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Targeted growth rates for long-horizon crude oil price forecasts

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ABSTRACT

This paper proposes growth rate transformations with targeted lag selection in order to improve the long-horizon forecast accuracy. The method targets lower frequencies of the data that correspond to particular forecast horizons, and is applied to models of the real price of crude oil. Targeted growth rates can improve the forecast precision significantly at horizons of up to five years. For the real price of crude oil, the method can achieve a degree of accuracy up to five years ahead that previously has been achieved only at shorter horizons.

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1. Introduction

The existing oil price forecasting literature provides evidence that models of the real price of oil outperform the no-change forecast at short horizons (Alquist, Kilian, and Vigfusson, 2013 and Baumeister and Kilian, 2012, 2014, 2015, among others). However, these studies all focussed on horizons of less than two years and were not intended for forecasting at longer horizons. Much less is known about forecasting the real price of crude oil at longer horizons. This paper focuses on extending the forecasting success of individual models of the real price of oil to horizons of up to five years by proposing the method of targeted growth rate transformations.

Longer-term forecasts are of central interest for investment decisions and public policy institutions. For example, if an oil producer decides to invest in drilling or an airline company decides to purchase a new fleet of aircraft, they will care about the payoff over the lifetime of the investment. Many policy institutions produce forecasts for longer horizons in order to inform policy decisions. While some studies have focused on horizons beyond five years (Bernard, Khalaf, Kichian, & Yelou, 2017), less is known about model performances for forecasting the real oil price at horizons of between two and five years. This paper fills this gap.

The paper proposes the method of targeted growth rate filtering, which is a modification of the standard forecasting method. Lags in growth rate transformations are chosen in order to target lower frequencies. The method removes high frequencies and emphasizes the use of certain low frequencies which correspond to particular forecast horizons. When applied to forecasting models of the real price of crude oil, the method improves the recursive forecast mean squared prediction error (MSPE) ratios and directional accuracy significantly at horizons of up to five years. The method of targeted growth rate transformations exhibits robust improvements in forecast performance, regardless of whether the real price of oil is in log levels or differences, as well as across sub-samples and for alternative oil price series. Employing this method can achieve a degree of accuracy at longer horizons that previously has been achieved only at shorter horizons.

The analysis begins by considering simple univariate benchmark models for forecasting the real price of crude oil at horizons of up to five years. An attempt is made to answer the open question of benchmarks at longer horizons and to determine whether simple models can provide

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better benchmarks than no-change forecasts. The evidence suggests that exponential smoothing and backward averages of the real price of oil can outperform no-change forecasts robustly for horizons beyond one year. The nochange forecast using the average real oil price over the last year provides a simple alternative rule for forecasting the real price of oil at horizons beyond one year, and works particularly well at the two- and three-year horizons.

Targeted growth rate transformations are then applied to univariate models for forecasting the real price of crude oil. This includes univariate autoregressive and fractional autoregressive models, as well as the low-frequency forecasting technique proposed by Müller and Watson (2016). Univariate autoregressive models have been documented consistently to outperform no-change forecasts up to six months ahead (Alguist et al., 2013; Baumeister & Kilian, 2012), and serve as an intuitive way to illustrate the modification of targeted growth rates to the standard univariate Box-Jenkins method (Box, Jenkins, & Reinsel, 2008). Applying targeted growth rate transformations to these methods can extend the out-of-sample forecast preference to longer horizons than is the case for models that rely on period-over-period growth rates. Univariate autoregressive models with targeted growth rate transformations can outperform no-change forecasts consistently for horizons of up to three years.

The method of targeted growth rates is also applied to multivariate forecast methods using vector autoregressive (VAR) models. Alquist et al. (2013) and Baumeister and Kilian (2014, 2015), among others, showed that monthly VAR models of the real price of crude oil produce forecasts that can beat the no-change forecast of the real price of crude oil for up to one year ahead. Applying targeted growth rate transformations to VARs can consistently outperform VAR models that rely on period-over-period growth rates in out-of-sample forecast performances at longer horizons.

Global real activity and global crude oil inventories are not observed directly or measured well. Various alternative series have been examined for forecasts at short horizons, by Baumeister and Kilian (2012, 2014) among others. The present paper is the first to extend this analysis to longer horizons by conducting a systematic investigation of alternative global real activity and crude oil inventory variables in VAR model forecasts for horizons of up to five years. Targeted growth rates applied to world industrial production and Kilian's global real activity index (Kilian, 2009) can produce comparable forecasts at longer horizons. Moreover, US crude oil and petroleum inventories are found to produce superior forecasts at longer horizons. This extra predictive power of US crude oil inventory series is consistent with the improved forecast performance at short-run forecasts that was first established by Baumeister, Guerin, and Kilian (2015) and used at shorter horizons by Baumeister, Kilian, and Lee (2014) and Baumeister and Kilian (2015).

This paper introduces targeted growth rate transformations and is intentionally focused. For example, it ignores real-time data constraints that have been shown to be crucial in forecasting the real price of oil (see e.g. Alquist et al., 2013; Baumeister and Kilian, 2012). Moreover, none of the models allow for stochastic variances (see e.g. Baumeister, Kilian, and Zhou, forthcoming). Similarly, no attempt is made to study forecast combinations (see e.g. Baumeister and Kilian, 2014, 2015). Finally, the analysis focuses on monthly data and forecast horizons. No quarterly models or forecasts are discussed (see e.g. Baumeister and Kilian, 2014, 2015). These extensions are exciting avenues for further research on targeted growth rate transformations.

The remainder of the paper is structured as follows. Section 2 introduces the method of targeted growth rate transformations for forecasting using spectral analysis. Section 3 analyzes the application of these methods to univariate real oil price forecasts. Section 4 extends the analysis to vector autoregression forecasts of the market for crude oil and examines their robustness to the use of alternative oil price series. Section 5 concludes.

2. Growth rate filter

Growth rate data transformations are applied commonly in time series econometrics. For example, simple period-over-period growth rates are used to achieve stationarity. Higher lags in growth rates are often used to produce more intuitive scales. For example, due to their intuitive format, macroeconomic data are often announced as year-over-year or quarter-on-quarter growth rates. This section provides the intuition behind targeted growth rate transformations and shows why it may be desirable to depart from the standard first lag when forecasting.

Let *Y* be a covariance-stationary series with absolutely summable autocovariances. Let $s_Y(\omega)$ be the population spectrum and $g_Y(\kappa)$ the autocovariance generating function of *Y*, where

$$s_{\rm Y}(\omega) = (2\pi)^{-1} g_{\rm Y}(e^{-i\omega}),$$
 (1)

and ω is the frequency with $\omega \in (0, \pi)$, and κ is a complex scalar. Let *X* be a transformation of *Y* given by X = h(L)Y, with $\sum_{-\infty}^{\infty} |h_j| < \infty$. The autocovariance generating function of *X* is known to be calculated from *Y* by:

$$g_X(\kappa) = h(\kappa)h(\kappa^{-1})g_Y(\kappa).$$
⁽²⁾

The population spectrum of *X* is:

$$s_X(\omega) = (2\pi)^{-1} h(e^{-i\omega}) h(e^{i\omega}) g_Y(\omega), \tag{3}$$

and hence, the population spectrum of *X* is related to that of *Y* by:

$$s_{X}(\omega) = h(e^{-i\omega})h(e^{i\omega})s_{Y}(\omega).$$
(4)

Thus, applying the h(L) filter to Y is the same as multiplying the spectrum of Y by $h(e^{-i\omega})h(e^{i\omega})$. The original series must be covariance stationary in order for $s_Y(\omega)$ to exist. Otherwise, the population spectrum is not zero at frequency zero.

The growth rate of *Y* can be approximated by applying the first difference filter to the log of *Y*. Hence, $h(e^{-\omega}) =$ 1 - L, and $h(e^{-i\omega})h(e^{i\omega})$ is given by $(1 - e^{i\omega})(1 - e^{-i\omega}) =$ $2 - 2\cos(\omega)$. Define the operator L^Z such that $L^Z x_t = x_{t-Z}$ for $Z \in \mathbb{R}$. More generally, transforming the logged variable *Y* using the difference on the *Z*th lag, $(1 - L^Z)$, to produce Download English Version:

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