

Bad Environments, Good Environments: A Non-Gaussian Asymmetric Volatility Model

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Motivation and Contribution 1/4

Hi!

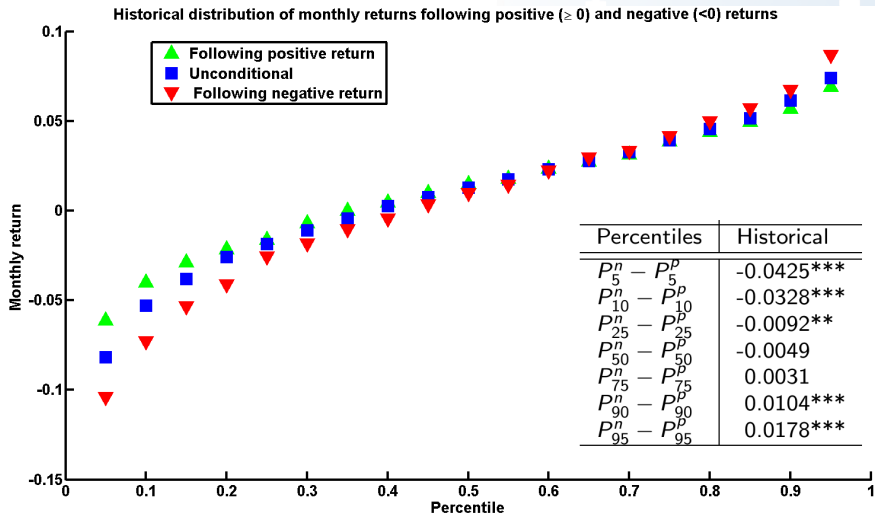
**I am abundant and,
unfortunately, do not
fit this slide.**

**Best Wishes,
GARCH literature**

Motivation and Contribution 2/4

- Given the size of the GARCH-literature, the barriers to entry are high:
 - Better empirical fit
 - Ease of estimation
 - Tractability for risk management applications

Motivation and Contribution 3/4



Motivation and Contribution 4/4

- Propose a novel GARCH model with non-Gaussianities:
 - **Better empirical fit:** superior fit of unconditional and especially **CONDITIONAL** return distribution!
 - **Ease of estimation:** Fast maximum likelihood estimation!
 - **Tractability for risk management applications:** Intuitive closed form expressions for conditional volatility, skewness, kurtosis and higher order moments!

Model 1/4: Setup

$$r_{t+1} = \mu + u_{t+1}$$

$$u_{t+1} = \omega_{p,t+1} - \omega_{n,t+1},$$

$$\omega_{p,t+1} \sim \sigma_p(\Gamma(p_t, 1) - p_t),$$

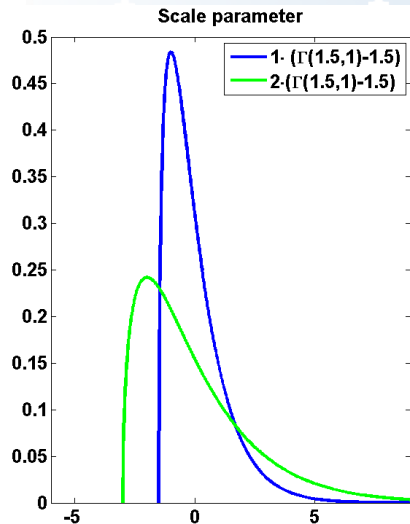
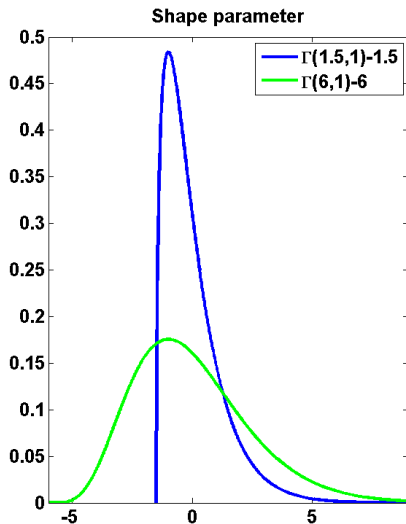
$$\omega_{n,t+1} \sim \sigma_n(\Gamma(n_t, 1) - n_t),$$

$$p_t = p_0 + \rho_p p_{t-1} + \phi_p^+ \frac{u_{t-1}^2}{2\sigma_p^2} \mathbb{1}_{u_{t-1} > 0} + \phi_p^- \frac{u_{t-1}^2}{2\sigma_p^2} \mathbb{1}_{u_{t-1} \leq 0},$$

$$n_t = n_0 + \rho_n n_{t-1} + \phi_n^+ \frac{u_{t-1}^2}{2\sigma_n^2} \mathbb{1}_{u_{t-1} > 0} + \phi_n^- \frac{u_{t-1}^2}{2\sigma_n^2} \mathbb{1}_{u_{t-1} \leq 0}.$$

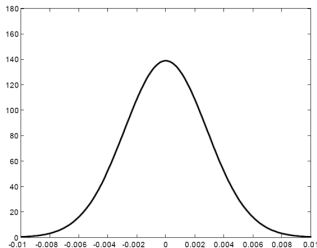
- Shock: demeaned gamma distributions (Bad Environments - Good Environments, BEGE, density): Bekaert and Engstrom (2010)
- Asymmetric impact of positive and negative innovations: Glosten, Jagannathan, Runkle (1993) (GJR)

Model 2/4: Gamma PDF

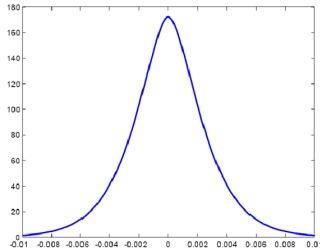


Model 3/4: BEGE PDF

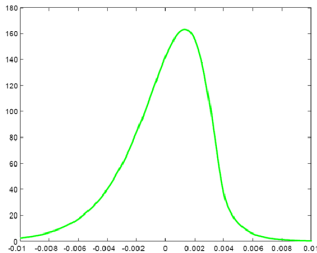
“Large” and equal p_t and n_t : Gaussian limit



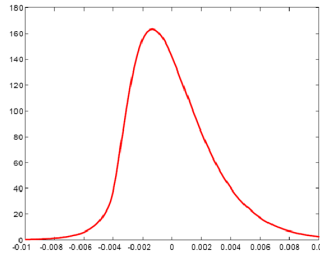
“Small” but still equal p_t and n_t : leptokurtic



Relatively large n_t : “Bad Environment”



Relatively large p_t : “Good Environment”



Model 4/4: Conditional Moments

- Intuitive theoretical expressions for (unscaled) moments:
 - $Var_t(r_{t+1}) = \sigma_p^2 p_t + \sigma_n^2 n_t$
 - $Skw_t(r_{t+1}) = 2(\sigma_p^3 p_t - \sigma_n^3 n_t)$
 - $Ex.Kur_t(r_{t+1}) = 6(\sigma_p^4 p_t + \sigma_n^4 n_t)$

Estimation 1/4: Data and Methodology

- Data: logarithmized US monthly aggregate equity returns 1926-2010
- BEGE density can be evaluated:
 - theoretically using Whittaker W function
 - numerically integrating over gamma distributions
- Fast estimation via MLE

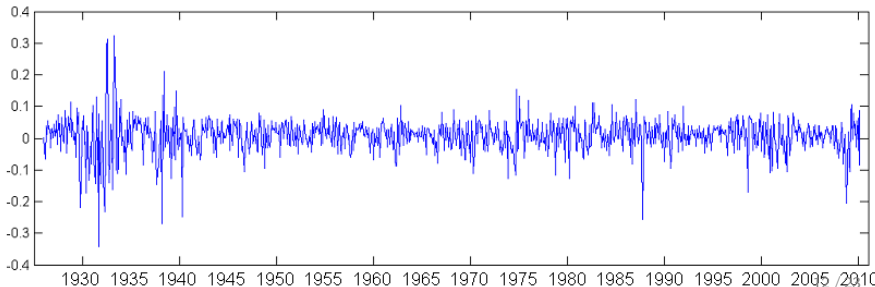
Estimation 2/4: Parameter Estimates

μ	0.0100 (0.0015)		
σ_p	0.0072 (0.0008)	σ_n	0.0282 (0.0087)
ρ_0	0.0890 (0.0070)	n_0	0.2204 (0.0111)
ρ_p	0.9099 (0.0009)	ρ_n	0.7822 (0.0086)
ϕ_p^+	0.0964 (0.0426)	ϕ_n^+	-0.0789 (0.0524)
ϕ_p^-	0.0128 (0.0139)	ϕ_n^-	0.3548 (0.0901)

Estimation 3/4: Input

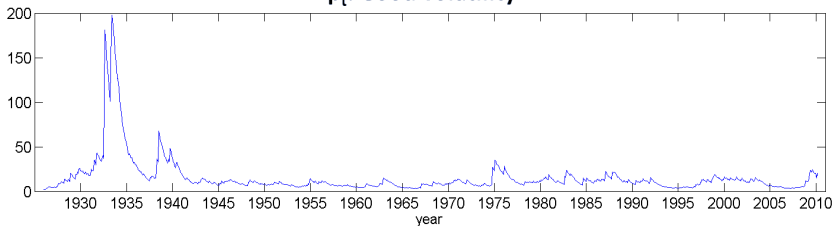
- Two types of volatility clustering:
 - large positive and negative returns: Great Depression, WWII, oil shocks in 70's
 - only large negative returns: Asia and Russia in late 90's, Dot-com, Great Recession

Logarithmized Historical Returns

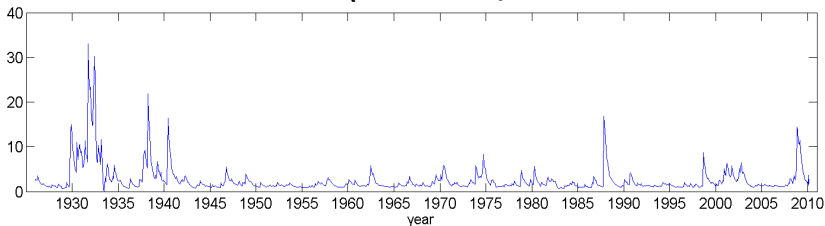


Estimation 4/4: Results

p_t : Good volatility



n_t : Bad volatility



Empirical fit 1/6: Overall fit

Model	Log-likelihood	BIC
BEGE	1724.26	-3372.32
BEGE, constant good volatility	1711.82	-3368.22
<i>t</i> -GJR-GARCH	1703.60	-3365.63
Multifractal RS model	1697.56	-3360.48
Symmetric BEGE	1695.50	-3349.43
2-regime w jump	1692.74	-3330.06
GJR-GARCH	1671.77	-3308.90

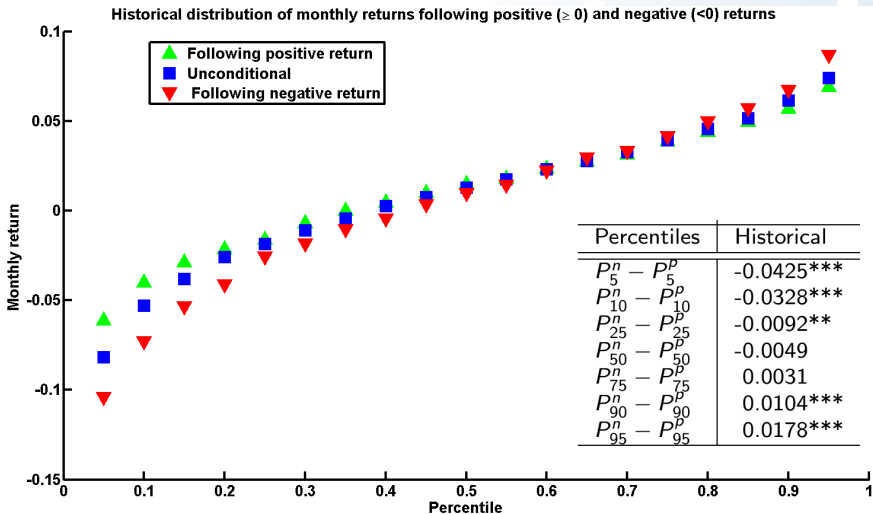
- Asymmetric right and left tails important, but regime-switching models do not seem to be a proper way to model that asymmetry
- Also time-varying good volatility is important

Empirical fit 2/6: Unconditional moments

- Generate time series of historical length from different models: 100,000 replications
- Compute proportion of replications where unconditional moment is less than or equal to its historical value

Model	Standard deviation	Skewness	Ex. Kurtosis
Historical value	0.0545	-0.5742	6.6134
Simulated p -values			
GJR-GARCH	0.6296	0.0120**	0.9580*
t -GJR-GARCH	0.8728	0.0326*	0.9101
2-regime w jump	0.5114	0.3021	0.8368
Multifractal	0.5763	0.0208**	0.9594*
BEGE	0.6127	0.5925	0.9319

Empirical fit 3/6: Conditional moments



Empirical fit 4/6: Conditional moments

- Generate time series of historical length from different models: 100,000 replications
- Compute proportion of replications where the difference between conditional percentiles is less than or equal to its historical value

Percentiles	Simulated p -values			
	t -GJR-GARCH	2-regime w jump	Multifractal	BEGE
$P_5^n - P_5^P$	0.0120**	0.0196**	0.0009***	0.0527
$P_{10}^n - P_{10}^P$	0.0081**	0.0017***	0.0001***	0.0350*
$P_{25}^n - P_{25}^P$	0.0474*	0.0248**	0.0478*	0.1761
$P_{50}^n - P_{50}^P$	0.0585	0.0578	0.0497*	0.0535
$P_{75}^n - P_{75}^P$	0.5493	0.6260	0.5740	0.2887
$P_{90}^n - P_{90}^P$	0.7978	0.8268	0.8151	0.6038
$P_{95}^n - P_{95}^P$	0.8698	0.8090	0.8830	0.7527

Empirical fit 5/6: Conditional moments

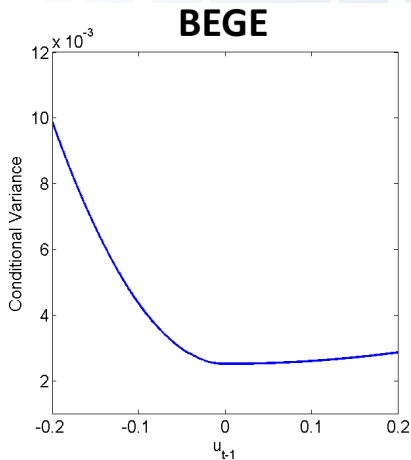
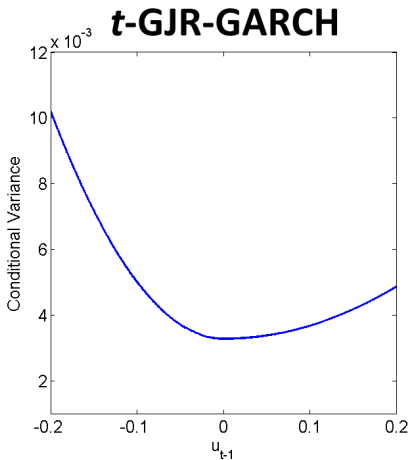
- Modified Jarque-Bera test:
 - at each time point compute CDF of the observation under the particular model
 - Inverse CDF to standard Gaussian
 - Test for the Gaussianity of the inverse CDF with Jarque-Bera test

Model	p -value
t -GJR-GARCH	0.0011***
2-regime w jump	0.0538*
Multifractal	0.0009***
BEGE	0.3756

Empirical fit 6/6: Other tests

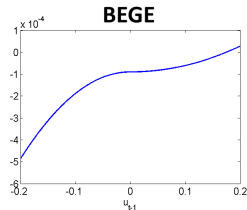
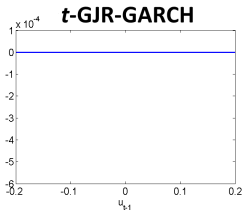
Test	Winner
Likelihood ratio tests	BEGE ✓
Engle-Manganelli "hit"-tests	BEGE ✓
Out-of-sample performance	BEGE ✓

Implications 1/3: Volatility News Impact Curves

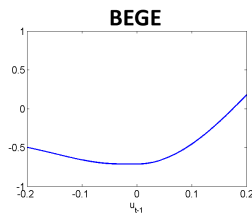
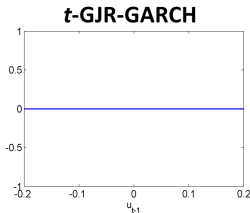


Implications 2/3: Skewness News Impact Curves

Unscaled Conditional Third Moment



Conditional Skewness



Implications 3/3: Risk-return trade-off

- Adding conditional mean:

$$r_{t+1} = 0.0096 - 0.9665\sigma_p^2 p_t + (-0.9665 + 1.9427)\sigma_n^2 n_t + u_{t+1}$$

(0.0025) (0.8587) (0.8587) (1.4333)

- Excess returns:

$$er_{t+1} = 0.0067 + 3.6378\sigma_p^2 p_t + (3.6378 - 4.4059)\sigma_n^2 n_t + u_{t+1}$$

(0.0011) (1.4900) (1.4900) (2.0741)

- Inconclusive evidence

Conclusions

- New GARCH model with tractable non-Gaussianities
- Beats standard GARCH and regime-switching models along several dimensions
- Many applications and extensions (e.g., realized variance models) \Rightarrow we provide the code!