International portfolio choice and the economic value of jump timing

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Overview

Questions

- How prevalent are jumps in international stock markets?
- How do these jumps impact volatility?
- What are the implications for asset allocation?
- Is there Economic Value in accounting for jumps?

Key results

- All 34 stock markets considered are characterized by jumps.
- Wide variation in numbers of jumps from 10 to 70. Evidence of co-jumping and systemic events.
- Removing jumps from the returns process improves asset allocation.
- A volatility-jump-timing strategy outperforms either a volatility-timing or a simple static strategy.
- Fine-tuning required with respect to jump persistence.

Systemic Risk and Jump Spillovers

- Das & Uppal (2004) - International stock returns characterized by jumps which tend to occur at the same time ⇒ systemic risk. Systemic risk reduces gains from diversification and penalizes investors for holding levered positions.
- Wu (2003) - examines impact of jumps and return predictability on dynamic asset allocation.
- Liu, Longstaff & Pan (2003) - event risk dramatically affects the optimal portfolio strategy. Consider jumps in both returns & volatility.
- Asgharian & Bengtsson (2006) - international jump spillover. Evidence that U.S. jumps spillover to other markets next day. Return correlations, however, contain little jump information.

Methodology

- Estimate jumps using SVCJ model using MCMC methods [Raggi, 2005] and ARJI-Garch [Chan and Maheu, 2002, Maheu and McCrudy, 2004].
- Replace jumps with max. (min.) return in previous 8 observations to produce a jump-adjusted return series.
- Use AG-DDC-GARCH model to forecast variance-covariance matrix.
- Follow Fleming, Kirby & Ostdiek (2001) procedure:
    1. Create a sample of 4,000 bootstrap returns [randomly select blocks of 10].
    2. Use unconditional mean returns and covariance matrix for static strategy, and conditional covariance matrix for dynamic strategies. Calculate optimal portfolio weights.
    3. Apply the weights to raw returns to calculate realized returns & various performance measures.
    4. Repeat 1,000 times.

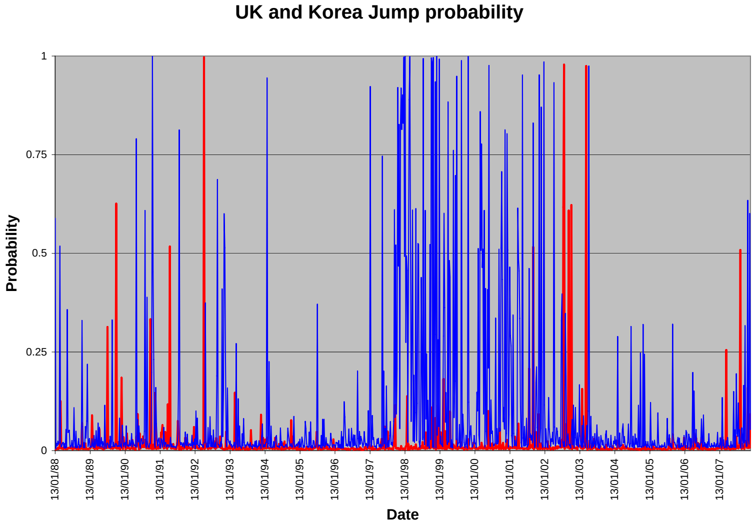
Data

- Sample: Initially: January 13, 1988 to November 28, 2007. Weekly returns constructed from Wednesday to Wednesday prices.
- Countries: 34 MSCI indices. Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland France, Germany, Hong Kong, Indonesia, Ireland, Italy, Japan, Jordan, Korea, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Portugal, Singapore, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and United States.
- All data was obtained from Datastream.
- Initial in-sample estimation period January 13, 1988 to December 27, 1995 [416 observations].
- Out-of-sample period January 3, 1996 to November 28, 2007 [622 observations]. Re-estimate recursively throughout this period to produce one-step-ahead forecasts.

Jump Estimation

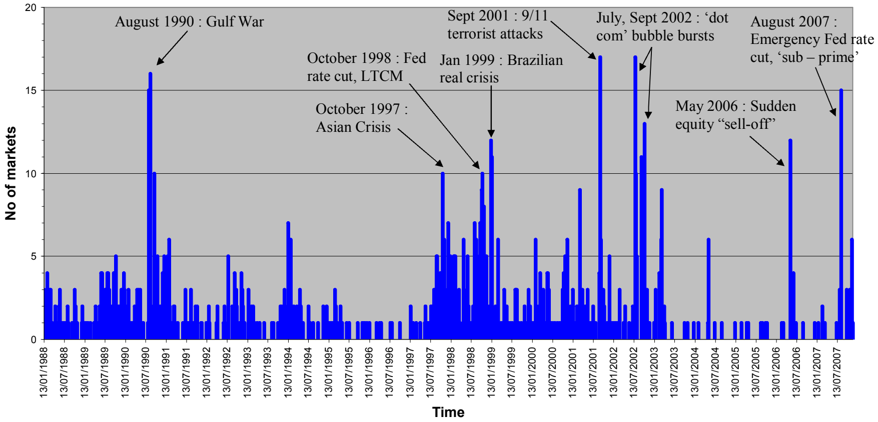
- Long-term volatility (θ) typically lower in developed markets.
- Large variation in the jump intensity, λ, across markets - 0.91 for the U.K. 9.27 for Brazil.
- Variation in number of detected jumps. Markets that have experienced crises tend to have higher numbers of jumps.

Jump probabilities



- A jump occurs when the probability exceeds 0.5. [Maheu & McCurdy, 2004]
- Two extremes, UK has the least jumps [10] while Korea exhibits the most [70].

Systemic jumps



- Systemic jumps [5 or more markets jump simultaneously] are possibly more frequent than one might think. [52 systemic jumps in 1038 weeks (5%)]

Economic Value

- Fleming, Kirby & Ostdiek (2001, 2003) - Demonstrate there is Economic Value to Volatility timing for a portfolio of Stocks, Bonds and Gold.
- Marquering & Verbeek (2004) - Use predictive macroeconomic and financial variables to show timing in both returns and volatility has economic value.
- Della Corte, Sarno & Tsiakias (2008) - apply concepts of economic value to exchange rate models.
- Guidolin & Timmermann (2008), Jondeau & Rockinger (2008) - introduce concept of distributional timing.

Mean-Variance portfolio optimization

- Examine both Minimum Risk and Maximum Return strategies.

Minimize risk

$$\min_{w_t}\{w_t'\Omega_{t+1}w_t\}$$
$$s.t. \quad w_t'\mu + (1 - w_t'\iota)r_f = \mu_p^*$$

Maximize return

$$\max_{w_t}\mu_p = w_t'\mu + (1 - w_t'\iota)r_f$$
$$s.t. \quad w_t'\Omega_{t+1}w_t = (\sigma_p^*)^2$$

- w_t is a $N \times 1$ vector of portfolio weights on risky assets, r_t.
- ι is a $N \times 1$ vector of ones.
- r_f is the return on a riskless asset. [6%]
- μ is the conditional expected return on the risky assets, r_t.
- Ω is the conditional variance-covariance matrix of r_t.
- $\mu_p^*(\sigma_p^*)$ is the portfolio target expected return (volatility).

Solution

$$\hat{w}_t = \frac{(\mu_p - r_f)\Omega_{t+1}^{-1}(\mu - \iota r_f)}{(\mu - \iota r_f)'\Omega_{t+1}^{-1}(\mu - r_f\iota)}$$

$$\hat{w}_t = \frac{\sigma_p^*\Omega_{t+1}^{-1}(\mu - \iota r_f)}{\sqrt{(\mu - \iota r_f)'\Omega_{t+1}^{-1}(\mu - \iota r_f)}}$$

Performance Metrics

- Sharpe Ratio: $SR_t = \frac{\mu_{p,t} - r_f}{\sigma_{p,t}}$
- Utility performance-fee [West, Edison & Cho, 1993; FKO, 2001]

$$U(W_t) = W_{t-1} r_{p,t} - \frac{a W_{t-1}^2}{2} r_{p,t}$$

$$r_{p,t} = (1 - w'_{t-1}\iota) r_f + w'_t r_t$$

$$\overline{U}(\cdot) = W_0 \sum_{t=1}^{T} \left(r_{p,t} - \frac{\gamma}{2(1+\gamma)} r_{p,t}^2 \right)$$

$$\sum_{t=1}^{T} \left((r_{d,t} - \Delta) - \frac{\gamma}{2(1+\gamma)} (r_{d,t} - \Delta)^2 \right) = \sum_{t=1}^{T} \left(r_{s,t} - \frac{\gamma}{2(1+\gamma)} r_{s,t}^2 \right)$$

- Calculate for $\gamma = 1, 10$. Δ is the max. weekly management fee such that the investor is indifferent between the static & dynamic strategies.
- Break-even transaction cost, τ^{BE} [Han, 2006] - level of transaction cost which eliminates the difference in utility between the static & dynamic strategies.

Results

Maximum return performance:

Target Vol.	Static			Volatility-timing			Static vs. Volatility-timing					Volatility-jump-timing			Static vs. Volatility-jump-timing				
	μ	σ	SR	μ	σ	SR	p-value	Δ_1	Δ_{10}	τ_1^{BE}	τ_{10}^{BE}	μ	σ	SR	p-value	Δ_1	Δ_{10}	τ_1^{BE}	τ_{10}^{BE}
8%	11.20	7.97	0.652	12.27	8.69	0.721	0.8709	132.3	86.3	5.93	3.70	12.36	8.35	0.762	0.9202	158.7	121.9	7.09	5.21
9%	11.49	9.02	0.609	12.78	9.51	0.713	0.8724	151.2	78.9	7.48	3.37	12.94	9.07	0.765	0.9260	177.2	111.5	8.50	4.67
10%	12.42	10.03	0.640	13.78	10.64	0.731	0.8837	167.7	69.3	8.14	2.97	13.93	10.13	0.784	0.9305	194.5	98.8	8.93	4.17
11%	13.31	11.01	0.664	14.64	11.75	0.735	0.8660	186.6	57.5	8.85	2.42	14.83	11.23	0.786	0.9361	211.7	83.4	9.81	3.44
12%	13.92	12.01	0.660	15.30	12.56	0.741	0.8747	201.3	45.0	9.77	1.88	15.54	12.21	0.782	0.9340	227.3	67.1	10.59	2.75
13%	14.46	12.95	0.654	16.08	13.96	0.722	0.8634	217.7	30.4	10.38	1.24	16.34	13.34	0.775	0.9209	241.5	48.3	11.21	1.94
14%	15.07	13.98	0.649	16.78	14.87	0.725	0.8761	231.4	11.7	10.99	0.48	17.03	14.31	0.771	0.9291	255.6	26.0	11.65	1.05
15%	16.04	15.03	0.668	17.65	15.88	0.734	0.8702	246.7	-7.5	11.71	-	17.91	15.48	0.769	0.9264	269.3	4.0	12.36	0.16
16%	16.27	16.01	0.642	18.17	16.90	0.720	0.8759	261.0	-29.2	12.28	-	18.94	16.87	0.767	0.9254	282.6	-20.5	13.23	-

- Mean return increases, volatility falls so naturally SR increases moving from static to volatility-timing to volatility-jump timing.
- Small improvement in SR leads to sizeable improvements in both performance fees (Δ_γ) & break-even transaction costs (τ_γ^{BE}).
- As target volatility ↑, Δ_1, τ_1^{BE} ↑ while $\Delta_{10}, \tau_{10}^{BE}$ ↓

Results

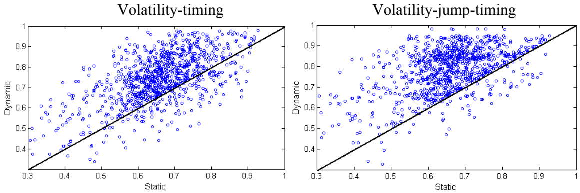
Minimum volatility performance:

Target return	Static			Volatility-timing			Static vs. Volatility-timing					Volatility-jump-timing			Static vs. Volatility-jump-timing				
	μ	σ	SR	μ	σ	SR	p-value	Δ_1	Δ_{10}	τ_1^{BE}	τ_{10}^{BE}	μ	σ	SR	p-value	Δ_1	Δ_{10}	τ_1^{BE}	τ_{10}^{BE}
8%	7.50	2.38	0.631	7.66	2.31	0.720	0.8693	3.9	34.8	0.17	1.37	7.75	2.30	0.761	0.9336	6.2	44.4	0.26	1.71
9%	8.46	3.89	0.632	8.62	3.72	0.705	0.8465	7.5	42.5	0.31	1.68	8.67	3.49	0.765	0.9450	9.8	52.1	0.40	2.04
10%	9.38	5.15	0.656	9.52	4.89	0.719	0.8402	11.6	50.2	0.47	1.98	9.59	4.61	0.779	0.9526	13.9	59.8	0.56	2.36
11%	10.41	6.75	0.653	10.54	6.28	0.723	0.8545	15.5	58.0	0.62	2.25	10.62	5.98	0.773	0.9476	17.8	67.6	0.73	2.61
12%	11.47	8.30	0.659	11.58	7.69	0.726	0.8672	19.6	67.4	0.80	2.62	11.68	7.34	0.774	0.9498	22.1	77.4	0.90	2.99
13%	12.51	10.15	0.641	12.62	9.24	0.716	0.8534	23.9	76.6	1.01	3.03	12.72	8.77	0.766	0.9353	26.2	86.1	1.11	3.33
14%	13.56	11.45	0.660	13.66	10.62	0.721	0.8377	28.6	85.8	1.18	3.32	13.77	10.08	0.771	0.9470	30.9	95.5	1.28	3.75
15%	14.39	12.75	0.658	14.47	11.72	0.723	0.8526	33.5	97.7	1.38	3.77	14.60	11.20	0.768	0.9360	35.8	107.3	1.44	4.19
16%	15.43	14.53	0.649	15.48	13.39	0.708	0.8442	38.2	109.5	1.51	4.39	15.64	12.77	0.755	0.9316	40.6	119.1	1.58	4.91

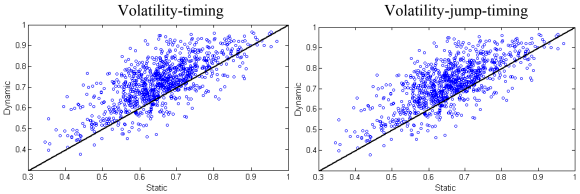
- For a given target volatility, the volatility-jump-timing strategy provides the highest expected return, lowest expected volatility and thus highest Sharpe Ratio.
- SR comparable (or higher) to max. return strategies. Performance fees, break-even transaction costs are, on average, less.

Sharpe Ratios

Maximum Return Objective



Minimum Volatility Objective



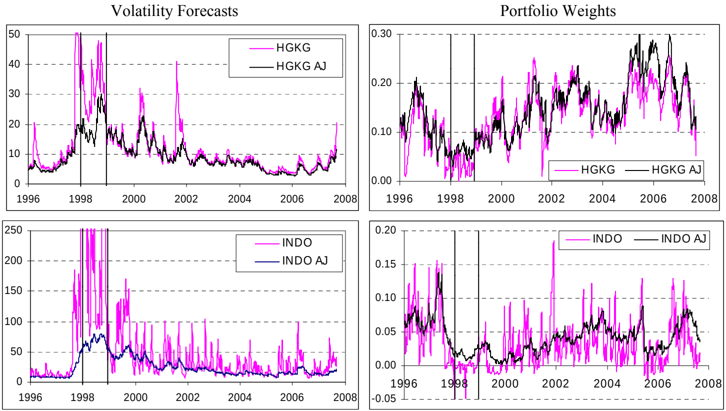
- Maximum Return - target vol. 12%, Minimum Volatility - target return 10%.

Year on Year

Year	No of jumps	Static			Volatility-timing			Static vs. Volatility-timing					Volatility-jump-timing			Static vs. Volatility-jump-timing				
		μ	σ	SR	μ	σ	SR	p-val	Δ_1	Δ_{10}	τ_1^{BE}	τ_{10}^{BE}	μ	σ	SR	p-val	Δ_1	Δ_{10}	τ_1^{BE}	τ_{10}^{BE}
1996	7	21.98	11.99	1.33	23.18	12.32	1.39	0.88	189.6	43.1	9.16	1.78	23.39	12.10	1.44	0.93	218.1	63.8	10.22	2.64
1997	93	-1.24	12.02	-0.60	0.24	12.68	-0.45	0.9	231	53.2	11.22	2.23	0.28	12.59	-0.45	0.91	232.2	54.3	11.01	2.24
1998	141	3.21	12.03	-0.23	4.76	12.86	-0.10	0.90	207.7	47.9	10.14	2.01	4.70	12.99	-0.10	0.89	195.4	41.2	8.22	1.64
1999	78	25.53	12.03	1.62	26.95	12.58	1.66	0.86	182.3	41.0	8.86	1.71	27.30	12.11	1.76	0.96	233.6	81.9	10.96	3.38
2000	74	-6.68	12.02	-1.05	-5.30	12.58	-0.90	0.89	239.0	54.7	11.59	2.29	-4.92	12.11	-0.90	0.93	241.6	63.2	11.34	2.58
2001	80	-2.03	12.02	-0.67	-0.64	12.62	-0.53	0.90	223.5	40.7	10.86	1.69	-0.29	12.15	-0.52	0.90	227.5	49.6	10.72	2.05
2002	91	-1.30	12.02	-0.61	0.15	12.64	-0.46	0.90	228.3	52.9	11.07	2.21	0.44	12.39	-0.45	0.91	237.2	59.5	11.17	2.45
2003	30	32.15	11.97	2.18	33.36	12.51	2.19	0.85	175.7	39.6	8.52	1.66	33.61	12.05	2.29	0.98	239.2	86.4	11.21	3.53
2004	10	25.68	12.00	1.64	27.06	12.38	1.70	0.86	188.1	42.9	9.15	1.79	27.30	12.01	1.77	0.94	230.2	73.6	10.79	3.02
2005	8	22.21	11.98	1.35	23.43	12.37	1.41	0.86	185.1	42.4	8.93	1.76	23.68	12.10	1.46	0.94	209.5	67.3	9.82	2.74
2006	25	25.27	12.02	1.60	26.65	12.49	1.65	0.85	183.1	41.1	8.89	1.71	26.92	12.02	1.74	0.95	226.6	78.4	10.62	3.22
2007	39	22.35	12.02	1.36	23.80	12.62	1.41	0.86	182.8	41.1	8.87	1.72	24.10	12.02	1.51	0.97	233.7	82.7	10.96	3.38

- The superiority of the volatility-jump-timing strategy is relatively robust throughout the entire out-of-sample period.
- However it is not better than volatility-timing in 1998.

Asian Crisis



- In 1998 volatility differs widely from the jump-adjusted measure. Portfolio weights deviate hugely in this period.
- Jump-adjusted strategy severely under-estimates volatility.

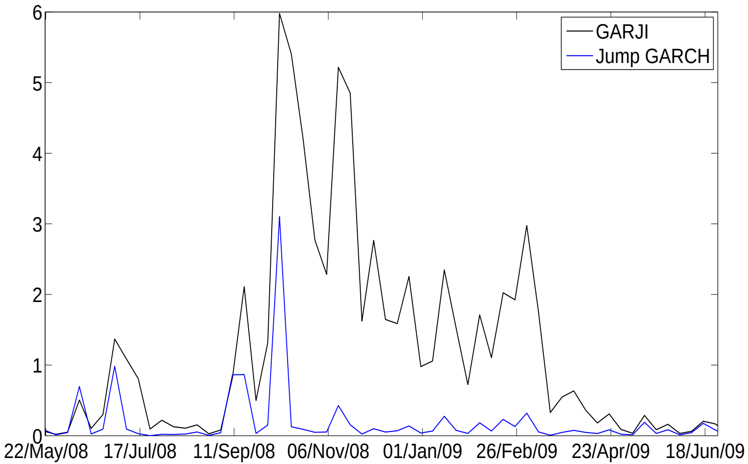
Summary

- Jump estimation: Jumps identified in all 34 markets, greater levels of intensity & identified jumps in developing/emerging markets. Evidence of systemic risk / co-jumping.
- Portfolio performance: Controlling for jumps leads to better estimates of the VCV matrix & better portfolio performance. $\Rightarrow$ “Smoothing" returns improves VCV estimation.
- Exception: Asian crisis – existence of jump persistence.

Extending the analysis

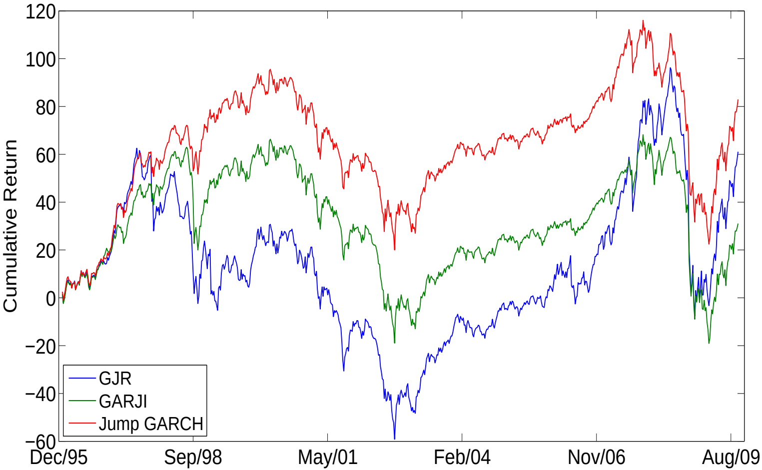
- Extend the sample to 7 October, 2009.
- Focus on ARJI-Garch and Jump GARCH to examine the impact of jump clustering and jump persistence.
- Expand utility function to consider 4 moments. Examine two-country portfolios.

Financial Crisis



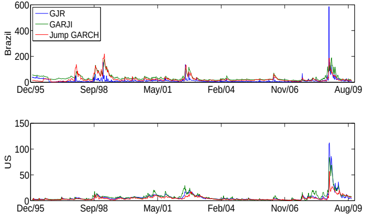
- Expected number of jumps in US returns May 2008 - June 2009.
- GARJI continues to suggest high number of jumps throughout November – February.

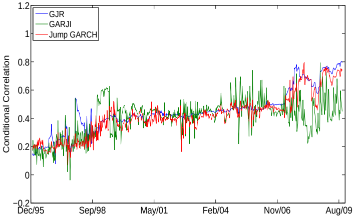
US – Brazil



- Two asset portfolio, utility function including 4 moments.
- Out-of-sample cumulative return.

US – Brazil





- Conditional variance is persistent post jump event.

- Correlations appear ‘too’ noisy for jump adjusted series.

Conclusions

- Identifying rare jumps and smoothing returns appears to improve VCV estimation and better portfolio performance.
- However this breaks down at times of crisis when there is clustering, greater jump persistence and co-jumping.
- Now focused on trying to better understand what happens during these periods and produce a ‘simple’ model or procedure which performs well in all environments.