# Forecast Adjustment Under Shocks: A Unification

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**Abstract**

Structural shocks to time series may give an observer reason to doubt the credibility of the default forecasting function. 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. We demonstrate the usefulness of similarity-based methods in forecasting and present several specific models that can benefit, along with formal results for some of those special cases.

# 1 Plan

## 1.1 What the paper should do

- Introduce an existing diffuse set of approaches to adjusting forecasts (2)
- Explain when/how similarity can help us forecast.
- distinguish the method from various tools that inspired it
- show a few special cases, both examples and formal results (5)
- discuss limitations of the method
- propose extensions (7.1)

## 1.2 What the paper should NOT do

- Wade too deeply into distance-based weighting details. We can refer to other work?
- wade too deeply into any of the special cases
- Tackle non-scalar random quantities (density forecasts, etc)
- Forecast combination

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## 2 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 key properties will be. In the familiar case of scalar time series, that can include its post-event direction, moments, sign, magnitude, duration, and correlation structure, all over an arbitrary horizon or perhaps multiple horizons. This is not to say that predicting the arrival of an event is easy. In some cases, it may be difficult or impossible, and therefore preparing for an antipicated shock is the best one can hope for.

This work focuses on model adjustment amid structual 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 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 task called post-shock forecasting, which we broadly define as forecasting under a known shock.

Forecast model adjustment, known most widely perhaps by the term intercept-correction, has received the most attention in several articles and book chapters [Hendry and Clements, 1994, Clements and Hendry, 1996, 1998]. Of special importance is the distinction between discretionary and automated intercepts corrections. Hendry and Clements [1994] define scalar intercept corrections to be automated when they follow the simple rule of adding an estimation residual $e_t$ to subsequent (possibly but not necessarily all) forecasts $\hat{f}_{t+1}, \hat{f}_{t+2}, ....$ This procedure can colloquially referred to as setting the model back on track [Hendry and Clements, 1994]. In Hendry and Clements [1994], after recounting the bipartite division of interception corrections in discretionary and automated varieties, the authors present a six-way taxonomy of information that a modeler possesses at the time a forecast is made. The authors also consider structural change in the data-generating process during the forecast period, including as early as the first point in the forecast period (specifically in the autoregressive structure), as well as what is for them the more interesting case: structural change between $T^* - 1$ and $T^*$. This current work finds both cases interesting. What if we could predict well the intercept shift that occurs between $T^*$ and $T^* + 1$?

Post-shock forecasting procedures have been explored in Lin and Eck [2021], Lundquist and Eck [2024], where the AR(1) and GARCH$(m, s)$ cases, respectively, are treated. Both works target additive parameters in scalar time series, predicting those random effects by aggegating information from other time series. The authors leave several stones unturned, including a more general, dare say comprehensive treatment of how to forecast under any sort of shock.

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 determinstic exogenous events in Engle and Patton [2001]). We employ fixed effect estimation on the basis of a well-established conceptual assumption that shocks of economic time series can be modeled as mixtures, in particular, mixtures of ordinary innovations and rare events (see Phillips [1996] and references therein). 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: so-called "discretionary" intercept corrections that attempt to account for future events, without hard-coding an ad-hoc adjustment into the model specification, and second, "automated" 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] a 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 procedures that discretionary or automated, a variety of choices for the collection of data assembled to perform the correction, whether the data is internal (i.e. from 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 a discretionary procedure for intercept correction that incorporates systematically 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 via comparison with a synthetic time series that that represents either the treatment or control unit. The synthetic unit is constructed using a convex combination of the donors. 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 one-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 times series, leaving unaccounted for the variability that accompanies predictions of a heteroskedastic time series. 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 occurring outside the time series under study. Likewise, we are not familiar with any prior work that attempts to account for anticipated nonzero errors using an explicit parametric adjustment, i.e., what we will call a "correction function".

## 2.1 Literature Review

### 2.1.1 Motivation for Intercept Correction

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

Here is an idea: if we believe that our most recent measurement of the series is noisy, we can disregard the point itself and instead take a convex combination of that point and the Lin and Eck [2021]-style prediction based on aggregation

Quinton-Guerrera and Zhong Guerrón-Quintana and Zhong [2017] - concerned with correcting $\beta$ using similarity

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

1. unconditional versus conditional, models;
2. internal versus external standards;
3. checking constancy versus adventitious significance;
4. ex ante versus ex post evaluation (skip this one?);
5. 1-step 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,..., H?
6. in-sample fixed coefficients versus continuous updating

## 2.2 The Meaning and Role of Similarity

Hume?

The notion of similarity appears in various statistical contexts, including matching, synthetic control, nearest-neighbor methods, not to mention the massive area of approximation theory.

Similar, in the strong sense, could mean that a shared DGP exists.

Quantitative ways of determining similarity

Distance function

Asymmetric distance functions are useful when we want to explore differences between donors and weight different contributors to that function differently.

What about qualitative ways of determining similarity – Lundquist and Eck [2024] donors are identified qualitatively

# 3 Setting

In order to motivate our procedure, we provide a visual illustration. In Figure [decide on which figure to include] we show how the aggregation of estimated excess volatilities from donors in the donor pool works when the correction function is a specially-chosen convex combination of fixed effects from the donor pool. Our method 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.

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

In this section, we introduce and discuss a particular approach to model adjustment that is motivated by the circumstances laid out in Section 3.

1. a random object to forecast that depends on a linear specification or a specification that can be linearized
2. a parametric model family shared by donors[1]
3. a correction term for the model family shared by donors
4. a parametric specification for the correction term

   This is important because with a parametric specification, we cannot get key scalars to take a convex combination of.

[1] 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 (or transformations of those residuals, e.g. to percentages) of those n models can be weighted to arrive at a correction term.

5. a reliable estimation procedure for the shared model.

   When we use fixed effect estimation (under ordinary assumptions), we can construct confidence intervals for the fixed effect estimates, and then assuming independence, we can get confidence intervals for convex combinations of fixed effect estimates.

   (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.
   (b) When will it be as simple as a fixed effect?
   (c) When will it be something besides a fixed effect?

7. a correction function, based on the correction term, that aggregates (i.e. maps) donor correction terms based on some notion of similarity

## 4.1 How is the proposed method distinct from existing tools?

## 4.2 Relaxation of Assumptions

### 4.2.1 How important is a shared DGP?

## 4.3 We can use the method on latent time series

See Lundquist and Eck [2024]

# 5 Model-Specific Considerations

## 5.1 ARIMA

Lin and Eck [2021]

## 5.2 GARCH

## 5.3 HAR

## 5.4 VAR

## 5.5 LSTM/GRU

- a
- b
- c
- d

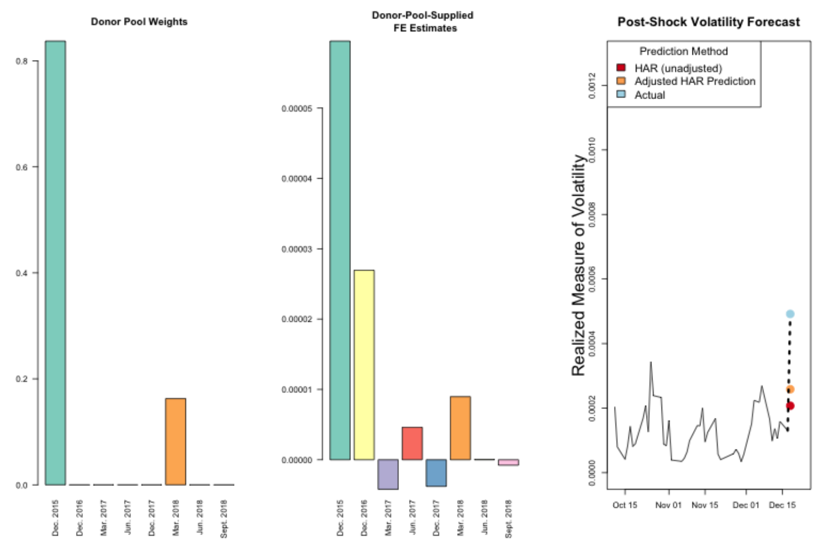


Figure 1: Volatility series of six i.i.d. GARCH processes, each of which experiences a volatility shock, indicated with a red vertical line, at a uniformly distributed point in the set $\{756, ..., 2520\}$ of trading days, corresponding to between 3 and 10 years of daily trading data.

# 6 Real Data Examples

# 7 Discussion

Are there any situations where we would want to intercept-correct using the post-shock term from Lin and Eck [2021] rather than the actual residual?

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.

- Binary Outcome Forecasts
- Density Forecasts
- Quantile Forecasts

## 7.1 Extensions

bias-variance tradeoff and MSE decomposition

## 7.2 Limitations

## 7.3 Forecast Combination

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, as is done in Lundquist and Eck [2024].

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