## Tests of Conditional Predictive Ability: Some Simulation Evidence

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# This paper ...

**[1]** Provide data-generating-processes (DGPs) that are consistent with Giacomini and White (2006, *Econometrica*)'s theoretical framework

[2] Analyze finite-sample properties of Giacomini and White (GW, hereafter)'s testing procedures for

- 1. Unconditional predictive ability
- 2. Conditional predictive ability

where forecasts are generated with

- 1. Fixed-window estimation scheme
- 2. Rolling-window estimation scheme

## In this discussion

I will talk about this paper in terms of ...

- 1. Relevance
- 2. Challenges

Then, I will list my comments on the paper

#### Relevance

Among 50 regular articles published over the last year in the *International Journal of Forecasting*:

- 25 papers perform statistical testing on equal-predictive-ability
- 20 papers report results based on Diebold-Mariano (DM)-type statistic with
  - Recursive-window estimation (11 papers)
  - Rolling-window estimation (8 papers)
  - Fixed-window estimation (1 paper)

### Challenges

Forecast target:  $y_{t+h}$ 

Two forecasts made at time t:  $f_{1,t}$  and  $f_{2,t}$ 

Define a loss differential

$$d_{t+h} = L(y_{t+h}, f_{1,t}) - L(y_{t+h}, f_{2,t})$$

where L(y, f) is a loss function

Consider two types of null hypotheses for equal predictive ability

$$E[d_{t+h}] = 0$$
 or  $E[d_{t+h}|\mathcal{F}_t] = 0$ 

## Challenges

Conditional predictive ability test:

$$E[d_{t+h}|\mathcal{F}_t]=0$$

GW's theory is based on a specific form of  $\mathcal{F}_t$ 

They assume that  $f_{1,t}$  and  $f_{2,t}$  are measurable with respect to  $\mathcal{F}_t$ 

For 1-step-ahead prediction,

- $(d_{t+1})$  becomes a martingale difference sequence (MDS)
- $(d_{t+1}z_t)$  becomes a MDS where  $z_t \in \mathcal{F}_t$
- Their asymptotic theory boils down to LLN/CLT for MDS

For *h*-step-ahead prediction,  $d_{t+h}$  is serially correlated only up to (h-1) displacements

#### Challenges Is this assumption realistic?

Assume a quadratic loss function,

$$d_{t+1} = (y_{t+1} - f_{1,t})^2 - (y_{t+1} - f_{2,t})^2$$

Simple arrangement shows that GW's null hypothesis holds when

$$E[y_{t+1}|\mathcal{F}_t] = \frac{1}{2}(f_{1,t} + f_{2,t})$$

For example, if  $f_{1,t}$  is unbiased, then  $f_{2,t}$  has to be unbiased.

It is hard to come up with such an example at least for me. But, the author came up with such an example

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## Comment 1: HAC-Bandwidth

**Comment 1:** If the paper was really about documenting a finite sample properties of GW's test procedures, then it is much more natural to **use a rectangular kernel rather than a Bartlett kernel** to estimate the long-run variance for "conditional" EPA test

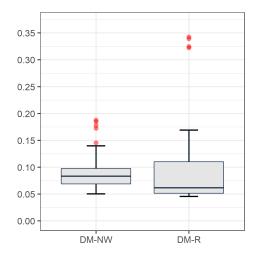
- Giacomini and White (2006) emphasized this in the paper. "Use HAC and truncate at (*h* – 1) for the conditional testing."
- Also emphasized in Giacomini (2010)

Under the conditional null hypothesis, it is better because ...

- Smaller size distortion due to less biased LRV estimation
- More powerful if the alternative entails a serial correlation

#### Comment 1: HAC-Bandwidth

Empirical distribution of actual sizes for all experiments considered in the author's paper (all 80 specifications), **nominal size = 5%** 



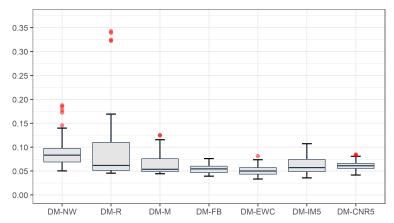
- DM-NW (This paper): Bartlett kernel with Newey and West's automatic bandwidth rule
- DM-R (GW's original rule) : Rectangular kernel truncated at (h 1)

## Comment 2: On size distortion

**Comment 2:** Most of size distortions that we saw from the author's exercises can be eliminated by using different approaches

- Recent tools from HAR-inference literature: Fixed-b asymptotics, t-statistic-based testing, randomization test using asymptotic symmetry, etc
- Accurate estimation of the long-run variance may not be an issue here (e.g., fixed-b asymptotics)

## Comment 2: On size distortion



- DM-NW: This paper
- DM-R: GW's original rule
- DM-M: Harvey et al. (1997)
- DM-FB: Kiefer and Vogelsang (2005)
- DM-EWC: Muller (2004)
- DM-IM: Ibragimov and Muller (2010)
- DM-CNR: Canay, Romano, Shaikh (2017)

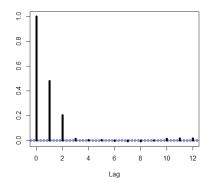
# Comment 3: Interesting property of the DGP

**Comment 3:** Conditional-Rolling DGP generates a very strong conditional heteroscedasticity in the loss differential

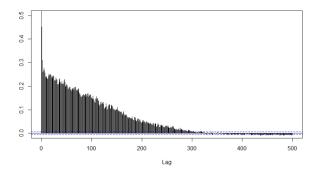
#### Comment 3: Interesting property of the DGP

For example, R = 175; Rbar = 175; h = 3; with P = 1000000;

ACF of  $d_{t+h}$  is MA(2) as expected



# Comment 3: Interesting property of the DGP ACF of $d_{t+h}^2$



Fitting MA(2)-GARCH(1,1) gives me the following estimates

 $\omega = 0.00, \quad \beta_1 = 0.23, \quad \beta_2 = 0.81$ 

where the GARCH equation is defined as

$$\sigma_t^2 = \omega + \beta_1 \mathbf{e}_{t-1}^2 + \beta_2 \sigma_{t-1}^2$$

## Comment 4: My personal view about GW

Conditional EPA testing:

 $E[d_{t+h}|\mathcal{F}_t] = 0$ 

GW's theory is based on a specific form of  $\mathcal{F}_t$ 

- ▶ For example,  $f_{1,t}$  and  $f_{2,t}$  are measurable with respect to  $\mathcal{F}_t$
- Theoretically convenient, more powerful test, etc.
- ▶ It makes sense if you want to know whether  $d_{t+h}$  is predictable
- However, for this null to hold we have to impose a very strong restrictions on f<sub>1,t</sub> and f<sub>2,t</sub>

## Comment 4: My personal view about GW

GW's conditional testing also used for explanatory analysis:

- ► Is *d*<sub>*t*+1</sub> statistically different from zero during recession?
- ► Is d<sub>t+1</sub> is associated with some economic variables (z<sub>t</sub>)?

One could perform a test based on

$$d_{t+h} = \beta_0 + \beta_1 z_t + \varepsilon_{t+h}$$

 $E[\varepsilon_{t+h}] = 0$  and  $E[\varepsilon_{t+h} \times z_t] = 0$ 

Then, just test  $\beta_0 = 0$  and  $\beta_1 = 0$  with HAR inference **WITHOUT** "truncation at (h-1)" admitting that  $\varepsilon_{t+h}$  can exhibit higher-order serial correlation

## Conclusion

This paper is very relevant for forecasters

This paper attacks a challenging problem

This paper offers several useful lessons for users of GW's tests