Synthetic Volatility Forecasting and Other Aggregation Techniques for Time Series Forecasting

Preliminary Exam

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3. Can we incorporate past events in a systematic, principled manner?

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- Structural shock to macroeconomy (scheduled news possibly pre-empted by additional news)

ECONOMY

Fed Likely to Consider 0.75-Percentage-Point Rate Rise This Week

Officials had signaled plans to raise interest rates in half-point increments before recent deterioration in data

By Nick Timiraos Follow

Updated June 13, 2022 7:47 pm ET

Example (Weekend of March 6th - 8th, 2020)

Coronavirus Health Executive Order

Public Safety

MARCH 7, 2020 | Albany, NY

At Novel Coronavirus Briefing, Governor Cuomo Declares State of Emergency to Contain Spread of Virus

Oil nose-dives as Saudi Arabia and Russia set off ‘scorched earth’ price war

PUBLISHED SUN, MAR 8 2020•9:01 AM EDT | UPDATED MON, MAR 9 2020•5:33 PM EDT

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

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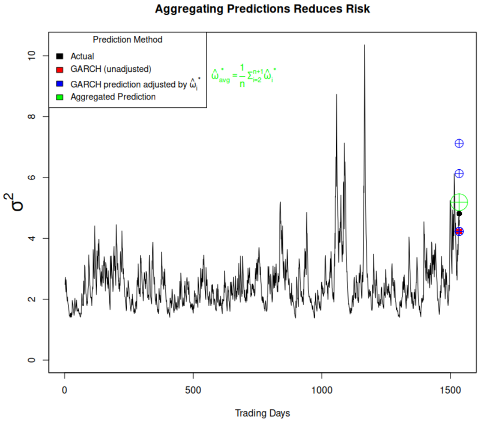

Figure: Predicting Volatility Using Only Arithmetic Mean of Donors

Background and related methods

Volatility Modeling

- GARCH is slow to react to shocks (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 Adjustment

- 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

Premise: 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 a basis upon which to
  - match to past events
  - match in a p-dimensional covariate space

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

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

$$a_t = \sigma_t \epsilon_t$$

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

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

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

Volatility Equation with an exogenous term: GARCH-X

$$\sigma_t^2 = \omega + \sum_{k=1}^{m} \alpha_k a_{t-k}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 + \gamma^T \mathbf{x}_t \ .$$

Model Preliminaries

Let $I(\cdot)$ be an indicator function.

Let T_i denote the time length of the time series i for $i = 1, \ldots, n+1$.

Let T_i^* denote the largest time index prior to news shock, with $T_i^* < T_i$ (i.e. we assume at least one post-shock observation).

Let $\delta, \mathbf{x}_{i,t} \in \mathbb{R}^p$.

Model Setup

For $t = 1, \ldots, T_i$ and $i = 1, \ldots, n+1$, the model $\mathcal{M}_1$ is defined as

$$\mathcal{M}_1: \quad \begin{aligned} \sigma^2_{i,t} &= \omega_i + \omega^*_{i,t} + \sum_{k=1}^{m_i} \alpha_{i,k} a^2_{i,t-k} + \sum_{j=1}^{s_i} \beta_{i,j} \sigma^2_{i,t-j} + \gamma_i^T \mathbf{x}_{i,t} \\ a_{i,t} &= \sigma_{i,t}((1 - D^{return}_{i,t})\epsilon_{i,t} + D^{return}_{i,t} \epsilon^*_i) \\ \omega^*_{i,t} &= D^{vol}_{i,t}[\mu_{\omega^*} + \delta' \mathbf{x}_{i,t} + u_{i,t}], \end{aligned}$$

with error structure

$$\begin{aligned} &\epsilon_{i,t} \overset{iid}{\sim} \mathcal{F}_\epsilon \text{ with } \mathrm{E}_{\mathcal{F}_\epsilon}(\epsilon) = 0, \mathrm{Var}_{\mathcal{F}_\epsilon}(\epsilon) = 1 \\ &\epsilon^*_{i,t} \overset{iid}{\sim} \mathcal{F}_{\epsilon^*} \text{ with } \mathrm{E}_{\mathcal{F}_{\epsilon^*}}(\epsilon) = \mu_{\epsilon^*}, \mathrm{Var}_{\mathcal{F}_{\epsilon^*}}(\epsilon^*) = \sigma^2_{\epsilon^*} \\ &u_{i,t} \overset{iid}{\sim} \mathcal{F}_u \text{ with } \mathrm{E}_{\mathcal{F}_u}(u) = 0, \mathrm{Var}_{\mathcal{F}_u}(u) = \sigma^2_u \\ &\epsilon_{i,t} \perp\!\!\!\perp \epsilon^*_{i,t} \perp\!\!\!\perp u_{i,t} \end{aligned}$$

where $D^{return}_{i,t} = I(t \in \{T^*_i + 1, \ldots, T^*_i + L_{i,return}\})$ and $D^{vol}_{i,t} = I(t \in \{T^*_i + 1, \ldots, T^*_i + L_{i,vol}\})$ and $L_{i,return}, L_{i,vol}$ denote lengths of log return and volatility shocks, respectively.

Model Details

Let $\mathcal{M}_0$ denote the subclass of $\mathcal{M}_1$ models such that $\delta \equiv 0$.

Note that $\mathcal{M}_0$ assumes that $\omega^*_{i,t}$ have no dependence on the covariates and are i.i.d. with $\mathbb{E}[\omega^*_i] = \mu_{\omega^*}$.

Our Model is Nested inside a Factor Model

Consider $\mathcal{M}_1$ in the context of the factor model from Abadie, Diamond, and Hainmueller 2010, where an untreated unit is governed by:

$$Y_{i,t}^{N} = \delta_t + \boldsymbol{\theta}_t^{'}\mathbf{Z}_i + \boldsymbol{\lambda}_t^{'}\boldsymbol{\mu}_i + \varepsilon_{i,t}$$

which nests the GARCH model's volatilty equation as well as the ARMA representation of a GARCH model, where

$\delta_t \sim \omega$, a location parameter shared across donors

$\boldsymbol{\theta}_t \sim \boldsymbol{\alpha}_k$, a vector of ARCH parameters and other coefficients shared across donors

$\mathbf{Z}_i \sim \boldsymbol{a}_{i,t-k}$, a vector of observable quantities specific to each donor

$\boldsymbol{\lambda}_t \sim \boldsymbol{\beta}_j$, a vector of GARCH parameters shared across donors

$\boldsymbol{\mu}_i \sim \boldsymbol{\sigma}^2_{i,t-j}$, a vector of latent quantities specific to each donor

Volatility Profile of a Time Series

Consider the $p \times n$ matrix that stores all donor and covariate information

$$\mathbf{V}_t = \begin{pmatrix} \hat{\alpha}_{1,t} & \hat{\alpha}_{t,2} & \cdots & \hat{\alpha}_{t,n} \\ \hat{\beta}_{1,t} & \hat{\beta}_{t,2} & \cdots & \hat{\beta}_{t,n} \\ \vdots & \vdots & \ddots & \vdots \\ RV_{1,t} & RV_{2,t} & \cdots & RV_{n,t} \\ RV_{1,t-1} & RV_{2,t-1} & \cdots & RV_{n,t-1} \\ \vdots & \vdots & \ddots & \vdots \\ IV_{1,t} & IV_{2,t} & \cdots & IV_{n,t} \\ IV_{1,t-1} & IV_{2,t-1} & \cdots & IV_{n,t-1} \\ \vdots & \vdots & \ddots & \vdots \\ |r_{1,t}| & |r_{2,t}| & \cdots & |r_{n,t}| \\ |r_{1,t-1}| & |r_{2,t-1}| & \cdots & |r_{n,t-1}| \end{pmatrix},$$

where RV denotes realized variance and IV the implied volatility

Significance of the Volatility Profile

Covariates chosen for inclusion in a given volatility profile may be any $\mathcal{F}_t$-measurable function, for example

- levels
- differences in levels
- log returns
- percentage returns
- absolute values of the above

Key criterion for inclusion: how plausible is the covariate as a proxy for risk conditions?

Forecasting

We present two forecasts:

$$\text{Forecast 1: } \hat{\sigma}^2_{unadjusted} = \hat{\mathbb{E}}[\sigma^2_{1,T_1^*+1}|\mathcal{F}_{T^*}] = \hat{\omega}_i + \sum_{k=1}^{m_i} \hat{\alpha}_{i,k} a^2_{i,t-k} + \sum_{j=1}^{s_i} \hat{\beta}_{i,j}\sigma^2_{i,t-j} + \hat{\gamma}_i^T \mathbf{x}_{i,t}$$

$$\text{Forecast 2: } \hat{\sigma}^2_{adjusted} = \hat{\mathbb{E}}[\sigma^2_{1,T_1^*+1}|\mathcal{F}_{T^*}] + \hat{\omega}^* = \hat{\omega}_i + \sum_{k=1}^{m_i} \hat{\alpha}_{i,k} a^2_{i,t-k} + \sum_{j=1}^{s_i} \hat{\beta}_{i,j}\sigma^2_{i,t-j} + \hat{\gamma}_i^T \mathbf{x}_{i,t} + \hat{\omega}^* \ .$$

Excess Volatility Estimators

- Observe the pair $(\{\hat{\omega}^*_i\}_{i=2}^{n+1}, \{\mathbf{v}_i\}_{i=2}^{n+1})$.

Nota bene: the weights $\{\pi_i\}_{i=2}^{n+1}$ are deterministic with respect to $\mathcal{F}_{T^*}$.

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- Following Abadie, Diamond, and Hainmueller 2010; Abadie and Gardeazabal 2003, let $\|\cdot\|_{\mathbf{S}}$ denote any semi-norm on $\mathbb{R}^p$, and define

$$\{\pi\}_{i=2}^{n+1} = \arg\min_{\pi} \|\mathbf{v}_{1,T^*} - \mathbf{V}_{T^*}\pi\|_{\mathbf{S}} \ .$$

Nota bene: the weights $\{\pi_i\}_{i=2}^{n+1}$ are deterministic with respect to $\mathcal{F}_{T^*}$.

Ground Truth Estimators

We use realized volatility (RV)

- "model-free" in the sense that it requires no modeling assumptions (Andersen and Benzoni 2010).
- RV can be decomposed into the sum of a continous component and a jump component, with the latter being less predictable and less persistent (Andersen, Bollerslev, and Diebold 2007), cited in De Luca et al. 2006, two factors that further motivate our method.

Realized Volatility Estimation

Examine K units of of time; each unit is divided into m intervals of length $\frac{1}{m}$. Let $p_t = \log P_t$, and let $\tilde{r}(t, \frac{1}{m}) = p_t - p_{t-\frac{1}{m}}$ (Andersen and Teräsvirta 2009).

Estimate variance of ith log return series using Realized Volatility of the K consecutive trading days that conclude with day t, denoted $RV_{i,t}^{K,m}$, using

$$RV_{i,t}^{K,m} = \frac{1}{K} \sum_{v=1}^{Km} \tilde{r}^2(v/m, 1/m),$$

where the K trading days have been chopped into Km equally-sized blocks.
Assuming the K units $\tilde{r}(t,1) = p_t - p_{t-1}$ are s.t. $\tilde{r}(t,1) \overset{iid}{\sim} N(\mu, \delta^2)$, it is easily verified that

$$\mathbb{E}[RV^{K,m}] = \frac{\mu^2}{m} + \delta^2,$$

which is a biased but consistent estimator of the variance. We pick $m = 77$, corresponding to the 6.5-hour trading day chopped into 5-minute blocks, omitting first five-minutes of the day.

Loss Functions

Aim: point forecasts for $\sigma^2_{1,T^*+h}|\mathcal{F}_{T^*}$, $h = 1, 2, ...,$, the *h*-step ahead conditional variance for the time series under study

Let L^h with the subscripted pair {prediction method, ground truth estimator}, denote the loss function for an *h*-step-ahead forecast using a given prediction function and ground truth estimator.

Loss Function Examples

For example, one loss possible function of interest in this study is the 1-step-ahead MSE using Synthetic Volatility Forecasting and Realized Volatility:

$$\text{MSE}^{1}_{\text{SVF, RV}} = (\hat{\sigma}^2_{SVF} - \hat{\sigma}^2_{RV})^2$$

Also of interest in mean absolute percentage error for an h-step-ahead forecast, defined as

$$\text{MAPE}^{h}_{method,groundtruth} = \frac{|\hat{\sigma}^2_{h,method} - \hat{\sigma}^2_{h,groundtruth}|}{\hat{\sigma}^2_{h,groundtruth}}$$

Our choice of Loss Function

Finally, we introduce the QL (quasi-likelihood) Loss (Brownlees, Engle, and Kelly 2011):

$$\mathrm{QL}^{h}_{method,groundtruth} = \frac{\hat{\sigma}^2_{h,method}}{\hat{\sigma}^2_{h,groundtruth}} - \log \frac{\hat{\sigma}^2_{h,method}}{\hat{\sigma}^2_{h,groundtruth}} - 1 \ .$$

What distinguishes QL Loss?

- Multiplicative rather than additive
- As Brownlees, Engle, and Kelly 2011 explain, "[a]mid volatility turmoil, large MSE losses will be a consequence of high volatility without necessarily corresponding to deterioration of forecasting ability. The QL avoids this ambiguity, making it easier to compare losses across volatility regimes."

Why apply our method to the 2016 US Election?

IYG **iShares U.S. Financial Services ETF**

Figure: Includes: JPM, BAC, WF, among other financial majors

1. **Model choice** GARCH(1,1) on the daily log return series of IYG in each donor
2. **Covariate Choice** log return Crude Oil (CL.F), the VIX (VIX) and the log return of the VIX, the log returns of the 3-month, 5-year, 10-year, and 30-year US Treasuries, return of the most recently available monthly spread between AAA and BAA corporate debt, widely considered a proxy for lending risk (Goodell and Vähämaa 2013; Kane, Marcus, and Noh 1996). We also include the log return in the trading volume of the ETF IYG itself, which serves as a proxy for panic.
3. **Donor pool construction** the three most recent US presidential elections prior to the 2016 election. The three US presidential elections are the only presidential elections since the advent of the ETF IYG. We exclude the midterm congressional elections in the US, which generate far lower voter turnout and feature no national races.
4. **Choice of estimator for volatility** Sum of squared 5-minute log returns of IYG on November 9th, 2016, otherwise known as the Realized Volatility estimator of volatility (Andersen and Teräsvirta 2009), as our proxy. We exclude the first five minutes of the trading day, resulting in a sum of 77 squared five-minute returns generated between 9:35am and 4pm.

2016 Election

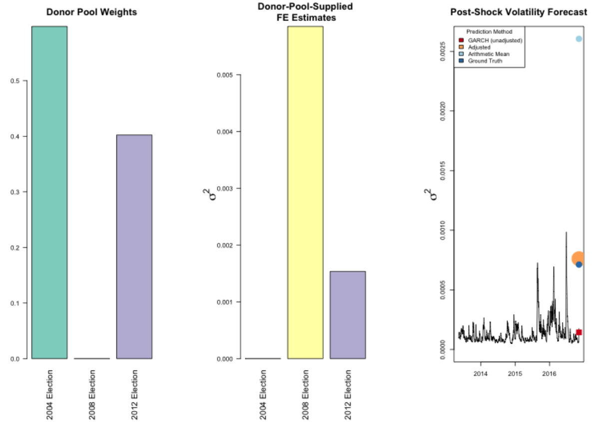

Figure: The volatility induced by the 2016 US election

Hypotheses to Test Via Simulations

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3. Distance-based weighting should outperform the arithmetic mean as the variability of $\mathbf{x}_{i,T^*}$ increases between donors
4. Distance-based weighting should underperform the arithmetic mean as μ_{ω^*} increases
5. When $D^{return}_{i,T^*+1} = 1 = D^{vol}_{i,T^*+1}$, i.e. when there is both a return shock and volatility shock, our adjustment methods should underperform due to failed identification in $a_{T^*+1} = \sigma_{T^*+1}\epsilon_{T^*+1}$

Simplest Simulation Setup

Most elementary simulation regime tests Hypothesis 1 and 2 by varying δ and $u_{i,t}$.

Recall an $\mathcal{M}_1$ model on the volatility, which is characterized by an exogenous shock to the volatility equation generated by an affine function of the covariates:

$$\mathcal{M}_1 : \begin{aligned} \sigma^2_{i,t} &= \omega_i + \omega^*_{i,t} + \textstyle\sum_{k=1}^{m_i} \alpha_{i,k} a^2_{i,t-k} + \sum_{j=1}^{s_i} \beta_{i,j} \sigma^2_{i,t-j} + \gamma_i^T \mathbf{x}_{i,t} \\ a_{i,t} &= \sigma_{i,t}((1 - D^{return}_{i,t})\epsilon_{i,t} + D^{return}_{i,t} \epsilon^*_i) \\ \omega^*_{i,t} &= D^{vol}_{i,t}[\mu_{\omega^*} + \delta' \mathbf{x}_{i,t} + u_{i,t}] \\ D^{return}_{i,t} &\equiv 0 \end{aligned}$$

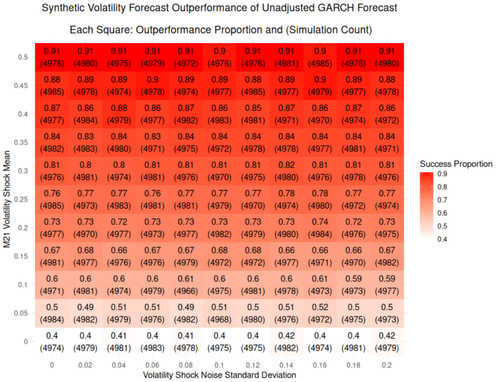


Figure: Fixed parameter values: $\alpha = .1, \beta = .82, \mu_x = 1, \sigma_x = .1$

If we switch the values of α and β, we see similar behavior.

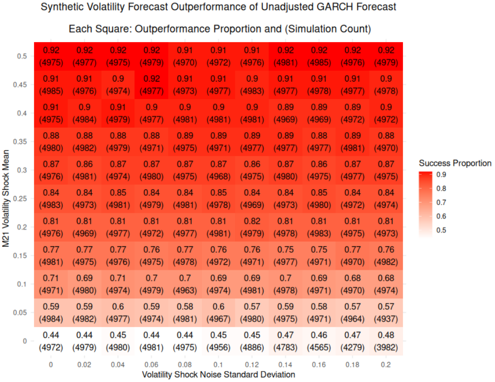


Figure: Fixed parameter values: $\alpha = .82, \beta = .1, \mu_x = 1, \sigma_x = .1$

We shall group the extensions into five buckets:

- How much can we automate?
- Alternatives for fixed effect estimation
- Alternative estimators and estimands
- What can you do with a volatility forecast?
- Where else is distanced-based weighting useful?

How much can we automate?

Alternative Ways of Estimating Fixed Effects

High-frequency data?

- Realized GARCH with High-Frequency Data
- Stochastic Volatility

Alternative Estimators and Estimands in Volatility Modeling

- Factors in volatility profile
- Overnight returns instead of open-to-close
- Signal Recovery Perspective (Ferwana and Varshney 2022)
- Stochastic Volatility: Correlation between errors
- Multivariate GARCH

What can you do with a volatility forecast?

- Value-at-Risk using SVF-based $\hat{\sigma}_t^2$

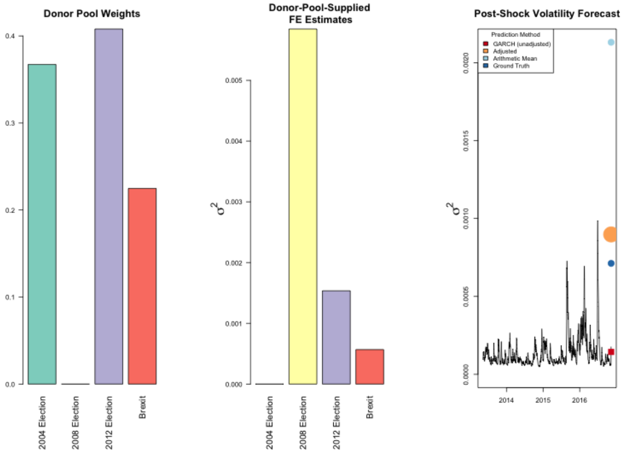
New Frontiers in Distance-based Weighting

- 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 $p \times T$ 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, $1 \leq i \leq j \leq p$.

We analyze the real data example with Brexit included.



References I

- Abadie, Alberto, Alexis Diamond, and Jens Hainmueller (2010). "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program". In: *Journal of the American Statistical Association* 105.490, pp. 493–505.
- Abadie, Alberto and Javier Gardeazabal (2003). "The Economic Costs of Conflict: A Case Study of the Basque Country". In: *American Economic Review* 93.1, pp. 113–132.
- Andersen, Torben G and Luca Benzoni (2010). "Stochastic volatility". In: *CREATES Research Paper* 2010-10.
- Andersen, Torben G, Tim Bollerslev, and Francis X Diebold (2007). "Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility". In: *The review of economics and statistics* 89.4, pp. 701–720.
- Andersen, Torben G and Timo Teräsvirta (2009). "Realized volatility". In: *Handbook of financial time series*. Springer, pp. 555–575.
- Andersen, Torben G et al. (2003). "Modeling and forecasting realized volatility". In: *Econometrica* 71.2, pp. 579–625.

References II

Brownlees, Christian T, Robert F Engle, and Bryan T Kelly (2011). "A practical guide to volatility forecasting through calm and storm". In: *Available at SSRN 1502915*.

Clements, Michael and David F Hendry (1998). *Forecasting economic time series*. Cambridge University Press.

Clements, Michael P and David F Hendry (1996). "Intercept corrections and structural change". In: *Journal of Applied Econometrics* 11.5, pp. 475–494.

De Luca, Giovanni et al. (2006). "Forecasting Volatility using High-Frequency Data". In: *Statistica Applicata* 18.

Dendramis, Yiannis, George Kapetanios, and Massimiliano Marcellino (2020). "A similarity-based approach for macroeconomic forecasting". In: *Journal of the Royal Statistical Society Series A: Statistics in Society* 183.3, pp. 801–827.

Ferwana, Ibtihal and Lav R Varshney (2022). "Optimal Recovery for Causal Inference". In: *arXiv preprint arXiv:2208.06729*.

Foroni, Claudia, Massimiliano Marcellino, and Dalibor Stevanovic (2022). "Forecasting the Covid-19 recession and recovery: Lessons from the financial crisis". In: *International Journal of Forecasting* 38.2, pp. 596–612.

References III

Goodell, John W and Sami Vähämaa (2013). "US presidential elections and implied volatility: The role of political uncertainty". In: *Journal of Banking & Finance* 37.3, pp. 1108–1117.

Guerrón-Quintana, Pablo and Molin Zhong (2017). "Macroeconomic forecasting in times of crises". In.

Hansen, Peter Reinhard, Zhuo Huang, and Howard Howan Shek (2012). "Realized GARCH: a joint model for returns and realized measures of volatility". In: *Journal of Applied Econometrics* 27.6, pp. 877–906.

Jiang, George J and Kevin X Zhu (2017). "Information shocks and short-term market underreaction". In: *Journal of Financial Economics* 124.1, pp. 43–64.

Kane, Alex, Alan J Marcus, and Jaesun Noh (1996). "The P/E multiple and market volatility". In: *Financial Analysts Journal* 52.4, pp. 16–24.

Lin, Jilei and Daniel J Eck (2021). "Minimizing post-shock forecasting error through aggregation of outside information". In: *International Journal of Forecasting*.