Unspanned Macroeconomic Risks in Oil Futures

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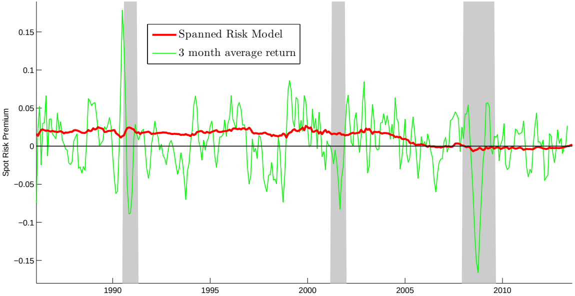
Motivation

- How do commodity futures interact with the real economy?
  - *“Higher output coupled with weaker demand from China and Europe has driven the price of crude down to $85”*
  - *“Low oil prices can help boost economic growth by reducing fuel bills and leaving consumers and companies with more money to spend on other things”*

- Average daily volumes for October 2014:
  - NYSE + NASDAQ, all stocks: $129B
  - WTI + Brent crude oil futures: $120B (1.4 billion barrels)

Motivation

- How do expected returns to crude oil futures vary over time?



- Standard pricing models say, not much

This Paper

- A “macro-finance” model for futures
  - Model both pricing and macroeconomic state variables
  - Incorporates unspanned macroeconomic risks:
    - State variables that affect expected returns and/or price forecasts, but are not identified in contemporaneous asset prices

This Paper

Results:

- *Negative feedback* between oil prices and real activity
  - Mediated by slope of the futures curve
- An *unspanned procyclical* risk premium in oil futures
- Strong relation between inventories and slope of the futures curve
- Applications to measuring the cost of carry and pricing real options

Prior Literature

1. Affine pricing models for commodities
    - Gibson and Schwartz (1990), Schwartz (1997), Schwartz and Smith (2000), Casassus and Collin-Dufresne (2005), Casassus, Liu and Tang (2013), Hamilton and Wu (2014)
    - Estimated from asset prices: no macroeconomic information
2. VARs with macroeconomic indexes and a spot price of oil
    - Hamilton (1983), Bernanke et al (1997), Hamilton (2003), Kilian (2009), Alquist and Kilian (2010), Coibion and Chinn (2013), Kilian and Vega (2013)
    - Silent on risk premia, term structure of futures prices

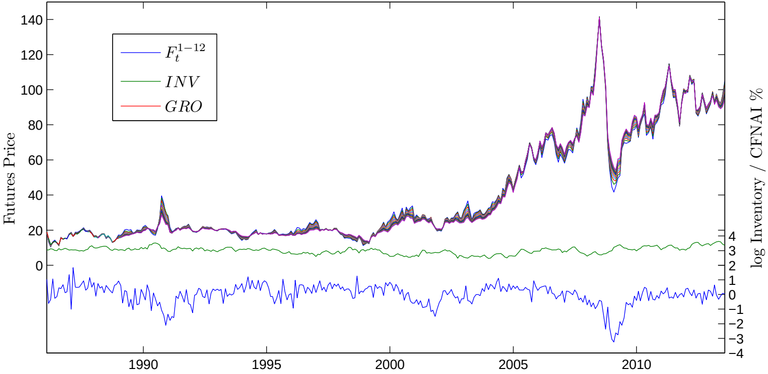
Data

- Summarize the data and show three stylized facts

Data

- Monthly data, 1986 - 2013
- NYMEX crude oil futures prices $F_t' = (F_t^{1m}, ..., F_t^{12m})$
  - Take logs $f_t' = (f_t^{1m}, ..., f_t^{12m})$
- Chicago Fed National Activity Index (CFNAI) - "*GRO*"
- Log of EIA's U.S. crude oil inventory ex SPR - "*INV*"

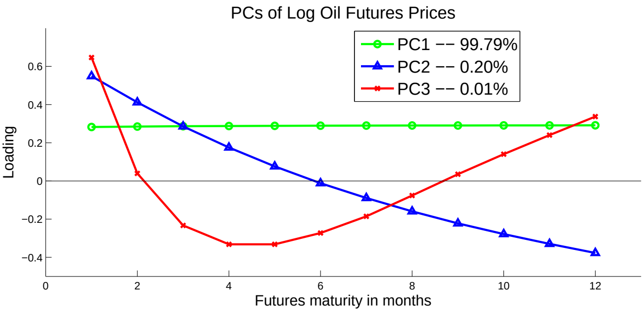
Data



F_t^{1-12}
INV
GRO
Futures Price
log Inventory / CFNAI %
140
120
100
80
60
40
20
0
4
3
2
1
0
−1
−2
−3
−4
1990
1995
2000
2005
2010

Fact 1

- The first two PCs explain > 99% of variation in log futures prices



- Similar for returns or changes in log prices

Fact 2

- *GRO* and *INV* are not well captured (spanned) by futures prices
- Project [*GRO*, *INV*] on futures prices:
  - First two PCs: $R^2 = [7\%, 27\%]$
  - First five PCs: $R^2 = [15\%, 30\%]$
  - All 12 futures maturities: $R^2 = [19\%, 31\%]$

Fact 3

- *GRO* has forecasting power for oil prices over and above the PCs

$$\Delta PC_{t+1} = \alpha + \beta_{1-5} PC_t^{1-5} + \beta_{GRO} GRO_t + \beta_{INV} INV_t + \epsilon_{t+1}$$

	ΔPC	
	Level	Slope
β_{GRO}	0.068**	-0.008
	(0.028)	(0.005)
β_{INV}	0.040	-0.032
	(0.236)	(0.047)
Adjusted $R^2(PC^{1-5})$	-0.6%	8.0%
Adj. $R^2(PC^{1-5} + M_t)$	1.7%	8.5%
F-ratio	9.5***	1.9

Model

- Spanned vs unspanned risks
- Model and estimate

Spanned Risks

- Affine pricing model: state vector X_t, with dimension N:

$$f_t = A + BX_t + \epsilon_t$$

- If B is full rank, we can rotate and translate to:

$$f_t = \hat{A} + \hat{B}\mathcal{P}_t + \hat{\epsilon}_t$$

where $\mathcal{P}_t$ are **any** N independent linear combinations of f_t

Spanned Risks

$$f_t = \hat{A} + \hat{B}\mathcal{P}_t + \hat{\epsilon}_t$$

- Implicit in previous affine pricing models
- Consequences:
  1. $\mathcal{P}_t$ and X_t have the same dimension
  2. Regressing elements of X_t on $\mathcal{P}_t$ has R^2 of 100%
  3. No information can forecast returns or prices conditional on $\mathcal{P}_t$

Unspanned Risks

- Suppose instead that some subspace of dimension $L < N$ is spanned by futures prices
- Consequences:
  1. $dim(\mathcal{P}_t) < dim(X_t)$
  2. Regressing elements of X_t on $\mathcal{P}_t$ has R^2 <100%
  3. Other information can forecast returns or prices conditional on $\mathcal{P}_t$

Model

- Recalling our three stylized facts, the model assumes:
  1. Two pricing factors $\mathcal{P}_t$ summarize log futures prices
  2. Macro factors M_t are not fully spanned by $\mathcal{P}_t$
  3. M_t can predict prices and/or returns conditional on $\mathcal{P}_t$

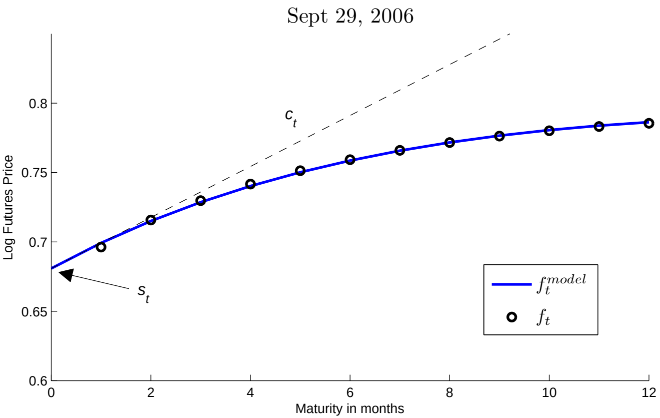
Model

- After estimation, rotate the spanned factors from $\mathcal{P}_t$ to $(s_t, c_t)'$
- s_t is the log spot price implied by the model
- The cost of carry c_t is defined by no-arbitrage:

$$S_t e^{c_t} = F_t^1 \quad \Rightarrow \quad c_t = f_t^1 - s_t$$

- Think $c_t = r_t + storage_t - convyield_t$

Model


Sept 29, 2006
Log Futures Price
Maturity in months
0.6
0.65
0.7
0.75
0.8
0
2
4
6
8
10
12
c_t
s_t
f_t^{model}
f_t

Model

- The model can be summarized in two equations:

$$\text{Physical: } \begin{bmatrix} \Delta s_{t+1} \\ \Delta c_{t+1} \\ \Delta M_{t+1} \end{bmatrix} = \begin{bmatrix} K^{\mathbb{P}}_{0sc} \\ K^{\mathbb{P}}_{0M} \end{bmatrix} + \begin{bmatrix} K^{\mathbb{P}}_{sc,sc} & K^{\mathbb{P}}_{sc,M} \\ K^{\mathbb{P}}_{M,sc} & K^{\mathbb{P}}_{MM} \end{bmatrix} \begin{bmatrix} s_t \\ c_t \\ M_t \end{bmatrix} + \Sigma \epsilon^{\mathbb{P}}_{t+1}$$

$$\text{Pricing: } \begin{bmatrix} \Delta s_{t+1} \\ \Delta c_{t+1} \end{bmatrix} = K^{\mathbb{Q}}_0 + K^{\mathbb{Q}}_1 \begin{bmatrix} s_t \\ c_t \end{bmatrix} + \Sigma_{sc} \epsilon^{\mathbb{Q}}_{t+1}$$

- Estimate on (f^{1-12}, GRO, INV) from 1986-2013

Model Estimate

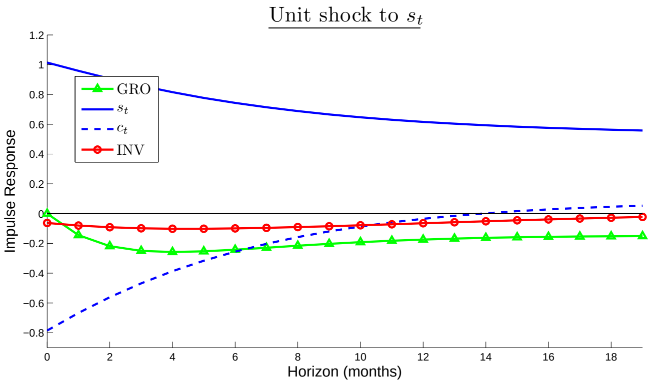
Feedback Matrix

		s_t	c_t	GRO_t	INV_t
s_{t+1}	0.008	0.994	0.061*	0.025***	0.038
	(0.006)	(0.009)	(0.033)	(0.008)	(0.082)
c_{t+1}	-0.007	0.016*	0.874	-0.015	-0.045
	(0.005)	(0.008)	(0.031)	(0.008)	(0.078)
GRO_{t+1}	0.001	−0.115**	0.051	0.618	-0.194
	(0.030)	(0.046)	(0.171)	(0.043)	(0.433)
INV_{t+1}	0.002	0.000	0.032***	-0.002	0.888
	(0.002)	(0.002)	(0.009)	(0.002)	(0.023)

Shock Volatilities

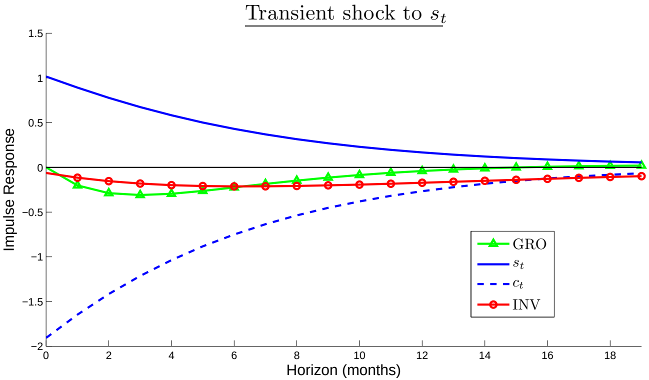
	s	c	GRO	INV
s	0.103			
c	-81%	0.057		
GRO	5%	-2%	0.530	
INV	-22%	27%	4%	0.028

Impulse Responses



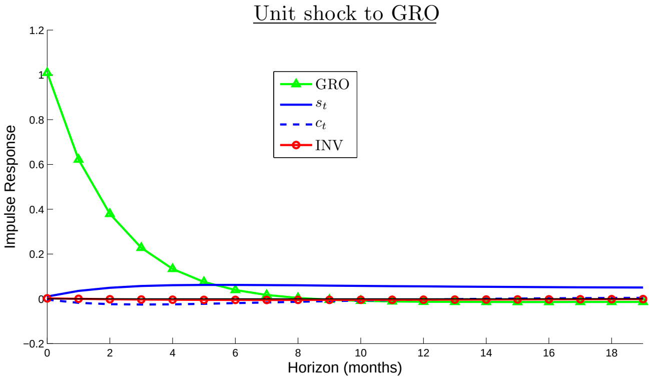
- About 60% of a typical oil shock is expected to persist indefinitely
- Lowers *GRO* indefinitely

Impulse Responses



- A transient shock to s_t lowers *GRO* transiently

Impulse Responses



- A 1% shock to *GRO* dies out, raises s_t by 6% indefinitely

Summary

- Feedback relationship between s_t and *GRO*
  - Persistent shocks to s_t lower *GRO* persistently
  - Transient shocks to s_t lower *GRO* transiently
  - Transient shocks to *GRO* raise s_t persistently
- Higher c_t forecasts higher inventories
- INV_t doesn't forecast anything but is strongly correlated with s_t, c_t
  - Physical inventories spanned by s_t, c_t

Risk Premiums – Spanned-Risk Model

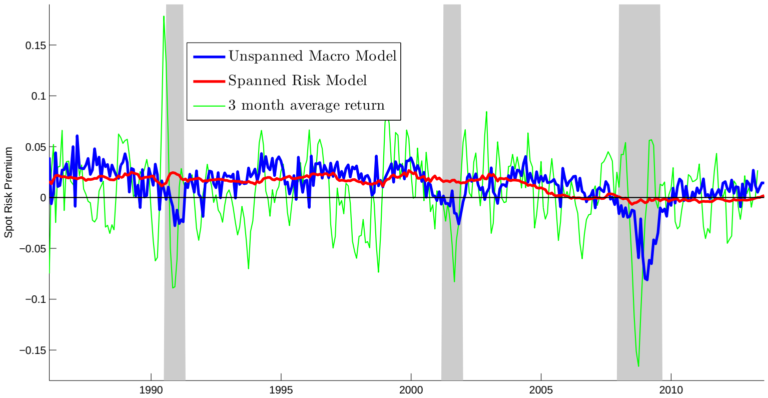
		s_t	c_t
Spot risk premium Λ_t^s	0.012	-0.003	-0.031
	(0.014)	(0.015)	(0.046)
Carry risk premium Λ_t^c	-0.010	0.025	-0.029
	(0.017)	(0.020)	(0.060)

Risk Premiums – Macro Model

		s_t	c_t	GRO_t	INV_t
Spot risk premium Λ_t^s	0.012	-0.003	-0.031	0.025***	0.075
	(0.014)	(0.015)	(0.046)	(0.009)	(0.102)
Carry risk premium Λ_t^c	-0.010	0.025	-0.029	-0.013	0.003
	(0.017)	(0.020)	(0.060)	(0.008)	(0.096)

- The premium to bearing spot price risk is procyclical

Risk Premiums



Risk Premiums – Rationale

- ICAPM: State variables are total wealth and the quantity of oil:

$$\Lambda_t^s = \beta_t^s \lambda_t^{mkt} - \lambda_t^{oil}$$

- Being long s_t provides a hedge against oil shocks
- In slumps, λ_t^{oil} is larger $\Rightarrow$ *procyclical* risk premium

Applications

Two applications:

1. Measuring the cost of carry
2. Valuing real options

Application – Cost of Carry

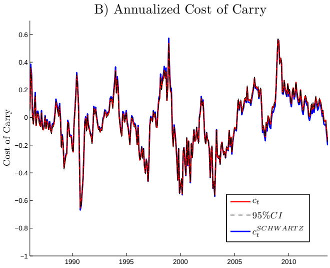
- Cross-section of prices = “snapshots of $\mathbb{Q}$-forecast”
- Factor structure in futures prices
- Consequence: $\mathbb{Q}$-parameters are precisely estimated

Application – Cost of Carry

- c_t is defined by the $\mathbb{Q}$-measure:

$$c_t = f_t^1 - s_t = E^{\mathbb{Q}}\left[\Delta s_t\right]$$

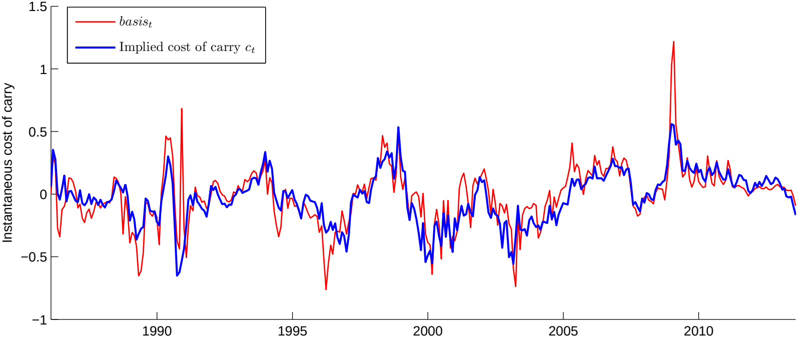
- Consequence: c_t is precisely estimated



Cost of carry vs basis

- The *basis* is the log spread $f_t^2 - f_t^1$
- Often used as a proxy for c_t
- How do the two compare?
  - c_t assumes the affine model
  - *basis* assumes no errors in $F_t^{1,2}$

Cost of carry vs basis



- c_t: $AR(1) = 0.88$, $\sigma = 10.0\%$
- $basis_t$: $AR(1) = 0.74$, $\sigma = 16.9\%$

Cost of carry vs basis

- Measure c_t from WTI (U.S.) and Brent (North Sea) oil futures
- Measure $basis_t$ from U.S. oil futures
- How do we know which is more meaningful?
  - Correlation with inventories: c_t 0.52, $basis_t$ 0.42
  - Horse race forecasting future inventories

c_t drives out the basis

	ΔINV_{t+1}		
c_t	0.031***		0.038***
	(0.008)		(0.010)
$basis_t$		0.016*	-0.009
		(0.009)	(0.012)
INV_t	−0.112***	−0.088***	−0.112***
	(0.022)	(0.023)	(0.022)
adj. R^2	6.4%	3.9%	6.2%
T	330	330	330

c_t^{BRENT} drives out the basis

	ΔINV_{t+1}		
c_t^{BRENT}	0.039^{***}		0.035^{**}
	(0.011)		(0.015)
$basis_t$		0.016^{*}	0.004
		(0.009)	(0.013)
INV_t	-0.105^{***}	-0.088^{***}	-0.107^{***}
	(0.026)	(0.023)	(0.028)
adj. R^2	6.3%	7.4%	6.0%
T	281	281	281

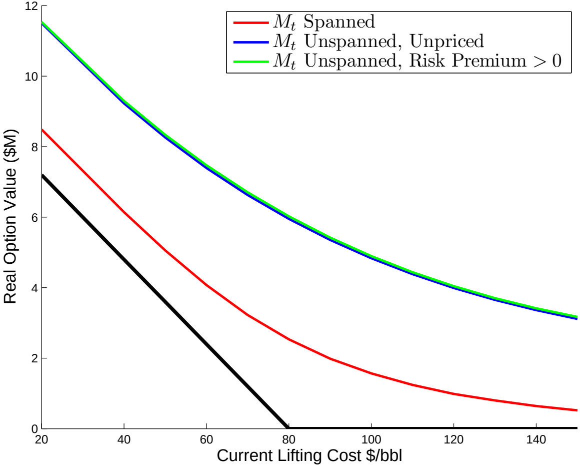
Application – Real Options

- Real options valuation
  - Classic topic for affine spanned-risk models
- Unspanned factors M_t cannot affect financial option prices
- But what if a real option's payoff depends on M_t
  - Pindyck (1993): Time-varying costs with a CAPM beta
- Moel and Tufano (2002) find time-varying costs at gold mines

Application – Real Options

- Classic example: Oil well
- Model as a strip of options to extract at lifting cost L_t and sell at S_t
- Exercised if $S_t > L_t$
- Log lifting cost l_t covaries with s_t and GRO

Real Options



Real Options

- Spanned-risk models miss a component of option value
  - Not because I_t varies less but because it has dynamics with s_t, c_t
- Adding unspanned macro risk raises well value by 35%-405%
  - More for 'out of the money' higher-cost wells
- Risk premium effect is much smaller
  - Adding a risk premium to *GRO* adds 0.99%-1.27% to well value

Conclusion

- Construct & estimate a macro-finance model for futures
  - Estimate on oil futures data, CFNAI real activity, and oil inventories
  - Feedback relationship between real activity and oil prices
  - Strong relationship between cost of carry and inventories

Conclusion

Two applications

- Measuring the physical cost of carry
  - Precisely pinned down by the data
  - Less volatile + slower moving than the basis
  - More related to current and futures inventories
- Valuing real options
  - Dynamics of unspanned macro risks generate large option value
  - Macro risk premiums have a smaller effect