

# Post-shock Volatility Forecasting Using Aggregated Shock Information

David Lundquist\*, Daniel Eck†

Department of Statistics, University of Illinois at Urbana-Champaign

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## Abstract

We develop a procedure for forecasting the volatility of a time series immediately following a news shock. Adapting the synthetic prediction framework of [Lin and Eck \[2021\]](#), we exploit series that have experienced similar shocks. We aggregate their shock-induced excess volatilities by positing the shocks to be affine functions of exogenous covariates. The volatility shocks 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 the unobservable but easily-estimated realized volatility (RV). A real-world application is provided, as are simulation results suggesting the conditions and hyperparameters under which our method thrives.

## 1 Introduction

Reacting to a seemingly unprecedented event might involve the question: what, if anything, does it resemble from the past? Such might be the case with event-driven investing strategies, where the identification of the event could arise via the news pages or corporate communications and hence contains a qualitative, narrative element [\[Kenton, 2022\]](#). Matching a current crisis to past events is a problem with unsurprising statistical angles: identification, sample size, weighting, risk, and robustness, among many others.

In the context of foreign exchange rate market structure, [Dominguez and Panthaki \[2006\]](#) argue “[w]hether news is scheduled or non-scheduled its influence on exchange rates may be related to the state of the market at the time of the news arrival. News that arrives during periods of high uncertainty may have different effects on the exchange rate, than news that arrives in calmer periods.” The authors also note that non-scheduled news may require more time for markets to digest, leading to greater heterogeneity (including but not limited to higher dispersion) of responses. We take inspiration from these findings, developing a method suitable to the conditions that typically accompany news shocks.

In this work we focus on the second central moment of a time series, the volatility. One of 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 may exhibit behavior that makes inapplicable and uninterpretable the traditional methods of time series analysis. In contrast, the return series is scale-free [\[Tsay, 2005\]](#), easily-interpreted, and often at least weakly stationary. Even if one could construct credible models for describing and forecasting price series and return series, that would not necessarily tell us much about the variability of such forecasts nor enlighten us about the evolution of the variability of  $(P_t)_{t \in \mathbb{N}}$  and  $(r_t)_{t \in \mathbb{N}}$  over time. Second, the literature on return series predictability based on news has undergone a considerable shift over the past 50 years (see [Boudoukh et al. \[2019\]](#) and references

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\*davidl11@illinois.edu

†dje13@illinois.edu

therein). Whereas once returns were thought to react to specific news events, now stock price movements are believed to be overwhelmingly noise-based.

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 in market price or derivative quantities like volatility. In this setting, regime-change models (see [Bauwens et al. \[2006\]](#) and citations therein) 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 to fit a model. Asymmetric GARCH models were an early attempt to account for fact that negative returns typically beget greater volatility than positive returns [[Hansen et al., 2012](#)]. Problematically, such models depend upon the observation of a negative return to provide the most updated volatility forecast, but under the circumstances posited herein, no such return has been observed.

Similar problems and more exist for Realized GARCH models [[Hansen et al., 2012](#)], which incorporates observable measures of volatility, known as “realized measures”, like implied volatility. Under the assumptions herein, no post-shock data is available, and even if it were, Realized GARCH does not promise to perform well, since Black-Scholes implied volatility is a biased estimator of volatility [[Mayhew, 1995](#), [Christensen and Prabhala, 1998](#)], with the bias increasing in times of crises, when options are likely to be out-of-the-money. GARCH models have been shown slow to adapt to spikes in volatility [[Andersen et al., 2003](#)]. [Engle \[2002\]](#) explored the use of implied volatility as an exogenous regressor in a GARCH model, that is, using a so-called GARCH-X model [[Sucarrat, 2020](#)]. Realized GARCH 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 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. **Two options here: either spell out the full Hansen idea or cut it.**

The approach herein can be viewed as an attempt to sidestep the functional complexity posited by Realized GARCH, with its minimum nine parameters to estimate [[Sharma et al., 2016](#)], by substituting modeling assumptions. Synthetic Volatility Forecasting proceeds under the assumption that similar news events occasion volatility shocks arising from a common shock distribution. The procedure proposed does not require post-shock information like returns or market-implied quantities from the time series under study. Hence, we also avoid questions about what realized measure to use and when as well as questions about the usefulness of high-frequency data, although these remain intriguing avenues for future work.

The primary methodological tool presented in this work is fixed effect estimation followed by an appropriate procedure for pooling those estimates. The use of fixed effect estimation for the study of structural shocks has a pedigree in macroeconomic analysis ([Romer and Romer \[1989\]](#) cited in [Kilian and Lütkepohl \[2017\]](#); see also discussion of deterministic exogenous events in [Engle and Patton \[2001\]](#)). In the forecasting literature, the term “intercept correction” has come to refer to a modeling technique in which nonzero errors are explicitly permitted [[Hendry and Clements, 1994](#), [Clements and Hendry, 1998](#)]. They summarize the literature as distinguishing two families of intercept correction: intercept corrections that attempt to account for future events, without hard-coding an ad-hoc adjustment into the model specification, and second, intercept corrections that attempt to adjust for persistent misspecification using past errors. [Guerrón-Quintana and Zhong \[2017\]](#) use weighted subsets of a scalar series’ own past to correct forecast errors by an additive term. [Dendramis et al. \[2020\]](#) introduces a similarity-based forecasting procedure for time-varying coefficients of a linear model. [Foroni et al. \[2022\]](#) employ a form of intercept correction in order to adjust forecasts to the COVID-19 shock in the spring of 2020 based on the proportional misses of the same model applied to the Great Recession.

A researcher interested in forecast adjustment can choose between an procedures that automated or non-automated, the collection of data assembled to perform the correction, whether the data is internal (the time series itself) or external, the parametric term to be corrected (e.g. intercept, coefficients), if

any, as well as the correction function (i.e. the mapping from the data to the corrective term), including the weighting applied to the assembled data (e.g. Nearest-Neighbor, arithmetic mean, kernel methods).

Our procedure is an automated procedure for intercept adjustments using either data internal or external to the time series under study. The correction function, as we shall see, involves an optimization step inspired by the causal inference literature. In particular, in [Abadie et al. \[2010\]](#), the authors build upon 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 the 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 \[2021\]](#) adapted these methods for the purpose of prediction. Their 1-step-ahead forecasts use distance-based-weighting to pool shock estimates from similar series according to the donor series’ similarity to the series under study. Their approach does not take into account the ARCH effects commonly observed in time series, especially financial time series, leaving unaccounted for 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.

Outside of [Lin and Eck \[2021\]](#), we know of no prior work that both introduces a parametric specification for nonzero errors and introduces a procedure for weighting appropriately the nonzero errors of similar shocks. Likewise, we are not familiar with any prior work that attempts to account for anticipated nonzero errors using an explicit parametric adjustment. This current work is a contribution to the forecast adjustment literature but also aims for the virtues of robustness, risk-minimization, and model interpretability, akin to the departures from nearest neighbors discussed in [Abadie and L’hour \[2021\]](#). [Guerrón-Quintana and Zhong \[2017\]](#), citing previous work, discuss that intercept corrections find their theoretical basis in the occurrence of structural breaks, whereas Nearest-Neighbor methods, being non-parametric, are theoretically more adept at accounting for nonlinearity. By using convex combinations of donor pool quantities to adjust forecasts, we are generalizing Nearest-Neighbor methods while also providing robustness, risk-minimization, and model interpretability.

In order to motivate our procedure, we show how the aggregation of estimated excess volatilities from donors in the donor pool works when the correction function is the arithmetic mean. As we see in [Figure 1](#), the arithmetic mean of excess volatilities provides perhaps the most straightforward and intuitive way of aggregating information from similar events. Taking the average also coincides with the  $K$ -Nearest-Neighbor estimator, where  $K$  is equal to the number of donors in the donor pool. Although using the arithmetic mean is intuitive and enjoys some empirical track record, its grounding in theory is much less impressive [[Timmermann, 2006](#)]. Synthetic Volatility Forecasting assumes a credible, parsimonious parameterization in which the shock is an affine transformation of several key covariates. The key intuition behind this shock parameterization is that as the strength of the linear signal increases relative to the idiosyncratic error, the GARCH estimation of these effects increases in accuracy. From this, it follows that the aggregated shock estimate increases in accuracy.

## 2 Setting

### 2.1 A Primer on GARCH

We 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 [[Box, 2013](#)] provides a framework for postulating and quantifying the autoregressive structure of  $r_t$ , all within the framework of frequentist statistics. These models assume a certain dependence structure between  $r_t$  and  $(r_k)_{k \leq t}$ , 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



Figure 1: The time series experiences a volatility shock at a uniformly distributed point in the interval  $[756, 2520]$  trading days, corresponding to trading years on the interval  $[3, 10]$ . We have truncated the series after  $T^* + 1$ . The GARCH prediction fails even to approach the volatility spike at  $T^* + 1$ , as do some adjusted predictions. In contrast, the GARCH forecast adjusted by  $\hat{\omega}^*$ , the arithmetic mean of the estimated shocks, recovers the shock in the time series under study.

[Bollerslev, 1986] models provide elegant alternatives to the homoskedasticity 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. As Cont [2001] explains, such an assumption is justified by the empirical finding that returns lack significant autocorrelation. We thus 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 past  $m$  values of  $r_t^2$ . The GARCH(m,s) framework take this one step further but modeling  $\sigma_t^2$  as a linear combination of the past  $m$  values of  $r_t^2$  and well as the past  $s$  values of  $\sigma_t^2$ . In functional form, a GARCH process (sometimes called a strong GARCH process [Francq and Zakoian, 2019, p. 19]) is given by

$$\begin{aligned}
\sigma_t^2 &= \omega + \sum_{k=1}^m \alpha_k a_{t-k}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 \\
a_t &= \sigma_t \epsilon_t \\
\epsilon_t &\stackrel{iid}{\sim} E[\epsilon_t] = 0, Var[\epsilon_t] = 1 \\
\forall k, j, \alpha_k, \beta_j &\geq 0 \\
\forall t, \omega, \sigma_t &> 0.
\end{aligned}$$

Assuming further that  $\sigma_t^2$  depends on a vector of exogenous covariates  $\mathbf{x}_t$ , we have a GARCH-X( $m, s$ ). The volatility equation then becomes

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

$$(2)$$

## 2.2 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 shock distributions. We first sharply distinguish between a volatility shock induced by a return series shock and a volatility shock directly affecting the volatility equation of a GARCH model, without mediation of the return series.

We will suppose that a researcher has multivariate time series data  $\mathbf{y}_{i,t}, t = 1, \dots, T_i$  and  $i = 1, \dots, n+1$ . Let  $\mathbf{y}_{i,t} = (r_{i,t}, \mathbf{x}_{i,t})$  where  $r_{i,t}$  is a scalar response (typically the log-return of a financial asset) and  $\mathbf{x}_{i,t}$  is a vector of covariates such that  $\mathbf{x}_{i,t} | \mathcal{F}_{i,t-1}$  is deterministic. Suppose that the analyst is interested in forecasting the volatility of  $r_{1,t}$ , the first time series in the collection. We require that each time series  $\mathbf{y}_{i,t}$  is subject to a news event following  $T_i^* \leq T_i + 1$  and before witnessing  $T_i^* + 1$ . We are implicitly leveraging the fact that financial assets are heavily traded during market hours, yet only thinly traded (if traded at all) outside market hours. In contrast, the arrival of market-moving news does not obey any such restrictions. In light of the foregoing, we can denote our collection of GARCH volatility equations of interest using the following notation

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

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 follows.

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

The random effects [stochastic](#) structure is as follows.

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

where  $D_{i,t}^{return} = I(t \in \{T_i^* + 1, \dots, T_i^* + L_{i,return}\})$  and  $D_{i,t}^{vol} = I(t \in \{T_i^* + 1, \dots, T_i^* + L_{i,vol}\})$  and  $L_{i,return}, L_{i,vol}$  denote the lengths of the log return and volatility shocks, respectively. Let  $\delta, \mathbf{x}_{i,t} \in \mathbb{R}^p$ . Let  $\mathcal{M}_0$  denote the subclass of  $\mathcal{M}_1$  models such that  $\delta \equiv 0$ . Notice that  $\mathcal{M}_0$  assumes that  $\omega_i^*$  have no dependence on the covariates and are i.i.d. with  $\mathbb{E}[\omega_i^*] = \mu_{\omega^*}$ .

For each of the  $p$  entries in  $\delta$ , the  $k$ th entry should have the property that  $\mathbb{E}[x_{i,t,k} \cdot \delta_k] > 0$ . In principle, you could have an  $\mathcal{M}_{21}$  shock with a covariate that, in expectation, has a negative marginal contribution to the cumulative shock.

## 2.3 Volatility Profile of a Time Series

This section is clunky. More description of the components of  $\mathbf{V}_{p,n}$  and the novelty of  $\mathbf{V}_{p,n}$  is needed. In this section, we make a novel contribution to the synthetic prediction framework by constructing a profile of a time series' volatility. Suppose that for each of the  $n$  donors, we posit  $p$  distinct covariates in the functional form of the shock. The volatility profile is defined as the  $pn \times n$  matrix

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

Several comments are in order here. Although as shown,  $\mathbf{V}_{p,n}$  displays 'balance' in that each of the  $p$  covariates is replicated  $n$  times, in practice, it may be that some donors do not possess or do not require such information.  $\mathbf{V}_{p,n}$  **more comments are needed?** Agreed on both comments in this section. I may need a section or at least a mention of how the Abadie et al. [2010] nests a GARCH model. After having done that, the volatility profile will make more sense, and it will be more justifiable to call it a volatility profile, I hope, than just a matrix of covariates.

### 3 Post-shock Synthetic Volatility Forecasting Methodology

#### 3.1 Forecasting

We present two forecasts:

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

A GARCH model is an ARMA on the squares of the observed scalar time series  $a_t^2$  [Tsay, 2005, Francq and Zakoian, 2019, p. 18, p. 46], assuming that  $a_t^2$  satisfies fourth-order stationarity. This fact matters for forecasting because the  $h$ -step-ahead forecasting function for GARCH model is, just like for an ARMA model, the conditional expectation function,  $\mathbb{E}[\sigma_{i,T^*+h}^2 | \mathcal{F}_{T^*}]$ , or practically speaking, the estimate thereof,  $\hat{\mathbb{E}}[\sigma_{i,T^*+h}^2 | \mathcal{F}_{T^*}]$  [Zivot, 2009]. Here we present one-step-ahead forecasts for a GARCH(1,1), without loss of generality. For  $h = 2, 3, 4, \dots$ , the conditional expectation is computed recursively, as is standard for iterative autoregressive forecasts.

#### 3.2 Excess Volatility Estimators

The problem of aggregating estimated donor shocks begins with the data constraints. Taking the estimated shocks as a given, we essentially observe the pair  $(\{\hat{\omega}_i^*\}_{i=2}^{n+1}, \{\mathbf{x}_{i,T^*}\}_{i=2}^{n+1})$ . We wish to recover weights  $\{\pi_i\}_{i=2}^{n+1} \in \Delta^n$  leading to favorable forecasting properties. These weights are used to compute  $\hat{\omega}^* := \sum_{i=2}^{n+1} \pi_i \hat{\omega}_i^*$ , our forecast adjustment term. Since the  $\{\pi_i\}_{i=2}^{n+1}$  are computed using  $\mathcal{F}_{T_i^*}$ , the set  $\{\pi_i\}_{i=2}^{n+1}$  is deterministic, *modulo* any stochastic ingredient in the numerical methods employed to approximate  $\mathbf{x}_{1,T^*}$  using a convex combination of donor covariates. We will say more about the properties of  $\omega_i^*$  in section 4.

Following Abadie and Gardeazabal [2003], Abadie et al. [2010], let  $\|\cdot\|_{\mathbf{S}}$  denote any semi-norm, and define

$$\{\pi\}_{i=2}^{n+1} = \arg \min_{\pi} \|\mathbf{v}_1 - \mathbf{V}_{p,n}\pi\|_{\mathbf{S}} .$$

There are at least two senses of optimal weights that one might be interested in. First, we can think of optimal weights as a set  $\{\pi_i\}_{i=2}^{n+1}$  such that  $\omega_1 = \sum_{i=2}^{n+1} \pi_i \hat{\omega}_i$ , i.e.,  $\omega_1$  is recovered perfectly, as it belongs to convex hull of the estimated shocks. Similarly,  $\mathbf{v}_1 = \sum_{i=2}^{n+1} \pi_i \mathbf{v}_i$ , meaning that . This is certainly a . There also exists a second sense of optimality, in which, for a given  $\sigma_t^2$ , the weights allow us to predict with zero loss.

#### 3.3 Ground Truth Estimators

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. In this work, we use a common estimator of the variance called realized volatility (RV), one which has the virtue of being “model-free” in the sense that it requires no modeling assumptions [Andersen and Benzoni, 2010]. The realized variance itself can be decomposed into the sum of a continuous component and a jump component, with the former being less predictable and less persistent [Andersen et al., 2007], cited in De Luca et al. [2006], two factors that further motivate the method employed herein.



Suppose we examine  $K$  units of time, where each unit is divided into  $m$  intervals of length  $\frac{1}{m}$ . We follow the notation of [Andersen and Teräsvirta \[2009\]](#). Let  $p_t = \log(P_t)$ , and let  $r(t, \frac{1}{m}) = p_t - p_{t-\frac{1}{m}}$ . 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. We will proceed using  $m = 77$ , corresponding to the 6.5-hour trading day chopped into 5-minute blocks, with the first block omitted in order to ignore unusual trading behavior at the start of the day.

### 3.4 Loss Functions

We are interested in point forecasts for  $\sigma_{1,T^*+h}^2 | \mathcal{F}_{T^*}$ ,  $h = 1, 2, \dots, H$ , the  $h$ -step ahead conditional variance for the time series under study, up to a forecast length of  $H$ . 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:

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

In more generality, for a volatility forecast with forecast length  $H$ , the MSE is

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

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

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

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

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

What distinguishes QL Loss is that it is multiplicative rather than additive. This serves as a basis for some of its virtues, both practical and theoretical. 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.” For this reason, we proceed to evaluate the method, both in simulations and real data examples, using the QL loss.



## 4 Properties of Volatility Shock and Shock Estimators

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 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. To do so 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 reflects the geometric decay of innovations in autoregressive 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  $\mathbf{x}_{i,t}$ . Assume also that  $r \geq 2$ , which is necessary in order to isolate the effects of the level shock  $\epsilon_{i,t}^*$ . Then

$$\begin{aligned} \sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r} &= \omega_i + \alpha_i a_{T^*+r}^2 + \beta_i \sigma_{i,T^*+r}^2 \\ &= \omega_i + \alpha_i (\sigma_{i,T^*+r} \epsilon_{T^*+r})^2 + \beta_i \sigma_{i,T^*+r}^2 \\ &= \omega_i + \sigma_{i,T^*+r}^2 (\alpha_i (\epsilon_{T^*+r})^2 + \beta_i) . \end{aligned} \tag{3}$$

In (3), observe that  $\omega_{i,t}^*$  and  $\epsilon_{i,t}^*$  each appear at most once, through the term  $\sigma_{i,T^*+r}^2$ . This might lead one to suspect geometric decay of the shocks  $\omega_{i,t}^*$  and  $\epsilon_{i,t}^*$ . 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 [Zivot, 2009]. 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 with unit-variance errors, all prior to the arrival of a volatility shock of length  $L_{\text{vol}} \geq 1$  and level shock of length  $L_{\text{level}} \geq 1$  at some time  $T^* + 1$ . Then for any  $r$  such that  $r \geq \max\{L_{i,\text{vol}}, L_{i,\text{level}}\} + 1$ ,*

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

**Proof of Proposition** We claim

$$\mathbb{E}[\sigma_{i,T^*+r+1}^2 | \mathcal{F}_{T^*+r}] = \mathbb{E}[\omega_i + \alpha a_{T^*+r}^2 + \beta \sigma_{i,T^*+r}^2 | \mathcal{F}_{T^*+r}] \tag{4}$$

$$= \omega_i + \mathbb{E}[\alpha(\sigma_{i,T^*+r}\epsilon_{T^*+r})^2 | \mathcal{F}_{T^*+r}] + \beta\sigma_{i,T^*+r}^2 \quad (5)$$

$$= \omega_i + \alpha\sigma_{i,T^*+r}^2 + \beta\sigma_{i,T^*+r}^2 \quad (6)$$

$$= \omega_i + \sigma_{i,T^*+r}^2(\alpha + \beta) . \quad (7)$$

The volatility equation of a GARCH(1,1) dictates that for any  $r$ , the one-step-ahead volatility is given by the expression inside the expectation in (4). By the mean-model assumption of a GARCH(1,1), we have  $a_{i,t} = \sigma_{i,t}\epsilon_{i,t}$ , and hence by substituting  $\sigma_{i,t}\epsilon_{i,t}$  for  $a_{i,t}$ , we arrive at equation (5) above. Using the unit-variance assumption regarding  $\epsilon_{T^*+r}$ , we can compute explicitly the expectation, yielding (6). Finally, by rearranging terms, we arrive at equation (7).  $\square$

In other words, for a GARCH(1,1), 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 1 to see that

$$\begin{aligned} \mathbb{E}[\sigma_{i,T^*+2}^2 | \mathcal{F}_{T^*+1}] &= \mathbb{E}[\omega_i + \alpha a_{i,T^*+1}^2 + \beta \sigma_{i,T^*+1}^2 | \mathcal{F}_{T^*+1}] \\ &= \omega_i + \mathbb{E}[\alpha(\sigma_{i,T^*+1}\epsilon_{T^*+1}^*)^2 | \mathcal{F}_{T^*+1}] + \beta\sigma_{i,T^*+1}^2 \\ &= \omega_i + \alpha\sigma_{i,T^*+1}^2(\mu_{\epsilon^*}^2 + \sigma_{\epsilon^*}^2) + \beta\sigma_{i,T^*+1}^2 \\ &= \omega_i + \sigma_{i,T^*+1}^2(\alpha(\mu_{\epsilon^*}^2 + \sigma_{\epsilon^*}^2) + \beta) . \end{aligned}$$

where  $(\alpha(\mu_{\epsilon^*}^2 + \sigma_{\epsilon^*}^2) + \beta)$  may be greater than 1, permitting explosive behavior, at least in the short term. After both shocks have been exhausted, their influence disappears quickly. This short-memory effect has implications for the method being developed herein:

1. There may be different risks associated with over/underestimating level shock and vol shock lengths. 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.

#### 4.1 Consistency of the Synthetic Volatility fixed effect estimators

**Proposition 2.** *Assume*

1. For each  $i$ ,  $\{a_{i,t}\}_{t=0,\dots,T_i}$  obeys a GARCH- $X(m, s)$ , as laid out in equation (1) process with volatility shocks found in  $\mathcal{M}_2$ , where  $T_i$  is the length of the  $i$ th series.
2. For each  $i$ ,  $\{\omega_{i,t}^*\}_{t=0,\dots,T_i}$  is potentially non-zero at  $\{T_i^* + 1, \dots, T_i^* + k\}$ ,  $\omega_{i,T^*+1}^* \equiv \dots \equiv \omega_{i,T^*+k}^*$ , and zero otherwise, where the arrival of  $T_i^*$  is governed by a time-invariant distribution on  $\{a_{i,t}\}_{t=0,\dots,T_i}$ .
3. The conditions in Assumption 0 of Han and Kristensen [2014] prevail.

Then  $\forall i, \hat{\omega}_{i,t}^* \xrightarrow{p} \mathbb{E}[\omega_i^*]$ .

**Lemma 1.** Under assumption 2,  $\forall i, \{\omega_{i,t}^*\}_{t=0,\dots,T_i}$  is a strictly stationary series.

**Proof of Lemma** Since the shock is assumed to arrive uniformly at random for each  $i$ ,  $1 \leq i \leq n+1$ , and last for a discrete number of indices, the sequence  $\{\omega_{i,t}^*\}_{t=0,\dots,T_i}$  is governed by a distribution  $F_{\{\omega_{i,t}^*\}_{t=0,\dots,T_i}}$  that is invariant to shifts in time.  $\square$

**Proof of Proposition** The result follows from the consistency proof of the QMLE in GARCH-X models, as established by [Han and Kristensen \[2014\]](#).  $\square$

## 4.2 Consistency of the Synthetic Volatility Forecast Function

**Proposition 3.** *Under the conditions in Proposition 2,  $\hat{\sigma}_{adjusted}^2 \xrightarrow{P} \sigma_{1,T^*+1}^2$ .*

**Proof of Proposition** Recall the conditional expectation of the variance for the GARCH-X( $m,s$ ) model:

$$\mathbb{E}_{T^*}[\sigma_{i,t+1}^2 | \mathcal{F}_t] = \omega_i + \omega_i^* + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t}.$$

By replacing parameters with their estimates, we arrive at the prediction

$$\hat{\sigma}_{i,t+1}^2 | \mathcal{F}_t = \hat{\omega}_i + \hat{\omega}_i^* + \sum_{k=1}^{m_i} \hat{\alpha}_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \hat{\beta}_{i,j} \hat{\sigma}_{i,t-j}^2 + \hat{\gamma}_i^T \mathbf{x}_{i,t},$$

which converges in probability to

$$\hat{\sigma}_{i,t+1}^2 | \mathcal{F}_t = \omega_i + \omega_i^* + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t}$$

as  $t \rightarrow \infty$  by a simple application of Slutsky's Theorem.  $\square$

## 4.3 Risk Minimization Using Synthetic Volatility Forecasting

We now evaluate the loss and risk of Synthetic Volatility Forecasts under two scenarios: first, under arbitrary distribution of  $\sigma_{t+1}^2$ , and then second, under the assumption that the data-generating process is correctly specified.

For 1-step-ahead forecast of  $\sigma_{t+1}^2$ , consider the difference

$$\begin{aligned} & QL(\hat{\sigma}_{t+1,unadjusted}^2, \sigma_{t+1}^2) - QL(\hat{\sigma}_{t+1,adjusted}^2, \sigma_{t+1}^2) \\ &= \left( \frac{\hat{\sigma}_{t+1,unadjusted}^2}{\sigma_{t+1}^2} - \log \frac{\hat{\sigma}_{t+1,unadjusted}^2}{\sigma_{t+1}^2} - 1 \right) - \left( \frac{\hat{\sigma}_{t+1,adjusted}^2}{\sigma_{t+1}^2} - \log \frac{\hat{\sigma}_{t+1,adjusted}^2}{\sigma_{t+1}^2} - 1 \right) \\ &= \frac{\hat{\sigma}_{t+1,unadjusted}^2 - \hat{\sigma}_{t+1,adjusted}^2}{\sigma_{t+1}^2} + \log \frac{\hat{\sigma}_{t+1,adjusted}^2}{\hat{\sigma}_{t+1,unadjusted}^2}. \end{aligned}$$

For simplicity, we work with a GARCH(1,1) that experiences a volatility shock at a single time point for which we would like to provide a point forecast. Then (8) can be expressed as

$$\frac{(\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2) - (\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2 + \hat{\omega}^*)}{\sigma_{t+1}^2} + \log \frac{\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2 + \hat{\omega}^*}{\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2} \quad (8)$$

$$= \log \frac{\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2 + \hat{\omega}^*}{\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2} - \frac{\hat{\omega}^*}{\sigma_{t+1}^2} . \quad (9)$$

By letting  $f(\hat{\omega}^*) = \log \frac{\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2 + \hat{\omega}^*}{\hat{\omega} + \hat{\alpha}a_t^2 + \hat{\beta}\sigma_t^2} - \frac{\hat{\omega}^*}{\sigma_{t+1}^2}$ , it's easily verified that as  $\hat{\omega}^* \rightarrow 0^+$ , the difference in the losses goes to zero. On the other hand, as  $\hat{\omega}^*$  becomes large, the difference in the losses turns negative, with the lesson being that  $\hat{\omega}^*$  must be in appropriate proportion to the volatility  $\sigma_{t+1}^2$  in order for the adjusted forecast to outperform the unadjusted forecast. This explains why it is so important to avoid using a naive adjustment estimator,  $\bar{\omega}^*$ , the arithmetic mean of the estimated shocks. We conclude this section with a broader result.

**Proposition 4.** *Assume the conditions in Propositions 2 and 3. Let  $1 \leq i \leq n+1$ .*

*Then  $QL(\hat{\sigma}_{t+1,unadjusted}^2, \sigma_{t+1}^2) - QL(\hat{\sigma}_{t+1,adjusted}^2, \sigma_{t+1}^2) \xrightarrow{p} \log \frac{\sigma_{t+1}^2}{\sigma_{t+1}^2 - \mathbb{E}[\omega_i^*]} - \frac{\mathbb{E}[\omega_i^*]}{\sigma_{t+1}^2} \geq 0$ . Hence, a correctly specified model will outperform the unadjusted forecast asymptotically.*

**Proof of Proposition** First, note that the function  $g : (-\infty, \mathbb{E}[\omega_i^*]) \rightarrow \mathbb{R}$  given by  $g(x) = \log \frac{\sigma_{t+1}^2}{\sigma_{t+1}^2 - x} - \frac{x}{\sigma_{t+1}^2}$  is nonnegative, and being continuous,  $g$  preserves consistency. The conclusion follows from fact that the model is correctly specified and consistency is guaranteed Proposition (3). **Proof appears to not be done. Although it looks like it is almost done. Should Propositions and equations referred to have parentheses around the number?**  $\square$

## 5 Numerical Examples

I do not think this should be broken up into short subsections. Can everything be written in paragraphs? I think more emphasis should be given to why the simulation hyperparameters were chosen.

### 5.1 Modeling Setup

In this section, we demonstrate the effectiveness of the proposed method using Monte Carlo simulations. The first simulation setup will use a  $\mathcal{M}_2$  model on the volatility. The second setup will be a dual shock, i.e. a shock to both the level and volatility.

#### 5.1.1 Most elementary simulation: one-day volatility shock

In order to investigate the Synthetic Volatility Forecasting method, our most elementary simulation uses  $\mathcal{M}_1$ . We vary only two parameters. 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:

Make sure to bring this into line with final model notation decisions.

$$\begin{aligned} \mathcal{M}_2: \quad & \sigma_{i,t}^2 = \omega_i + \omega_i^* + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \\ & a_{i,t} = \sigma_{i,t}(\epsilon_{i,t}(1 - D_{i,t}^{level}) + \epsilon_i^* D_{i,t}^{level}) \\ & \omega_i^* = \mu_{\omega^*} + \delta' \mathbf{x}_{i,T_i^*} + \varepsilon_i \\ & D_{i,t}^{level} \equiv 0 \end{aligned}$$

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

It's worth discussing whether a simultaneous shock to the level and volatility makes sense or adds much.

Consider now a shock to both the volatility and the level beginning at  $T^* + 1$ . In particular, we will explore the performance of the method when a  $\mathcal{M}_2$  shock hits the volatility, while an  $\mathcal{M}_1$  shock hits the level. There is a good reason we explore an  $\mathcal{M}_1$  shock to the level: we have no method to account for an  $\mathcal{M}_2$  shock.

*Hypothesis:* Method should do less well under a concomitant volatility and level shock. A dual shock is in essence a squared observable with two independent sources of randomness.

## 5.2 Performance Metrics

We compare adjusted and unadjusted forecasts using QL Loss, calculating the fraction of the simulations that the adjusted forecast dominates the unadjusted forecast.

## 5.3 Monte Carlo results

Here we cite [Francq and Zakoian \[2019, p. 22\]](#) in motivating simulations for large  $\alpha$  values and then large  $\beta$  values.

In Figure 2, when only two parameters are varied, the volatility shock signal and the volatility shock noise, we observe several encouraging phenomena. First, for any column selected, an increasing trend exists as the shock signal increases. Second, 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 no better at GARCH than a flip of a coin.

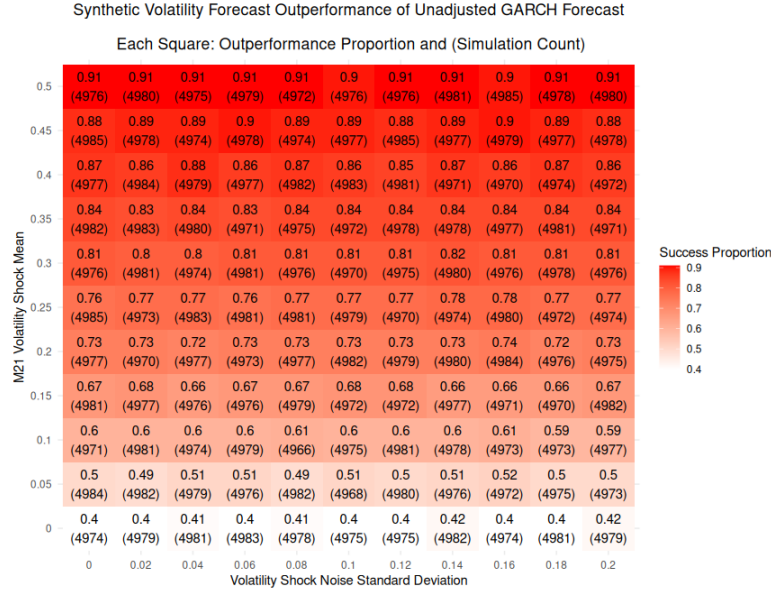


Figure 2: Fixed parameter values:  $\alpha = .1, \beta = .82, \mu_x = 1, \sigma_x = .1$

If we switch the values of  $\alpha$  and  $\beta$ , we see similar behavior, as in 3. However, for small values of the shock mean, increasing noise does lead to fewer converged simulations, likely due to large negative realizations of the noise term, which in turn lead to near-zero and even negative estimates of the terms  $\omega_i^*$ .

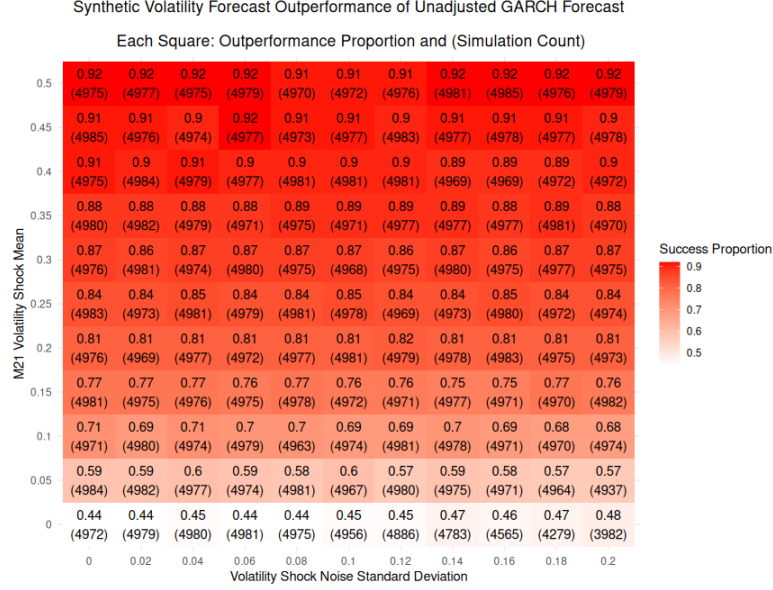
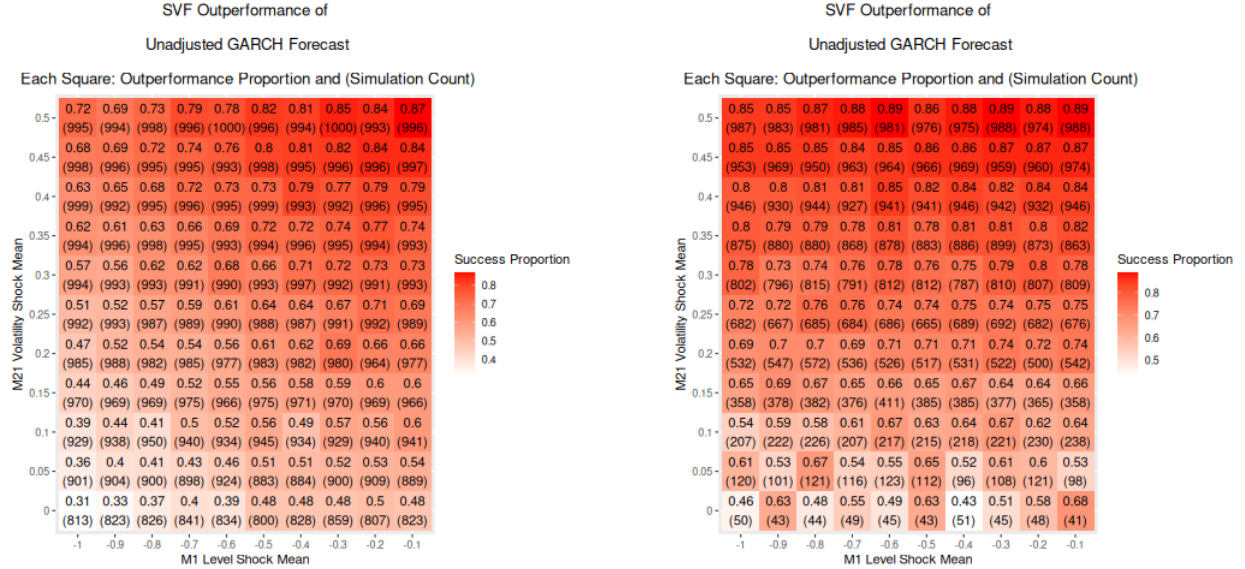


Figure 3: Fixed parameter values:  $\alpha = .82, \beta = .1, \mu_x = 1, \sigma_x = .1$



(a)  $\alpha = .1, \beta = .82, \mu_x = 1, \sigma_x = .1$

(b)  $\alpha = .82, \beta = .1, \mu_x = 1, \sigma_x = .1$

Figure 4: A figure with two subfigures

## 6 Real Data Example

We show the applicability of Synthetic Volatility Forecasting using a real data example that sits at the crossroads of financial trading and electoral politics. In the spring of 2016 in the United States, 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.

From an ex-ante perspective, several qualities of the 2016 US election cycle as well as the candidates themselves made the election difficult to prognosticate. The Electoral College permits victory without a majority or even plurality of the popular vote, which can render presidential races more competitive than a raw vote total would, elevating the uncertainty surrounding the country’s future leadership. The election featured no incumbent, ruling out any incumbent-advantage of the empirical, “statistical” kind distinguished by [Mayhew \[2008\]](#). The Republican Party candidate espoused unorthodox, populist positions on matters such as healthcare, trade, and foreign policy, some of which could be considered rare in either of the major two parties. Additionally, Donald J. Trump, lacking any experience in government — either electoral or appointed service — possessed neither a voting record nor any on-the-job performance for voters to judge or his opponents to attack. As one financial industry professional commented, comparing the 2016 election to the upcoming 2024 election, “this time the markets will be aware of both possibilities and price them to some extent — we wouldn’t expect the same volatility as we saw in 2016 after the election” [[News, 2024](#)]. Gleaning signals from financial options markets and betting markets, [Wolfers and Zitzewitz \[2016\]](#) predicted that markets would decline prodigiously upon a Trump victory. Finally, the election outcome delivered significant “news”, in the econometric sense of the word, in the simple sense that it was not predicted. [Goodell and Vähämaa \[2013\]](#) found support for the theory that the polling-implied probabilities of election outcomes encode information about future macroeconomic conditions, which is itself reflected in market volatility. In its final post before the election result, acclaimed forecasting outfit 538, headed by economist Nate Silver, predicted a Clinton victory with a probability of .714, more than 2-to-1 odds [[Silver, 2016](#)], suggesting that Trump’s victory was at least somewhat surprising.

For all of these reasons and more, the aftermath of the 2016 presidential election meets the standard of an interesting and notable event for which a quantitative researcher might seek a volatility point prediction. On a more technical level, the election outcome was not known until the evening of election day, well after the closing of financial markets at 4pm Eastern Time. This satisfies the condition that the shock be not yet digested by liquid markets. We therefore proceed to make the following technical specifications in order to predict the volatility of financial services ETF IYG<sup>1</sup> (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. For the time series under study and the donor series alike, we fit a GARCH(1,1) on almost four years of market data prior to the shock.
2. **Covariate Choice** We choose covariates that could plausibly satisfy the model assumptions spelled out earlier, that is, risk-related and macroeconomic covariates that could plausibly be weighted and summed in a shock distribution. We thus choose the 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, as well as the log-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](#),

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<sup>1</sup>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.



Kane et al., 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** Synthetic Control, an a tool of causal inference, often goes about weighting control units by first identifying a natural set of donors or standard donors such as the untreated units within a set of subnational units like US states or Spanish provinces [Abadie and Gardeazabal, 2003, Abadie et al., 2010]. While such a procedure does not necessarily preclude considered judgments (e.g. should Canadian provinces be used as donors for a treated US state?), as a tool of small- $n$  prediction, distanced-based weighting faces a decidedly more difficult task in constructing a donor pool. I do not think we should antagonise the synthetic control literature. Let's just state our donors and then leave some differences between us and Abadie et al. brief. I see. I can leave out the judgment that it's more difficult to build a donor pool.

For our purposes, we choose 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 (i.e. those held in even years not divisible by four), which generate far lower voter turnout and feature no national races.

4. **Choice of estimator for volatility** We use the 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.

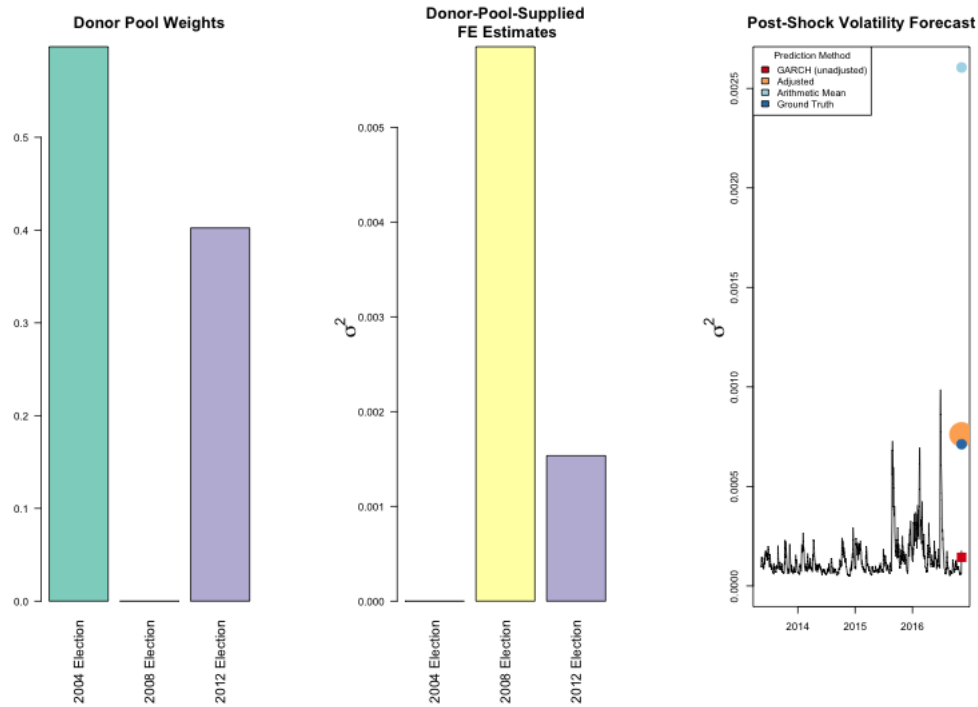
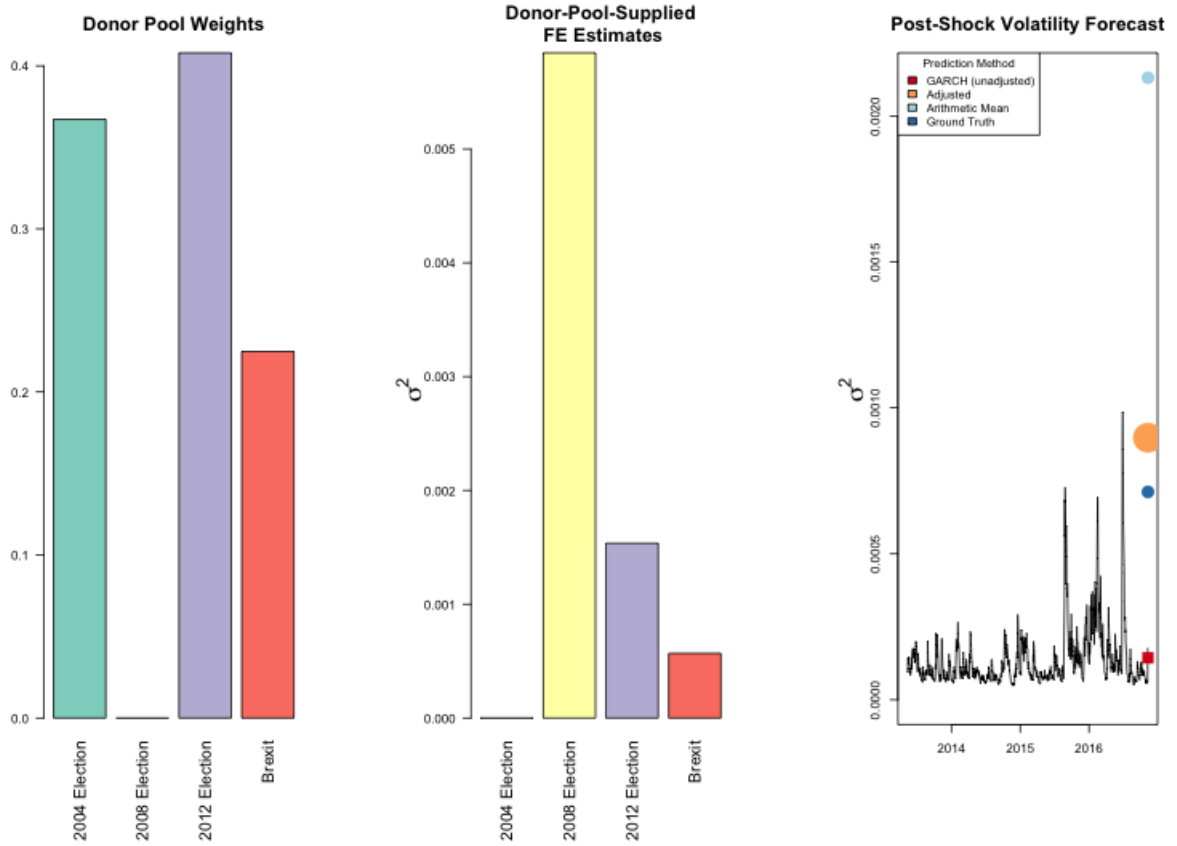


Figure 5: The volatility induced by the 2016 US election

We now discuss the three subplots in Figure 5 in order from left to right. On the left, we see that distanced-based weighting places nearly equal weight on the 2004 and 2012 elections, with only negligible

weight on the 2008 election, when financial market conditions were extreme across nearly every dimension. Assuming an approximately correct specification of the covariates, this is interpreted to mean that even of the 2016 US election had a general climate of risk and tension less extreme than 2008 and more similar to the 2004 and 2012 elections. In the middle plot, we notice that the fixed effect estimates for 2008 and 2012 are considerable, with only 2004 registering a near-zero fixed effect estimate. The fixed effect estimates quantify the amount of surprise the US election results delivered (strictly speaking, not only the presidential race but all November elections in the US with the ability to influence financial markets) under the assumption of a GARCH(1,1). As estimates gleaned from only one data point per time series, they are theoretically high in variance. On the right, we observe in black the fitted values of  $\sigma^2$  given the GARCH(1,1) for the time series under study. We also observe four points, all indicated by the legend: three predictions and the ground truth. We include the prediction derived by adjusting the GARCH(1,1) prediction by the arithmetic mean of the fixed effect estimates. As is evident, the Synthetic Volatility Forecasting method comes reasonably close the ground truth. The prediction is not only directionally correct; it far outperforms the unadjusted prediction. Remarkably, the arithmetic-mean based prediction here demonstrates the inherent risk in failing to weight each donor appropriately. The 2008 election receives far more weight than is called for, as simple averaging ignores the radically different conditions on the evening of those two events.

Naturally, one might ask how sensitive this prediction is to at least two kinds of model specification: donor pool specification and covariate specification. There are two responses to these concerns. First, although the practitioner lacks a priori knowledge of the adequacy of the donors with respect to the time series under study, it is possible to gauge the diversity of the donor information by examining the singular values of the volatility profile. In the prediction presented here, the no singular value represents more than 50% of the sum of singular values. Indeed, the first four singular values descend from 50% to 25% to 21% to 5% of the the cumulative variation, indicating a low concentration or redundancy of information. Second, we follow [Steegen et al. \[2016\]](#) in executing a multiverse analysis. In particular, in the supplement, we carry out leave-one-out analyses on both the donor set and the covariate set. Additionally, in the supplement, we show that with Brexit added as a donor, the results are unchanged, due to the fact that Brexit’s covariates do not lie in the convex hull of 2004, 2012, and the time series under study.



## 7 Discussion

### 7.1 Justifying the Shock Parameterization

Not all of the volatility of an asset return may be related to news [Boudoukh et al., 2019]. This explains our inclusion of an idiosyncratic noise term in the shock specification. However, this point also gestures in the direction of possible unexplained variation in the shocks.

Chinco et al. [2019] find that for predicting 1-minute returns, highly transitory firm-specific news is useful. The authors conclude that news about fundamentals is predictive.

There is an important question about the stability of the GARCH parameters under the presence of an exogenous shock. There are at least two reasons that we do not herein explore parameter instability or methods to adjust for it. First, the marginal effect of coefficient changes at the shock time would, under the assumptions in this work, be swamped by the random effect. Second, the estimation of post-shock parameter values would require at least several — better yet dozens — of post-shock data points, whereas this work assumes access to zero post-shock data points. However, we do leave over that similarity-based estimators for the GARCH coefficients could be produced, for example, by adapting the methods of Dendramis et al. [2020]. This section seems better suited for the Discussion section. Agreed. It has been moved.

## 7.2 Connection to forecast combination methods

Because the method proposed uses a point in  $\Delta^n$ , it is important to head-off possible confusion. What we are proposing is not a forecast combination method. What we aggregating and weighting (not combining) is subcomponents of forecasts, not forecasts themselves. Moreover, from a broader perspective, forecast combination is an inapt term for what is being proposed here. First, the donors are not forecasts. **This does not seem to be complete. Also, is there a way to get this into a paragraph as a minor point?**

## 7.3 Why is the proposal here like and unlike KNN regression?

We are not trying to learn a function, first and foremost. We are trying to estimate a parameter.

KNN runs into the problem: the curse of dimensionality. In contrast, large  $p$  is not a problem in synthetic methods, because the thing estimated is the vector  $w$  with  $n - 1$  degrees of freedom. For KNN, a high-dimensional space, i.e. large  $p$ , corresponding to many covariates, is a difficult space in which to work with distances [Hastie et al., 2009]. In contrast, large  $p$  is not a problem in and of itself for synthetic control — in fact, asymptotic results exist for  $p$  [Abadie et al., 2010].

As is pointed out in Hastie et al. [2009], KNN regression performs well when  $K$  is chosen small enough that one can simply average the points  $\{y_i\}_{i=1}^{N_{train}}$  in the neighborhood around each  $\{y_i\}_{i=1}^{N_{test}}$  to get good predictions. As we have noted above, the arithmetic mean-based estimator of  $\omega^*$ , denoted  $\bar{\omega}^*$ , corresponds to KNN when  $K = n$ , the number of donors. Fundamentally, the idea that  $n$  is small enough and the donors are homogeneous enough that one could simply average the  $\hat{\omega}_i$  is at odds with the assumed variation in the shock effects.

In KNN regression, the hyperparameter  $K$  must be learned. In Synthetic Volatility Forecasting, the number of donors is not learned. A donor pool is curated, and then careful rules of thumb can be applied to determine whether a given donor should be included or excluded. While it would not necessarily hurt to ‘learn’ the appropriate number of donors to use, this information would probably not be as useful as knowing which donors and covariates provide the basis for the best forecasts. This brings us to a deeper point about the distinction between Synthetic Prediction in the way of Lin and Eck [2021] **Synthetic Prediction is not yet a term that can be referenced in this way. Perhaps you can say Synthetic Prediction in the way of Lin and Eck (2021) and this present work.** and KNN. In KNN, the exogenous variables are taken as a given and ‘nearness’ to object-to-predict depends on the distance function chosen. In contrast, in Lin and Eck [2021], the determination of nearness begins with a qualitative step, i.e. curating the units between which we will calculate distances and from we will ultimately derive weights. **I think this paragraph is fine, and the above three bullet points can be removed.**

## 7.4 Should we gather as many donors as possible and pick them quantitatively?

It would be counter to the method proposed to assemble a vast number of donors, lacking careful scrutiny of the qualitative fit, and let the optimization simply pick the donors, via weighting. What makes a donor good is not merely its quantitative fit but its qualitative fit as well.

Abadie and Vives-i Bastida [2022] make a similar point about large donor pools. What matters is that the donors chosen are properly situated in the  $p$ -dimensional predictor space, so as to allow proper estimation of the weights.

## 7.5 Why not use the covariates as covariates in the GARCH model alone or in the GARCH model as well?

The data-generating process does not specify that volatility series are well-modeled using ever-present exogenous covariates, and this is fundamentally due to the lack of theoretical justification for such an exogeneity assumption. **I am not sure if this needs to be here. If so, then it can probably be combined with other points in this discussion to form a larger paragraph.**

## 7.6 Adjustment Using OLS on the Donor Shocks

Consider least-squares estimation for the weight vector  $\vec{w}$ :

$$\vec{w}_{OLS} = \arg \min_{\vec{w}} \|\hat{\omega}^* - \mathbf{V}_{p,n} \vec{w}\|_2$$

One immediately visible problem is that this optimization problem is an optimization problem over  $p$ -vectors  $\vec{w}$  — i.e. a linear combination of the covariates, whereas what we seek is an  $n$ -vector — a linear combination of donors.

There is no guarantee that  $\vec{w}_{OLS}$  would perform poorly as a tool for producing  $\hat{\omega}^*$ , but given the small number of donors supposed in our setting, it is risky. **I think this should be removed or mentioned as a comment in the section where weights are introduced.** I will think about where to put this. The deep point that could be made, and perhaps should be made, is that finding an optimal or at least suitable convex combination of the donors works because of the assumptions about the DGP, and those assumptions don't necessarily support OLS much.

## 7.7 If we assume knowledge of the covariates that parameterize the shock, why not estimate each parameter individually?

**consider removing** I am considering moving this to the part where I discuss that the GARCH model is nested inside the factor model from Abadie et al. [2010].

1. Degrees of freedom is first consideration
2. Each estimate will be quite noisy.

## 7.8 Connection to Stochastic Volatility

SV stipulates that at any time point, both the return distribution and volatility could each be subject to separate shocks [Andersen and Benzoni, 2010]. **This seems incomplete.**

## 7.9 News shock literature review

We adapt the news shock framework of Kilian and Lütkepohl [2017]:

$$z_{T^*+1}^{\text{nonscheduled news shock}} := z_{T^*+1}^{\text{nonscheduled news}} - \mathbb{E}_{T^*}[z_{T^*+1}^{\text{nonscheduled news}}]$$

In our adapted schema, irregular news shocks are  $\mathcal{F}_{T^*}$ -zero-expectation events governed by a GARCH-X process. As such,  $z_{T^*+1}^{\text{irregular news shock}}$  admits of the decomposition  $z_{T^*+1} = \sigma_{T^*+1} \epsilon_{T^*+1}$ . **This seems incomplete.**

## 7.10 Improvements of this current work over its predecessor

This present work extends Lin and Eck [2021] principally by substituting the GARCH model for an AR(1), i.e. modeling both the mean and volatility of a univariate time series. We permit both shocks in the mean model and volatility model of GARCH. As ancillary improvements, the current work permits the shock periods to be of any length, formally  $L_{\text{vol}}, L_{\text{level}} \in \mathbb{Z}^+$ , and the weights applied to the donor pool can come from more exotic subsets of  $\mathbb{R}^n$ .

At a technical level, the most substantial insight related to Lin and Eck [2021] is that the GARCH model provides an elegant forecast function for squared observations of the time series under study. To see this, 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  $\mathcal{M}_0$  and  $\mathcal{M}_1$ , we obtain the standard ARMA representation of a GARCH(m,s): **I thought this was needed earlier in the manuscript. If so, then it does not need to be repeated here. I think this section can be made shorter.** Yes I think in earlier versions, it appeared earlier in the manuscript. In any case, it is not an original result and can perhaps be referred to rather than demonstrated at length.

$$a_{i,t}^2 = a_{i,t}^2 - \sigma_{i,t}^2 + \sigma_{i,t}^2 = \eta_{i,t} + \sigma_{i,t}^2 = \eta_{i,t} + \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} \sigma_{i,t-j}^2 + \gamma_i^T \mathbf{x}_{i,t} \quad (10)$$

$$= \eta_{i,t} + \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{m_i} \alpha_{i,k} a_{i,t-k}^2 + \sum_{j=1}^{s_i} \beta_{i,j} (a_{i,t-j}^2 - \eta_{i,t-j}) + \gamma_i^T \mathbf{x}_{i,t} \quad (11)$$

$$= \eta_{i,t} + \omega_i + \omega_i^* D_{i,t} + \sum_{k=1}^{\max\{m_i, s_i\}} (\alpha_{i,k} + \beta_{i,k}) a_{i,t-k}^2 - \sum_{j=1}^{s_i} \beta_{i,j} \eta_{i,t-j} + \gamma_i^T \mathbf{x}_{i,t} \quad (12)$$

Then for any  $i, t$ ,  $\mathbb{E}[a_{i,t}^2 | \mathcal{F}_{t-1}]$  is nothing more than the conditional expectation of the right-hand side of (12), where  $\mathbb{E}[\eta_{i,t}] = 0$  for any  $i, t$ .

1. 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 in the donor pool. 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?
2. See Tsay p. 133: 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  $\sigma_{i,t+1}^2 = \omega_i + (\alpha_i + \beta_i) \sigma_{i,t}^2 + \alpha_1 \sigma_{i,t}^2 [\epsilon_{i,t}^2 - 1] = \omega_i + (\alpha_i + \beta_i) \sigma_{i,t}^2 + \alpha_1 \sigma_{i,t}^2 [\epsilon_{i,t}^2 - 1]$ . 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.

## 7.11 Model Adjustment Using Synthetic Methods: A Global Overview

**It is a good idea to begin defining a new subfield of forecasting based on the common methodologies of this work and Lin and Eck (2021).**

Here we distinguish what in this work is essential and inessential to synthetic forecasting.

1.  $k$ -dimensional random object to predict
2. a parametric model shared among donors
3. a correction term for the model family shared by donors
4. a parametric specification for the correction term
5. **an estimation procedure that is reliable for estimating parameters.**
6. **an aggregation method for estimates of the correction term in the donor pool where the aggregation is designed to favor donors that are similar to the object that we want to predict**
7. **replace the unknown correction term that has yet to be realized in the object under study with the aggregate correction term computed in the previous step.**

## 7.12 News Sentiment

Within the vast literature on financial sentimental analysis, there exists a sub-literature on financial volatility forecasting using news and news sentiment [Atkins et al., 2018]. The setting herein is one where the valence of the sentiment is reasonably well-understood, and hence the direction of volatility can be well-predicted, although not perfectly, by human intuition.

## 7.13 Uniqueness of the weight vector $\vec{w}$

Ask Dan: should we include this at all?

Some of the comments and results from Lin and Eck [2021] apply here, while some additional comments may be in order: because  $(\mathbb{R}^n, \|\cdot\|)$  is a Chebyshev space, for any element  $x$  and any convex set  $C \subset \mathbb{R}^n$ , there exists a unique element  $y \in C$  that minimizes  $\|x - y\|$ . However, the pre-image of  $y$  with respect to a particular operator and constraint set might not be unique.

Let  $p'$  denote the number of linearly independent rows of  $\mathbf{X}$ .

	$X \in \text{Conv}(\mathbf{X})$	$X \notin \text{Conv}(\mathbf{X})$
$p' \geq n$	Perfect fit; fit unique	Fit not perfect; fit unique
$p' < n$	Perfect fit, not necessarily unique, Caratheodory applies [Abadie and Vives-i Bastida, 2022]	Fit not perfect, not necessarily unique, Caratheodory applies

## 7.14 Value-at-Risk Under Shocks

## 8 Supplement

We analyze the real-world example with Brexit included and using the daily log-return in the Pound-Dollar exchange rate as a covariate.

Note that by inspecting the fit of the distance-based weighting approximation quantitatively, we can gain some degree of foresight into how well the forecast will be.



## References

- Alberto Abadie and Javier Gardeazabal. The economic costs of conflict: A case study of the basque country. *American Economic Review*, 93(1):113–132, 2003.
- Alberto Abadie and Jérémy L’hour. A penalized synthetic control estimator for disaggregated data. *Journal of the American Statistical Association*, 116(536):1817–1834, 2021.
- Alberto Abadie and Jaume Vives-i Bastida. Synthetic controls in action. *arXiv preprint arXiv:2203.06279*, 2022.
- 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 Luca Benzoni. Stochastic volatility. *CREATES Research Paper*, (2010-10), 2010.
- Torben G Andersen and Timo Teräsvirta. Realized volatility. In *Handbook of financial time series*, pages 555–575. Springer, 2009.
- Torben G Andersen, Tim Bollerslev, Francis X Diebold, and Paul Labys. Modeling and forecasting realized volatility. *Econometrica*, 71(2):579–625, 2003.
- Torben G Andersen, Tim Bollerslev, and Francis X Diebold. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The review of economics and statistics*, 89(4):701–720, 2007.
- Adam Atkins, Mahesan Niranjan, and Enrico Gerding. Financial news predicts stock market volatility better than close price. *The Journal of Finance and Data Science*, 4(2):120–137, 2018.
- Luc Bauwens, Arie Preminger, and Jeroen VK Rombouts. Regime switching garch models. 2006.
- Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327, 1986.
- Jacob Boudoukh, Ronen Feldman, Shimon Kogan, and Matthew Richardson. Information, trading, and volatility: Evidence from firm-specific news. *The Review of Financial Studies*, 32(3):992–1033, 2019.
- 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.
- Alex Chinco, Adam D Clark-Joseph, and Mao Ye. Sparse signals in the cross-section of returns. *The Journal of Finance*, 74(1):449–492, 2019.
- Bent J Christensen and Nagpurnanand R Prabhala. The relation between implied and realized volatility. *Journal of financial economics*, 50(2):125–150, 1998.
- Michael Clements and David F Hendry. *Forecasting economic time series*. Cambridge University Press, 1998.
- Rama Cont. Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative finance*, 1(2):223, 2001.

- Giovanni De Luca et al. Forecasting volatility using high-frequency data. *Statistica Applicata*, 18, 2006.
- Yiannis Dendramis, George Kapetanios, and Massimiliano Marcellino. A similarity-based approach for macroeconomic forecasting. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 183(3):801–827, 2020.
- Kathryn ME Dominguez and Freyan Panthaki. What defines ‘news’ in foreign exchange markets? *Journal of International Money and Finance*, 25(1):168–198, 2006.
- 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.
- Robert F Engle and Andrew J Patton. What good is a volatility model? *Quantitative finance*, 1(2):237, 2001.
- Claudia Foroni, Massimiliano Marcellino, and Dalibor Stevanovic. Forecasting the covid-19 recession and recovery: Lessons from the financial crisis. *International Journal of Forecasting*, 38(2):596–612, 2022.
- Christian Francq and Jean-Michel Zakoian. *GARCH models: structure, statistical inference and financial applications*. John Wiley & Sons, 2019.
- John W Goodell and Sami Vähämaa. Us presidential elections and implied volatility: The role of political uncertainty. *Journal of Banking & Finance*, 37(3):1108–1117, 2013.
- Pablo Guerrón-Quintana and Molin Zhong. Macroeconomic forecasting in times of crises. 2017.
- Heejoon Han and Dennis Kristensen. Asymptotic theory for the qmle in garch-x models with stationary and nonstationary covariates. *Journal of business & economic statistics*, 32(3):416–429, 2014.
- 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.
- Trevor Hastie, Robert Tibshirani, and Jerome Friedman. *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media, 2009.
- D Hendry and M Clements. On a theory of intercept corrections in macroeconometric forecasting. 1994.
- Alex Kane, Alan J Marcus, and Jaesun Noh. The p/e multiple and market volatility. *Financial Analysts Journal*, 52(4):16–24, 1996.
- Will Kenton. Event-driven investing strategies and examples, 2022. URL <https://www.investopedia.com/terms/e/eventdriven.asp>.
- 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.
- David R Mayhew. Incumbency advantage in us presidential elections: The historical record. *Political Science Quarterly*, 123(2):201–228, 2008.

- Stewart Mayhew. Implied volatility. *Financial Analysts Journal*, 51(4):8–20, 1995.
- Bloomberg News. Election 2024: What will markets do with trump victory over biden?, Jan 2024. URL <https://www.bloomberg.com/news/articles/2024-01-21/trump-s-2016-win-shook-markets-traders-won-t-get-fooled-again>.
- Christina D Romer and David H Romer. Does monetary policy matter? a new test in the spirit of friedman and schwartz. *NBER macroeconomics annual*, 4:121–170, 1989.
- Prateek Sharma et al. Forecasting stock market volatility using realized garch model: International evidence. *The Quarterly Review of Economics and Finance*, 59:222–230, 2016.
- Nate Silver. 2016 election forecast, Nov 2016. URL <https://projects.fivethirtyeight.com/2016-election-forecast/>.
- Sara Steegen, Francis Tuerlinckx, Andrew Gelman, and Wolf Vanpaemel. Increasing transparency through a multiverse analysis. *Perspectives on Psychological Science*, 11(5):702–712, 2016.
- 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.
- Ruey S Tsay. *Analysis of financial time series*, volume 543. John wiley & sons, 2005.
- Justin Wolfers and Eric Zitzewitz. What do financial markets think of the 2016 election. *Unpublished manuscript. brook. gs/2njI8U3*, 2016.
- Eric Zivot. Practical issues in the analysis of univariate garch models. In *Handbook of financial time series*, pages 113–155. Springer, 2009.