

# Post-shock Volatility Forecasting Using Aggregated Shock Information

David Lundquist\*, Daniel Eck†

Department of Statistics, University of Illinois at Urbana-Champaign

June 5th, 2023

## Abstract

We develop a novel procedure for forecasting the volatility of a time series under study immediately following an exogenous shock. Adapting the synthetic prediction framework of [Lin and Eck \[2021\]](#), we exploit series that have experienced similar shocks. We extract volatility signals from these series in order to aggregate properly their shock-induced excess volatilities. The volatility spikes are modeled as random effects and estimated as fixed effects. The aggregation of these estimates is done in service of adjusting the h-step-ahead GARCH forecast of the time series under study by an additive term. The adjusted and unadjusted forecasts are evaluated using three families of benchmarks: the unobservable but easily-estimated realized volatility (RV) of the time series under study, implied volatility, and the empirical volatility over horizons of varying length. We also compare the performance of the adjusted forecast to the performance of the Realized GARCH forecast, which is known to react faster to rapidly-changing volatility than GARCH incorporating implied volatility. Finally, we combine Realized GARCH modeling with the synthetic prediction framework, using Realized GARCH in both the estimation of random effects as well as the forecast for the time series under study. Real-world illustrations are provided, as are simulation results suggesting the conditions under which our approach's hyperparameters can be tuned for best performance.

## 1 Introduction

The most important stochastic phenomenon of many time series  $(P_t)_{t \in \mathbb{N}}$ , especially financial time series, is the volatility of the return series  $(r_t)_{t \in \mathbb{N}}$ . A financial asset's price series and daily return series may exhibit behavior that makes inconvenient and uninterpretable the traditional methods of time series analysis. In contrast, the volatility of the return series may be less noisy, less structurally dependent on external factors, and more easily modeled as a weakly stationary process. Yet even if one could model and forecast price series and return series with high accuracy, that would not necessarily tell us much about the variability of such forecasts nor enlighten us about the evolution of the variability of  $(P_t)_{t \in \mathbb{N}}$  over time. Modern portfolio management and theory requires information about at least the first two moments of a return series, if not higher. For these reasons and others, volatility modeling has come to dominate financial econometrics over the past four decades.

However, no matter how a time series or its transformations are modeled, forecasting in the presence of exogenous shock events requires a methodological framework that sensibly incorporates relevant information that has yet to manifest itself in market price or derivative quantities like volatility. In this setting, regime-change models are of little use because under the assumption of a known exogenous shock, there is no need to estimate a regime-change time, nor is there data following the exogenous shock event

---

\*davidl11@illinois.edu

†dje13@illinois.edu

to fit a model. Asymmetric GARCH models were an early attempt to account for fact that negative returns typically beget larger volatility than positive returns [Hansen et al., 2012]. As a separate problem, GARCH models have been shown slow to adapt to spikes in volatility (find first authors to point this out). Engle [2002] explored the use of implied volatility as an external regressor in a GARCH model, that is, using so-called GARCH-X models [Sucarrat, 2020]. Hansen et al. [2012] propose Realized Garch, which aims to solve both the asymmetry problem as well as the slow-reaction problem by introducing a "measurement equation" as a tool for modeling the contribution to the conditional variance made by the market-implied volatility measure. The key insight is that that the market-implied volatility measure is not independent of the conditional variance posited by the GARCH model. Therefore, including the external measure must be done in a way that accounts for this dependence.

The approach herein can be viewed as an attempt to sidestep the functional complexity posited by Realized GARCH by substituting modeling assumptions. Synthetic Volatility Forecasting proceeds under the assumption that similar unscheduled news events occasion volatility shocks arising from a common shock distribution.

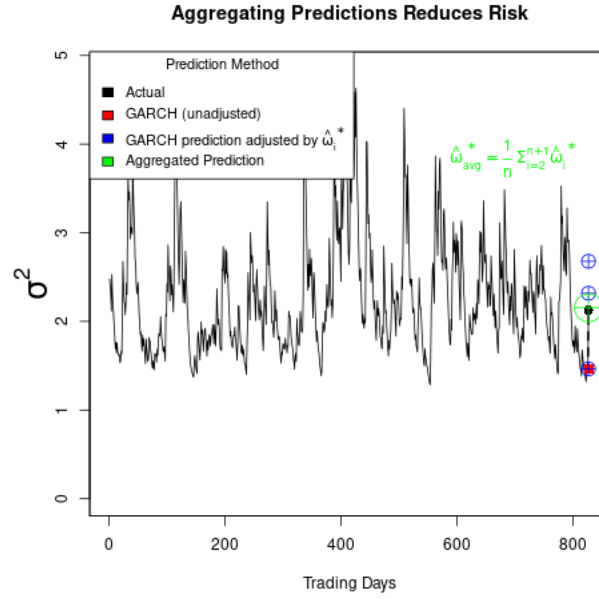


Figure 1: An example of aggregating shock estimates using the arithmetic mean

As we see in 1, the arithmetic mean of estimated shock effects provides perhaps the most straightforward and intuitive way of aggregating information from similar events. Aggregating forecasts using the arithmetic mean is more than merely intuitive; it possesses an empirical pedigree and is known to be optimal under rather restrictive conditions [Timmermann, 2006]. Synthetic volatility forecasting lacks these restrictions and instead assumes a credible, parsimonious parameterization in which the shock is an affine transformation of several key covariates.

We adapt the news shock framework:

$$z^{\text{irregular news shock}} := z^{\text{irregular news}} - \mathbb{E}_{T^*}[z^{\text{irregular news}}] \quad [\text{Kilian and Lütkepohl, 2017}]$$

## 2 Setting

We follow convention and define the daily log-return as  $r_t = \log(\frac{P_{t+1}}{P_t})$ , where  $P_t$  denotes the price at time  $t$ . The class of ARIMA(p,d,q) models developed in the mid-to-late 20th century [Box, 2013] provides a framework for postulating and quantifying the autoregressive structure of  $r_t$ , all within the framework of frequentist statistics and maximum-likelihood estimation of parameters. These models assume a certain dependence structure between  $r_t$  and  $(r_k)_{k \leq t}$ , as well as all observations in between, yet their errors – often called innovations in the financial time series context due to how they represent the impact of new information – are nevertheless assumed to be i.i.d. with mean zero and constant variance. The ARCH [Engle, 1982] and GARCH [Bollerslev, 1986] models provide elegant alternatives to the constant-variance assumption. In fact, the GARCH framework in its most basic form disregards  $r_t$  and instead turns its interest to the series  $r_t^2$  (when properly centered, i.e. after assuming a mean-model for returns).

To that end, let  $a_t = r_t - \mu_t$ , where  $\mu_t$  is the mean of the log return series  $r_t$ . Implicitly, we are committing ourselves to a mean-model for  $r_t$  in which  $\mu_t$ , the expected daily log-return, may vary with time, while  $a_t$  is simply the noise. As Cont [2001] explains, such an assumption is justified by the empirical finding that returns lack significant autocorrelation. We derive a mean-zero process  $(a_t)_{t \in \mathbb{N}}$  with the property that  $\mathbb{E}[a_t^2] = \text{Var}[a_t]$ . Under the assumption of time-invariant volatility, the series  $a_t^2$  should exhibit no autocorrelation at any lag  $\ell \geq 1$ . This assumption motivates tests for so-called ARCH effects, that is, tests for the clustering of volatility. These tests explore the alternative hypothesis that  $\sigma_t^2$  is not only a time-varying parameter but furthermore a function of past squared residuals of the mean model. In particular, the ARCH(m) model is an autoregressive model in which  $\sigma_t^2$  is fitted using a linear combination of the  $m$  past values of  $a_t^2$ . The GARCH(m,s) framework take this one step further but modeling  $\sigma_t^2$  as a linear combination of the  $m$  past  $a_t^2$  values and well as the  $s$  past values of  $\sigma_t^2$ . In functional form,

$$\begin{aligned}\sigma_t^2 &= \omega + \sum_{k=1}^m \alpha_k a_{t-k}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 \\ a_t &= \sigma_t \epsilon_t\end{aligned}$$

Assuming further that  $\sigma_t^2$  depends on a vector of exogenous covariates  $\mathbf{x}_t$  (a so-called “GARCH-X”), we have

$$\begin{aligned}\sigma_t^2 &= \omega + \sum_{k=1}^m \alpha_k a_{t-k}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 + \gamma^T \mathbf{x}_t \\ a_t &= \sigma_t \epsilon_t\end{aligned}$$

We will suppose that a researcher has multivariate time series data  $\mathbf{y}_{i,t}$ ,  $t = 1, \dots, T_i$  and  $i = 1, \dots, n+1$ . We let  $\mathbf{y}_{i,t} = (y_{i,t}, \mathbf{x}_{i,t}, \mathbf{v}_{i,t})$  where  $y_{i,t}$  is a scalar response,  $\mathbf{x}_{i,t}$  is a vector of covariates that are revealed to the analyst prior to the observation of  $y_{1,t}$ , and  $\mathbf{v}_{i,t}$  is a vector of market-implied volatility metrics for the series  $i$  that are available prior to the market open at time  $t$ . Suppose that the analyst is interested in forecasting the volatility of  $y_{1,t}$ , the first time series in the collection. We require that each time series  $\mathbf{y}_{i,t}$  is subject to a news event immediately following  $T_i^* \leq T_i + 1$  and before witnessing  $T_i^* + 1$ . To define an interesting setting, we will suppose that  $T_1^* = T_1 + 1$ , and  $1 < T_i^* < T_i + 1$  for  $i \geq 2$ . We will suppose that  $\mathbf{x}_{i,t=T_i^*}$  and  $\mathbf{v}_{i,t=T_i^*}$  are observed before the shock is manifested on  $y_{i,t=T_i^*+1}$ .

In light of the foregoing, we can rewrite the GARCH framework we are interested in as such

$$\sigma_{i,t}^2 = \omega_i + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \begin{pmatrix} \mathbf{x}_{i,t} \\ \mathbf{v}_{i,t} \end{pmatrix}$$

$$a_{i,t} = \sigma_{i,t} \epsilon_{i,t}$$

We are interested in a multihorizon point forecast for  $\sigma_{1,T^*+h}^2$ ,  $h = 1, 2, \dots, H$ , the  $h$ -step ahead conditional variance for the time series under study, up to a maximum forecast horizon of  $H$ . The forecast performance evaluation uses three distinct loss functions, each computed using three families of estimators for the ground truth that we seek. 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. For example, one loss function of interest in this study is the 1-step-ahead MSE using Synthetic Volatility Forecasting and Realized Volatility:

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

In more generality, for an multihorizon volatility forecast with maximum forecast length  $H$ , the loss function is

$$MSE_{method,groundtruth}^H = \frac{1}{H} \sum_{h=1}^H (\hat{\sigma}_{h,method}^2 - \hat{\sigma}_{h,groundtruth}^2)^2$$

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

$$MAPE_{method,groundtruth}^H = \frac{1}{H} \sum_{h=1}^H \frac{|\hat{\sigma}_{h,method}^2 - \hat{\sigma}_{h,groundtruth}^2|}{\hat{\sigma}_{h,groundtruth}^2}$$

Finally, we introduce the QL (quasi-likelihood) Loss [Brownlees et al., 2011]:

$$QL_{method,groundtruth}^H = \frac{1}{h} \sum_{h=1}^H \left( \frac{\hat{\sigma}_{h,method}^2}{\hat{\sigma}_{h,groundtruth}^2} - \log \frac{\hat{\sigma}_{h,method}^2}{\hat{\sigma}_{h,groundtruth}^2} - 1 \right)$$

What distinguishes QL Loss is that it is multiplicative rather than additive. This serves as a basis for some of its virtues. As Brownlees et al. [2011] explains, "[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."

## 2.1 Ground Truth Estimators

The price series of a financial asset is a sequence of observable random variables; in particular, for any  $t$ ,  $P_t$  is realized at  $t$  and henceforth no longer random, under the assumption that  $(P_t)_{t \in \mathbb{N}}$  is adapted to  $\mathcal{F}_t$ . Time series econometrics has a vast inventory of approaches for modeling  $P_t$ . In contrast, the time-varying parameter  $\sigma_t^2$  is a quantity for which even identifying an observable effect in the real world is far more challenging. Approaches come in two basic forms: model-independent and model-dependent. The naive approach of constructing a rolling unbiased estimator of the variance of a price series is analogous to using a rolling average to estimate the mean of a price series. Implicitly, these approaches assume a simple, if unrealistic, covariance structure. Additionally, they offer very little in the way of forward guidance (predictiveness) regarding the series at hand. For that reason, in this section, we propose three families of estimators of the ground truth that we aim to forecast.

### 2.1.1 Market-Implied Volatility

Here we introduce implied volatility, a quantity that is derived using the equilibrium price of call and put options on the underlying financial asset.

We note also that Black-Scholes implied volatility is a biased estimator of volatility [Christensen and Prabhala, 1998].

Find citation that Black-Scholes implied volatility is especially biased in times of a crisis.

### 2.1.2 Realized Volatility

Suppose we examine  $K$  units of time, where each unit is divided into  $m$  intervals of length  $1/m$ . We follow the notation of Andersen and Teräsvirta [2009]. Let  $p_t = \log(P_t)$ , and let  $r(t, 1/m) = p_t - p_{t-1/m}$ . We estimate the variance of a log-return series using Realized Volatility, denoted  $RV_{K,m}$ , using

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

Assuming that the  $K$  units  $r(t, 1) = p_t - p_{t-1}$  are such that  $r(t, 1) \stackrel{iid}{\sim} N(\mu, \delta^2)$ , 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.

### 2.1.3 Historical Volatility

As discussed in section 2, daily returns exhibit insignificant autocorrelation. Such a finding could be used to motivate using the empirical volatility. This is just the unbiased estimator of log-return  $\sigma^2$  over the preceding  $M$  days.

## 2.2 Volatility Profile of a Time Series

In this section we make a novel contribution to the synthetic prediction framework by constructing a profile of a time series' volatility. Suppose we have  $D$  donors and for each of those  $D$  donors,  $q$  distinct measurements and/or covariates of volatility. Abusing notation for RV ( I need some clever way to index (a) date, (b) donor, (c) how many days were used to get the measurement, we have...

$$\mathbf{V}_{q,D} = \begin{pmatrix} \alpha_{T^*,1} & \alpha_{T^*,2} & \cdots & \alpha_{T^*,D} \\ \beta_{T^*,1} & \beta_{T^*,2} & \cdots & \beta_{T^*,D} \\ \vdots & \vdots & \ddots & \vdots \\ RV_{T^*,1} & RV_{T^*,2} & \cdots & RV_{T^*,D} \\ RV_{T^*-1,1} & RV_{T^*-1,2} & \cdots & RV_{T^*-1,D} \\ \vdots & \vdots & \ddots & \vdots \\ IV_{T^*,1} & IV_{T^*,2} & \cdots & IV_{T^*,D} \\ IV_{T^*-1,1} & IV_{T^*-1,2} & \cdots & IV_{T^*-1,D} \\ \vdots & \vdots & \ddots & \vdots \\ AbsoluteReturn_{T^*,1} & AbsoluteReturn_{T^*,2} & \cdots & AbsoluteReturn_{T^*,D} \\ AbsoluteReturn_{T^*-1,1} & AbsoluteReturn_{T^*-1,2} & \cdots & AbsoluteReturn_{T^*-1,D} \\ \vdots & \vdots & \ddots & \vdots \\ Volume_{T^*,1} & Volume_{T^*,2} & \cdots & Volume_{T^*,D} \\ Volume_{T^*-1,1} & Volume_{T^*-1,2} & \cdots & Volume_{T^*-1,D} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta RV_{T^*,1} & \Delta RV_{T^*,2} & \cdots & \Delta RV_{T^*,D} \\ \Delta RV_{T^*-1,1} & \Delta RV_{T^*-1,2} & \cdots & \Delta RV_{T^*-1,D} \\ \vdots & \vdots & \ddots & \vdots \end{pmatrix}$$

## 2.3 Aggregation Mechanism

Here we explain how we use the volatility profile to arrive at a set of nonnegative weights that sum to 1.

In [Abadie et al. \[2010\]](#), the authors advance previous work in causal inference whereby a treatment effect can be estimated by creating a synthetic time series that represents either the treatment or control unit. The synthetic unit is constructed using a convex combination of so-called donor series. The particular convex combination employed is a function of the distance between the time series under study and the donors. [Lin and Eck \[2021\]](#) adapt these methods for the purpose of prediction. Their 1-step-ahead forecasts take inspiration from distance-based-weighting, pooling shock estimates from similar series according to the series' similarity to the series under study. Their approach does not take into account the ARCH effects commonly observed in time series, especially financial times series, leaving unaccounted the variability that accompanies predictions of a heteroskedastic time series. In this present study, we focus on only volatility forecasting. We furthermore depart from the synthetic prediction framework by weighting series not by their covariates (which would be most appropriate for estimating the parameters of time series' mean model) but by their volatility profile.

## 2.4 Model setup

In this section, we will describe the assumed dynamic panel models for which post-shock aggregated estimators are provided. The basic structures of these models are the same for all time series in the analysis, the differences between them lie in the setup of the shock effect distribution. We first sharply distinguish between a volatility shock induced by a return-series shock at time  $T^*$

### 2.4.1 Volatility Shock Model

Let  $I(\cdot)$  be an indicator function,  $T_i$  be the time length of the time series  $i$  for  $i = 1, \dots, n+1$ , and  $T_i^*$  denote the largest time index prior to the arrival of the news shock, with  $T_i^* < T_i$ . For  $t = 1, \dots, T_i$  and  $i = 1, \dots, n+1$ , the model  $\mathcal{M}_1$  is defined as

$$\mathcal{M}_1: \sigma_{i,t}^2 = \omega_i + \omega_i^* D_{i,t}^{vol} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \quad (1)$$

$$a_{i,t} = \sigma_{i,t}(\epsilon_{i,t}(1 - D_{i,t}^{level}) + \epsilon_i^* D_{i,t}^{level}) \quad (2)$$

where  $D_{i,t}^{vol} = I(t \in \{T_i^* + 1, \dots, T_i^* + L_{i,vol}\})$ ,  $D_{i,t}^{level} = I(t \in \{T_i^* + 1, \dots, T_i^* + L_{i,level}\})$  and  $\mathbf{x}_{i,t} \in \mathbb{R}^p$ , with  $p \geq 1$ . We assume that the  $\mathbf{x}_{i,t}$  are fixed.<sup>12</sup> For  $i = 1, \dots, n+1$  and  $t = 1, \dots, T_i$ , the random effects structure for  $\mathcal{M}_1$  is:

$$\begin{aligned} \omega_i^* &\stackrel{iid}{\sim} \mathcal{F}_{\omega^*} \text{ with } E_{\mathcal{F}_{\omega^*}}(\omega_i^*) = \mu_{\omega^*}, \text{Var}_{\mathcal{F}_{\omega^*}}(\omega_i^*) = \sigma_{\omega^*}^2 \\ \epsilon_i^* &\stackrel{iid}{\sim} \mathcal{F}_{\epsilon^*} \text{ with } E_{\mathcal{F}_{\epsilon^*}}(\epsilon_i^*) = \mu_{\epsilon^*}, \text{Var}_{\mathcal{F}_{\epsilon^*}}(\epsilon_i^*) = \sigma_{\epsilon^*}^2 \\ \varepsilon_{i,t} &\stackrel{iid}{\sim} \mathcal{F}_{\varepsilon} \text{ with } E_{\mathcal{F}_{\varepsilon}}(\varepsilon_{i,t}) = 0, \text{Var}_{\mathcal{F}_{\varepsilon}}(\varepsilon_{i,t}) = 1 \\ \omega_i^* &\perp\!\!\!\perp \epsilon_i^* \perp\!\!\!\perp \gamma_i \perp\!\!\!\perp \varepsilon_{i,t}. \end{aligned}$$

The model  $\mathcal{M}_1$  is defined by a volatility equation and mean equation, as is any GARCH model. The choice to model the volatility shock  $\omega_i^*$  as an additive random effect is straightforward. However, the

<sup>1</sup>Need to determine what difference it makes to a GARCH-X model, if any, for the covariates to be random.

<sup>2</sup>As for implied volatility as a covariate, the argument for regarding it as a non-random quantity is that we are not primarily concerned with what IV is trying to estimate. We're concerned with IV itself as a primitive quantity that affects volatility through market sentiment. 'It is what it is.'

choice to model the level effect  $\epsilon_{i,t}^*$  as a temporary rupture in the otherwise i.i.d. sequence of innovations  $\epsilon_{i,t}$  stands in need of deeper justification. One way of arguing for this choice is that, in a discrete time series model, if we assume the arrival of news in the time between  $T^*$  and  $T^* + 1$ , we do not have an easy way to express a conditional distribution of the innovation  $\epsilon_{T^*+1}$  given the overnight arrival of information. Using  $\epsilon_{i,t}^*$  thus breaks this impasse. This defense also explains why we do not parameterize the level shock at  $T^* + 1$  as a sum of two shocks,  $\epsilon_{i,T^*+1}$  and  $\epsilon_{i,T^*+1}^*$ , which would represent the level shock as generated by two independent sources of stochasticity. This would be inelegant and would also lack motivation as a practical level. While we want to model the shock at  $T^* + 1$  as large in absolute value, we also want to retain the property of a unitary source of noise.

Note that under the popular GARCH(1,1), a dual level-volatility shock has an marginal effect on the conditional variance  $\sigma_{i,t}^2$  that should be familiar to scholars of GARCH models. As usual, assume  $\alpha + \beta < 1$ . Furthermore, assume that both the volatility shock  $\omega_i^*$  and the level shock  $\epsilon_{i,t}^*$  are of length one only, and consider a circumstance with no exogenous regressor  $\mathbf{x}_{i,t}$ . Consider also the case where  $r \geq 2$ , which is necessary in order to isolate the effects of the level shock  $\epsilon_{i,t}^*$ . Then

$$\sigma_{i,T^*+r+1}^2 = \omega_i + \alpha_i a_{T^*+r}^2 + \beta_i \sigma_{i,T^*+r}^2 \quad (3)$$

$$= \omega_i + \alpha_i (\sigma_{i,T^*+r} \epsilon_{T^*+r})^2 + \beta_i \sigma_{i,T^*+r}^2 \quad (4)$$

$$= \omega_i + \sigma_{i,T^*+r}^2 (\alpha_i (\epsilon_{T^*+r})^2 + \beta_i) \quad (5)$$

In (3), observe that  $\omega_i^*$  and  $\epsilon_{i,t}^*$  each appear at most once, through the term  $\sigma_{T^*+r}^2$ . This might lead one to suspect geometric decay of the shocks  $\omega_i^*$  and  $\epsilon_i^*$ . Such a suspicion is easier to substantiate by examining the conditional expectation of the variance,  $\mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}]$ , which also happens to be the principal forecasting tool for a GARCH model. Indeed, if we assume unit variance for all  $\epsilon_{i,t}$  except, of course,  $\epsilon_{i,t}^*$ , then we have

$$\begin{aligned} \mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}] &= \mathbb{E}[\omega_i + \alpha a_{T^*+r}^2 + \beta \sigma_{i,T^*+r}^2 | \mathcal{F}_{T^*+r}] \\ &= \omega_i + \mathbb{E}[\alpha (\sigma_{i,T^*+r} \epsilon_{T^*+r})^2 | \mathcal{F}_{T^*+r}] + \beta \sigma_{i,T^*+r}^2 \\ &= \omega_i + \alpha \sigma_{i,T^*+r}^2 + \beta \sigma_{i,T^*+r}^2 \quad (\text{Due to the unit variance assumption}) \\ &= \omega_i + \sigma_{i,T^*+r}^2 (\alpha + \beta) \end{aligned}$$

By repeated substitution, in conditional expectation, the shock is  $\mathcal{O}((\alpha + \beta)^r)$ . We generalize this observation in the following proposition.

**Proposition 1.** *Let  $a_t$  be a mean-zero time series obeying a GARCH(1,1) specification prior to the arrival of a volatility shock of length  $L_{vol} \geq 1$  and level shock of length  $L_{level} \geq 1$  at some time  $T^* + 1$ . Then for any  $r$  such that  $r - 1 \geq \max\{L_{i,vol}, L_{i,level}\}$ ,*

$$\mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}] = \omega_i + \sigma_{i,T^*+r}^2 (\alpha + \beta) \quad (6)$$

$$(7)$$

**Proof of Proposition** We claim

$$\mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}] = \mathbb{E}[\omega_i + \alpha a_{T^*+r}^2 + \beta \sigma_{i,T^*+r}^2 | \mathcal{F}_{T^*+r}] \quad (8)$$

$$= \omega_i + \mathbb{E}[\alpha (\sigma_{i,T^*+r} \epsilon_{T^*+r})^2 | \mathcal{F}_{T^*+r}] + \beta \sigma_{i,T^*+r}^2 \quad (9)$$

$$= \omega_i + \alpha \sigma_{i,T^*+r}^2 + \beta \sigma_{i,T^*+r}^2 \quad (10)$$

$$= \omega_i + \sigma_{i,T^*+r}^2 (\alpha + \beta) \quad (11)$$

$$(12)$$

The volatility equation of a GARCH(1,1) dictates that for any  $r$ , the one-step-ahead volatility is given by  $\sigma_{i,T^*+r+1}^2 = \omega_i + \alpha a_{i,T^*+r}^2 + \beta \sigma_{i,T^*+r}^2$ . By the mean-model assumption of a GARCH(1,1), we have  $a_{i,t} = \sigma_{i,t} \epsilon_{i,t}$ . By substitution, we arrive at equation (2) above. Using the unit-variance assumption regarding  $\epsilon_{T^*+r}$ , we can compute explicitly the expectation in (2). Finally, by rearranging terms, we arrive at equation (4).  $\square$

In other words, once two time points removed from the longest shock length, the volatility shock and level shock can be subsumed into one. However, prior to being two time points removed, there is no such guarantee. For example, one can take  $r = 1$  and level shock of length at least one to see that

$$\mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}] = \mathbb{E}[\omega_i + \alpha a_{i,T^*+1}^2 + \beta \sigma_{i,T^*+1}^2 | \mathcal{F}_{T^*+1}] \quad (13)$$

$$= \omega_i + \mathbb{E}[\alpha (\sigma_{i,T^*+1} \epsilon_{i,T^*+1}^*)^2 | \mathcal{F}_{T^*+1}] + \beta \sigma_{i,T^*+1}^2 \quad (14)$$

$$= \omega_i + \alpha \sigma_{i,T^*+1}^2 (\mu_{\epsilon^*}^2 + \sigma_{\epsilon^*}^2) + \beta \sigma_{i,T^*+1}^2 \quad (15)$$

$$= \omega_i + \sigma_{i,T^*+1}^2 (\alpha (\mu_{\epsilon^*}^2 + \sigma_{\epsilon^*}^2) + \beta) \quad (16)$$

For each of the  $p$  entries in delta, the  $k$ th entry should have the property that

$$\mathbb{E}[x_{i,t,k} * \delta_k] > 0$$

In principle, you could have an M21 shock with a covariate that, in expectation, has a negative marginal contribution to the cumulative shock

Moreover, after both shocks have been exhausted, their influence disappears quickly. This short-memory effect has implications for the method being developed herein:

1. Estimation of effects in donor pool should err on the side of underestimating, not overestimating, the length of the max shock, since overestimation of the shock length brings with it the risk of underestimating  $\omega^*$ .
2. An operator of the method needs some idea of how long the operator expects the shock in the time series under study to be. Such an idea will guide her trust in the choice of  $k$  in the  $k$ -step ahead forecast the operator produces. There are couple of obvious strategies: take all the donors, and over all the donor shock lengths, take the minimum. Alternatively, one could take the maximum.
3. There may be different risks associated with over/underestimating level shock and vol shock lengths.

In many settings, it is reasonable to model a volatility shock as occurring without a rupture in the mean-zero, i.i.d. sequence  $\epsilon_{i,t}$ . In cases like this, outsize movement in the observable random variable  $a_{i,t}$  is due solely to the shock  $\omega_i^*$ . Using the ARMA representation of a GARCH(m,s) model, we can see clearly how the random effect  $\omega_i^*$  increases the expectation of the nonnegative random variable  $a_{i,t}^2$ . The unconditional mean of an ARMA model tells that the random effects simply contribute to the intercept term:

$$\mathbb{E}[a_{i,t}^2] = \frac{\omega_i + \mathbb{E}[\omega_i^*]}{1 - \sum_{k=1}^{\max(m,s)} (\alpha_{i,k} + \beta_{i,k})}$$

However, since it is not known a priori for which  $t$  the effect  $\omega_i^*$  will be nonzero, this fact is of little practical guidance.



## 2.5 Unbiasedness of the Synthetic Volatility fixed-effect estimators and Synthetic Volatility prediction functions

Recall models  $\mathcal{M}_1$  and  $\mathcal{M}_2$ :

$$\begin{aligned}\mathcal{M}_1: \sigma_{i,t}^2 &= \omega_i + \omega_i^* D_{i,t}^{vol} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \\ a_{i,t} &= \sigma_{i,t} (\epsilon_{i,t} (1 - D_{i,t}^{level}) + \epsilon_i^* D_{i,t}^{level}) \\ \sigma_{i,t}^2 &= \omega_i + \omega_i^* D_{i,t}^{vol} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \\ \mathcal{M}_2: a_{i,t} &= \sigma_{i,t} (\epsilon_{i,t} (1 - D_{i,t}^{level}) + \epsilon_i^* D_{i,t}^{level}) \\ \omega_i^* &= \mu_{\omega^*} + \delta' \mathbf{x}_{i,T_i^*+1} + \tilde{\epsilon}_i,\end{aligned}$$

We will discuss these two models in the context of a shock in only the volatility, i.e. with  $D_{i,t}^{level} \equiv 0$ .

Abadie et al. [2010] discuss the unbiasedness of SCM estimators in the context of an autoregressive model. It is well-known that a GARCH(m,s) model has an ARMA representation. This suggests that, at the very least, when applied to an autoregressive process such as an ARCH model, Synthetic Volatility Forecasting provides an unbiased prediction. We therefore set out to show three results of increasing difficulty and complexity.

**Proposition 2.** *Under  $\mathcal{M}_1$  and  $\mathcal{M}_2$ , if the volatility series follows an ARCH(1) model, then under the assumptions in Abadie et al. [2010],  $\hat{\omega}^*$  is an unbiased estimator of  $\omega^*$ .*

**Proof of Proposition** First, for each  $i, t$ , define  $\eta_{i,t} := a_{i,t}^2 - \sigma_{i,t}^2$ , and by adding  $\eta_{i,t}$  to both sides of the conditional variance specification of  $\mathcal{M}_1$  and  $\mathcal{M}_2$ , we obtain the standard ARMA representation of a GARCH(m,s):

$$\begin{aligned}a_{i,t}^2 &= a_{i,t}^2 - \sigma_{i,t}^2 + \sigma_{i,t}^2 = \eta_{i,t} + \sigma_{i,t}^2 = \eta_{i,t} + \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \\ &= \eta_{i,t} + \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} (a_{i,t-j}^2 - \eta_{i,t-j}) + \gamma_i^T \mathbf{x}_{i,t} \\ &= \eta_{i,t} + \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{\max\{m_i, s_i\}} (\alpha_{i,k} + \beta_{i,k}) a_{i,t-k}^2 - \sum_{j=1}^{s_i} \beta_{i,j} \eta_{i,t-j} + \gamma_i^T \mathbf{x}_{i,t}\end{aligned}$$

where the  $a_{i,t}^2$  (the autoregressive terms) are observable and the  $\eta_{i,t}$  (the moving average terms) are not. Next, as shown in Abadie et al. [2010], under the autoregressive model

$$\begin{aligned}y_{i,t} &= \alpha_{i,t-1} y_{i,t-1} + \beta_t \mathbf{X}_{i,t} + u_{i,t} \\ \mathbf{X}_{i,t} &= \gamma_{t-1} y_{i,t-1} + \boldsymbol{\Pi}_{t-1} \mathbf{X}_{i,t-1} + \mathbf{v}_{i,t}\end{aligned}$$

and the assumptions that we, the practitioner, choose  $\{w_i^*\}_{2 \leq i \leq n+1}$  such that

$$\sum_{i=2}^{n+1} w_i^* Y_{i,T^*} = Y_1^* \quad \text{and} \quad \sum_{i=2}^{n+1} w_i^* \mathbf{X}_{i,T^*} = \mathbf{X}_{1,T^*}^*$$

and  $u_{i,t}, \mathbf{v}_{i,t}$  are mean-zero conditional of  $\mathcal{F}_t = \{Y_{i,t}, \mathbf{X}_{i,t}\}_{\text{needs subscript here}}$ .

then with even just one pre-treatment period, the synthetic control estimator is unbiased. Applying this result to Synthetic Volatility Forecasting, assume we choose  $\{w_i^*\}_{2 \leq i \leq n+1}$  such that

$$\sum_{i=2}^{n+1} w_i^* a_{i,T^*}^2 = a_{1,T^*}^2 \quad \text{and} \quad \sum_{i=2}^{n+1} w_i^* \mathbf{X}_{i,T^*} = \mathbf{X}_{1,T^*}^*$$

Assume further that  $\omega_i \equiv 0$  in  $\mathcal{M}_1$  and  $\mathcal{M}_2$ . Then it follows immediately that under the ARCH(1) model with time-varying parameters

$$\begin{aligned} a_{i,t}^2 &= \alpha_{i,t-1} a_{i,t-1}^2 + \beta_t \mathbf{X}_{i,t} + u_{i,t} \\ \mathbf{X}_{i,t} &= \gamma_{t-1} a_{i,t-1}^2 + \boldsymbol{\Pi}_{t-1} \mathbf{X}_{i,t-1} + \mathbf{v}_{i,t} \end{aligned}$$

$\sum_{i=2}^{n+1} w_i^* a_{i,T^*+1}^2 - a_{1,T^*+1}^2$  is an unbiased estimator of the news shock. By inverting the ARMA representation of GARCH(m,s) above, we could recover an unbiased estimator of the news shock  $\sum_{i=2}^{n+1} w_i^* \sigma_{i,T^*+1}^2 - \sigma_{1,T^*+1}^2$  if we could observe the terms  $\sigma_{i,t}^2$  or estimate them without bias. In practice, we do neither. In particular, we do not observe  $a_{1,T^*+1}^2$  until it is too late, and hence Sythethic Volatility Forecasting approaches the problem from the opposite direction: estimating  $\omega_1^* = \sum_{i=2}^{n+1} w_i^* \sigma_{i,T^*+1}^2 - \sigma_{1,T^*+1}^2$  in order to estimate  $\sigma_{1,T^*+1}^2$ . To this end, consider

$$\begin{aligned} a_{i,t}^2 &= \alpha_{i,t-1} a_{i,t-1}^2 + \beta_t \mathbf{X}_{i,t} + u_{i,t} \\ \mathbf{X}_{i,t} &= \mathbf{v}_{i,t} \\ \beta_t &\equiv 0, \forall t \neq T^* \\ \beta_t &= \delta, t = T^* \end{aligned}$$

Observe then that  $\omega_i^*$ , as defined in  $\mathcal{M}_1$  and  $\mathcal{M}_2$ , is subsumed within the model above, where the  $\mu_{\omega^*}$  term in  $\mu_{\omega^*} + \delta' \mathbf{x}_{i,T^*+1} + \varepsilon_i$  can be accounted for in the first entry of  $\mathbf{X}_{i,T^*+1}$  and  $\delta$  without loss of generality. Since each  $\omega_i^*$  is a function of  $\mathbf{X}_{i,T^*}$  and a mean-zero noise term,

□

**Proposition 3.** *Under  $\mathcal{M}_1$  and  $\mathcal{M}_2$ , if the volatility series follows an ARCH(p) model, then under the assumptions in [Abadie et al. \[2010\]](#),  $\hat{\omega}^*$  is an unbiased estimator of  $\omega^*$ .*

**Proof of Proposition** Place here

□

**Proposition 4.** *Under  $\mathcal{M}_1$  and  $\mathcal{M}_2$ , if the volatility series follows an GARCH(m,s) model, then under the assumptions in [Abadie et al. \[2010\]](#),  $\hat{\omega}^*$  is an unbiased estimator of  $\omega^*$ .*

**Proof of Proposition** Place here

□

## 2.6 Why not parameterize the volatility shock as a change in coefficients?

1. Swamped by shock: If the goal is near-term forecasting, then we don't really care how those coefficients may be changing. The assumption is that if any changes occur, their influence cannot account for the large shock. Given that the GARCH parameters for a stationary GARCH process must sum to less than 1, there is an upper bound to the forecastable change.
2. Practically infeasible: If we did that, we would need quite a few time points to reliably estimate the change in the GARCH parameters. We don't have that.

## 2.7 Improvements of this current work over its predecessor

1.  $y_{i,t}$  have shocks in both volatility and level.
2. The shocks can have length greater than 1.
3. The method under development does not strictly require knowledge of the length of the shocks in the donor pool, but correctly sizing up those shock lengths is helpful to proper estimation of the shocks. However, an important question remains: even if the donor pool shock lengths are assumed to be known, how do we advise the operator to forecast the time series under study? For how long is the forecast reliable? Should we take a convex combination of the donor pool shock lengths? Or mean? Or minimum of the donor pool shock lengths?
4. We may want a loss function that is asymmetric, i.e. penalizes upward and downward misses differently.
5. Lin+Eck 2021 requires exogenous information to arrive strictly between  $T^*$  and  $T^* + 1$ . However, we may want to relax this requirement so as to permit the exogenous information to be concurrent with the trading session or end of session on  $T^* + 1$ .
6. By offering more linear combination methods for the donor pool shocks (e.g. unit ball, affine hull, convex cone), we give the operator the ability to use donors such that the donor outcome series is negatively correlated with the time series under study.
7. See Tsay p. 94: if  $t$  is the last index that has been observed, then our two-step-ahead forecast is made easier by rewriting the volatility equation as  $\sigma_{i,t+1}^2 = w_i + (\alpha_i + \beta_i)\sigma_{i,t}^2 + \alpha_1\sigma_{i,t}^2[\epsilon_{i,t}^2 - 1] = w_i + (\alpha_i + \beta_i)\sigma_{i,t}^2 + \alpha_1\sigma_{i,t}^2[\epsilon_{i,t}^2 - 1]$ . Usually, we assume unit variance (though not necessarily a  $N(0,1)$ ). However, what is the variance is smaller than 1? Then in conditional expectation, the term  $\alpha_1\sigma_{i,t}^2[\epsilon_{i,t}^2 - 1]$  will be negative. So it seems that for level shock, we want the signal to noise ratio to be large because the mean is high, not because the variance is low.

Notice that  $\mathcal{M}_1$  assumes that  $\omega_i^*$  are i.i.d. with  $\mathbb{E}[\omega_i^*] = \mu_{\omega^*}$  for  $i = 1, \dots, n+1$ . We also consider a model where the shock effects are linear functions of covariates with an additional additive mean-zero error. For  $i = 1, \dots, n+1$ , the random effects structure for this model (model  $\mathcal{M}_2$ ) is:

$$\begin{aligned} \sigma_{i,t}^2 &= \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \\ \mathcal{M}_2: \quad a_{i,t} &= \sigma_{i,t}(\epsilon_{i,t}(1 - D_{i,t}^{level}) + \epsilon_i^* D_{i,t}^{level}) \\ \omega_i^* &= \mu_{\omega^*} + \delta' \mathbf{x}_{i,T_i^*+1} + \tilde{\epsilon}_i, \end{aligned} \tag{17}$$

where the added random effects are

$$\omega_i^* \stackrel{iid}{\sim} \mathcal{F}_{\omega^*} \text{ with } \mathbb{E}_{\mathcal{F}_{\omega^*}}(\omega_i^*) = \mu_{\omega^*}, \text{Var}_{\mathcal{F}_{\omega^*}}(\omega_i^*) = \sigma_{\omega^*}^2$$

	$\Sigma_\delta = I_p$	$\Sigma_\delta \neq I_p$
$\Sigma_{x_{i,T^*}} = I_p$	Easiest to model	Captures reasonable possibility of non-zero correlation in random effects
$\Sigma_{x_{i,T^*}} \neq I_p$	Captures empirically-verified phenomenon of non-zero correlation in covariates	Implausibly complicated to model

$$\begin{aligned}
\epsilon_i^* &\stackrel{iid}{\sim} \mathcal{F}_{\epsilon^*} \text{ with } \mathbb{E}_{\mathcal{F}_{\epsilon^*}}(\epsilon_i^*) = \mu_{\epsilon^*}, \text{Var}_{\mathcal{F}_{\epsilon^*}}(\epsilon_i^*) = \sigma_{\epsilon^*}^2 \\
\delta &\stackrel{iid}{\sim} \mathcal{F}_\delta \text{ with } \mathbb{E}_{\mathcal{F}_\delta}(\delta) = \mu_\delta, \text{Var}_{\mathcal{F}_\delta}(\delta) = \Sigma_\delta \\
\varepsilon_{i,t} &\stackrel{iid}{\sim} \mathcal{F}_\varepsilon \text{ with } \mathbb{E}_{\mathcal{F}_\varepsilon}(\varepsilon_{i,t}) = 0, \text{Var}_{\mathcal{F}_\varepsilon}(\varepsilon_{i,t}) = 1 \\
\tilde{\varepsilon}_i &\stackrel{iid}{\sim} \mathcal{F}_{\tilde{\varepsilon}} \text{ with } \mathbb{E}_{\mathcal{F}_{\tilde{\varepsilon}}}(\tilde{\varepsilon}_i) = 0, \text{Var}_{\mathcal{F}_{\tilde{\varepsilon}}}(\tilde{\varepsilon}_i) = \sigma_{\tilde{\varepsilon}}^2 \\
\omega_i^* &\perp\!\!\!\perp \epsilon_i^* \perp\!\!\!\perp \gamma_i \perp\!\!\!\perp \delta \perp\!\!\!\perp \varepsilon_{i,t} \perp\!\!\!\perp \tilde{\varepsilon}_i.
\end{aligned}$$

We further define the parameter sets

$$\begin{aligned}
\Theta &= \{(\omega_i^*, \epsilon_i^*, \gamma_i, \delta, \varepsilon_{i,t}, \tilde{\varepsilon}_i) : t = 1, \dots, T_i, i = 2, \dots, n+1\}, \\
\Theta_1 &= \{(\omega_i^*, \epsilon_i^*, \gamma_i, \delta, \varepsilon_{i,t}, \tilde{\varepsilon}_i) : t = 1, \dots, T_i, i = 1\},
\end{aligned} \tag{18}$$

where  $\Theta$  and  $\Theta_1$  can be adapted to  $\mathcal{M}_1$  by dropping  $\delta$ . We assume this for notational simplicity.

## 2.8 Forecasting

Here we make reference to Tsay p. 133 and explain, very similarly to Tsay, that the prediction function for a GARCH(m,s) is very similar to an ARMA prediction function. Modeled after section 2.2 here <https://arxiv.org/pdf/2008.11756.pdf>

$$\mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}]$$

## 3 Simulation Setup and Results

Having introduced the model parameters above, we introduce estimation techniques that can be varied

### 3.1 Most elementary simulation setup

In order to investigate the Synthetic Volatility Forecasting method

As we see in 2, when only two parameters are varied, the shock signal and the shock noise, we observe several encouraging phenomena:

- For nearly any row selected in the grid, a pronounced downward trend in the outperformance rate of the SVF exists.
- For any column selected, an increasing trend exists as the shock signal increases.
- For almost all small values of the shock signal, the outperformance rate hovers around .5, supporting the hypothesis that in the absence of a signal, any level of noise renders the method anemic.

### 3.2 Dual shock: both a level and volatility shock at $T^*+1$

*Hypothesis:* Method should do less well under level shock.

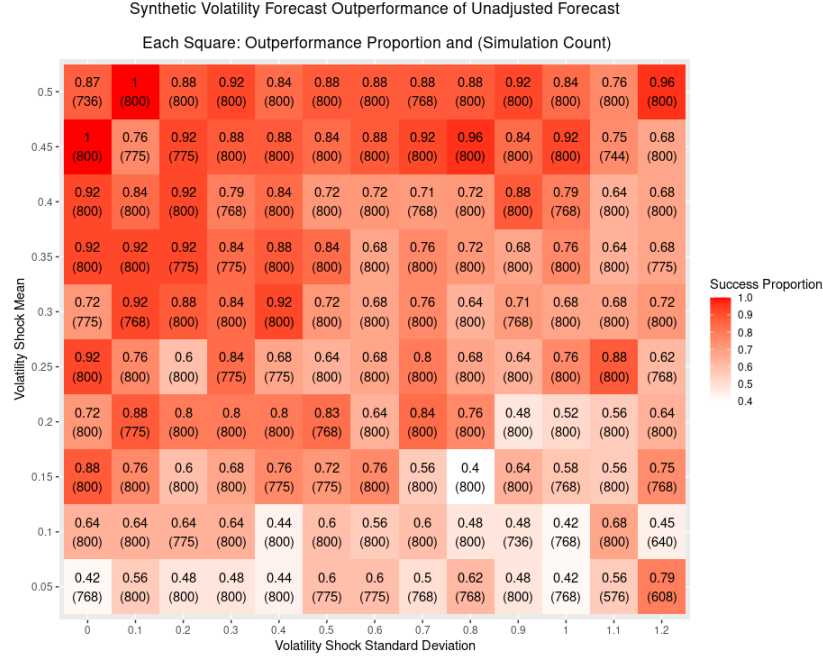


Figure 2: Fixed parameter values:  $\alpha = .1, \beta = .82, \mu_x = 1, \sigma_x = .1$  (verify)

### 3.3 Shorter Series

### 3.4 Fat tails in innovations

### 3.5 Lengthening the measurement period

### 3.6 Changing the optimization norm for distance-based weighting

### 3.7 Asymmetric GARCH

## 4 Real Data Example

My show the applicability of Synthetic Volatility Forecasting using an real data example that sits at the crossroads of market trading and electoral politics. In the spring of 2016 in the USA, the Republican Party's primary election process narrowed down candidates until Donald J. Trump cleared the threshold of votes to win the nomination formally at the party's convention that summer. He would go on to face the Democratic Party's nominee, Hillary Rodham Clinton. As is well-known, the Electoral College has the capability of making presidential races more competitive than a raw vote total might, generating a corresponding increase in uncertainty about the country's leadership. From ex-ante perspective, several key qualities of this particular US election cycle as well as the candidates themselves might also be considered volatility-inducing. The election featured no incumbent, which foreclosed any incumbent-advantage. The Republican Party candidate took up unorthodox positions on matters such as healthcare and trade policy, positions that could be considered rare in either of the major two parties. Additionally, Donald J. Trump, lacking any record in government service – either electoral or appointed service – gave his opponent no voting record to attack and more broadly, presented both the electorate and political prognosticators with a complete novelty. For these reasons, the result and aftermath of the 2016 presidential election meets the standard of an interesting and notable event for which a quantitative researcher might on-demand predictions. On a more technical level, the result of the election arrived in the evening of election day, following the closing of financial markets at 4pm Eastern Time. This meets

the standard of a shock that has not yet been digested by liquid markets. We therefore proceed to make the following technical specifications in order to predict the volatility of financial services ETF IYG (an ETF composed of American financial majors JPMorgan, Bank of American, etcetera) on Wednesday November 9th, 2016.

1. **Model choice:** We assume a GARCH(1,1) for the daily log-return series of IYG in each donor. As argued in [Hansen and Lunde \[2005\]](#), a GARCH(1,1) is rarely dominated by more heavily-parameterized GARCH specifications. It thus provides a defensible choice when motivation or time for choosing another model is lacking.
2. **Covariate Choice**
3. **Donor pool construction**
4. **Choice of estimator for volatility**

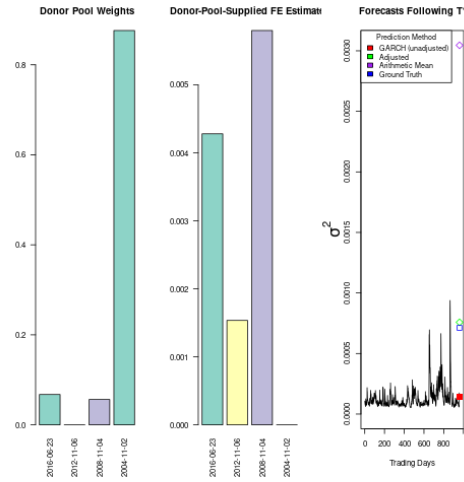


Figure 3: The volatility induced by the 2016 US election results using Brexit as a donor.

We shall discuss [5](#) soon.

It has been noted that GARCH effects are more attenuated in aggregated returns [[Zivot, 2009](#)], which suggests against using the S&P 500 or similar indices as an example.

We also introduce simulation parameters that can be varied but are not random effects

1. Length of the volatility shock
2. Length of the level shock

## 5 Connection to Signal Recovery

## 6 Supplement

We analyze the real-world example with Brexit included

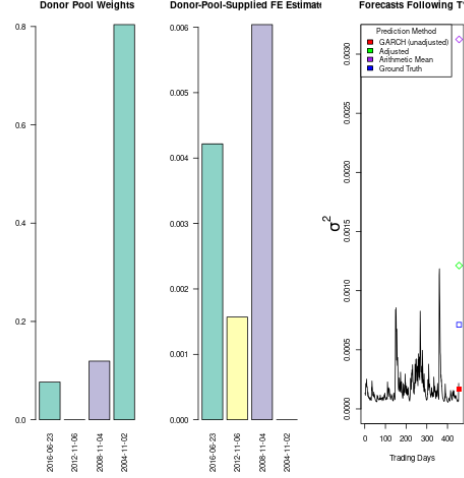


Figure 4: The volatility induced by the 2016 US election results without using Brexit as a donor.

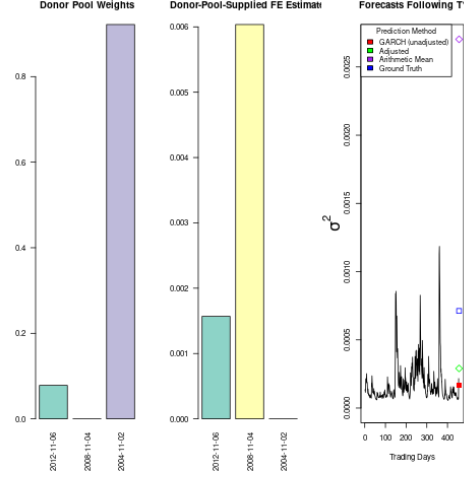


Figure 5: The volatility induced by the 2016 US election results without using Brexit as a donor.

	Vershynin (2018)	Lin and Eck (2021)	SynthVolForecasting
observed quantity	$y_i$	NA	NA
estimated quantity	NA	$\alpha_i$	$\omega_i^*$
signal	$A_i x$	$\mu + \delta' x_{i,T^*}$	$\mu + \delta' x_{i,T^*}$
prior information	$x \in T$ , $T$ a convex	across donors, linear shock function equal in distribution	across donors, linear shock function equal in distribution
key assumption(s)	$A_i$ independent $\forall i$ , isotropic too?	$x_{i,T^*}$ independent across donors; independent entries of $x_{i,T^*}$	$x_{i,T^*}$ independent across donors; independent entries of $x_{i,T^*}$
noise	$w$	$\tilde{\varepsilon}$	$\tilde{\varepsilon}$
strategy	Observe $y_i$ ; then estimate $x$ with small expected L2 loss	Estimate $\alpha_i$ for $i = 2, \dots, n + 1$ ; then take convex combination to predict $\alpha_1$	Estimate $\omega_i^*$ for $i = 2, \dots, n + 1$ ; then take convex combination to predict $\omega_1^*$

## References

- Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic control methods for comparative case studies: Estimating the effect of california’s tobacco control program. *Journal of the American Statistical Association*, 105(490):493–505, 2010.
- Torben G Andersen and Timo Teräsvirta. Realized volatility. In *Handbook of financial time series*, pages 555–575. Springer, 2009.
- Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327, 1986.
- George Box. Box and jenkins: time series analysis, forecasting and control. In *A Very British Affair: Six Britons and the Development of Time Series Analysis During the 20th Century*, pages 161–215. Springer, 2013.
- Christian T Brownlees, Robert F Engle, and Bryan T Kelly. A practical guide to volatility forecasting through calm and storm. *Available at SSRN 1502915*, 2011.
- Bent J Christensen and Nagpurnanand R Prabhala. The relation between implied and realized volatility. *Journal of financial economics*, 50(2):125–150, 1998.
- Rama Cont. Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative finance*, 1(2):223, 2001.
- Robert Engle. New frontiers for arch models. *Journal of Applied Econometrics*, 17(5):425–446, 2002.
- Robert F Engle. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the econometric society*, pages 987–1007, 1982.
- Peter R Hansen and Asger Lunde. A forecast comparison of volatility models: does anything beat a garch (1, 1)? *Journal of applied econometrics*, 20(7):873–889, 2005.
- Peter Reinhard Hansen, Zhuo Huang, and Howard Howan Shek. Realized garch: a joint model for returns and realized measures of volatility. *Journal of Applied Econometrics*, 27(6):877–906, 2012.
- Lutz Kilian and Helmut Lütkepohl. *Structural vector autoregressive analysis*. Cambridge University Press, 2017.
- Jilei Lin and Daniel J Eck. Minimizing post-shock forecasting error through aggregation of outside information. *International Journal of Forecasting*, 2021.
- Genaro Sucarrat. garchx: Flexible and Robust GARCH-X Modelling. MPRA Paper 100301, University Library of Munich, Germany, May 2020. URL <https://ideas.repec.org/p/pramprapa/100301.html>.
- Allan Timmermann. Forecast combinations. *Handbook of economic forecasting*, 1:135–196, 2006.
- Eric Zivot. Practical issues in the analysis of univariate garch models. In *Handbook of financial time series*, pages 113–155. Springer, 2009.