | January 1991 - November 2008 | April 2002 - November 2008 |
| Indonesia | January 1989 - August 2009 | May 2004 - August 2009 |
| Lebanon | January 1989 - April 2010 | April 1998 - April 2010 |
| Malaysia | January 1988 - March 2010 | December 1997 - March 2010 |
| Mexico | January 1988 - May 2010 | December 1997 - May 2010 |
| Peru | January 1990 - May 2010 | December 1997 - May 2010 |
| Philippines | January 1995 - February 2008 | December 1997 - February 2008 |
| South Africa | January 1988 - August 2009 | December 1997 - August 2009 |
| Turkey | January 1988 - May 2010 | December 1997 - May 2010 |
| Venezuela | February 1986 - November 2009 | December 1997 - November 2009 |

**Note**: Data availability.

# Application- Defining the crisis periods 1

**1- The Currency Crises**

Market pressure index (MPI) KLR(1998)

$$\text{KLRm}_{n,t} = \frac{\Delta e_{n,t}}{e_{n,t}} - \frac{\sigma_e}{\sigma_r}\frac{\Delta r_{n,t}}{r_{n,t}} + \frac{\sigma_e}{\sigma_i}\Delta i_{n,t}, \tag{10}$$

Currency crisis variable:

$$CC_{n,t} = \begin{cases} 1, & \text{if } \text{KLRm}_{n,t} > 1.5\sigma_{\text{KLRm}_{n,t}} + \mu_{\text{KLRm}_{n,t}} \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

# Application- Defining the crisis periods 2

**2- The Banking Crises**

Banking pressure index (*BPI*) von Hagen and Ho (2004)

$$BPI_{n,t} = \frac{\Delta\gamma_{n,t}}{\sigma_{\Delta\gamma}} + \frac{\Delta r_{n,t}}{\sigma_{\Delta r}}, \quad (12)$$

Banking crisis variable:

$$BC_{n,t} = \begin{cases} 1, & \text{if } \mathrm{IMP}_{n,t} > P_{BPI,90,n} \\ 0, & \text{otherwise.} \end{cases} \quad (13)$$

# Application- Defining the crisis periods 3

**3- The Sovereign Debt Crises**

Pescatori and Sy (2007) use the CDS spread.

Sovereign debt crisis variable:

$$SC_{n,t} = \begin{cases} 1, & \text{if CDSspread}_{n,t} > \mathit{Kernel\ Threshold}_n \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

# Application- Defining the crisis periods 4

TABLE 2 – Percentage of crisis periods

| | Bivariate model | | Trivariate model | | |
|---|---|---|---|---|---|
| | Currency crisis | Banking crisis | Currency crisis | Banking crisis | Debt crisis |
| Argentina | **5.13** | **8.90** | 4.00 | **6.67** | **10.0** |
| Brazil | 3.77 | **7.19** | 0.00 | 3.33 | 2.67 |
| Chile | **6.07** | **10.0** | **5.79** | **5.79** | 3.31 |
| Colombia | 4.95 | **9.90** | **9.22** | **12.8** | 0.00 |
| Ecuador | **5.73** | **9.93** | **6.67** | **10.8** | **6.67** |
| Egypt | **6.76** | **9.96** | 4.17 | **7.30** | **7.30** |
| El Salvador | 3.65 | **9.85** | 0.00 | 0.00 | 2.50 |
| Indonesia | 5.30 | **9.90** | 0.00 | **14.0** | **6.25** |
| Lebanon | **9.62** | **9.96** | 1.38 | **8.97** | 2.76 |
| Malaysia | 3.10 | **10.0** | 4.05 | **6.08** | 4.73 |
| Mexico | **6.50** | **9.93** | 0.00 | **9.33** | 0.00 |
| Panama | 0.00 | **9.89** | 0.00 | **6.38** | 0.00 |
| Peru | 4.45 | **8.22** | 0.00 | **10.7** | 0.00 |
| Phillipines | 4.90 | **9.80** | **5.69** | **6.50** | 3.25 |
| South Africa | **6.71** | **9.89** | **7.09** | **7.80** | 4.26 |
| Turkey | 4.80 | **8.56** | 4.00 | **6.67** | 0.00 |
| Venezuela | **7.33** | **10.1** | 4.17 | **7.64** | 2.78 |

**Note**: A percentage of crisis superior to 5% is represented in bold.

# Application- Bivariate vs trivariate DPM 1

TABLE 3 – Bivariate Analysis

| Country | | 3 months $\theta$ | 3 months $\Omega$ | 6 months $\theta$ | 6 months $\Omega$ | 12 months $\theta$ | 12 months $\Omega$ |
|---|---|---|---|---|---|---|---|
| Argentina | currency<br>banking | $\begin{bmatrix} + & + \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} . & + \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ |
| Chile | currency<br>banking | $\begin{bmatrix} + & . \\ . & . \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & . \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} . & - \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ |
| Ecuador | currency<br>banking | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ |
| Egypt | currency<br>banking | $\begin{bmatrix} + & . \\ - & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ - & + \end{bmatrix}$ | $\begin{bmatrix} 1 & - \\ - & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & - \\ - & 1 \end{bmatrix}$ |
| Lebanon | currency<br>banking | $\begin{bmatrix} + & . \\ - & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ |
| Mexico | currency<br>banking | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ . & . \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ . & . \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ |
| South Africa | currency<br>banking | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & . \\ . & 1 \end{bmatrix}$ |
| Venezuela | currency<br>banking | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} + & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ | $\begin{bmatrix} . & . \\ . & + \end{bmatrix}$ | $\begin{bmatrix} 1 & + \\ + & 1 \end{bmatrix}$ |

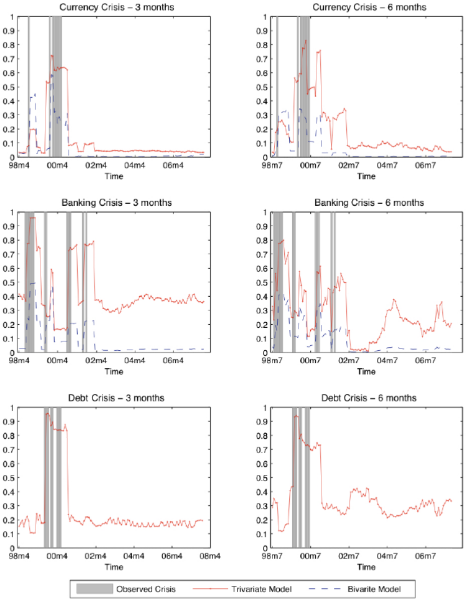
# Application- Bivariate vs trivariate DPM 2

TABLE 4 – Trivariate Analysis

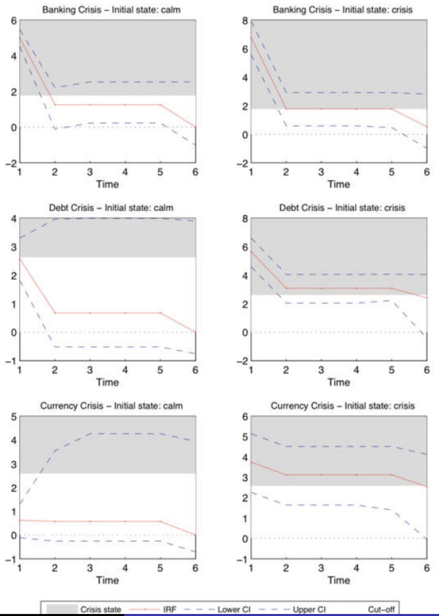
| Country | | 3 months $\theta$ | 3 months $\Omega$ | 6 months $\theta$ | 6 months $\Omega$ |
|---|---|---|---|---|---|
| Ecuador | currency | . . + | 1 . . | . + + | 1 . . |
| | banking | . + . | . 1 . | . + . | . 1 . |
| | sovereign | . . + | . . 1 | . . + | . . 1 |
| South Africa | currency | + . . | 1 . + | + . . | 1 . + |
| | banking | . . . | . 1 . | . . . | . 1 . |
| | sovereign | . . + | + . 1 | . . + | + . 1 |

**Note**: Two different lags of the dependent variable are used, namely 3 and 6 months. '$\theta$' stands for the parameters of the lagge crisis variables, while $\Omega$ represents the variance-covariance matrix. A'+'/'-' sign means that the coefficient is significant an positive/ negative, while a '.' indicates its non-significance. For example, in the case of Ecuador, 3 months, sovereign debt crise have a positive and significative impact on the probability of occurrence of currency crises.

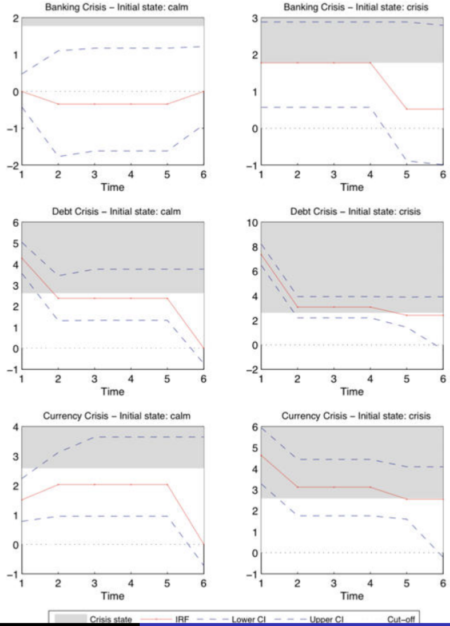
# Application- Ecuador 1



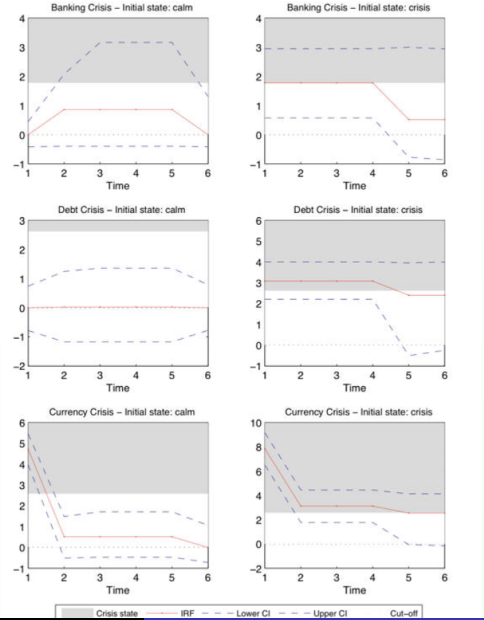
# Application- Ecuador 2



# Application- Ecuador 3



# Application- Ecuador 4



# Conclusion

1. This paper develops a multivariate dynamic probit model for financial crisis model,
2. It allows to model the potential mutation of a crisis into another one.
3. We also propose an exact Maximum Likelihood estimation.
4. MDP shows better in-sample properties as it takes into account crisis mutation.

$\rightarrow$ Powerful tool for real life implementation...