Forecasting Oil Prices and Quantifying Oil Price Risks

Christiane Baumeister

Bank of Canada

Lutz Kilian

University of Michigan

CEPR

Motivation

● When discussing an economy's energy security, the first and foremost question is what oil price risks this economy faces.

● These risks arise from unpredictable fluctuations in the real price of oil.

<u>Implications:</u>

1. We can reduce these risks by using improved forecasting methods.
2. We can quantify the remaining risks based on density forecasts of the real price of oil.

Background

- The <u>real price of oil</u> is one of the key variables in the model-based macroeconomic projections generated by central banks, private sector forecasters, and international organizations.

- Few studies to date on how to forecast the real price of oil.

  Alquist, Kilian, Vigfusson (2011, Hdbk chapter)

- Until now none that are conducted in real time.

  Baumeister and Kilian (2012, forthcoming: JBES)

Why Real-Time Data Matter

1. Even preliminary data may become available only with a lag.
2. Past data are continuously revised for several years.

$\Rightarrow$ Unlike in many other contexts, these features affect both the no-change forecast and alternative forecasting models.

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.

Stylized Facts about the Revisions

- The average number of revisions ranges from 1 for the U.S. refiners' acquisition cost for crude oil imports to 9 in the global crude oil production data.

- Most revisions occur one month after the first release, but revisions may continue for several years.

- For U.S. oil market data, revisions are complete within two years.

- Revisions are unforecastable.

- No benchmark revisions (unlike in NIPA data).

Delays in Data Availability Require Nowcasting

- Extrapolate based on the average rate of change up to that point in time:
  - World oil production
  - U.S. CPI
  - U.S. crude oil inventories

- Extrapolate at rate of growth of WTI:
  - U.S. RAC for crude oil imports

- Extrapolate using no-change forecast:
  - Ratio of OECD over U.S. petroleum inventories

Key Parameters for Forecasting Horserace

- 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 $h \in \{1,3,6,9,12\}$
- EOS Approach
- Variables to be forecast:

  Real refiners' acquisition cost for crude oil imports

  Real West Texas Intermediate price of crude oil

<u>Remark</u>: Brent oil price only starts in May 1987

Real-Time Forecast Accuracy: Candidate Models

1. No-change forecast (random walk forecast)
2. Recursive AR and ARMA forecasts
3. Recursive VAR forecasts motivated by global oil market model of Kilian and Murphy (2011)

   VAR variables:
   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

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

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

5. 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	**0.750**	**0.806**	**0.997**	**0.824**
3	**0.808**	**0.874**	**0.981**	**0.763****
6	**0.993**	1.004	**0.987**	1.046
9	1.022	1.045	**0.966**	1.101
12	**0.974**	1.081	**0.912**	1.107

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	**0.568***	**0.613***	0.441	**0.568***
3	**0.596***	**0.650***	0.491	**0.632***
6	**0.530**	**0.581**	**0.502**	**0.608***
9	**0.542**	**0.551**	**0.551***	**0.551**
12	**0.597***	**0.578**	**0.569***	**0.555****

Real WTI Price:
Real-Time Recursive MSPE Ratio Relative to No-Change Forecast

Horizon	VAR(12)	BVAR(24)	Oil Futures	Price of Raw Materials
1	**0.882**	**0.864**	1.004	**0.820**
3	**0.925**	**0.869**	**0.999**	**0.744****
6	1.035	**0.938**	1.002	1.040
9	1.035	**0.945**	**0.981**	1.099
12	**0.987**	**0.952**	**0.932**	1.112

Real WTI Price:
Real-Time Recursive Directional Accuracy of VAR Forecast

Horizon	VAR(12)	BVAR(24)	Oil Futures	Price of Raw Materials
1	**0.550***	**0.559****	0.460	**0.550****
3	**0.605***	**0.605***	0.477	**0.609***
6	**0.525**	**0.590**	**0.502**	**0.590***
9	**0.519**	**0.564**	**0.547***	**0.565****
12	**0.611***	**0.611***	**0.559***	**0.574****

Punchline

● Large out-of-sample MSPE reductions relative to no-change forecast up to six 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.

Limitations of Standard Oil Price Forecasts

● Standard forecasts based on reduced-form regressions or based on oil futures prices do not allow us to assess the effects of hypothetical events (such as a global recovery, a financial crisis, an unexpected oil supply disruption, or a period of growing political tension in the Middle East) on the baseline oil price forecast.

● Baumeister and Kilian (mimeo 2012) present new tools designed to address this question.

Real-Time Forecast Scenarios

● Real-time conditional projections of how the oil price forecast would deviate from the unconditional forecast benchmark under hypothetical scenarios about future demand and supply conditions in the global market for crude oil.

● Such scenarios can be constructed from the structural moving-average representation of the same type of VAR model we already showed to have real-time forecasting ability earlier.

● All we need to do is add the identifying assumptions of Kilian and Murphy (2011).

Four Structural Shocks

1. Shock to the flow of crude oil production ("flow supply shock")
2. Shock to the demand for crude oil driven by the global business cycle ("flow demand shock")
3. Shock to the demand for above-ground oil inventories arising from forward-looking behavior ("speculative demand shock")
4. Residual oil demand shock that captures all structural shocks not otherwise accounted for and has no direct economic interpretation (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 Decompositions

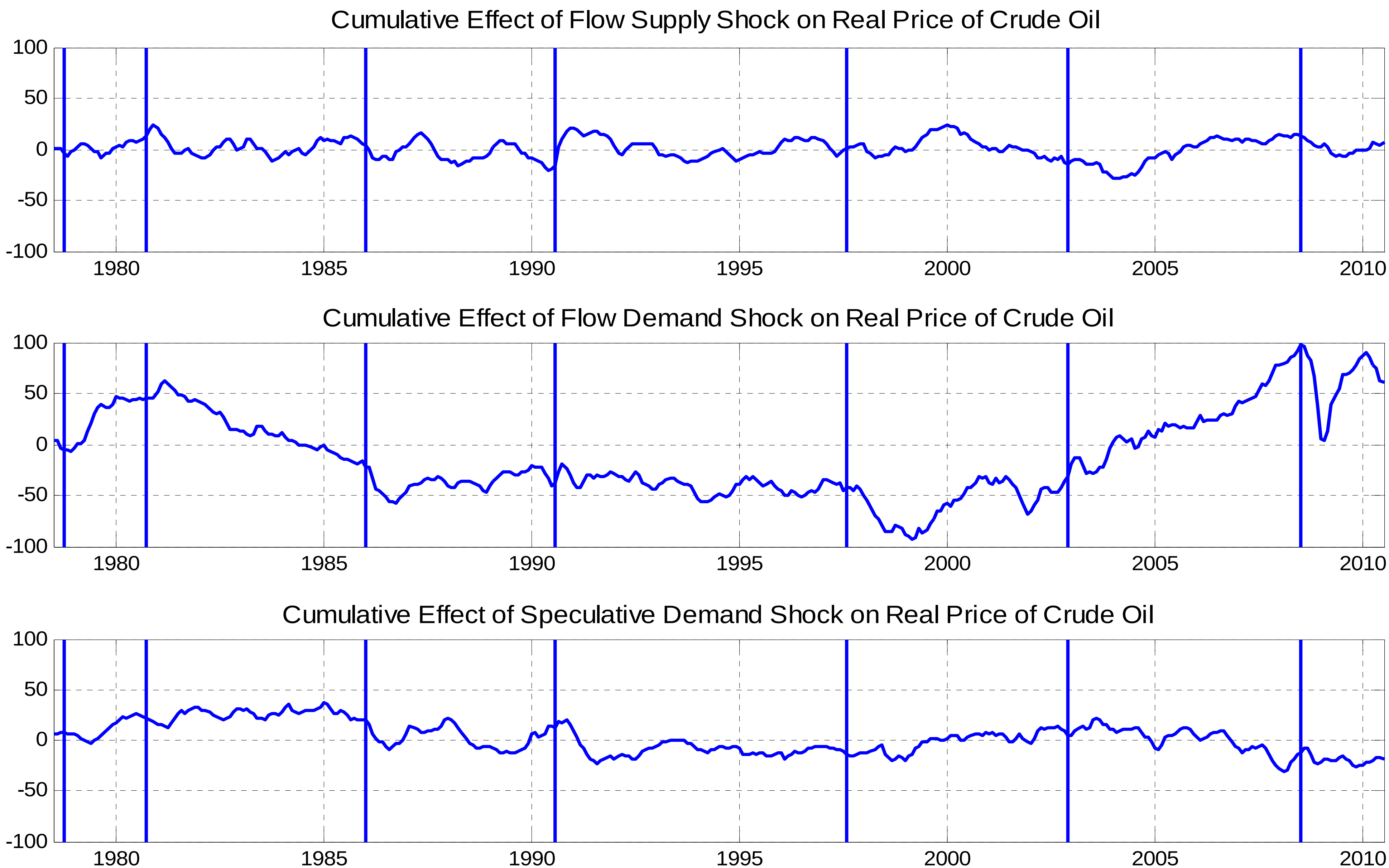
- Under the maintained assumption of stationarity, the structural moving average representation of the estimated VAR model allows us to decompose historical fluctuations in the data into orthogonal components corresponding to different oil demand and oil supply shocks.

- Let

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

where y_t refers to the current observation, Θ_i denotes the matrix of structural impulse responses at lag $i = 0,1,2,...,$and w_t denotes the vector of mutually uncorrelated structural shocks (see Lütkepohl 2005).

Historical Decomposition for Real U.S. RAC for Imports



Forecast Scenarios

$$y_{t+h} = \sum_{i=0}^{\infty} \Theta_i w_{t+h-i} = \underbrace{\sum_{i=0}^{h-1} \Theta_i w_{t+h-i}}_{Future} + \underbrace{\sum_{i=h}^{\infty} \Theta_i w_{t+h-i}}_{y_t}$$

- Setting all future structural shocks to zero results in the baseline reduced-form VAR forecast.

- Feeding in a sequence of nonzero future structural shocks provides a conditional forecast (also see Waggoner and Zha REStat 1999).

- The difference in the path of y_{t+h}, $h = 1, 2, \ldots$, provides the required adjustment to the baseline forecast.

Forecast Scenarios

● The structural MAR coefficients used in constructing scenarios are based on ex-post revised data to allow the best possible estimate of the effect of a given sequence of future structural shocks.

● Like impulse responses, VAR forecast scenarios are time-invariant. They do not necessarily have to be recomputed every month, except to the extent that a longer sample offers efficiency gains in estimating the structural model.

● The key difference to impulse response analysis is that forecast scenarios involve a sequence of future shocks rather than a one-time shock.

Forecast Scenarios

● Often historical events provide guidance about realistic structural shock sequences.

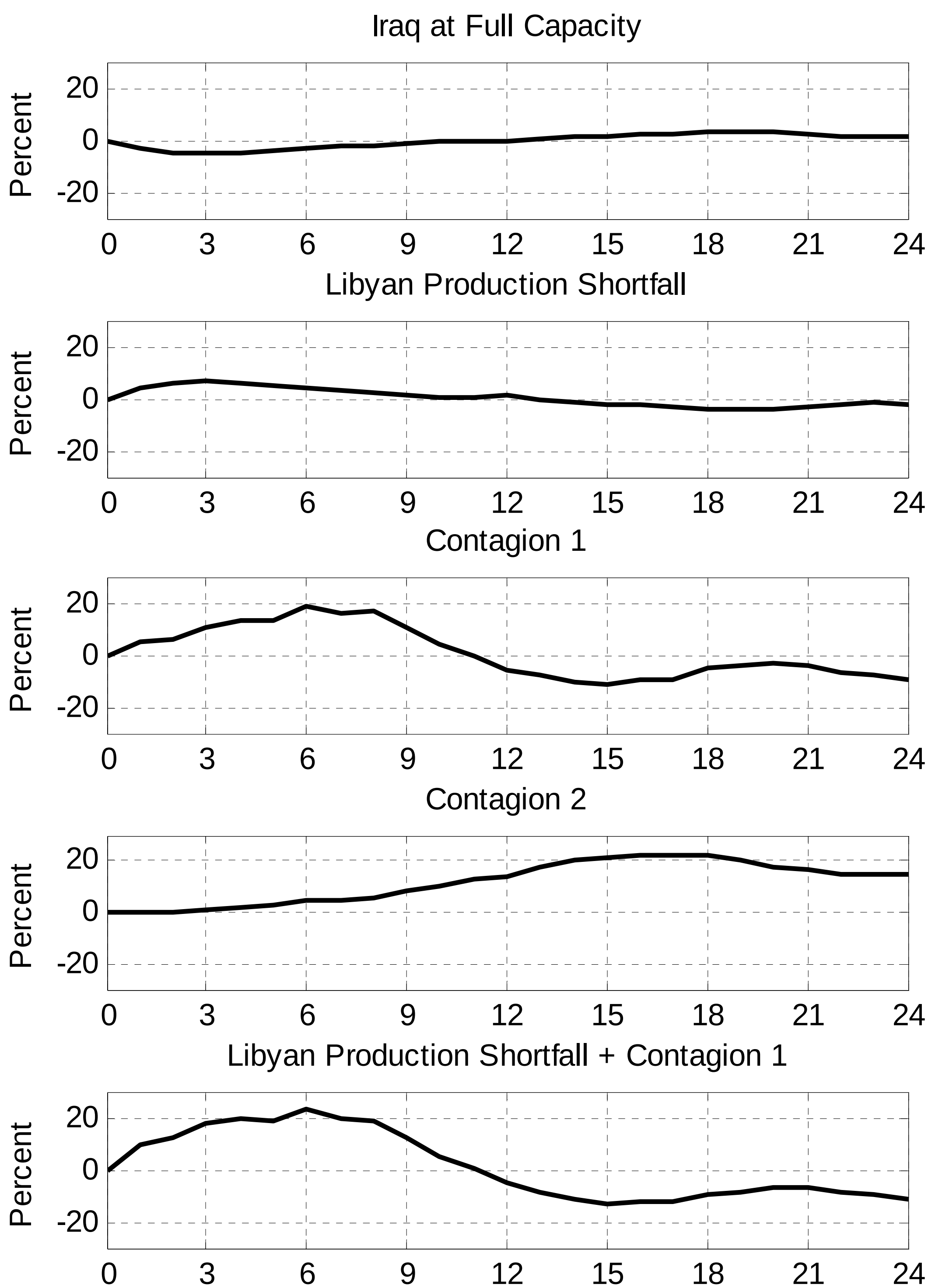
Example: The effect of another Asian crisis on flow demand.

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

Example: The effect of shutting down Iranian oil production.

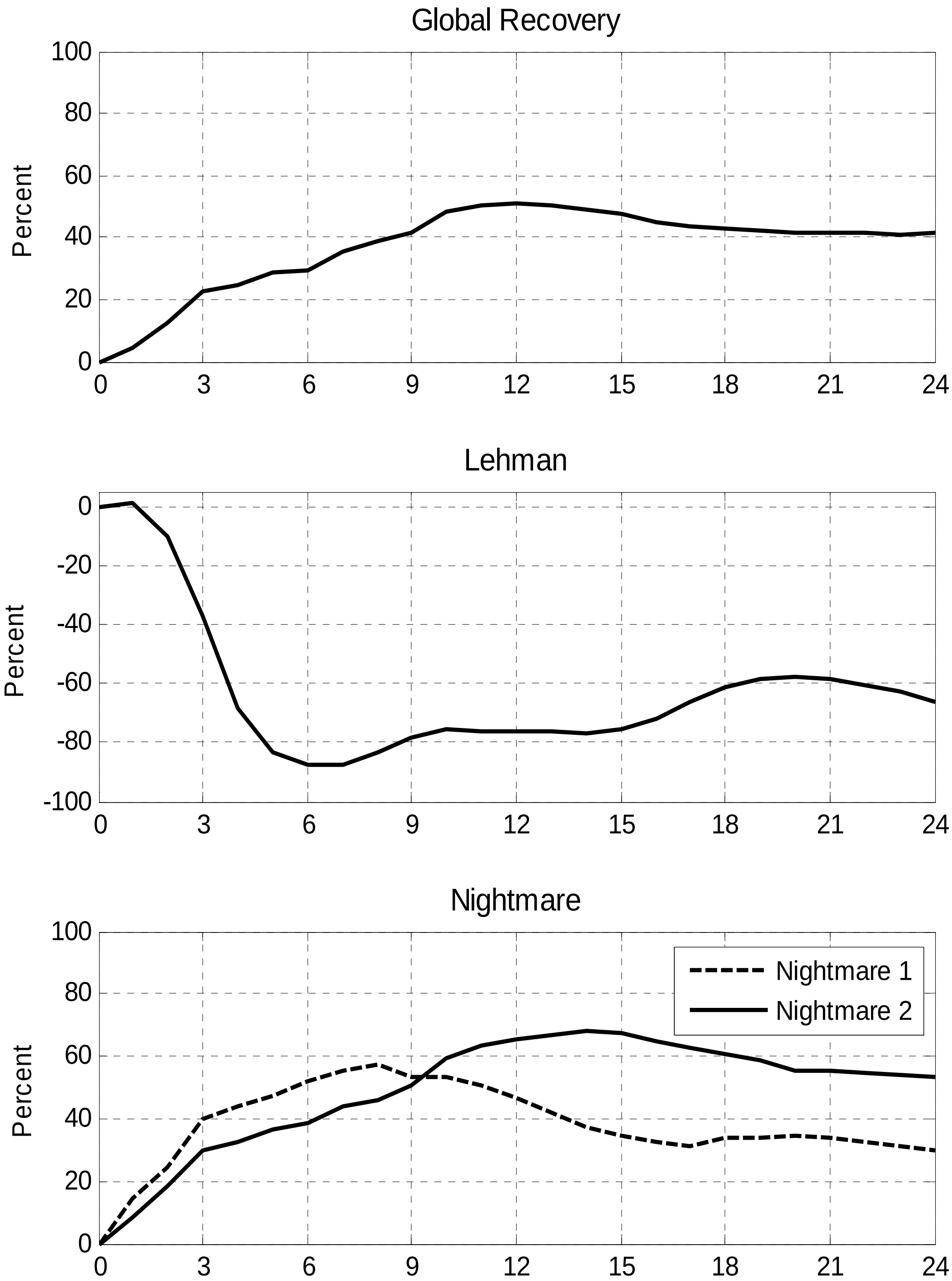
Forecast Scenarios for Real Refiners' Acquisition Cost

Percent Deviations from Baseline Forecast



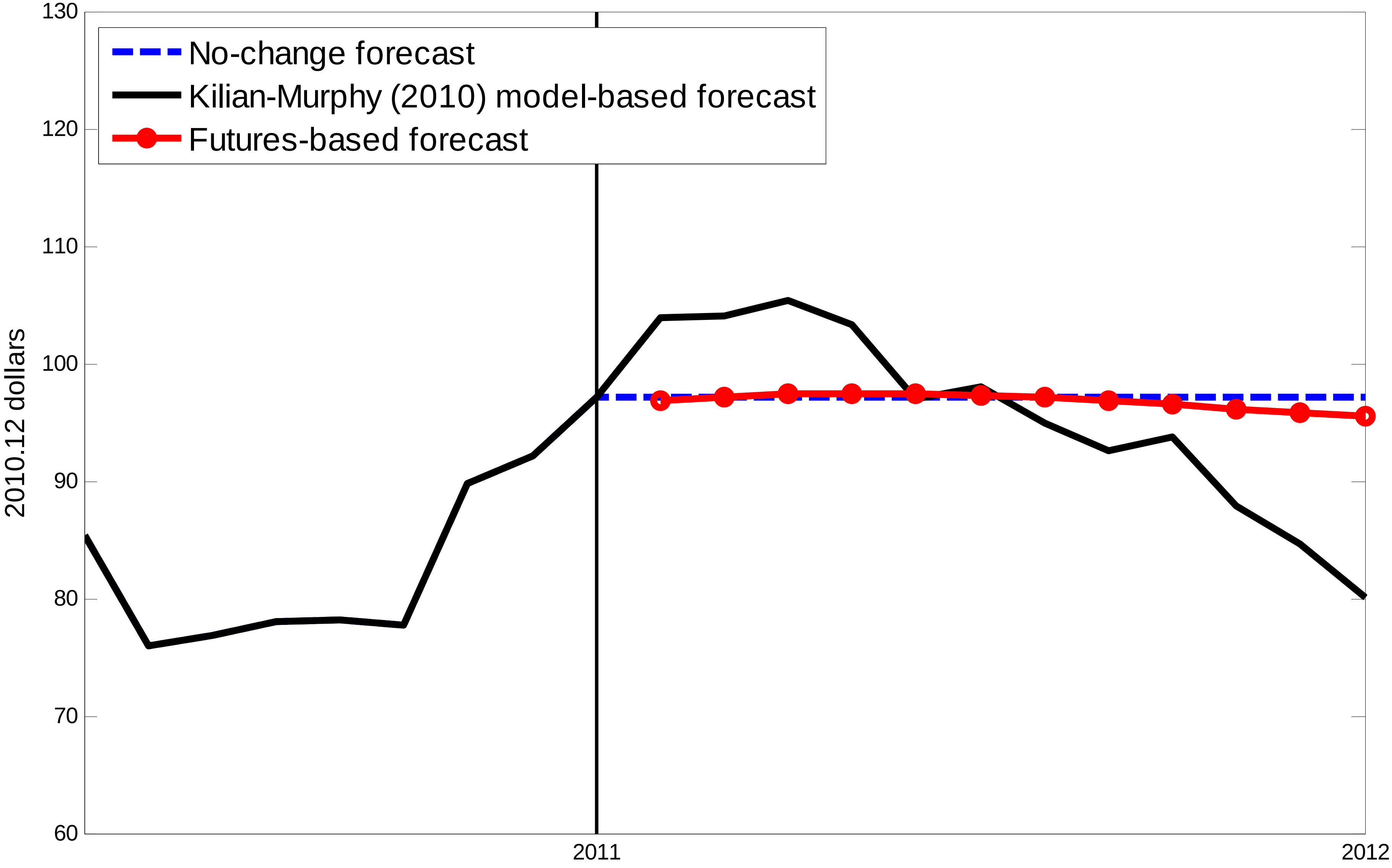
Forecast Scenarios for Real Refiners' Acquisition Cost

Percent Deviations from Baseline Forecast

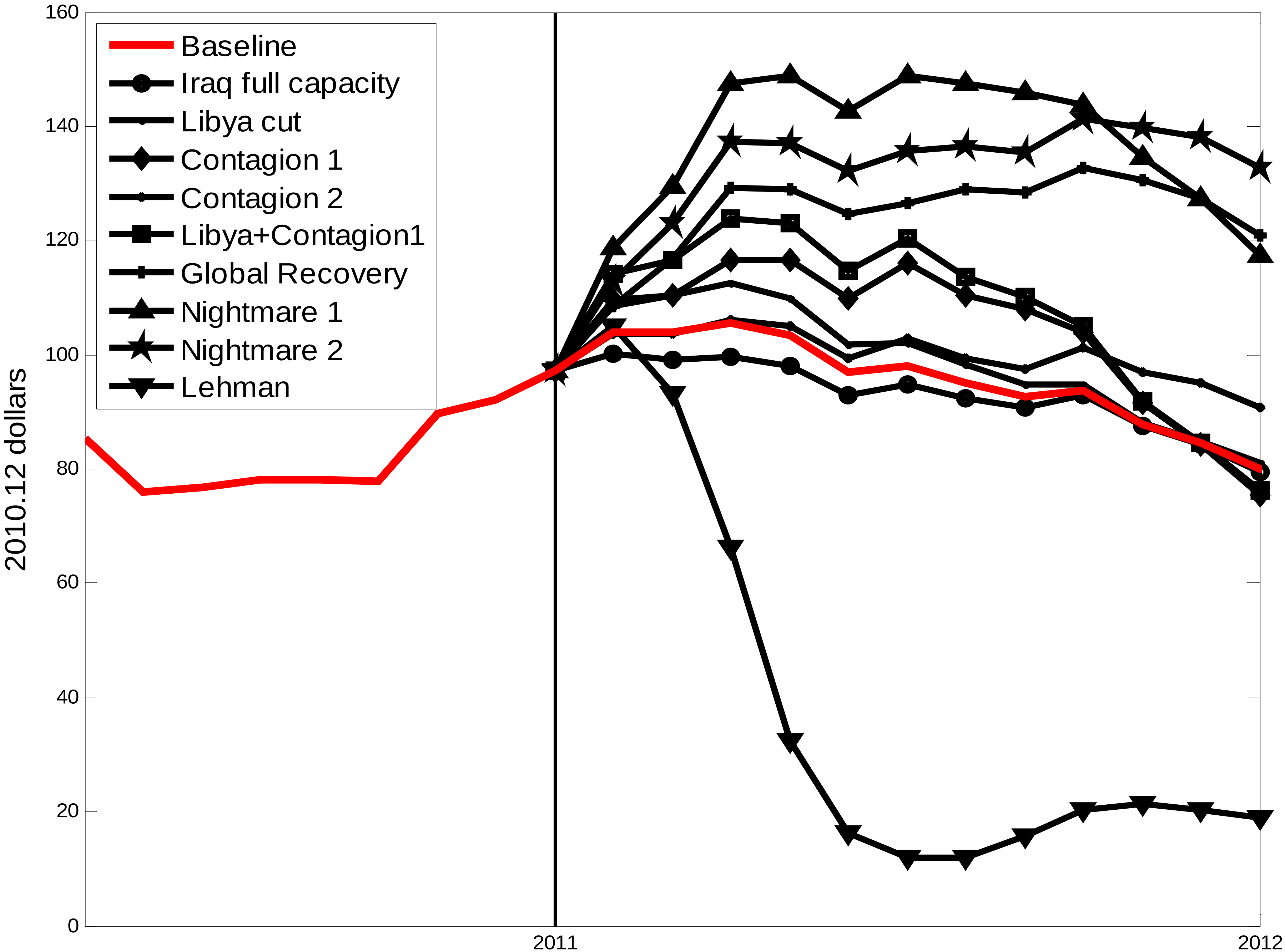


NOTES: The two *nightmare scenarios* combine the global recovery scenario with the Libyan production shortfall scenario and with the contagion 1 and contagion 2 scenarios, respectively.

Real-Time Forecasts of
Real U.S. Refiners' Acquisition Cost as of 2010.12



Sensitivity Analysis as of 2010.12



Formal Risk Analysis in Real Time

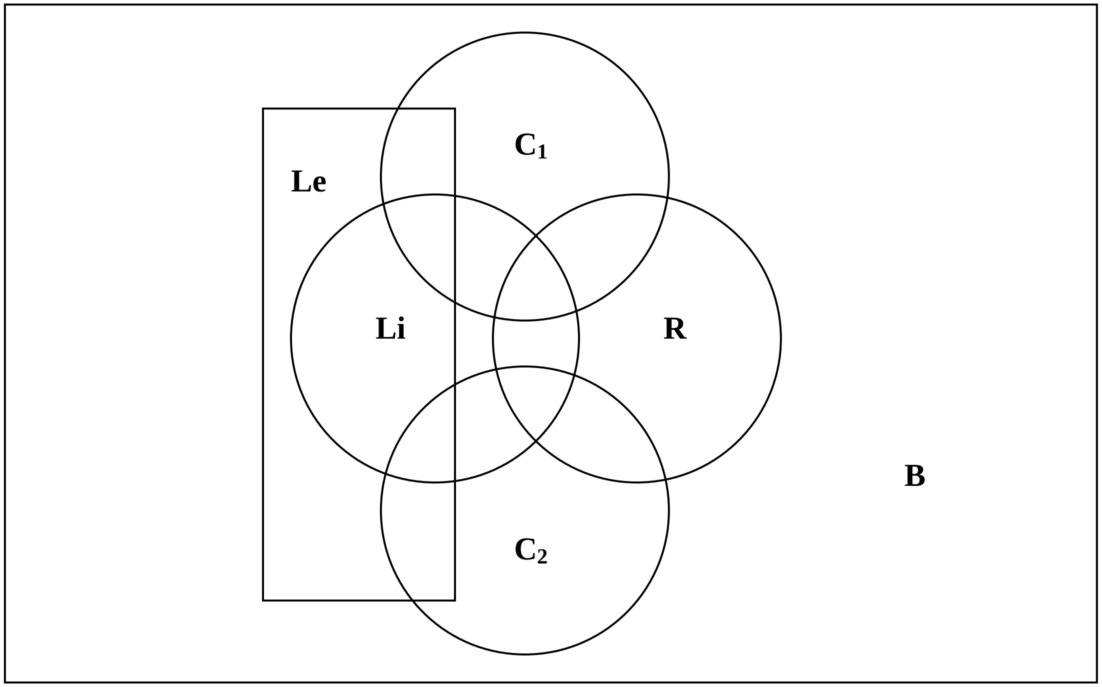
● Probability weighted densities for scenarios

● Risk measures for real price of oil.

Example: Real price in excess of $100 or below $80.

● Building on Kilian and Manganelli (JMCB 2007, JMCB 2008), we can quantify how upside and downside oil price risks change with the probability weights attached to the scenarios.

Event Analysis using Venn Diagrams
An Illustrative Example

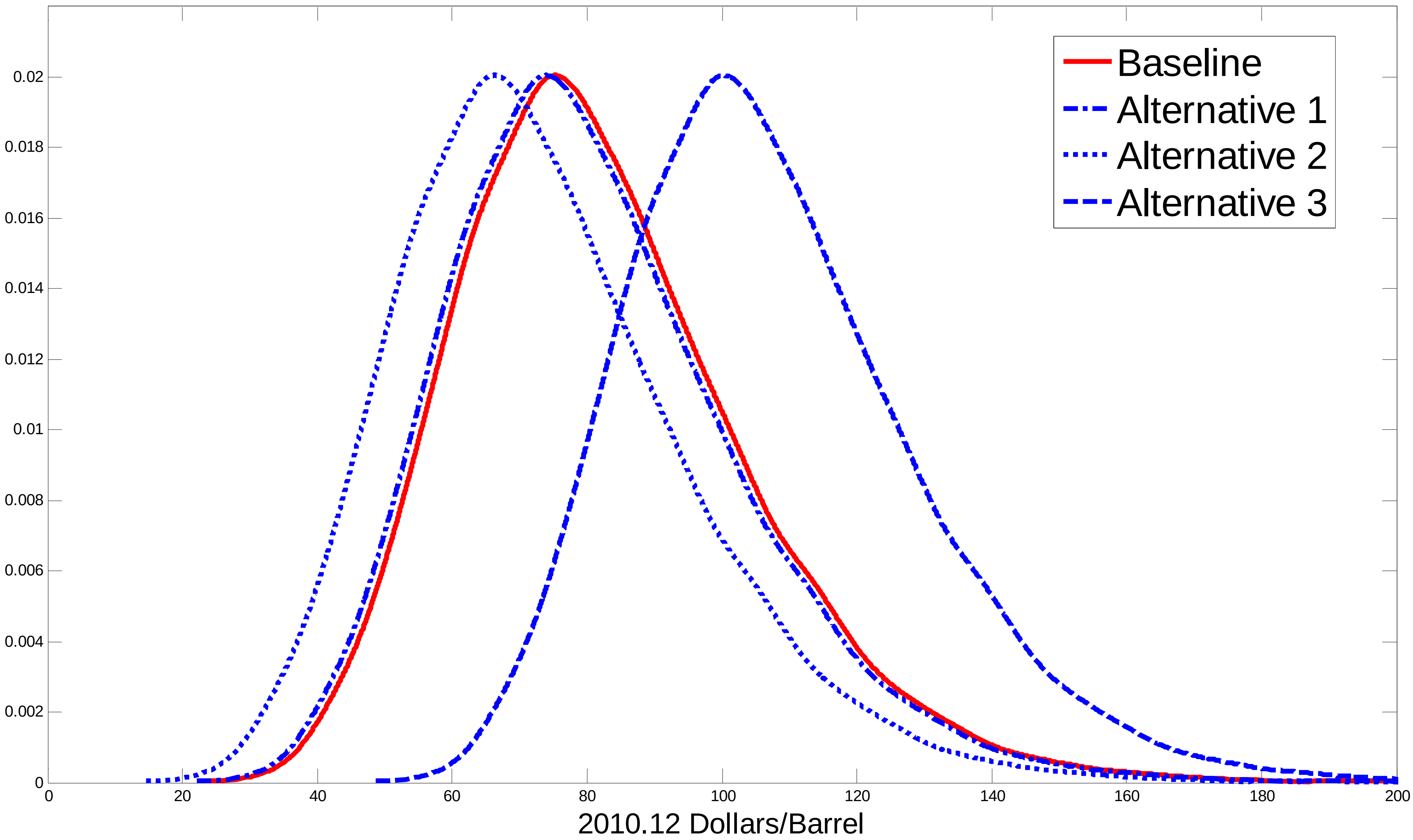


NOTES: B stands for *baseline*, Le for *Lehman*, Li for *Libyan production shortfall*, R for *global recovery*, C_1 and C_2 stand for *contagion 1* and *contagion 2*. We abstract from the *Iraq at full capacity* scenario for expository purposes. The Le and R scenarios are mutually exclusive, as is the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

- Consider the events of R_{t+h} exceeding an upper threshold of $\overline{R}$ (upside risk) and of R_{t+h} falling below the lower threshold of $\underline{R}$ (downside risk):
- $\alpha \geq 0$ and $\beta \geq 0$ denote the user's degree of risk aversion:

1. Target probabilities:

$$\alpha = \beta = 0 \quad \Rightarrow \quad DR_0 = -\Pr(R_{t+h} < \underline{R}) \text{ and } UR_0 = \Pr(R_{t+h} > \overline{R})$$

2. Probability-weighted expected shortfall/excess:

$$\alpha = \beta = 1 \quad \Rightarrow \quad DR_1 = E(R_{t+h} - \underline{R} \mid R_{t+h} < \underline{R}) \Pr(R_{t+h} < \underline{R})$$

$$UR_1 = E(R_{t+h} - \overline{R} \mid R_{t+h} > \overline{R}) \Pr(R_{t+h} > \overline{R}).$$

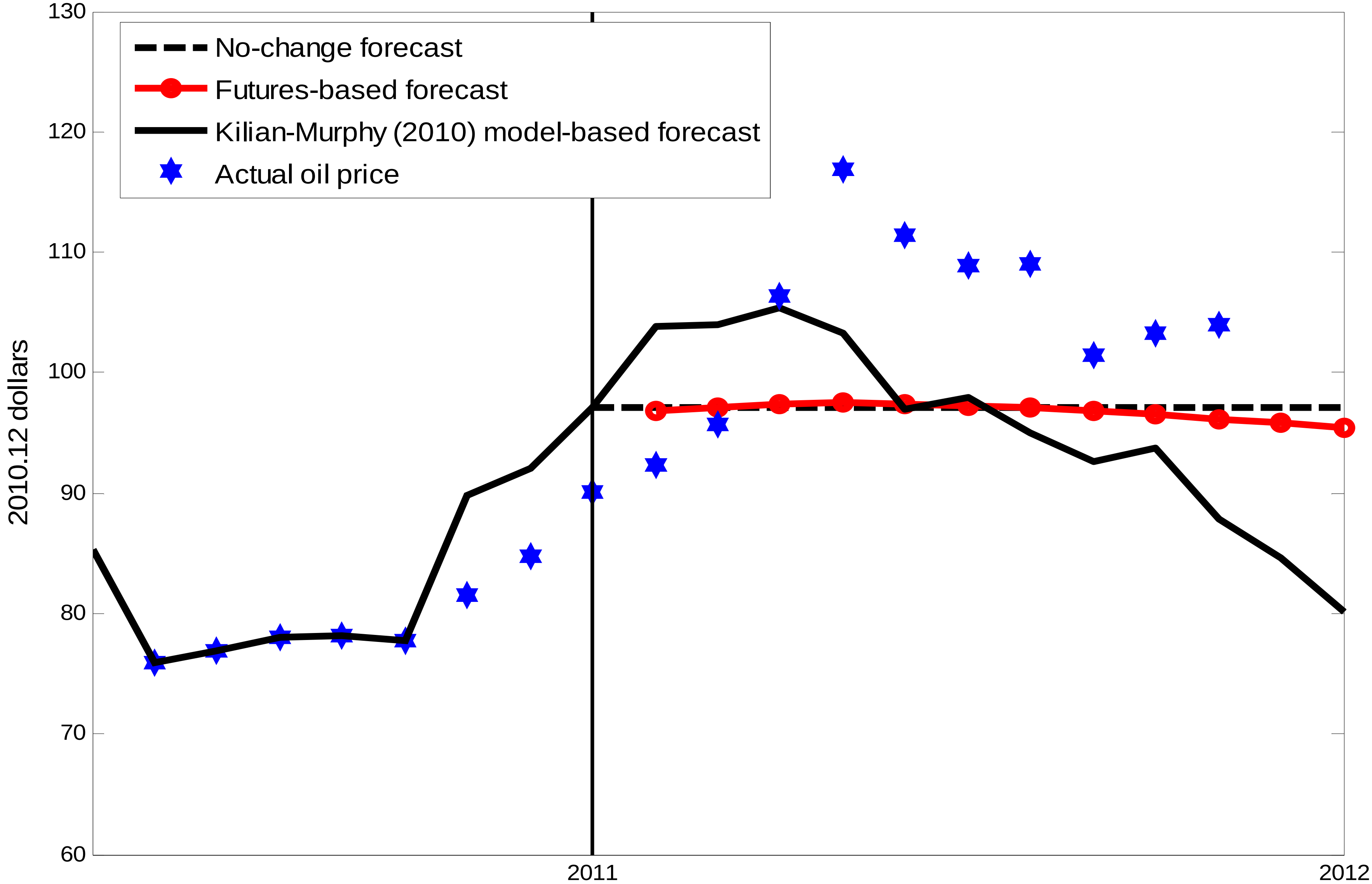
Risk Measures for Probability Weighted Forecast Scenarios
Upside Risks

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	0.67	13.53	9.06
	6	0.46	17.09	7.93
	12	0.20	16.70	3.27
	24	0.23	23.13	5.37
1	3	0.72	14.25	10.19
	6	0.41	16.63	6.79
	12	0.18	16.50	3.02
	24	0.21	22.93	4.82
2	3	0.61	12.72	7.72
	6	0.26	15.10	3.89
	12	0.12	15.81	1.88
	24	0.16	22.40	3.60
3	3	0.93	21.01	19.54
	6	0.74	21.82	16.15
	12	0.60	21.16	12.64
	24	0.47	25.56	11.92

Risk Measures for Probability Weighted Forecast Scenarios
Downside Risks

Scenario	h	$P(R_{t+h} < 80)$	$E(R_{t+h} - 80 \mid R_{t+h} < 80)$	$E(R_{t+h} - 80 \mid R_{t+h} < 80) \times \Pr(R_{t+h} < 80)$
Baseline	3	0.02	5.34	0.11
	6	0.15	8.22	1.25
	12	0.51	14.37	7.26
	24	0.52	18.32	9.59
1	3	0.02	5.11	0.08
	6	0.19	8.82	1.71
	12	0.53	14.97	7.94
	24	0.56	19.53	10.94
2	3	0.03	5.29	0.16
	6	0.36	11.50	4.09
	12	0.66	18.86	12.50
	24	0.65	23.07	14.95
3	3	0.00	3.15	0.01
	6	0.03	6.04	0.18
	12	0.08	6.41	0.51
	24	0.23	10.35	2.35

How Did We Do?



No-change forecast
Futures-based forecast
Kilian-Murphy (2010) model-based forecast
Actual oil price
2010.12 dollars
130
120
110
100
90
80
70
60
2011
2012

What if We Had Foreseen the Libyan Supply Cut?