Are Product Spreads Useful for Forecasting Oil Prices? An Empirical Evaluation of the Verleger Hypothesis*

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Abstract

Notwithstanding a resurgence in research on out-of-sample forecasts of the price of oil in recent years, there is one important approach to forecasting the real price of oil which has not been studied systematically to date. This approach is based on the premise that demand for crude oil derives from the demand for refined products such as gasoline or heating oil. Oil industry analysts such as Philip Verleger and financial analysts widely believe that there is predictive power in the *product spread*, defined as the difference between suitably weighted refined product market prices and the price of crude oil. Our objective is to evaluate this proposition. We derive from first principles a number of alternative forecasting model specifications involving product spreads and compare these models to the no-change forecast of the real price of oil. We show that not all product spread models are useful for out-of-sample forecasting, but some models are, even at horizons between one and two years. The most accurate model is a time-varying parameter model of gasoline and heating oil spot price spreads that allows for structural change in product markets. We document MSPE reductions as high as 20% and directional accuracy as high as 63% at the two-year horizon, making product spread models a good complement to forecasting models based on economic fundamentals, which work best at short horizons.

JEL: Q43, C53, G15

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1 Introduction

Oil price forecasts affect the economic outlook of oil-importing as well as oil-exporting countries. Accurate oil price forecasts are required, for example, to guide natural resource development and investments in infrastructure. They also play an important role in preparing budget and investment plans. Users of oil price forecasts include international organizations, central banks, governments at the state and federal level as well as a range of industries including utilities and automobile manufacturers.

In recent years there has been a resurgence in research on the question of how to forecast the price of commodities in general and the price of oil in particular, at least at horizons up to a year or two. One strand of this literature has examined in depth the predictive power of oil futures prices (see, e.g., Knetsch 2007; Alquist and Kilian 2010; Reeve and Vigfusson 2011; Alquist, Kilian and Vigfusson 2013). Another strand of the literature has focused on the predictive content of changes in oil inventories, oil production, macroeconomic fundamentals, and exchange rates (see, e.g., Chen, Rogoff, and Rossi 2010; Baumeister and Kilian 2012; 2014a,b; Alquist, Kilian and Vigfusson 2013). A third strand has looked at the forecasting ability of professional and survey forecasts (see, e.g., Sanders, Manfredo, and Boris 2008; Alquist, Kilian and Vigfusson 2013, Bernard, Khalaf, Kichian, and Yelou 2013). The emerging consensus from this literature is that economic fundamentals help forecast the real price of oil, at least during times of large and persistent movements in economic fundamentals, but only at short horizons. In contrast, the forecasting ability of monthly and quarterly judgmental forecasts, and survey expectations tends to be low and that of oil futures prices mixed at best.

It may seem that these studies would cover the universe of widely used predictors for the price of oil. There is, however, another important approach to forecasting the real price of oil which has not been studied systematically to date. This alternative approach is based on the premise that demand for crude oil derives from the demand for refined products such as gasoline or heating oil.[1] The idea of derived demand has a long tradition in academic research on oil markets (see, e.g., Verleger 1982; Lowinger and Ram 1984). For example, Verleger (1982) advocates that spot market prices for petroleum products are the primary determinants of crude oil prices, allowing one to express the price of crude oil as a weighted average of refined product prices. A common view is that refiners view themselves as price takers in product markets and cut their volume of production when they cannot find crude oil at a price commensurate with product prices. In time, this reduction in the demand for crude oil will lower the price of crude oil and the corresponding reduction in the supply

[1] The nature of this final demand is left unspecified. Changes in final demand may reflect business cycle fluctuations or shifts in consumer preferences, for example. For further discussion also see Kilian (2010).

of products will boost product prices (see Verleger 2011). This reasoning suggests that the difference between refined product market prices and the purchase price of crude oil should have predictive power for the price of crude oil. We refer to this hypothesis as the *Verleger hypothesis*, given its antecedents in Verleger's work, but note that this view is widespread among oil industry analysts. For example, energy consultant Kent Moors interprets crack spreads as market oil price expectations and forecasts higher oil prices based on increasing gasoline spreads and heating oil spreads (see Moors 2011). Similarly, Goldman Sachs in April 2013 cut its oil price forecast citing significant downward pressure on product spreads, which it interpreted as an indication of reduced demand for products (see Strumpf 2013).

The same reasoning also plays an important role in financial markets. It is common to trade futures contracts and options based on crack spreads (see, e.g., Haigh and Holt 2002; Chicago Mercantile Exchange 2012). The *crack spread* refers to the approximate ratio in which refined products such as gasoline or heating oil are produced from crude oil. There is not one single crack spread that applies to all refineries, but the most commonly used ratio is 3:2:1, which refers to refiners' ability to produce two barrels of gasoline and one barrel of heating oil from three barrels of crude oil. Because the spread between crude prices and refined product prices is the main driver of refinery profit margins, futures contracts and options have been established to allow refining companies to hedge their price risk related to the crack spread. Traders express the *crack spread* in terms of futures prices of a given maturity h as

$$\frac{2}{3}F_{t+h,t}^{gasoline} + \frac{1}{3}F_{t+h,t}^{heating\ oil} - 1F_{t+h,t}^{crude\ oil},$$

where all date t futures prices have been expressed in dollars per barrel (see Figure A1 in the not-for-publication appendix). An obvious question of interest is whether the information contained in product price spreads (also known as product margins) may be used to improve on the no-change forecast of the price of crude oil, as is widely believed in the industry. For example, Evans (2009) cites the oil market analyst Philip K. Verleger as forecasting a decline in the price of oil based on a weakening 3:2:1 crack spread on the NYMEX.

Although there is a large literature relying on error correction models of the relationship between oil prices and product prices, few studies to date have examined the problem of forecasting the price of oil out of sample and none of those studies evaluates the out-of-sample forecast accuracy of product spread models against the no-change forecast, making it difficult to interpret these results.[2]

[2] For example, the one-week ahead analysis of the predictive power of the 3:2:1 crack spread during 2000-08 in Murat and Tokat (2009) is not conducted out of sample, as their discussion of the results might suggest, but is based on full-sample regression estimates.

Moreover, existing studies limit their attention to forecast horizons of one month only and rely on forecast evaluation periods that are too short to be informative. A case in point is the analysis in Lanza, Manera, and Giovannini (2005).

The objective of our paper is to investigate systematically and in real time the forecasting power of product spreads for the real price of oil. Our evaluation period extends from early 1992 until September 2012. We derive a number of alternative model specifications based on the notion that the price of oil can be expressed as a weighted average of product prices. We follow most industry analysts in focusing on the prices for gasoline and heating oil. The four basic forecasting approaches considered include: (1) the crack spread model, (2) models of individual product spreads, (3) the weighted product spread model expressed relative to the current spot price of oil, and (4) equal-weighted forecast combinations of individual product spread models. Our analysis also distinguishes between spot and futures prices and explores the benefit of additional parameter restrictions, resulting in the most comprehensive analysis of these models to date. The maximum forecast horizon considered is 24 months in line with the needs of applied forecasters at central banks and at the U.S. Energy Information Administration (EIA). We compare the out-of-sample accuracy of each of the forecasting models to the no-change forecast of the real price of oil. This random walk benchmark is widely used in the literature. Indeed, some observers have questioned whether it is possible to forecast the price of oil with any degree of accuracy at all.[3]

We find that not all product spread models are useful for out-of-sample forecasting, but some models yield statistically significant MSPE reductions as large as 6% at horizons between one and two years. This result is noteworthy in that to date no other forecasting method has been able to beat the no-change forecast of the real price of oil at horizons between one and two years (see, e.g., Baumeister and Kilian 2012, 2014b). The most accurate single-spread forecasting model overall is a model based on the gasoline spot spread alone. Heating oil spreads are far less accurate predictors than gasoline spreads. Weighted product spread models are never more accurate than gasoline spread models. Perhaps surprisingly, there is no evidence of forecasting models based on the commonly cited 3:2:1 crack spread having out-of-sample forecasting ability.

In addition to these models, we also explore forecast combinations based on rolling or recursive inverse MSPE weights that adapt over time to each predictor's recent forecast performance. The latter approach allows us to address concerns, expressed in Verleger (2011), that the marginal market that determines the price of crude oil in models of derived demand tends to evolve over time. For example, whereas the marginal product market for many years was the gasoline market, more

[3]For example, Peter Davies, chief economist of British Petroleum, has taken the position that "we cannot forecast oil prices with any degree of accuracy over any period whether short or long" (see Davies 2007).

recently the market for diesel and heating oil has evolved into the marginal market, according to Verleger. For the same reason we also investigate the usefulness of time-varying parameter (TVP) forecasting models for linear combinations of the gasoline and heating oil spreads. While there is no indication that forecast combinations are more accurate than the gasoline spread model alone, a suitably restricted TVP model yields further improvements in out-of-sample forecast accuracy. This TVP model is more accurate than the random walk model at all forecast horizons we consider. We document MSPE reductions as high as 20% and directional accuracy as high as 66%, making this specification the most useful forecasting approach overall.

The remainder of the paper is organized as follows. Section 2 discusses the data and describes the forecasting environment. In section 3, we derive the main forecasting models. Section 4 contains the out-of-sample results for alternative oil price measures. In section 5, we relax the assumptions underlying conventional product spread models by allowing for smooth structural change. We also consider extensions to European oil and product prices as well as global forecasting models. We conclude in section 6. Additional results are contained in a not-for-publication appendix.

2 The Forecasting Environment

Our objective is to compare the real-time out-of-sample forecast accuracy of selected product spread models for the average monthly real price of crude oil. The focus on the average price is consistent with the objective of government agencies reporting oil price forecasts. The focus on the real price of oil is standard in the literature because it is the real price of oil that matters for economic decision making. Extensions to the problem of forecasting the nominal price of oil are straightforward and are discussed in the not-for-publication appendix. Our baseline analysis focuses on the monthly average of the West Texas Intermediate (WTI) spot price as reported in the FRED database of the Federal Reserve Bank of St. Louis. This price refers to the U.S. dollar price of a barrel of a type of crude oil known as West Texas Intermediate for immediate delivery in Cushing, Oklahoma. WTI prices are commonly used as reference prices in writing contracts for the delivery of crude oil and are available in real time.

We also report an alternative set of results for the monthly U.S. refiners' acquisition cost for crude oil imports, which refers to the average U.S. dollar price per barrel paid by U.S. refineries for crude oil imported from abroad. The U.S. refiners' acquisition cost for crude oil imports is a better proxy for the global price of crude oil than the WTI price. It is reported in the *Monthly Energy Review* of the U.S. EIA. Unlike the WTI price it is available only with a delay and subject to revisions. Real-time data for the refiners' acquisition cost since July 1986 were obtained from the real-time database of Baumeister and Kilian (2012), suitably updated to include vintages from January 1991 until March 2013. Both crude oil price series were deflated using the real-time U.S. consumer price index for all urban consumers from the same database.

The crude oil price predictors considered below rely on spot and futures prices for gasoline, heating oil and WTI crude oil. All predictors are available without delay and are not subject to revisions. The price of WTI crude oil futures is from Bloomberg. Averages of daily futures prices at maturities of 1 to 6 months are available starting in July 1986.

The futures contract for conventional regular unleaded gasoline for delivery in New York Harbor ceased trading after the January 2007 contract. Starting in October 2005, it was replaced by a gasoline futures contract for reformulated blendstock for oxygenate blending (RBOB) for delivery in New York Harbor. We use the futures price for regular gasoline from July 1986 until December 2005 and the futures price of RBOB gasoline from January 2006 onwards. Daily gasoline futures prices are available at maturities of 1, 3, and 6 months from Bloomberg. We construct monthly averages, starting in July 1986 for 1- and 3-month contracts and starting in November 1986 for 6-month contracts, by averaging the daily futures prices. The corresponding spot price for delivery of regular gasoline in New York Harbor is obtained from the EIA. This series is available for the entire period of July 1986 until March 2013. There is no RBOB spot price series for delivery in New York, making it impossible to construct a gasoline spot price the same way as for the futures contracts.

Futures contracts for No. 2 Heating Oil are also for delivery in New York Harbor. We constructed averages of the daily futures price data provided by Bloomberg. For maturities of 1 through 9 months the sample starts in July 1986; for the 12-month maturity it starts in August 1989. The corresponding spot price since July 1986 is constructed as the average of the daily heating oil spot price provided by the EIA.

Whereas crude oil prices are reported in U.S. dollars per barrel, gasoline and heating oil prices are reported in cents per gallon. All product prices are transformed to dollars per barrel, which involves multiplying each product price by 42 gallons/barrel and dividing by 100 cents/dollar.

Yet another common benchmark for oil prices is the price of Brent crude oil, which refers to a grade of North Sea oil traded on the Intercontinental Exchange (ICE) in London. Some of our extensions in section 5 rely on data for the spot price of Brent crude oil provided by *Argus Media*. These data start in January 1990 and are backcast using Brent spot prices from the Intercontinental Exchange (ICE) and the growth rate of the WTI price. The best proxy for the European product market is the Rotterdam market. Daily product prices for the Rotterdam market are also provided by *Argus Media*, starting in January 1990. The heating oil spot price series is backcast using the rate of change in the price of New York Harbor No. 2 Heating Oil. The corresponding Rotterdam gasoline spot price series only starts in 2005, which is too short for our purposes. Similarly, there are no suitable time series for Rotterdam product futures prices. All prices are converted to dollars/barrel, as appropriate. The raw data are expressed in dollars/metric ton. One metric ton corresponds to 7.5 barrels of crude oil. Monthly data are constructed by taking averages of the daily data.

The forecast evaluation period runs from January 1992 to September 2012. To the extent that forecasting models are estimated, the model estimates are updated recursively, as is standard in the oil price forecasting literature (see, e.g., Baumeister and Kilian 2012, 2014b). The reason is that forecasts of the real price of oil based on rolling regressions are systematically less accurate than forecasts based on recursive regressions, as shown in the not-for-publication appendix. We forecast the ex-post revised real price of oil in levels rather than in logs. Real oil prices from the March 2013 vintage of real-time data are used to proxy for the ex-post revised data, against which all forecasts are evaluated.

Our objective is to assess the real-time out-of-sample forecasting ability of models based on product price spreads. We evaluate the forecasts in question in terms of their mean-squared prediction error (MSPE) relative to the no-change forecast of the real price of oil and based on their directional accuracy. Under the null hypothesis of no directional accuracy, the success ratio of the model at predicting the direction of change in the price of oil should be no better than tossing a fair coin with success probability 0.5. Tests of the null of no directional accuracy are conducted using the test of Pesaran and Timmermann (2009). Where appropriate, we assess the statistical significance of the MSPE reductions based on the test of Diebold and Mariano (1995) for nonnested models without estimation uncertainty or based on the test of Clark and West (2007) for nested models with estimation uncertainty.[4]

3 Forecasting Models

In this section, the forecasting models to be evaluated in sections 4 and 5 are derived. Some of these models are already used in practice or have been discussed in the literature, while others are new.

[4] The latter test (like similar tests in the literature) is biased toward rejecting the null of equal MSPEs because it tests the null of no predictability in population rather than the null of equal out-of-sample MSPEs (see Inoue and Kilian 2004). It also ignores the real-time nature of the inflation data used in our forecasting exercise (see Clark and McCracken 2009). Thus, these test results have to be viewed with caution. The alternative test of Giacomini and White (2006) does not apply either in our context because it does not allow for recursive estimation. For further discussion of the problem of out-of-sample inference see Kilian (2014).

3.1 The Benchmark Model

The benchmark model for the forecast accuracy comparisons in this paper is a random walk model without drift. This model implies that the best forecast of the future price of crude oil is the current price of crude oil. It also implies that the direction of change in the price of oil is unforecastable such that the probability of the price of crude oil increasing equals that of the price of crude oil decreasing. In other words, the model implies the no-change forecast

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil},$$

where R_t^{oil} denotes the current monthly real price of crude oil. This benchmark is standard in the literature on forecasting oil prices and more generally in the literature on forecasting asset prices. The question of interest in this paper is whether alternative forecasting models based on the spread of refined product prices over the price of crude oil may outperform this benchmark.

3.2 Verleger's Decomposition

The idea of using petroleum product prices to explain the price of crude oil dates back to Verleger (1982) who noted that the value V of a barrel of crude oil at time t can be expressed as a weighted average of the nominal market prices, P_t^i, of the principal products of a refiner:

$$V_t = \sum_{i=1}^{n} w_i P_t^i, \tag{1}$$

where the weights w_i reflect technological constraints. The nominal dollar price of a barrel of crude oil a refiner is willing to pay in a competitive market, or the spot price of crude oil, P_t^{oil} , corresponds to this value adjusted for transportation costs, s_t, and the refining costs, c_t:

$$P_t^{oil} = V_t - s_t - c_t. \tag{2}$$

These costs are typically treated as a constant in empirical work. From this relationship, we may infer that, up to a constant,

$$P_t^{oil} = \sum_{i=1}^{n} w_i P_t^i,$$

and hence

$$P_{t+h}^{oil} = \sum_{i=1}^{n} w_i P_{t+h}^{i}, \tag{3}$$

where P_{t+h}^{i} is the spot price of product i at $t + h$.

Verleger (2011) discusses how to use the static model embodied in equation (3) to predict the price of oil. It is important to stress that Verleger's objective is not to forecast the price of oil, as the term *prediction* may seem to suggest, but rather to explain the evolution of the price of oil in terms of that of the contemporaneous product prices. In contrast, our objective in this paper is to derive from Verleger's decomposition suitable forecasting models that can be implemented in real time to generate out-of-sample forecasts. As we show below, there are several alternative specifications that can be derived from equation (3).

3.3 Using Product Futures Spreads

Given date t information, the conditional expectation of (3) is:

$$\mathbb{E}P_{t+h|t}^{oil} = \sum_{i=1}^{n} w_i \mathbb{E}P_{t+h|t}^{i} \tag{4}$$

In the absence of a risk premium, arbitrage ensures that the expectation of the spot market price for product i equals the current futures price of product i:

$$\mathbb{E}P_{t+h|t}^{i} = F_{t+h,t}^{i}, \quad i = 1, ..., n. \tag{5}$$

Combining equations (4) and (5) yields:

$$\mathbb{E}P_{t+h|t}^{oil} = \sum_{i=1}^{n} w_i F_{t+h,t}^{i}, \tag{6}$$

where $F_{t+h,t}^{i}$ is the futures price of product i in period t with maturity h periods. Dividing both sides of equation (6) by P_t^{oil}, and taking logs on both sides, we obtain:

$$\log\left(\mathbb{E}\frac{P_{t+h|t}^{oil}}{P_t^{oil}}\right) = \log\left(\sum_{i=1}^{n} w_i F_{t+h,t}^{i}\right) - \log P_t^{oil}. \tag{7}$$

Using the approximation $\log(1 + x) \approx x$, equation (7) can be expressed as:

$$\mathbb{E}\left(p_{t+h|t}^{oil} - p_t^{oil}\right) = \log\left(\sum_{i=1}^{n} w_i F_{t+h,t}^{i}\right) - p_t^{oil} \tag{8}$$

where lower case letters denote the natural log of prices. Equation (8) suggests the regression model

$$\triangle p_{t+h|t}^{oil} = \alpha + \beta \left[\log \left(\sum_{i=1}^{n} w_i F_{t+h,t}^{i} \right) - p_t^{oil} \right] + \varepsilon_{t+h}, \tag{9}$$

where α and β are estimated recursively by the method of least squares and $\triangle p_{t+h|t}^{oil} = p_{t+h|t}^{oil} - p_t^{oil}$. This motivates the forecasting model:

$$\widehat{P_{t+h|t}}^{oil} = P_t^{oil} \exp \left\{ \hat{\alpha} + \hat{\beta} \left[\log \left(\sum_{i=1}^{n} w_i F_{t+h,t}^{i} \right) - p_t^{oil} \right] \right\} \tag{10}$$

which implies that we can forecast the real price of crude oil as:

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp \left\{ \hat{\alpha} + \hat{\beta} \left[\log \left(\sum_{i=1}^{n} w_i F_{t+h,t}^{i} \right) - p_t^{oil} \right] - \mathbb{E}(\pi_{t+h}^{h}) \right\} \tag{11}$$

where π_{t+h}^{h} denotes the inflation rate from t to $t+h$.

In practice, we approximate $\mathbb{E}(\pi_{t+h}^{h})$ by the recursively estimated average inflation rate since July 1986. The rationale for discarding the earlier data is that by 1991.12, it was readily apparent that the Volcker disinflation of the early 1980s had succeeded by mid-1986. The not-for-publication appendix shows that our forecast accuracy results for the real price of oil remain virtually unchanged, if we replace this inflation forecast by a forecast from the fixed-ρ inflation gap model of Faust and Wright (2013), which has been shown to be the most accurate model-based inflation forecast.

3.3.1 The Single Futures Spread Model

We first propose the single futures spread model for product i where $i \,\epsilon \,\{gasoline,\ heating\ oil\}$. It immediately follows from equation (11) with w_i either 0 or 1 that

$$\widehat{R_{t+h|t}}^{oil,i} = R_t^{oil} \exp \left\{ \hat{\alpha} + \hat{\beta} \left[f_{t+h,t}^{i} - p_t^{oil} \right] - \mathbb{E}(\pi_{t+h}^{h}) \right\}, \tag{12}$$

where $f_{t+h,t}^{i}$ is the log of the futures price of product i at time t with maturity h periods.

3.3.2 The Crack Spread Futures Model

It is important to recognize that refined products are produced from a barrel of crude oil in approximately fixed proportions. In characterizing the refining process, it is common to ignore less important refined products such as jet fuel and to focus on gasoline and heating oil only.[5] Refining

[5] The reason is that the market traditionally has been concerned with forecasting the price of light sweet crude oil which produces little residual fuel.

crude oil typically involves producing two barrels of gasoline and one barrel of heating oil from three barrels of crude oil, resulting in a so-called *crack spread* of 3:2:1.[6] Participants in mercantile exchanges rely on the crack spread expressed in terms of the date t futures prices with maturity h:

$$F_{t+h,t}^{CS} \equiv \frac{2}{3}F_{t+h,t}^{gas} + \frac{1}{3}F_{t+h,t}^{heat} - F_{t+h,t}^{oil}, \tag{13}$$

where all prices are expressed in dollars per barrel, $F_{t+h,t}^{gas}$ denotes the date t futures price of gasoline of maturity h and $F_{t+h,t}^{heat}$ denotes the date t futures price of heating oil of maturity h. Note that this spread differs from the spread defined in equation (11). Whereas in one case we normalize relative to the current spot price, in the other case we normalize relative to the current futures price.

A common view in financial markets is that the crack spread is the expected change in the spot price of crude oil (see, e.g., Evans 2009). This view has been articulated by Verleger (2011), for example. Verleger appeals to a model, in which refiners view themselves as price takers in product markets and cut their volume of production when they cannot find crude oil at an expected price commensurate with expected product prices. As Verleger explains, in time, this reduction in the demand for crude oil will lower the spot price of crude oil and the corresponding reduction in the supply of product will boost product prices. This reasoning suggests that the difference between refined product market futures prices and the purchase price of crude oil for delivery in the near future should have predictive power for the spot price of crude oil and motivates the forecasting model:

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp\left\{\hat{\alpha} + \hat{\beta}\left[\log\left(\frac{2}{3}F_{t+h,t}^{gas} + \frac{1}{3}F_{t+h,t}^{heat} - F_{t+h,t}^{oil}\right)\right] - \mathbb{E}(\pi_{t+h}^{h})\right\}. \tag{14}$$

3.3.3 The Weighted Product Futures Spread Model

Despite its popularity, the crack spread forecasting model (14) cannot be derived from (3) and is not related to specification (11). Thus, there is no reason to expect model (14) to work well in practice. In contrast, an alternative specification that can be formally derived from (3) and that is similar in spirit to the Verleger model is obtained by setting $w_1 = 2/3$ and $w_2 = 1/3$ in the forecasting model (11), resulting in

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp\left\{\hat{\alpha} + \hat{\beta}\left[\log\left(\frac{2}{3}F_{t+h,t}^{gas} + \frac{1}{3}F_{t+h,t}^{heat}\right) - p_t^{oil}\right] - \mathbb{E}(\pi_{t+h}^{h})\right\}. \tag{15}$$

[6] Other common crack spread ratios are 5:3:2 and 2:1:1, depending on the type of refining process.

3.3.4 Equal-weighted Combination of Single Product Futures Spread Models

Finally, a more flexible approach to combining information from single product spreads is to assign equal weight to the gasoline and heating oil futures spread forecasts:

$$\widehat{R_{t+h|t}}^{oil} = \frac{1}{2}\sum_{i=1}^{2}\widehat{R_{t+h|t}}^{oil,i}. \tag{16}$$

The motivation for this approach is that, even if one forecasting model by itself is more accurate than the other, the less accurate model may still have additional predictive information not contained in the more accurate model, allowing one to improve on the forecast accuracy of the more accurate model by taking a weighted average of the two forecasts.

3.4 Using Product Spot Spreads

An alternative approach to deriving a product spread model is to postulate cointegration between product spot prices and the spot price of crude oil such that $\log\left(\sum_{i=1}^{n} w_i P_t^i\right) - p_t^{oil} \sim I(0)$. It is well known that gasoline prices and crude oil prices, for example, move together in the long run (see, e.g., Lanza et al. 2005; Kilian 2010). This cointegration relationship may be motivated, for example, based on a model in which refiners are price takers in the crude oil market, as suggested by Brown and Virmani (2007). As in typical long-horizon regressions used in empirical finance, under the maintained hypothesis of cointegration, current deviations of suitably weighted spot prices of refined products from the spot price of crude oil would be expected to have predictive power for changes in the spot price of crude oil (see, e.g., Mark 1995; Kilian 1999):

$$\triangle p_{t+h|t}^{oil} = \alpha + \beta\left[\log\left(\sum_{i=1}^{n} w_i P_t^i\right) - p_t^{oil}\right] + \varepsilon_{t+h}.$$

The same cointegration relationship may also be motivated based on a model in which refiners are price takers in the product market, as suggested by Verleger (2011). Recall equation (3)

$$\mathbb{E}P_{t+h|t}^{oil} = \sum_{i=1}^{n} w_i \mathbb{E}P_{t+h|t}^{i}$$

and replace the expected product prices by no-change forecasts. After taking logs and subtracting p_t^{oil} from both sides, we obtain:

$$\triangle p_{t+h|t}^{oil} = \alpha + \beta\left[\log\left(\sum_{i=1}^{n} w_i P_t^i\right) - p_t^{oil}\right] + \varepsilon_{t+h}, \tag{17}$$

allowing us to forecast the real price of oil as:

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp\left\{\hat{\alpha} + \hat{\beta}\left[\log\left(\sum_{i=1}^{n} w_i P_t^i\right) - p_t^{oil}\right] - \mathbb{E}(\pi_{t+h}^h)\right\} \tag{18}$$

As in section 3.3, there are several special cases.

3.4.1 The Single Spot Spread Model

When $n = 1$, the single product spot spread model is

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp\left[\hat{\alpha} + \hat{\beta}\left(p_t^i - p_t^{oil}\right) - \mathbb{E}(\pi_{t+h}^h)\right], \tag{19}$$

where $i \,\epsilon \{gasoline,\ heating\ oil\}$.

3.4.2 The Weighted Product Spot Spread Model

Similarly, we can derive from (19) the weighted product spot spread model:

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp\left\{\hat{\alpha} + \hat{\beta}\left[\log\left(\frac{2}{3}P_t^{gas} + \frac{1}{3}P_t^{heat}\right) - p_t^{oil}\right] - \mathbb{E}(\pi_{t+h}^h)\right\}. \tag{20}$$

3.4.3 Equal-weighted Combination of Single Product Spot Spread Models

As in the case of futures spreads, we also explore equal-weighted combinations of the forecasts based on gasoline and heating oil spot spreads:

$$\widehat{R_{t+h|t}}^{oil} = \frac{1}{2}\sum_{k=1}^{2} \widehat{R_{t+h|t}}^{oil,k}. \tag{21}$$

4 Baseline Results

The models considered for the forecast comparison include a large number of forecasting models based on various product futures price spreads and product spot price spreads, the predictive ability of which we examine below.

4.1 Real WTI

We start our analysis with the results for the real WTI price. Table 1 presents the results for futures product spreads and Table 2 shows the corresponding results for the product spot spreads. In all cases, the product spreads are constructed by relating the product price to the corresponding WTI price of crude oil.

4.1.1 Futures Spreads

The first five columns of Table 1 show the results for product futures spread models based on $\widehat{\alpha}$ and $\widehat{\beta}$. There are no statistically significant gains in directional accuracy for any model, but there is some evidence of MSPE reductions. For example, the gasoline spread model is about as accurate as the no-change forecast at horizon 1, but more accurate at horizons 3 and 6. At the latter horizon, the reduction in the MSPE by 10% is statistically significant at the 10% level. On the other hand, the heating oil spread model has higher MSPEs than the no-change forecast at all horizons by as much as 11%. The equal-weighted forecast combination of the gasoline and heating oil spread forecasts is somewhat less accurate than the gasoline spread forecast, but the reduction in the MSPE at horizon 3 is more precisely estimated and statistically significant at the 5% level. The weighted product spread is even less accurate than the equal-weighted forecast combination, but also statistically significant at the 5% level at horizon 3. In contrast, there are no gains in forecast accuracy when using the widely cited futures crack spread. We conclude that the best forecasting model is the gasoline spread model.

The next five columns of Table 1 explore whether restricting the intercept of the spread models to zero increases the forecast accuracy. This intercept reflects transportation costs and refining costs, as discussed earlier. To the extent that these costs are small, one would expect an exclusion restriction on the intercept to trade off forecast variance for forecast bias, potentially resulting in a lower MSPE. Table 1 confirms this conjecture. Not only does the gasoline futures spread yield reductions in the MSPE at all horizons, once $\alpha = 0$ is imposed, but the model also has improved directional accuracy. The relative accuracy of alternative models compared with the gasoline futures spread is not affected. An additional reason for imposing this restriction is that the unrestricted estimate of α often is negative, which is inconsistent with the underlying economic model.

We conclude that the gasoline futures spread model with $\alpha = 0$ imposed is the preferred forecasting model and much more accurate than models that combine information about gasoline and heating oil futures prices, including the futures crack spread. The latter result is likely to be surprising to practitioners who rely on the crack spread, but was to be expected in light of the discussion in section 3. We also obtained very similar results for the crack spread model when forecasting the nominal oil price instead of the real price of oil, for example, or when replacing the log specification for the crack spread by a levels specification.

4.1.2 Spot Spreads

An obvious limitation of the results in Table 1 is that we cannot forecast beyond six months, except when using the heating oil spread which has no predictive power for the real price of oil at any horizon. This observation motivates a closer examination of the product spot spread models. The first four columns of Table 2 show that none of the unrestricted product spot spread models decisively outperforms the no-change forecast.

This result changes once we impose $\alpha = 0$ in the next four columns of Table 2. In that case, the gasoline spot spread model yields reductions in the MSPE at every horizon. The reductions in the MSPE are not quite as large at short horizons as for the gasoline futures spread model, but persist and indeed increase at horizons between one and two years. The reductions in the MSPE of as much as 6% may seem small, but have to be viewed in conjunction with the MSPE ratios of forecasting models based on economic fundamentals, which at the same horizons are systematically larger than 1.[7] Moreover, the reductions are statistically significant at horizons 6, 9, 12, 15, 18, and 24. Indeed, this is one of very few models capable of generating systematic reductions in the MSPE of the real price of oil at horizons between one and two years. As before, the gasoline spread model is much more accurate than the other models, with the weighted product spread being the second-most accurate model. None of these models has much directional accuracy.

4.2 Real U.S. Refiners' Acquisition Cost for Crude Oil Imports

We now turn to the problem of forecasting the real U.S. refiners' acquisition cost for crude oil imports. This alternative oil price series is of independent interest for forecasters interested in the real price of oil in global markets. The only difference compared with the earlier analysis is the variable to be predicted. The spread regressions from which α and β are estimated remain unchanged.

Table 3 shows results for selected models. We focus on the gasoline spread models, which are consistently most accurate mirroring the pattern found for the real WTI price forecasts. In general, the reductions in the MSPE are larger for the refiners' acquisition cost than for the WTI price, however. For example, the unrestricted gasoline futures spread model generates statistically significant reductions in the MSPE at horizons 1, 3, and 6 as high as 11%. With $\alpha = 0$ imposed, the MSPE reductions are still as high as 6%. For the corresponding gasoline spot spread model with $\alpha = 0$ imposed, there are MSPE reductions at all horizons reaching 7% in some cases. The reductions are statistically significant at horizons 6, 9, 12, 15, 18, and 24. As to the ranking of

[7] Although these results are not shown, we note that the MSPE reductions of the gasoline spot spread model do not extend to even longer horizons. As expected, in the longer run, the no-change forecast remains the best forecasting model.

different models, the same comments apply as for the real WTI price. We conclude that our results for the real WTI price apply more broadly.

4.3 Sensitivity Analysis: Evaluation Period

The most striking result in our analysis so far is the ability of the gasoline spot spread model with $\alpha = 0$ in Tables 2 and 3 to outperform the no-change forecast of the real price of oil at horizons between one and two years. An important question is whether these recursive MSPE reductions are driven by one or two unusual episodes in the data or whether they are more systematic. The left panel of Figure 1 addresses this question by plotting the recursive MSPE ratio at horizon 24 for the evaluation period since January 1997. We disregard the earlier MSPE ratios which are based on too short a recursive evaluation period to be considered reliable. For illustrative purposes we focus on the real U.S. refiners' acquisition cost for crude oil imports. The last entry on the right corresponds to the entry for horizon 24 in the sixth column of Table 3. The plot shows that the performance of the gasoline spread model is systematic and not driven by one or two unusual events in the data. There is a clear pattern. Initially, the no-change forecast was more accurate than the gasoline spread model, albeit to a declining degree over time. Since 2004 the gasoline spread model has been systematically more accurate than the no-change forecast in every month. This pattern is suggestive of the estimates of β becoming increasingly more precise, as the length of the recursive estimation window increases, allowing more accurate forecasts.

Indeed, the right panel of Figure 1 shows that a similar pattern applies to the heating oil spot spread model with $\alpha = 0$ in that the recursive MSPE ratio of this model, while initially slightly below 1, quickly stabilizes in the range slightly above 1 and remains there for the rest of the evaluation period. The consistently inferior accuracy of the heating oil spot spread model is not surprising in light of Verleger's (2011) observation that the price of crude oil is determined in the marginal product market, which, according to Verleger, has been the gasoline market throughout much of our evaluation period. We conclude that, again, the results do not appear to be driven by unusual events in the data. Qualitatively similar results hold for other long horizons, as documented in the not-for-publication appendix.

4.4 Sensitivity Analysis: WTI vs. Brent

All forecasting models so far relied on the WTI price of crude oil in constructing the spread variables. Historically, the WTI price and the Brent price of crude oil have tended to move together and the WTI price was widely regarded as a benchmark for the price of crude oil. As Figure A3 in the online appendix shows, that relationship broke down after 2010, when physical and legal constraints on U.S. oil exports resulted in a simultaneous glut of crude oil in Cushing, Oklahoma, and shortage of crude oil in Europe. To the extent that the Brent price of crude oil in recent years has been considered a better benchmark for global oil prices than the WTI price, even U.S. traders have switched toward benchmarking a weighted average of WTI and Brent prices. This fact suggests that we may be mismeasuring the product spread in 2011 and in 2012, causing us to understate the predictive ability of product spread models.

We deal with this concern by constructing a synthetic oil price series which equals the WTI price until April 2010, but consists of the average of WTI price and Brent price thereafter. This rule of thumb roughly approximates the weights attached by many practitioners. Using this refined measure of the spot price of oil, we found very similar forecast accuracy results. While this modification indeed tends to increase the MSPE reductions, the differences are in the third decimal place of the MSPE ratio. This result is consistent with time series plots of the recursive MSPE ratios of the models considered in Table 2, which provide no indication of the forecast accuracy of the WTI-based product spread models deteriorating in 2011 and 2012 (figures not shown).[8]

5 Beyond the Crack Spread Model

The simplicity of product spread forecasting models is appealing, yet there are reasons to be wary. One concern is that the global price of crude oil is likely to be determined by the refined product that is in highest demand. This feature of the oil market follows from the fact that refined products are produced jointly in approximately fixed proportions. Verleger (2011), for example, suggests that traditionally, gasoline was this marginal product and that the marginal market in the world for gasoline was the United States. As of late, according to Verleger, this product has been diesel fuel (which is almost interchangeable with heating oil), with Europe becoming the marginal market. Verifying conjectures about the marginal market is difficult, given the complexity of global oil and product markets and the lack of data, but Verleger's rationale for time variation in the predictive relationship between product spreads and the price of oil is persuasive. To the extent that products are produced in roughly fixed proportions, shifts in the demand for one refined product in one part of the world may have a disproportionate predictive power for the price of oil.

This predictive relationship is further complicated by the fact that different refiners use different

[8] Yet another possibility would have been to rely on the composite U.S. refiners' acquisition cost for oil (available from the EIA), which captures at least part of the transportation cost, in constructing the product spread. Unlike WTI or Brent prices, the refiners' acquisition cost is not available in real time, however, making it a potentially less reliable predictor. For that reason we did not consider this alternative specification.

grades of crude oil inputs, which in turn are associated with different proportions of refined product outputs, making it more difficult to predict which market will tighten and which will suffer from a glut in response to rising demand for, say, diesel fuel, even granting that trade in products over time may alleviate the resulting market imbalances. Moreover, there is reason to believe that the predictive relationships that industry analysts appeal to are not stable for a host of other reasons not related to shifts in marginal markets such as crude oil supply shocks, changes in environmental regulations, changes in refining technology, local capacity constraints in refining and unexpected refinery outages, or other market turmoil. In this section, we deal with two forecasting approaches that allow the weight assigned to gasoline spreads and heating oil spreads to evolve smoothly over time in recognition of these arguments.

5.1 Inverse MSPE Weights

A simple approach to allowing for such time variation is to weight forecasts from the gasoline and heating oil spread models in proportion to the inverse MSPE of each forecasting model. The smaller the MSPE is at period t, the larger the weight in constructing the combination forecast:

$$\widehat{R_{t+h|t}}^{oil} = \sum_{k=1}^{2} v_{k,t} \widehat{R_{t+h|t}}^{oil,k}, \quad v_{k,t} = \frac{m_{k,t}^{-1}}{\sum_{j=1}^{2} m_{j,t}^{-1}}, \tag{22}$$

where $m_{k,t}$ is the rolling or recursive MSPE of model k in period t. The advantage of inverse MSPE weights is that they allow the forecast combination to adjust according to the recent performance of each forecasting model (see, e.g., Diebold and Pauly 1987, Stock and Watson 2004). We considered rolling weights based on window lengths of 12, 24 and 36 months in addition to recursive weights. The window length makes no difference for the qualitative results, so only results for window length 24 are reported.

Table 4 shows selected results. For expository purposes, we focus on the results for the real U.S. refiners' acquisition cost for crude oil imports. Qualitatively similar, if generally weaker, results are obtained for the real WTI price. Unlike for the results in Table 3, no method exists that would allow us to evaluate the statistical significance of MSPE reductions in Table 4. The reason is that the models to be compared evolve over time, invalidating conventional tests of equal predictive accuracy for recursive regressions. Table 4 demonstrates that overall none of the four specifications considered yields recursive MSPE ratios as low as the gasoline spread model in Table 3 with $\alpha = 0$ imposed.

5.2 TVP Models

An alternative approach is to allow for time variation in the parameters of the product spread model. In an effort to allow for the weights on each spread to evolve freely, we recursively estimate

$$\triangle p^{oil}_{t+h|t} = \alpha_t + \beta_{1t}\left[p^{gas}_t - p^{oil}_t\right] + \beta_{2t}\left[p^{heat}_t - p^{oil}_t\right] + \varepsilon_{t+h},$$

where $\varepsilon_{t+h} \sim NID(0, \sigma^2)$, the time-varying coefficients $\theta_t = [\alpha_t\ \beta_{1t}\ \beta_{2t}]'$ evolve according to a random walk as $\theta_t = \theta_{t-1} + \xi_t$, and ξ_t is independent Gaussian white noise with variance Q. This state-space model is estimated using a Gibbs sampling algorithm. The conditional posterior of θ_t is normal, and its mean and variance can be derived via standard Kalman filter recursions (see Kim and Nelson 1999). Conditional on an estimate of θ_t, the conditional posterior distribution of σ^2 is inverse Gamma and that of Q is inverse Wishart. This allows us to construct the TVP model forecast

$$\widehat{R_{t+h|t}}^{oil} = R^{oil}_t \exp\left\{\hat{\alpha}_t + \hat{\beta}_{1t}\left[p^{gas}_t - p^{oil}_t\right] + \hat{\beta}_{2t}\left[p^{heat}_t - p^{oil}_t\right] - \mathbb{E}(\pi^h_{t+h})\right\} \tag{23}$$

by Monte Carlo integration as the mean of the forecasts simulated based on $1,000$ Gibbs iterations conditional on the most recent data. Our forecasts take into account that the parameters continue to drift over the forecast horizon according to their law of motion. The first 30 observations of the initial estimation period are used as a training sample to calibrate the priors and to initialize the Kalman filter.

The first column of Table 5 shows that, when all parameters are freely estimated, the forecast accuracy of this TVP model is satisfactory only at horizons up to 15 months. Restricting α to 0, however, as shown in the second column of Table 5, greatly increases the model's forecast accuracy at longer horizons. The MSPE ratios are below 1 at all forecast horizons and frequently lower than for the fixed parameter gasoline spread model with $\alpha = 0$. In addition, the model tends to have large, if mostly statistically insignificant, directional accuracy. We conclude that overall this TVP spread model is the most accurate forecasting model for the real U.S. refiners' acquisition cost for crude oil imports. Similar results also hold for the real WTI price, but are not shown to conserve space. We also note that allowing for stochastic volatility in the error term in addition does not improve the forecast accuracy of the TVP model.

An interesting question is how well the TVP model would have done based on the information conveyed by the gasoline spread alone. The third column and fourth column of Table 5 show that this simpler TVP model also works well. At some horizons it is slightly more accurate than the combined spreads. Nevertheless, at longer horizons the model in the second column is somewhat more accurate. Again, qualitatively similar results hold when forecasting the real WTI price.

It may be tempting to interpret the slope parameter estimates of the TVP regression model in light of Verleger's discussion of marginal product markets. This is not possible. Determining the marginal product market is next to impossible given the complex economic relationships in question and the lack of suitable data. Not only is there no known timeline of when marginal markets shifted and in what direction, against which the TVP model estimates could be evaluated, but, as discussed earlier, time variation in the spread regression may also arise for many reasons not related to Verleger's interpretation. This means that we have to be careful not to associate parameter shifts with shifts in the marginal U.S. product market necessarily.

5.3 Extensions to European Markets

So far we have focused on the problem of forecasting the real U.S. refiners' acquisition cost of crude oil imports and the real U.S. WTI. A natural question is how well these methods work when forecasting the real spot price of Brent crude oil. Extending our approach to Brent crude oil is not straightforward because of data limitations. The best proxy for the product spread in European markets comes from the Rotterdam market, as reported by *Argus Media*. Given the lack of longer time series for the Rotterdam gasoline spot price, we can only consider a forecasting model based on the spot spread of the Rotterdam heating oil price over the Brent price of crude oil. This model performs quite poorly compared with the no-change forecast, not unlike the corresponding results for the U.S. data reported in Table 2, with or without allowing for time variation in the parameters.

Although it is not feasible to apply most product spread models that we have discussed to the Brent market, there is a promising alternative, which involves forecasting the real U.S. refiners' acquisition cost of crude oil imports as discussed earlier and then rescaling these price forecasts by assuming that the current spread of the Brent price over the refiners' acquisition cost remains unchanged in the future. A similar approach has already been used successfully in Baumeister and Kilian (2014b) in the context of a different class of forecasting models. We leave this extension to future research.

5.4 Towards a Global TVP Model

The empirical success of the U.S. gasoline product spread compared with the U.S. heating oil spread in our analysis is intriguing. One possible explanation of this result is that the United States has been the marginal market for gasoline for most of our sample. It is the marginal market in which global product prices are determined, according to Verleger (2011), which may help explain the greater predictive power of the U.S. gasoline spread. In contrast, Europe in recent years has been viewed by some observers as the marginal market for diesel and heating oil. Diesel and heating oil may be treated as indistinguishable for our purposes. An interesting extension of our analysis therefore is a combination of European and U.S. product spread models that takes account of shifting geographical locations of the marginal market. Specifically, we consider the global TVP model

$$\triangle p_{t+h|t}^{oil} = \alpha_t + \beta_{1t}\left[p_t^{N.Y.,\ gas} - p_t^{WTI}\right] + \beta_{2t}\left[p_t^{Rotterdam,heat} - p_t^{Brent}\right] + \varepsilon_{t+h},$$

where the oil price variable on the left-hand side may refer to the WTI price, the Brent price, or the U.S. refiners' acquisition cost for crude oil imports, respectively. The implied forecast is:

$$\widehat{R_{t+h|t}}^{oil} = R_t^{oil} \exp\left\{\hat{\alpha}_t + \hat{\beta}_{1t}\left[p_t^{N.Y.,\ gas} - p_t^{WTI}\right] + \hat{\beta}_{2t}\left[p_t^{Rotterdam,heat} - p_t^{Brent}\right] - \mathbb{E}(\pi_{t+h}^h)\right\}. \tag{24}$$

This specification treats the U.S. as the marginal market for gasoline and Europe as the marginal market for heating oil and diesel and allows their relative weights to evolve over time, consistent with the views expressed in Verleger (2011). It should be noted that this specification is also of interest because it provides an alternative solution to the problem of forecasting the real price of Brent crude oil even in the absence of suitable data on European gasoline price spreads.

Our results, which are not shown to conserve space, indicate that regardless of the dependent variable, the out-of-sample forecast accuracy of this specification is erratic even allowing for time-varying weights. There is little support for a global model of product spreads. When forecasting the WTI price or the U.S. refiners' acquisition cost of crude oil imports, systematically more accurate forecasts are obtained using the methods discussed earlier. For the real price of Brent crude oil, the global TVP model does not generate large or systematic reductions in the MSPE, but there are systematic, if statistically insignificant, gains in directional accuracy.

6 Conclusion

In recent years, there has been increasing interest in the relationship between oil prices and prices of refined products (see, e.g., Kilian 2010; Büyüksahin and Fattouh 2013). This paper explored the predictive content of product spreads for the WTI spot price of crude oil. Our forecasting approach mirrored methods favored by industry analysts in that we relied on spot and futures prices of gasoline and heating oil in constructing the product spreads. Although industry analysts and the financial press tend to focus on product spreads in the futures market, the limited availability of product futures price data at longer maturities makes it impossible to evaluate the forecast accuracy of futures spread models except at short horizons. To the extent that we can compare models based on futures price spreads and spot price spreads at horizons up to six months, models based on futures prices tend to be slightly more accurate, but overall the accuracy is similar. As we demonstrated, the advantage of models based on spot price product spreads is that they allow the construction of forecasts of the real price of oil at the longer horizons of interest to policymakers and industry analysts.

While there is no empirical support for the notion that the widely cited futures crack spread beats the no-change forecast, we documented that product spreads in general contain useful predictive information about the future real price of crude oil, even at forecast horizons between one and two years. This result is remarkable in that oil prices along with stock prices and exchange rates are among the most difficult variables to forecast. Indeed, few forecasting models yield statistically significant improvements on the random walk model for the real price of oil at these horizons. The only other known example is a model based on U.S. crude oil inventories in Baumeister, Guérin and Kilian (2014). This result is of particular interest in that forecasting models for the real price of oil based on economic fundamentals tend to be most accurate at horizons of one and three months, but increasingly less accurate at longer horizons. This fact suggests that forecast combinations of models based on economic fundamentals and models based on product spreads would be a promising direction for future research. This is a question pursued in more detail in related ongoing work by Baumeister and Kilian (2013) and Baumeister, Kilian and Lee (2014).

Our analysis revealed several robust patterns in forecasting the real price of oil. First, models based on the gasoline spread in particular tend to be more accurate than models based on the heating oil spread, models based on weighted product spreads, models based on the crack spread, and equal-weighted forecast combinations of gasoline spread and heating oil spread models. This is true for both futures spreads and spot spreads.

Second, imposing parameter restrictions may improve the forecast accuracy of spread models, regardless of the specification. For the preferred model based on the gasoline spread a specification that sets the intercept to zero tends to generate the largest and most statistically significant MSPE reductions relative to the no-change forecast. For the real WTI price, this model yields statistically significant reductions in the MSPE at horizons 6, 9, 12, 15, 18, and 24. Moreover, this model is equally accurate when applied to the U.S. refiners' acquisition cost for crude oil imports, which is a better proxy for global oil prices than the WTI price, especially in recent years. Either way, there is no indication of the forecast accuracy worsening, as the gap between the WTI price and the Brent price of crude oil widened in recent years.

Third, we emphasized that, from an economic point of view, there is no reason to expect any one product spread to be a good predictor throughout the sample. There are strong reasons to expect the forecasting ability of different product spreads to evolve over time in response to shifts in final demand and other determinants ignored by Verleger's model (see Verleger 2011). We therefore also investigated forecasting methods that allow for smooth structural change in the weights assigned to gasoline and heating oil spot spreads. We showed that inverse MSPE weighted forecast combinations of suitably restricted gasoline and heating oil spread models tend to be less accurate than the most accurate constant parameter forecasting model based on the gasoline spread alone. A suitably restricted TVP model, however, has lower MSPE than the most accurate gasoline spread model at most horizons and has lower MSPE than the random walk model at all horizons up to two years. It also has high, if mostly statistically insignificant directional accuracy. We concluded that this TVP model is the most accurate product spread forecasting approach overall for forecasting the real U.S. refiners' acquisition cost of oil imports or the real WTI price. We also noted that similar forecasting approaches cannot be applied to the problem of forecasting the real price of Brent crude oil, given the lack of suitable data.

Finally, Verleger's (2011) analysis stressed that shifting demand patterns worldwide may affect the world price of oil. In particular, he conjectured that over time the predictive power of European product spreads for heating oil and diesel for the global price of oil has increased. We found no empirical support for this conjecture. In fact, global TVP forecasting models based on U.S. and European product spreads that allow for shifting demand patterns worldwide were generally less accurate in forecasting the real WTI price and the real U.S. refiners' acquisition cost than models based on U.S. product spreads.

Although our analysis focused on forecasting the real price of oil, we note that our approach can be easily adapted to forecasting the nominal price of oil. The not-for-publication appendix shows that these nominal oil price forecasts tend to be as accurate as or more accurate than the real oil price forecasts. These results reinforce our conclusion that there is valuable predictive information in product spot price spreads that can be exploited in real time.

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Table 1: Forecast Accuracy of Futures Spread Models for the Real WTI Price

	$\hat{\alpha}, \hat{\beta}$					$\alpha = 0, \hat{\beta}$				
Horizon	(1) Gasoline futures spread	(2) Heating oil futures spread	(3) Equal-weighted combination of (1) and (2)	(4) Weighted futures product spread	(5) Futures crack spread	(1) Gasoline futures spread	(2) Heating oil futures spread	(3) Equal-weighted combination of (1) and (2)	(4) Weighted futures product spread	(5) Futures crack spread
	MSPE Ratios Relative to No-Change Forecast									
1	1.009	1.013	1.004	1.018	1.028	**0.994**	1.010	1.001	**0.999**	1.014
3	**0.976**	1.056	**0.987**	1.030	1.076	**0.978****	1.043	1.008	1.001	1.046
6	**0.899****	1.106	**0.977***	**0.983***	1.146	**0.948***	1.086	1.009	**0.992**	1.078
9	-	1.093	-	-	-	-	1.076	-	-	-
12	-	1.090	-	-	-	-	1.041	-	-	-
	Success Ratios									
1	0.474	**0.502**	0.470	0.454	**0.518**	**0.574**	**0.542**	**0.566**	**0.574**	**0.550**
3	**0.543**	0.498	**0.530**	**0.539**	0.478	**0.591***	**0.530**	**0.579**	**0.575**	**0.510**
6	**0.508**	0.496	0.492	0.484	0.455	**0.566**	**0.521**	**0.537**	**0.541**	**0.545**
9	-	**0.523**	-	-	-	-	**0.510**	-	-	-
12	-	**0.521**	-	-	-	-	0.454	-	-	-

NOTES: Boldface indicates improvements on the no-change forecast. Statistically significant reductions in the MSPE according to the Clark-West test and statistically significant improvements in directional accuracy according to the Pesaran-Timmermann test are marked using * (5% significance level) and ** (10% significance level).

Table 2: Forecast Accuracy of Spot Spread Models for the Real WTI Price

Horizon	$\hat{\alpha}, \hat{\beta}$ (1) Gasoline spot spread	(2) Heating oil spot spread	(3) Equal-weighted combination of (1) and (2)	(4) Weighted spot product spread	$\alpha = 0, \hat{\beta}$ (1) Gasoline spot spread	(2) Heating oil spot spread	(3) Equal-weighted combination of (1) and (2)	(4) Weighted spot product spread
				MSPE Ratios Relative to No-Change Forecast				
1	1.015	1.010	1.009	1.017	**0.999**	1.008	1.003	1.002
3	1.032	1.028	1.018	1.040	**0.998**	1.023	1.008	1.007
6	1.015	1.043	1.024	1.032	**0.978****	1.037	1.006	**0.998**
9	1.067	1.056	1.060	1.067	**0.965***	1.052	1.006	**0.989**
12	1.016	1.051	1.028	1.057	**0.940***	1.040	**0.987**	**0.970****
15	**0.993**	1.035	1.004	1.053	**0.936***	1.031	**0.980**	**0.966**
18	1.026	1.006	1.011	1.062	**0.969****	1.041	1.001	**0.990**
21	1.025	**0.995**	1.006	1.048	**0.987**	1.058	1.017	1.004
24	**0.979**	1.006	**0.981**	1.018	**0.940***	1.054	**0.990**	**0.968****
				Success Ratios				
1	0.462	**0.546**	**0.506**	0.454	**0.554**	**0.534**	**0.566**	**0.562**
3	0.445	**0.518**	0.494	0.453	**0.575**	0.482	**0.555**	**0.563**
6	0.443	**0.557**	**0.512**	0.455	**0.541**	0.459	**0.508**	**0.541**
9	0.461	**0.585**	**0.573**	0.494	0.419	0.419	0.465	0.469
12	0.445	**0.576**	**0.525**	0.483	**0.504**	0.370	0.416	0.437
15	0.477	**0.592****	**0.506**	0.443	0.494	0.434	0.396	0.438
18	0.474	**0.603***	**0.530**	**0.535**	0.440	0.397	0.440	0.435
21	0.485	**0.555**	**0.520**	**0.507**	0.437	0.349	0.384	0.415
24	0.451	**0.531**	0.465	**0.504**	0.491	0.367	0.416	0.474

NOTES: Boldface indicates improvements on the no-change forecast. Statistically significant reductions in the MSPE according to the Clark-West test and statistically significant improvements in directional accuracy according to the Pesaran-Timmermann test are marked using * (5% significance level) and ** (10% significance level).

Table 3: Forecast Accuracy of Gasoline Spot and Futures Spread Models for the Real U.S. Refiners' Acquisition Cost for Crude Oil Imports

Horizon	(1) $\hat{\alpha}, \hat{\beta}$ Gasoline futures spread	(2) $\alpha = 0, \hat{\beta}$ Gasoline futures spread	(1) $\hat{\alpha}, \hat{\beta}$ Gasoline spot spread	(2) $\alpha = 0, \hat{\beta}$ Gasoline spot spread
	MSPE Ratios Relative to No-Change Forecast			
1	**0.942***	**0.979***	**0.974***	**0.989**
3	**0.919****	**0.966***	1.005	**0.990**
6	**0.891****	**0.945***	1.012	**0.978****
9	-	-	1.056	**0.963***
12	-	-	1.011	**0.934***
15	-	-	**0.993**	**0.931***
18	-	-	1.013	**0.971****
21	-	-	**0.998**	**0.986**
24	-	-	**0.956***	**0.934***
	Success Ratios			
1	0.482	**0.590**	0.478	**0.562**
3	**0.534**	**0.599***	0.429	**0.583**
6	**0.521**	**0.570**	0.455	**0.545**
9	-	-	0.486	0.436
12	-	-	0.454	**0.521**
15	-	-	0.468	**0.516**
18	-	-	0.470	0.470
21	-	-	**0.502**	0.454
24	-	-	0.443	**0.500**

NOTES: Boldface indicates improvements on the no-change forecast. Statistically significant reductions in the MSPE according to the Clark-West test and the Diebold-Mariano test, respectively, and statistically significant improvements in directional accuracy according to the Pesaran-Timmermann test are marked using * (5% significance level) and ** (10% significance level).

Table 4: Forecast Accuracy of Recursive and Rolling MSPE^{-1}-Weighted Model Combinations for the Real U.S. Refiners' Acquisition Cost for Crude Oil Imports

Horizon	Recursive weights		Rolling weights based on a window length of 24 months	
	$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$	$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$
	Spot spread	Spot spread	Spot spread	Spot spread
	MSPE Ratios Relative to No-Change Forecast			
1	**0.992**	**0.994**	**0.992**	**0.994**
3	1.006	1.005	1.005	1.000
6	1.020	1.003	1.020	1.003
9	1.048	1.003	1.048	1.002
12	1.017	**0.977**	1.019	**0.978**
15	**0.997**	**0.970**	1.001	**0.970**
18	**0.989**	**0.996**	**0.989**	**0.996**
21	**0.964**	1.009	**0.964**	1.009
24	**0.943**	**0.977**	**0.942**	**0.978**
	Success Ratios			
1	**0.502**	**0.574**	0.498	**0.574**
3	0.490	**0.563**	0.486	**0.563**
6	**0.512**	**0.512**	**0.516**	**0.508**
9	**0.593****	0.473	**0.593****	0.473
12	**0.534**	0.450	**0.534**	0.450
15	**0.519**	0.426	**0.511**	0.426
18	**0.535**	0.440	**0.543**	0.435
21	**0.537**	0.406	**0.533**	0.406
24	0.460	0.434	0.460	0.438

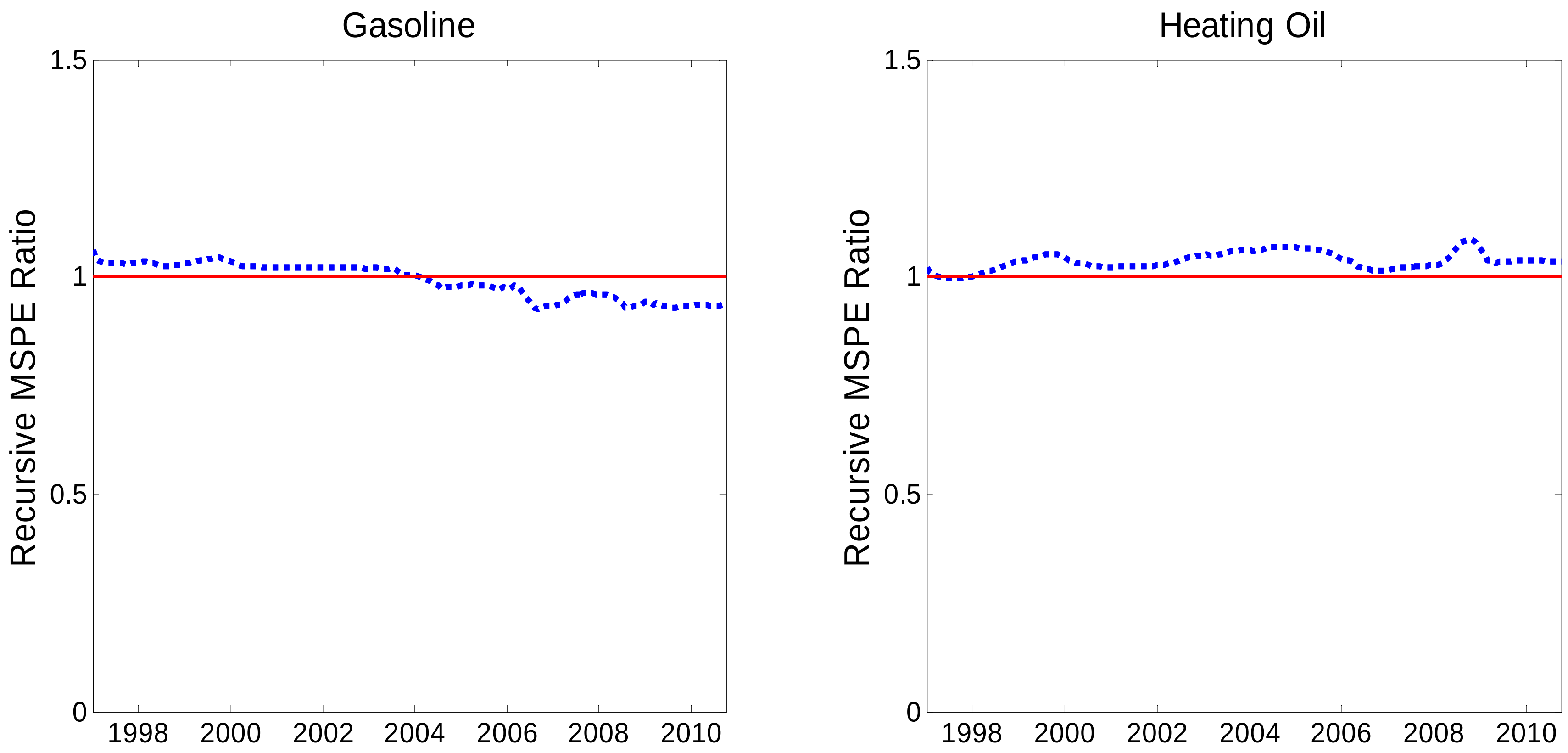
NOTES: All models combine information from the gasoline spread and heating oil spread. Boldface indicates improvements on the no-change forecast. There are no tests with which to assess the statistical significance of the MSPE reductions in the context of this table. Statistically significant improvements in directional accuracy according to the Pesaran-Timmermann test are marked using * (5% significance level) and ** (10% significance level).

Table 5: Forecast Accuracy of TVP Product Spread Models for the Real U.S. Refiners' Acquisition Cost for Crude Oil Imports

Horizon	Gasoline and Heating Oil Spreads		Gasoline Spread Only	
	$\hat{\alpha}_t, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\alpha_t = 0, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\hat{\alpha}_t, \hat{\beta}_t$	$\alpha_t = 0, \hat{\beta}_t$
	Spot spread	Spot spread	Spot spread	Spot spread
	MSPE Ratios Relative to No-Change Forecast			
1	**0.984**	**0.997**	**0.973**	**0.993**
3	**0.990**	**1.000**	**0.986**	1.010
6	**0.957**	**0.972**	**0.958**	1.007
9	**0.909**	**0.892**	**0.900**	**0.963**
12	**0.894**	**0.865**	**0.845**	**0.912**
15	**0.945**	**0.878**	**0.855**	**0.903**
18	1.013	**0.905**	**0.953**	**0.916**
21	1.110	**0.911**	**0.930**	**0.907**
24	**0.979**	**0.800**	**0.865**	**0.811**
	Success Ratios			
1	**0.502**	**0.586**	**0.566**	**0.586**
3	**0.518**	**0.579**	**0.559**	**0.587**
6	0.496	**0.541**	**0.525**	**0.578**
9	0.490	**0.560**	**0.506**	**0.593**
12	0.479	**0.613**	**0.521**	**0.618**
15	0.443	**0.647**	**0.532**	**0.638**
18	0.496	**0.660****	**0.552**	**0.651**
21	**0.524**	**0.659**	**0.646**	**0.655**
24	**0.500**	**0.633**	**0.580**	**0.633**

NOTES: The TVP models are estimated using Kalman filter recursions. Boldface indicates improvements on the no-change forecast. There are no tests with which to assess the statistical significance of the MSPE reductions in the context of this table. Statistically significant improvements in directional accuracy according to the Pesaran-Timmermann test are marked using * (5% significance level) and ** (10% significance level).

Figure 1: Real-Time Recursive MSPE Ratio of Spot Spread Models Relative to No-Change Forecast of Real U.S. Refiners' Acquisition Cost of Oil at the 24-Month Horizon



NOTES: All models shown have been estimated with $\alpha = 0$ imposed. The plot shows the evolution of the MSPE ratio over the evaluation period since 1997. This increases the reliability of the MSPE estimates and allows the MSPE ratio to stabilize.

NOT-FOR-PUBLICATION APPENDIX: Are Product Spreads Useful for Forecasting? An Empirical Evaluation of the Verleger Hypothesis

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This appendix provides additional results to demonstrate the robustness of our main findings.

1 Alternative inflation adjustment

To assess the robustness of our forecasts of the real price of oil to the adjustment for inflation, we adapted the fixed-ρ inflation gap model proposed in Faust and Wright (2013) to generate monthly out-of-sample inflation forecast. Table A1 shows that we obtain virtually identical results with this alternative inflation adjustment as in our original approach.

2 Forecasts of the nominal oil price

Tables A2 and A3 show the results for forecasts of the nominal refiners' acquisition cost of imported crude oil and of the nominal WTI spot price, respectively. The most successful forecasting models are as accurate as or even more accurate than the corresponding real oil price forecasts, confirming that the main results are not driven by our choice of inflation forecast.

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3 Instabilities in the predictive relationship

Our results in the paper are based on recursive estimates of the forecasting models. An alternative approach is to estimate forecasting models based on rolling windows of data. Table A4 evaluates the accuracy of rolling forecasts of the real refiners' acquisition cost of crude oil imports based on window lengths $w \in \{12, 24, 36\}$. The table shows that forecasts based on rolling windows perform poorly compared to recursive forecasts, regardless of the length of the window. Note that it is not possible to increase w to 48 given the length of the initial sample size.

4 Additional figures

Figure A1 shows the popular 3:2:1 futures crack spread at the 3-month horizon for the period January 1992 to March 2013. Figure A2 displays the time series behavior of selected product spot spreads and 3-month product futures spreads. Figure A3 shows the evolution of the spread between the WTI spot price and the Brent spot price over the period January 1992 to September 2012. Figure A4 plots the recursive MSPE ratios for the gasoline and heating oil spot spread models at horizons $h \in \{6, 12, 18\}$ starting in January 1997. It shows how robust the predictive relationship is over time.

Table A1: Forecast Accuracy of Product Spread Models for the Real U.S. Refiners' Acquisition Cost for Crude Oil Imports Using the Fixed-Rho Inflation-Gap Model of Faust and Wright (2013) for Inflation Adjustment

Horizon	Gasoline and Heating Oil Spreads		Gasoline Spread Only			
	$\hat{\alpha}_t, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\alpha_t = 0, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\hat{\alpha}_t, \hat{\beta}_t$	$\alpha_t = 0, \hat{\beta}_t$	$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$
	Spot spread	Spot spread	Spot spread	Spot spread	Spot spread	Spot spread
	MSPE Ratios Relative to No-Change Forecast					
1	**0.984**	**0.996**	**0.972**	**0.992**	**0.974***	**0.988**
3	**0.991**	1.001	**0.986**	1.011	1.005	**0.991**
6	**0.959**	**0.975**	**0.960**	1.011	1.014	**0.980****
9	**0.911**	**0.895**	**0.903**	**0.969**	1.059	**0.965***
12	**0.896**	**0.870**	**0.846**	**0.919**	1.013	**0.936***
15	**0.946**	**0.884**	**0.854**	**0.911**	**0.993**	**0.932**
18	1.012	**0.908**	**0.951**	**0.921**	1.014	**0.968***
21	1.112	**0.919**	**0.928**	**0.912**	**0.988**	**0.979**
24	**0.979**	**0.807**	**0.863**	**0.820**	**0.948****	**0.925***
	Success Ratios					
1	**0.502**	**0.582**	**0.562**	**0.586**	0.462	**0.558**
3	**0.518**	**0.575**	**0.567**	**0.583**	0.429	**0.587**
6	**0.508**	**0.545**	**0.525**	**0.574**	0.455	**0.562**
9	0.494	**0.564**	**0.515**	**0.598**	0.469	0.452
12	0.479	**0.618**	**0.542**	**0.609**	0.454	**0.508**
15	0.443	**0.643**	**0.540**	**0.643**	0.464	**0.536**
18	**0.535**	**0.660****	**0.582**	**0.655**	0.496	0.483
21	**0.515**	**0.659**	**0.651**	**0.651**	**0.520**	0.489
24	**0.527**	**0.633**	**0.584**	**0.628**	0.443	**0.518**

NOTES: The TVP models are estimated using Kalman filter recursions. Boldface indicates improvements on the no-change forecast. There are no tests with which to assess the statistical significance of the MSPE reductions for the TVP models. Statistically significant reductions in the MSPE according to the Clark-West test for the constant-coefficient models and significant improvements in directional accuracy according to the Pesaran-Timmermann test for all models are marked using * (5% significance level) and ** (10% significance level).

Table A2: Forecast Accuracy of Product Spread Models for the Nominal U.S. Refiners' Acquisition Cost for Crude Oil Imports

Horizon	Gasoline and Heating Oil Spreads		Gasoline Spread Only			
	$\hat{\alpha}_t, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\alpha_t = 0, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\hat{\alpha}_t, \hat{\beta}_t$	$\alpha_t = 0, \hat{\beta}_t$	$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$
	Spot spread	Spot spread	Spot spread	Spot spread	Spot spread	Spot spread
	MSPE Ratios Relative to No-Change Forecast					
1	**0.989**	1.004	**0.977**	1.001	**0.975****	**0.992**
3	**0.997**	1.008	**0.993**	1.022	1.005	**0.996**
6	**0.959**	**0.976**	**0.960**	1.019	1.014	**0.983**
9	**0.902**	**0.884**	**0.894**	**0.971**	1.059	**0.960***
12	**0.883**	**0.860**	**0.831**	**0.913**	1.003	**0.923***
15	**0.909**	**0.866**	**0.823**	**0.895**	**0.971**	**0.908***
18	**0.965**	**0.871**	**0.904**	**0.887**	**0.977**	**0.925***
21	1.041	**0.872**	**0.868**	**0.864**	**0.936**	**0.916***
24	**0.901**	**0.752**	**0.792**	**0.765**	**0.879***	**0.855***
	Success Ratios					
1	**0.518**	**0.598**	**0.586**	**0.602**	0.482	**0.598**
3	**0.543**	**0.579**	**0.571**	**0.591**	0.474	**0.591**
6	**0.557**	**0.566**	**0.549**	**0.582**	**0.512**	**0.586**
9	**0.573**	**0.622**	**0.573**	**0.627**	**0.544**	**0.631**
12	**0.550**	**0.660****	**0.605**	**0.651**	**0.521**	**0.651**
15	**0.545**	**0.664**	**0.604**	**0.668**	**0.511**	**0.668**
18	**0.599**	**0.668**	**0.672****	**0.672**	**0.565**	**0.672**
21	**0.555**	**0.690**	**0.686**	**0.686**	**0.585**	**0.673**
24	**0.611**	**0.664**	**0.664**	**0.668**	**0.589**	**0.673**

NOTES: The TVP models are estimated using Kalman filter recursions. Boldface indicates improvements on the no-change forecast. There are no tests with which to assess the statistical significance of the MSPE reductions for the TVP models. Statistically significant reductions in the MSPE according to the Clark-West test for the constant-coefficient models and significant improvements in directional accuracy according to the Pesaran-Timmermann test for all models are marked using * (5% significance level) and ** (10% significance level).

Table A3: Forecast Accuracy of Product Spread Models for the Nominal WTI Spot Price

Horizon	Gasoline and Heating Oil Spreads		Gasoline Spread Only			
	$\hat{\alpha}_t, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\alpha_t = 0, \hat{\beta}_{1t}, \hat{\beta}_{2t}$	$\hat{\alpha}_t, \hat{\beta}_t$	$\alpha_t = 0, \hat{\beta}_t$	$\hat{\alpha}, \hat{\beta}$	$\alpha = 0, \hat{\beta}$
	Spot spread	Spot spread	Spot spread	Spot spread	Spot spread	Spot spread
	MSPE Ratios Relative to No-Change Forecast					
1	1.037	1.025	1.012	1.010	1.013	1.001
3	1.020	1.017	1.011	1.028	1.031	1.004
6	**0.954**	**0.975**	**0.955**	1.022	1.018	**0.986**
9	**0.899**	**0.889**	**0.889**	**0.987**	1.077	**0.969****
12	**0.882**	**0.883**	**0.830**	**0.952**	1.019	**0.940****
15	**0.926**	**0.903**	**0.819**	**0.943**	**0.984**	**0.927****
18	**0.974**	**0.903**	**0.903**	**0.930**	1.009	**0.941***
21	1.085	**0.943**	**0.899**	**0.923**	**0.995**	**0.936****
24	**0.940**	**0.820**	**0.822**	**0.840**	**0.919**	**0.878***
	Success Ratios					
1	**0.526**	**0.594**	**0.582**	**0.598**	0.478	**0.594**
3	**0.547**	**0.567**	**0.559**	**0.579**	**0.502**	**0.579**
6	**0.545**	**0.570**	**0.537**	**0.586**	**0.500**	**0.590**
9	**0.556**	**0.598**	**0.556**	**0.602**	**0.527**	**0.606**
12	**0.542**	**0.618**	**0.571**	**0.618**	**0.521**	**0.618**
15	**0.532**	**0.651**	**0.583**	**0.655**	0.489	**0.655**
18	**0.582**	**0.651**	**0.655**	**0.655**	**0.547**	**0.655**
21	**0.533**	**0.668**	**0.664**	**0.664**	**0.563**	**0.651**
24	**0.597**	**0.650**	**0.650**	**0.655**	**0.575**	**0.659**

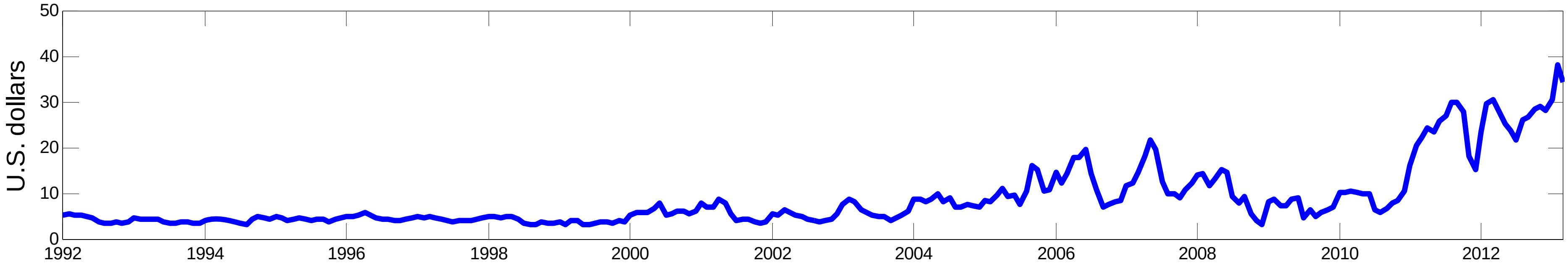
NOTES: The TVP models are estimated using Kalman filter recursions. Boldface indicates improvements on the no-change forecast. There are no tests with which to assess the statistical significance of the MSPE reductions for the TVP models. Statistically significant reductions in the MSPE according to the Clark-West test for the constant-coefficient models and significant improvements in directional accuracy according to the Pesaran-Timmermann test for all models are marked using * (5% significance level) and ** (10% significance level).

Table A4: Forecast Accuracy of Gasoline Spot Spread Models for the Real U.S. Refiners' Acquisition Cost for Crude Oil Imports – Recursive versus Rolling Forecasts

Horizon	(1) $\alpha = 0, \hat{\beta}$ Recursive Window	(2) $\alpha = 0, \hat{\beta}$ 12-Month Rolling Window	(1) $\alpha = 0, \hat{\beta}$ 24-Month Rolling Window	(2) $\alpha = 0, \hat{\beta}$ 36-Month Rolling Window
	MSPE Ratios Relative to No-Change Forecast			
1	**0.989**	1.169	1.050	1.017
3	**0.990**	1.386	1.079	1.062
6	**0.978****	1.377	1.179	1.046
9	**0.963***	1.482	1.352	1.046
12	**0.934***	1.582	1.184	**0.923***
15	**0.931***	1.557	1.005	**0.930****
18	**0.971****	1.544	1.179	1.130
21	**0.986**	1.660	1.410	1.313
24	**0.934***	1.424	1.332	1.215
	Success Ratios			
1	**0.562**	**0.566****	**0.510**	0.494
3	**0.583**	**0.530**	0.490	**0.522**
6	**0.545**	0.480	0.447	0.434
9	0.436	0.473	0.469	**0.506**
12	**0.521**	0.492	0.471	0.487
15	**0.516**	0.485	0.481	**0.523**
18	0.470	0.410	0.422	0.483
21	0.454	0.406	0.432	**0.502**
24	**0.500**	0.443	0.496	**0.540**

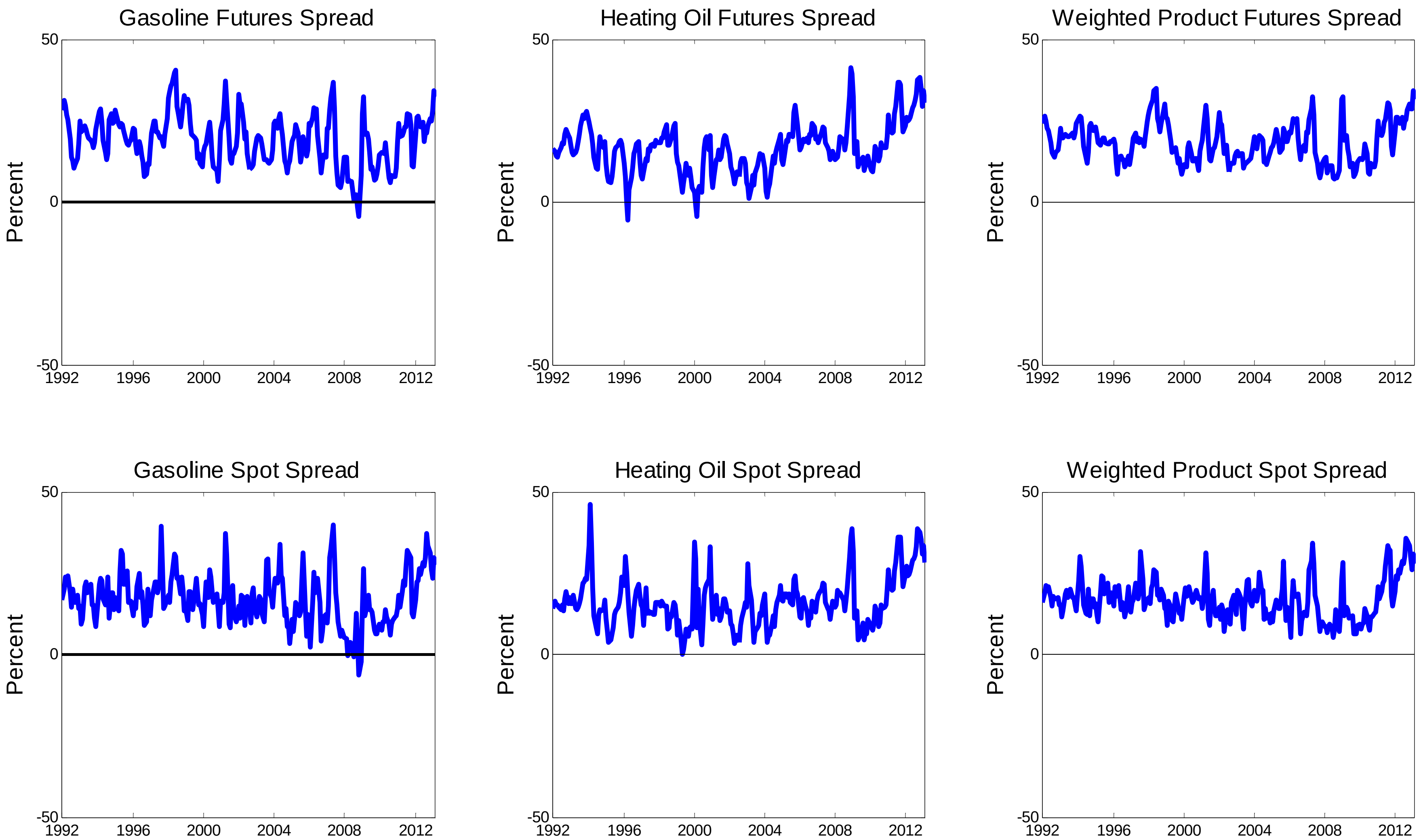
NOTES: Boldface indicates improvements on the no-change forecast. Statistically significant reductions in the MSPE according to the Clark-West test, and statistically significant improvements in directional accuracy according to the Pesaran-Timmermann test are marked using * (5% significance level) and ** (10% significance level).

Figure A1: 3-Month 3:2:1 Futures Crack Spread: 1992.1-2013.3



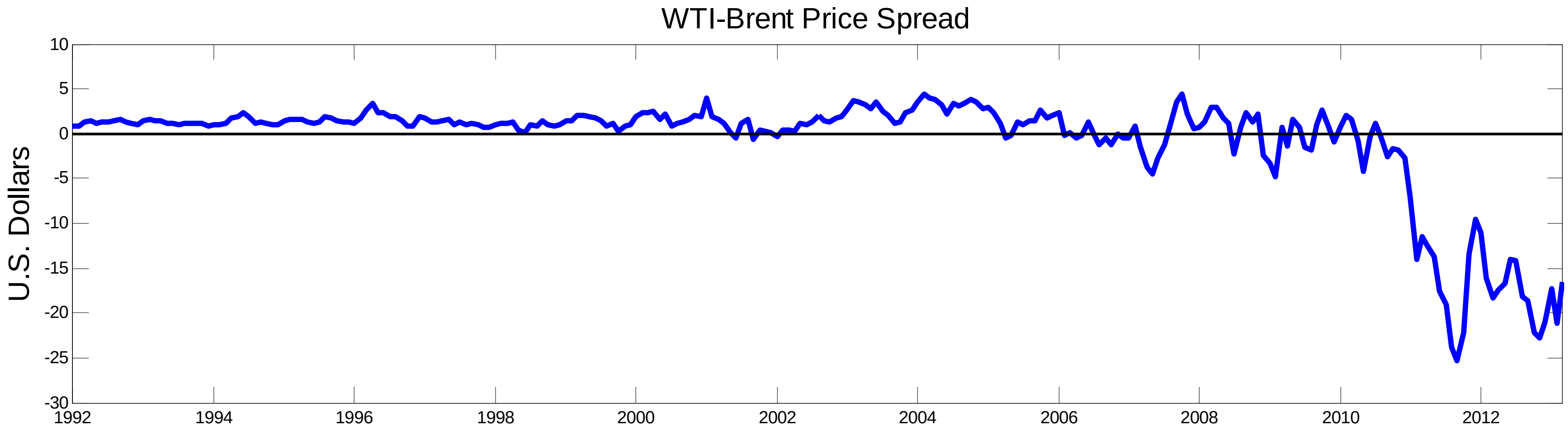
NOTES: The data construction and data sources are described in the paper.

Figure A2: Selected Product Spreads: 1992.1-2013.3



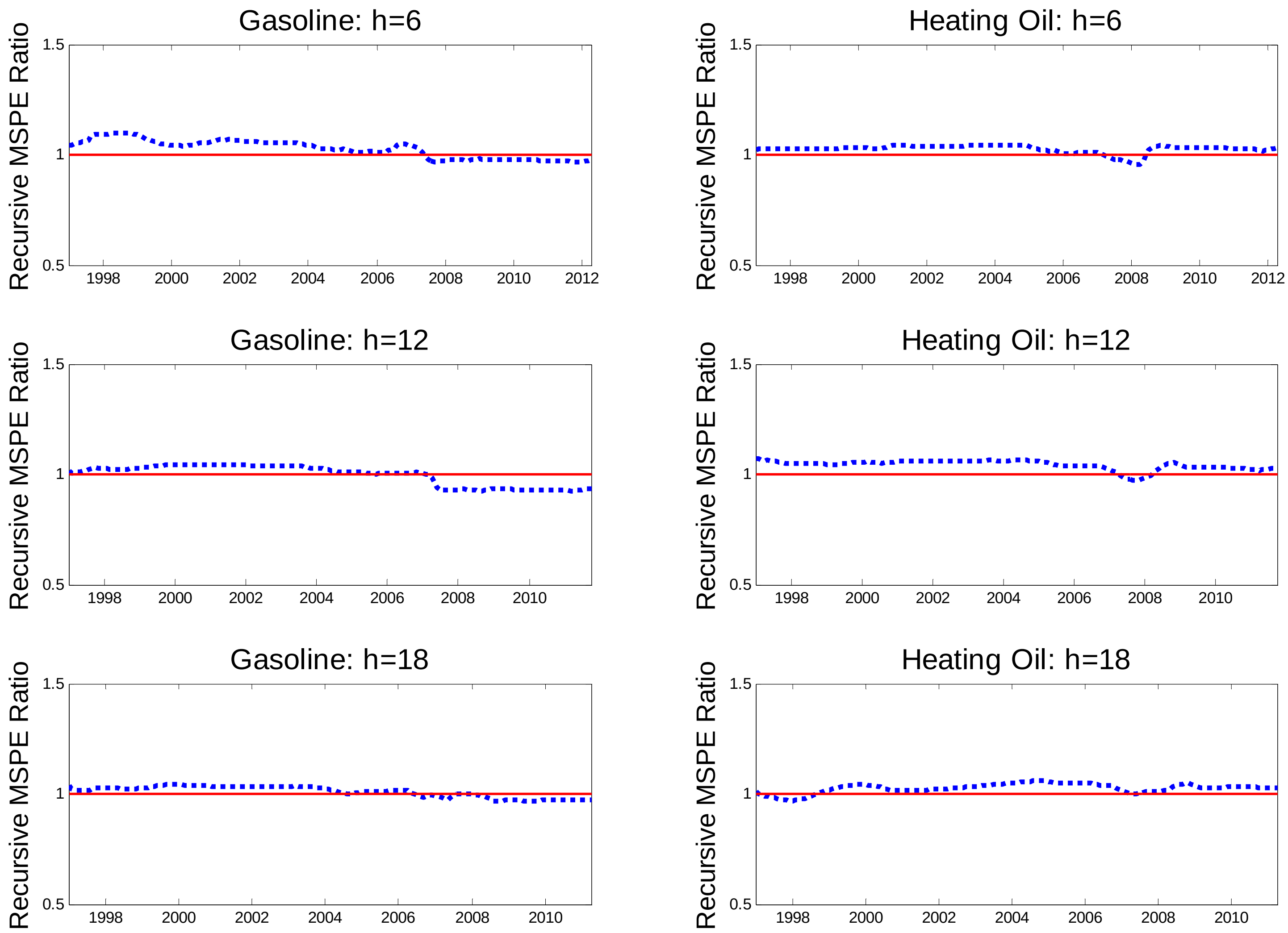
NOTES: The data construction and data sources are described in the paper. All futures spreads refer to 3-month maturities.

Figure A3: Spread of WTI Spot Price over Brent Spot Price



Source: ICE and EIA.

Figure A4: Real-Time Recursive MSPE Ratios of Spot Spread Models Relative to No-Change Forecast of Real U.S. Refiners' Acquisition Cost of Oil at *h*-Month Horizon



NOTES: All models shown have been estimated with $\alpha = 0$ imposed. The plot shows the evolution of the MSPE ratio over the evaluation period since 1997. This increases the reliability of the MSPE estimates and allows the MSPE ratio to stabilize.