

# Is There a Contagion? A Frequency-Domain Analysis of Stock Market Comovements During the Subprime Crisis

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  - calculated changes in the high-frequency portion of the covariance indicate a contagion for the majority of pairs of countries
- Implications for international portfolio management: changes in comovements (e.g., Calvet, Fisher and Thompson, 2006)



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- Cross-spectral analysis complements a conventional time-domain framework
- Proposed test for contagion avoids biases associated with the correlation breakdown tests

# Why frequency domain?

Second-moment analyses can produce spurious results

Higher correlation *per se* should not necessarily indicate a contagion, as one expects higher correlations during periods of high volatility (e.g., Bekaert, Harvey and Ng, 2005)

Correlation coefficients are conditional on market volatility  $\Rightarrow$  simple correlation coefficients may be biased (e.g., Forbes and Rigobon, 2002)

The paper overcomes the biases that heteroskedasticity brings to the tests for contagion

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  - the interdependence of financial markets is immune to changes in the economic environment?
  - what if the weight is shifted away from the trend component of covariance and toward irregular components?

# Contagion

No consensus regarding a single theoretical or empirical procedure to identify a contagion (e.g., Forbes and Rigobon, 2001, Pericoli and Sbracia, 2003, Bekaert, Harvey and Ng, 2005)

Recent studies acknowledge that contagion should be characterized by “abnormally” high comovements

This paper: (i) “volatility spillovers” and (ii) significant increase in comovements

# Fundamentals?

No consensus on the definition of economic fundamentals, and that fundamentals are likely to be country-specific (Bekaert, Harvey and Ng, 2005)

Fundamentals-based models of contagion usually have low explanatory power (Fratzscher, 2003); weak link between financial volatility and macroeconomic variables (Calvet, Fisher and Thompson, 2006); model specification

⇒ need a pragmatic approach

# Extant tests for contagion

- latent factor model (Dungey, Fry, González-Hermosillo and Martin, 2002): parameters depend on the change in volatility between noncrisis and crisis periods
- correlation test (Forbes and Rigobon, 2002): compares (unconditional) correlations of asset returns
- dummy variables (Favero and Giavazzi, 2002): how outliers in the data for one country affects return equations for other countries
- fixed time effects (Baur and Fry, 2009)
- coskewness-based test (Fry, Martin and Tang, 2010)

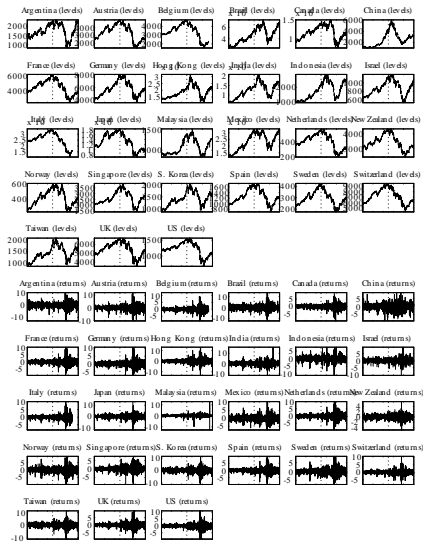
# Data: 27 international stock market indices, 2005–2009

Country	Stock Market Index*	Stock Returns <sup>†</sup>						
		Mean	Median	Min	Max	St. Dev.	Skewness	Kurtosis
Argentina	Merval Buenos Aires (MERV)	0.04	0.14	-12.95	10.43	1.99	-0.62	8.39
Austria	Vienna ATX	0.01	0.13	-10.25	12.02	1.93	-0.30	8.43
Belgium	Bel-20 Brussels (BFX)	-0.02	0.02	-8.32	12.08	1.47	0.18	12.84
Brazil	IBOVESPA Sao Paulo (BVSP)	0.08	0.16	-12.10	13.68	2.12	-0.03	8.18
Canada	TSX Composite index (Toronto)	0.02	0.11	-9.79	9.37	1.49	-0.66	10.96
China	Shanghai Composite (SSE)	0.07	0.12	-9.26	9.03	2.00	-0.34	5.65
France	CAC 40 Paris	0.00	0.04	-9.47	10.59	1.53	0.08	11.51
Germany	DAX	0.03	0.11	-7.43	10.80	1.50	0.16	11.67
Hong Kong	Hang Seng index	0.04	0.08	-12.58	12.41	1.92	0.09	11.05
India	BSE SENSEX Bombay (BSE 30)	0.08	0.15	-11.60	15.99	1.96	0.08	8.76
Indonesia	Jakarta Composite (JKSE)	0.08	0.17	-10.95	7.62	1.66	-0.66	8.94
Israel	Tel Aviv TV-100 IND	0.05	0.02	-10.54	9.71	1.59	-0.46	7.90
Italy	Milan MIBTEL	-0.04	0.06	-8.60	10.37	1.39	-0.06	12.15
Japan	Nikkei 225	-0.01	0.05	-12.11	12.22	1.75	-0.45	11.75
Malaysia	Kuala Lumpur (KLSE)	0.03	0.05	-12.97	12.79	1.05	-0.96	46.25
Mexico	IPC (MXX)	0.07	0.17	-7.27	10.44	1.62	0.16	7.42
Netherlands	Amsterdam AEX General	0.00	0.08	-9.59	10.03	1.57	-0.21	12.26
New Zealand	NZ-50 Gross Index (NZ50)	0.01	0.04	-4.94	5.81	0.86	-0.29	7.16
Norway	Oslo Exchange	0.05	0.20	-9.71	9.19	1.92	-0.63	7.40
Singapore	Straits Times Index (STI)	0.03	0.07	-9.22	7.53	1.45	-0.34	8.67
S. Korea	Seoul Composite (KS11)	0.05	0.16	-11.17	11.28	1.62	-0.59	10.04
Spain	Madrid IGBM (SMSI)	0.02	0.10	-9.68	9.87	1.45	-0.16	11.36
Sweden	Stockholm General	0.02	0.09	-7.38	8.63	1.54	0.03	7.69
Switzerland	Swiss SMI	0.01	0.07	-8.11	10.79	1.30	0.08	11.59
Taiwan	Taiwan Weighted (TWII)	0.05	0.16	-11.17	11.28	1.62	-0.59	10.04
UK	TSE 100	0.01	0.06	-9.26	9.38	1.41	-0.13	11.52
US	S&P 500	0.00	0.08	-9.47	10.96	1.51	-0.24	13.12

\*The indexes are daily adjusted closing prices between January 2005 and December 2009.

<sup>†</sup>Daily log-differences.

# Data: levels and returns





# Cospectral Analysis

Determine the relative importance of cycles of different frequencies in accounting for stock market comovements

Before and during the subprime mortgage crisis

Cospectral methods do not require specification of a model  $\Rightarrow$  the results are not based on rigid modeling assumptions

# Cospectral Analysis

Any covariance-stationary process  $x_t$  can be expressed as the Fourier transform decomposition of  $x_t$ :

$$x_t = \bar{x} + \sum_{k=1}^m [a_k \cos(\omega_k t) + b_k \sin(\omega_k t)]$$

$n$  is the number of observations,  $\bar{x}$  is the mean value of  $x$ ,  $m$  is the number of frequencies in the Fourier decomposition,  $a_k$  are the cosine coefficients,  $b_k$  are the sine coefficients, and  $\omega_k$  are the Fourier frequencies ( $\omega_k = \frac{2\pi k}{n}$ )

⇒ the value of  $x_t$  is a weighed sum of periodic functions of different amplitudes and wavelengths

# Cospectral Analysis

Calculate amplitude cross-periodograms  $J_k^{xy}$  for each pair of countries:

$$J_k^{xy} = \frac{n}{2} (a_k^x a_k^y + b_k^x b_k^y) + i \frac{n}{2} (a_k^x b_k^y - b_k^x a_k^y),$$

$J_k^{xy}$  shows the contribution of the  $k$ th harmonic to the total covariance between two data series

To produce less volatile and more consistent estimates of the cross-spectrum a triangular kernel is used to smooth the real part of cross-periodogram ordinates

# Cospectral Analysis

Compare the cospectra (the real components of the cross-spectra) for all pairs of countries for the two periods

The cross-spectrum  $s_{xy}(\omega)$  integrates to the unconditional covariance

The area under the cospectrum is equal to the covariance between  $x$  and  $y$

# Changes in covariance due to high frequencies

Calculate the percent change in cospectral density due to high frequencies after the onset of the crisis

The irregular components of stock market covariance are expected to become relatively more important during a crisis

Covariances between the stock market returns are positive at some frequencies and negative at others

# Changes in covariance due to high frequencies

Percent change in high-frequency covariance:

$$\Delta COV^{high} = \frac{COV_{crisis}^{high} - COV_{tranquil}^{high}}{COV_{tranquil}^{high}} \text{sign} \left( COV_{tranquil}^{high} \right) \cdot 100$$

$COV_{crisis}^{high} = 2 \int_{\omega_1}^{\pi} \hat{c}_{xy}(\omega) d\omega$  is the portion of the covariance of stock market returns that is attributed to cycles with frequencies greater than or equal to  $\omega_1$

# Changes in covariance due to high frequencies

To calculate the contribution of various frequencies, we multiply the cospectral density  $\hat{c}_{xy}(\omega_k)$  by  $\frac{4\pi}{n}$ , where  $n$  is the number of observations in a time series, and sum over the relevant frequencies

Compare the contributions of frequencies  $\omega \geq 0.45$  (4 weeks)

# Changes in covariance: examples

$$\textcircled{1} \text{COV}_{\text{tranquil}}^{\text{high}} = -1, \text{COV}_{\text{crisis}}^{\text{high}} = -2 \Rightarrow \Delta\text{COV}^{\text{high}} = -100\%$$



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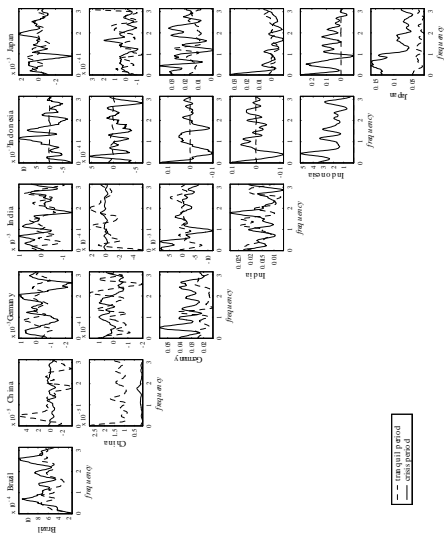
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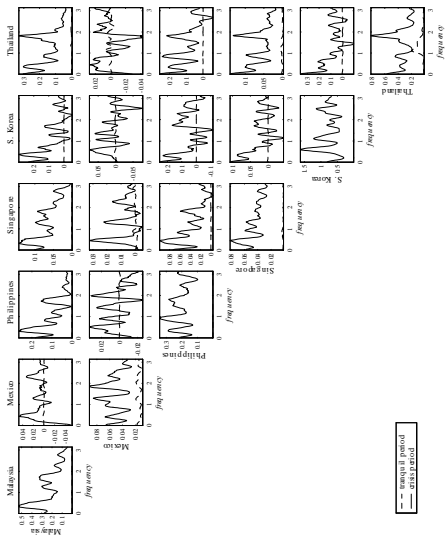
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- the formula gives us a 200% percent change, which conforms to both the numerics and the fact that the covariance has gone up
- the ordinary percent change formula would have registered a spurious  $-200\%$  change

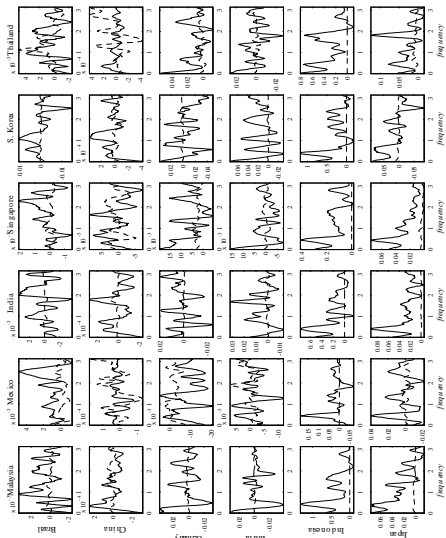
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# Cospectral Densities

- Spectral densities for most countries are larger during the crisis
- Cospectral densities are several orders of magnitudes smaller during the crisis for geographically distant countries
- Crisis period is characterized by much more volatile spectra and cospectra at both high and low frequencies
- For many pairs of countries the crisis manifested itself in greater comovements particularly along the high-frequency components
- The low-frequency (or trend) components are relatively more important during the tranquil period

# Is there a contagion?

Country	Brazil	China	Germany	India	Indonesia	Japan
Brazil	38 <sup>C</sup>					
China	53 <sup>C</sup>	-85				
Germany	-116	358 <sup>C</sup>	63 <sup>C</sup>			
India	86 <sup>C</sup>	42 <sup>C</sup>	-3017	-2		
Indonesia	293 <sup>C</sup>	-1082	-2220	1000 <sup>C</sup>	121215 <sup>C</sup>	
Japan	-13	134 <sup>C</sup>	35 <sup>C</sup>	-233	11417 <sup>C</sup>	1980
Malaysia	808 <sup>C</sup>	-395	-122	-1063	291770 <sup>C</sup>	10250
Mexico	909 <sup>C</sup>	-39	-424	-1804	17053 <sup>C</sup>	3130
Philippines	1698 <sup>C</sup>	-98	579 <sup>C</sup>	908 <sup>C</sup>	77172 <sup>C</sup>	608260
Singapore	423 <sup>C</sup>	-80	70 <sup>C</sup>	-270	112899 <sup>C</sup>	5580
S. Korea	543 <sup>C</sup>	649 <sup>C</sup>	-685	5357 <sup>C</sup>	270456 <sup>C</sup>	2190
Thailand	23 <sup>C</sup>	-137	200 <sup>C</sup>	-8597	74082 <sup>C</sup>	2220

# Comparison of time- and frequency domain results

Percent change in *overall* v. *high-frequency* covariances

$[0.9, 1.1] \Rightarrow$  accurate;  $<0 \Rightarrow$  spurious

# Comparison of time- and frequency domain results

Country	Brazil	China	Germany	India	Indonesia	Japan
Brazil	1.24 <sup>I</sup>					
China	1.53 <sup>I</sup>	0.99 <sup>A</sup>				
Germany	5.52 <sup>I</sup>	1.10 <sup>A</sup>	1.05 <sup>A</sup>			
India	0.66 <sup>I</sup>	0.36 <sup>I</sup>	44.86 <sup>I</sup>	0.45 <sup>I</sup>		
Indonesia	-0.88 <sup>S</sup>	1.51 <sup>I</sup>	1.24 <sup>I</sup>	-1.58 <sup>S</sup>	0.92 <sup>A</sup>	
Japan	-0.22 <sup>S</sup>	0.74 <sup>I</sup>	0.75 <sup>I</sup>	-4.64 <sup>S</sup>	0.87 <sup>I</sup>	0.95 <sup>A</sup>
Malaysia	1.16 <sup>I</sup>	2.06 <sup>I</sup>	-1.40 <sup>S</sup>	0.55 <sup>I</sup>	0.78 <sup>I</sup>	0.80 <sup>I</sup>
Mexico	1.01 <sup>A</sup>	4.98 <sup>I</sup>	1.14 <sup>I</sup>	4.27 <sup>I</sup>	0.79 <sup>I</sup>	1.00 <sup>A</sup>
Philippines	1.28 <sup>I</sup>	1.23 <sup>I</sup>	0.59 <sup>I</sup>	0.98 <sup>A</sup>	0.64 <sup>I</sup>	0.03 <sup>I</sup>
Singapore	1.18 <sup>I</sup>	1.54 <sup>I</sup>	0.54 <sup>I</sup>	3.04 <sup>I</sup>	0.94 <sup>A</sup>	0.87 <sup>I</sup>
S. Korea	0.28 <sup>I</sup>	0.72 <sup>I</sup>	0.99 <sup>A</sup>	0.63 <sup>I</sup>	0.03 <sup>I</sup>	0.49 <sup>I</sup>
Thailand	-3.78 <sup>S</sup>	1.47 <sup>I</sup>	0.64 <sup>I</sup>	-3.02 <sup>S</sup>	1.01 <sup>A</sup>	0.88 <sup>I</sup>

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# Sensitivity Analysis

Checks robustness of the results w.r.t.:

- starting date of the financial crisis (July 1, 2007)
- choice of the cut-off frequency ( $\omega \geq 0.45$ )
- cut-off for the percent change in the high-frequency covariance (10%)

# Conclusions

- Cospectrum-based test for contagion
- Complements time-domain techniques
- Stronger interdependencies during crisis
- Cospectral densities are several orders of magnitudes smaller during the crisis for geographically distant countries (similar sets of fundamentals, more trade/investment interdependencies?)

# Extensions

## Capital controls

Links that facilitate transmission of a crisis (e.g., international trade, exchange rate changes, liquidity effects, common creditors)

International portfolio management