Measuring and Hedging The Adverse Effects of Oil Price Decline: A Global View

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Abstract
In this paper, we dissect the influence of plunge in oil prices into three parts. To begin with, the analysis of relationships between oil price fluctuation and US stock prices in different industries reveals that industry sensitivities to changes in oil prices can be asymmetric. Our research shows significant interaction between most industries and oil prices. Further study uses a VAR-GARCH model to estimate hedge ratios across 30 industries. At the micro level, we propose general strategies and effectiveness metrics for institutional investors to construct their hedging portfolios. At the macro level, the global market is experiencing a reallocation of wealth across different categories of countries. After a literature review of researches associated with oil price declines in history, we discuss the current decline's impact on economies. Based on an extended model of Hamilton's analysis, we demonstrate that oil while exporting countries are having a hard time, importers will enjoy small rises in their GDP.

Keywords
oil price risk, estimation risk, hedging effectiveness, sovereign wealth funds, global wealth redistribution

Contents

Introduction

Driven by the plunging price of a barrel of oil, which has fallen more than 70 percent since June 2014, oil industry is currently in its deepest downturn since the 1990s. While oil production is not declining fast enough in the United States and other countries, that could begin to change this year. Demand for fuels is recovering in some countries, but it still requires a year or two for crude price recovery. Thus oil price plunge will continue affecting everyone: producers, exporters, governments, and consumers.

At the micro level, changes in the price of oil, a key factor in the production process, affect financial performance and/or cash flows of firms, in turn influencing firms' dividend payments, retained earnings, and equity prices [12]. In 2008, Nandha and Faff [20] studied the short-term link between oil prices and thirty-five DataStream global industries. They found that price rises have a negative impact on all but the oil and gas industries. Later research shows that the relationships between oil prices and industry stock returns actually differ from country to country and from industry to industry. For example, while oil prices have a negative influence on the returns of transport industry in developed economies, there appears to be no evidence of a significant role for oil price in Asian and Latin American countries [19].

Our report first focuses on analyzing the relationship between oil price fluctuations and US stock prices in various industries. From the viewpoint of portfolio management, after identifying the heterogeneity of industry sensitivities to oil, we can find means of diversification during oil price decline. We also attempt to propose strategies for institutional investors (e.g. in the world of endowments, foundations, and coorperate and public pension plans) to hedge or rebalance their portfolios.

At the macro level, drop in oil prices deeply affects various categories of countries as well as financial stability in general. While no two countries will experience the drop in the same way, they share some common traits. Oil importers among advanced economies and emerging markets benefit from higher household income, lower input costs, and improved external positions. Oil exporters will take in less revenue, and their budgets and external balances will be under pressure. In the last part of this report, we analyze the redistributive effects on wealth and macroeconomic impact on global growth.

1. Industry sensitivities to oil price

1.1 Measurement of differential impact on stocks

In this part, we will examine the differential impact of oil price and oil return volatility on excess stock returns and return volatilities of thirteen different industries in the U.S. economy. Understanding whether oil price changes constitute a systematic asset pricing risk at the industry level is essential for making appropriate investment and corporate management decisions. Four major types of industries are studied [7]:

- **oil-substitute** (Coal, Electric and Gas Utility)
- **oil-related** (Oil Extraction, Petroleum Refinery)
- **oil-user** (Building, Chemical, Plastic, Metal, Machinery, Transportation Equipment, Air Transportation)
- **financial** (Depository Institutions, and Insurance)

1.1.1 Data Sources

To investigate the relationship between U.S. industry stock returns and oil price changes, daily data from December 11, 1998 to December 28, 2015 are used.

The return on one-month crude oil futures (ROF), traded on the New York Mercantile Exchange (NYMEX), is used as the oil return variable and it is calculated as $\log(p_t/p_{t-1})$ (p is the price of one-month oil futures). The one-month futures data are used mainly for the following two reasons. First, spot prices are more heavily affected by temporary random noise than the futures prices are [23]. Also, for firms engaging in hedging, the effectiveness of such hedging activities is usually judged by the variability of corresponding futures prices.

For stock returns in various industries, we use Ken French's industry returns data[1]. The portfolios include all NYSE, AMEX, and NASDAQ firms with the necessary data (except several breakpoints with only NYSE firms). The excess market return (*RM*) is the value-weight excess return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t.

The three Fama–French factors include the excess return on the market (*RM*), the performance of small stocks relative to big stocks (*SMB*, Small Minus Big), and the performance of value stocks relative to growth stocks (*HML*, High Minus Low) [2]. *SMB* accounts for the elements of risk associated with firm size, and *HML* accounts for elements of risk associated with valuation. In general, industries with high *SMB* coefficients tend to move together with low market capitalization firms, while industries with high *HML* coefficients are more likely to be strongly correlated with value stocks [9].

1.1.2 Endogenous break point identification

In analyzing the aforementioned time series data sets, we allow the break points to be determined endogenously. To investigate the possibility of structural breaks, we applied the Zivot and Andrews (ZA) test procedure [24] to the full sample period. Similar to the ADF and PP tests, the Z&A test has, as its null hypothesis, that the dynamics of the respective series are characterised by a unit root. However, the Z&A test makes allowance for the possible existence of an one-off structural change under the alternative hypothesis. This is an attractive feature of the test since Zivot and Andrews have demonstrated that the ADF and PP tests have low power in the presence of a structural break.

Based on our criterion described above, we iterate the procedure and identify four breaks from Apr 4, 1983 to Feb 1, 2016:

- November 20, 1985 (t-statistic = -4.4664)[3]
- June 24, 2004 (t-statistic = -4.2998)
- September 22, 2008 (t-statistic = -4.4399)
- September 24, 2014 (t-statistic = -3.2179)

As is shown in Figure 1, there were a number of significant oil-related events surrounding these dates [4].

We will conduct the following estimation within a subperiod from September 2008 to September 2014. During this period, the Augmented Dicky–Fuller (ADF) test statistics exceed the critical values at the one-percent level in all cases. Therefore, the null hypothesis of unit root is rejected across all industries. Data from September 2014 to the end of 2015 will be employed in our out-of-sample analysis for forecasting evaluation and understanding portfolio investment implications of the in-sample results.

1.2 Augmented Fama-French model

To describe the impact of crude oil-futures return and its volatility on industry stocks, we can describe the industry ex-

[1] accessed from the datasets "Industry Portfolios" in Feburary 2016 at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[2] accessed from the datasets "Historical Benchmark Returns" in Feburary 2016 at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[3] For significance level at 0.1, critical value = -4.58.

[4] Source for annotation: Hamilton, James, "Historical Oil Shocks," Unniversity of California; various news sources; Goldman Sachs Global Investment Research.

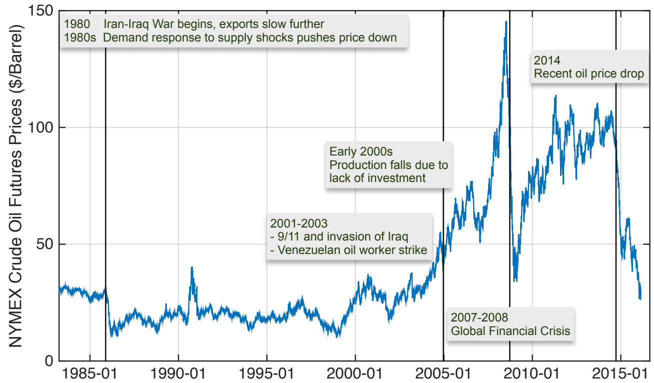

Figure 1. Break points identified with Z&A test

cess stock return ($ER_{i,t}$) as a function of the three Fama–French factors, daily return on one-month crude oil futures (ROF_t), and conditional volatility of oil futures return ($CVOF_t$):

$$\begin{aligned} ER_t =& a_0 + a_1 RM_t + a_2 SMB_t + a_3 HML_t + a_4 ROF_{t-1} \\ &+ a_5 CVOF_{t-1} + \varepsilon_t \end{aligned} \tag{1}$$

Some recent researches have shown that the relationship between oil and economic activity is not entirely linear. In fact, negative oil price shocks (price increases) tend to have larger impacts on growth than positive shocks do [16, 4]. To empirically distinguish asymmetry in sensitivities of various industries to oil price shocks, the model is revised as follows:

$$\begin{aligned} ER_t =& a_0 + a_1 RM_t + a_2 SMB_t + a_3 HML_t + a_4^+ D_{t-1} ROF_{t-1}^+ \\ &+ a_4^- (1 - D_{t-1}) ROF_{t-1}^- + a_5 CVOF_{t-1} + \varepsilon_t, \end{aligned} \tag{2}$$

in which D_{t-1} is a dummy variable taking a value 1 if ROF is positive and 0 if it is negative. Accordingly, if a_4^+ and a_4^- are not statistically different from each other, there is no asymmetry to oil price increases and decreases in this model.

The GARCH (1,1) specification, introduced by Bollerslev [3], is used to model industry returns and their conditional volatility ($h_{i,t}$), and to trace the persistence of shocks to industry returns. We utilize a two-step process in introducing conditional volatility of oil futures returns into modeling stock returns. In the first step, the daily conditional volatility of oil futures returns ($CVOF$) is generated from an Auto-Regressive-GARCH model (AR (8)-GARCH (1, 1)). The lag structure in this model is selected by using the Akaike Information Criterion (AIC). In the second step, this data series is subsequently used in estimating the industry return models.

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 CVOF_{t-1} \tag{3}$$

To capture the fat-tail property of the return distribution, the analytical specification of the model for each industry is based on t-distribution of the error term [2], i.e. $\varepsilon_t | I_{t-1} \sim t(0, h_t, \nu), t = 1, 2, 3, ..., T$ (I_{t-1} denotes the information available at time $t-1$). The log-likelihood function with the t-distribution with variance (h_t) and degree of freedom $\nu \in (2, +\infty)$ takes the following form is

$$\begin{aligned} \ln L =& T \left[\ln \Gamma\left(\frac{\nu-1}{2}\right) - \ln \Gamma\left(\frac{\nu}{2}\right) - 0.5 ln(\pi(\nu-2)) \right] \\ & - 0.5 \sum_{t=1}^{T} \left[\ln h_t + (\nu+1) \ln\left(1 + \frac{\varepsilon^2}{h_t(\nu-2)}\right) \right]. \end{aligned} \tag{4}$$

Then the parameter vector $\Theta = [a_k, \beta_l, \nu_i; k = 0, 1, ..., 5; l = 0, 1, ..., 3; i = 1]$ can be estimated using the maximum likelihood technique.

1.3 Estimation of industry sensitivities

1.3.1 Empirical results

Estimation of the augmented Fama-French factor model above using GARCH (1,1) framework gives sensitivities of all industries examined (see Table 2).

It is important for investors to fully account for the differences in oil sensitivities when implementing industry-based investment strategies. However, it is reasonable to be concerned whether industry sensitivities to oil prices can be precisely estimated.

1.3.2 Estimation risk for oil price betas

As is shown in the empirical results, industry sensitivities to changes in the price of oil can be asymmetric. Also, the oil price betas depend on whether oil is an input or an output, as well as the indirect effect of oil prices on the industry [22]. More specifically, industry sensitivities depend on the degree of competition and concentration, and on the capacity to transfer oil price shocks and minimize the impact of these shocks on its profitability [5].

It is noteworthy that weekly data may better capture the interaction of oil and stock price changes than daily or monthly data. Using weekly data in the analysis instead of daily data significantly, in general, reduces potential biases that may arise such as the bid-ask effect, non-synchronous trading days, etc. Also, it has advantage over using monthly data since the latter may have some bearing on asymmetry in responses of stock returns to oil price shocks [11].

1.3.3 Causality tests

The unconditional correlation between crude oil price returns and returns of stocks in various industries is visualized in Figure 2, which varies greatly from 0.0237 to 0.9339 for US. To further examine the relationships between oil price changes and industry stock returns, we conducted Granger causality test between return series. In this section, we use daily WTI Crude Oil Spot Price[5] for oil price, and daily value weighted average returns for 30 industry portfolios within the same sample period (from September 2, 2008 to December 28,

[5]accessed from "WTI Crude Oil Spot Price Cushing, OK FOB" dataset at https://www.quandl.com/data/DOE/RWTC-WTI-Crude-Oil-Spot-Price-Cushing-OK-FOB

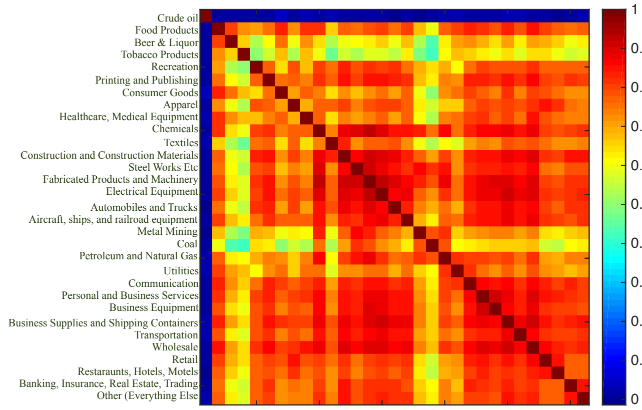

Figure 2. Correlation between crude oil price and value weighted average return of 30 industries

Table 1. F-statistics of Granger causality test (critical value at 10% sig. level is 2.7083)

	Food	**Beer**	**Smoke**	**Games**	**Books**	**Hshld**
$O \rightarrow S$	274.44	146.66	139.31	254.82	275.45	197.71
$S \rightarrow O$	10.14	5.28	4.42	0.29	2.63	7.75
	Clths	**Hlth**	**Chems**	**Txtls**	**Cnstr**	**Steel**
$O \rightarrow S$	189.15	177.23	444.58	186.20	363.39	445.36
$S \rightarrow O$	0.23	2.73	5.86	1.13	1.99	3.56
	FabPr	**ElcEq**	**Autos**	**Carry**	**Mines**	**Coal**
$O \rightarrow S$	556.77	379.29	300.11	291.67	566.83	550.19
$S \rightarrow O$	4.19	4.71	4.36	3.94	1.75	2.75
	Oil	**Util**	**Telcm**	**Servs**	**BusEq**	**Paper**
$O \rightarrow S$	129.89	309.57	305.28	264.44	300.27	299.97
$S \rightarrow O$	10.34	14.73	4.26	1.36	1.32	2.67
	Trans	**Whlsl**	**Rtail**	**Meals**	**Fin**	**Other**
$O \rightarrow S$	213.27	312.85	160.98	183.24	226.29	228.55
$S \rightarrow O$	2.04	2.72	0.23	0.73	1.80	5.61

2015). Since some variables as well as their bilateral effects can be very sensitive to the time lag in analysis, we implement the tests for lags ranging from 1 to 10. Then the lag length is chosen using the Bayesian Information Criterion.

As is shown in Table 1 [6], there is bidirectional causality between oil price changes and Automobiles and Trucks, Food and Beverages, Oil and Gas, Utilities industries, and Consumer Goods. Unidirectional Granger causality from oil to stock returns is significant for Recreation, Apparel, Retail, and Financials. To sum up, causality test results further demonstrate the significant interactions between oil prices and stock prices in most industries. Such causality relationship implies the possibility of improving predictability of oil price or stock price using information from specific industry stocks and the oil market [21]. These results also help us understand that despite the relative exogeneity of oil prices, macroeconomic and financial variables do affect world oil prices as well [8].

[6]For $S \rightarrow O$, the null hypothesis is that there is no causality from stock market returns to oil price changes. For $O \rightarrow S$, the null hypothesis is that there is no causality from oil price changes to stock market returns.

2. Hedging strategies for institutional investors

In addition to market level analysis, industry-level analysis is crucial in revealing the effects of oil price shocks masked by the aggregate stock market effect. The knowledge of the relative sensitivities of industry stock returns to changes in oil prices would be of benefit for risk management purposes. As is demonstrated by Mohamed Arouri *et al*, taking the cross-market volatility spillovers estimated from the VAR-GARCH models often leads to diversification benefits and hedging effectiveness better than those of commonly used multivariate volatility models such as the CCC-GARCH of Bollerslev (1990), the diagonal BEKK-GARCH of Engle and Kroner (1995), and the DCC-GARCH of Engle (2002) [6]. Thus for hedging purposes, we will use another bivariate VAR-GARCH model in this part.

2.1 VAR-GARCH model for volatility spillover

For each pair of industry stock returns and oil returns, the bivariate VAR(1)-GARCH(1,1) model has the following specification for the conditional mean [17]:

$$\begin{cases} R_t = \mu + \Phi R_{t-1} + \varepsilon_t \\ \varepsilon_t = H^{\frac{1}{2}} \eta_t \end{cases} \tag{5}$$

where $R_t = (r_t^S, r_t^O)'$ is the vector of returns of stock and oil price respectively. Φ is a 2×2 coefficient matrix $\Phi = \begin{pmatrix} \phi_1 & 0 \\ 0 & \phi_2 \end{pmatrix}$, and $\varepsilon_t = (\varepsilon_t^S, \varepsilon_t^O)'$ is the error term vector. $\eta_t = (\eta_t^S, \eta_t^O)'$ refers to a sequence of independently and identically distributed ($i.i.d$) random errors. $H_t = \begin{pmatrix} h_t^S & h_t^{SO} \\ h_t^{SO} & h_t^O \end{pmatrix}$ is the matrix of conditional variances of stock and oil returns, in which

$$\begin{aligned} h_t^S &= C_S^2 + \beta_{S1}^2 \times h_{t-1}^S + \alpha_{S1}^2 \times (\varepsilon_{t-1}^S)^2 && (6) \\ &+ \beta_{S2}^2 \times h_{t-1}^O + \alpha_{S2}^2 \times (\varepsilon_{t-1}^O)^2, \\ h_t^O &= C_O^2 + \beta_{O1}^2 \times h_{t-1}^O + \alpha_{O1}^2 \times (\varepsilon_{t-1}^O)^2 && (7) \\ &+ \beta_{O2}^2 \times h_{t-1}^S + \alpha_{O2}^2 \times (\varepsilon_{t-1}^S)^2. \end{aligned}$$

Let ρ be the constant conditional correlation, then the conditional covariance between stock and oil returns can be modeled as:

$$h_t^{SO} = \rho \times \sqrt{h_t^S} \times \sqrt{h_t^O} \tag{8}$$

Table 2. Industry sensitivity coefficient estimates (t-value of errors)

Industry	Constant	RM_t	SMB_t	HML_t	ROF_t^+	ROF_t^-	$CVOF_{t-1}$	R^2_{adj}
Food	155.8908	-0.0008	0.0131	0.6301	-3.8854	-6.1960	5.5806	0.4255
T stats	2.7817	-2.7625	1.4499	16.6748	-0.9831	-1.7907	0.2453	-
Beer	127.5959	-0.0006	0.0098	0.6479	-1.0891	-10.2683	1.1090	0.3242
T stats	1.8031	-1.7900	0.8586	13.5799	-0.2182	-2.3503	0.0386	-
Smoke	138.0149	-0.0007	0.0188	0.6539	-0.6344	-6.2696	65.0068	0.1770
T stats	1.3203	-1.3155	1.1141	9.2777	-0.0861	-0.9714	1.5317	-
Games	-48.7499	0.0003	-0.0148	1.2729	-4.6364	4.4085	-20.6063	0.6717
T stats	-0.7198	0.7359	-1.3571	27.8747	-0.9708	1.0543	-0.7494	-
Books	9.2089	0.0000	-0.0135	1.0593	-1.2888	0.1531	-14.5173	0.6755
T stats	0.1653	-0.1494	-1.5002	28.1991	-0.3281	0.0445	-0.6418	-
Hshld	75.8741	-0.0004	0.0050	0.7344	-0.6049	-7.9502	-27.0791	0.5208
T stats	1.4255	-1.4121	0.5780	20.4646	-0.1612	-2.4193	-1.2531	-
Clths	-14.6119	0.0001	-0.0001	1.1056	4.7252	-13.8569	-29.8004	0.5614
T stats	-0.1995	0.1989	-0.0105	22.3911	0.9150	-3.0649	-1.0023	-
Hlth	80.9199	-0.0004	0.0081	0.7910	1.7488	-7.4698	19.7834	0.5521
T stats	1.5168	-1.5103	0.9434	21.9887	0.4648	-2.2678	0.9133	-
Chems	92.0305	-0.0005	0.0119	1.0626	9.2586	2.8751	-8.2744	0.6647
T stats	1.6140	-1.6085	1.2996	27.6390	2.3026	0.8167	-0.3574	-
Txtls	22.4537	-0.0001	0.0090	1.1840	8.4056	3.7368	-28.2836	0.4453
T stats	0.2257	-0.2242	0.5625	17.6528	1.1983	0.6085	-0.7003	-
Cnstr	-10.9074	0.0001	-0.0103	1.1513	1.2659	-1.2010	12.0454	0.6881
T stats	-0.1869	0.1936	-1.0909	29.2603	0.3076	-0.3333	0.5084	-
Steel	11.5521	-0.0001	-0.0059	1.4067	7.0353	21.6450	21.0174	0.6428
T stats	0.1418	-0.1372	-0.4486	25.6048	1.2244	4.3027	0.6353	-
FabPr	2.5865	0.0000	-0.0011	1.2529	7.0909	9.0190	-25.9581	0.7372
T stats	0.0453	-0.0368	-0.1212	32.5185	1.7597	2.5565	-1.1189	-
ElcEq	8.4336	0.0000	-0.0094	1.2473	5.6853	2.4503	-17.3400	0.7363
T stats	0.1493	-0.1341	-1.0280	32.7409	1.4269	0.7024	-0.7559	-
Autos	-35.8204	0.0002	-0.0170	1.2544	7.7145	3.9488	-33.3706	0.5533
T stats	-0.4191	0.4275	-1.2332	21.7663	1.2799	0.7483	-0.9616	-

Industry	Constant	RM_t	SMB_t	HML_t	ROF_t^+	ROF_t^-	$CVOF_{t-1}$	R^2_{adj}
Carry	-44.4773	0.0002	-0.0084	1.0131	-1.2141	4.9126	-13.7412	0.5678
T stats	-0.6634	0.6761	-0.7732	22.4127	-0.2568	1.1869	-0.5048	-
Mines	-61.9252	0.0003	-0.0160	0.8475	10.7837	27.5128	46.4524	0.2635
T stats	-0.5259	0.5306	-0.8406	10.6747	1.2986	3.7843	0.9716	-
Coal	125.4569	-0.0006	0.0019	1.0792	26.8536	33.6721	-12.4904	0.2276
T stats	0.7399	-0.7337	0.0705	9.4395	2.2457	3.2163	-0.1814	-
Oil	125.6900	-0.0006	0.0133	0.7201	16.8032	17.1543	2.3728	0.4212
T stats	1.8017	-1.7912	1.1852	15.3093	3.4156	3.9828	0.0838	-
Util	123.8498	-0.0006	0.0149	0.4241	0.0454	1.4306	16.0161	0.2234
T stats	2.0897	-2.0778	1.5546	10.6118	0.0109	0.3910	0.6656	-
Telcm	93.7532	-0.0005	0.0072	0.9191	-5.8714	3.2721	10.3561	0.6428
T stats	1.7971	-1.7812	0.8537	26.1297	-1.5960	1.0159	0.4889	-
Servs	-38.8230	0.0002	-0.0118	1.2861	-2.3504	-2.7335	13.2277	0.7672
T stats	-0.7263	0.7337	-1.3699	35.6838	-0.6235	-0.8283	0.6095	-
BusEq	-82.7259	0.0004	-0.0146	1.3810	-2.7260	3.1024	9.9726	0.6810
T stats	-1.1572	1.1610	-1.2696	28.6524	-0.5408	0.7029	0.3436	-
Paper	84.5239	-0.0004	0.0068	0.9340	5.6287	-6.7282	-13.5327	0.6331
T stats	1.5871	-1.5806	0.7896	26.0110	1.4988	-2.0463	-0.6259	-
Trans	83.2557	-0.0004	0.0134	0.9501	3.6503	-5.7999	-48.3942	0.6227
T stats	1.4927	-1.4859	1.4905	25.2639	0.9280	-1.6842	-2.1370	-
Whlsl	57.4863	-0.0003	0.0095	0.9394	-3.1139	4.8581	17.3768	0.7171
T stats	1.2841	-1.2762	1.3188	31.1189	-0.9863	1.7576	0.9560	-
Rtail	10.0309	0.0000	-0.0061	0.9919	-2.8780	-13.8382	-5.6552	0.6736
T stats	0.1914	-0.1817	-0.7265	28.0705	-0.7787	-4.2768	-0.2658	-
Meals	-8.4812	0.0000	-0.0021	0.8620	-1.1127	-5.6085	4.7033	0.5614
T stats	-0.1484	0.1552	-0.2244	22.3709	-0.2761	-1.5896	0.2027	-
Fin	-4.4305	0.0000	-0.0139	1.0621	-0.5187	-5.2126	-51.1637	0.7421
T stats	-0.0931	0.1167	-1.8150	33.0944	-0.1545	-1.7738	-2.6476	-
Other	88.2520	-0.0004	0.0098	1.0405	-1.0289	-4.4742	-25.7635	0.6381
T stats	1.4927	-1.4896	1.0257	26.1009	-0.2468	-1.2257	-1.0733	-

Table 3. Estimation of VAR-GARCH model for volatility spillover and hedging ratios

Industry	C_S	C_O	$H(1,1)$	$H(2,1)$	$H(2,2)$	$A(1,1)$	$A(1,2)$	$A(2,1)$	$A(2,2)$	$B(1,1)$	$B(1,2)$	$B(2,1)$	$B(2,2)$	Likelihood	W_t^{SO}	β_t^i
Food	0.0005	0.0717	0.0017	0.0036	0.1291	0.2249	-0.4203	0.0006	0.2931	0.9709	-0.0995	-0.0001	0.9451	2015.0985	0.0000	2.1303
T stats	1.2063	4.0880	5.5961	0.1144	7.5351	10.7033	-0.2230	0.8304	10.8125	198.4895	-0.2249	-0.2542	101.3692	-	-	-
Beer	0.0007	0.0697	0.0019	-0.0434	0.1040	0.2307	4.8499	-0.0016	0.2214	0.9660	-1.4236	0.0007	0.9605	1939.8505	0.2351	-22.6946
T stats	1.6329	3.7702	5.2858	-1.2116	3.1280	9.7073	3.6527	-2.1480	7.5680	172.7066	-3.4056	2.4241	107.8427	-	-	-
Smoke	0.0008	0.0852	0.0017	0.0454	0.1704	0.2324	6.2355	-0.0008	0.2175	0.9691	-1.3165	0.0001	0.9534	1670.0043	0.0000	26.9393
T stats	1.8409	3.3976	5.1104	0.8672	5.5538	9.5467	3.5780	-1.2842	9.2515	178.7899	-3.4441	0.4510	93.7783	-	-	-
Games	0.0010	0.0959	0.0020	-0.0133	0.2275	0.1976	16.8277	-0.0009	0.2121	0.9711	-4.0022	0.0004	0.9463	960.4347	0.0597	-6.6745
T stats	2.1764	2.7007	6.1778	-0.2141	5.1145	6.8925	4.8534	-2.4785	7.5747	192.1583	-3.7409	1.9141	84.1069	-	-	-
Books	0.0007	0.0698	-0.0017	-0.0223	0.2194	0.2172	8.7173	-0.0007	0.2343	0.9709	-2.2246	0.0002	0.9535	1120.9334	0.0784	12.7855
T stats	1.7507	2.0283	-5.5182	-0.4281	6.8865	9.6250	4.2562	-1.9124	8.3992	185.9749	-3.6751	1.7410	117.2793	-	-	-
Hshld	0.0008	0.0516	0.0017	0.0286	0.1256	0.2136	5.8136	-0.0011	0.2389	0.9723	-1.3998	0.0003	0.9523	1883.2477	0.0000	16.9706
T stats	1.8083	2.6052	4.9715	0.8268	5.9259	8.9768	3.7658	-1.7470	9.2111	185.0409	-3.6222	1.3933	112.4731	-	-	-
Clths	0.0009	0.0806	0.0018	-0.1175	0.1170	0.1369	13.8968	-0.0021	0.1562	0.9730	-1.9925	0.0005	0.9613	1194.8752	0.3372	-64.0316
T stats	2.3186	2.3855	5.3305	-1.9467	1.8264	3.1245	6.4929	-4.1636	4.0546	213.3437	-4.0741	3.0194	154.2543	-	-	-
Hlth	0.0009	0.0893	0.0016	-0.0135	0.1707	0.2035	6.2471	-0.0009	0.2893	0.9750	-1.0285	0.0002	0.9307	1846.3137	0.0758	-8.3266
T stats	2.3914	3.9457	5.3871	-0.3535	8.5951	9.7503	4.5510	-1.8809	13.2593	230.1214	-3.3874	1.2479	97.8197	-	-	-
Chems	0.0010	0.0715	-0.0020	0.0245	0.1303	0.1313	20.3726	-0.0025	0.0964	0.9670	-4.4546	0.0009	0.9461	1332.5906	0.0000	-12.3884
T stats	2.6826	2.4796	-5.0990	0.4128	3.0645	3.6911	8.7743	-7.3862	2.8584	195.9609	-7.9981	4.5498	86.3686	-	-	-
Txtls	0.0003	0.1311	0.0021	-0.0173	0.1513	0.2563	-6.1860	0.0006	0.1842	0.9600	2.9071	-0.0002	0.9754	828.9017	0.1033	-8.0612
T stats	0.7123	3.1875	5.8539	-0.3796	4.6196	10.6617	-2.4827	1.6751	7.3940	141.8088	3.9990	-2.5918	190.8168	-	-	-
Cnstr	0.0008	0.0447	-0.0011	0.1271	0.2031	0.1321	22.8971	-0.0021	0.1073	0.9721	-3.8480	0.0006	0.9428	1030.0268	1.0000	-117.8532
T stats	1.9816	1.3261	-1.7495	0.6855	1.4825	3.2797	8.4008	-6.1365	2.7555	207.0879	-6.2547	2.5124	68.7926	-	-	-
Steel	0.0002	0.0741	0.0027	-0.1559	0.0000	0.1788	-9.4625	0.0021	0.2132	0.9377	20.7582	-0.0024	0.9328	834.2520	0.5043	-57.9774
T stats	0.5426	1.9962	3.3530	-1.6058	0.0000	8.1941	-3.7636	7.1500	7.7578	81.7558	17.6322	-21.3725	93.5941	-	-	-
FabPr	0.0008	0.0695	0.0019	-0.0310	0.1215	0.0752	22.5252	-0.0027	0.0985	0.9664	-4.3767	0.0010	0.9433	1246.3379	0.1774	-16.6029
T stats	2.2277	2.4898	4.0567	-0.4911	3.1080	2.6873	11.3719	-9.0455	3.1666	184.1449	-7.6903	6.9119	94.5604	-	-	-
ElcEq	0.0007	0.0883	0.0036	-0.1625	0.0215	-0.0101	28.0621	-0.0003	0.1658	0.4254	59.1426	0.0123	-0.3617	1233.7900	0.4744	-44.9185
T stats	1.7469	2.9030	12.6647	-5.2432	0.2730	-0.4375	12.5774	-0.8253	5.3827	9.3085	27.0667	25.5126	-8.4264	-	-	-
Autos	0.0007	0.0772	0.0020	-0.1343	0.0770	0.1043	22.9669	-0.0027	0.0674	0.9602	-5.2450	0.0009	0.9539	1055.2323	0.3921	-68.3175
T stats	1.7953	2.1343	4.1855	-1.8394	0.6218	3.9982	11.3311	-10.5215	2.7345	165.7363	-7.5944	6.8194	107.8159	-	-	-
Carry	0.0008	0.0831	0.0019	-0.0775	0.1749	0.1424	15.7677	-0.0021	0.1932	0.9745	-3.5288	0.0009	0.9367	1379.7067	0.2393	-41.0014
T stats	2.2655	2.9740	4.9666	-1.4358	5.0663	5.2331	11.0943	-6.4625	6.7239	220.1485	-7.6667	8.2853	103.5956	-	-	-
Mines	0.0008	0.0102	-0.0019	-0.0570	0.2505	0.2569	13.2518	-0.0006	0.2142	0.9620	-2.9509	0.0001	0.9547	859.0840	0.1520	29.4230
T stats	2.3038	0.2358	-5.3600	-0.7190	5.8692	10.2737	4.0835	-1.9715	8.4280	149.5642	-3.1940	0.6098	107.7489	-	-	-
Coal	0.0008	0.0326	0.0021	-0.1897	0.0017	0.2133	12.3098	0.0003	0.1976	-0.8651	-64.1231	-0.0029	0.8749	288.4734	0.5005	-90.4996
T stats	1.8186	0.5429	7.8998	-5.1364	0.0050	11.6852	3.6701	2.9962	11.5712	-42.8066	-11.6091	-11.2196	51.0942	-	-	-
Oil	0.0001	0.0535	0.0016	0.0212	0.1694	0.1619	-8.9841	0.0018	0.3166	0.9771	0.9846	-0.0004	0.9298	155.6916	0.0000	12.8745
T stats	0.2669	2.1090	4.7098	0.4782	7.1382	5.4583	-3.9704	2.7991	11.6056	231.9518	1.7532	-1.3716	80.4934	-	-	-
Util	0.0007	0.0583	0.0020	-0.0148	0.1156	0.2221	5.2255	-0.0012	0.2759	0.9678	-1.3956	0.0006	0.9456	1935.0113	0.1140	-7.4929
T stats	1.7349	3.0291	5.9876	-0.5421	5.8307	9.8470	3.9703	-1.8751	10.5393	169.8020	-3.3713	2.2281	118.4688	-	-	-
Telcm	0.0009	0.0902	0.0017	0.0108	0.1398	0.2229	6.2797	-0.0006	0.2776	0.9712	-1.0938	0.0001	0.9438	1715.0697	0.0000	6.2463
T stats	2.0599	4.3853	5.6274	0.3310	7.6699	9.5686	2.8262	-0.9498	10.6673	204.1422	-2.0093	0.3973	124.0238	-	-	-
Servs	0.0012	0.1056	0.0025	-0.2338	0.0045	0.1371	16.7834	-0.0006	0.2452	0.8966	20.4712	0.0071	-0.8217	1591.5010	0.4979	-92.3101
T stats	2.9036	4.2039	10.5217	-8.6854	0.0684	7.6436	9.1978	-1.9690	8.6123	120.5321	13.6970	15.1370	-44.7436	-	-	-
BusEq	0.0010	0.0816	-0.0012	0.2186	0.1019	0.1167	17.2542	-0.0027	0.1778	0.9756	-2.5638	0.0010	0.9201	1450.5860	0.6532	-178.8942
T stats	2.4074	2.8922	-4.3565	11.8319	3.8147	12.0051	11.4790	-10.2070	6.8912	293.3792	-4.7849	8.3572	143.7868	-	-	-
Paper	0.0010	0.0803	0.0019	0.0100	0.1387	0.1702	14.1651	-0.0021	0.1746	0.9723	-3.2398	0.0008	0.9437	1589.6782	0.0000	5.3427
T stats	2.8561	3.2397	5.4232	0.2143	5.3656	5.8280	8.4248	-4.1587	5.8299	204.4043	-8.3032	3.8358	105.7490	-	-	-
Trans	0.0006	0.0810	-0.0019	0.1153	0.0000	0.0220	19.2115	-0.0033	-0.0024	0.9629	-4.4375	0.0013	0.9554	1366.5878	0.5042	-59.2322
T stats	1.6052	2.9266	-3.9618	2.9329	0.0000	0.6096	11.4410	-12.2249	-0.0683	160.2195	-7.6895	6.6510	121.6232	-	-	-
Whlsl	0.0009	0.0886	0.0017	-0.0287	0.1645	0.1513	12.8677	-0.0021	0.2288	0.9771	-2.0992	0.0007	0.9292	1676.5855	0.1358	-16.8743
T stats	2.1880	3.9696	5.4008	-0.5996	6.6630	5.3196	8.1517	-4.4922	8.5537	207.8575	-4.7305	3.4075	85.6153	-	-	-
Rtail	-0.0002	0.0848	0.0016	-0.0345	0.1249	0.1942	-8.8447	0.0023	0.2204	0.9708	1.6073	-0.0004	0.9519	1750.6371	0.1848	-21.2375
T stats	-0.4318	3.6613	4.0306	-0.8292	5.7863	7.1640	-4.5905	4.5577	9.6666	166.8741	3.7417	-2.3561	123.9328	-	-	-
Meals	0.0005	0.0750	0.0028	-0.0833	0.0000	0.2681	4.9243	0.0005	-0.2153	0.9511	-1.9778	0.0007	0.9708	1667.9648	0.5083	-29.6978
T stats	1.2100	3.2633	7.6275	-3.5105	0.0000	10.8483	2.0159	0.7530	-12.1965	123.1271	-4.1780	3.3681	217.2817	-	-	-
Fin	0.0010	0.1167	0.0016	-0.1910	-0.0015	0.1543	14.6995	0.0010	0.2779	0.9767	-7.6581	-0.0015	-0.9232	1209.5566	0.5041	-117.3178
T stats	2.4057	3.8861	6.5926	-6.8520	-0.0043	8.2644	5.8115	4.6886	9.2663	234.9978	-4.3861	-2.3314	-60.8206	-	-	-
Other	0.0009	0.0733	0.0018	0.0232	0.1236	0.2182	8.6597	-0.0006	0.2404	0.9717	-1.9374	0.0002	0.9524	1575.3710	0.0000	12.7394
T stats	2.3071	3.0242	6.8114	0.7369	5.9022	9.6881	2.9808	-1.0034	8.2635	206.2509	-3.2352	1.2057	148.4069	-	-	-

For simplicity, in this part we do not consider the asymmetric impact of negative and positive shocks on conditional variances. The volatility transmission across the oil and stock markets over time is governed through the cross values of error terms (i.e. $(\varepsilon^O_{t-1})^2$ and $(\varepsilon^S_{t-1})^2$), which capture the impact of direct effects of shock transmission; as well as those of lagged conditional volatilities (i.e. h^O_{t-1} and h^S_{t-1}), which directly account for the transfer of risk between markets [1]. Therefore, this empirical model simultaneously allows for long-run volatility persistence, as well as shock and volatility transmissions between the oil and stock markets. The parameters of the above bivariate model can be obtained by quasi-maximum likelihood estimation (QMLE), which is robust to any departure from normality conditions [17].

2.2 Hedging effectiveness in various industries

For investors hoping to hedge adverse impacts from oil price movements with stocks, the situation can be interpreted as an optimization problem to minimize the portfolio risk without reducing expected returns. Follow the works by Kenneth Kroner *et al*, we know that for a portfolio consisting of crude oil and stocks from various industries, the optimal weight of oil holding is [14, 13]:

$$w^{SO}_t = \begin{cases} 0 & (if\ \dfrac{h^S_t - h^{SO}_t}{h^O_t - 2h^{SO}_t + h^S_t} < 0) \\ \dfrac{h^S_t - h^{SO}_t}{h^O_t - 2h^{SO}_t + h^S_t} & (if\ \dfrac{h^S_t - h^{SO}_t}{h^O_t - 2h^{SO}_t + h^S_t} \in [0,1]) \\ 1 & (if\ \dfrac{h^S_t - h^{SO}_t}{h^O_t - 2h^{SO}_t + h^S_t} > 1) \end{cases} \quad (9)$$

Investors can also determine the optimal hedge ratio β_t (hedge 1\$ in the oil market with β^i_t \$ in stocks S_i):

$$\beta^i_t = \frac{h^{S_iO}_t}{h^{S_i}_t} \quad (10)$$

The average values of optimal weights and hedge ratios for each industries are listed in Table 3.

After running the portfolio simulations with the optimal portfolio designs and hedging ratios given above, we can judge the effectiveness of hedging by examining the realized hedging errors [15]:

$$HE = \left(\frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \right), \quad (11)$$

in which Var_{hedged} is the variance of the return on the oil-stock portfolios, $Var_{unhedged}$ is the variance of the return on the portfolio consisting of oil only. A higher HE indicates greater hedging effectiveness in terms of the portfolio's variance reduction [6]. Intuitively, corresponding hedging strategies should be more favorable for institutional investors.

2.3 Adverse impact on institutional investors

Institutional investors such as pension funds, investment advisors, and endowments are long-term investors who always keep a close eye on the volatility of oil prices. Market-wide, the Bloomberg Commodity Index, which tracks goods like gold and oil, has fallen by approximately 30 percent since oil prices began their slide in June 2014. Generally speaking, energy companies may make up 5 to 10 percent of the kind of diversified portfolio used by pensions and other retirement funds. Most major pension plans or retirement plans, unless they have a very unique approach than other investors, all have exposure to the recent downward movement.

US and UK institutional investors generally invest a relatively large portion in oil and gas sector covering areas such as exploration, production, refining, marketing, and storage. According to MSCI ACWI, pension funds in the U.S. have about 50% invested in public market equities, with about 8% in the energy sector. Pension funds in the UK have even larger exposure to the change of oil price. Since 15% to 18% of the U.S. high-yield market is exposed to energy, the problem should be quite pressing for those who invest in high-yield market.

Falling oil price has both opportunities and pitfalls. Institutional investors have to balance the adverse impacts on their portfolio against growth opportunities the situation may create in other sectors in which they also invested. There is a wealth transfer, which will have a positive impact on the economy because the reduced cost in transportation will end up being spent elsewhere. As for the negative impacts, one of the main concerns for pension funds would be the link between falling oil prices and lower inflation. The falling inflation will lead to lower bond yields with a subsequent rise in liabilities. The changes in oil price also make equity holders care more about dividends, and make bond holders worry about the risk of defaults.

2.4 Strategies to hedge or rebalance portfolios

In order to maintain a stable cash flow and minimize the exposure to oil price declines, institutional investors can hedge their positions in oil with stocks from various industries. We use principal component analysis (PCA) in this part to validate the feasibility of such an approach. During the sample period, a portfolio including (value weighted) stocks from 15 selected industries (i.e. first 15 principal components), for example, can hedge 91% of the exposure to oil price variation. A portfolio including (value weighted) stocks from 6 selected industries (i.e. first 6 principal components) can hedge over 80% of the exposure.

3. Macro impacts of oil price decline

3.1 Sovereign wealth funds

Due to the oil price plunge, the primary oil-exporting countries are faced with budget deficit for the first time in decades. The growth rate of assets in sovereign wealth funds, which used to be rapid is now slowing down. Some of the assets have started to withdraw from their buffers. In the short term, most oil-exporting countries have set aside enough buffers to deal with temporary drops in oil price. However, what they fear most is a persistent low level of oil prices and passive reactions of policymakers.

In the past few decades, oil price stayed at a high position which leads to huge income buildup. It resulted in current account surpluses and the accumulation of foreign assets. Therefore, the governments needed to set up sovereign wealth funds to manage the increasing scale of assets and income. The global asset distribution was typical during that period of time - concentrated in a few countries, with a significant portion of assets allocated in equities and bonds.

Specifically, the high oil price in early twentieth century lead to aggregation of the current account for exporters to \$630 billion in 2011. This number is even bigger than the emerging Asia market combined. However, the accounting surpluses began to fade away in 2015. What is worse, this oil price plunge has not shown clear signs of reversing so far. The prediction in the next five years indicated that current account balance may recover to approximately \$200 billion.

After exploring the empirical impacts of the plunge on sovereign wealth funds in many typical oil-exporting countries, we discover that the domestic indicators are significant. The fallout on global asset pricing is based on the part of wealth fund which is not hedged by a portfolio composed of other parts of the market. Also, since this price decrease is primarily driven by supply factors, it may cut off some paths of asset aggregation as well. As a consequence, the emerging Asia (oil importers) is rising in terms of their asset accumulation rate, while oil exporters are enduring a decline of funds. The strategy to tackle this redistribution of sovereign wealth funds should be made by oil-exporting countries.

3.2 Redistributive effects on wealth

In general, the overall impact of decreasing oil price is determined by whether importers have a lower marginal nature to save compared with exporters. The plunge has brought wealth to emerging Asian countries and other advanced economies. The former are always regarded as high-saving countries, while the latter have a low propensity to save. To view this from an international prospective, the plunge will lead to lower saving and higher interest rates. However, the overall influence on are not easy to state accurately. The savings of funds and market operations are highly related to current external account balances and governments' fiscal and monetary policy.

One thing that needs our attention in the global market is that oil-exporting countries are those whose wealth funds are important holders of US treasury debt and private equity. A back-of-the-envelope calculation shows that before the decreases of oil prices, countries of the Gulf Cooperation Council (GCC) alone have a combined fiscal surplus at about \$100 billion in 2015, which is expected to increase to \$200 billion in five years. But after the decline, the surpluses transferred to deficits at \$145 billion, which is predicted to be 5 times worse in five years. The changes in net asset of GCC alone are estimated to reach nearly \$1000 billion in the following years. These countries can choose to fund their deficits by either tapping the debt markets or liquidating reserves.

In general, a decline in foreign exchange reserves places upward pressure on developed market yields since the bulk of reserves are allocated to fixed income [7]. According to a recent working paper by Federal Reserve, "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 in the short run." Gulf producers control a huge amount of foreign assets and thus play an important role in these flows after the dramatic plunge in oil prices. For example, Qatar, Bahrain, Saudi Arabia, Kuwait, Oman, and the UAE hold approximately \$2.5 trillion in combined reserves [8].

The relationship between governments and oil exporters is subtle when the oil price is low. Governments will not be willing to transfer revenues to these funds like before. According to the study by the IMF, only some of the Middle East oil exporters has a buffer that may last over 25 years. Others have a relatively small buffer, for instance, Bahrain and Yemen are estimated to use up their buffer in two years. Most of the exporters have an average buffer that will last four to seven years. If we suppose that they can still borrow funds to finance their spending, the government will still need to tighten their belts to reach the aim of maintaining a stable economic environment and passing the oil wealth to the next generation.

3.3 Impacts on global growth

To evaluate the wealth redistribution effects across the country and the net macroeconomic impact on global market, studies have been conducted to analyze the fallout of oil price on GDP's of different countries.

3.3.1 Model

Based on recent literatures on oil prices and macroeconomic indicators, Mork's model dealing with the oil price falling in 1980s is a rational choice for explaining the similar situations [18]. Using empirical data during the sample period, we run regression of the following linear model:

$$\begin{aligned} y_t = \quad & \alpha+\beta_1 y_{t-1}+\beta_2 y_{t-2}+\beta_3 y_{t-3}+\beta_4 y_{t-4} \\ & +\beta_5 o_{t-1}+\beta_6 o_{t-2}+\beta_7 o_{t-3}+\beta_8 o_{t-4}+\varepsilon, \end{aligned} \tag{12}$$

in which y_t is the annual GDP growth rate in quarter t (and $y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}$ are its four lags) [9], and o_t is the percent change of nominal oil price in quarter t (and $o_{t-1}, o_{t-2}, o_{t-3}$, o_{t-4} are its four lags). We apply this regression to eight countries respectively in order to explain redistributive effect

[7] Source: Deutsche Bank analysis

[8] Source: IIF, Deutsche Bank

[9] We collected nominal GDP data of United States, European Union and Australia from 1980 to 2015 using *Edatasea*, together with the same period oil price data from *WTI crude oil price* data sets.

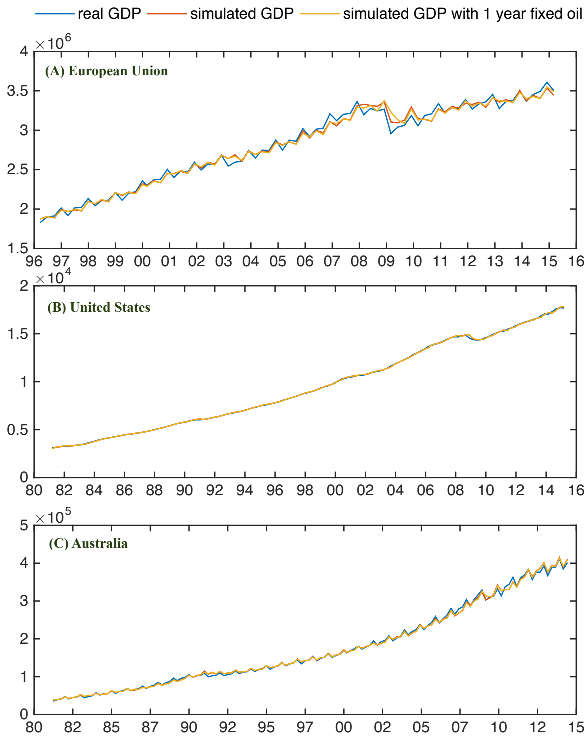

Figure 3. Quarterly GPD simulation based on oil price data

and macroeconomic fluctuations of oil exporters, oil importers and large economies [10].

3.3.2 Model results

In this part, we run the OLS regression of GDP growth rates against percent changes of oil prices in the United States, European Union and Australia. These three countries are chosen as representatives of oil importers and exporters. In general, all three country's in-sample GDP can be well explained by the factors (each country has an R^2 larger than 0.9). The regression coefficients indicate that an oil price decline gives rise to an economy decline to some extent in oil exporters like Australia, but a rise in importers. As is shown in Figure 3, we may use this model and estimated coefficients to simulate GDP in selected countries and compare them with real data in the sample [10]. Statistical results of this regression[11] are shown in Table 4.

From the graph above, it is clear that the United States and European Union are having a growth in their GDP, respectively 1.4% and 0.17%. It is noteworthy that the United States cannot be simply categorized into oil importers. As is mentioned above, its treasury bonds are closely related to sovereign funds. Thus the net effect of comprehensive influence of oil price drops is a meaningful topic to study about. For the European Union, the effects seem to be more obvious. As one of the largest oil importing economy, its rise in GDP can be significantly related to the decline in oil prices.

Table 4. Important statistics of regression

	Europe	US	Australia
R^2	0.9886	0.9998	0.9984
$\left(\frac{GDP_{real}}{GDP_{simulate}}\right)_{year}$	1.0140	1.0017	0.9882
$\left(\frac{GDP_{real}}{GDP_{simulate}}\right)_{quarter}$	1.0041	0.9913	0.9822

3.3.3 Model Evaluation

The model is first used by Hamilton in his research dealing with the oil price decline in 1980s. In a similar situation, it also fits well to explain the macro economy now. However, since the model tries to capture strong autocorrelation in data, it uses only 2 time series to estimate 8 coefficients and 1 constant term. A large number of factors may lead to a high R^2, but it does not necessarily mean that the model tells a good story.

Despite all the fragility of this model, it is still very popular in academic researches due to its good explanatory power and accurate tendency prediction. While it is hard to generalize a model to measure the impacts of falling oil prices on the global market, policy makers different groups of countries can get a general idea on how to react. Importers may become the lenders rather than the borrowers like before. This price decline should always be an alarm to remind them of the erratic nature of the economy in today's world.

4. Discussion

In this paper, we first demonstrated the interaction between oil price and different industries in the stock market. Not only have oil price declines posed impacts on recreation, apparel, retail and financial industries, these industries are also affecting the oil price. Our analysis of hedging effectiveness revealed both the feasibility of constructing portfolios against oil price exposure, and the potential pressure for those sovereign wealth funds holding large amount of U.S treasury bond.

In the last two parts we dissected the macro economy influence that the oil price plunge has brought about. Specifically, the impacts posed on oil exporters and importers are usually in opposite directions. Exporters begin to take on their buffers while importers earn more than before. What requires our special attention is that the redistribution of wealth on a global scale and its side effects (e.g. unsteady market, low market expectation, etc.) will continue to change the market landscape.

The models used in these analyses composed a relative completed view from micro to macro level. Even so, our mod-

[10] Quarterly GDP measured in domestic currency of corresponding countries.

[11] The average is taken for last year; (t-1) stands for last quarter.

els and estimations are inevitably susceptible to uncertainties, noise, and unsolid assumptions in the analysis that are hard to eliminate. We will focus on validating model design and improving robustness of estimation in future work.

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