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# An Exploration of Oil Price Interplay with the Economy: How to Hedge Equity Against Oil Price Risk

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## Background

*In times of rapid change, experience could be your worst enemy. -J. Paul Getty*

The aphorism is no less apropos today than when first spoken. China demand always rises. OPEC modulates supply to keep oil prices buoyant. Interest rates don't go negative, and they certainly don't stay there. In recent times, an unchecked appeal to experience would prove costly. Amidst the uncertainty driven in part by a departure from the statements above, the global economy has had to contend with a dramatic decrease in oil price levels. Oil exporting giants like Saudi Arabia who in very recent memory were forecasting tremendous current account surpluses have now reversed those forecasts and have begun selling off assets in sovereign wealth funds (SWF). The turbulence has caused the flow of money across nations and across the United States to change, if not reverse. All this in the backdrop of the liquidity crisis of 2008 increases the pressure on SWF managers to sell. The interplay of oil prices and economic factors has become a pivotal component in determining the future economic state. This incentivizes portfolio managers to develop a comprehensive model that reveals the net impact of oil price movements on the economy and equities.

In this note, we explore the mechanics of how changes in oil price affect both the economy-at-large and industry-specific equity returns. In the context of quantitative finance, we interpret J. Paul Getty's remark as motivation for forward-looking estimation, and this guides our approach to develop a forward-looking "oil-beta" hedging strategy that leverages the volatility forecasting of an SVAR-GARCH model with regime changes.

Oil price and its relationship to the economy has been extensively modeled in the literature, yet it remains elusive to cite an established approach. A key point of contention, debated for decades, is the endogeneity of oil price with respect to a given regression model [1, 2, 3]. In one camp, perhaps best regarded as the mainstream opinion, Hamilton and Hooker use Granger causality arguments to support the position that oil price shocks arise exogenously with respect to macro variables. That is to say, they claim macro variables do not contribute in a statistically significant way to the forecasting of oil prices and therefore shocks in oil prices are not caused by contemporaneous shocks in economic fundamentals. In the other camp, Kilian [3] contests that oil price shocks are indeed endogenous to the economy. This position is supported by certain central banks [4]. Here, it is argued that oil price is influenced by global macroeconomic conditions. The latter argument is centered on fundamental supply and demand drivers to price changes. It is argued that oil price changes are driven by shocks to supply and demand, and so the analysis should be centered on these shocks rather than their aggregate manifested in oil price movements. Through this decomposition of price movements, macro variable responses are mapped directly to supply and demand shocks. Research in this vane has produced evidence that the impact of oil price changes on the economy actually depends on the driver of that change [5]. In our view, it is irrefutable that oil price returns are influenced by shocks in supply or demand, and an approach that centers on this dependency can not only circumvent the endogeneity issue altogether, but also reveal a decomposed causation structure with respect to supply and demand.

A separate issue that has divided the oil price literature (whether explicitly or implicitly) has been the nature of volatility. A fair number of authors have asserted constant volatility in oil price models [6, 7, 8], despite a large body of literature indicating the contrary [9, 10, 11, 12, 13]. For example, evidence for regime shifting in oil price modeling is well-documented and may be linked to OPEC policy, fundamental changes in the global economy, or the US fracking boom for example [14, 15]. Especially relevant here, regime shifts have been shown to affect hedging ratios in mean-variance hedging optimizations [16]. In this study, we demonstrate that the assumption of constant volatility is not well supported by historical data and therefore choose a model with time-varying volatility.

Another point of interest with strong empirical support is an asymmetry in response to oil price returns [17, 18]. In particular, it is suggested that a positive shock in oil price confers a negative impact on the economy that is far greater than the positive effect on the economy conferred by a negative oil price shock.

Finally, autocorrelation in oil-price returns has been found to be an important factor in oil price dynamics, indicating a need for time-lagged variables in price modeling [18].

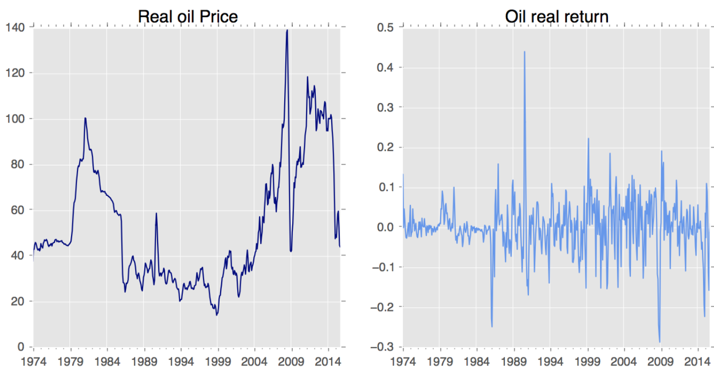


**Figure 1.** Real Oil Price and Oil Real Return

Figure 1 tells a storied history of the oil price, which we will only touch upon here. First, the shocks in 1986, 1990 and 2007-2008 cannot be overlooked. In 1986, the global economy witnessed a dramatic supply shock as oil nominal prices fell to about $12 a barrel. The OPEC countries failed to gain cooperation with non-OPEC oil producing countries, so they maintained a high level of oil production and ultimately dragged the oil price down. This is not an unfamiliar situation to us today. This incident has also proved to be a regime shift as indicated by a standard Bai and Perron test on the oil price return [19] . In 1990, the oil price increased dramatically as the Gulf War broke off. The fear of possible global supply disruptions resulted in an oil-specific demand shock. However, this was not necessarily a regime shift as the influence did not cause a prolonged effect. The latest shock was in 2009, as the recovery from the subprime crisis took off and the U.S. hydraulic fracking boom escalated. Because of the dramatic and persistent change in supply, we have incorporated this shock as a regime shift in our model.

## Modeling Framework and Hedging Strategy

Bearing in mind the model will ultimately be applied in an equity market "oil-beta" hedging strategy, we first consider the simplest regression model and note its limitations.

$$R_t^{Stock} = \beta R_t^{Oil} + \varepsilon_t \tag{1}$$

First, $\beta = \beta_t$ is surely a function of time. That is, the joint distribution of stock returns and oil returns changes over time. Worse, it is well-documented that there are regime shifts in oil price returns. Second, the classic ordinary least squares assumption of error exogeneity is not upheld here. For example, aggregate demand will influence both stock and oil price returns [7]. Third, the constant volatility assumption is violated in this market as a result of collusion, speculative trading, war and unrest, and other factors [20, 21, 22, 10].

Considering these perspectives, an efficient model will:

- Adjust to regime shifts
- Account for time-varying volatility
- Allow for volatility forecasting
- Incorporate asymmetric responses to oil price movements
- Decouple effects of supply and demand shocks

In order to arrive at a solution that addresses the elements above, we chose a model architecture that combines elements from existing price models. We began with the structural vector autoregression (SVAR) framework developed by Kilian and Park (2009). The SVAR architecture imposes a forecasting error structure for oil price returns that is dependent only on shocks in supply and demand. The details of the imposed structure are discussed more thoroughly below. Next, we addressed the limitation of constant volatility by introducing regime breaks and multivariate GARCH volatility modeling. The addition of a GARCH volatility process has the added benefit of permitting conditional covariance forecasting; that is, it provides a forward-looking approach. This of course is a vital capability for any hedging model. In summary, the SVAR-GARCH framework with added regime shifts is a reasonable approach to estimate the time-varying joint distribution of oil price returns and equity returns. In addition, the nature of the model structure allows for a deeper study of the complex interplay between oil price returns and equity returns in light of supply and demand shocks.

The SVAR-GARCH model is constructed as follows:

$$A_0 y_t = \alpha_0 + \alpha_1 MD_t + \sum_{i=1}^{i=p} A_i y_{t-i} + \varepsilon_t \tag{2}$$

$$\varepsilon_t = D_t^{1/2} z_t \tag{3}$$

$$E[\varepsilon_t] = 0, \;\; E[\varepsilon_t \varepsilon_t'] = D_t, \;\; E[\varepsilon_t \varepsilon_s] = 0, \;\; \forall t \neq s \tag{4}$$

$$d_{i,t} = \delta_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i d_{i,t-1} + \gamma V D_t \tag{5}$$

where $d_{i,t}$ is the $i^{th}$ diagonal element in diagonal matrix $D_t$, representing the conditional variances for elements in $\varepsilon_t$. $z_t$ is a vector of four independent white noise variables, $p$ is the number of lags, $MD_t$ is the dummy variable for mean regime shift and $VD_t$ is the dummy variable for variance regime shift. Matrix $A_t$ is the autoregression parameters to estimate. Equation 2 is estimated using the reduced-form VAR as presented in equation 5.

$$y_t = A_0^{-1}\alpha_0 + A_0^{-1}\alpha_1 MD_t + A_0^{-1}\sum_{i=1}^{i=p} A_i y_{t-i} + A_0^{-1}\varepsilon_t \quad (6)$$

Following Kilian and Park (2009), the four dependent variables in vector $y_t$ are (in order):

1.) Year on year percent change in global crude oil production data from U.S. Energy Information Administration (EIA).

2.) Real Economic Activity (REA). The percent deviations from global real economic activity trends in industrial commodity markets based on a monthly index based on bulk dry cargo ocean freight rates. This index "automatically incorporates the effects of increased real activity in newly emerging economies such as China or India" as commented by Killian and Park (2009)[7][1]. Common macroeconomic activity indicators, such as monthly industrial production data, normally don't cover emerging counties, which can't capture the economic growth slow down of these economies.

3.) Real price of refiner acquisition cost of crude oil from EIA. The real prices are adjusted for inflation using the Consumer Price Index (CPI) available from the Bureau of Labor Statistics with 10/2015 as the base.

4.) Real industry stock returns. The real returns are calculated as U.S. industry return from Kenneth French Data Library subtracted by core inflation rate.[2]

The data were from January 1974 to October 2015 at monthly frequency. The four inputs were stationary as measured by the Augmented Dickey-Fuller test with confidence greater than 99%. To determine the optimal number of lags in the autoregression, we examined the AIC/BIC criterion up to 24 lags. The results were consistent across all the industries and time periods studied, and they all showed that the model with 13 lags yielded the minimum AIC. To determine the quality of the model fit, the time series of model residuals was studied. A purely constant volatility model, like the one implemented by Kilian and Park (2009), results in overt volatility regime shifts in the residual time series (data not shown) and the residuals fail a lagrange multiplier test for white noise. This motivated a model with time-varying volatility. Plotted in Figure 2 are residuals for: 1.) an SVAR model with regime shifts and constant within-regime volatility and 2.) an SVAR model with regime shifts and GARCH-process volatility. Of course the residuals have different meanings. In the first case, they are simply $\varepsilon_t$ in Equation 2 and there is no GARCH expansion of $\varepsilon_t$. In the second, they are $z_t$ in Equation 3. In either case, it is ideal that they follow four i.i.d. white noise processes. The advantage of the GARCH feature is apparent upon inspection of the aggregate demand residuals time series (second row from top, Figure 2). Under a constant within-regime volatility assumption, there is astructural break in volatility beginning in 2009 with high probability. Relaxing this assumption by allowing for autocorrelation in volatility reveals that in fact, no structural break is needed, as evidenced by a more consistent residual variance across the range. A similar, but more subdued effect is observed in oil-specific demand shock prior to 1986. While the SVAR-GARCH with regime shift model is superior in this sense to constant within-regime volatility model, the oil supply shock residuals are still not resolved to a strong white noise process. Nonetheless, the variance-covariance matrix of residuals for the SVAR-GARCH with regime-shift model is near identity and we view the residual structure as evidence for an appropriate model selection.


**Figure 2.** Residual plot comparison for SVAR with regime shifts with (right panel) and without (left panel) a GARCH volatility process.

[1] Index of global real economic activity in industrial commodity markets http://www-personal.umich.edu/~lan/reaupdate.txt

[2] Kenneth French data library http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

As described by Kilian and Park [7], movements in oil price can be ascribed to contemporaneous shocks in oil supply, global aggregate demand, and oil-specific demand. In theory (and as we show in Figure 3) these same factors can cause contemporaneous changes in global oil production, global economic activity, and indeed, idiosyncratic equity returns themselves. Thus, equity returns and oil price returns share common contemporaneous drivers. The interplay of contemporaneous drivers leads to a well defined structural model. The SVAR disturbances in the model are:

$$e_t = \begin{bmatrix} e_t^{\Delta Global\ oil\ production} \\ e_t^{REA} \\ e_t^{Real\ oil\ price\ return} \\ e_t^{Stock\ return} \end{bmatrix}$$

$$e_t = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{Oil\ supply\ shock} \\ \varepsilon_t^{Aggregate\ demand\ shock} \\ \varepsilon_t^{Oil-specific\ demand\ shock} \\ \varepsilon_t^{Stock-specific\ shock} \end{bmatrix}$$

$$e_t = A_0^{-1}\varepsilon_t = A_0^{-1}D_t^{1/2}z_t = S_t z_t$$

$$S_t = A_0^{-1}D_t^{1/2}$$

$$\Sigma_t = E[e_t e_t'] = E[A_0^{-1}\varepsilon_t \varepsilon' A_0^{-1}\prime] = A_0^{-1}E[\varepsilon\varepsilon']A_0^{-1}\prime$$
$$= A_0^{-1}D_t A_0^{-1}\prime = S_t S_t'$$

The structural restrictions imposed by Kilian and Park (2009) address the endogeneity problem associated with standard VAR models and allow for the study of forecast error variance decomposition. The multivariate GARCH innovations provide forward looking estimates of the conditional covariance and volatility used for the time-varying "oil price beta" estimation, which coincides with traditional static unconditional beta formula.

### Oil risk beta hedging strategy

To hedge out oil price risk, investors could construct a two-asset portfolio consisting of stocks and oil futures. In a dynamic hedging setting, we assume the joint distribution of stock returns and oil futures returns are changing overtime. At time $t$, the hedging position in oil futures is $\beta_t$, so the future return of this two-asset hedged portfolio will be $x_{t+1} = s_{t+1} - \beta f_{t+1}$, where $s_{t+1}$ is future stock return and $f_{t+1}$ is oil future return at $t+1$.

## Results and Discussion

The time-varying hedging ratio can be used as a sensitivity measure of stock return to oil price changes. In this section, we would like to show how this dynamic hedging strategy can be applied as a useful tool to hedge against oil price movements. The strategy can be applied not only to single stock returns but also to industry returns. The variance-covariance matrix between industry return and oil price return can be estimated conveniently by the model. To test the effectiveness of our hedging strategy for various industries we have calculated the Sharpe ratio and 3-year realized correlation of the hedged and unhedged portfolios Table 1.

| | Sharpe Ratio | | Correlation | |
|---|---|---|---|---|
| Sector | Unhedged | Hedged | Unhedged | Hedged |
| Market | 0.1591 | 0.1902 | 0.2816 | 0.1888 |
| Chemicals | 0.1397 | 0.1523 | 0.3150 | 0.2445 |
| Autos | 0.0800 | 0.0976 | 0.2827 | 0.2369 |
| Aeros | 0.1412 | 0.1487 | 0.1876 | 0.1821 |
| Oil | 0.1259 | 0.1496 | 0.2735 | 0.1476 |
| Consumers | 0.1499 | 0.1622 | 0.2918 | 0.1717 |
| Financial | 0.1233 | 0.1464 | 0.2918 | 0.1641 |

**Table 1.** Sharpe Ratio and Average 3-year Correlation of Hedged vs. Unhedged Portfolios Across Industries.

A key test of the effectiveness of the hedging strategy is to compare the correlation between oil price returns and the hedged portfolio returns over a fixed width sliding window of 3 years. Ideally, these correlations should be less than those of the unhedged portfolio. Indeed this is the case for average 3-year correlation as tabulated in Table 1.


**Figure 3.** Variance Decomposition of Real Oil and Stock Returns. Blue: stock market-specific shock, Green: oil-specific demand shock, Yellow: aggregate demand shock, Red: oil supply shock.

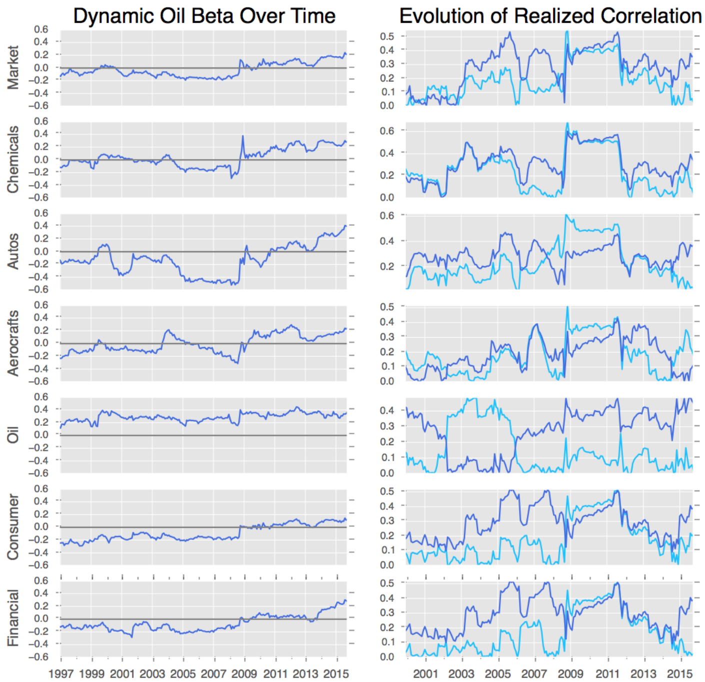


**Figure 4.** (Left) Dynamic oil risk beta for market and industrial returns from 1997 to present.(Right) Correlation between industries and oil price with backward looking 3 year window. The lighter blue is the correlation of the hedged portfolio return with oil price change while the darker blue line is that of the unhedged portfolio.

One of the concerns in our strategy is the rebalance frequency. The forecasting capability is limited by the GARCH(1,1) process we have in our model. Because it would be costly to adjust the hedging ratio in the portfolio from month to month, we would like to study the stability of the "oil price beta" for each industry to reduce the rebalancing cost. As has been shown in Figure 4 to the left, the sensitivity of different industries to oil price follow similar trends. However, the volatility of these betas fluctuates overtime. This indicates a static hedging strategy would be ineffective, especially during periods of financial distress.

Another limitation to our result is that while we impose the same regime shift across industries we could have overlooked the lead-lag relationship of the regime shift to various industries. While the same shock to oil price could first propagate to the consumer sector as the household spares money from the dropping oil prices, the effect could later expand to investment in durables and fixed assets. The correlation graphs seem to all share the same pattern during 2009 which is about the same time we imposed the regime shift. The artificial shift seems to have helped with Chemicals, Consumers and Financial sector as well as the market in general. The relatively poor performance in Auto can be attributed to the lagged response.

There could also be other idiosyncratic shocks we could not possibly get a comprehensive view of. For example, the crossing of the two correlation lines for auto on the right could be explained by the auto bailout between 2008 and 2010. Similarly, the crossing of the two lines for Aero towards the end of 2014 could be a result from the unexpected terrorism attacks on September 11th 2011. Another unexpected supply shock to oil sector happened around 2003 when the U.S. invaded Iraq which consequently, diminished oil production 2 million barrels [23].

## Hedging with oil futures and basis risk

In practice, to hedge out oil risk, industrial practitioners utilize energy derivatives ranging from OTC contracts to oil options[3]. However, hedging with derivatives such as future contracts, introduces basis risk, as the mark-to-market return of futures can be deviated from daily return of spot crude oil. To derive the optimal hedging ratio, we base our hedging strategy in the familiar context of mean-variance portfolio optimization [24]. The setting of the optimization strategy is as follows:

An unhedged investor receives a return of $s_t$ on the portfolio. To hedge the portfolio against changes in oil price, the investor buys an amount, $h_t$, of a hedging instrument that receives returns $f_t$, yielding a future portfolio return of:

$$x_{t+1} = s_{t+1} - h_t f_{t+1}$$

The investor holding this portfolio has utility function as:

$$U_t(x_{t+1}) = E_t(x_{t+1}) - \gamma Var_t(x_{t+1})$$

where $\gamma$ is the degree of risk aversion and $\gamma > 0$. The expected utility $U_t$, expected return $x_{t+1}$, and total variance of the portfolio $Var_t$ are denoted by $t$ to indicate that they are conditional on information available at time $t$. The investor will choose $h_t$ to maximize his/her mean-variance utility function, $U_t$, which results in the following convex optimization problem:

$$\max_h : E_t(s_{t+1}) - h_t E_t(f_{t+1}) - \gamma[Var_t(s) + h_t^2 Var_t(f) - 2hCov_t(s_{t+1}, f_{t+1})]$$

With solution $h_t^*$ given by:

$$h_t^* = \frac{E_t(f_{t+1}) - 2\gamma Cov_t(s_{t+1}, f_{t+1})}{2\gamma Var_t(f_{t+1})}$$

[3] Crude Oil Natural Gas Hedging Study: http://www.mercatusenergy.com/oil-gas-hedge-study-download

As oil future return is a martingale, $E_t(f_{t+1}) = 0$.Thus, the optimal time-varying hedging ratio is :

$$h_t^* = \frac{Cov_t(s_{t+1}, f_{t+1})}{Var_t(f_{t+1})}$$

where $s_{t+1}$ is the return of spot crude oil from next period, and $f_{t+1}$ is oil future's return. The optimal hedging ratio, covariance, and variance are based on information available at time $t$.

A bivariate VECM-GARCH model, including spot oil return and oil future return, can be used to estimate the time-varying optimal hedging ratio. The error correction term is added because the two returns are highly likely to be cointegrated [25]. Then with the optimal hedging ratios, mutilplied by the dynamic oil beta described above, investors and industrial practitioners could hedge oil price risk dynamically.

## Estimation risk and model risk

To get a sense of the estimation risk of our model, bootstrap inference or Monte Carlo simulation for the error band of the dynamic beta estimation can be performed via the following algorithm:

1.) Estimate the full SVAR-GARCH model and keep the estimated residuals.

2.) Either bootstrap residuals or simulate the errors term from standard normal distribution.

3.) Use the estimated model to generate artificial data for re-estimation.

4.) Estimate the full model using the artificial data and calculate the dynamic oil beta.

5.) Repeat the above procedure N times to create the error bands.

Following the assumptions in the structural VAR model, the shocks are treated as predetermined with respect to stock return, real economic activities, oil production, and oil price returns. However, if there is a regime shift in any of the variables without specification or identification, our model would provide misleading oil price betas. And hedging across regime shifts performs unsatisfactorily in our back-testing. While there has been interests in the modelling of regime shifts in economic and financial time series, there is no clear consensus regarding the forecasting abilities of these models and the outputs of the model heavily depending on the identifications the user imposes [26, 27]. Another limitation of our model is that we didn't incorporate the asymmetric effects from positive and negative oil return on stock market. Researchers have documented the phenomenon[28, 29, 30]. The unsatisfactory hedging performance for automobile industry between 2003 - 2008 might be caused by this missing component. Our symmetric model apparently over-predicts the conditional covariance between automobile industrial return and oil return.

## Implications for Investors' Portfolio Choice

One may start to wonder what the future holds for the next oil price shock. Will OPEC sustain its oil production levels or will it revert to its previous strategy of oil price control? Is the price of oil going to remain low for a decade as it did after 1986, or will it rebound back to 2013 levels?

From the perspective of an institutional investor, such as a pension fund portfolio manager, the focus should be on long term relative returns. The model we presented can be leveraged to forecast the near term volatility conditional on oil price changes (and other factors observed in the model). The variance decomposition we have shown in Figure 3 can also be used to decouple the supply shock from the demand shock. However, it would be too risky to take the hedging ratio we have proposed and hold it in blind faith for the long run. Despite the estimation risk and model risk we have mentioned in the previous section, it is important to understand the nature of the underlying shocks during times of dramatic price movements. As can be seen from the variance decomposition graph in Figure 3, although both oil and stock market movements are mainly driven by their specific shocks, the importance of supply shock on oil price change was relatively smaller than that of the demand shock especially after 1986 when OPEC decided to change their policy from focusing on prices to one of focusing on market share. We are able to spot another shift in the importance of the aggregate demand shock on market return after 2009. This shift has been explained by Kilian and Murphy 2014 as speculative demand shock. It is also of interest that oil specific demand shock tends to give a relatively prolonged effect in contrast to the drastic decreasing effect in aggregate demand.

To understand the cumulative effect of such a sequence of shocks, it's necessary to construct a historical variance decomposition of the effect of each of the shocks on the real return of oil and U.S. stock market. The decompositions from SVAR estimation in Figure 3 demonstrate that both oil and stock market movements are mainly driven by their specific shocks. The decomposition captures the supply regime shift in global oil production as the red portion contributes less to both oil return and market return after 1986. Also, it captures the oil-specific demand shock during Gulf War in 1990. The aggregate demand shock becomes more important after the global financial crisis in 2008 and the graphs also pick up the current trend in oil supply shock.

## Sovereign Wealth Funds

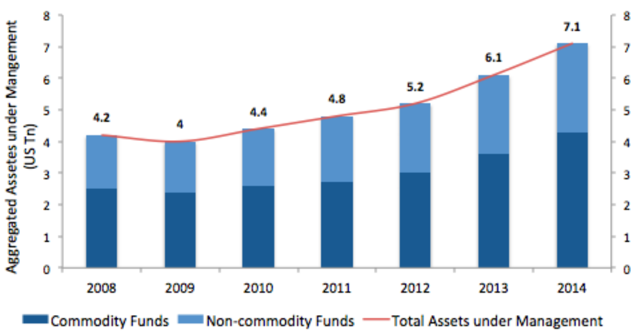


**Figure 5.** Sovereign Wealth Fund AUM Data by Year. *Source: The 2015 Preqin Sovereign Wealth Fund Review, Sovereign Wealth Fund Institute*

Sovereign Wealth Funds (SWFs) is a recently coined term for government-owned investment funds which invest in different financial assets ranging from equity markets to precious metals. SWFs exist for savings and stabilization. Savings funds target accumulation of wealth; whereas stabilization funds focus on building up enough reserves to withstand a severe economic downturn. SWFs have attracted more attention by the financial industry because the aggregated assets under management (AUM) by SWFs has been increasing consistently and at a fast pace. By the end of 2014, AUM of SWFs reached 7.1 Trillion U.S. dollars. It is also worth noticing than 57% of the AUM is from oil and gas related funds (Figure 5), and 40% of the funds are located in Middle-East (Figure 6). Accordingly, SWFs are sensitive to oil price returns.

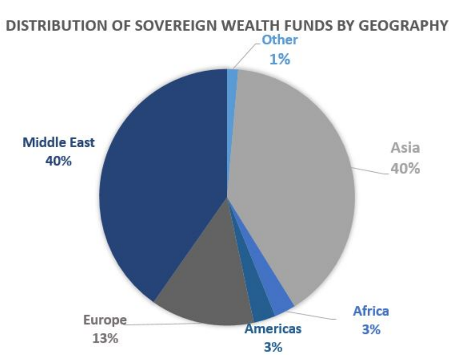


**Figure 6.** Sovereign Wealth Fund AUM Data by Region in 2015.
*Source: The 2015 Preqin Sovereign Wealth Fund Review, Sovereign Wealth Fund Institute*

The precipitous drop of oil prices since 2014 has stressed oil exporting nations. As depicted in Figure 7, the aggregate current account balance of exporters increases when oil price is high and decreases when oil price is low. Following oil price increases beginning in the early 2000s, the aggregate current account balance of exporters ultimately reached about $501 billion by 2011. Yet, by 2015, the balances had nearly vanished altogether. To maintain the fiscal sustainability in a depressed oil environment, oil exporters are pressured to liquidate assets. This is a key mandate of certain SWFs.

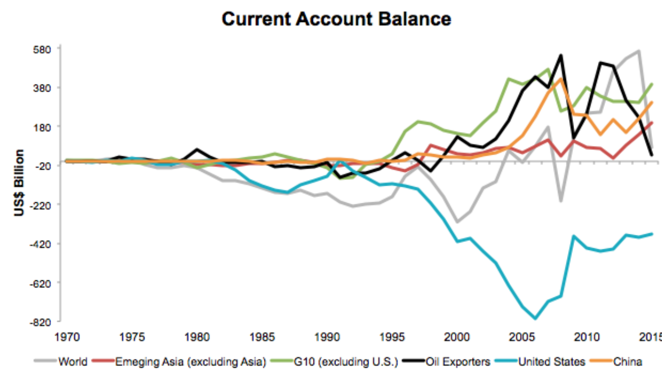


**Figure 7.** Historical Current Account Balance 1970-2014 with 2015 Projection.
*Source:World Bank Database*

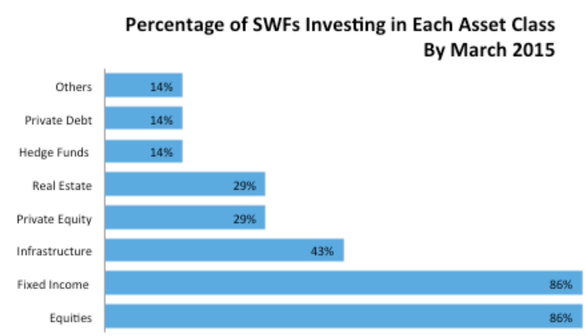


**Figure 8.** Oil exporters holdings of US treasuries (Billion USD) and SWF investments in different asset classes.
*Source:The 2015 Preqin Sovereign Wealth Fund Review*

Among the current holdings of SWFs, U.S. treasuries and stocks are most likely to be liquidated first. The major three reasons are 1.) in terms of foreign investments, the SWFs have high motivation to invest in U.S.financial markets as most of them are denominated in USD; 2.) 86% of SWFs are investing in equities and fixed-incomes (Figure 8); 3.) U.S. treasuries and stocks are highly liquid. In fact, it shouldn't go without notice that oil exporters are the 4th largest investor in U.S. treasuries [31].

In the short run, on one hand, the liquidation in U.S. equities puts downward pressure on stocks. An additive effect is that the sell-off of cross-border investments from SWFs have more negative impact on stock prices relative to sell-off of domestic transactions. [32]. Acquisitions of domestic firms by foreign SWFs increase the firm value more than the domestic SWFs acquisitions.

On the other hand, SWFs' liquidation in U.S treasuries may have compensatory effects. According to Morgan Stanley Wealth Management, SWFs have pulled nearly $100 billion of their funds from asset managers before the end of 2015. U.S. Federal Reserve economists have estimated that "if foreign official inflows into U.S. Treasuries were to decrease in a given month by $ 100 billion, 5-year Treasury rates would rise by about 40-60 basis points". This will push rates up to the highest level since 2011 [33]. Together with tightening monetary policy, these observations forecast strengthening of the U.S. dollar. The appreciation in U.S. dollar will drive up consumption and thus the aggregated demand in the economy. The strengthening U.S. dollar will also lead to increased costs for foreign oil importers which is a negative oil specific demand shock. Taken together the positive aggregated demand shock, the negative oil specific demand shock from liquidation in treasury, and the negative stock specific shock from equity sell-off will drive changes in real economic activity, oil price returns, and stock returns. The specific effects on oil production, REA, oil price returns, and equity returns will depend on the relative magnitudes of the shocks and on the concurrent shock in oil supply. However, if this shock is taken to be zero, the SVAR-GARCH model can provide directional forecasts for the dependent variables given the signs of these shocks. The sign and magnitude of the elements in the structural matrix, $A_0^{-1}$ provide the means to make these predictions.

The analysis above is complicated by the opacity of SWFs and potential monetary policy actions. "At least five of the 29 forum members don't publish public annual reports. At least four don't disclose their asset size." [34]. This makes it more challenging to analyze exactly how much U.S. equity and treasuries SWFs are holding. Secondly, if oil price declines are persistent, and the Fed continues to hike rates and absorb all excess reserves, this may expose the banking system to risks of oil debt contagion.[35]

## Redistribution of Wealth

"Wealth is a stock, not a flow" [36]. The wealthiest nations have the highest capital stock. That is to say, they have the highest potential for future income and consumption. While we concede that GDP is a flow and therefore far from an ideal substitute for wealth, it is a close and correlated proxy. Because there is abundant data available for GDP and because there are important observations to be made from it, we center this analysis on GDP.

To understand the flow of money and wealth distribution with respect to changes in the global oil market, nations were divided into four different categories: Developed Market (DM) Importers, DM Exporters, Emerging Market (EM) Importers and EM exporters. To focus specifically on redistribution, GDP from each nation was normalized by total world GDP to calculate GDP share. The evolution of percent change in GDP share provides insight into the redistribution of global wealth.

The impact of oil price returns on GDP share is complex. Oil exporters will have less revenue when oil price is low, which is likely to result in spending cuts. This will have a negative impact on short term economic growth in these nations [37]. Changes in GDP share of exporters is 54.7% correlated with % change in crude oil price, whereas that of importers is 71.8% negatively correlated with % change in curde oil price.2 This impact is more serious for emerging markets oil exporters, e.g. Mexico, Venezuela, Colombia, Russia and nations in the Gulf Cooperation Council as oil production is a significant source of their GDP [38]. This could be reflected from correlations too. Changes in GDP share of DM exporters is 44.2% correlated with changes in crude oil. However, for EM exporters, this number is 51.6%. They are dealing with serious shortfalls in revenue. As shown in Figure 9, oil exporter percent change in GDP share slowed down drastically and became negative in 1985 and 1998, and vice-versa for 1973. However, for those oil exporters in developed countries, e.g. Canada, their structure of capital income is more diversified. Their GDP growth did slow down in the event of negative oil shocks, but compared to EM exporters, the drop in growth rate is much smaller. The loss in oil industry is offset by cost benefits from other industries. On the other hand, a sliding oil price will result in higher consumption in oil importing economies. This effect is more obvious in emerging markets as they are fast growing. Net-net, when oil prices decreases, the wealth from oil exporters will be transferred to oil importers. EM exporters give up more wealth to oil importers than DM exporters. EM importers receive more wealth from oil exporters than DM importers.

However, during economic downturn, as evident from the Great Financial Crisis, GDP growth rate across countries is likely to drop and in some countries, this number may even became negative.

We have similar observation within US. In the major oil producing states, including Texas, North Dakota, Oklahoma, Alaska and California, which are suffering from the low oil price. The percentage change in share of GDP of oil export-

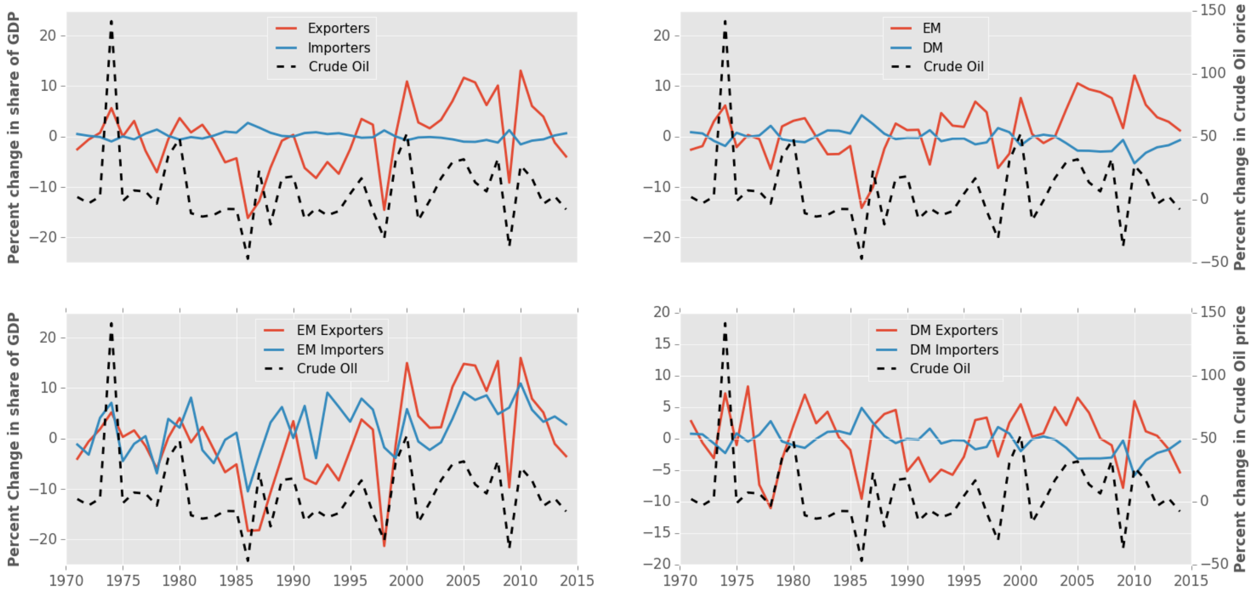


**Figure 9.** **Right-axis**-Changes in Oil Price.**Left-axis**- Top Left: Changes in aggregated GDP in exporting countries and importing countries as a share of GDP.
Top Right: Changes in aggregated GDP in DM countries and EM countries as a share of GDP.
Bottom Left: Changes in aggregated GDP in EM exporters and EM importers as a share of GDP.
Bottom Right: Changes in aggregate GDP in DM exporters and DM importers as a share of GDP
*Source: Bloomberg*

| Exporters | | Importers | |
|---|---|---|---|
| DM Exporters | 44.2% | DM Importers | -53.4% |
| EM Exporters | 51.6% | EM Importers | 28.8% |
| EM | 42.7% | DM | -51.4% |
| Exporters | 54.7% | Importers | -71.8% |
| 5 States | 65.4% | Other States | -65.2% |

**Table 2.** Correlations between changes in crude oil price and changes in GDP share for different nation groupings.

ing states is more volatile and it's positively related to the changes in oil price (Figure 10). When oil prices decline, the oil production revenue in the 5 states decreases. We use the aggregate GDP share of all the states excluding the 5 major exporters mentioned above as a proxy for aggregate GDP from oil importers within U.S.. In the events of oil prices decline, the share of GDP of oil exporters within U.S. increases and that of oil importers within U.S. decreases. There is a positive correlation between changes in GDP share in these 5 oil exporting states and changes in the crude oil price. This correlation in other states is negative. In other words, the wealth from U.S. oil exporting states will be transferred to U.S. oil importing states when oil prices decline. When they increase, the reverse is true.

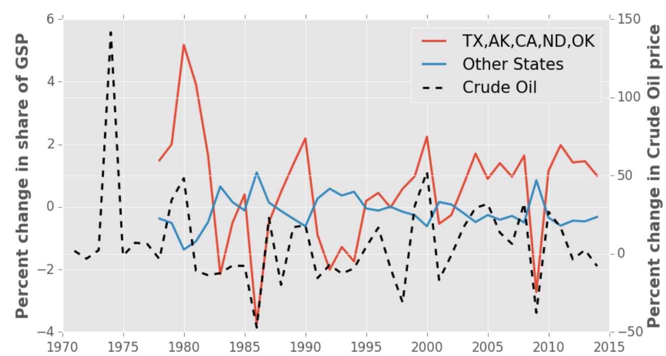


**Figure 10.** **Right-axis**-Changes in Oil Price, **Left-axis**-Changes in aggregate GDP of 5 major oil exporting states and other states as a share of U.S. GDP
*Source: Bloomberg*

## Net Impact of Oil Price Decline on Global Growth

In the previous sections, we have established some of the effects oil prices have on the economies of nations. Here, we address the net macroeconomic impact of sustained oil price declines. The income gains from low oil prices benefit the private sector through lower costs of energy (except the energy sector), and the income losses from oil prices are detrimental to the public sector [39]. *Pass-through* is an important policy-sensitive concept to bear in mind when measuring the transmission of oil price decreases to the consumer. Pass-through describes the penetrance of oil price fluctuations to prices consumers actually pay, say at the gas pump. It is defined as the rate of change in retail gas prices relative to crude oil price.

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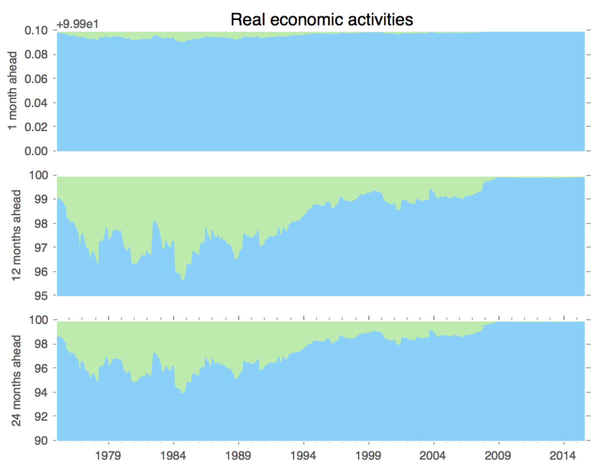


**Figure 11.** Variance decomposition of real economic activities. Blue: aggregate demand shock, Green: oil supply shock.

As discussed briefly earlier in this manuscript and far more thoroughly in the literature [40, 18], the impact of oil price shocks on national growth can be asymmetric and can depend on the idiosyncrasies of the individual nation. In particular, a positive shock is generally found to be more impactful than a commensurate, but negative one. This conclusion speaks to the importance of using a structural VAR setup to deconvolute the effects of individual supply and demand shocks to the economy. Therefore, to develop a position on the net macroeconomic impact of the *current* drop in oil prices will require that drop be explained in terms of the individual shocks.

In our model, the net macroeconomic impact depends on the following factors driving the oil prices: aggregate demand, oil-specific demand, and supply. According to the IMF [39], "*Econometric techniques, such as univariate regressions with a measure of global economic activity or vector error autoregressions, place a larger weight on supply factors than on demand factors in explaining the oil price fall.*"

However, these univariate regression models do not address the potential of endogeneity, an issue which we explicitly address within the framework of a structural VAR model. The variance decomposition of the SVAR-GARCH model with regime shifts (Figure 3) indicates that the recent oil price decline is being led by oil-specific demand shocks rather than supply shocks.

Given that the oil price decline is concamitant with both a global supply glut and a significant decrease in growth rate of the world's second largest economy, it is not obvious how to decouple the effects of supply and demand on oil price. We extend this analysis to infer the relative roles of oil supply and aggregate demand on global growth vis a vis a variance decomposition of REA. Real economic activity is the closest measure among the dependent variables to global economic growth. We provide support here for the argument that although the glut in supply is real, the more prominent driver of oil prices is in fact a demand shock. As shown in Figure 11, supply shocks contributed to REA more significantly in the 1980s and early 1990s than today. In fact, the model produces the surprising interpretation that demand shocks explain nearly all of the current forecasting error in REA, which represents a significant deviation from the seemingly analagous situation following 1986 when OPEC did not modulate oil price via output.

This interpretation is not wholly unreasonable. Kilian refers to the fact that since then Libya, Iraq, and Syria combined have increased their production by 18% and US has increased shale oil gas production [41]. However, the OPEC nation's production grew only by 0.23%, resulting in a world increase of 0.9%. There are two issues with these numbers. Firstly, 0.9% is a significant but not overwhelming increase supply. Secondly, an increase in production can be considered as a supply *'shock'* only if it exceeds the expected supply. On the other hand decrease in freight carrier movements and world shipping index, combined with fall in prices across all commodities lends strength to the argument that these prices are the result of slowdown in demand and not excess supply. The reluctance of oil exporters to cut down productions has led to increased inventories around the world but that is also a symptom of the low demand. If the current situation is indeed demand driven, akin to 2008, then we can say that global economic growth will slow. This dovetails well with what is currently being observed in the global economy, especially in emerging and developing economies. Therefore, we expect a slowdown in global growth in the current scenario.

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