Identifying Bubbles in Latin American Equity Markets: Phillips-Perron-based Tests and Linkages

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Banco de México
December 2016

Outline

Identification of Financial Bubbles

- Identification of financial bubbles can be critical:
  - The most recent financial crisis originated form a real estate prices bubble.
  - Dot-com bubble had effects on economic growth, employment, and the financial system.
  - A timely identification can provide a window for policies.
  - Particularly important in emerging economies that might be more fragile.
  - Contagion might be present.
- Focus on Latin American emerging markets:
  - Developing markets have increased their share in global GDP from 40% in 2000 to 49% in 2010.
  - LA has shown steady growth in the sizes of its equity markets in the last two decades.

Existence of Bubbles and Monetary Policy

- Eugene Fama and Robert Shiller on bubbles.
  - Fama: I don't even know what a bubble means (The New Yorker, 2010)
  - Shiller: Wrote a book on bubbles, Irrational Exuberance (2010)
- Alan Greenspan, Ben Bernarke and Nouriel Roubini on monetary policy and bubbles.
  - Greenspan and Bernarke: Various arguments against the use of monetary policy to target asset prices.
  - Roubini: Central banks should react to bubbles.
    - Optimal monetary policy rules imply targeting of asset prices.
    - Monetary policy should react to asset prices even under uncertainty on the existence of bubbles.
    - Monetary authorities should attempt to carefully 'prick' a bubble.
    - It is inconsistent to have monetary policy that reacts to bursting bubbles but not rising bubbles.

Detection of Bubbles

- Tests for excess volatility (Kleidon, 1986; LeRoy and Porter, 1981; Marsh and Merton, 1986; Shiller, 1980).
- Tests for bubble premiums (Hardouvelis, 1988; Rappoport and White, 1993).
- Tests for the cointegration of dividends and prices (Diba and Grossman, 1988).
- Duration dependence test (McQueen and Thorley, 1994).
- Parametric fits and non-parametric log-frequency analysis (Johansen and Sornette, 2001).
- As structural breaks (Escobari, Damianov and Bello, 2015).
- Recursive procedures (Phillips, Shi and and Yu, 2015).

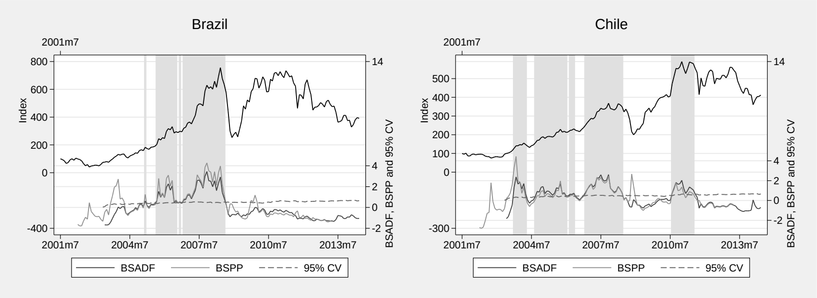
Contribution

- Employ the recently developed methods of Phillips, Wu and Yu (2011) and Phillips, Shi and and Yu (2015)—real time bubble detection.
- Identify the beginning and end of bubble periods in six Latin American equity markets.
- PWY and PSY are based on the *ADF* tests. Propose a similar recursive procedure based on *PP* (uses an heterocedasticity- and autocorrelation-consistent covariance matrix).
- Estimate a DCC GARCH model to study the links between bubbles.
- Strong evidence of bubbles for Brazil, Chile, Colombia, Mexico, and Peru. No evidence for Argentina.
- The findings are consistent between the *ADF*-based and the *PP*-based tests.
- Clear overlap of bubbles across markets.
- Bubbles for Chile, Colombia and Peru match the months leading up to MILA in May 2011.

Data

- 14 years with monthly observations from July 2000 through June 2014.
- Inflation-adjusted stock indices for Argentina, Brazil, Chile, Colombia, Mexico, Peru, and the S&P 500.

Figure: Time series graphs for Brazil and Chile



Link between Explosive Behavior and Bubbles

- The PWY and PSY methods as well as our proposed tests identify explosive behavior.
- Explosive behavior is not necessarily empirical evidence of bubbles.
- Let B_t denote the bubble, i.e., $B_t = P_t - P_t^f$.
- Asset pricing equation for the market fundamentals:

$$P_t^f = \sum_{i=0}^{\infty} \left(\frac{1}{1+r_f} \right)^i E_t(D_{t+i} + U_{t+i})$$

- D_t: Dividend, r_f: Risk-free interest rate, U_t: Unobserved market fundamentals.
- If bubbles satisfy the property $E_t(B_{t+1}) = (1+r_f)B_t$, then in the presence of bubbles P_t will be explosive.
- If D_t is $I(1)$ and U_t is at most $I(1)$, then explosive behavior in P_t can be interpreted as bubbles.

Identifying Explosive Behavior

Begin with the following Augmented Dickey-Fuller structure:

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} y^i_{r_1,r_2} \Delta P_{t-i} + \epsilon_t,$$

where $\epsilon \overset{iid}{\sim} N(0, \sigma^2_{r_1,r_2})$, and r_1 and r_2 denote fractions of the total sample size.

We are interested in the following test statistic:

$$ADF^{r_2}_{r_1} = \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})}.$$

Single Episodes of Explosive Behavior

PWY propose using the following (forward recursive) Supremum *ADF* statistic:

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} ADF_0^{r_2}.$$

There is explosive behavior when the *SADF* statistic is greater than the right tailed critical values.
The limit distribution of the *SADF* statistic given by:

$$\sup_{r_2 \in [r_0, 1]} \frac{\int_0^1 W dW}{\int_0^1 W^2}.$$

The null hypothesis is that there are no explosive versus the alternative of explosive behavior.

Multiple Episodes of Explosive Behavior

PSY propose using the following (double recursive) Generalized *SADF* statistic:

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} ADF_{r_1}^{r_2}.$$

There is explosive behavior when the *SADF* statistic is greater than the right tailed critical values.

Once we identify that a series has an explosive behavior, we use a backward *sup ADF* (*BSADF*) series to identify the windows where this price exuberance exists. The *BSADF* statistic is defined as:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}.$$

The Beginning and the End of Bubbles

The beginning and the end of bubble periods are given by:

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) > \text{scv}_{r_2}^{\alpha} \right\}$$

and

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + 1/T, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) < \text{scv}_{r_2}^{\alpha} \right\}$$

where $\text{scv}_{r_2}^{\alpha}$ denotes the $100(1-\alpha)\%$ critical value of the *SADF* statistic based on $\lfloor r_2 T \rfloor$.

Phillips-Perron-based Tests

Phillips-Perron (PP) can be viewed as an ADF that is robust to serial correlation by using the Newey-West heteroscedasticity- and autocorrelation-consistent covariance matrix estimator. We use the following PP statistic:

$$PP_{r_1}^{r_2} = \sqrt{\frac{\hat{\gamma}_{0,T}}{\hat{\lambda}_T^2}} \frac{\hat{\beta}_{r_1,r_2}}{s.e.(\hat{\beta}_{r_1,r_2})} - \frac{1}{2}\left(\hat{\lambda}_T^2 - \hat{\gamma}_{0,T}\right)\frac{1}{\hat{\lambda}_T}\frac{T \cdot s.e.(\hat{\beta}_{r_1,r_2})}{s_T}$$

That has the corresponding SPP, $GSPP$, and $BSPP$ statistics:

$$SPP(r_0) = \sup_{r_2 \in [r_0,1]} PP_0^{r_2}, \quad GSPP(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} PP_{r_1}^{r_2}, \quad BSPP_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} PP_{r_1}^{r_2}$$

The limit distributions of each test are calculated via Monte Carlo simulations.

ADF-based and *PP*-based Test Statistics

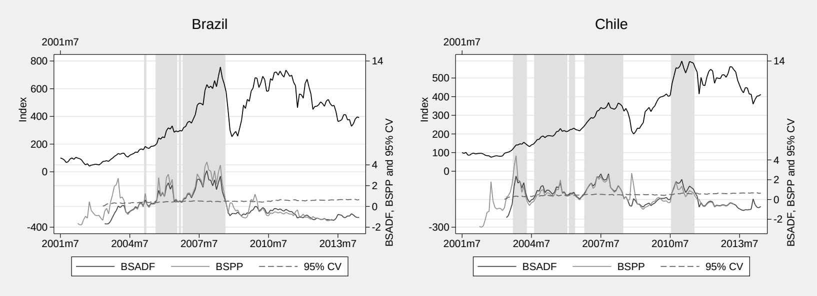
Table: *ADF*-based and *PP*-based Test Statistics

	(1)	(2)	(3)	(4)
	Supremum		Generalized Supremum	
	SADF	*SPP*	*GSADF*	*GSPP*
Panel A. Test Statistics:				
Argentina	0.198	0.762	0.905	0.963
Brazil	3.447*	3.778*	3.447*	4.273*
Chile	2.608*	3.675*	2.608*	4.436*
Colombia	11.334*	10.480*	11.334*	10.480*
Mexico	3.398*	3.530*	3.398*	3.530*
Peru	6.647*	6.243*	6.670*	6.243*
S&P 500	0.521	0.752	2.038†	4.373*
Panel B. Finite Sample Critical Values:				
90%	0.934		1.540	
95%	1.243		1.882	
99%	1.907		2.359	

Notes: The *SADF* and *GSADF* statistics follow PWY and PSY, while the *SPP* and *GSPP* are proposed in this article. The 95% critical values based on Monte Carlo simulations with 2,000 replications (sample size 156). * significant at 1%; † significant at 5%; ‡ significant at 10%.

GSADF Defined Bubble Periods

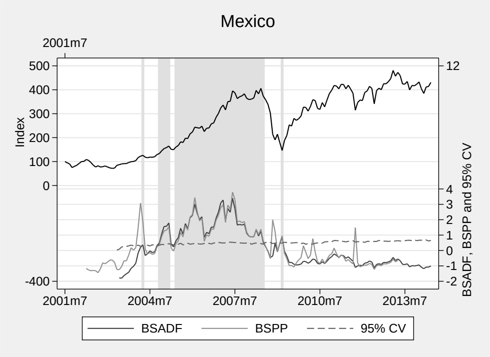
Figure: Time series graphs for Brazil and Chile



- Bubbles prior to the 2007 financial crisis.
- Brazil, no bubble around 2008.

GSADF and *GSPP* Results for Mexico

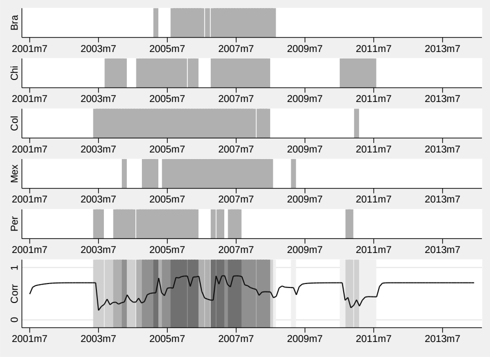
Figure: *GSADF* and *GSPP* Results for Mexico



- Implosion in March, 2009.

GSADF Defined Bubble Periods

Figure: *GSADF* Defined Bubble Periods



- Bubbles prior to the 2007-2009 financial crisis are evident in all markets.
- Common macroeconomic shocks across these countries.
- Integrated Latin American Market (MILA).

Links between Bubbles across Equity Markets

Table: Unconditional Correlations

	(1) Brazil	(2) Chile	(3) Colombia	(4) Mexico	(5) Peru
Panel A. BSADF versus BSPP Correlations:					
ADF vs. *PP*	0.902	0.788	0.972	0.899	0.957
Panel B. Unconditional Correlations:					
Brazil	1.000				
Chile	0.499	1.000			
Colombia	0.577	0.648	1.000		
Mexico	0.811	0.583	0.708	1.000	
Peru	0.282	0.541	0.673	0.436	1.000

Notes: In Panel A, the correlation is between the *BSADF* and the *BSPP* sequences. In Panel B, bubble periods as defined by the *GSADF* at the 95% critical level.

- Some evidence of links between bubbles across equity markets.

Dynamic Conditional Correlation Model

Model the following mean equation:

$$BU_t = \delta_0 + \delta_1 BU_t^{\text{S\&P500}} + \varepsilon_t.$$

where $BU_t = (BU_t^{\text{Bra}}, BU_t^{\text{Chi}}, BU_t^{\text{Col}}, BU_t^{\text{Per}}, BU_t^{\text{Mex}})'$,
$\varepsilon_t = (\varepsilon_t^{\text{Bra}}, \varepsilon_t^{\text{Chi}}, \varepsilon_t^{\text{Col}}, \varepsilon_t^{\text{Per}}, \varepsilon_t^{\text{Mex}})'$, and $\varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$.
We model the time-variation of the variance-covariance matrix H_t:

$$H_t = G_t C_t G_t,$$

where G_t is a (5×5) diagonal matrix, and C_t is the (5×5) correlation matrix of interest.
The elements of G_t are $\sqrt{g_t^i}$, with $i = (\text{Bra}, \text{Chi}, \text{Col}, \text{Per}, \text{Mex})$.

Dynamic Conditional Correlation Model

Engle (2002) suggest a two stage approach to estimate H_t:

1. Estimate $\sqrt{g_t^i}$ by fitting univariate volatility models.
2. Transform the residuals from the first stage using $u_t^i = \varepsilon_t^i / \sqrt{g_t^i}$, to use them when estimating the DCC.

The evolution of the correlations follows:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 u_{t-1} u'_{t-1} + \theta_2 Q_{t-1},$$

where $\bar{Q} = E[u_t u'_t]$ is the unconditional variance-covariance matrix of u_t, and Q_t is the time-varying conditional variance-covariance matrix of u_t. To make sure C_t contains ones in the main diagonal:

$$C_t = \mathrm{diag}\left(\frac{1}{\sqrt{q_t^{\text{Bra}}}}, \cdots, \frac{1}{\sqrt{q_t^{\text{Mex}}}}\right) Q_t \mathrm{diag}\left(\frac{1}{\sqrt{q_t^{\text{Bra}}}}, \cdots, \frac{1}{\sqrt{q_t^{\text{Mex}}}}\right),$$

where q_t^i for $i = (\text{Bra}, \text{Chi}, \text{Col}, \text{Per}, \text{Mex})$ are the main diagonal elements of Q_t.

Dynamic Conditional Correlation Model Estimates

Table: Estimation Results DCC-GARCH Model

	(1) Brazil	(2) Chile	(3) Colombia	(4) Peru	(5) Mexico
Panel A. Mean Equations:					
δ_0	0.0440*	0.161*	0.185*	0.0908‡	0.158*
	(0.0109)	(0.0526)	(0.0505)	(0.0379)	(0.0582)
δ_1	-0.0399	-0.135*	-0.148*	-0.0669	0.105
	(0.0510)	(0.0789)	(0.0864)	(0.0591)	(0.113)
Panel B. Variance Equations:					
c	0.00364*	0.0606*	0.141*	0.0202*	0.0288‡
	(0.000805)	(0.0192)	(0.0417)	(0.00539)	(0.0120)
a	0.500*	0.592*	0.890*	0.554*	0.256*
	(0.110)	(0.150)	(0.192)	(0.112)	(0.0739)
b	0.578*	0.337‡	-0.0540	0.543*	0.728*
	(0.0416)	(0.135)	(0.128)	(0.0532)	(0.0658)
Panel C. Multivariate DCC Equation:					
θ_1			0.494*		
			(0.0570)		
θ_2			0.141*		
			(0.0444)		
Observations			156		
χ^2			16.49		
χ^2 (p-value)			0.00559		

Notes: The figures in parentheses are standard errors. * significant at 1%; † significant at 5%; ‡ significant at 10%. The mean bubble equation is: $BU_t = \delta_0 + \delta_1 BU_t^{S\&P500} + \varepsilon_t$, with $BU_t = (BU_t^{Bra}, BU_t^{Chi}, BU_t^{Col}, BU_t^{Per}, BU_t^{Mex})'$, $\varepsilon_t = (\varepsilon_t^{Bra}, \varepsilon_t^{Chi}, \varepsilon_t^{Col}, \varepsilon_t^{Per}, \varepsilon_t^{Mex})$, and $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$. The variance equations: $h_t^i = c^i + a^i h_{t-1}^i + b^i(\varepsilon_{t-1}^i)^2$ for $i = $ (Bra, Chi, Col, Per, Mex).

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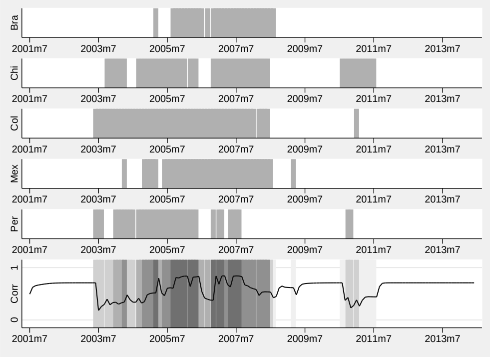
Peru	0.282	0.541	0.673	0.436	1.000
Panel C. Conditional Correlations:					
Brazil	1.000				
Chile	0.767	1.000			
Colombia	0.787	0.853	1.000		
Mexico	0.903	0.807	0.830	1.000	
Peru	0.607	0.659	0.813	0.646	1.000

Notes: In Panel A, the correlation is between the *BSADF* and the *BSPP* sequences. In Panels B and C, bubble periods as defined by the *GSADF* at the 95% critical level. In Panel C, correlations are conditional on bubbles in the S&P 500, estimated with the methods in Engle (2002).

Average Dynamic Conditional Correlations

Figure: Average Dynamic Conditional Correlations



- Strong evidence of interdependence between bubble periods across these equity markets.

Summary of Contribution

- Employ the recently developed methods of PWY (2011) and PSY (2015).
- Identify the beginning and end of bubble periods in six Latin American equity markets.
- PWY and PSY are based on the *ADF* test. Propose a similar recursive procedure based on *PP* (uses an heterocedasticity- and autocorrelation-consistent covariance matrix).
- Estimate a DCC GARCH model to study the links between bubbles.
- Strong evidence of bubbles for Brazil, Chile, Colombia, Mexico, and Peru. No evidence for Argentina.
- The findings are consistent between the *ADF*-based and the *PP*-based tests.
- Clear overlap of bubbles across markets prior to the 2007 financial crisis.
- Bubbles for Chile, Colombia and Peru match the months leading up to MILA in May 2011.

Conclusion

- *ADF*-based and *PP*-based tests coincide in 92.9% of the times when labeling bubble periods.
- Consistent across the *ADF*-based and *PP*-based tests, LA bubbles appear earlier and last longer than bubbles in the S&P 500.
- Additional research topics after identifying bubble periods, for example:
    - Regime changes.
    - Differentiated effects of monetary policy (bubble vs. no bubble).
    - More light on:
        - Should central banks respond to movements in asset prices? (Bernarke and Gertler, 2001 AER)
        - Why central banks should burst bubbles (Roubini, 2006)