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Market Fragility and International Market Crashes

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The Presentation at a Glance

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Paper Synopsis

Objective

Develop a measure identifying international ***systematic risk*** exposure

Study

- A measure, "***Fragility Index"*** developed based on Pukthuanthong and Roll (2009)'s market integration measure
- Test whether this measure implies the risk of a negative shock propagating international and of multiple markets jointly crashing

Findings

Increase in FI ***leads*** periods in which an increase in the probabilities of market crashes, ***and*** of ***joint*** co-exceedances across markets

Contributions

1. We present ex-ante measure that shows a strong and positive relation with …..
   - prob (extreme market crashes)
   - prob (crashes propagating across markets)

2. Extend the contagion literature by identifying an important factor that relates to the likelihood of a shock in one market propagating internationally

3. Extend the systematic risk literature by presenting a generalizable and flexible measure

4. Provides implications to policy makers and portfolio managers

$R_{j,t}$

Pukthuanthong and Roll (2009)

- A measure of time-varying integration based on R-square of the following:

$$R_{j,t} = \sum_{i=1}^{10} \beta_{j,i} PC_{i,t} + e_{j,t}$$

$R_{j,t}$ represents the US Dollar-denominated return for country or index *j* during day *t*,

$PC_{i,t}$ represents the *i*th principal component during day *t* estimated based on Pukthuanthong and Roll (2009)

  - Based on the covariance matrix in the previous year computed with the returns from 17 major countries, the "pre-1974 cohort"

- The loadings across countries on the 1st PC or the world factor and others are ***measurable***

Intuition

- Extend the Pukthuanthong and Roll (2009) measure of integration to provide an estimate of ***systematic risk*** within international equity markets

- PC 1 is a factor that drives the ***greatest*** proportion of world stock returns
  - **Not** restricted to equal the overall market portfolio

- A ***negative*** shock to the underlying world factor or ***PC1*** ➔ severe market declines across multiple countries
  - If the shock occurs during a period in which average to this exposure is ***high***

Fragility index

- ***Cross-sectionall average*** of time-varying loadings on the world market factor or ***<u>PC1</u>*** across countries at each point in time

- ***Fragility Index*** ("FI") indicate ….
  - periods in which international equity markets are much more ***susceptible*** to a negative shock to the world market factor PC1

- Measure is generalizable and flexible
  - Capture any economic variable that increases loadings on the world market factor
  - Allows inclusion of a large international sample of countries in a study

Why loading on PC1, not R-square?

- Integration may be a necessary but ***not*** a sufficient criteria to identify periods of high systematic risk
- Assume 2 world factors, Salt and Water
- Country A relies mostly on Salt; country B relies mostly on Water

$$R_A = \beta_{salt,A} Salt + \beta_{water,A} Water + \varepsilon_A \quad (1)$$

$$R_B = \beta_{salt,B} Salt + \beta_{water,B} Water + \varepsilon_A \quad (2)$$

$$Adj - R^2_{(1)} = Adj - R^2_{(2)} \quad \text{but} \quad \beta_{salt,A} > \beta_{salt,B}$$

- Country A has ***positive*** exposure while country B has ***negative*** exposure on Salt

$$R_A = \beta_{salt,A} Salt + \beta_{water,A} Water + \varepsilon_A$$

$$R_B = -\beta_{salt,B} Salt + \beta_{water,B} Water + \varepsilon_A$$

- Negative shock in Salt will hurt A but benefit B

Why loading on PC1, not R-square?

- When integration is ***high***, but countries exhibit ***varying*** exposure to underlying factors, we would ***not*** expect a shock to an underlying factor to manifest across many markets

- Only when integration is ***high***, and when many countries exhibit a ***similar*** exposure to ***an underlying factor***, we would expect a shock to that underlying factor to impact many markets

Detail measure of FI

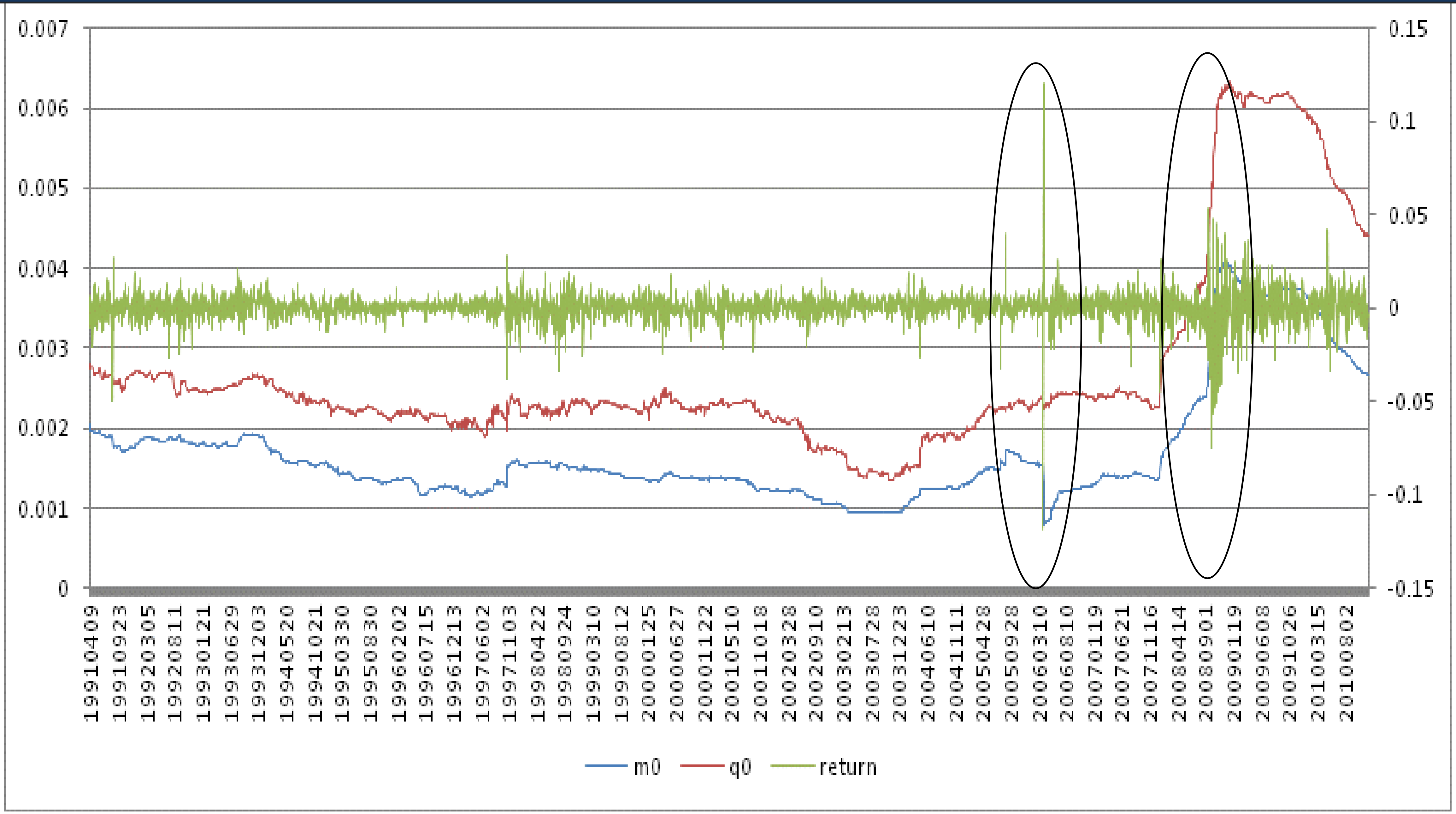
- For a given day *t*, we calculate the average of the loading on the first principal component, $\beta_{j,1,t-1}$, which is estimated across days ***<u>t-500</u>*** through day ***<u>t-1</u>*** as a 500-day rolling window across all relevant countries, and define this variable as $\mu_{PC1,t}$, which we call the "Fragility Index."

- Given our measure of fragility, we define a day as fragile or not, based on whether FI calculated through the previous day exceeds a given threshold percentile (80th, 90th, 95th, and 98th percentiles, for example).

- Define fragility based on $\mu_{PC1,t} > Pk(\mu_{PC1})$ in which $Pk(\mu_{PC1,t})$ represents the *k*th percentile of μ_{PC1} .

- The later analyses that implement logistic regressions do ***<u>not</u>*** require knowledge of full-sample percentiles.

FI through time



- m0 and q0 to represent the mean and the 75th percentile of the Fragility index $\beta_{j,i,t}$ plotted on the LHS.
- 'Return' represents the equal-weighted all country index return, and is plotted on the RHS.

Define bad return days

- Identify a crash sub-sample as all days in which $R_{j,t} \leq Pk(R_j)$ for arbitrary return percentile threshold *k*.

- Within this setting $R_{j,t}$ represents the return to index *j* during day *t* and $Pk(R_j)$ represents a specified threshold percentile of full-sample returns for index *j*.

- Define ***negative co-exceedances*** as days in which multiple countries or cohorts each experience a return below the threshold in question.

Data

- Global stock indexes from 82 countries from the Datastream

- Classify countries into 3 cohorts based on countries appearance in the Datastream
  - Before 1984 as Cohort 1 (developed markets)
  - During 1984-1993 as Cohort 2 (developing markets)
  - After 1993 as Cohort 3 (emerging markets)

- Averaging countries into cohort index returns mitigates ***non-synchronous trading*** issues as component countries would be spread across the globe and thus these components would trade through out the day

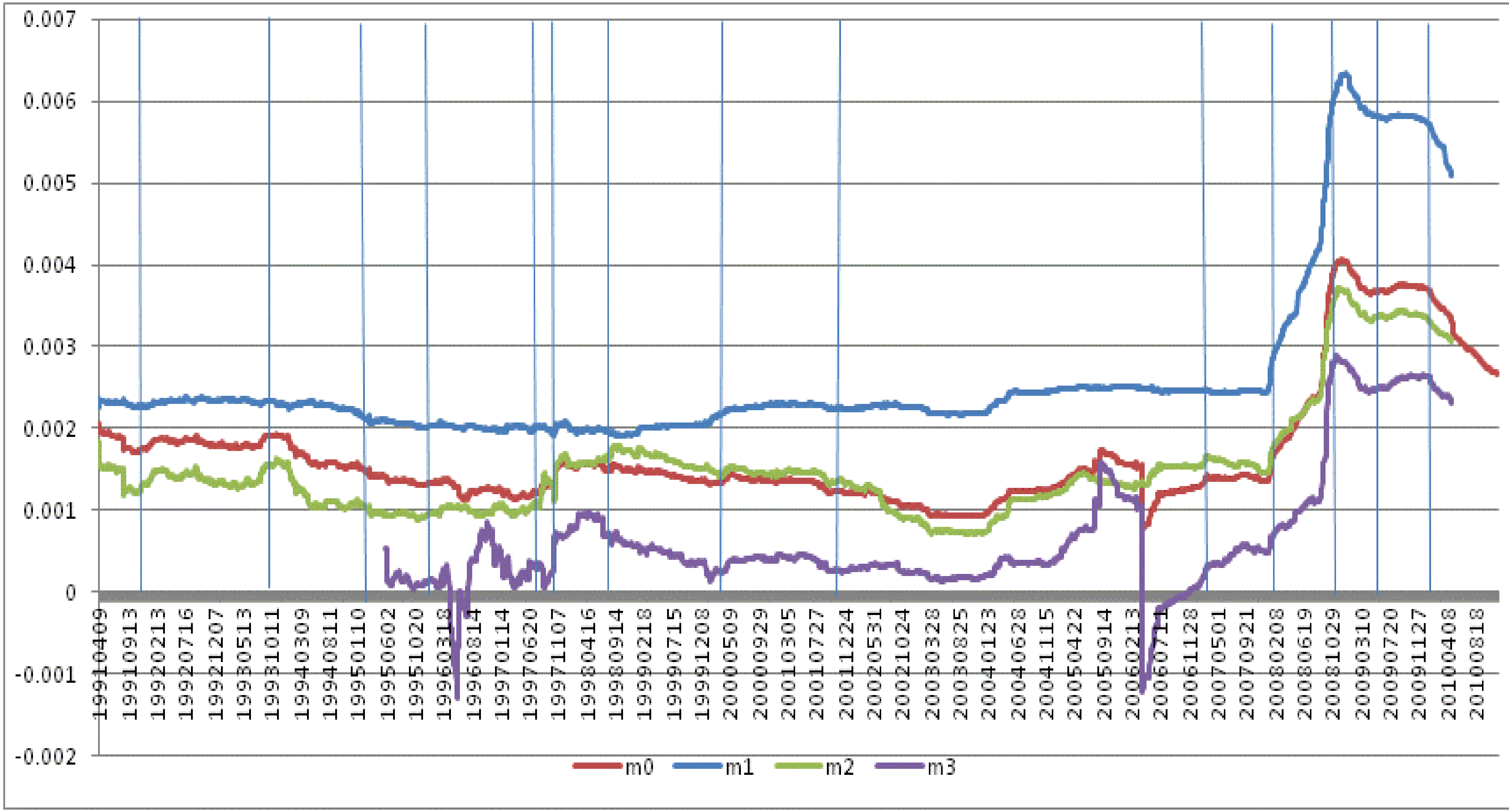
Findings

- Increases in FI ***leads*** periods in which the probabilities of market crashes, and of joint co-exceedances across markets

- Given the high levels of risk, prob(global crash across multiple countries) > prob (local crashes confined within a smaller number of countries)

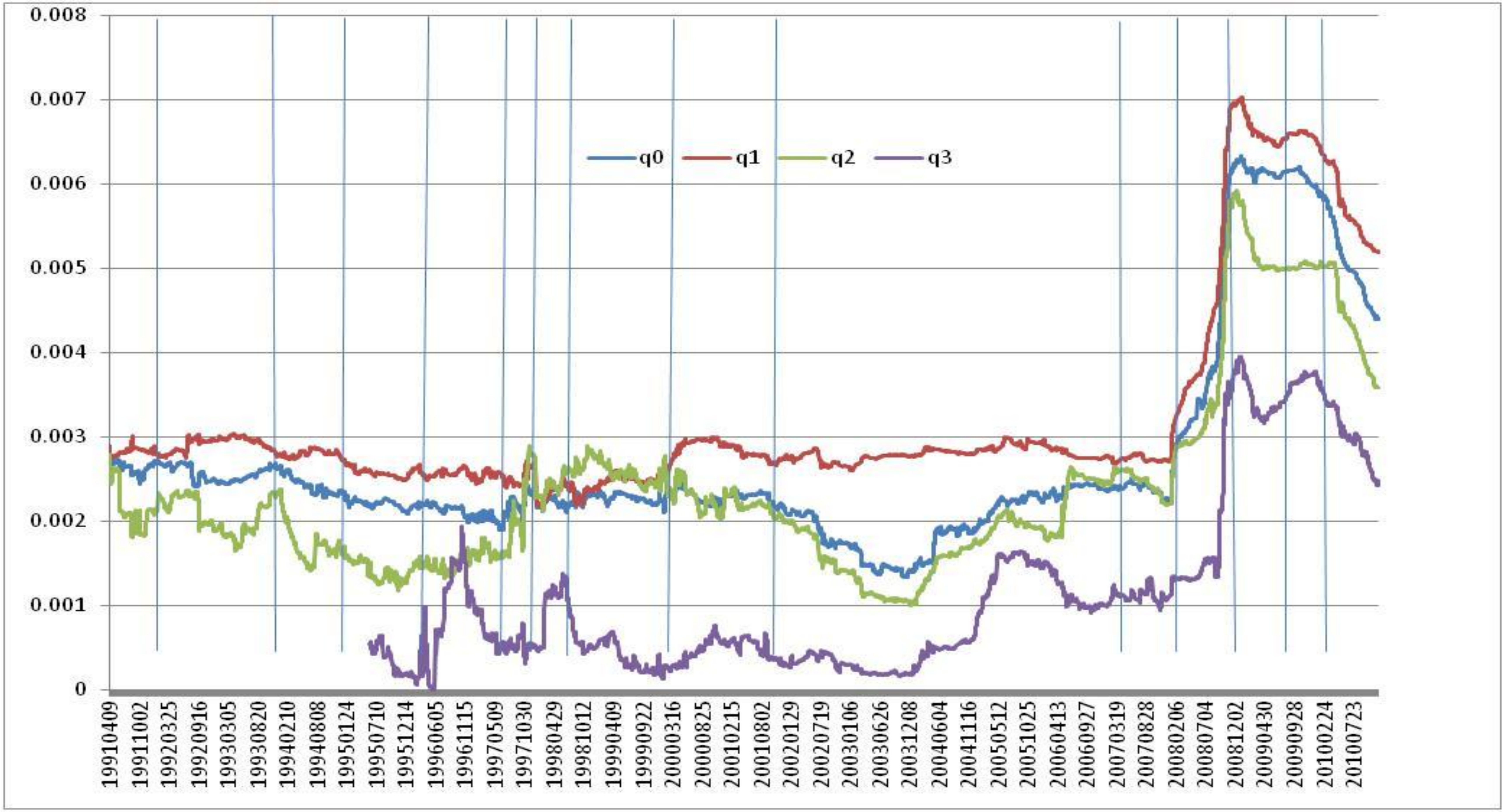
- Fragility is based on the coefficient, $\beta_{j,i,t}$ on the 1st principal component according to Pukthuanthong and Roll (2009) in which country stock returns are regressed on 10 principal components using daily observations from day *t*-500 through day *t*-1.

FI across cohorts and global crises



- m0, m1, m2, and m3 represent the mean of $\beta_{j,i,t}$ at a given point in time for all cohorts, Cohorts 1, 2, 3, respectively.
- Cohorts 1, 2, and 3 include countries first appearing on DataStream since pre-1974 to 1983, 1984-1993, and post-1993, respectively

Crisis and 75th percentile



- q0, q1,q2, and q3 represent the 75th percentile of $\beta_{j,i,t}$ at a given point in time for all cohorts, Cohorts 1, 2, 3, respectively.
- Cohorts 1, 2, and 3 include countries first appearing on DataStream since pre-1974 to 1983, 1984-1993, and post-1993, respectively

Average returns across risk states

	$Cohort_{all}$			$Cohort_1$			$Cohort_2$			$Cohort_3$		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Panel A: Full-sample summary statistics												
	0.0254	0.0719	0.8046	0.0234	0.0875	1.1217	0.0210	0.0702	0.7731	0.0344	0.0569	1.1814
Panel B: Statistics across mean of $\beta_{j,i,t}$												
1st decile	0.1075	0.1515	0.5164	0.0532	0.1343	0.9910	0.1208	0.1224	0.4605	0.0617	0.0591	0.5212
2nd decile	0.0235	0.0538	0.5153	0.0520	0.0875	0.5651	0.0191	0.0060	0.3860	0.0978	0.0896	0.4669
3rd decile	0.1052	0.1040	0.3931	0.0304	0.0686	0.6249	0.0286	0.0795	0.5357	0.2122	0.0689	2.2370
4th decile	0.0991	0.0737	0.7785	0.0436	0.1199	0.7184	0.0625	0.0801	0.5019	0.0777	0.0703	0.4693
fifth decile	-0.0107	0.0404	0.4755	-0.0562	0.0235	0.9391	-0.0215	0.0012	0.6566	0.0669	0.0566	0.4900
6th decile	-0.0006	0.0329	0.6113	-0.0209	-0.0134	0.9605	-0.0180	0.0288	0.6902	0.0749	0.0684	0.6476
7th decile	0.0224	0.0725	0.6760	0.1093	0.1818	0.8595	0.0485	0.1441	0.8113	-0.0362	0.0541	0.6742
8th decile	-0.0276	0.0578	0.9863	0.0752	0.1564	0.8160	0.0447	0.1314	0.8280	-0.1280	-0.0300	2.2038
9th decile	-0.1170	0.0224	1.0872	-0.1291	-0.0442	1.7080	-0.0992	-0.0042	0.9887	-0.0697	0.0189	0.9673
tenth decile	0.0524	0.1538	1.3939	0.0771	0.1779	2.0568	0.0247	0.1352	1.3536	-0.0138	0.0553	1.1322

- As FI increases from the 1st to 10th decile, mean returns decrease
- A plunge in returns is most drastic in Cohort 3
- Standard deviation increases as FI increases

Conditional market crash probabilities

- Ex - Expected number of crashes if FI and crashes are independent
- f- The actual number of occurrences
- f/n - The empirical probability of a crash conditional on FI exceeding the ith percentile

Note

1. The actual number of occurrences (f) is higher than the expected number of crashes (Ex) when FI is greater than a ith percentile

Ex > f when FI<ith percentile but Ex <f
When FI>ith percentile

2. f/n when FI>ith percentile is greater
Than f/n when FI<ith percentile

	$R_{j,t} \leq P20\%$	$R_{j,t} \leq P10\%$	$R_{j,t} \leq P5\%$	$R_{j,t} \leq P2\%$
$Ex(X \mid \mu_{PC1,t} < P80\%(\mu_{PC1}))$	598.36	299.18	149.59	59.20
$f(X \mid \mu_{PC1,t} < 80\%(\mu_{PC1}))$	498	213	90	27
$f/n(X \mid \mu_{PC1,t} < P80\%(\mu_{PC1}))$	16.63	7.11	3.01	0.90
$Ex(X \mid \mu_{PC1,t} > P80\%(\mu_{PC1}))$	149.64	74.82	37.41	14.80
$f(X \mid \mu_{PC1,t} > P80\%(\mu_{PC1}))$	250	161	97	47
$f/n(X \mid \mu_{PC1,t} > P80\%(\mu_{PC1}))$	33.38	21.50	12.95	6.28
$H_0: d = 0$	9.042	9.145	7.857	5.952
	(0.000)	(0.000)	(0.000)	(0.000)
$Ex(X \mid \mu_{PC1,t} < P90\%(\mu_{PC1}))$	673.28	336.64	168.32	66.61
$f(X \mid \mu_{PC1,t} < 90\%(\mu_{PC1}))$	627	288	128	47
$f/n(X \mid \mu_{PC1,t} < P90\%(\mu_{PC1}))$	18.61	8.55	3.80	1.39
$Ex(X \mid \mu_{PC1,t} > P90\%(\mu_{PC1}))$	74.72	37.36	18.68	7.39
$f(X \mid \mu_{PC1,t} > P90\%(\mu_{PC1}))$	121	86	59	27
$f/n(X \mid \mu_{PC1,t} > P90\%(\mu_{PC1}))$	32.35	22.99	15.78	7.22
$H_0: d = 0$	5.477	6.483	6.260	4.304
	(0.000)	(0.000)	(0.000)	(0.000)
$Ex(X \mid \mu_{PC1,t} < P95\%(\mu_{PC1}))$	710.64	355.32	177.66	70.30
$f(X \mid \mu_{PC1,t} < 95\%(\mu_{PC1}))$	673	319	147	56
$f/n(X \mid \mu_{PC1,t} < P95\%(\mu_{PC1}))$	18.92	8.97	4.13	1.57
$Ex(X \mid \mu_{PC1,t} > P95\%(\mu_{PC1}))$	37.36	18.68	9.34	3.70
$f(X \mid \mu_{PC1,t} > P95\%(\mu_{PC1}))$	75	55	40	18
$f/n(X \mid \mu_{PC1,t} > P95\%(\mu_{PC1}))$	40.11	29.41	21.39	9.63
$H_0: d = 0$	5.815	6.073	5.720	3.716
	(0.000)	(0.000)	(0.000)	(0.000)

Conditional probabilities of joint crashes

Based on cohort indexes, this is a number of cohort crashing

- Ex - Expected number of crashes if FI and crashes are independent
- f- The actual number of occurrences
- f/n - The empirical probability of a crash conditional on FI exceeding the ith percentile

Note

1. The actual number of occurrences (f) is higher than the expected number of crashes (Ex) when FI is greater than a ith percentile

Ex > f when FI<ith percentile but Ex<f when FI>ith percentile

2. f/n when FI>ith percentile is greater than f/n when FI<ith percentile

Panel A: Crash defined as $R_{j,t} \leq P20\%$					
Risk state	Statistic	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$\mu_{PC1,t} \leq P80\%$	$f(X)$	2038	531	270	156
	$f/n(X)$	68.05	17.73	9.02	5.21
$\mu_{PC1,t} \geq P80\%$	$f(X)$	436	79	76	158
	$Ex(X)$	494.93	122.03	69.22	62.82
	$f/n(X)$	58.21	10.55	10.15	21.09
	χ^2	7.02	15.78	0.66	144.23
		(0.071)	(0.001)	(0.883)	(0.000)
$\mu_{PC1,t} \leq P90\%$	$f(X)$	2253	576	309	232
	$f/n(X)$	66.85	17.09	9.17	6.88
$\mu_{PC1,t} \geq P90\%$	$f(X)$	221	34	37	82
	$Ex(X)$	247.14	60.94	34.56	31.37
	$f/n(X)$	59.09	9.09	9.89	21.93
	χ^2	2.76	11.91	0.17	81.74
		(0.430)	(0.008)	(0.982)	(0.000)
$\mu_{PC1,t} \leq P95\%$	$f(X)$	2378	593	324	262
	$f/n(X)$	66.85	16.67	9.11	7.37
$\mu_{PC1,t} \geq P95\%$	$f(X)$	96	17	22	52
	$Ex(X)$	123.57	30.47	17.28	15.68
	$f/n(X)$	51.34	9.09	11.76	27.81
	χ^2	6.15	5.95	1.29	84.10
		(0.105)	(0.114)	(0.732)	(0.000)
$\mu_{PC1,t} \leq P98\%$	$f(X)$	2442	600	339	289
	$f/n(X)$	66.54	16.35	9.24	7.87
$\mu_{PC1,t} \geq P98\%$	$f(X)$	32	10	7	25
	$Ex(X)$	48.90	12.06	6.84	6.21
	$f/n(X)$	43.24	13.51	9.46	33.78
	χ^2	5.84	0.35	0.00	56.91
		(0.120)	(0.950)	(1.000)	(0.000)

Conditional probabilities of joint crashes

- Ex - Expected number of crashes if FI and crashes are independent
- f- The actual number of occurrences
- f/n - The empirical probability of a crash conditional on FI exceeding the ith percentile

Note

1. The actual number of occurrences (f) is higher than the expected number of crashes (Ex) when FI is greater than a ith percentile

Ex > f when FI<ith percentile but Ex <f when FI>ith percentile

2. f/n when FI>ith percentile is greater than f/n when FI<ith percentile

Panel B: Crash defined as $R_{j,t} \leq P10\%$

Risk state	Statistic	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$\mu_{PC1,t} \leq P80\%$	$f(X)$	2540	296	107	52
	$f/n(X)$	84.81	9.88	3.57	1.74
$\mu_{PC1,t} \geq P80\%$	$f(X)$	538	66	45	100
	$Ex(X)$	615.76	72.42	30.41	30.41
	$f/n(X)$	71.83	8.81	6.01	13.35
	χ^2	9.82	0.57	7.00	159.27
		(0.020)	(0.903)	(0.072)	(0.000)
$\mu_{PC1,t} \leq P90\%$	$f(X)$	2816	328	127	99
	$f/n(X)$	83.56	9.73	3.77	2.94
$\mu_{PC1,t} \geq P90\%$	$f(X)$	262	34	25	53
	$Ex(X)$	307.47	36.16	15.18	15.18
	$f/n(X)$	70.05	9.09	6.68	14.17
	χ^2	6.72	0.13	6.35	94.18
		(0.081)	(0.988)	(0.096)	(0.000)
$\mu_{PC1,t} \leq P95\%$	$f(X)$	2961	342	138	116
	$f/n(X)$	83.24	9.61	3.88	3.26
$\mu_{PC1,t} \geq P95\%$	$f(X)$	117	20	14	36
	$Ex(X)$	153.74	18.08	7.59	7.59
	$f/n(X)$	62.57	10.70	7.49	19.25
	χ^2	8.78	0.20	5.41	106.30
		(0.032)	(0.978)	(0.144)	(0.000)
$\mu_{PC1,t} \leq P98\%$	$f(X)$	3039	354	145	132
	$f/n(X)$	82.81	9.65	3.95	3.60
$\mu_{pC1,t} \geq P98\%$	$f(X)$	39	8	7	20
	$Ex(X)$	60.84	7.15	3.00	3.00
	$f/n(X)$	52.70	10.81	9.46	27.03
	χ^2	7.84	0.10	5.31	96.15
		(0.049)	(0.992)	(0.150)	(0.000)

Logistic regressions within cohort index

	$Cohort_{all}$	$Cohort_1$	$Cohort_2$	$Cohort_3$
		$R_{j,t} \leq P20\%$		
$Coef_{\mu_{PC1}}$	4.450	2.376	5.240	4.192
	(0.000)	(0.000)	(0.000)	(0.000)
		$R_{j,t} \leq P10\%$		
$Coef_{\mu_{PC1}}$	6.378	3.741	7.520	6.063
	(0.000)	(0.000)	(0.000)	(0.000)
		$R_{j,t} \leq P5\%$		
$Coef_{\mu_{PC1}}$	8.125	4.938	8.416	8.736
	(0.000)	(0.000)	(0.000)	(0.000)
		$R_{j,t} \leq P2\%$		
$Coef_{\mu_{PC1}}$	9.808	6.829	8.568	10.587
	(0.000)	(0.000)	(0.000)	(0.000)

Logistic regressions across cohorts

	$R_{j,t} \leq P20\%$	$R_{j,t} \leq P10\%$	$R_{j,t} \leq P5\%$	$R_{j,t} \leq P2\%$
Panel A: $\sum X_i \geq 1$				
$Coef_{\mu_{PC1}}$	2.192	4.256	6.623	8.159
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: $\sum X_i \geq 2$				
$Coef_{\mu_{PC1}}$	4.979	7.186	8.525	9.244
	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: $\sum X_i = 3$				
$Coef_{\mu_{PC1}}$	7.569	9.942	10.364	13.543
	(0.000)	(0.000)	(0.000)	(0.000)
Panel D: $\sum X_i$				
$Coef_{\mu_{PC1}}$	3.430	4.917	6.828	8.229
	(0.000)	(0.000)	(0.000)	(0.000)

When ALL cohorts crash

Predictive power of FI beyond volatility and R-square

Panel A: GARCH forecasted volatilty

	$Coef_{\mu_{PC1}}$	$Coef_{\sigma}$
$Y_t = I_{\sum X_i \geq 1}$	5.933	10.056
	(0.000)	(0.000)
$Y_t = I_{\sum X_i \geq 2}$	7.759	10.445
	(0.000)	(0.000)
$Y_t = I_{\sum X_i = 3}$	9.428	12.428
	(0.000)	(0.000)
$Y_t = \sum X_i$	6.107	11.286
	(0.000)	(0.000)

Panel B: Cross-sectional average standard deviation

	$Coef_{\mu_{PC1}}$	$Coef_{\sigma}$
$Y_t = I_{\sum X_i \geq 1}$	4.188	1.427
	(0.000)	(0.000)
$Y_t = I_{\sum X_i \geq 2}$	5.688	1.599
	(0.000)	(0.001)
$Y_t = I_{\sum X_i = 3}$	9.778	0.305
	(0.000)	(0.674)
$Y_t = \sum X_i$	4.402	1.409
	(0.000)	(0.000)

Panel C: World index standard deviation

	$Coef_{\mu_{PC1}}$	$Coef_{\sigma}$
$Y_t = I_{\sum X_i \geq 1}$	2.950	1.753
	(0.007)	(0.000)
$Y_t = I_{\sum X_i \geq 2}$	3.467	2.397
	(0.024)	(0.000)
$Y_t = I_{\sum X_i = 3}$	8.027	1.066
	(0.002)	(0.344)
$Y_t = \sum X_i$	3.149	1.749
	(0.004)	(0.000)

Panel D: Cross-sectional average adjusted R-square

	$Coef_{\mu_{PC1}}$	$Coef_{AR}$
$Y_t = I_{\sum X_i \geq 1}$	5.445	0.015
	(0.000)	(0.363)
$Y_t = I_{\sum X_i \geq 2}$	5.972	0.033
	(0.003)	(0.184)
$Y_t = I_{\sum X_i = 3}$	9.307	0.014
	(0.003)	(0.721)
$Y_t = \sum X_i$	5.701	0.014
	(0.000)	(0.384)

Logistic regressions for robustness

Alteration	$Coef_{\mu_{PC1}}$
Benchmark Case: Table 5, Panel D, crashes defined based on fifth percentile of returns	6.828 (0.000)
Sample period: 12/29/1994-12/31/2007	15.284 (0.000)
Sample period: 12/01/2000 – 11/30/2010	7.635 (0.000)
FI estimation: 60 day rolling-window	6.302 (0.000)
FI specification: FI estimated from 60 day rolling-window subtract FI estimated from 500 day rolling window	3.773 (0.000)
FI estimation: 60 day rolling-window. Results analyzed only in months April through December	3.958 (0.000)
FI specification: 75th percentile of Beta	4.096 (0.000)
FI specification: Standard deviation of Beta	6.382 (0.000)
Crash definition: Absolute return below -5%	13.201 (0.000)
Only observations not preceded by a crash within any cohort in the previous 10 trading days	5.854 (0.000)
Only observations not preceded by a crash within any cohort in the previous 20 trading days	6.823 (0.001)
Only observations not preceded by a crash within any cohort in the previous 50 trading days	10.974 (0.017)

Contributions

1. We present ex-ante measure that shows a strong and positive relation with …..
   - prob (extreme market crashes)
   - prob (crashes propagating across markets)

2. Extend the contagion literature by identifying an important factor that relates to the likelihood of a shock in one market propagating internationally

3. Extend the systematic risk literature by presenting a generalizable measure

4. Provides implications to policy makers and portfolio managers

Conclusions

- The probability of financial ***interdependence*** is ***highest*** during periods in which many countries share a high exposure to the ***world market factor or PC1***

- Based on Pukthuanthong and Roll (2009) integration analysis, we develop FI as the ***cross-sectional average loading on the world factor*** across countries

- Our FI is a strong predictor of market crashes.
  - FI ↑ → Prob (a crash in all 3 cohorts) ↑

    → Prob (***all*** cohorts crashing) > Prob (only 1 or 2 cohorts crashing)

Thank you for your attention