

Quantifying the Effects of Online Bullishness...

Investor Attention and FX Market Vol...

by Mao, Counts, Bollen
by Goddard, Kita, Wang

Discussion by Peter Reinhard Hansen



European University Institute

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Quantifying the Effects of Online Bullishness on International Financial Markets

by Huina Mao, Scott Counts, and Johan Bollen

- Simple Classification (Positive or Negative) of Twitter feeds & Google search queries.
- Twitter Bullishness predicts daily returns one-day-ahead.
 - One standard deviation increase in Twitter Bullishness \rightarrow 12.56 bps higher return.

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- Classifier: Algorithms..
- Dictionary: Negative words from Harvard psychosocial dictionary.
 - “many words that are classified as negative [in a psychosocial sense] are not negative in a financial context”.
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- Regression

$$R_t = \alpha + \sum_{i=1}^5 \beta_i R_{t-i} + \sum_{i=1}^5 \chi_i T_{t-i}^B + \sum_{i=1}^5 \delta_i Vol_{t-i} + \phi Exog_t + \epsilon_t$$

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- Can you predict risk adjusted returns?
 - E.g. What is the resulting Sharpe ratio?

$$\frac{r_t}{\sigma_t}$$

- What if T_t^B is correlated with volatility.
- What if T_t^B is correlated with the variables in $Exog_t$? Monday?
- Do the results hold Out-of-Sample?

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- Search Volume Index (SVI) for Currency pairs. E.g. USD/EUR.
- Predicts
 - Trading Volume
 - Volatility
 - Variance Risk Premium
- Discuss how findings relate to various theories.

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- Contemporaneous correlation.

$$Volatility_t = \lambda_0 + \lambda_1 SVI_t + \lambda_2 Volatility_{t-1}$$

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- VAR(2)

$$SVI_t = \beta_0 + \beta_1 Vol_{t-1} + \beta_2 SVI_{t-1} + \beta_3 SVI_{t-2} + \beta_4 Vol_{t-2} + \eta_{1t}$$

$$Vol_t = \lambda_0 + \lambda_1 SVI_{t-1} + \lambda_2 SVI_{t-2} + \lambda_3 Vol_{t-1} + \lambda_4 Vol_{t-2} + \eta_{2t}$$

- Volatility from GARCH(1,1)

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha r_{t-1}^2$$

- GARCH is “slow”. Responds slowly to big changes in volatility.
 - Estimation unreliable if $T < 1000$.

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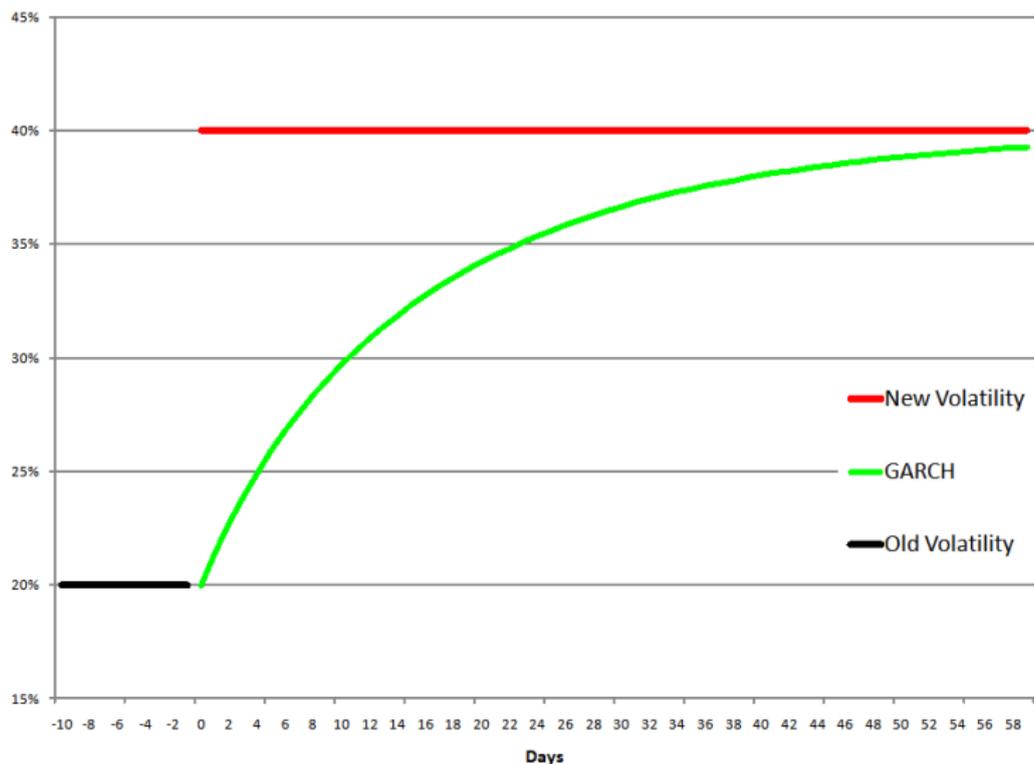
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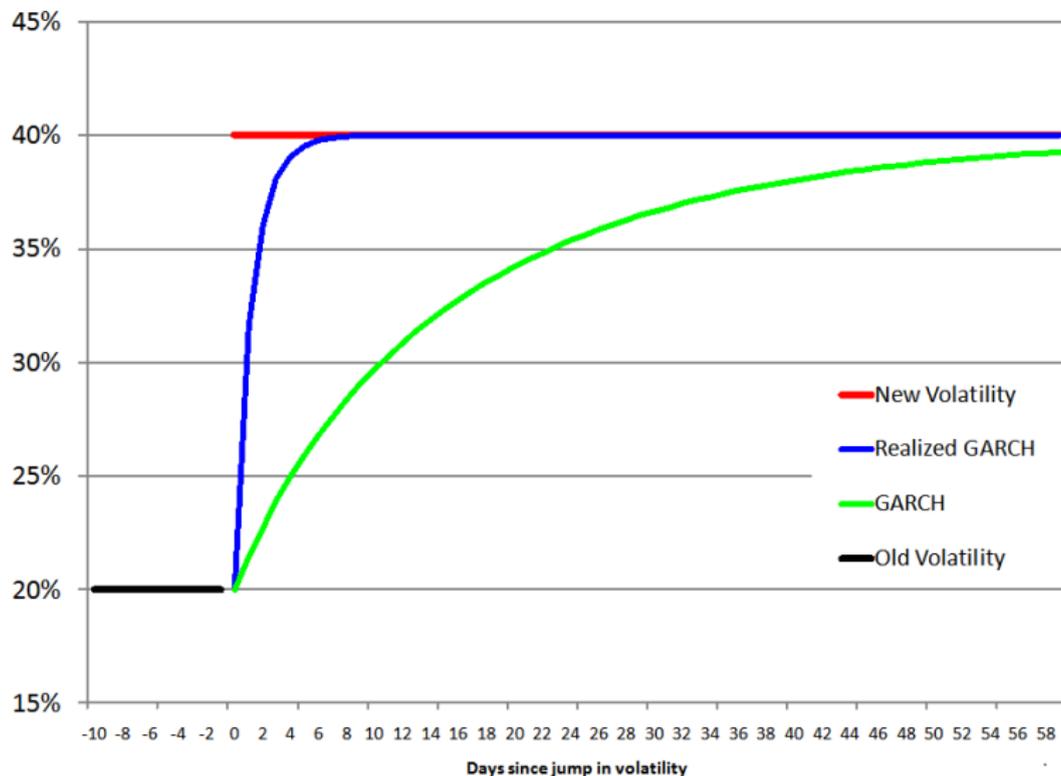
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GARCH is Slow



GARCH-X with a Realized Measure is Fast



- Extended GARCH

$$\sigma_t^2 = \exp(\lambda_0 + \lambda_1 SVI_t) + \gamma \sigma_{t-1}^2 + \dots$$

problematic because σ_t^2 is no longer \mathcal{F}_{t-1} -measurable.

- Realized GARCH

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \gamma x_{t-1},$$

- x_t is realized measure of volatility computed from high-frequency data.

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- Dynamic association with an evolutionary component.
- Conditional one-period-ahead models. SVI etc. taken as exogenous predictor.
- Not a complete model. There will be a need to model these variables.

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