Measuring and Hedging Oil Price Sensitivities: A Global Impact Study

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1 Introduction

The New Year has brought turmoil to global markets. Large sell-offs and high volatility in equity markets have been attributed to the continuing decline in the price of oil, which dipped below $30 a barrel for the first time since 2003. There is no sign of an imminent rebound as Saudi Arabia and other OPEC leaders maintain high production levels in an effort to enforce market competitiveness [3]. Making matters more complex, the dramatic fall in oil over the past 18 months has coincided with other underlying market trends, including tightening monetary policy in the US, fresh rounds of quantitative easing in the EU and Japan, a strengthening dollar, slowing demand in China, and weak global growth.

Taking into account current global conditions, this paper builds a novel framework with which to estimate, and subsequently, hedge oil price exposure in various industry sectors. Section 2 introduces the current and historical oil environment. Sections 3 and 4 estimate oil sensitivities of these industries, propose strategies with which to hedge the volatile changes in the oil price, and outline the risks inherent in such strategies. Section 5 examines the impact of Sovereign Wealth Fund liquidations. Sections 6 and 7 explore the macroeconomic and state-wide impacts, respectively, and Section 8 offers our outlook on global growth.

2 Background

In June 2014, the oil price began its latest significant and persistent decline. This has had a marked effect on the profitability of various industries. In particular, one can see from Figure 1 that the energy and chemical industries have suffered the most, while the consumer and financial industries have outperformed the S&P 500.

With global markets more connected than ever, there is a need for a framework to reliably monitor oil price sensitivities of industries and individual companies. Violent price movements in oil are not uncommon, and there can be significant risks to the profitability of oil-exposed companies. In order for institutional investors to effectively hedge these risks, sensitivity estimates must be measured in a precise and timely manner.

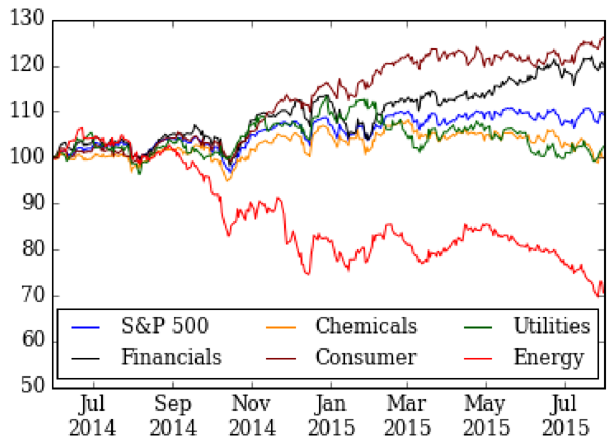

Figure 1: *Recent Industry Equity Performance [9]*

In estimating sensitivities, it is important to understand the dynamics of the absolute level of and relative changes in the oil price. Figure 2 shows alternating periods of persistence and mean-reversion in the West Texas Intermediate (WTI) crude oil price.

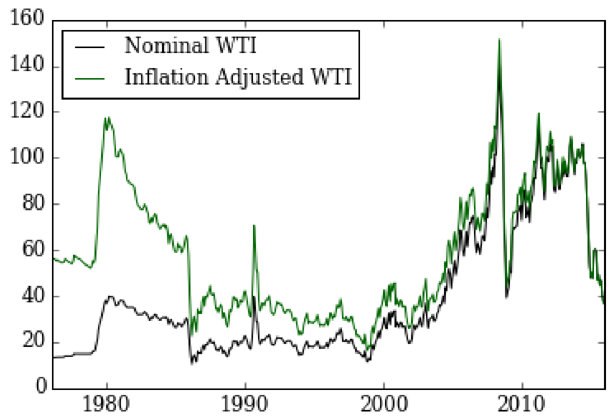

Figure 2: *Historical WTI Oil Price: 1976 to 2016 [4]*

Examining Figure 2 in the context of Figure 3, it is interesting to note how many countries are continuing to extract oil below or near the cost of production. In fact, these tremendous swings in the price of oil, oscillating between (1) a state of high-margin oligopolistic pricing and (2) a state of intense shake-out competition, inspired our decision to model the price of oil using a two-state Hidden Markov Regime-Switching model [6].

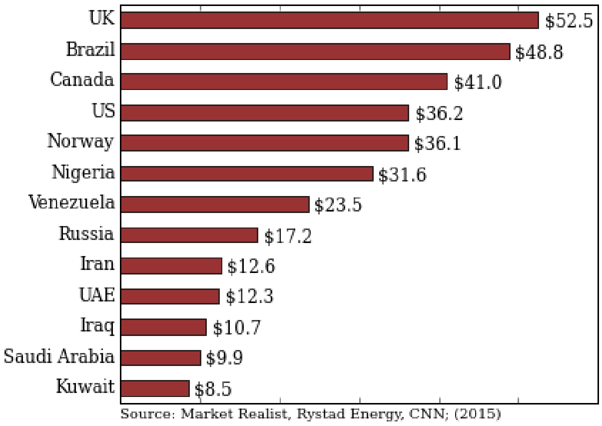

Figure 3: *Total Cost to Produce One Barrel of Crude Oil*

In our regime-switching model, a latent two-state system governs the evolution of the oil price. Specifically, the unconditional mean varies between an up-state (high price) and down-state (low price). We believe this binary mechanism is necessary to capture the stochastic shifts between competitive and oligopolistic pricing in the oil market.

3 Model Overview

In order to capture the evolution of monthly real WTI oil prices from 1978-2016, we propose two time-series models (with the exception of Section 4.2, we use real WTI oil prices throughout):

1. Auto-Regressive AR(2):

$$log(P_t) = \alpha + \beta_1 log(P_{t-1}) + \beta_2 log(P_{t-2}) + \epsilon_t$$

$$\mu = \frac{\alpha}{1 - \beta_1 - \beta_2}$$

$$\epsilon_t = \sigma^2 z_t \qquad z_t \sim N(0,1)$$

2. Regime-Switching Auto-Regressive model RS-AR(2):

$$log(P_t) = \alpha_s + \beta_1 log(P_{t-1}) + \beta_2 log(P_{t-2}) + \epsilon_t$$

$$\mu_s = \begin{cases} \dfrac{\alpha_{up}}{1 - \beta_1 - \beta_2} & \text{if } s = up \\ \dfrac{\alpha_{down}}{1 - \beta_1 - \beta_2} & \text{if } s = down \end{cases}$$

$$\epsilon_t = \sigma^2 z_t \quad z_t \sim N(0,1) \quad P = \begin{pmatrix} p_{u,u} & p_{d,u} \\ p_{u,d} & p_{d,d} \end{pmatrix}$$

We can model the log WTI oil price in this way because it satisfies the stationarity conditions as per the Dickey-Fuller test. Both models include second order lag terms due to statistically significant first and second partial correlations.

3.1 Model Estimates

We fit the AR(2) and RS-AR(2) models using Maximum Likelihood Estimation. This yields the following parameter estimates:

1. Auto-Regressive AR(2):

Parameter	Estimate	t-statistic
α	7.30e-2	2.1
β_1	1.16	36.8
β_2	-1.82e-1	-5.7
σ^2	7.60e-3	19.9

All parameter estimates for the AR(2) model are significant at the 5% level. The coefficient on the first lag, β_1, is positive and relatively large in magnitude, while β_2 is negative and smaller in magnitude.

2. Regime-Switching Auto-Regressive model RS-AR(2):

Parameter	Estimate	t-statistic
α_u	5.15e-1	7.1
α_d	3.99e-1	6.8
β_1	1.06	22.4
β_2	-1.79e-1	-4.0
σ^2	6.56e-3	14.4
$p_{u,u}$	98.5%	4.3
$p_{d,d}$	98.7%	4.1

The RS-AR(2) model parameters and state probabilities are also statistically significant. The signs and magnitudes of the β coefficients are similar to those of the AR(2) model. In addition, the state-dependent constant values have significantly greater t-statistics than the AR(2) model's constant estimate. The coefficients for both models satisfy the necessary conditions to be stationary.

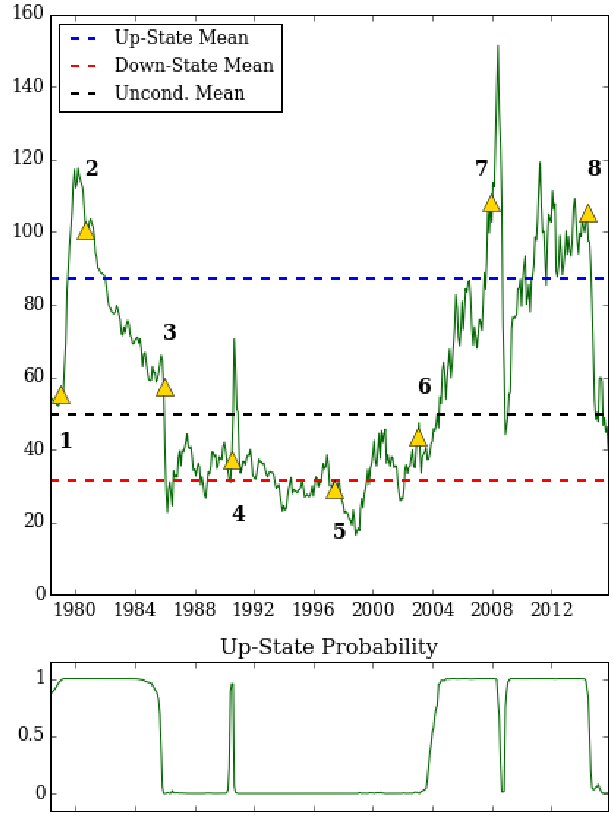

Figure 4: *WTI Price (USD); Historical Oil Shocks; Up-State Probabilities from RS-AR(2)*

3.2 Model Validation

Figure 4 shows the historical WTI oil price series with the unconditional means implied by the AR(2) and RS-AR(2) models. The bottom panel shows the conditional probability of being in the up-state across time. As a qualitative validation step, we annotate the price series with major historical events that affected the supply and/or demand of oil. We find that many of these important events line up with the implied regime switches of the model (see Table 1).

To compare the out-of-sample performance between the AR(2) and RS-AR(2) models, we perform an expanding window sum of squared errors test. We begin by creating a test data set by setting aside 120 months of data from the end of the log WTI oil price time series. We fit both an AR(2) and a RS-AR(2) to the remaining data (training set), forecast the next data point, and store the squared error of the forecast compared to the realized price. We iteratively add a month of data to the training set (expanding the window), re-estimate the model, and re-calculate the squared error. Figure 5 shows the performance of the expanding window AR(2) and the RS-AR(2) sum of squared errors test over the last 120 months.

Event	Description [7]
1	Iranian revolution
2	Iran-Iraq war
3	Saudi Arabia increases production after cutting nearly 75% of output during 1981-1985
4	Iraq invades Kuwait
5	East Asian Crisis
6	US invades Iraq
7	Start of US recession/GFC
8	Beginning of oil's recent slide

Table 1: *List of Major Oil-related Events*

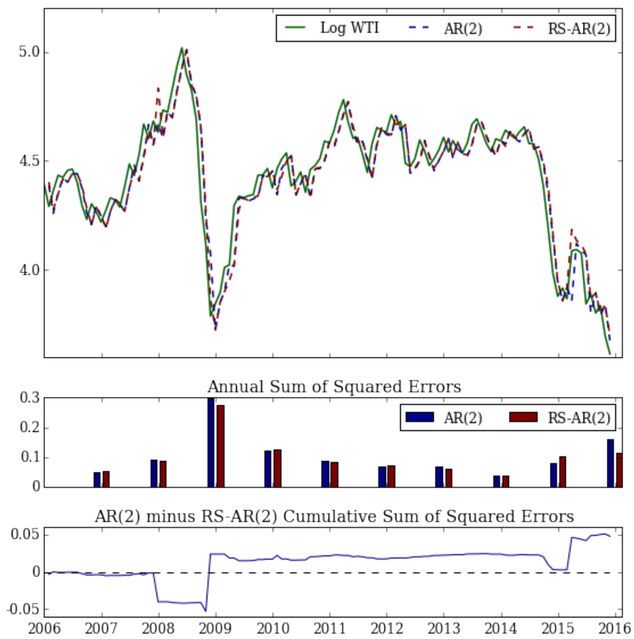

Figure 5: *Expanding Window Validation Results*

Model	Sum Squared Errors
AR(2)	1.0554
RS-AR(2)	1.0076

Table 2: *Validation Sum of Squared Errors*

The regime-switching model provides superior out-of-sample forecasting for the oil price. In particular, the RS-AR(2) model outperforms over the last 12 months, during oil's most recent slide.

4 Hedging Strategies

4.1 Oil Beta Estimation

Industry oil price sensitivities are estimated using a two-factor model of the S&P 500 returns and the changes in the oil price. Industry and market returns are in excess of the risk-free rate.

We estimate the following models:

1. Constant beta model:

$$r_{ind}^{ex} = \beta_{mkt} r_{mkt}^{ex} + \beta_{oil} r_{oil} + \epsilon$$

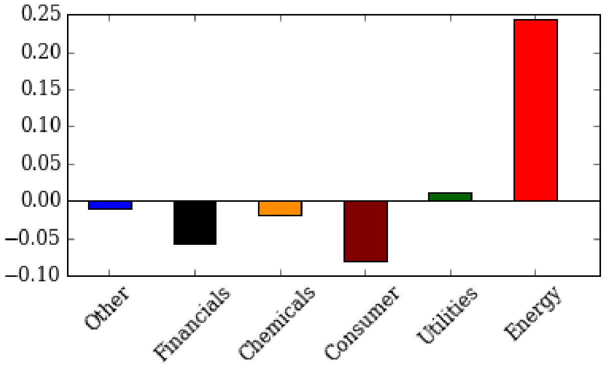

Figure 6: *Constant Oil Return Beta for Select Industries*

2. Time-varying beta model

$$r_{ind}^{ex} = \beta_{t,mkt} r_{mkt}^{ex} + \beta_{t,oil} r_{oil} + \epsilon$$

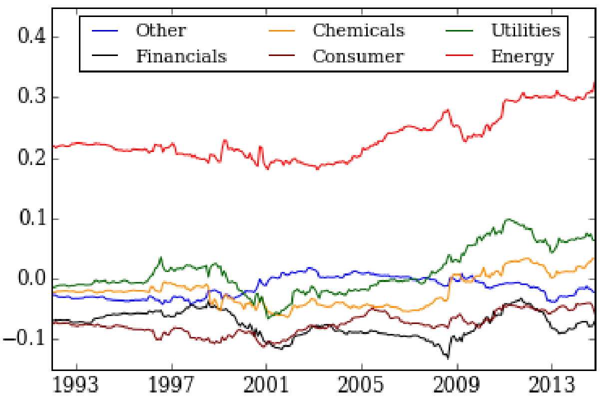

Figure 7: *Time-varying Oil Return Beta for Select Industries*

3. Two-state regime-switching beta model

$$r_{ind}^{ex} = p_{up}\left(\beta_{up,mkt} r_{mkt}^{ex} + \beta_{up,oil} r_{oil}\right) + p_{down}\left(\beta_{down,mkt} r_{mkt}^{ex} + \beta_{down,oil} r_{oil}\right) + \epsilon$$

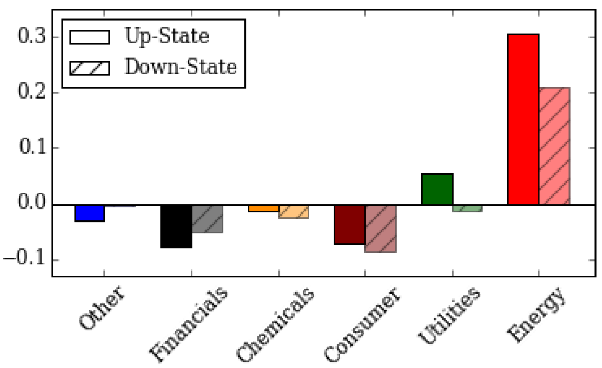

Figure 8: *Regime-Switching Oil Return Betas for Select Industries*

In our regime-switching model, we assume two different sets of betas with respect to market and oil returns: one set for the up-state and one for the down-state. Therefore, we weigh each beta's contribution by the smoothed probability of being in an up- or down-state in estimating and forecasting.

The time-varying betas shown in Figure 7 clearly display a regime switch in the data, especially for the energy and utility sectors.

4.2 Oil Beta Validation

To validate the beta sensitivities, we compare the out-of-sample hedging performance on the last 60 months of data. The betas are calculated with data up to month *n*, and are subsequently used to construct oil price hedges over the following month (*n+1*). Then, we calculate the net industry returns, after adjusting for the oil hedge. This process is repeated for all 60 months in the sample. Specifically, we are hedging on a monthly basis and rolling over the hedge according to the updated beta values. We use spot WTI prices as a proxy for 1-month forward prices and compare volatility of unhedged returns with hedged returns using the three models. Table 3 presents the monthly volatility of returns of the four methods tested: unhedged, constant beta, time-varying beta (TV), and regime-switching (RS) beta strategies.

Industry	Unhedged	Const	TV	RS
Chemical	3.47%	3.50%	3.73%	3.38%
Energy	5.57%	4.38%	5.72%	4.02%
Bus. Eq.	4.19%	4.04%	4.11%	3.86%
Dur.	6.57%	6.63%	6.90%	6.51%
HC	3.24%	3.30%	3.38%	3.27%
Manufac.	4.74%	4.63%	4.91%	4.35%
Money	4.76%	4.90%	4.76%	4.87%
Non-Dur.	2.96%	3.08%	3.11%	3.05%
Other	4.00%	3.99%	4.06%	3.88%
Shops	3.38%	3.54%	3.41%	3.63%
Telecom	3.45%	3.41%	3.51%	3.30%
Utilities	3.11%	3.10%	3.13%	3.10%

Table 3: *Volatility of Returns for Hedging Strategies*

The reduction in the return volatility indicates the hedge is working as intended by diminishing the oil return component. From our previous results, the model that offers the best forecast of oil prices should provide the best hedge. As can be seen from Table 3, the regime-switching model indeed gives the best result in the form of lower return volatility for most industries.

4.3 Practical Considerations

4.3.1 Industries

Individual companies can hedge exposure to oil based on the sensitivity of some earnings metric, such as revenue or EPS, to the oil price. They could construct a hedge utilizing 3-month (12-month) forwards such that these quarterly (annual) earnings metrics are less influenced by the price of oil. However, as noted in Hull's *Options, Futures and other derivatives* [8], if hedging is not the usual practice in the industry, then it may be unwise for a company to hedge. This would happen in an industry in which changes in raw material and other input costs are quickly reflected in the price of the output produced. In this case, a company that does not hedge will have almost constant profit margins, but one that does hedge will have fluctuating profit margin.

This paper considers hedging strategies for the industries assuming that the markets are efficient, and thus changes in equity prices truly (and immediately) reflect the changes in fundamentals (i.e. the earnings). With this assumption, hedges can be constructed to hedge industry oil price risk using t-month forwards, as we demonstrated in Section 4.2 using 1-month forwards.

4.3.2 Institutional Investors

Institutional investors can use the framework described in this paper to calculate sensitivities of their portfolios to oil. As in case of the industries, we can regress historical fund returns (instead of industry returns) against the oil price to calculate the oil beta and use that to construct a hedge.

$$r_{port}^{ex} = \beta_{mkt} r_{mkt}^{ex} + \beta_{oil} r_{oil} + \epsilon$$

Alternatively, investors could add a risk appetite constraint when constructing their portfolios:

$$\left| \sum_{i=1}^{n} w_i \cdot \beta_i \right| \leq c$$

where w_i is the portfolio weight for each industry or company i, and c is some desired upper bound on the portfolio oil exposure.

Also, while WTI was the oil price series used in this report, different oil price series could be used in this framework. For example, Brent crude oil could be used by institutional investors to estimate oil price sensitivity of European companies.

5 Liquidation of Sovereign Wealth Funds

The market size of sovereign wealth funds (SWFs) reached over \$7.2 trillion in June 2014 as global equity markets rallied and the funds continued to accumulate assets [12]. The timing of this peak coincided with the onset of the recent oil price slide.

Table 4 displays IMF projections of 2016 government budget breakeven oil prices and SWF assets for select oil exporting countries. With oil prices now consistently trading well below these prices, it is expected that many SWFs will be forced to sell assets to fulfill government obligations [11]. In other words, for the first time in many years these SWFs must transition from being net buyers to net sellers of financial securities and other assets.

Country	Gov't Budget Breakeven Oil Price*	SWF(s) AUM**
Saudi Arabia	95.8	637.6
Kuwait	51.8	592
UAE	67.5	1,124.8
Norway	47.7	824.9
Qatar	57.8	256

Source: Fitch Ratings, IMF, SWF Institute

*Projected 2016; USD

**As of December 2015; Billions of USD

Table 4: *Breakeven Oil Prices and SWF Sizes*

Originally liquidity providers, these institutions are now extracting a large portion of the liquidity injected by central banks. In addition, this transition is occurring as China and other emerging market nations are reducing foreign-exchange reserves, mainly through selling USD-denominated assets.

This liquidation leads to higher volatility and downward pressure on asset prices, particularly in the more liquid equities and investment grade bonds. The increase in volatility and fall in prices may act as feedback that leads to further selling. This mechanism will result in higher correlations across asset classes, including those between equities and the price of oil [10], as shown previously.

These effects may be short-term. However, if SWFs begin to shed more illiquid assets, such as real estate and corporate bonds, these effects may persist and affect the broader market. The regime-switching model indicates there has been a recent transition into a down-state for oil. Depressed prices across asset classes due to systematic selling will lead to lower global demand and contribute to further suppressed oil prices. Large-scale selling by the SWFs, particularly those of oil exporting nations, could directly keep the price of oil in the down-state for a prolonged period of time. This certainly has hedging implications for companies and institutional investors alike.

Furthermore, an IMF article referencing a paper written by the federal reserve states that "if foreign official inflows into U.S. Treasuries were to decrease in a given month by $100 billion, five-year Treasury rates would rise by about 40-60 basis points in the short run, with a long-run effect of about 20 basis points." [1] This increase in interest rates will strengthen the U.S. dollar and serve to put continued downward pressure on the price of oil. The reflexive nature of this relationship further supports the inertial characteristics of the regime-switching model.

A framework to capture structural shifts is necessary to precisely estimate fluctuating sensitivities. Otherwise, the sensitivities will be poorly estimated and hedges employed by institutional investors and companies would be less effective and possibly harmful. Section 4.2 demonstrates that a regime-switching model can offer better hedging results than the constant beta and time-varying strategies. We believe this out-performance arises from its ability to capture dramatic price changes, such as those in 2008 and the most recent slide.

6 Global Macro Effects

6.1 Economic Growth

In this section, we study how the GDP growth of a country changes with respect to the price of oil. Investigating this relationship helps infer how wealth is redistributed globally in both high and low oil price regimes.

6.1.1 Importers

Specifically, for oil importing countries with well diversified economies such as the United States, Japan and South Korea, we anticipate that a low oil price will have either very little effect or a slightly beneficial effect on GDP growth. Since oil is consumed as an input for many industries and products, the lower cost should boost profitability and subsequently bolster wealth.

This intuition is supported by the results reported in Table 5. We regress GDP growth on log WTI and find that the beta estimates of oil importers (USA, Japan and South Korea) are negative and statistically significant.

6.1.2 Exporters

For large oil exporting countries such as Saudi Arabia, Russia and Iran, a low oil price coupled with an inelastic short-term demand for oil yields lower margins, profitability, and, ultimately, GDP growth. Referring again to Table 5, Russia presents a relatively significant positive slope whereas Saudi Arabia shows only a weakly positive slope. Counter-intuitively, Iran breaks the pattern of oil exporting countries showing statistically insignificant negative beta. We posit that, since Iran was engaged in many geopolitical conflicts during our period of examination, the GDP growth is far too erratic to extract a proper relationship.

Country	$\hat{\beta}$	t-statistic
United States	-0.015	-2.90
Japan	-0.015	-2.11
South Korea	-0.031	-3.66
Saudi Arabia	0.008	0.59
Russia	0.036	1.84
Iran	-0.011	-0.50

Table 5: *GDP Growth vs WTI Price by Country*

To provide intuition and chronology, Figure 9 plots GDP growth and log WTI from 1978 to 2015 for the same six countries as in Table 5.

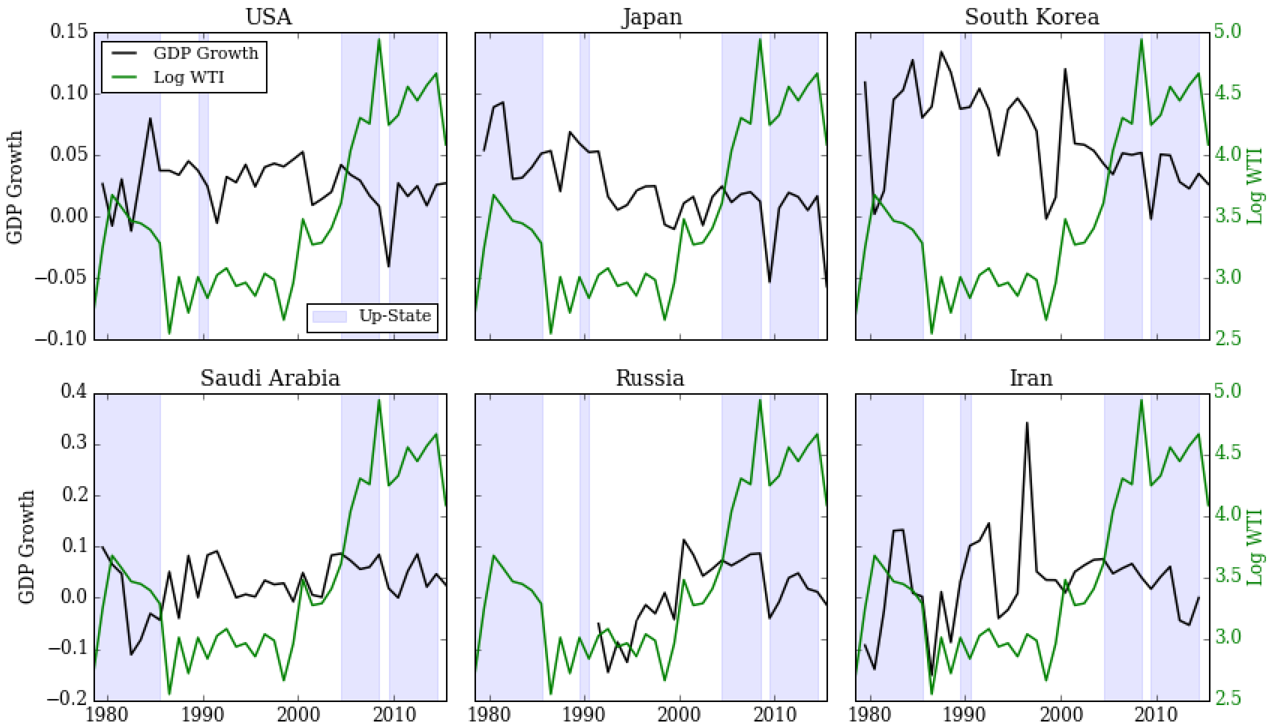

Figure 9: *GDP Growth of Oil Exporters and Importers and Log WTI (1978-2015)*

6.2 Market Share Distribution

Since the demand for oil is relatively inelastic, prices are generally dictated by supply-side forces. Thus, analyzing international market share dynamics as a function of oil price provides valuable insight into how the distribution of wealth will evolve in our current low oil price regime.

Figure 11 shows market share with respect to oil prices for the six countries with the greatest market share of oil production as of 2015. The countries are: United States, Saudi Arabia, Russia, China, Canada, and United Arab Emirates. Table 6 shows the regression beta estimates as well as their respective t-statistics.

Country	$\hat{\beta}$	t-statistic
United States	-0.732	-4.02
Saudi Arabia	0.334	5.17
Russia	2.321	29.66
China	0.341	18.02
Canada	0.452	13.13
UAE	0.218	11.18

Table 6: *Market Share vs WTI Price by Country*

The betas suggest that all of the largest oil producers, except for the United States, stand to lose market share as a result of low oil prices. An interesting feature of this market is that high prices tend to coincide with an oligopoly of concentrated suppliers. In low oil price states production becomes much more competitive. This effect is explored in Figure 10 where we regress the Herfindahl index against the real log WTI oil price. The Herfindahl index represents the relative level of competition among market suppliers wherein a high value signals low competition and vice-versa.

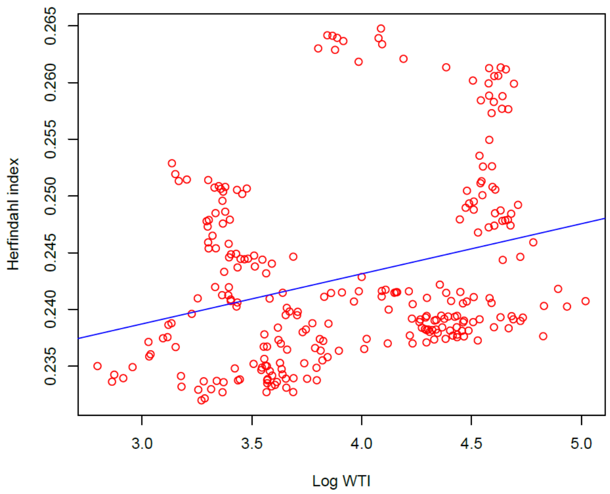

Figure 10: *Market Competition vs log WTI Oil Price*

6.3 Current Account Balance

Figure 12 displays the current account (CA) balances as a percentage of GDP for the G7 nations,

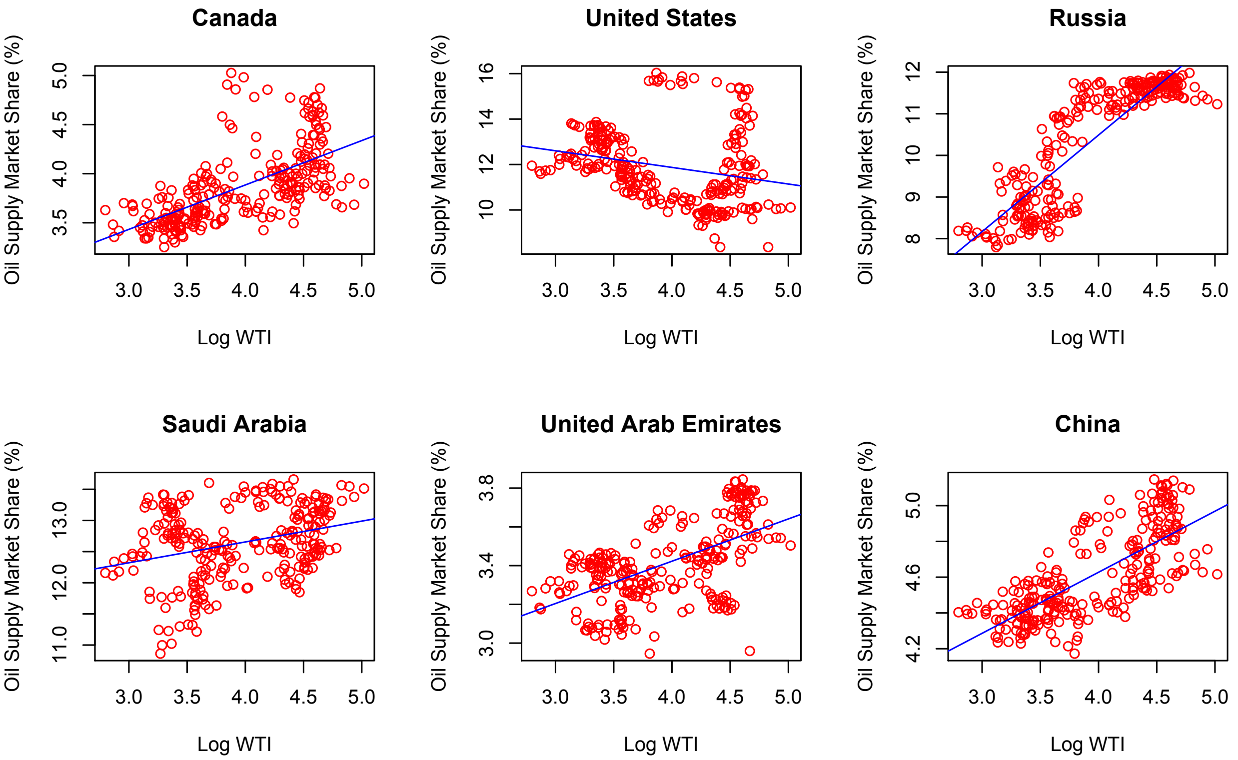

Figure 11: *Global Market Share by Country vs Log WTI*

emerging markets (EM), and the Middle East. In up-states, middle eastern nations have higher CA balances, yet these balances shrink in the transition to and during down-states. This trend has been particularly evident since 2004, with the Middle East having large surpluses that contracted in the short down-state in 2008, increasing in the up-state from 2009-2014, and sharply decreasing in the last year. Conversely, the G7 nations and emerging markets have higher or increasing CA balances during down-states.

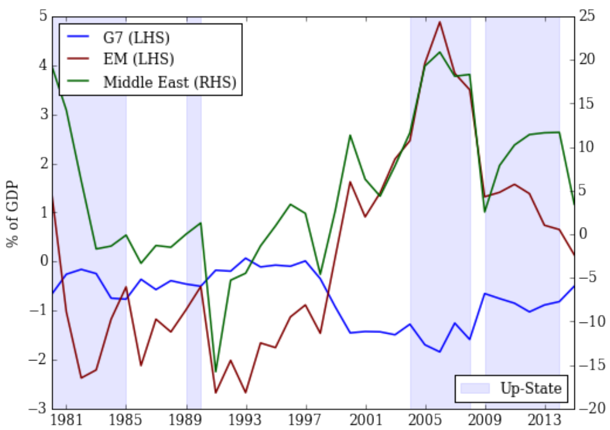

Figure 12: *Current Account Balance in Regimes [2]*

As this transition to a down-state occurs, capital should flow from oil exporting nations, which ran large surpluses in the 2000s, to developed nations and emerging markets. The latter nations may provide more investment opportunities and can utilize this capital in more productive ways, eventually boosting overall growth.

This transition may take a few years to take full effect, and the short-term impacts may be painful, but an extended period of time in the down-state regime will have stronger net positive effects on global growth than a continuation in the up-state that occurred over the better part of the last decade.

7 State-wide Effects

7.1 Market Share Distribution

We reproduce the market share analysis using the six states with the largest market share of oil supply in the US, namely: Alaska, California, New Mexico, Texas, North Dakota and Oklahoma. We note that Alaska and California have historically claimed large market shares in low oil price regimes and stand to benefit the most if current low oil prices persist.

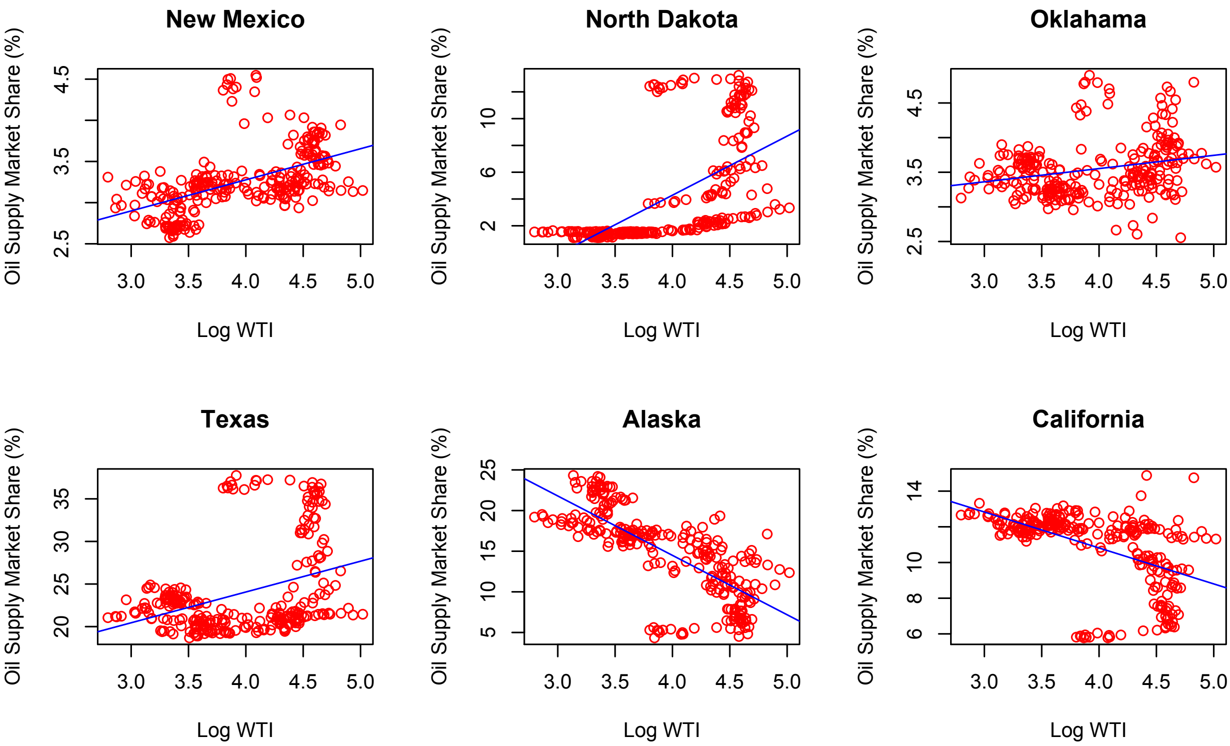

Figure 13: *US Market Share by State vs Log WTI*

State	$\hat{\beta}$	t-statistic
AK	-7.308	-18.390
CA	-2.015	-9.969
TX	3.614	6.407
NM	0.378	9.819
ND	4.413	12.359
OK	0.191	4.152

Table 7: *Market Share vs WTI Price by State*

7.2 Unemployment Rates

Finally, we examine the relationship between oil prices and monthly state unemployment rates since 1976. In addition, we gather total oil production and total oil consumption by state [14] and rank each accordingly. The unemployment rate is another metric that helps gauge the economic environment of a given state, and the combination of these rates with the oil production/consumption rankings serves as a reasonable proxy for wealth redistribution. In other words, one can infer how investment and consumption is changing between high oil producing states and high oil consuming states as the price of oil fluctuates.

For a net oil producing state, we expect lower unemployment rates as the oil price soars, resulting in a negative correlation between the unemployment rate and WTI price. On the other hand, we expect a positive correlation between the unemployment rate of an oil consuming state and WTI price.

State	ρ	p-value	Con. Rank	Prod. Rank
TX	-0.05	0.3054	1	1
CA	0.33	<0.0001	2	10
FL	0.23	<0.0001	3	31
ND	-0.39	<0.0001	40	8
WV	-0.21	<0.0001	36	4

Table 8: *Unemployment Rate vs WTI Price by State*

Table 8 shows the rank of a state by consumption (Con. Rank) and by production (Prod. Rank), the Pearson correlation between its unemployment rate and WTI price and the p-value of the test. These results agree with the claims above. For net oil consuming states, such as California and Florida, we observe a significant positive correlation; whereas for net oil producing states, such as North Dakota and West Virginia, we observe a significant negative correlation. Interestingly, Texas is both the largest consumer and largest producer, and oil price has a contradicting effect to its overall employment. Hence, the correlation is not statistically different from zero for Texas.

8 Moving Forward

The analysis presented in this paper leads us to believe that the oil market is fully transitioning to a down-state regime that may last for years. Specifically, the expected number of years before a regime switch, implied by our RS-AR(2) model, is roughly 6.5 years.

There are a number of reasons why this most recent decline is unique, including the risk of massive-scale SWF liquidation (Section 5), weakness across developed economies, precarious sovereign debt levels among emerging markets, and a strong dollar within a tightening US monetary environment.

We expect to see more negative impact in the short-term as the world adjusts to the new down-state of oil prices. US fixed investment in energy accounted for more the 10% of total private non-residential investment [3]. Declines of capital investment in this industry in an already low capital investment environment will have adverse effects on growth. In addition, many oil companies across the world will continue to produce below cost in an effort to service debt. This will act as an ongoing deflationary force, putting pressure on prices, wages, and overall demand.

Ultimately, we believe the long-term effects of this low oil environment should benefit the global economy, especially the US. Historically low oil prices present a number of benefits, including heightened GDP growth for developed and diversified countries, relatively larger CA balances for developed and oil importing countries, and stronger market competition leading to cheap oil for emerging industries and states.

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