

# Synthetic Volatility Forecasting and Other Aggregation Techniques for Time Series Forecasting

## Preliminary Exam

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# A seemingly unprecedented event might make one ask

- ① What does it resemble from the past?
- ② What past events are most relevant?
- ③ Can we incorporate past events in a systematic, principled manner?

# When would we ever have to do this?

- Event-driven investing strategies (unscheduled news shock)
- Pairs trading strategies
- Structural shock to macroeconomic conditions (scheduled news possibly pre-empted by news shock)
- Biomedical panel data subject to exogenous shock or interference

## Example

Example: weekend of March 7th and 8th, 2020

# Oil nose-dives as Saudi Arabia and Russia set off 'scorched earth' price war

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## Example

# Oil crashes by most since 1991 as Saudi Arabia launches price war



By [Matt Egan](#), CNN Business

🕒 3 minute read · Updated 3:21 PM EDT, Mon March 9, 2020

# Punchline of the paper

Forecasting is possible under structural shocks, so long as we incorporate external information to account for the nonzero errors.

# Background and related methods

## Volatility Modeling

- GARCH is slow to react (Andersen et al. [2003](#))
- Asymmetric GARCH models catch up faster but need post-shock data
- Realized GARCH (Hansen, Huang, and Shek [2012](#)), in our setting, would require post-shock information and/or high-frequency data in order to outperform, and the model is highly parameterized

# Background and related methods

## Forecast Augmentation

- Clements and Hendry [1998](#); Clements and Hendry [1996](#) laid the groundwork for modeling nonzero errors in time series forecasting
- Guerrón-Quintana and Zhong [2017](#) use a series' own errors to correct the forecast for that series
- Dendramis, Kapetanios, and Marcellino [2020](#) use a similarity-based procedure to correct linear parameters in time series forecasts
- Foroni, Marcellino, and Stevanovic [2022](#) adjust pandemic-era forecasts using intercept correction techniques and data from Great Financial Crisis
- Lin and Eck [2021](#) use distanced-based weighting (a similarity approach) to aggregate and weight fixed effects from a donor pool

# Outline

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  - Model Setup
  - Volatility Profile of a Time Series
- 3 Post-shock Synthetic Volatility Forecasting Methodology
- 4 Properties of Volatility Shock and Shock Estimators
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- 7 Discussion
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  - Signal Recovery
  - Synthetic Impulse Response Functions
- 9 Supplement



# The news has broken but markets are closed

- After-hours trading provides a poor forum in which to digest news
- The news constitutes public, material information relevant to one or more traded assets
- The qualitative aspects of the news provide basis upon which to match to past events

# A Primer on GARCH

Let  $\{a_t\}$  denote an observable, real-valued discrete-time stochastic process. We say  $\{a_t\}$  is a strong GARCH process with respect to  $\{\epsilon_t\}$  iff

$$\sigma_t^2 = \omega + \sum_{k=1}^m \alpha_k a_{t-k}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2$$

$$a_t = \sigma_t \epsilon_t$$

$$\epsilon_t \stackrel{iid}{\sim} E[\epsilon_t] = 0, \text{Var}[\epsilon_t] = 1$$

$$\forall k, j, \alpha_k, \beta_j \geq 0$$

$$\forall t, \omega, \sigma_t > 0$$

# Our Model is Nested Within GARCH-X

# Volatility Profile

$$V_{\tau,n} = \begin{pmatrix} \alpha_{\tau,n,1} & \alpha_{\tau,n,2} & \cdots & \alpha_{\tau,n,n} \\ \beta_{\tau,n,1} & \beta_{\tau,n,2} & \cdots & \beta_{\tau,n,n} \\ \vdots & \vdots & \ddots & \vdots \\ RV_{\tau,n,1} & RV_{\tau,n,2} & \cdots & RV_{\tau,n,n} \\ RV_{\tau,n,-1,1} & RV_{\tau,n,-1,2} & \cdots & RV_{\tau,n,-1,n} \\ \vdots & \vdots & \ddots & \vdots \\ IV_{\tau,n,1} & IV_{\tau,n,2} & \cdots & IV_{\tau,n,n} \\ IV_{\tau,n,-1,1} & IV_{\tau,n,-1,2} & \cdots & IV_{\tau,n,-1,n} \\ \vdots & \vdots & \ddots & \vdots \\ AbsoluteReturn_{\tau,n,1} & AbsoluteReturn_{\tau,n,2} & \cdots & AbsoluteReturn_{\tau,n,n} \\ AbsoluteReturn_{\tau,n,-1,1} & AbsoluteReturn_{\tau,n,-1,2} & \cdots & AbsoluteReturn_{\tau,n,-1,n} \\ \vdots & \vdots & \ddots & \vdots \\ Volume_{\tau,n,1} & Volume_{\tau,n,2} & \cdots & Volume_{\tau,n,n} \\ Volume_{\tau,n,-1,1} & Volume_{\tau,n,-1,2} & \cdots & Volume_{\tau,n,-1,n} \end{pmatrix}$$

# What's the method here?

$$2 = 3$$

# Some things to think about with papers like this

# Simplest Simulation Setup

# A more benign example

Example (Coverging at the slowest rate possible)

Fix  $\alpha = 1, \beta > 1$ . Let  $\lambda_i = \frac{1}{i \log^\beta(i+1)}$ .





# How noise is hidden just right

After all of this waiting, we formalize the notion under discussion.

Definition (Asymptotically Benign)

We analyze the real-world example with Brexit included.

# Bibliography

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