

Forecast Adjustment Under Shocks: A Unification

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Abstract

This work systematizes and unifies the rich landscape of model adjustment and model correction methods, with a special focus on forecast adjustment under the presence of shocks.

1 Introduction

For various modeling and prediction tasks in time series and panel data, the salient challenge is not predicting when an event will occur but what its direction, sign, magnitude, duration, correlation structure, or after-effects will be. This is not to say that predicting when a given event will occur is easy. In some cases, it may be difficult or impossible, and in those situations in particular, preparing for the shock is the best one can hope for.

This work focuses on model adjustment amid structural shocks that undermine the reliability of the model at hand. Forecasting under anticipated shocks raises unavoidable questions: should the forecast model be abandoned in favor of a discretionary or ad-hoc or one-off adjustment? Does the discretion of a forecaster rule out a quantitative method for making the adjustment? What is the ultimate purpose of the adjustment, and how it is to be used? For how long is the adjustment necessary or reliable?

Herein we systematize and unify a range of conceptual approaches and tools that have developed across the broad ecosystem of the econometric and forecasting literatures. Additionally, we delineate a specific type of forecasting problem called post-shock forecasting, which we broadly define as forecasting when the a shock intervenes.

difference between discretionary and automated [[Hendry and Clements, 1994](#)]

Setting the model back on track [[Hendry and Clements, 1994](#)]

what we are talking about here is not forecast combination, but there may be, nevertheless, a role for forecast combination: combining the forecasts generated by small differences in covariate and/or donor choice

The role and meaning of similarity

How important is a shared DGP?

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Bias-variance tradeoff and MSE decomposition

Mismeasured data is discussed in [Hendry and Clements, 1994, p. 166] as a motivator for intercept correction. Could similarity-based correction help?

The forecast horizon — does it matter? If so, how so? Lin and Eck [2021] has a one-period horizon. Clements and Hendry [1998]p. 203 discuss how long to keep the forecast adjustment in place. For a corrected “slope parameter”, the effect of h is not so clear.

1.1 Literature Review

Three Clements and Hendry books

- 1994
- 1998
- 1999

Quinton-Guerrera and Zhong

Evaluating a Model by Forecast Performance Clements and Hendry [2005]

- unconditional versus conditional
- internal versus external evaluation
- constancy versus adventitious
- skip
- 1step versus multi-horizon forecasts – this is a relevant question to ask in the context of post-shocking forecasting: should we correct the earliest forecast and then allow the shock to propagate, or should we just correct each term in the horizon, $h=1, 2, \dots, H$?

1.2 Model Adjustment Using Similarity-Based Parameter Correction: A Global Overview

1. a random object to forecast that depends on a linear specification
2. a parametric model family shared by donors
3. a correction term for the model family shared by donors
4. a parametric specification for the correction term
5. a reliable estimation procedure for the shared model
 - (a) This should be straightforward
6. a reliable estimation procedure for the correction term
 - (a) This might not be straightforward. Some models like GARCH, for example, might deliver very noisy estimates for indicator variables that occur just once.
7. a correction function that aggregates (i.e. maps) donor correction terms based on some notion of similarity

Emphasize that there is a non-parametric version of the above: for example, one can use LSTM to predict each of the donor shocks, and then the residuals of those n models can be weighted to arrive at a correction term.

2 Setting

3 Model-Specific Considerations

3.1 ARIMA

3.2 GARCH

3.3 HAR

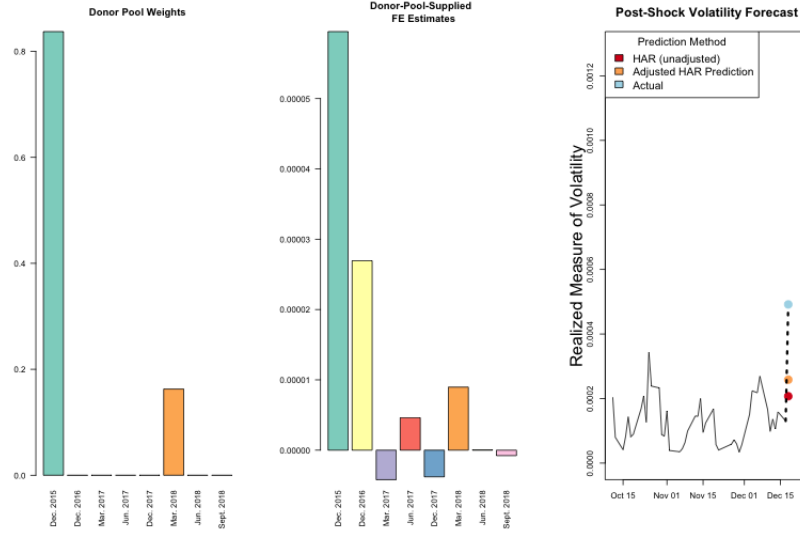


Figure 1: Volatility series of six i.i.d. GARCH processes, each of which experiences a volatility shock, indicated with a red vertical line, at a uniformly distributed point in the set $\{756, \dots, 2520\}$ of trading days, corresponding to between 3 and 10 years of daily trading data.

3.4 VAR

4 Real Data Examples

5 Discussion

- Binary Outcome Forecasts
- Density Forecasts
- Quantile Forecasts

References

- Michael Clements and David F Hendry. *Forecasting economic time series*. Cambridge University Press, 1998.
- Michael P Clements and David F Hendry. Evaluating a model by forecast performance. *Oxford Bulletin of Economics and Statistics*, 67:931–956, 2005.
- D Hendry and M Clements. On a theory of intercept corrections in macroeconometric forecasting. 1994.
- Jilei Lin and Daniel J Eck. Minimizing post-shock forecasting error through aggregation of outside information. *International Journal of Forecasting*, 2021.