Forecasting the Real Price of Oil: A Review of Recent Results

Lutz Kilian
University of Michigan

Baumeister and Kilian (JBES 2012):

Real-Time Forecasts of the Real Price of Oil

Background

● Users of real oil price forecasts include governments at the state and federal level, international organizations, central banks, and many industries (e.g., utilities, auto manufacturers).

● Few studies to date have examined how to forecast the real price of oil:

Alquist, Kilian, Vigfusson (Hdbk chapter 2013)

● Even fewer allow for real-time data constraints:

Baumeister and Kilian (JBES 2012, IER forthcoming)

Why real-time data constraints matter for forecasting

1. Even preliminary data may become available only with a lag.

2. Past data are continuously revised for several years.

The Baumeister-Kilian Real-Time Data Set

- Comprehensive monthly real-time data set consisting of vintages for 1991.1 through 2010.12, each covering data extending back to 1973.1.
- Real-time data constructed from a variety of sources, many of which are not available in electronic form.
- Both backcasting and nowcasting techniques are used to fill gaps in the real-time data.

Key Parameters for Forecasting Horserace

- Variable to be forecast:

  Real U.S. refiners' acquisition cost for crude oil imports

- Evaluation window: 1992.1-2010.6.
- Data for 1992.1-2010.6 in the 2010.12 vintage are treated as ex-post revised data when evaluating the forecast accuracy
- Forecasts horizons $h \in \{1,3,6,9,12\}$
- End-of-sample approach

Real-Time Forecast Accuracy: 4 Candidate Models

1. No-change forecast (random walk forecast)
2. Recursive vector autoregressive (VAR) forecasts motivated by the global oil market model of Kilian and Murphy (JAE forthcoming)

   <u>VAR variables:</u>
   1. Percent change in global crude oil production
   2. Index of global real activity
   3. Real price of oil
   4. Change in above-ground global crude oil inventories

3. Forecasts extrapolating the real price of oil based on the oil futures spread adjusted for expected inflation.

$$R_{t+h|t} = R_t \left(1 + f_t^h - s_t - \pi_t^h\right)$$

4. Forecasts extrapolating the real price of oil based on recent changes in non-oil industrial commodity prices adjusted for expected inflation.

$$R_{t+h|t} = R_t \left(1 + \pi_t^{h,industrial\ raw\ materials} - \pi_t^h\right)$$

Real U.S. Refiners' Acquisition Cost of Imports:
Real-Time Recursive MSPE Ratio Relative to No-Change Forecast

Horizon	VAR(12)	BVAR(24)	Oil Futures	Price of Raw Materials
1	**0.75**	**0.81**	**1.00**	**0.82**
3	**0.81**	**0.87**	**0.98**	**0.76****
6	**0.99**	1.00	**0.99**	1.05
9	1.02	1.05	**0.97**	1.10
12	**0.97**	1.08	**0.91**	1.11

Real U.S. Refiners' Acquisition Cost of Imports:
Real-Time Recursive Directional Accuracy of VAR Forecast

Horizon	VAR(12)	BVAR(24)	Oil Futures	Price of Raw Materials
1	**0.57***	**0.61***	0.44	**0.57***
3	**0.60***	**0.65***	0.49	**0.63***
6	**0.53**	**0.58**	**0.50**	**0.61***
9	**0.54**	**0.55**	**0.55***	**0.55**
12	**0.60***	**0.58**	**0.57***	**0.56****

Punchline for Monthly Forecasts

● Large out-of-sample MSPE reductions relative to no-change forecast up to three months (up to 25% in real time); smaller reductions up to one year.

● High and statistically significant real-time directional accuracy for horizons up to one year (as high as to 65%).

● The model works especially well during financial crisis.

● This VAR model not only beats the random walk, but also is more accurate than forecasts based on oil futures prices.

Baumeister and Kilian (2013):

Real-Time Analysis of Oil Price Risks using Forecast Scenarios

Limitations of Standard Oil Price Forecasts

● Standard forecasting models do not allow answers to "what-if" questions about the effects of hypothetical events on the oil price forecast.

● For example, how would the following hypothetical events affect the forecast of the real price of oil?

a. A global recovery
b. An unexpected oil supply disruption in Middle East
c. Growing political tension in the Middle East

● Answering this type of question involves the construction of <u>forecast scenarios</u>.

Two Requirements for Building Forecast Scenarios

1. Forecast scenarios can only be constructed from a structural economic model of demand and supply.
2. For the forecast scenario to be meaningful the structural model also must be a good out-of-sample forecasting model.

⇨ The structural model of Kilian and Murphy (JAE forthcoming) satisfies both conditions.

Structural Model of the Global Market for Crude Oil

Kilian & Murphy (JAE forth.) and Kilian & Lee (JIMF forth.):

- Monthly data for 1973.2-2010.6:

  1. Percent change in global crude oil production
  2. Index of global real activity (in deviations from trend)
  3. Real price of oil
  4. Change in above-ground global crude oil inventories

- The inclusion of inventories in the model matters. It allows us to capture the effects of shifts in expectations about demand and supply.

Four Demand and Supply Shocks in Model

1. Shock to the flow of crude oil production (“flow supply shock”)
2. Shock to the demand for crude oil associated with the global business cycle (“flow demand shock”)
3. Shock to the demand for above-ground oil inventories arising from forward-looking behavior not already captured by other shocks (“speculative demand shock”)
4. Residual demand shock that collectively captures all shocks not otherwise accounted for (e.g., weather shocks, shocks to inventory technology or preferences, idiosyncratic changes in SPR).

Identifying Assumptions:

- Sign restrictions on impact responses of the four observables to each structural shock.
- Bound on the impact price elasticity of oil supply.
- Bound on the impact price elasticity of oil demand.
- Dynamic sign restrictions for response to oil supply shock.

Historical Decomposition

$$y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i} \approx \sum_{i=0}^{t-1} \Theta_i w_{t-i},$$

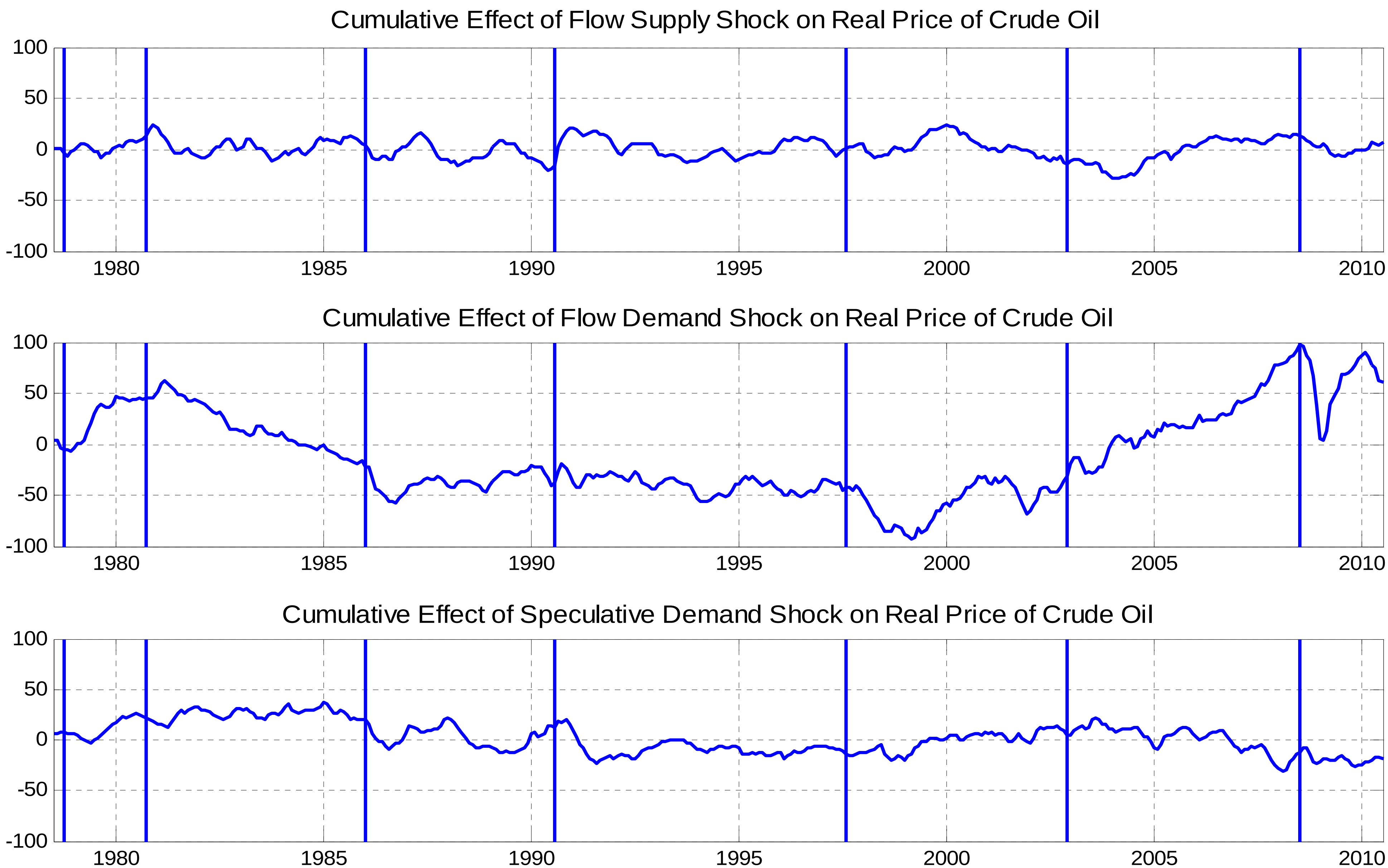
where

y_t refers to the current observation

Θ_i denotes the matrix of structural impulse responses at lag $i = 0,1,2,...,$

w_t denotes the vector of mutually uncorrelated structural shocks

Historical Decomposition for Real U.S. RAC for



Forecast Scenarios

$$y_{t+h} = \underbrace{\sum_{i=0}^{h-1} \Theta_i w_{t+h-i}}_{\textit{Effect of future shocks}} + \underbrace{\sum_{i=h}^{\infty} \Theta_i w_{t+h-i}}_{\substack{\textit{Effect of past shocks} \\ (\textit{known at } t)}}$$

● Setting all future demand and supply shocks to zero in expectation results in the baseline unconditional forecast.

● Feeding in a sequence of nonzero future shocks <u>in expectation</u> provides a conditional forecast.

- ⇨ The difference in the path of y_{t+h}, $h = 1, 2, \ldots$, provides the required adjustment to the baseline forecast.
- ⇨ Note that scenarios are not intended to determine likely outcomes, but to help us understand the consequences of unlikely events.

Where Do these Future Shocks Come From?

● Often historical events provide guidance about realistic demand and supply shock sequences.

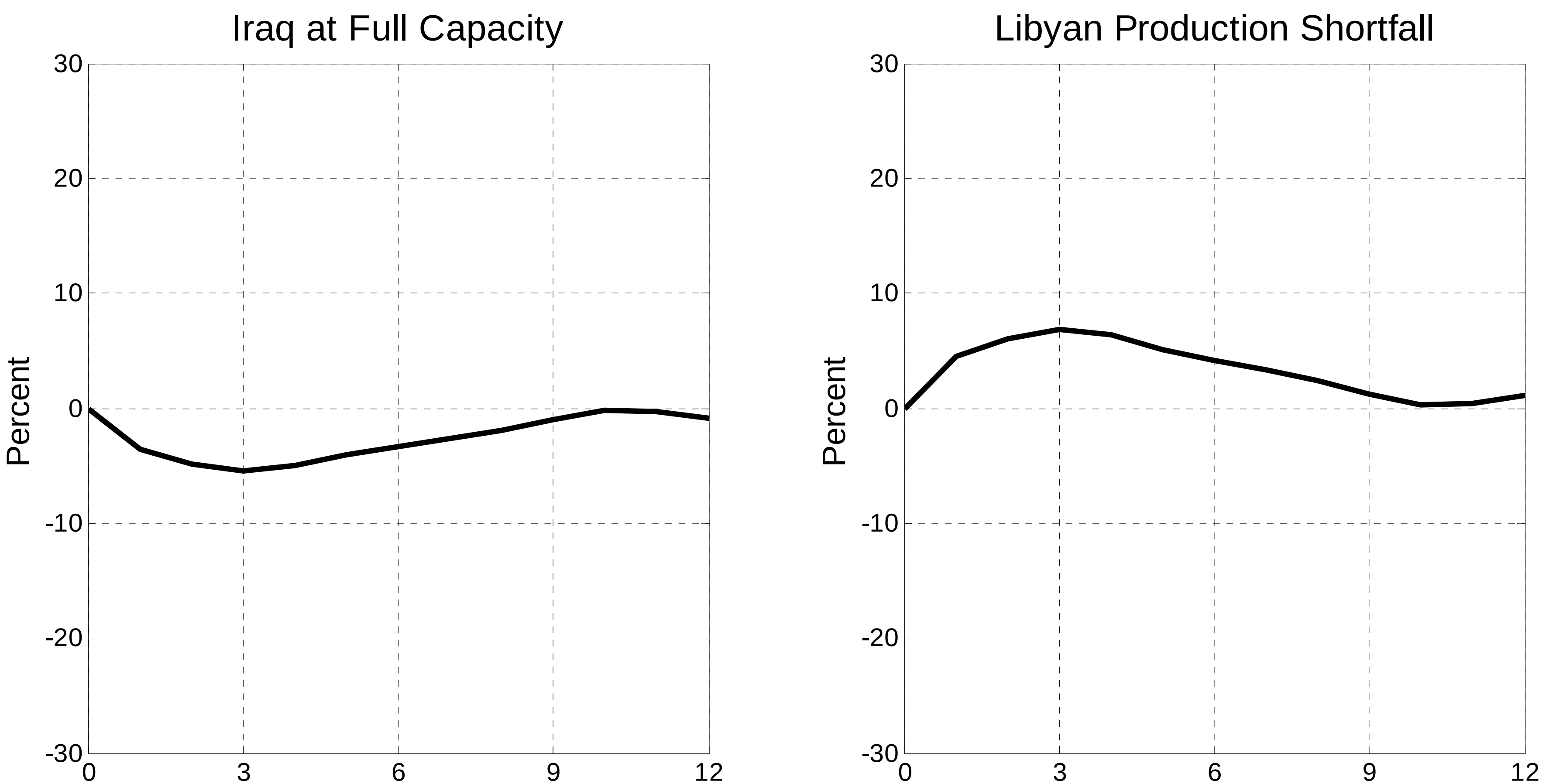
Example: The effect of another Asian crisis on flow demand.

● Alternatively, we may specify purely hypothetical sequences reflecting thought experiments.

Example: The effect of shutting down Iranian oil production.

Forecast Scenarios for Real Price of Crude Oil (1)

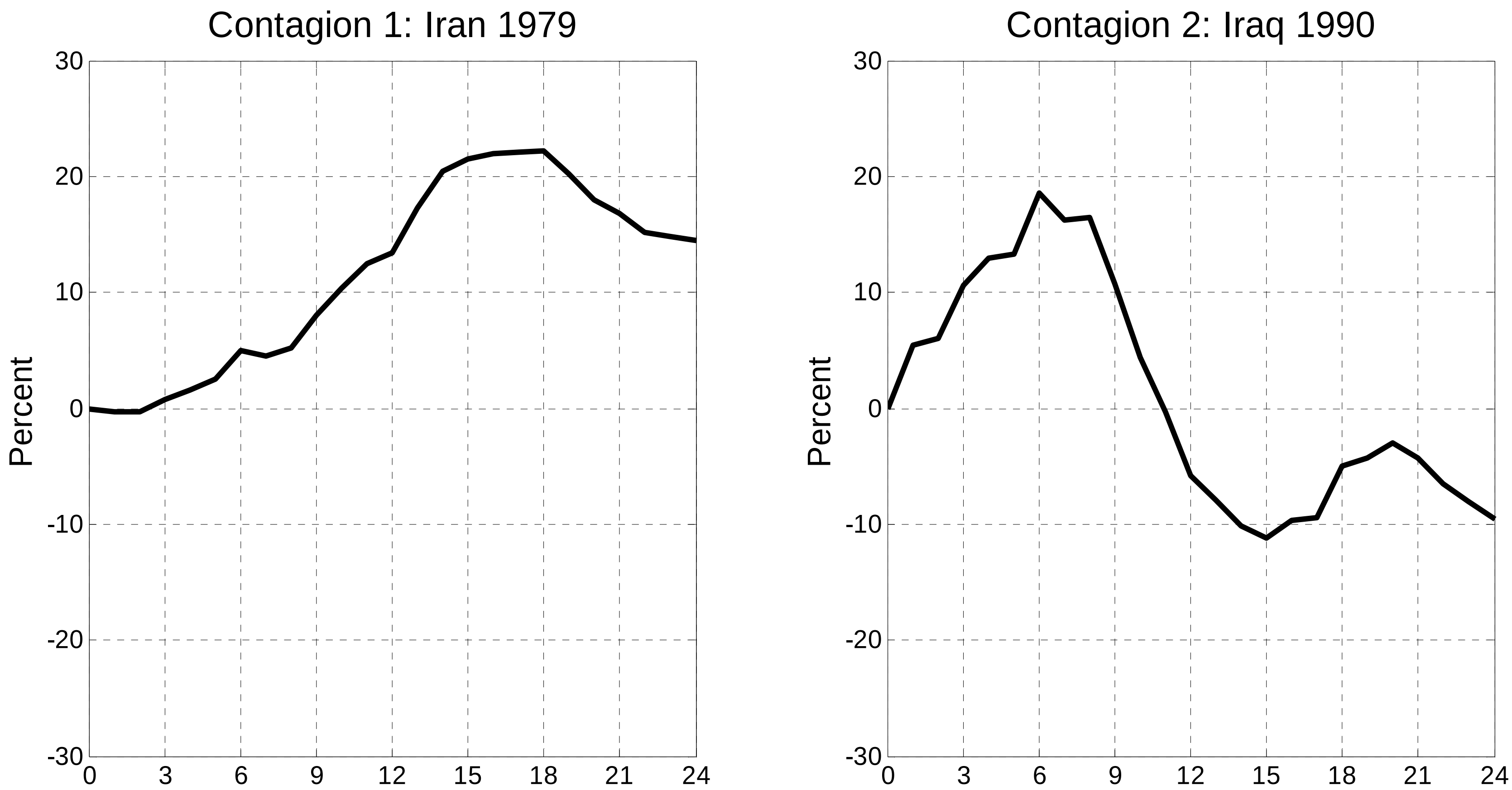
Percent Deviations from Baseline Forecast



Source: Baumeister and Kilian (2013)

Forecast Scenarios for Real Price of Crude Oil (2)

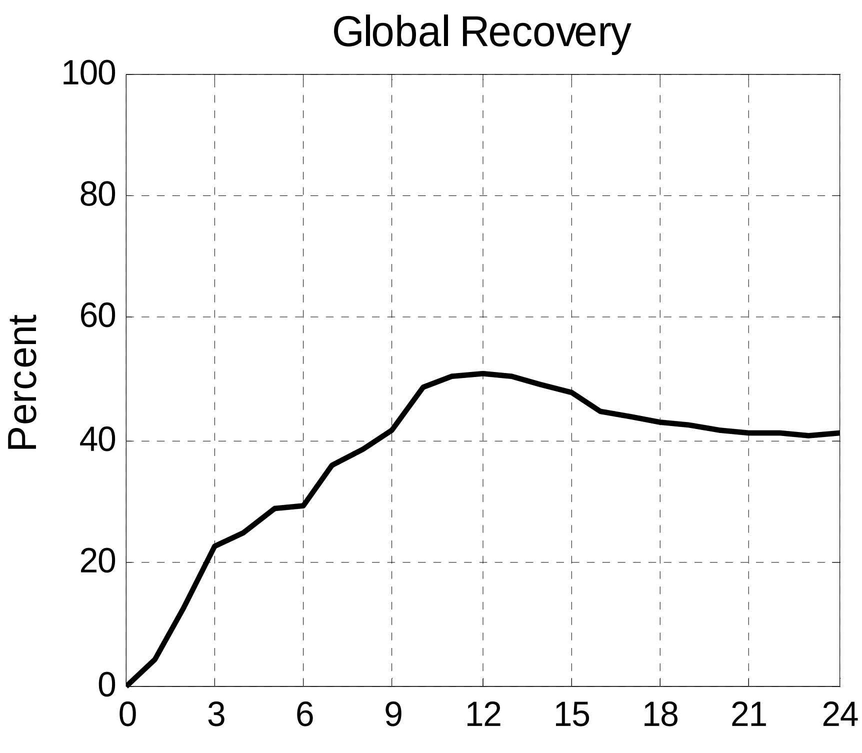
Percent Deviations from Baseline Forecast

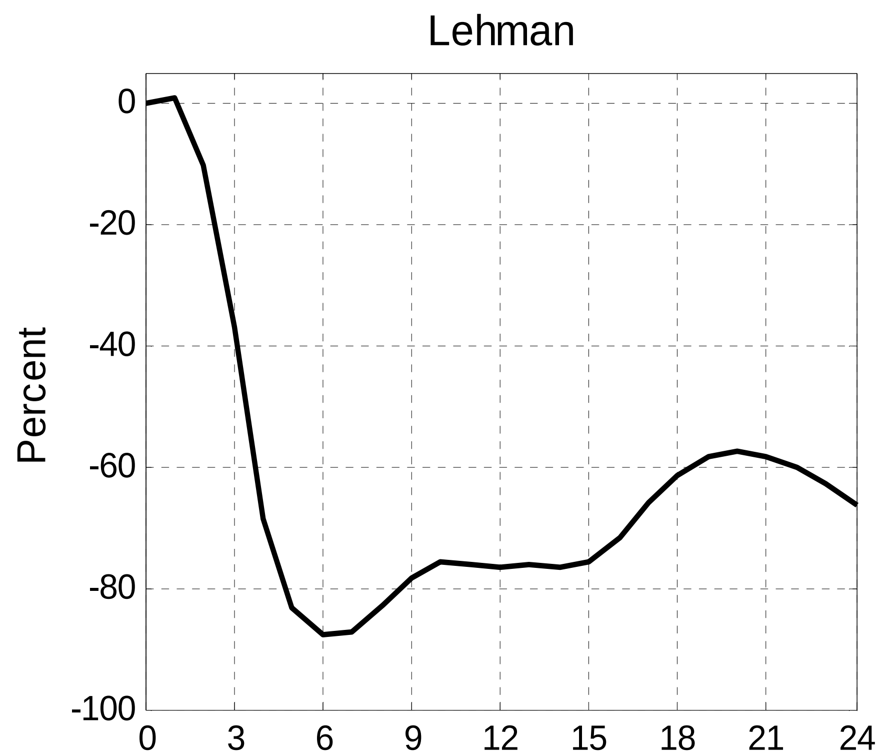


Source: Baumeister and Kilian (2013)

Forecast Scenarios for Real Price of Crude Oil (3)

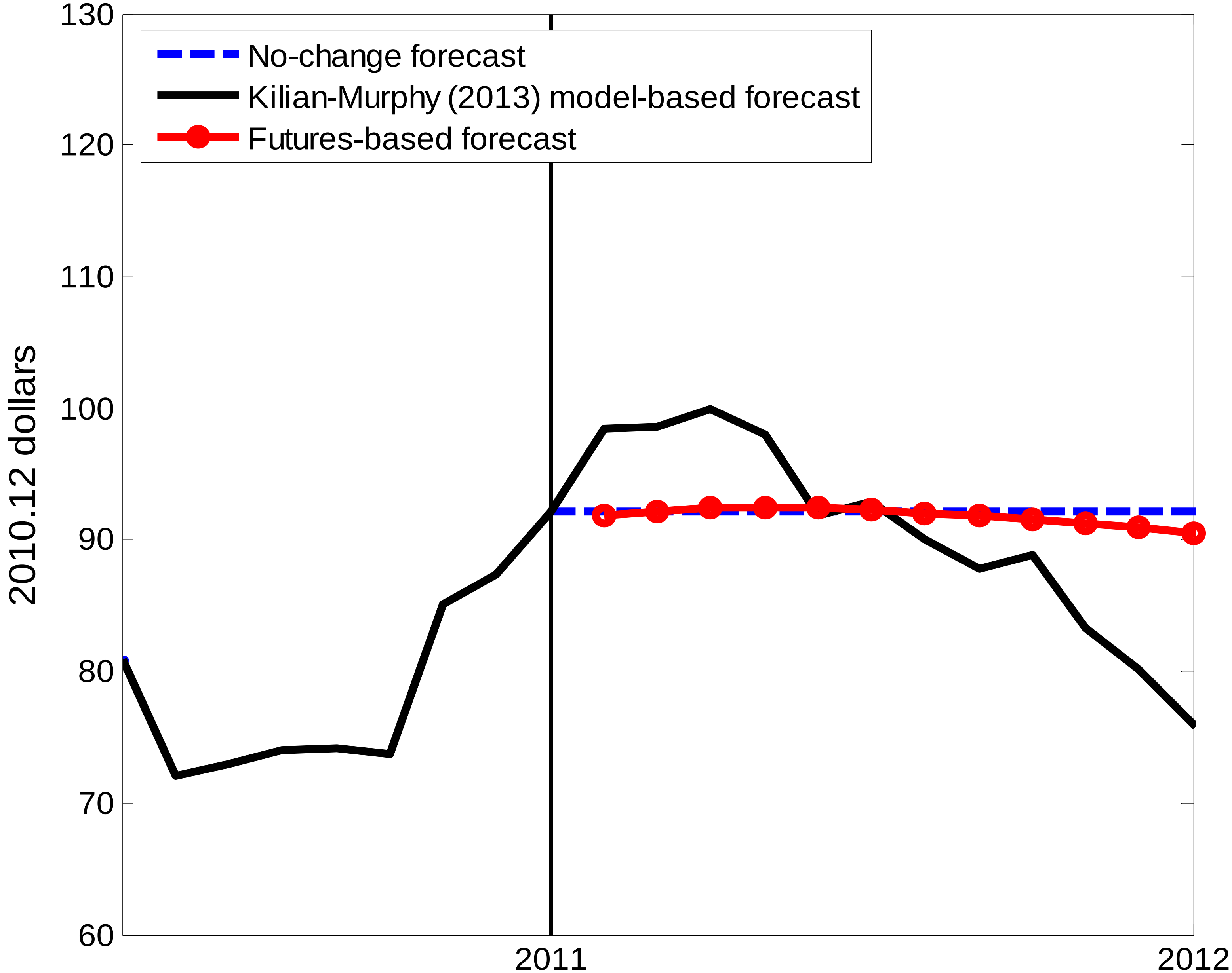
Percent Deviations from Baseline Forecast



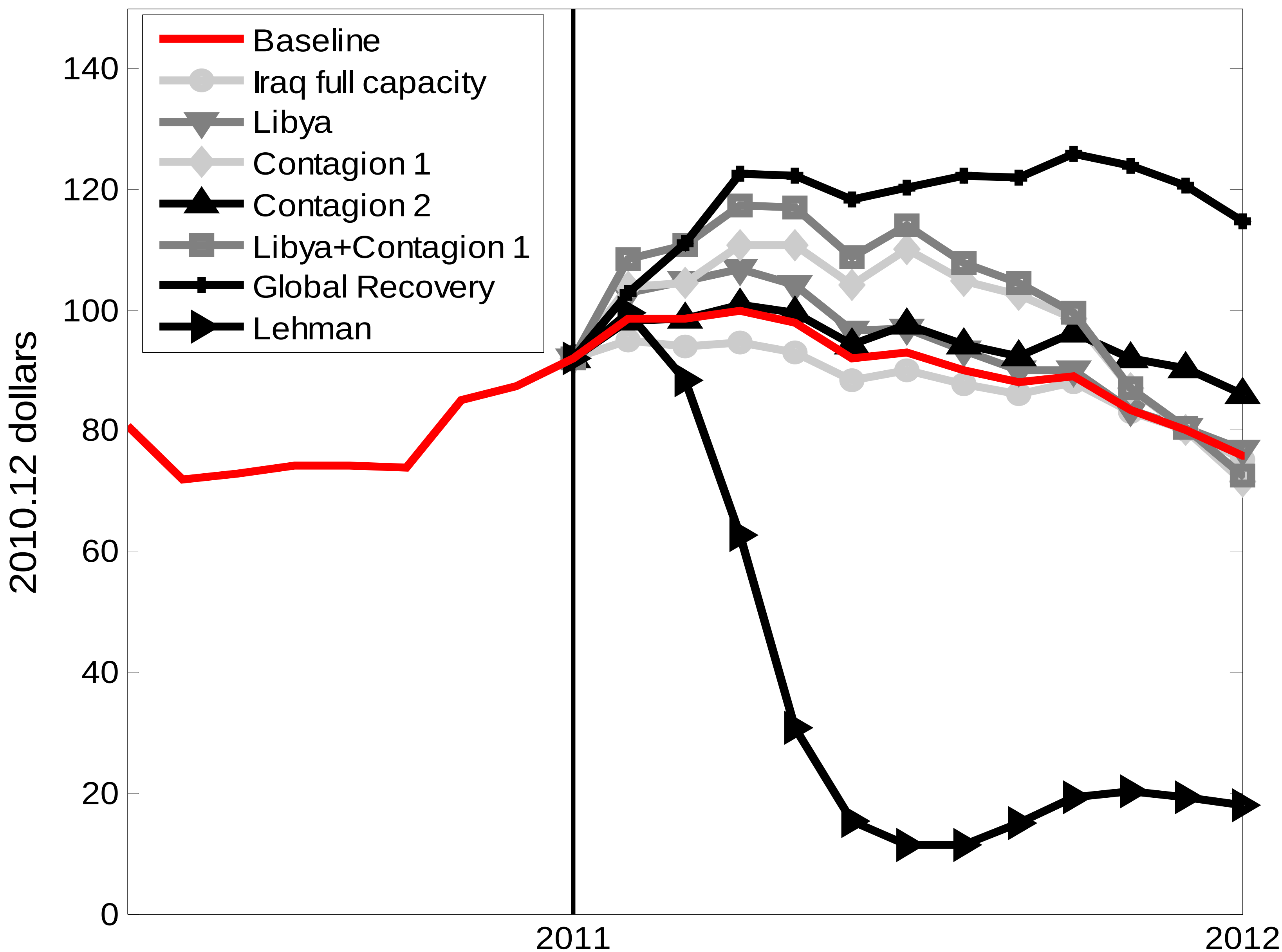


Source: Baumeister and Kilian (2013)

Real-Time Forecasts of
Real Price of Crude Oil as of 2010.12



Sensitivity Analysis as of 2010.12



Forecast Uncertainty

● Conditional point forecasts (just like unconditional point forecasts) are expectations that are surrounded by uncertainty.

● This uncertainty can be captured by predictive densities.

● The predictive density of a conditional forecast is the same as that for the unconditional forecast up to a location shift.

Formal Risk Analysis in Real Time

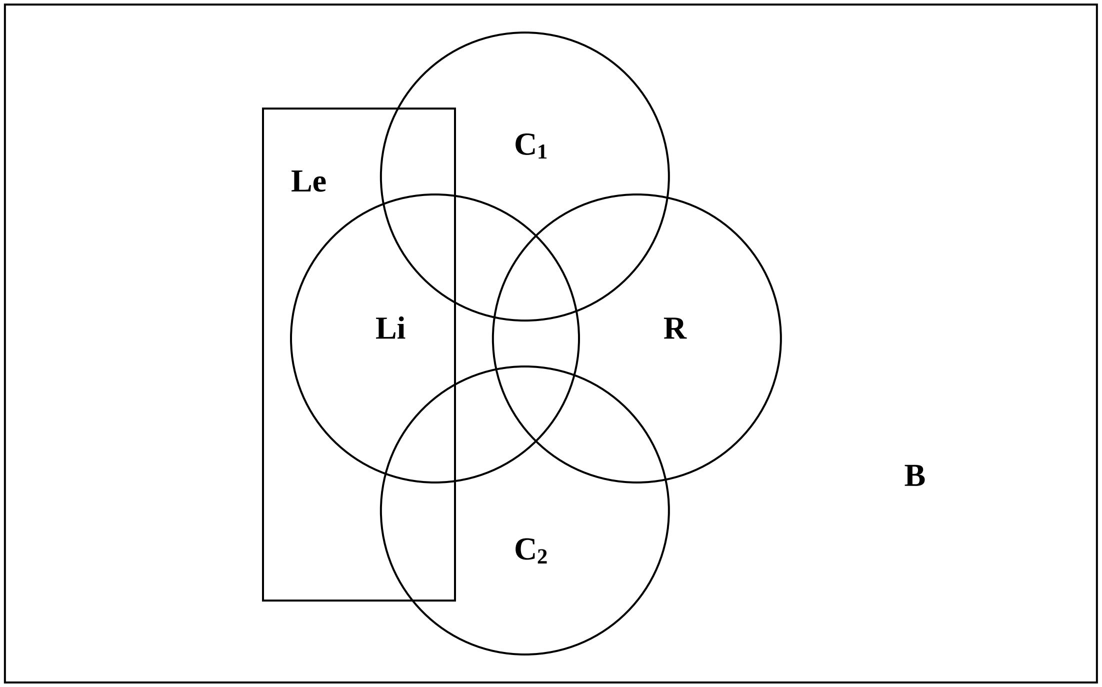
Step 1: Compute the predictive density from the VAR model.

Step 2: Assign probabilities to each scenario (where some scenarios are mutually exclusive while other may occur simultaneously).

Step 3: Compute the probability-weighted density for the real price of oil across all scenarios.

Step 4: Compute formal risk measures for this density.

Event Analysis using Venn Diagrams
An Illustrative Example

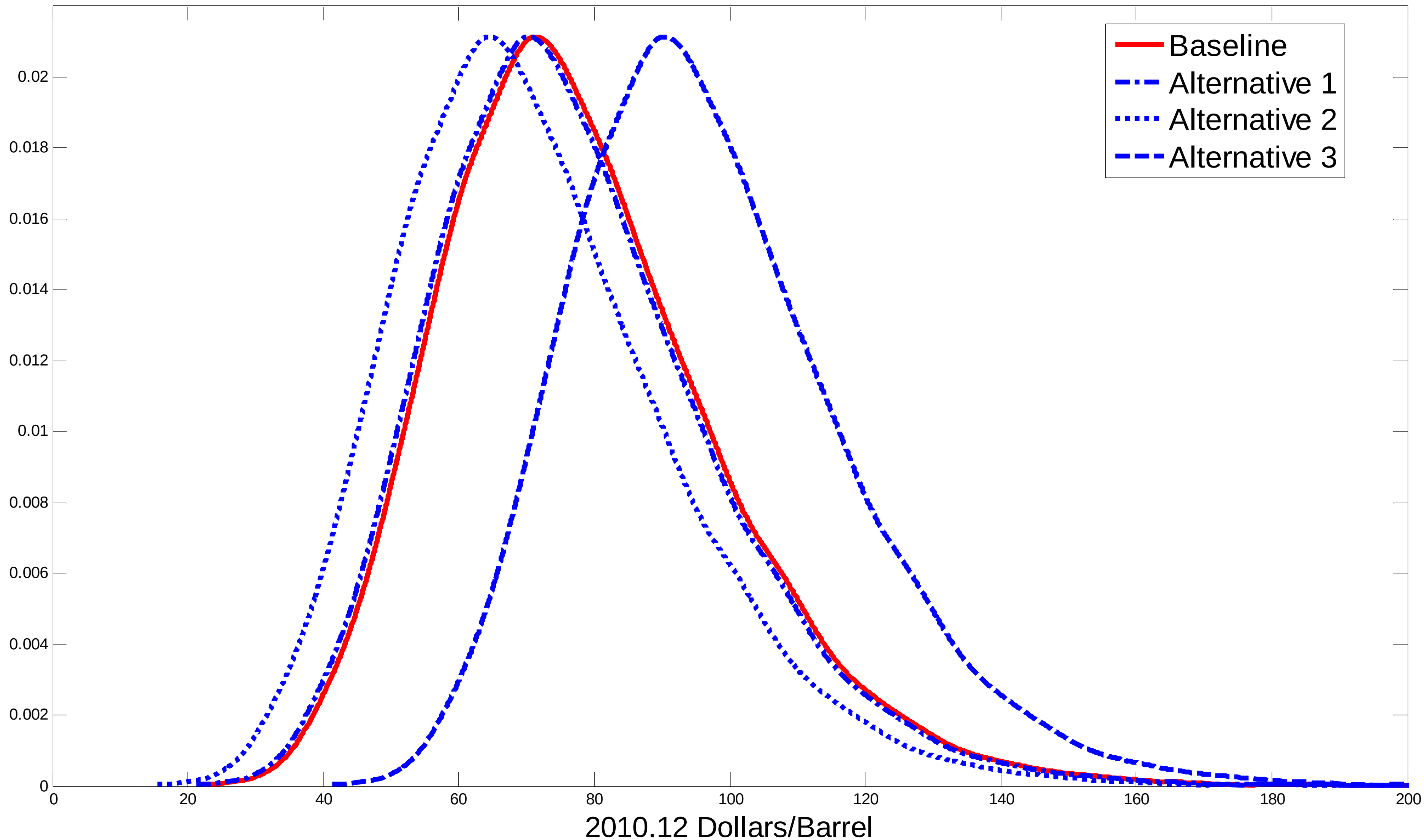


NOTES: B stands for *baseline*, Le for *Lehman*, Li for *Libyan production shortfall*, R for *global recovery*, C_1 and C_2 stand for *contagion 1* and *contagion 2*. We abstract from the *Iraq at full capacity* scenario for expository purposes. The Le and R scenarios are mutually exclusive, as is the baseline scenario with the other scenarios. Likewise C_1 and C_2 are treated as mutually exclusive.

Probability Weights for Forecast Scenarios

Events	Baseline	Weighted Forecast Scenarios Alternative 1: Moderately Pessimistic	Alternative 2: Pessimistic on Economy	Alternative 3: Optimistic on Economy
B	1	0.41	0.31	0.16
C_2	0	0.16	0.16	0.11
$Li \cap C_2$	0	0.05	0.05	0.05
$Li \cap C_2 \cap R$	0	0.03	0.03	0.03
$C_2 \cap R$	0	0.04	0.04	0.04
$Li \cap C_1 \cap R$	0	0.03	0.03	0.03
$Li \cap C_1$	0	0.05	0.05	0.05
C1	0	0.16	0.16	0.11
$R \cap C_1$	0	0.04	0.04	0.04
$Li \cap R$	0	0.07	0.07	0.07
Le	0	0.13	0.23	0.08
$Le \cap Li$	0	0.03	0.03	0.03
$Le \cap C_1$	0	0.01	0.01	0.01
$Le \cap C_1 \cap Li$	0	0.01	0.01	0.01
$Le \cap C_2$	0	0.01	0.01	0.01
$Le \cap C_2 \cap Li$	0	0.01	0.01	0.01
R	0	0.14	0.14	0.59
Li	0	0.22	0.22	0.17
I	0	0	0	0

Real-Time Probability-Weighted 1-Year Ahead Predictive Densities for the Real Price of Oil as of 2010.12: An Illustrative Example



How to Measure Oil Price Risks

- Let R_{t+h} denote the real price of oil h months from now.
- Risks about R_{t+h} are not symmetric in general:

  <u>Examples:</u>
  Consumers of oil are much more concerned with unexpectedly high oil prices than low oil prices.

  Producers of oil are much more concerned with unexpectedly low oil prices than high oil prices.

<u>Problem</u>: Volatility-based measures of risk treat increases and declines in the price of oil symmetrically.

Probability-weighted expected shortfall/excess

Consider the events of R_{t+h} exceeding an upper threshold of \$100 (upside risk) and of R_{t+h} falling below the lower threshold of \$80 (downside risk). Then:

<u>Downside risk:</u>

$$DR = E(R_{t+h} - 80 \mid R_{t+h} < 80)\Pr(R_{t+h} < 80)$$

<u>Upside risk:</u>

$$UR = \underbrace{E(R_{t+h} - 100 \mid R_{t+h} > 100)}_{Tail-conditional\ \exp ectation}\underbrace{\Pr(R_{t+h} > 100)}_{Tail\ \ probability}$$

For further discussion see Kilian and Manganelli (JMCB 2007, 2008).

Upside Risks for Probability Weighted Forecast Scenarios
Real-Time Forecasts as of December 2010

Scenario	h	$P(R_{t+h}>100)$ %	$E(R_{t+h}-100 \mid R_{t+h}>100)$ \$	$E(R_{t+h}-100 \mid R_{t+h}>100) \times \Pr(R_{t+h}>100)$
Baseline	3	50	11.03	5.56
	6	36	15.25	5.42
	12	14	15.40	2.22
Moderately Pessimistic	3	56	11.51	6.42
	6	31	14.81	4.60
	12	14	15.29	2.08
Pessimistic	3	44	10.49	4.57
	6	19	13.69	2.59
	12	10	14.76	1.41
Optimistic	3	86	16.78	14.48
	6	63	18.41	11.60
	12	40	17.82	7.10

Source: Baumeister and Kilian (2013). h denotes the forecast horizon in months.

Baumeister and Kilian (IER forthcoming):

What Central Bankers Need to Know about Forecasting Oil Prices

Oil Price Forecasts for Central Banks

1. Quarterly Horizons

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?

2. Other Oil Price Measures: WTI, Brent

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 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.

3. Foreign central banks forecast the real price of oil in domestic consumption units

<u>Examples</u>: Bank of Canada, Norges Bank, ECB

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.

4. Other issues:

Model Specification:

Alternative measures of global real activity

Structural Change:

TVP-VAR Models

Model Misspecification:

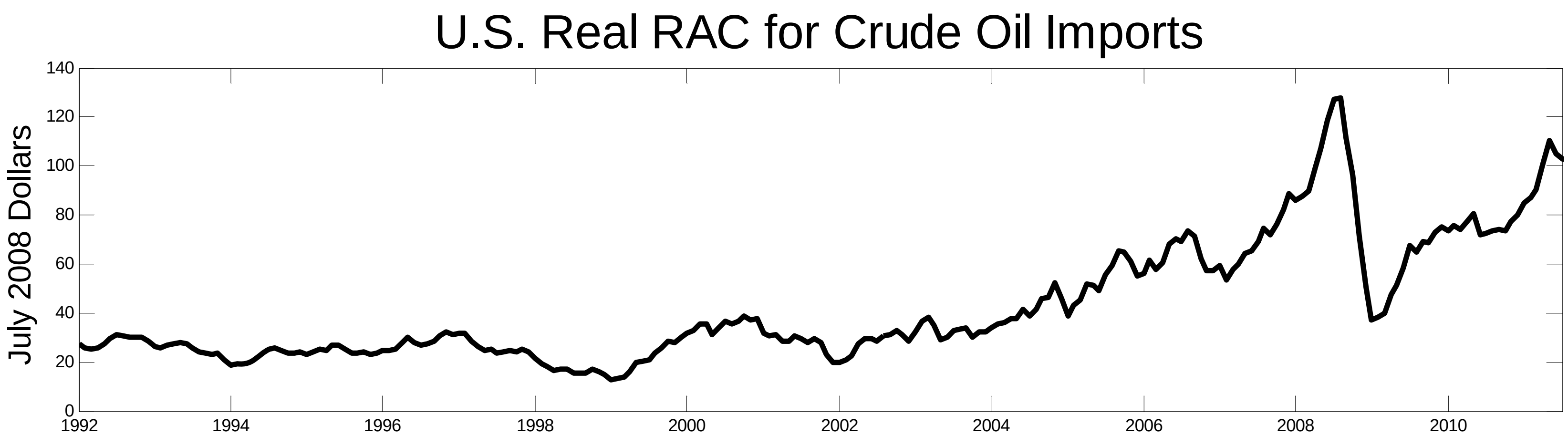
Forecast Combinations

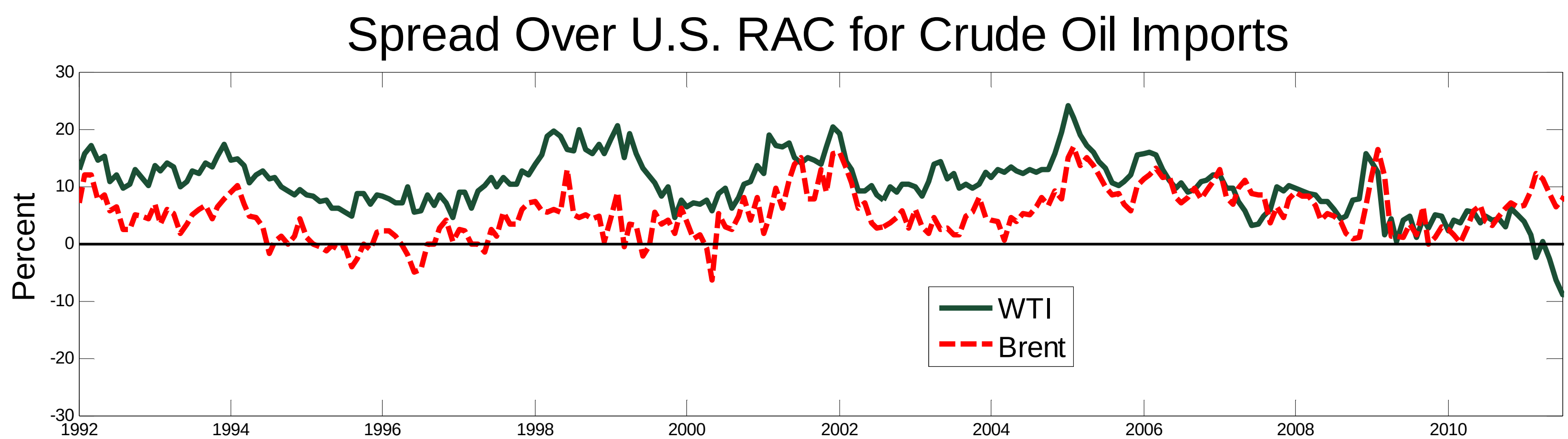
Real-Time Accuracy of Recursive Forecasts of the
Quarterly Real U.S. Refiners' Acquisition Cost for Imports

Quarterly Horizon	Quarterly NC-Forecast	Monthly VAR(12)	Oil Futures	Quarterly VAR(p) $p=4$	$p=6$	$p=8$	Quarterly BVAR(p) $p=4$	$p=6$	$p=8$
				(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	1.17	1.32	1.40	1.13	1.10	1.13
3	**0.98**	1.02	**0.99**	1.05	1.09	1.13	1.02	**0.98**	1.03
4	**0.99**	1.01	**0.93**	1.02	1.06	1.18	1.01	**0.99**	1.05
				(b) Success Ratio					
1	-	**0.69***	**0.59***	**0.55**	**0.62***	**0.56**	**0.56**	**0.63***	**0.67***
2	-	**0.58***	**0.52**	**0.53**	**0.58**	**0.53**	**0.55**	**0.64***	**0.64***
3	-	**0.57**	**0.57***	0.45	0.50	**0.51**	**0.53**	**0.58**	**0.54**
4	-	**0.60***	**0.61***	0.48	**0.61**	**0.55**	**0.52**	**0.60**	**0.57**

NOTES: All MSPE ratios have been normalized relative to the monthly no-change forecast. Boldface indicates an improvement on the monthly no-change forecast.

Alternative Oil Prices and Their Relationship Since 1992:





Real-Time Accuracy of Recursive Forecasts of the Quarterly Real WTI Price

Quarterly Horizon	Quarterly No-Change Forecast	Monthly VAR(12)	Monthly VAR(12) + NC-Forecast for Spread	Oil Futures	Quarterly BVAR(6)	Quarterly BVAR(6) + NC-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	1.10
3	**0.99**	1.02	1.01	1.07	**0.96**	**0.98**
4	**0.99**	1.01	1.00	**1.00**	**0.95**	**0.98**
			(b) Success Ratio			
1	-	**0.65***	**0.69***	**0.54***	**0.55**	**0.60***
2	-	**0.61***	**0.61***	**0.52**	**0.57**	**0.58**
3	-	**0.51**	**0.58**	**0.57***	**0.59**	**0.59**
4	-	**0.56**	**0.60***	**0.59***	**0.65***	**0.63**

Real-Time Accuracy of Recursive Forecasts of the Quarterly Real Brent Price

Quarterly Horizon	Quarterly NC Forecast	Monthly VAR(12)	Monthly VAR(12) + NC-Forecast for Spread	Oil Futures	Quarterly BVAR(6)	Quarterly BVAR(6) + NC-Forecast for Spread
			(a) MSPE Ratio			
1	1.68	**0.92**	**0.89**	1.69	1.73	1.61
2	1.11	**0.98**	**0.98**	1.44	1.15	1.12
3	**0.99**	1.01	1.04	1.22	1.00	1.00
4	**0.99**	1.01	1.03	-	1.00	1.01
			(b) Success Ratio			
1	-	**0.72***	**0.68***	**0.51**	**0.59**	**0.59**
2	-	**0.61***	**0.62***	**0.53**	**0.60**	**0.62****
3	-	**0.51**	**0.57****	**0.53**	**0.54**	**0.57**
4	-	**0.60***	**0.57****	-	**0.52**	**0.56**

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

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.

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

	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	
Quarterly Horizon	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***

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.

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**	-
6	**0.52**	0.47	-
7	**0.50**	0.49	-
8	**0.52**	**0.52**	-

NOTES: The hybrid method treats the 4-quarter forecast from the monthly VAR(12) model as the forecast for horizons 5 through 8.

Baumeister and Kilian (2013):

Forecasting the Real Price of Oil in a Changing World:
A Forecast Combination Approach

Why forecast combinations?

1. Even the most accurate forecasting models do not work equally well at all times.

2. Some forecasting models are more accurate at short horizons and others at longer horizons.

3. Even the forecasting model with the lowest MSPE may potentially be improved by incorporating information from other models with higher MSPE.

4. One can think of forecast combinations as providing insurance against possible model misspecification and smooth structural change.

Four Forecasting Models in Combination

1. Iteratively generated forecasts of $R_{t+h|t}^{oil}$ from VAR(12) model with intercept for $y_t = \left[\Delta prod_t, rea_t, r_t^{oil}, \Delta inv_t \right]'$

2. Forecasts from

$$R_{t+h|t}^{oil} = R_t^{oil} \left(1 + \pi_t^{h,industrial\ raw\ materials} - E_t(\pi_t^h)\right),$$

3. Forecasts from

$$R_{t+h|t}^{oil} = R_t^{oil} \left(1 + f_t^h - s_t - E(\pi_t^h)\right), \ h \leq 18$$

4. Forecast from TVP-Model of Gasoline and Heating Oil Spreads

Step 1: Recursively estimate the time-varying regression model

$$\Delta s_{t+h|t} = \beta_{1t}\left[s_t^{gas} - s_t\right] + \beta_{2t}\left[s_t^{heat} - s_t\right] + \varepsilon_{t+h}$$

where s_t^{heat} is the log of the nominal U.S. spot price of heating oil
s_t^{gas} is the log of the nominal U.S. spot price of gasoline

Step 2: Construct the TVP model forecast:

$$\hat{R}_{t+h|t}^{oil} = R_t^{oil} \exp\left\{\hat{\beta}_{1t}\left[s_t^{gas} - s_t\right] + \hat{\beta}_{2t}\left[s_t^{heat} - s_t\right] - E_t(\pi_t^h)\right\}$$

For further discussion see Baumeister, Kilian and Zhou (2013).

Forecast combination weights

1. Equal weights:

$$\hat{R}^{oil}_{t+h|t} = \sum_{k=1}^{4} \omega_{k,t} \hat{R}^{oil,k}_{t+h|t}, \qquad \omega_{k,t} = \frac{1}{4}$$

2. Inverse MSPE weights based on recursive or rolling windows:

$$\hat{R}^{oil}_{t+h|t} = \sum_{k=1}^{4} \omega_{k,t} \hat{R}^{oil,k}_{t+h|t}, \qquad \omega_{k,t} = \frac{m_{k,t}^{-1}}{\sum_{j=1}^{4} m_{j,t}^{-1}}$$

$\Rightarrow$ Equal weights work best in practice

Horserace

The initial estimation period ends in 1991.12.

Evaluation period: 1992.1-2012.9.

Evaluation criterion: Recursive MSPE and success ratio

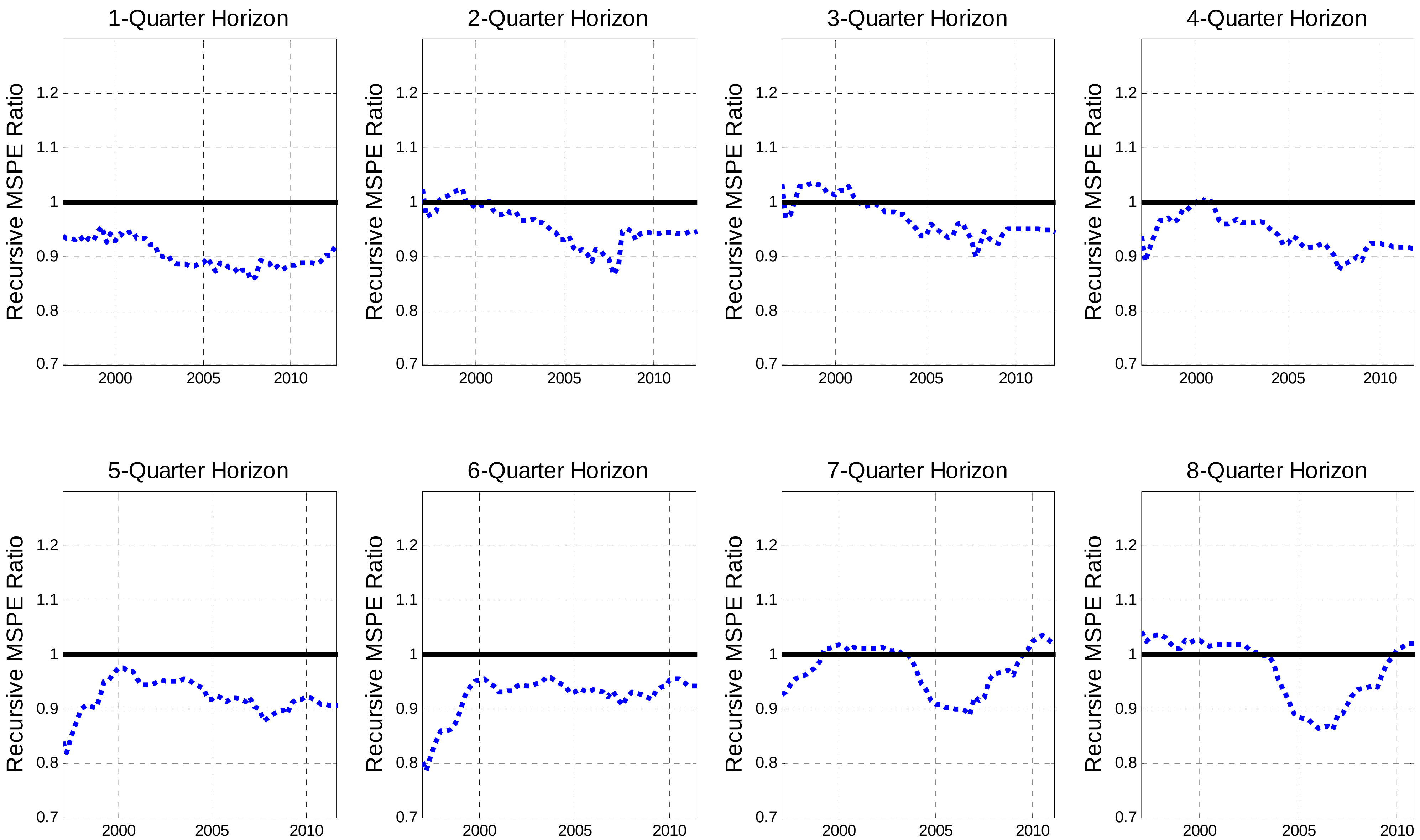
Real-Time Forecast Accuracy of Forecast Combination with Equal Weights

	RAC for Oil Imports	Real WTI Price
Monthly Horizon	Recursive MSPE Ratios	
1	**0.897**	**0.880**
3	**0.874**	**0.873**
6	**0.949**	**0.956**
9	**0.939**	**0.943**
12	**0.892**	**0.902**
15	**0.893**	**0.906**
18	**0.957**	**0.959**
21	1.065	1.064
24	1.029	1.017
	Success Ratios	
1	**0.554***	**0.517**
3	**0.609***	**0.592***
6	**0.556**	**0.543**
9	**0.580****	**0.562**
12	**0.609***	**0.605***
15	**0.650***	**0.617***
18	**0.601***	**0.577****
21	**0.550**	**0.550**
24	**0.561**	**0.551**

Real-Time Forecast Accuracy of Forecast Combinations at Quarterly Horizons

Quarterly Horizon	RAC for Oil Imports: Four Models	RAC for Oil Imports: TVP Spread Model Only	Real WTI Price: Four Model	Real WTI Price: TVP Spread Model Only
		MSPE Ratios		
1	**0.906**	1.020	**0.882**	1.034
2	**0.928**	1.016	**0.929**	1.009
3	**0.928**	**0.905**	**0.935**	**0.906**
4	**0.894**	**0.854**	**0.895**	**0.851**
5	**0.883**	**0.871**	**0.894**	**0.889**
6	**0.929**	**0.900**	**0.935**	**0.913**
7	1.054	**0.929**	1.057	**0.976**
8	1.057	**0.883**	1.048	**0.936**
		Success Ratios		
1	**0.688***	**0.713***	**0.700***	**0.700***
2	**0.628***	**0.615****	**0.654***	**0.641***
3	**0.658***	**0.553**	**0.645***	**0.592**
4	**0.716***	**0.635**	**0.676***	**0.649**
5	**0.625***	**0.681**	**0.611***	**0.611**
6	**0.614***	**0.657**	**0.600****	**0.643**
7	**0.544**	**0.691**	**0.559**	**0.677**
8	0.470	**0.652**	0.485	**0.652**

Real-Time Recursive MSPE Ratio Relative to No-Change Forecast for RAC for Oil Imports: Quarterly Equal-Weighted Forecast Combination



Concluding Remarks

1. There is robust evidence that we can improve on the random walk forecast of the real price of oil at horizons up to 6 quarters or 18 months.

2. There is a tradeoff between maximum accuracy ex post at a given horizon and robustness across horizons and over time.

3. The task of selecting most accurate models/model combination in real time remains elusive.

4. Data challenges:

   Global industrial production data no longer published
   Dry cargo freight rates show suspicious drop in 2011.

⇨ Forecast combinations need to be watched and maintained.