# 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

- What does it resemble from the past?
- What past events are most relevant?
- On 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 (Weekend of March 6th - 8th, 2020)



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

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



By Matt Egan, CNN Business

② 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 Realized GARCH 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

- Introduction
- 2 Setting
- 3 Post-shock Synthetic Volatility Forecasting Methodology
- Properties of Volatility Shock and Shock Estimators
- Real Data Example
- 6 Numerical Examples
- Discussion
- 8 Future directions for Synthetic Volatility Forecasting
- 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

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

$$a_t = \sigma_t \epsilon_t$$

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

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

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

## Model Setup

populate once model choice is firm

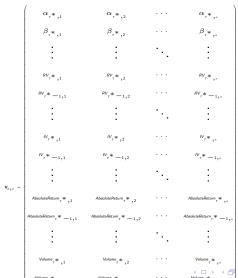


#### Our Model is Nested Within GARCH-X

Populate once notational details are decided.



# Volatility Profile of a Time Series



#### What's the method here?

$$2 = 2$$



# Forecasting

## Excess Volatility Estimators

#### **Ground Truth Estimators**

#### Loss Functions

# Simplest Simulation Setup

We also have simulations for...



#### Additional Simulations

### Alternative Data-Generating Processes

- Could we do all of the above with high-frequency data?
- Realized GARCH with High-Frequency Data
- Stochastic Volatility

# Alternative Estimators and Estimands in Volatility Modeling

- Realized GARCH with High-Frequency Data
- Overnight returns instead of open-to-close
- Value-at-Risk using SVF-based  $\hat{\sigma}_t^2$
- Signal Recovery Perspective (Ferwana and Varshney 2022)
- Stochastic Volatility: Correlation between errors

## New Frontiers in Aggregation Methods

- Integrate lessons from literature on under/over reactions to information shocks (Jiang and Zhu 2017)
- Synthetic Impulse Response Functions

# Synthetic Impulse Response Functions: A Proposal

- Suppose we have a multivariate time series of dimension ptimesT subject to shocks from a common shock distribution
- Using an IRF estimate aggregated from the first n shocks of interest, we predict the response of variable i from variable j,  $1 \le i \le j \le p$ .

We analyze the real-world example with Brexit included.

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