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ABSTRACT

What Central Bankers Need to Know about Forecasting Oil Prices*

Recent research has shown that recursive real-time VAR forecasts of the real price of oil tend to be more accurate than forecasts based on oil futures prices of the type commonly employed by central banks worldwide. Such monthly forecasts, however, differ in several important dimensions from the forecasts central banks require when making policy decisions. First, central banks are interested in forecasts of the quarterly real price of oil rather than forecasts of the monthly real price of oil. Second, many central banks are interested in forecasting the real price of Brent crude oil rather than any of the U.S. benchmarks. Third, central banks outside the United States are interested in forecasting the real price of oil measured in domestic consumption units rather than U.S. consumption units. Addressing each of these three concerns involves modeling choices that affect the relative accuracy of alternative forecasting methods. In addition, we investigate the costs and benefits of allowing for time variation in VAR model parameters and of constructing forecast combinations. We conclude that quarterly forecasts of the real price of oil from suitably designed VAR models estimated on monthly data generate the most accurate forecasts among a wide range of methods including forecasts based on oil futures prices, nochange forecasts and forecasts based on models estimated on quarterly data.

JEL Classification: C53, E32 and Q43
Keywords: central banks, forecasting methods, oil futures prices, out-of-sample forecast, quarterly horizon, real price of oil, real-time data and VAR

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1. Introduction

Central banks worldwide rely on real-time forecasts of the quarterly real price of oil. Until recently, it has been common for central banks to employ forecasts based on oil futures prices. This practice has been called into question by recent results that out-of-sample forecasts of the monthly real price of oil based on oil futures prices tend to be less accurate than recursive real-time forecasts based on vector autoregressive (VAR) models that include data on global crude oil production, global real economic activity, the real price of oil, and changes in global above-ground crude oil inventories (see Baumeister and Kilian 2012a,b). How informative these research results are for central bankers is not clear, however, because the monthly forecasts in question differ in several important dimensions from the forecasts central banks worldwide require as an input for policy decisions.

First, central banks are interested in forecasts of the quarterly real price of oil rather than forecasts of the monthly real price of oil because their macroeconomic models tend to be specified at quarterly frequency. This distinction raises several important practical questions for real-time forecasters. For example, is it better to average monthly forecasts of the real price of oil or to forecast from a model estimated at quarterly frequency? Is the appropriate random walk benchmark the most recent quarterly real price of oil or the most recent monthly real price of oil? How does time aggregation to quarterly frequency affect the specification of forecasting models? How does time aggregation affect the properties of conventional central bank oil price forecasts based on oil futures prices?

Second, many central banks are interested in forecasting the Brent price of oil rather than the U.S. refiners' acquisition cost for crude oil imports or the price of West Texas Intermediate crude oil. Given the recent instability in the spread of the Brent price over the WTI price and given the increasing importance of the Brent price as a benchmark for global oil markets, this raises the question of how to model and forecast the real price of Brent crude oil in particular. This task is further complicated by the fact that Brent prices are available only back to mid-1987. Possible modeling choices include, for example, backcasting the Brent price on the basis of alternative oil price series and modeling the spread as a random walk to be added to the baseline forecasting VAR model.

Third, central banks are interested in forecasting the real price of oil measured in domestic consumption units. For example, the European Central Bank requires forecasts of the real price of oil in European consumption units, whereas the Bank of Canada in Canadian consumption units. This requires the inclusion of the real exchange rate in the real-time forecasting model for all countries but the United States. One option is to simply augment the quarterly forecasting model by one variable; another is to treat the quarterly real exchange rate as a random walk. The relative merits of these strategies are unknown.

Each of these departures from the framework studied in Baumeister and Kilian (2012a) involves new modeling choices that may affect the relative accuracy of alternative forecasting approaches. Our objective in this paper is to provide guidelines for central banks worldwide about how to construct the most accurate real-time forecasts of the quarterly real price of oil.

The change from monthly to quarterly forecast horizons also allows us to address several other important modeling issues. The first issue is how to specify the global real economic activity measure in oil market VAR forecasting models. One common choice is the monthly global shipping index originally developed in Kilian (2009); an alternative measure is the OECD estimate of monthly industrial production for the OECD economies and six emerging economies. The set of possible proxies becomes even wider once we allow for the use quarterly data. It includes not only quarterly aggregates of conventional monthly measures, but OECD estimates of quarterly real GDP for the OECD economies. To date nothing is known about the relative merits of these proxies for forecasting the real price of oil. A closely related question is which transformation of the OECD real activity measures (e.g., percent changes, detrended log data) is most successful in the out-of-sample setting.

A second important concern is that the predictive relationships in global oil markets may be subject to smooth structural change. While the use of time-varying parameter vector autoregressive (TVP-VAR) models is not feasible when working with large-dimensional monthly VAR forecasting models, it becomes possible when working with quarterly VAR models. An obvious question is whether modeling possible smooth structural change as a TVP-VAR model improves the accuracy of oil price forecasts relative to linear VAR models.

A third and related concern is that, given the inevitable misspecification of all forecasting models, central banks may be better off relying on forecast combinations rather than one forecasting method only. For example, an important question faced by all central banks is whether a combination of forecasts based on oil futures prices and forecasts based on econometric models is more accurate than model-based forecasts alone.

Our analysis shows that the monthly random walk model is considerably more accurate than the quarterly random walk model, reflecting the informational advantages of using the most recent monthly observation for a given quarter. In fact, it is easy to find short-horizon forecasts that seemingly outperform the random walk benchmark by a wide margin, if the random walk benchmark is based on the most recent quarterly average. The mean-squared prediction error (MSPE) rankings are reversed when using the monthly random walk as the benchmark, however. This result also provides intuition for our finding that quarterly VAR models tend to be less accurate than monthly VAR(12) models in forecasting the quarterly real price of oil. The latter result holds true regardless of which real activity variable, lag order, or estimation method is used, and regardless of how the real activity variable and the real price of oil are specified. It also holds after allowing for smooth structural change in the quarterly model.

In addition, the monthly VAR(12) specification for the real refiners' acquisition cost for crude oil imports is more accurate than quarterly forecasts of the real price of oil based on monthly oil futures prices. This result also holds when forecasting the real price of Brent crude oil and the real price of WTI crude oil. The best way to forecast the latter oil prices is to augment the baseline monthly VAR forecasting model for the real refiners' acquisition cost for crude oil imports with a no-change forecast for the spread of these prices over the U.S. refiners' acquisition cost. Likewise, the most accurate forecasts for the real price of oil in non U.S. consumption units are obtained by scaling the forecast of the U.S. real price of oil by the most recently observed real exchange rate.

Finally, there is little evidence that forecast combinations improve forecast accuracy compared with the best-performing monthly VAR model forecast. Only simple averages of forecasts based on oil futures prices and the monthly VAR(12) model forecasts show any promise at all. Whether a central bank would want to use the latter type of forecast combination depends on which oil price the central bank is concerned with and on how much weight it gives to the objective of directional accuracy.

The remainder of the paper is organized as follows. Section 2 describes the forecasting environment and the construction of the real-time data underlying our analysis. Section 3 focuses on the problem of forecasting the real price of oil in U.S. consumption units. We first discuss the choice of the random walk benchmark for the quarterly real price of oil. Then we show how to generate quarterly forecasts from monthly oil market VAR models and compare the results to conventional forecasts based on oil futures prices and to forecasts from quarterly VAR models. Next we evaluate alternative approaches to extending the baseline results for the U.S. refiners' acquisition cost for crude oil imports to other crude oil benchmarks such as West Texas Intermediate (WTI) crude oil and Brent crude oil. Finally, we explore the merits of alternative proxies for global real activity in monthly and quarterly VAR models, and we investigate the costs and benefits of allowing for time variation in the VAR model parameters. Section 4 discusses how to adapt the analysis to the problem of forecasting the real price of oil in the consumption units of other countries. We focus on the examples of Canada, Norway and the Euro area. In section 5, we examine the question of whether central banks should rely on forecast combinations rather than relying on one forecasting method only. In particular, we ask whether a combination of forecasts based on oil futures prices and forecasts based on econometric models is more accurate than model-based forecasts alone. Section 6 discusses several extensions. The concluding remarks are in section 7.

2. The Forecasting Environment

2.1 Background

The objective throughout this paper is to forecast the quarterly average of the real price of oil at horizons of up to one year. Our focus on the average price is consistent with the fact that agencies such as the U.S. Energy Information Administration (EIA) produce forecasts of the quarterly price of oil. There are two basic approaches to constructing forecasts of the quarterly real price of oil. One option is to forecast the monthly real price of oil for each horizon between 1 and 12 months and to convert these monthly forecasts into quarterly averages. This approach allows one to rely on well-established methods of forecasting the real price of oil at monthly frequency. The other option is to re-specify the forecasting model for quarterly data. We consider both approaches in this paper.

Our analysis covers a wide range of alternative forecasting methods for the quarterly real price of oil including many monthly and quarterly reduced-form VAR forecasting models, monthly and quarterly no-change forecasts, forecasts based on oil futures prices, and forecast combinations. Our simulated out-of-sample exercise mimics the real-time constraints on the availability and reliability of the data used by each forecasting method, providing an indication of how each method would have fared on the last twenty-five years of data. We consider two loss functions. First, we construct the recursive MSPE of each forecasting method relative to the MSPE of a random walk benchmark model. A ratio below unity indicates a reduction in MSPE relative to the random walk benchmark model. The choice of the random walk benchmark is conventional. It does not affect the ranking of the forecasting methods, but facilitates the comparison with earlier results in the literature. Second, we compute the success ratio corresponding to the fraction of times the recursive forecast correctly predicts the direction of change in the real price of oil. The loss functions are evaluated in terms of the level of the real price of oil rather than its log-level because it is the level that matters for policy discussions at central banks.

2.2 The Real-Time Data Set

The use of real-time data raises two distinct complications. One is that even preliminary data often become available only with a lag; the other complication is that data will be continuously revised after they become available. These features of the data require us to keep track of each *vintage* of data, containing the data actually known to real-life forecasters at each point in time, when evaluating each method's simulated out-of-sample accuracy.[1] Our real-time data set builds on the existing real-time database documented in Baumeister and Kilian (2012a) which consists of monthly vintages of real-time

[1] For a more detailed exposition of the real-time data problem the reader is referred to Croushore (2011).

data for 1991.1-2011.12, each of which extends back to 1973.1.

The series included in this database allow the real-time construction of the four model variables underlying the oil market VAR model of Kilian and Murphy (2012): (1) the growth rate of global oil production, (2) the Kilian (2009) shipping index of global real economic activity, (3) the real price of oil (obtained by deflating the nominal price of oil by the U.S. CPI), and (4) the change in global crude oil inventories obtained by scaling U.S. crude oil inventories by the ratio of OECD petroleum inventories over U.S. petroleum inventories. The database also allows the construction of real-time forecasts of the real price of oil based on WTI futures prices.[2] For the purpose of our analysis, we extend this real-time database to include several additional time series that allow the construction of real-time real exchange rates for selected countries and that allow us to explore alternative oil price measures and alternative measures of global real economic activity.

Brent Oil Prices

One addition is spot and futures prices for Brent crude oil traded on the Intercontinental Exchange. The data are provided by Bloomberg. Monthly averages of daily Brent oil prices are only available back to 1987.6. We extrapolated the monthly Brent spot price series back to 1973.1 at the rate of change in the U.S. refiners' acquisition cost for crude oil imports, which is widely considered a good proxy for the global price of crude oil. We also added the corresponding futures price of Brent crude oil at maturities of 1 through 9 months. Maturities of 10 through 12 months are only available starting in April 1994. The Brent data are available in real time and not subject to revisions.

Nominal Exchange Rates for Canada, Norway and the Euro Area

Monthly averages of the daily nominal spot exchange rates for the Canadian dollar, the Norwegian

[2] Specifically, we use the following monthly series from this database: 1) the average daily WTI spot price of crude oil, 2) averages of daily WTI oil futures prices at maturities between 1 and 12 months, 3) an index of bulk dry cargo ocean shipping freight rates, 4) the nominal U.S. refiners' acquisition cost for crude oil imports, 2) world crude oil production, 5) U.S. crude oil inventories, 6) U.S. petroleum inventories, 7) OECD petroleum inventories, 8) the U.S. consumer price index for all urban consumers and 9) the U.S. producer price index for crude oil. The nominal shipping rate data are obtained from Kilian (2009) for 1973.1 through 1984.12 and are extrapolated through 2010.12 using the Baltic Dry Cargo Index (BDI) from Bloomberg.

kroner, and the Euro with respect to the U.S. dollar were obtained from the Federal Reserve Board database. The Euro exchange rate prior to January 1999 was constructed based on the U.S. dollar/ECU exchange rate. The nominal exchange rate data are available in real time by construction.

Consumer Price Indices for Canada, Norway and the Euro Area

For the construction of real-time real exchange rates, monthly consumer price indices for Canada, Norway, the Euro area and the U.S. are obtained from the *Original Release Data and Revisions Database* for the OECD Main Economic Indicators. Vintages start in February 1999 and contain data back to 1973. The missing vintages for 1991.1 to 1999.1 are approximated by mimicking the constraints on the real-time availability of the CPI data. We adjust the ex-post revised OECD CPI data to reflect a one-month delay in the real-time availability of the CPI data to the forecaster.[3] Gaps in the availability of these pseudo real-time CPI data are filled by nowcasting the most recent monthly observation based on the average rate of inflation up to that point in time. This simple nowcasting procedure works well for the U.S. data, as shown in Baumeister and Kilian (2012a). The resulting pseudo real-time data reflect constraints on the real-time availability of the data, but do not reflect data revisions across vintages. There is reason to believe that the latter effect is small, however, given evidence from the U.S. as well as Germany that consumer prices are rarely revised and, if so, only to a small extent.[4]

Alternative Measures of Global Real Economic Activity

Another addition to the database is a monthly index of industrial production for the OECD economies and six major non-OECD economies including China, India, Brazil, South Africa, Indonesia and the Russian Federation (abbreviated as OECD+6). The index is available back to 1973.1 from the OECD's *Main*

[3] Although in the OECD real-time database there tends to be a two-month lag in the availability of CPI data for the countries in question, it can be shown that national central banks provide data on consumer prices with a delay of only one month, making it reasonable to impose a one-month delay.

[4] For the Euro area, matters are more complicated than for Canada and Norway because the real-time data for the harmonized consumer price index (HICP) for the Euro area compiled by the OECD are not compatible with the U.S. CPI data due to benchmark revisions. This fact matters for the construction of real exchange rates (also see Giannone, Henry, Lalik, and Modugno (2010) for related discussion). In constructing the Euro-dollar real exchange rate, we therefore rely on pseudo real-time equivalents for the HICP and U.S. CPI data based on the December 2011 vintage throughout.

Economic Indicator database. Yet another addition is the quarterly real GDP index for all OECD economies from the same source which is based on purchasing power parity weights as of 2005 and spans the period 1973Q1 to 2011Q3. While it is not possible to construct a true real-time version of these global real activity measures that captures data revisions over time, we can construct pseudo real-time data that account for delays in the real-time availability of these data. In constructing these pseudo real-time data we impose a delay of three months for the OECD+6 industrial production data and of two quarters for the OECD real GDP data based on the observable delay at the end of 2011. We nowcast the resulting gaps in the global real activity data by extrapolating the most recent observation at the average rate of growth in the earlier data. Our analysis also accounts for the fact that all subsequent data transformations for these real activity data must be applied in real time.

2.3. The Construction of the Quarterly Real-Time Data

Quarterly real-time data, as required by quarterly VAR forecasting models, may be constructed from this monthly real-time data set as follows. The quarterly growth rate of global oil production is constructed as the log difference of the last monthly observation for each quarter. Similarly, changes in global crude oil inventories are computed as the difference of the last monthly observation for each quarter. Quarterly averages of the (suitably updated) Kilian (2009) index of global real activity and of the real price of oil are constructed as the average of the three monthly real-time observations for each quarter. The same approach applies to the construction of quarterly averages of and quarterly growth rates of industrial production in the OECD+6 economies.

2.4. The Construction of the Ex-Post Revised Quarterly Real Price of Oil

The objective throughout this paper is to forecast the final release of the real price of oil after all revisions have taken place. Allowing for pre-sample observations, the estimation period for monthly data starts in 1974.2. The evaluation period extends from 1992.1 to 2011.6. For quarterly models the estimation period starts in 1974.II and the evaluation period covers 1992.I through 2011.II. When evaluating the forecasting methods, we treat the data up to 2011.6 in the 2011.12 vintage as our proxy for the ex-post revised data.

The implicit premise is that all data revisions underlying the real oil price data have taken place within half a year, which is consistent with evidence presented in Baumeister and Kilian (2012a).

3. Quarterly Forecasts for the United States

The problem of forecasting the quarterly real price of oil has not been studied to date, making it necessary to discuss a number of methodological issues and modeling choices.

3.1. The Random Walk Benchmark

As in the literature on forecasting asset prices, the traditional benchmark in forecasting the real price of oil has been the random walk forecast or no-change forecast (see, e.g., Alquist, Kilian and Vigfusson 2012). The highest frequency at which a no-change forecast of the real price of oil can be constructed is monthly because CPI data are not available at higher frequency. Thus, when forecasting the monthly real price of oil, the random walk benchmark is clearly defined. When forecasting the quarterly real price of oil, in contrast, there are two ways of constructing a no-change forecast. We may rely on the most recent quarterly real price of oil ("quarterly no-change forecast") or we may use the last monthly observation for the real price of oil in the most recent quarter ("monthly no-change forecast"). Which random walk benchmark will have the lower MSPE in practice is not clear ex ante. On the one hand, to the extent that the real price of oil moves up (or down) persistently, one would expect the monthly no-change forecast to have lower squared errors except in the rare event of a turning point in the data. On the other hand, monthly no-change forecasts are noisier by construction than forecasts based on quarterly averages, which will inflate their MSPE.

The first column of Table 1 shows that at forecast horizons of one and two quarters, the monthly no-change forecast is clearly more accurate than the quarterly no-change forecast. For example, the one-quarter-ahead MSPE of the quarterly no-change forecast is 68% higher than that of the monthly no-change forecast. Two quarters ahead the difference is still 11%. At longer horizons, in contrast, the differences are minimal with little to choose between the two random walk forecasting models. We conclude that the monthly no-change forecast is the only credible benchmark for judging the forecasting ability of alternative forecasting methods. Hence, all MSPE results in this paper are normalized relative to the MSPE of the monthly no-change forecast of the quarterly real price of oil.

3.2. Using the Monthly Oil Market VAR Model to Generate Quarterly Forecasts

Although the random walk is a tough benchmark to beat, Baumeister and Kilian (2012a) showed that it is possible to beat the no-change model for the monthly real price of oil in real time at horizons of up to 12 months. The most successful forecasting models in that study are reduced-form VAR models of the real price of oil containing data on global real activity, global oil production, and global oil inventories that matter for the determination of the real price of oil according to economic theory. A natural starting point for our analysis thus is the type of monthly VAR forecasting model found to work well in the analysis in Baumeister and Kilian (2012a):

$$y_t^M = \nu + B_1 y_{t-1}^M + ... + B_{12} y_{t-12}^M + u_t^M, \quad u_t^M \sim (0, \Omega)$$

where y_t^M is a 4×1 vector of monthly model variables containing the growth rate of global crude oil production, the Kilian (2009) business cycle index of global real economic activity, the real U.S. refiners' acquisition cost of crude oil imports, and the change in global above-ground crude oil inventories. Here ν refers to the vector of intercepts, $B_i, i = 1,...,12,$ denotes the 4×4 dimensional matrices of slope parameters, and Ω is the variance-covariance matrix of the innovations. The monthly VAR model is estimated by the method of least squares.[5] Forecasts of the quarterly real price of oil are constructed as the average of the forecasts for each month contained in a given quarter.

It should be noted that, notwithstanding the excellent performance of this forecasting model for the monthly real price of oil in earlier research, there is no a priori reason why this model should be equally accurate at forecasting the quarterly real price of oil. Not only did Baumeister and Kilian only report results for a subset of the relevant monthly horizons, but the monthly forecasts in question will be

[5] Adding more lags is not advisable unless Bayesian estimation methods are used. A monthly BVAR(24) model, for example, yields slightly higher directional accuracy, but also higher MSPEs, especially at longer horizons. Moreover, Bayesian estimation does not improve the accuracy of the VAR(12) model, which is why we focus on the unconstrained VAR model. We also evaluated univariate monthly AR(p) models, $p \in \{6, 12, 24\}$, for the real price of oil, but the results were not as accurate as for the monthly VAR(12) model and are not reported.

correlated. This makes it impossible to infer from the MSPE ratio of a forecast at the 12-month horizon, for example, what the MSPE ratio should be for the quarterly average over the horizons of 10, 11, and 12 months.

Table 1 shows that this forecasting approach is remarkably accurate nevertheless. The monthly VAR(12) model yields MSPE reductions relative to the monthly no-change forecast of 20% one quarter ahead and of 7% two quarters ahead. At longer horizons, the monthly VAR(12) model has about the same MSPE as the benchmark model. Moreover, unlike the no-change forecast, the VAR forecast has directional accuracy ranging from 57% to 69%, depending on the horizon. This compares with a success ratio of 50% under the null hypothesis of no directional accuracy. Such success ratios are remarkably high by the standards of the empirical finance literature (see, e.g., Pesaran and Timmermann 1995). Except for the third quarter, the gains in directional accuracy are statistically significant based on the test of the null of no directional accuracy discussed in Pesaran and Timmermann (2009).[6]

3.3. Oil Futures-Based Forecasts of the Quarterly Real Price of Oil

A central banker would raise the obvious question of how these VAR results compare to conventional quarterly forecasts generated on the basis of oil futures prices. While there are no oil futures prices for the U.S. refiners' acquisition cost for crude oil imports, we may use the expected change in the WTI price of oil to extrapolate from the current real refiners' acquisition cost:

$$R_{t+h|t}^{M} = R_t^{M}\left(1+ f_t^{M,WTI,h} - s_t^{M,WTI} - \pi_t^{M,h}\right), \quad h = 1,...,12, ,$$

where R_t^M denotes the level of the monthly real U.S. refiners' acquisition cost for crude oil imports, $f_t^{M,WTI,h}$ is the log of the monthly average nominal WTI futures price of h months maturity, and $s_t^{M,WTI}$ is the corresponding monthly nominal WTI spot price in logs. Under standard assumptions used by practitioners, $f_t^{M,WTI,h} - s_t^{M,WTI}$ may be viewed as the expected change in the nominal WTI spot price over

[6] Although we report tests of statistical significance for the success ratios in Table 1, we do not provide measures of statistical significance for the MSPE reductions except in the case of the quarterly no-change forecasts and the futures-based forecasts. The reason is that such tests are not available for iterated forecasts subject to regression estimation error (see Clark and McCracken 2009). Nor is it possible to rely on bootstrap methods to simulate the critical values of tests of equal predictive accuracy in our iterated real-time setting.

the next h months (see, e.g., Alquist and Kilian 2010). The term $\pi_t^{M,h}$ denotes the expected cumulative inflation rate over the next h months, which in practice can be approximated based on the cumulative inflation rate over the last h months. Given the small magnitude of the inflation rate compared with fluctuations in the nominal price of oil over the horizons of interest, this approximation is adequate, as shown in Baumeister and Kilian (2012a). The monthly real oil price forecasts generated using this method are averaged by quarter to produce the quarterly forecasts of the real refiners' acquisition cost.

Table 1 shows that the MSPE of the oil futures-based forecast does not significantly improve on the monthly no-change forecast at any horizon.[7] In fact, it is less accurate than the no-change forecast at the two-quarter horizon and about as accurate as the no-change forecast at the one-quarter and three-quarter horizons. Only at the four-quarter horizon, the relative MSPE improves, but the improvement is not statistically significant. This does not mean that the there is no information in the futures-based forecast, however. Table 1 indicates much higher directional accuracy than reported in Baumeister and Kilian (2012a) for the same model evaluated at monthly frequency, illustrating our earlier point that the results for quarterly horizons cannot be inferred from existing results in the literature for monthly horizons. The success ratios range from 52% to 61% and are statistically significant at three of four quarterly horizons, yet they are typically lower than for the monthly VAR(12) model we considered earlier.

3.4. Forecasts from Quarterly Oil Market VAR Models

As discussed in section 2, an alternative approach to generating forecasts of the quarterly real price of oil is to re-specify the VAR model in question at quarterly frequency:

$$y_t^Q = \nu + B_1 y_{t-1}^Q + ... + B_p y_{t-p}^Q + u_t^Q, \quad u_t^Q \sim (0,\Omega),\ p \in \{4,6,8\},$$

where y_t^Q denotes the 4×1 vector of quarterly model variables obtained by time aggregation from the data used in the monthly VAR models. Time aggregation will affect the dynamics of the VAR model, so

[7] Given the absence of parameter estimation error, this test is conducted based on the *DM*-test statistic of Diebold and Mariano (1995).

we explore three alternative lag order settings. Given that a model with more than four autoregressive lags may be too heavily parameterized for unrestricted estimation, we estimate these VAR models alternatively using the method of least squares and the Bayesian estimation method developed by Giannone, Lenza, and Primiceri (2010) for VAR forecasting models.[8] Models estimated using the latter methods are denoted as BVAR models, whereas models estimated by the method of least-squares are denoted as VAR models.

Table 1 shows that the quarterly BVAR(6) model is the most accurate forecasting model among all models estimated on quarterly data. Even the BVAR(6) model, however, tends to have much higher MSPEs than the monthly no-change forecast. At the one-quarter horizon, the loss in accuracy is 58%. Compared with the monthly no-change model, the one-quarter ahead MSPE almost doubles. While the BVAR(6) forecasting model has some directional accuracy, overall, it is clearly dominated by the monthly VAR(12) model. We conclude that quarterly VAR and BVAR models cannot be recommended.

3.5. Alternative Crude Oil Benchmarks

3.5.1. West Texas Intermediate

So far we have focused on the U.S. refiners' acquisition cost for crude oil imports, which traditionally has been a good indicator for the price of oil in global markets. An alternative benchmark that tends to receive more attention in the press is the price of WTI crude oil. The latter price was subject to U.S. government regulation until the early 1980s, making it less suitable for a VAR analysis of the global market for crude oil. Figure 1 illustrates the differences between these oil price series. There are two ways of modeling the quarterly real price of WTI. One approach is to replace the real U.S. refiners' acquisition cost by the real WTI price in the VAR(12) baseline model. This approach disregards the fact that the real WTI price strictly speaking is not appropriate for modeling global oil markets. Table 2 shows

[8] Giannone, Lenza, and Primiceri (2010) propose a method for selecting a Gaussian prior for the VAR parameters in real time. Their approach avoids the temptation of searching for priors that ex post generate more accurate forecasts and preserves the real-time nature of the forecasting exercise. The prior mean for all model variables, including the real price of oil, is chosen such that VAR coefficients are shrunk toward independent white noise under the assumption of stationarity. The degree of shrinkage is determined by the marginal data density.

that this approach still works reasonably well in practice, but the extent of the gains in accuracy relative to the monthly no-change forecast is somewhat diminished. For example, whereas the same type of model in Table 1 produced MSPE reductions of 20% one quarter ahead, the corresponding reduction in Table 2 is only 7%. Likewise, the one-quarter ahead directional accuracy falls from 69% to 65%.

An alternative and more appealing approach is to retain the baseline VAR model of Table 1, but to convert the resulting forecasts to the WTI benchmark. This conversion requires a forecast of the spread of the WTI price over the U.S. refiners' acquisition cost for crude oil imports. A parsimonious way of forecasting this spread is to use a no-change forecast. Table 2 shows that this alternative approach indeed works better. For example, it produces an MSPE reduction of 15% and a success ratio of 69% one quarter ahead. Overall, these results are similar to those for the baseline monthly VAR(12) model in Table 1.

The modified monthly VAR(12) model based on the spread also is more accurate than forecasts based on WTI futures. In fact, the futures-based model tends to have higher MSPEs than the monthly no-change forecast. While its directional accuracy is higher than that of the monthly no-change forecast, futures-based forecasts have lower directional accuracy than the suitably modified monthly VAR(12) model. Finally, Table 2 shows that the quarterly no-change forecast and a range of quarterly VAR forecasting models including the BVAR(6) model do not perform well by any metric.

3.5.2. Brent

Traditionally, the spread between different crude oil benchmarks has been stable over time. An interesting recent development in global oil markets has been that the spread of the price of Brent crude oil has grown disproportionately relative to the price of U.S. benchmarks such as the WTI. Indeed, some observers have suggested that the marginal barrel of oil today is being priced at the Brent benchmark, making the Brent price de facto a measure of the global price of crude oil. The lower panel of Figure 1 shows the evolution of the spread of the Brent price over the U.S. refiners' acquisition cost for crude oil imports and the corresponding spread of the WTI price over the U.S. refiners' acquisition cost for crude oil imports since 1992. Although the implicit spread between Brent and WTI has widened since 2011, the spread of the Brent price over the U.S. refiners' acquisition cost is not unusual by historical standards.

As in the case of the WTI price, there are two ways of modeling the real price of Brent crude oil. One approach is to substitute the real Brent price for the real refiners' acquisition cost in the baseline monthly VAR(12) model. Given that Brent prices do not exist prior to 1987.6, this approach requires backcasting the Brent price at the rate of change in the U.S. refiners' acquisition cost. The other approach is to retain the original model, but to treat the Brent price spread as a random walk in forecasting the quarterly real price of Brent. The latter approach does not require any backcasting of the Brent price data. Table 3 shows that both approaches work well, but the model based on the Brent price spread overall appears slightly more accurate. In particular, the latter model has lower MSPE at short horizons and significant directional accuracy at all horizons.

In contrast, forecasts based on Brent futures prices cannot be recommended. The futures-based model has much higher MSPE than the monthly no-change forecast and no significant directional accuracy. Likewise, the quarterly no-change forecast and the quarterly VAR models, while superior to the forecast based on Brent oil futures prices, do not perform well.

3.6. Alternative Measures of Global Real Activity

One of the reasons that VAR forecasting models tend to be more accurate than univariate forecasting models of the real price of oil is the inclusion of a proxy for global real economic activity (see Alquist, Kilian and Vigfusson 2012). In the baseline model we rely on the monthly global shipping index originally developed in Kilian (2009) that by now has become standard in modeling the real price of oil. This global business cycle index, while appealing for reasons discussed in Kilian (2009), is not the only possible choice, however, and little is known about the trade-offs between different specifications of this variable. One alternative is the use of OECD data on monthly industrial production in the OECD economies and in six emerging economies (China, India, Brazil, Russia, South Africa, and Indonesia). We explore three transformations of these industrial production data: A specification in growth rates, a business cycle index obtained by applying a one-sided HP-filter to these data, and a business cycle index obtained by linear deterministic detrending.[9] All these transformations are implemented in real time, as are the corresponding transformations underlying the shipping index.

For expository purposes, Table 4 focuses on the baseline monthly VAR(12) model. We consider all three oil price specifications. Table 4 shows that using the shipping index always produces lower MSPE ratios than using industrial production, regardless of the data transformation. When it comes to directional accuracy, no model uniformly dominates all others, but on average the specification involving the growth rate of industrial production has slightly higher directional accuracy than the specification involving the shipping index. This gain in directional accuracy comes at the cost of a higher MSPE, however.

We also examined this same question for the quarterly VAR specification where in addition to the quarterly version of the industrial production index for the OECD+6 economies and a quarterly version of the Kilian shipping index, we employed the OECD estimate of quarterly real GDP in the OECD economies.[10] Extensive comparisons of a wide range of models showed that the quarterly version of the shipping index for all three oil price measures tends to yield lower MSPEs and higher directional accuracy than all other real activity measures. None of these quarterly models, however, comes close to matching the accuracy of the monthly VAR models.

3.7. Does Allowing for Time Variation Help in Forecasting the Quarterly Price of Oil?

There are many economic reasons to expect linear VAR models of the global market for oil to be at best an approximation to a more general TVP-VAR model. For example, capacity constraints in oil production and in oil inventory holdings, delays in oil production responses to investment decisions, and changes in energy intensity over time may cause the dynamic relationship between oil market variables to evolve over time. Indeed, TVP-VAR models have been used to describe the evolution of the global market for

[9] We implement the one-sided HP filter, as discussed in Stock and Watson (1999).

[10] In related work, Baumeister and Peersman (2012) used a measure of quarterly world industrial production from the *United Nations Monthly Bulletin of Statistics*. Although this index is available in real time, it has not been updated since 2008.Q3 pending the implementation of ISIC Revision 4. For that reason, this index was not included in our comparison.

crude oil, although those models have been smaller in dimension and simpler than the VAR model underlying our analysis (see, e.g., Baumeister and Peersman 2012).

The fact that TVP-VAR models seem plausible ex ante does not necessarily mean that TVP-VAR models should replace VAR models in forecasting the real price of oil, however. An obvious concern is that in practice TVP-VAR models may over-parameterize the data, resulting in poor out-of-sample accuracy. While several recent studies have reported that TVP-VAR model forecasts may improve on VAR forecasts of quarterly macroeconomic aggregates (see, e.g., Cogley, Morozov, and Sargent 2005, D'Agostino, Gambetti, and Giannone 2012, D'Agostino and Surico 2012), the usefulness of the TVP-VAR model for forecasting the real price of oil has yet to be explored.

One immediate problem with the TVP-VAR approach is that estimation of such models requires computationally intensive nonlinear estimation methods that prohibit applications to models with a large number of variables and/or autoregressive lags. For example, it is not possible in practice to estimate monthly VAR oil market models with 12 or more lags allowing for time variation in the parameters. This means that at best some of the quarterly models of oil markets may be estimated allowing for time variation in the parameters. For expository purposes, we focus on the TVP-VAR(4) model:

$$y_t^Q = \nu_t + B_{1,t} y_{t-1}^Q + \ldots + B_{4,t} y_{t-4}^Q + u_t^Q, \quad u_t^Q \sim N(0, \Omega_t)$$

where y_t^Q is a 4×1 vector of quarterly model variables containing the growth rate of global crude oil production, the Kilian (2009) real activity index, the real U.S. refiners' acquisition cost of crude oil imports and the change in global crude oil inventories. Here ν_t refers to the vector of time-varying intercepts, and $B_{i,t}, i = 1, \ldots, 4,$ denotes 4×4 dimensional matrices of time-varying slope parameters. Given that each model parameter is allowed to evolve according to a random walk, four lags allow for considerable flexibility in fitting the data. The model also allows for time variation in the variance-covariance matrix of the innovations, Ω_t.

The TVP-VAR model is re-estimated recursively in real-time using Bayesian techniques, as described in Kim and Nelson (1999). For further details, the reader is referred to the technical appendix to

Baumeister and Peersman (2012).[11] There are no closed form solutions for the forecasts of the real price of oil in the TVP-VAR model. Instead, forecasts are obtained by simulating the posterior predictive density. In practice, at each point in time forecasts are obtained by first randomly drawing 5,000 starting values for the model parameters and simulating for each starting value the future path of the model parameters based on their law of motion. For each such path we then simulate the evolution of the quarterly price of oil, conditional on the four most recent data points, by randomly drawing from the time-varying distribution of the error terms. This results in 5,000 future paths of the quarterly real price of oil up to the maximum horizon of interest. For each forecast horizon, we compute various summary measures of the central tendency of the simulated forecasts.[12]

A natural starting point is the posterior mean of the forecasts obtained by Monte Carlo integration. Table 5 shows that the TVP-VAR model has somewhat lower MSPE at the one-quarter horizon than both the quarterly VAR(4) model and the quarterly BVAR(6) model, which we showed to be most accurate among all quarterly VAR and BVAR models. This ranking is reversed at horizons of two, three and four quarters, however. More importantly, from the point of view of applied users, the TVP-VAR(4) model has much higher MSPE than the monthly VAR(12) model at all horizons. For example, its one-quarter-ahead MSPE ratio is 1.45 compared with 0.80 for the linear monthly VAR model. Nor does the TVP-VAR model systematically improve on the directional accuracy of the monthly VAR(12) forecast. Although the TVP-VAR(4) model provides some gains in directional accuracy at longer horizons, its directional accuracy is much reduced at the one-quarter horizon.

An obvious concern is that TVP-VAR(4) forecasts obtained by Monte Carlo integration may be sensitive to outliers. For comparison we also report forecasts based on the trimmed posterior mean and the posterior median at each horizon. Table 5 shows that controlling for outliers does not alter the

[11] We do not refer to this model as a TVP-BVAR model because the priors for this model are diffuse, in contrast to the informative priors developed for the VAR model by Giannone, Lenza and Primicieri (2010) that we used for our BVAR models.

[12] Our approach differs from D'Agostino, Gambetti and Giannone (2012) and D'Agostino and Surico (2012) who condition on the pointwise medians of the posterior coefficient estimates in generating their point forecasts. Instead, we construct our point forecasts by integrating over the full range of posterior forecasts without taking computational shortcuts.

substance of the earlier results for the posterior mean forecast. We conclude that allowing for time variation in the VAR parameters does not improve the accuracy of the forecasts of the quarterly real price of oil. Quarterly TVP-VAR models based on conventional prior specifications tend to be much less accurate than standard monthly VAR models. The remainder of the paper therefore focuses on linear monthly VAR forecasting models.

4. Forecasting the Quarterly Real Price of Oil in Foreign Consumption Units

Oil in global markets is predominantly traded in dollars. When forecasting the real price of oil it is common to deflate the nominal price of oil by the U.S. CPI. This allows one to measure the real cost of purchases of oil in terms of U.S. consumption goods. This practice is perfectly adequate for the Federal Reserve Board, but central banks in other countries are concerned with the real cost of purchasing crude oil in terms of their domestic basket of consumption goods. Moreover, the U.S. benchmarks for crude oil such as the U.S. refiners' acquisition cost or WTI need not be representative for other countries. For example, the European Central Bank views the price of Brent crude oil as the relevant benchmark, as does the Norges Bank in Norway.

In this section, we explore how to adapt our analysis to generate forecasts of the real price of oil of the type required by the Bank of Canada, the Norges Bank and the European Central Bank, as three representative examples. Whereas the latter two central banks focus on the real price of Brent crude oil, the Bank of Canada has traditionally focused on the real price of WTI crude oil.

For Canada, we take as our starting point the best forecasting model for the price of WTI in terms of U.S. consumption goods. Table 2 suggests that we take as our starting point the monthly VAR(12) model for the U.S. refiners' acquisition cost for crude oil imports. That forecast may be converted to the WTI benchmark using a simple no-change forecast of the spread of the WTI price over the U.S. refiners' acquisition cost for crude oil imports. This leaves the conversion from U.S. consumption goods to Canadian consumption goods, which requires a forecast of the Canadian-U.S. real exchange rate. There are two ways of generating a forecast for this real exchange rate. One approach is to rely on a simple no-change forecast of the real exchange rate, given that fluctuations in the real exchange rate are dominated by fluctuations in the nominal exchange rate.[13] The advantage of this approach is that we can rely on the same forecasting model we already showed to work well for the United States.

The other approach is to augment the original global oil market VAR model by the real exchange rate, resulting in the five-variable VAR(12) model. Which approach is more accurate will depend in part on how close the real exchange rate is to a random walk. It also will depend on how much the estimation of the additional model parameters will inflate the MSPE of the model in finite samples. The entries on the right of panel (a) in Table 6 show that the approach of treating the real exchange rate as a random walk works quite well. There is some increase in the one-quarter ahead and two-quarter ahead MSPE ratios compared to the corresponding result in Table 2, but that is to be expected, for now we also must account for uncertainty in the real exchange rate. Nevertheless, Table 6 shows some reductions in the MSPE relative to the monthly no-change forecast one quarter and two quarters ahead. Three and four quarters ahead, the MSPE ratios are about as high as that of the monthly no-change forecast. The directional accuracy of the model actually improves from 69% to 73% at the one-quarter horizon and is statistically significant at the 5% level. At higher horizons, the observed gains in directional accuracy are somewhat lower than for the U.S. model in Table 2 and not statistically significant.

Including the real exchange rate in the VAR model, as shown on the left in panel (a) of Table 6, produces MSPE ratios more in line with Table 2, but at the cost of losing all directional accuracy beyond the first quarter. Likewise VAR models that replace the real U.S. refiners' acquisition cost for imports with the real WTI price of oil (rather than forecasting the price spread) proved inferior regardless of how the real exchange rate is modeled. The latter results are not shown to conserve space.

Much the same approach also works for Norway (panel b) and the Euro area (panel c) with the difference that now we are relying on the no-change forecast of the spread of the Brent price over the U.S. refiners' acquisition cost. The latter approach also avoids having to backcast the Euro area exchange rate

[13] In practice, we found the last monthly observation of the most recent quarter to be a better predictor than the most recent quarterly average real exchange rate. Only the former results are reported.

further than the early 1990s. The results in Table 6 are quite similar to those shown for the United States in Table 3. For Norway and the Euro area, the reduction in the MSPE ratio is 10% one quarter ahead. Two quarters ahead, the two models' MSPEs are essentially tied with the monthly no-change forecast and three and four quarters ahead their MSPE is somewhat higher. On the other hand, there is strong and mostly statistically significant evidence of directional accuracy, even four quarters ahead. For example, the success ratio for the Euro area is 68% one quarter ahead and 59% four quarters ahead.

Even granting that the MSPE reductions for Canada, Norway and the Euro area are somewhat less pronounced than when forecasting the corresponding real price of oil in U.S. consumption units, these forecasts remain useful for central banks given their directional accuracy.

5. Forecast Averaging

It is common in applied work to guard against model misspecification by averaging results of alternative forecasting models. For example, a question of obvious interest to central bankers is whether they should abandon conventional forecasts of the real price of oil based on oil futures prices in favor of vector autoregressive forecasts or rely on a weighted average of these two forecasts. In response to this question we now explore the possibility that a linear combination of several forecasts is more accurate than any one of the forecasting models. Such a finding would be in line with evidence in Stock and Watson (2003), for example, who provide an example of how simple combination forecasts may improve on the best of the available forecasting methods.

Table 7 presents results for several oil price measures. In each case we focus on the equal-weighted combination of the forecast from the best-performing monthly VAR(12) model and the forecast based on oil futures prices. The first column shows that forecast averaging may indeed reduce the MSPE of the forecast of the U.S. real refiners' acquisition cost, especially at longer horizons, but this improvement comes at the expense of lower directional accuracy. Qualitatively similar results hold for the real WTI price in the second column, whereas for the real Brent price in the third column there are no improvements in accuracy at all. Thus, overall the evidence is mixed. Whether a central bank would want to use this type of forecast combination depends on which oil price the central bank is concerned with and on how much weight it gives to the objective of directional accuracy.

Other forecast combinations (not shown to conserve space) only proved less accurate. For example, combining the quarterly TVP-VAR model with the monthly VAR(12) model systematically worsened the forecast accuracy compared with the best-performing VAR(12) model. Moreover, combinations involving additional forecast methods in various combinations had higher MSPE than the combination shown in Table 7. With the partial exception of the results in Table 7 there is no indication that such forecast combinations can be recommended to central banks.

6. Extensions

6.1. Longer Forecast Horizons

Many central banks are interested in forecasts of the quarterly real price of oil for horizons as high as two years. Our focus so far has been on forecasts at horizons of up to four quarters only. Indeed, one would not expect the forecasting methods we considered to be more accurate than a no-change forecast at longer horizons. Further extensive analysis (not shown to conserve space) indicates that, at the two-year horizon, the monthly VAR forecast of the quarterly real price of oil has an MSPE ratio of about 1.1 relative to the monthly no-change forecast. Although forecasts from the monthly VAR model retain some directional accuracy at these longer horizons, the success ratios are at most 0.58 and never statistically significant beyond the five-quarter horizon. On the other hand, the quarterly no-change forecast yields MSPE reductions between 2% and 6% relative to the monthly no-change forecast. This finding suggests that we replace the monthly VAR model forecast by the quarterly no-change forecast at horizons beyond one year.

The latter proposal is not without limitations, however. In policy settings the path of oil prices receives much attention. One potential concern is that replacing the monthly VAR model forecasts at horizons beyond four quarters by the quarterly no-change forecast may introduce a discontinuity in the forecast path between the four-quarter and five-quarter horizons. One way of addressing this concern is to treat the monthly VAR model forecast for the fourth-quarter horizon as the forecast for the remaining quarters, which ensures a smooth forecast path. Table 8 shows that this alternative proposal results in similar forecast accuracy at horizons beyond one year than the baseline monthly VAR model for the U.S. refiners' acquisition cost for crude oil imports. In other words, the cost of insisting on a smooth forecast path is an increase in the MSPE of between 10% and 15%.

6.2. The Link between Forecasts of the Real Price of Oil and the Nominal Price of Oil

Based on economic theory, a model involving only real variables is the natural framework in which to forecast the real price of oil. One potential concern is that our forecasting success for the real price of oil may simply reflect the monthly VAR model's ability to forecast inflation at short horizons. It can be shown that this is not the case (see Alquist, Kilian and Vigfusson 2012). Indeed, this point is quite obvious because much of the variability in the nominal price of oil stems from variation in the real price of oil rather than variation in inflation. Nor is it necessary to develop a separate forecasting model for the nominal price of oil. Given the CPI forecasts routinely generated by central banks, it is straightforward to generate the implied forecast path for the nominal price of oil from our VAR forecasts.

7. Conclusion

Central banks rely on forecasts of the real price of oil when making policy decisions. We provided strong evidence that the U.S. real price of oil may be forecast several quarters ahead, provided suitable forecasting methods are employed. For monthly VAR(12) models containing data on global crude oil production, global real economic activity, global crude oil inventories and the U.S. real price of oil, for example, we obtained real-time reductions in the MSPE between 7% and 20% at the one-quarter horizon and between 2% and 7% at the two-quarter horizon, depending on the choice of the oil price series. At longer horizons, the MSPEs of these models are similar to those of the monthly no-change forecast. These models are much more accurate at the one-quarter and two-quarter horizon than conventional central bank forecasts based on oil futures prices. Futures-based forecasts of the real WTI price and of the real Brent price have particularly large out-of-sample MSPEs. For example, using Brent futures prices to forecast the real price of Brent crude oil one quarter ahead increases the MSPE by 69% relative to using the no-change forecast.

In addition, the same monthly VAR(12) forecasting models yield strong and often statistically significant gains in directional accuracy. For example, at the one-quarter horizon the success ratio ranges from 69% to 72% and even at the four-quarter horizon the success ratio is between 56% and 60%. Such directional accuracy is high by the standards of the empirical finance literature (see, e.g., Pesaran and Timmermann 1995). It also is higher than the directional accuracy of forecasts based on oil futures spreads, especially at short horizons.

Central banks outside the United States face the more complicated problem of forecasting the quarterly real price of oil in terms of domestic consumption units. This involves a forecast of the real exchange rate in addition, making it even more challenging to generate accurate real-time forecasts. For the examples of Canada, Norway and the Euro area, we compared several alternative forecasting approaches and showed that even for those countries real-time MSPE reductions between 7% and 10% are possible at the one-quarter horizon and up to 3% at the two-quarter horizon. At longer horizons the MSPEs of the most accurate forecasting models are about as good as the monthly no-change forecast in the case of Canada, and slightly worse in the case of Norway and of the Euro area. While the MSPE reductions are at best modest, the directional accuracy of these forecasts remains consistently high in all three cases. It ranges from 65% to 73% at the one-quarter horizon, for example, and lies between 55% and 60% at the four-quarter horizon.

Much of our analysis focused on comparing alternative approaches to forecasting the quarterly real price of oil. The forecasting methods we discussed in this paper were specifically designed to reflect the forecasting environment faced by central bankers. First, we demonstrated that, among the no-change forecasts, a forecast based on the most recent monthly observation is far more accurate in the short run than the no-change forecast based on the most recent quarterly average. This result reflects the persistent increases and decreases in the real price of oil. At longer horizons, there is little to choose between these methods. Thus the choice of the random walk benchmark is crucial and choosing an inferior benchmark can make alternative forecasting models spuriously accurate.

Second, we showed that VAR forecasting models based on monthly data are far more accurate in all dimensions than the corresponding VAR forecasting models estimated on quarterly data. This result is robust to various changes in the specification of the quarterly model and in the estimation method. Third, when modeling the WTI price or the Brent price, working with a baseline VAR model for the U.S. real refiners' acquisition cost for crude oil imports and treating the spread of the WTI and Brent prices over the U.S. refiners' acquisition cost for crude oil imports as a random walk without drift yields more accurate forecasts than replacing the real oil price series in the original VAR model. Likewise, relying on a no-change forecast of the real exchange rate in conjunction with the original VAR forecasting model for the U.S. real price of oil is more accurate than augmenting the original VAR model by the real exchange rate. This is true even when using Bayesian estimation methods.

Fourth, we provided evidence that the shipping index of global economic activity proposed by Kilian (2009) indeed lowers the MSPE of VAR forecasting models of the quarterly real price of oil compared with alternative measures including world real GDP or industrial production for the OECD and six emerging economies. This result does not depend on how these alternative measures of real activity are transformed during the analysis. While the Kilian (2009) global shipping index also has high directional accuracy, specifications based on the growth rate of OECD+6 industrial production in some cases yield even higher directional accuracy by a small margin, but at the expense of a lower MSPE.

Fifth, we found that allowing for time variation in the VAR parameters does not improve forecast accuracy. Finally, we demonstrated that forecast combinations do not systematically improve the accuracy of the forecast of the quarterly real price of oil and often worsen it. The most interesting finding was that an equal-weighted average of the VAR(12) model forecast and the forecast based on oil futures prices reduces the MSPE for the refiner's acquisition cost and for the WTI oil price beyond the one-quarter horizon, but increases the MSPE for the Brent oil prices compared with the VAR(12) model forecast. Moreover, reductions in the MSPE, if any, came at the expense of lower directional accuracy.

There may be alternative forecasting methods that could further improve the accuracy of short-horizon forecasts, however. One question left unexamined in this paper is whether factor-augmented VAR forecasting models – or alternatively large-scale Bayesian VAR forecasting models of the type discussed in Banbura, Giannone, and Reichlin (2010) – would be able to improve on existing VAR forecasting models of the quarterly real price of oil. One problem with the use of such large-scale models is the difficulty of obtaining suitable real-time data. Another possible extension would involve the use of mixed-frequency forecasting methods in the tradition of the Mixed Data Sampling (MIDAS) model or mixed frequency VAR models (see, e.g., Andreou, Ghysels, and Kourtellos 2010; Schorfheide and Song 2011). For example, one could explore the additional forecasting ability of daily nominal spot and futures prices for the quarterly real price of oil.

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Table 1. Real-Time Accuracy of Recursive Forecasts of the Quarterly Real U.S. Refiners' Acquisition Cost for Imports

Quarterly Horizon	Quarterly No-Change Forecast	Monthly VAR(12)	Oil Futures	VAR(p) $p=4$	VAR(p) $p=6$	VAR(p) $p=8$	BVAR(p) $p=4$	BVAR(p) $p=6$	BVAR(p) $p=8$
				(a) MSPE Ratio					
1	1.68	**0.80**	**0.99**	1.59	1.86	2.18	1.65	1.58	1.62
2	1.11	**0.93**	1.06	1.24	1.38	1.45	1.18	1.15	1.18
3	**0.98**	1.02	**0.99**	1.16	1.20	1.24	1.11	1.07	1.12
4	**0.99**	1.01	**0.93**	1.08	1.11	1.23	1.07	1.04	1.11
				(b) Success Ratio					
1	**0.63***	**0.69***	**0.59***	**0.55**	**0.62***	**0.56**	**0.56**	**0.63***	**0.67***
2	**0.61***	**0.58***	**0.52**	**0.53**	**0.58**	**0.53**	**0.54**	**0.63****	**0.60****
3	**0.59****	**0.57**	**0.57***	0.46	0.49	**0.50**	**0.51**	**0.56**	**0.54**
4	**0.61***	**0.60***	**0.61***	0.47	**0.60**	**0.53**	**0.51**	**0.58**	**0.55**

NOTES: All MSPE ratios have been normalized relative to the monthly no-change forecast. Boldface indicates an improvement on the monthly no-change forecast. With the exception of the oil futures forecast and the quarterly random walk forecast, the statistical significance of the real-time recursive MSPE ratio cannot be assessed because no valid statistical tests are available in the literature. None of the improvements, if any, produced by the oil futures forecast and the quarterly random walk forecast in this and subsequent tables are statistically significant. For the success ratio improvements that are statistically significant at the 5% (10%) level based on test of the null of no directional accuracy in Pesaran and Timmermann (2009) are marked * (**).

Table 2. Real-Time Accuracy of Recursive Forecasts of the Quarterly Real WTI Price

Quarterly Horizon	Quarterly No-Change Forecast	Monthly VAR(12)	Monthly VAR(12) with No-Change Forecast for Spread	Oil Futures	Quarterly BVAR(6)	Quarterly BVAR(6) with No-Change Forecast for Spread
			(a) MSPE Ratio			
1	1.67	**0.93**	**0.85**	1.06	1.57	1.55
2	1.11	**0.97**	**0.94**	1.13	1.07	1.09
3	**0.99**	1.02	1.01	1.07	**0.97**	1.00
4	**0.99**	1.01	1.00	**1.00**	**0.97**	1.01
			(b) Success Ratio			
1	**0.67***	**0.65***	**0.69***	**0.54***	**0.55**	**0.60***
2	**0.62***	**0.61***	**0.61***	**0.52**	**0.58**	**0.59**
3	**0.64***	**0.51**	**0.58**	**0.57***	**0.59**	**0.59**
4	**0.59***	**0.56**	**0.60***	**0.59***	**0.64**	**0.61**

NOTES: See Table 1.

Table 3. Real-Time Accuracy of Recursive Forecasts of the Quarterly Real Brent Price

Quarterly Horizon	Quarterly No-Change Forecast	Monthly VAR(12)	Monthly VAR(12) with No-Change Forecast for Spread	Oil Futures	Quarterly BVAR(6)	Quarterly BVAR(6) with No-Change Forecast for Spread
			(a) MSPE Ratio			
1	1.68	**0.92**	**0.89**	1.69	1.61	1.67
2	1.11	**0.98**	**0.98**	1.44	1.16	1.19
3	**0.99**	1.01	1.04	1.22	1.06	1.07
4	**0.99**	1.01	1.03	-	1.06	1.06
			(b) Success Ratio			
1	**0.63***	**0.72***	**0.68***	**0.51**	**0.59**	**0.59**
2	**0.61***	**0.61***	**0.62***	**0.53**	**0.62**	**0.62**
3	**0.59***	**0.51**	**0.57****	**0.53**	**0.55**	**0.55**
4	**0.61***	**0.60***	**0.57****	-	**0.55**	**0.55**

NOTES: See Table 1. Brent futures prices with a maturity of 10 through 12 months are not available for our evaluation period.

Table 4. Real-Time Accuracy of Recursive Forecasts of the Quarterly Real Price of Oil: Alternative Monthly Measures of Global Real Activity in the VAR(12) Model

				MSPE Ratio Quarterly Horizon				Success Ratio Quarterly Horizon			
Source	Transformation	Measure	Coverage	1	2	3	4	1	2	3	4
				U.S. Refiners' Acquisition Cost for Imports							
Kilian (2009)	-	Shipping Index	World	**0.80**	**0.93**	**1.02**	**1.01**	0.69*	0.58*	0.57	0.60*
OECD	Growth Rate	Industrial Production	OECD+6	0.83	0.96	1.06	1.06	**0.72***	**0.56***	**0.59***	**0.61***
OECD	HP Filtered	Industrial Production	OECD+6	0.88	1.01	1.15	1.19	0.68*	0.55*	0.49	0.47
OECD	Linearly Detrended	Industrial Production	OECD+6	0.83	1.00	1.10	1.10	0.71*	0.60*	0.59	0.56
				WTI Price							
Kilian (2009)	-	Shipping Index	World	**0.93**	**0.97**	**1.02**	**1.01**	0.65*	0.61*	0.51	0.56
OECD	Growth Rate	Industrial Production	OECD+6	0.93	1.00	1.05	1.03	**0.67***	**0.58***	**0.58***	**0.63***
OECD	HP Filtered	Industrial Production	OECD+6	0.94	1.01	1.10	1.11	0.71*	0.55**	0.53	0.51
OECD	Linearly Detrended	Industrial Production	OECD+6	0.96	1.03	1.09	1.05	0.64*	0.58*	0.57	0.57
				Brent Price							
Kilian (2009)	-	Shipping Index	World	**0.92**	**0.98**	**1.01**	**1.01**	0.72*	0.61*	0.51	0.60*
OECD	Growth Rate	Industrial Production	OECD+6	1.01	1.07	1.11	1.09	**0.64***	**0.62***	**0.59***	**0.63***
OECD	HP Filtered	Industrial Production	OECD+6	1.03	1.10	1.17	1.21	0.65*	0.56*	0.50	0.52**
OECD	Linearly Detrended	Industrial Production	OECD+6	1.08	1.13	1.16	1.14	0.67*	0.60**	0.61**	0.57

NOTES: All MSPE ratios have been normalized relative to the monthly no-change forecast. For each oil price series the measure with the lowest average MSPE and the measure with the highest average success ratio is shown in bold. The penalty parameter for the one-sided HP filter was set to 129,600 for all monthly data following Ravn and Uhlig (2002). Statistically significant success ratios at the 5% (10%) level are marked * (**).

Table 5. Real-Time Accuracy of Recursive Forecasts of the Quarterly Real U.S. Refiners' Acquisition Cost from a Quarterly TVP-VAR(4) Model

Quarterly Horizon	Posterior Mean	Posterior Trimmed Mean	Posterior Median
1	1.45	1.48	1.48
2	1.20	1.23	1.26
3	1.18	1.19	1.20
4	1.55	1.21	1.23
1	**0.58**	**0.58**	**0.62***
2	**0.65***	**0.61****	**0.60***
3	**0.62**	**0.55**	**0.55**
4	**0.64**	**0.56**	**0.56**

NOTES: All results are obtained by Monte Carlo integration from the pointwise posterior distribution of the TVP-VAR model forecasts. The trimmed mean eliminates the top and bottom 0.5 percent of the posterior forecasts.

Table 6. International Comparison of the Real-Time Accuracy of Quarterly Forecasts of the Real Price of Oil in Domestic Consumption Units

Quarterly Horizon	Real Exchange Rate included in Baseline Monthly VAR(12) Model for RAC and No-Change Forecast of the Spread of the Benchmark Price over the RAC		Baseline Monthly VAR(12) Model for RAC with No-Change Forecasts of the Real Exchange Rate and of the Spread of the Benchmark Price over the RAC	
	MSPE Ratio	Success Ratio	MSPE Ratio	Success Ratio
		(a) Canada: WTI benchmark		
1	**0.84**	**0.62***	**0.93**	**0.73***
2	**0.96**	**0.48**	**0.97**	**0.60***
3	1.04	**0.50**	1.02	**0.54**
4	1.03	**0.47**	**1.00**	**0.55**
		(b) Norway: Brent benchmark		
1	**0.92**	**0.60***	**0.90**	**0.65***
2	1.07	**0.58***	**0.98**	**0.61***
3	1.15	**0.53**	1.07	**0.55**
4	1.15	**0.53**	1.05	**0.60***
		(c) Euro Area: Brent benchmark		
1	**0.96**	**0.69***	**0.90**	**0.68***
2	1.08	**0.60***	1.01	**0.61***
3	1.17	**0.57****	1.08	**0.54**
4	1.17	**0.61***	1.06	**0.59***

NOTES: Boldface indicates an improvement on the monthly no-change forecast. For the success ratio improvements that are statistically significant at the 5% (10%) level are marked * (**). For the real-time recursive MSPE ratio the degree of statistical significance cannot be reported because no valid statistical tests are available in the literature.

Table 7. Real-Time Accuracy of Equal-Weighted Combination of the Monthly VAR(12) Model Forecast and the Forecast Based on Oil Futures

Quarterly Horizon	U.S. Refiners' Acquisition Cost for Crude Oil Imports	WTI Price	Brent Price
		(a) MSPE Ratio	
1	**0.81**	**0.84**	1.09
2	**0.89**	**0.92**	1.07
3	**0.88**	**0.90**	**0.98**
4	**0.81**	**0.82**	**-**
		(b) Success Ratio	
1	**0.71***	**0.68***	**0.60***
2	0.48	0.49	**0.55**
3	0.47	0.49	**0.51**
4	**0.53****	**0.55***	**-**

NOTES: The VAR forecasts for the real WTI price and real Brent price are obtained from the baseline model for the U.S. refiners' acquisition cost by applying the most recent price spread. Brent futures prices with a maturity of 10 through 12 months are not available for our evaluation period.

Table 8. Real-Time Accuracy of Selected Forecasts at Longer Horizons U.S. Refiners' Acquisition Cost for Imports

Quarterly Horizon	Monthly VAR(12)	Hybrid Method	Quarterly No-Change Forecast
		(a) MSPE Ratio	
5	1.06	1.07	**0.97**
6	1.12	1.13	**0.95**
7	1.15	1.13	**0.95**
8	1.14	1.07	**0.97**
		(b) Success Ratio	
5	**0.58***	**0.54**	**0.53**
6	**0.52**	0.47	0.47
7	**0.50**	0.49	0.46
8	**0.52**	**0.52**	0.42

NOTES: The hybrid method treats the four-quarter forecast from the monthly VAR(12) model as the forecast for horizons 5 through 8. Boldface indicates an improvement on the monthly no-change forecast.

Figure 1. Alternative Oil Prices and Their Relationship Since 1992