Volatility Forecasting Using Similarity-based Parameter Correction and Aggregated Shock Information

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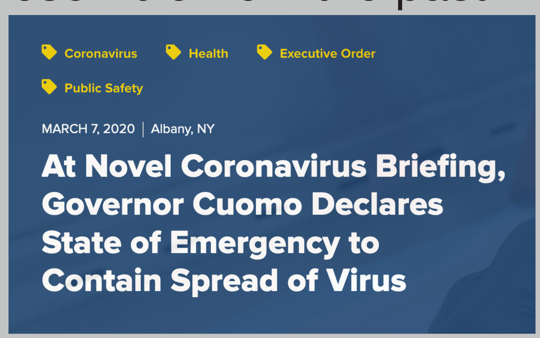
Introduction - Reacting to the Unprecedented

1. Reacting to a seemingly unprecedented event might involve the question: what, if anything, does it resemble from the past?



2. Matching a current crisis to past events is a problem with unsurprising statistical angles: identification, sample size, weighting, risk, and robustness.
3. Here we employ a method to improve our GARCH-X volatility forecasts under unprecedented conditions.

The Family of GARCH-X Volatility Models

We define a family of $n+1$ univariate times series, each of length T_i, $i = 1, \ldots n+1$. For each i, there exists a news shock that occurs strictly between T_i^* and T_i^*+1, and for each i, there exists a GARCH-X model

$$\sigma^2_{i,t} = \omega_i + \sum_{k=1}^{m_i} \alpha_{i,k} a^2_{i,t-k} + \sum_{j=1}^{s_i} \beta_{i,j} \sigma^2_{i,t-j} + \gamma_i^T \mathbf{v}_{i,t} + \omega^*_{i,t} \tag{1}$$

$$a_{i,t} = \sigma_{i,t}\epsilon_{i,t} \tag{2}$$

with the “unprecedented” shocks parameterized by

$$\omega^*_{i,t} = D^{vol}_{i,t}[\mu_{\omega^*} + \delta^T \mathbf{v}_{i,T_i^*+1} + u_{i,t}] \tag{3}$$

where $\mathbf{v}_{i,T_i^*+1}$ is a vector of variables that reflects and encodes prevailing risk conditions, and all other errors are mean-zero and idiosyncratic.

Objective

Provide a one-step-ahead volatility forecast for the *time series under study*, i.e. the first time series in the family above. We will denote the series $i = 2, \ldots, n+1$ the *donor series*, from which we will extract information.

Methodology

We estimate the ”unprecedented” shocks in the donor pool (i.e., $i = 2, 3, \ldots n+1$) using fixed-effect estimation during the shock times, yielding shock estimators $\{\hat{\omega}_i\}_{i=2}^{n+1}$. The aggregated adjustment estimator is given by

$$\hat{\omega}^* = \sum_{i=2}^{n+1} \pi_i \hat{\omega}^*_{i,*} \tag{4}$$

where the weights $\{\pi i\}_{i=2}^{n+1}$ are a convex combination chosen to minimize the distance between $\mathbf{v}_{i,T_i^*}$ and the convex hull of $\{\mathbf{v}_{i,T_i^*}\}_{i=2}^{n+1}$, similar to the Synthetic Control approach in causal inference [1, 2]. The weights $\{\pi i\}_{i=2}^{n+1}$ help us to build a ‘clone’ of the shock that will hit the time series under study.

Evaluating Forecasts with QL Loss

$$\mathrm{QL}^h_{method,groundtruth} = \frac{\hat{\sigma}^2_{h,groundtruth}}{\hat{\sigma}^2_{h,method}} - \log\frac{\hat{\sigma}^2_{h,groundtruth}}{\hat{\sigma}^2_{h,method}} - 1\ . \tag{5}$$

- What distinguishes Quasi-likelihood Loss is that it is multiplicative rather than additive. For this reason and others, we proceed to evaluate the method, both in simulations and real data examples, using the QL loss.
- This has benefits, both practical and theoretical. As [3] explain, the technical properties of the QL Loss allow researchers to compare forecasts across heterogeneous time series, whereas additive loss functions like MSE unfairly penalize forecasts made under market turbulence.

Real Data Example: Aftermath of Donald Trump’s 2016 Victory

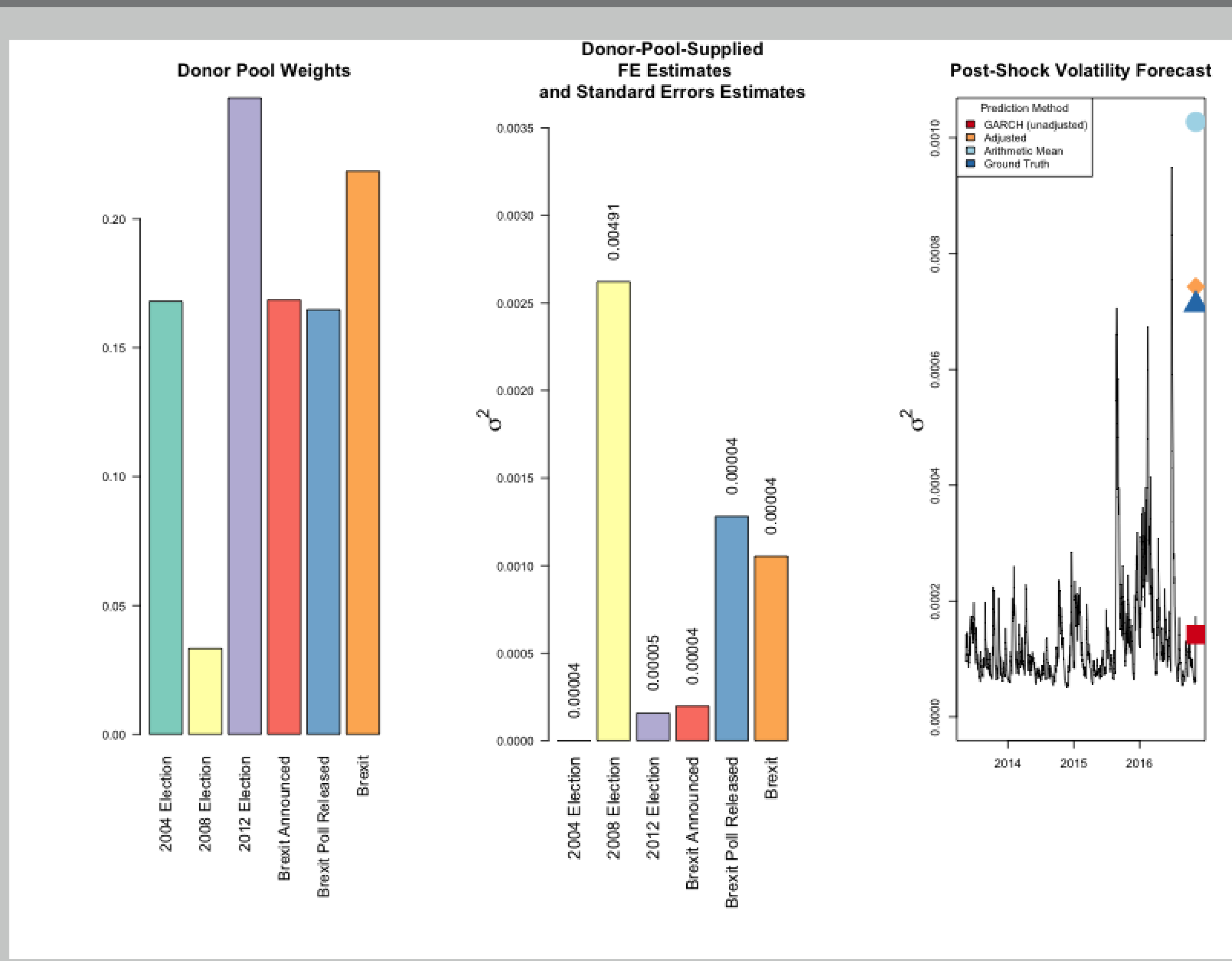


Figure 1: Donor pool weights (left panel), individual shock effects (center panel), and forecasts (right panel). In the right panel, we predict the volatility of the financial services exchange-traded fund IYG on November 9th, 2016. The adjusted prediction nearly recovers the realized volatility, which is consistently estimated using high-frequency data.

Conclusions

1. When structural shocks undermine the credibility of the default forecasting model, a new method is called for.
2. Here we have attempted to model news shocks as parameterized by prevailing risk conditions.
3. We have also proposed an aggregation mechanism that allows in the incorporation of past shock information in a principled manner.
4. Future directions may involve applications to HAR forecasts, VAR-based forecasts of multivariate time series, and impulse response functions.

References

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