

The new benchmark for forecasts of the real price of crude oil

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The views expressed in this paper are those of the authors and no responsibility for them should be attributed to the Bank of Canada.

What is a good forecast?

- ▶ Suppose we want to evaluate a forecast of X_{t+h}
- ▶ Common practice: compare accuracy of your forecast against

$$\textit{no-change benchmark} \equiv X_t$$

- ▶ X_t is optimal forecast under the random walk hypothesis
→ accuracy-improvements over NCB imply that
 - series is predictable in general
 - our forecast is more useful than “naive” approach
- ▶ **But: this approach not informative for temporally aggregated data**
 - lower-frequency series constructed by *averaging* or summation (e.g., real commodity prices, interest rates, ...)

The new benchmark

- ▶ Random walk hypothesis applies to high-frequency series
 - aggregated data are predictable by construction (Working 1960)
 - conventional NCB is not the optimal forecast
- improvements over conventional NCB not informative about RWH

- ▶ New no-change benchmark:

last high-frequency observation

- optimal under random walk hypothesis
 - restores original interpretation of comparison with NCB
- $\approx 45\%$ improvement in MSPE for monthly/quarterly averages of daily data for 1-step-ahead prediction

Application to the real price of crude oil

- ▶ Real price of crude oil typically based on averaged data (Kilian 2009; Baumeister & Hamilton 2019)
 - ▶ Existing literature: model-based forecasts beat NCB (Baumeister & Kilian 2012, 2014, 2015; Alquist et al. 2013; Snudden, 2018; Funk, 2018; Garratt et al., 2019)
 - ▶ New no-change benchmark based on monthly closing price of oil
 - $\approx 40\%$ improvements in accuracy at 1-step-ahead prediction
 - using closing prices for estimation improves traditional models
 - but: most models do *not* beat the new benchmark
- oil prices are more difficult to predict than previously thought

Intuition under the RW null hypothesis

- ▶ Forecaster's goal is to predict X_{t+h} given time t information

$$X_t \equiv \frac{1}{n} \sum_{i=1}^n y_{t,i}$$

t = month; i = day of month; n = # of days in month

- ▶ Null hypothesis: daily observations follow random walk

$$y_{t,i} = y_{t,i-1} + \epsilon_{t,i}, \quad \text{for } i = 1, \dots, n$$

$\epsilon_{t,i}$ is a mean-zero, *iid* error term with variance σ_ϵ^2

- What is the optimal forecast in this setting?
- What are the consequences of using X_t to evaluate forecasts?

The optimal forecast under the RWH

- ▶ Optimal forecast in MSPE terms is the conditional expectation

$$E_t(X_{t+h}) = E(X_{t+h} | y_{1,1}; \dots ; y_{t,n}; Z_1; \dots ; Z_t)$$

- ▶ RWH: conditional expectation of each future daily obs

$$E_t(y_{t+h,i}) = y_{t,n} \quad \text{for all } h > 0, i = 1, \dots, n$$

⇒ conditional expectation of each future average obs

$$E_t(X_{t+h}) = E_t\left(\frac{1}{n} \sum_1^n y_{t+h,n}\right) = y_{t,n}$$

- ▶ New benchmark is the optimal forecast under the RWH:

last high-frequency observation in period t $\equiv y_{t,n}$

Comparing the no-change forecasts X_t and $y_{t,n}$

- ▶ What is the MSPE of $y_{t,n}$ relative to the conventional NCB X_t ?

MSPE for conventional benchmark:

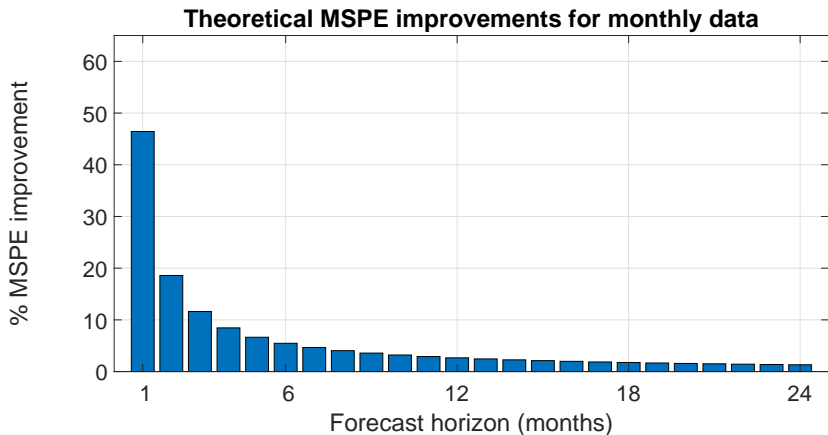
$$E \left[(X_t - X_{t+h})^2 \right] = \left((h-1) \cdot n + \frac{(n+1) \cdot (2n+1)}{6n} + \frac{(n-1) \cdot (2n-1)}{6n} \right) \sigma_\epsilon^2$$

MSPE for new benchmark:

$$E \left[(y_{t,n} - X_{t+h})^2 \right] = \left((h-1) \cdot n + \frac{(n+1) \cdot (2n+1)}{6n} \right) \sigma_\epsilon^2$$

- ▶ $y_{t,n}$ has lower MSPE than X_t under the RWH
- ▶ All forecasting gains occur at the 1-step ahead prediction
 - forecast gain is constant, forecast error increases with h
⇒ relative improvements largest for short horizons

MSPE ratios of the two NCBs



Consequences for forecast comparisons

- ▶ Conventional NCB is not the optimal forecast under the RWH
- ▶ Moreover, ΔX_t is autocorrelated (Working 1960)

$$X_t - X_{t-1} = \frac{1}{n} \left[\sum_{i=1}^n i \cdot \epsilon_{t-1,i} + \sum_{j=1}^n (n+1-j) \cdot \epsilon_{t,j} \right]$$

⇒ improvements over no-change forecast X_t are expected *even under the random walk null hypothesis*

⇒ improvements over no-change forecast $y_{t,n}$ are evidence against *the random walk null hypothesis*

- ▶ Using $y_{t,n}$ as a benchmark
 - maintains original spirit of comparisons with the NCB
 - more difficult to achieve when HF observations are persistent

Application: Forecasting the real price of crude oil

- ▶ Forecast of the monthly real price of crude oil in standard setting (Baumeister & Kilian 2012, 2014, 2015; Alquist et al. 2013)
 - real oil price is deflated average of daily nominal prices

$$\bar{p}_t^r = \frac{\frac{1}{n} \sum_{i=1}^n p_{t,i}}{CPI_t}$$

- goal: forecast \bar{p}_{t+h}^r given month t information
- ▶ The new benchmark: series of monthly closing prices

$$p_t^{r,closing} = \frac{p_{t,n}}{CPI_t}$$

Econometric models

1. Univariate time series models

- AR (log-level and percent changes)
- ARMA(1,1)
- ARFI

2. VAR models (Kilian & Murphy 2014)

- percent change in global crude oil production
 - real economic activity indicator (Kilian 2009)
 - real price of oil
 - change in above-ground global crude oil inventories
- > unrestricted least-squares estimation
- > Gaussian BVAR with prior variance (Giannone, Lenza & Primiceri 2010)

3. Futures price curve

4. Equal-weight forecast combination

Implementation

Following Baumeister & Kilian (2012):

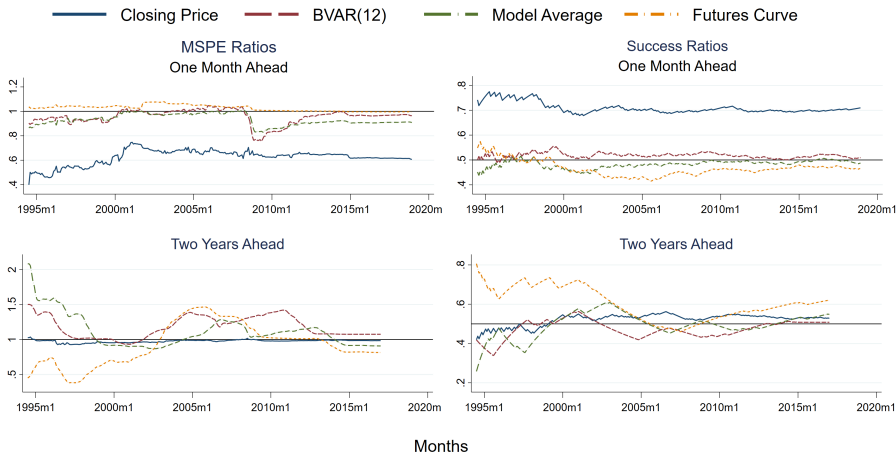
- ▶ Real-time data
- ▶ Out-of-sample forecasts with expanding window
 - estimation period starts 1973M2
 - out-of-sample evaluation 1992M1 - 2018M12
- ▶ All models estimated with average prices
- ▶ Criteria: MSPE ratio and directional accuracy
 - displayed relative to conventional NCB
 - improvements over the new NCB are in **bold**
 - standard tests for inference
(Diebold & Mariano 1995, Pesaran and Timmermann 2009)

Baseline results: Real WTI prices, real-time data

Months Ahead	Last WTI Close Price	BVAR(12)	VAR(12)	AR(12)	AR(12) % Δ	ARFI(1)	ARMA(1,1)	Futures Curve	Model Averaging
MSPE Ratios									
1	0.61***	0.97	1.01	0.94	0.95*	0.93	0.92	1.00	0.91
3	0.89**	1.00	1.00	0.97	0.99	0.96	0.95	0.97	0.92
6	0.95**	1.05	1.04	1.00	1.04	0.99	0.95	0.96	0.95
12	0.96**	1.10	1.11	1.00	1.10	1.00	0.94	0.85**	0.94
24	0.99	1.08	1.06	1.02	1.19	1.04	0.96	0.82*	0.91
Success Ratios									
1	0.71***	0.51	0.54**	0.52	0.49	0.52	0.53	0.47	0.49
3	0.60***	0.53	0.54*	0.49	0.57**	0.49	0.50	0.49	0.52
6	0.56**	0.53	0.55*	0.48	0.54	0.49	0.46	0.53	0.51
12	0.59***	0.49	0.56**	0.53	0.50	0.51	0.50	0.61***	0.51
24	0.53	0.51	0.55	0.57	0.47	0.55	0.56	0.62***	0.55

Note: ***, **, and * denote significant improvement over the average no-change forecast at the 1%, 5%, and 10% level. **Bold values indicate significant improvements over the last closing price no-change forecast at the 5 percent level.**

Evolution of baseline WTI Real price forecasts: Real-time data



Note: Dynamic, recursive, out-of-sample forecasts 1992M1–2018M12. The forecast criteria reported include the recursive MSPE expressed as a ratio relative to the monthly average no-change forecast. All forecast criteria are evaluated in the levels of the real price of oil. The first 30 months are dropped to reduce starting-point effects.

Interpreting baseline results

- ▶ Large(!) forecasting gains for short forecast horizons
- ▶ Actual vs. predicted MSPE ratios (RWH for daily data)

Horizon (months)	1	3	6	12	24
Theoretical	0.54	0.88	0.95	0.97	0.99
Empirical (revised data)	0.60	0.89	0.95	0.96	0.99

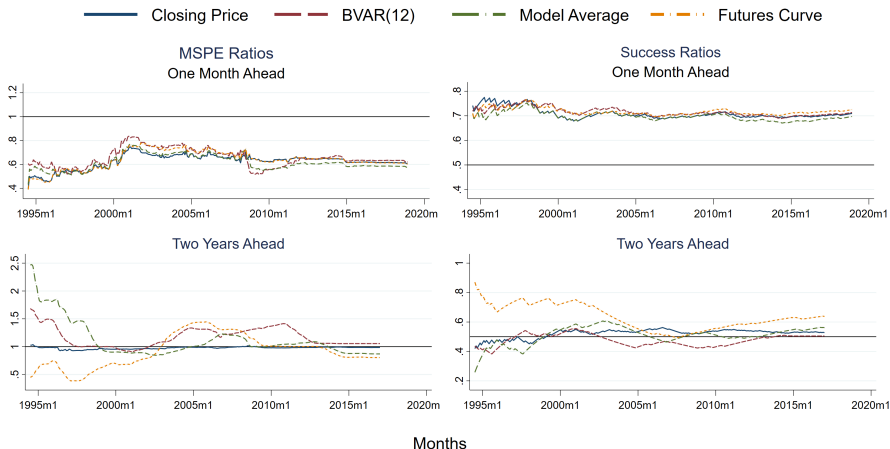
- ▶ Robustness: remarkably similar results for
 - various estimation / evaluation periods
 - different oil price series (Brent, RAC, nominal prices)
 - ex-post revised data, nominal price, quarterly data
- ▶ What about estimating models with closing prices?

Models estimated with last closing price

Months Ahead	Last WTI Close Price	BVAR(12)	VAR(12)	AR(2)	AR(1) % Δ	ARFI(2)	ARMA(1,1)	Last Future Price Curve	Model Averaging
MSPE Ratios									
1	0.61***	0.62**	0.73*	0.57***	0.62***	0.57***	0.57***	0.60***	0.58***
3	0.89**	0.90	0.91	0.85	0.93*	0.86	0.86	0.88**	0.82*
6	0.95**	0.98	0.97	0.89	1.04	0.89	0.90	0.92*	0.87
12	0.96**	1.05	1.06	0.90	1.15	0.90	0.91	0.84**	0.87*
24	0.99	1.06	1.06	0.95	1.48	0.95	0.97	0.80*	0.87
Success Ratios									
1	0.71***	0.71***	0.66***	0.71***	0.73***	0.72***	0.71***	0.73***	0.70***
3	0.60***	0.58**	0.56**	0.57**	0.62***	0.60***	0.60***	0.60***	0.59***
6	0.56**	0.58**	0.58**	0.52	0.58**	0.51	0.52	0.55	0.55
12	0.59***	0.54	0.58**	0.54	0.59**	0.51	0.53	0.63***	0.54
24	0.53	0.51	0.57*	0.58	0.56	0.55	0.54	0.64***	0.56

Note: ***, **, and * denote significant improvement over the average no-change forecast at the 1%, 5%, and 10% level. **Bold values indicate significant improvements over the last closing price no-change forecast at the 5 percent level.**

Evolution of real-time closing-price WTI forecasts



Note: Dynamic, recursive, out-of-sample forecasts 1992M1–2018M12. The forecast criteria reported include the recursive MSPE expressed as a ratio relative to the monthly average no-change forecast. All forecast criteria are evaluated in the levels of the real price of oil. The first 30 months are dropped to reduce starting-point effects.

Take-away

- ▶ Aggregating higher-frequency data
 - introduces loss of information (e.g., Rossana & Seater 1995)
 - *changes interpretation of standard forecast comparisons*
- use closing observations for estimation & *forecast evaluation*
- ▶ New benchmark for real price of crude oil changes assessments of models & oil price predictability:
 - daily oil prices are “random walkish”
 - real price of crude oil is predictable by construction
 - but most models do not beat the new benchmark
- ▶ Averaging can be desirable, but watch out for settings in which
 - series of interest is temporally aggregated
 - underlying data is persistent

Thank you!