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# OIL VOLATILITY AND THE OPTION VALUE OF WAITING: EVIDENCE FROM THE OPEC

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## ABSTRACT

*Given the striking oil price volatility of recent years, much has been published about its effects on production. Most of these studies, however, focus on the effects in the largest economies. In this paper, we develop a Panel-VAR approach to test whetherprevious results also apply to OPEC: Do OPEC member countries suffer significant production delays resulting from high oil price volatility?We found evidence that supports this hypothesis.*

## 1. INTRODUCTION

In recent years, there have been an increasing number of studies on the effects of oil volatility—and thus uncertainty —ona country's production(see Cunado, Gil-Alana and De Gracia (2009), Kogan, Livdan, and Yaron (2009), Wang, Wu, and Yang (2008), and Chang, Daouk, and Wang (2009), Switzer and El-Khoury (2007), and Bergin and Glick (2007)). Given the impressive price volatility of oil prices, which rocketed to $145 in 2007, plunged to $40 by 2009, and increased once again to $120 in 2011, one would expect that this uncertainty be reflected in worldwide production.This idea is supported by the extensive theoretical literature on investing under uncertainty,which shows that firms will delay production when facing uncertainty (Brennan and Schwartz (1985), Majd and Pindyck (1987), and Brennan (1990)).

Within this framework, Bernanke (1983) showed that if oil prices are volatile, firms will delay production and investment until this volatility has cleared. Furthermore, Bredin, Elder, & Fountas (2011) found a negative impact of oil volatility on production for four of the G-7 countries, Canada, France, England, and the United States. The authors explained that an increase in uncertainty about the return on an investment decision [production] may tend to increase the advantage inwaiting, rather than committing to the investment. Thus, we expect that this will be even stronger for OPEC, since the production (and GDP) of those countries is highly dependent on oil.

Real GDP growth rate for OPEC members was 5% in 2008, 1% in 2009, and 3.5% in 2010. In comparing growth rates, we see that both OPEC and non-OPEC members had almost the

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same average growth rate in 2008:non-OPEC members had a 5.01% GDP growth, compared to a 5.00% growth for the counterparts. However, since oil prices plunged in 2009, OPEC members have fallen behind non-OPEC members: while in 2009 and 2010 non-OPEC members had 2.3% and 6.0% GDP growth rates respectively, OPEC members attained only 1% and3.5%. Furthermore, if we consider that industrial production is a percentage of GDP, it should be expected that industrial production also be affected by this decrease in GDP growth[1].

According to the U.S. Energy and Information Administration, OPEC members had $750 billion of net oil export revenues in 2010 and $847 billionin 2011. In contrast, OPECearned $571 billion in net oil export revenues during 2009, a 41% decrease from 2008. Thus it can be seen that the volatility of oil prices has generated high levels of revenueuncertainty for the oil exporting countries. This can also affect companies operating in OPEC countries.Not surprisingly, such firms are impacted by the uncertainty of those countries' revenues, thereby possibly delaying production or business activities.

Therefore, it is important to study how shocks on oil prices affect industrial production of the OPEC members. Barros, *et al.*,(2010) show that shocks affecting OPEC's oil production have persistent effects in the long run for all countries, and in some cases the effects are expected to be permanent. The objective of this paper is to study how shocks in oil prices have affected industrial production for OPEC members.

Following Bredin, Elder, &Fountas (2011), we examine the option value of waiting for OPEC member countries. Our studycan be considered an extension of theirs, since it expands this analysis beyond the G-7 countries to the oil cartel as well. However it differs from previous studies in that it relies on a panel data structure. We took this approach because we were able to collect only limited time series data for each country, and grouping the data together in a panel diminishes small sample bias. The panel accounts for 11 cross-sections— all the OPEC members except Qatar— and 14 years of time series data for each cross-section. Additionally, the panel incorporates data for industrial production in billions of dollars, consumer price indexes, a benchmark interest rate, and oil price volatility.

Wefound evidence that the measurement of oil price volatility is cointegrated with industrial production. The data suggests that there is a negative effect of oil volatility on industrial production. Yetmany of the coefficient estimates are not statistically significant.They are, however, economically significant. This negative impact is persistent, at least in magnitude, for different empirical specifications. Overall, we found evidence supporting the thesis that for every 1% increase in oil volatility, industrial production in the OPEC members can decrease anywhere from 2 to 20 basis points.

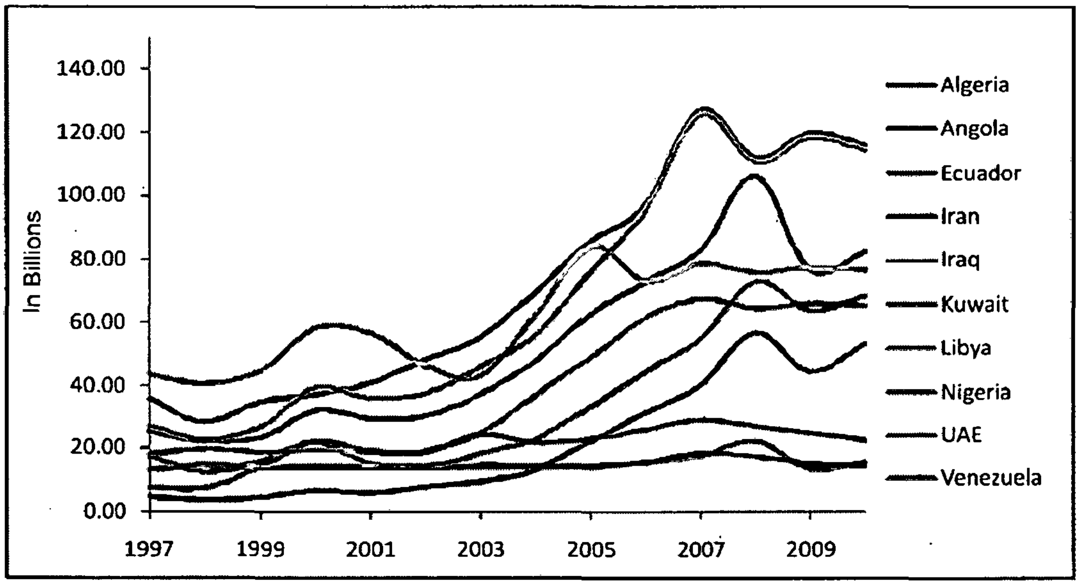
The remainder of the paper is structured as follows:In section 2, we develop the necessary test for the correct specification of the empirical model. Section 3 shows the Panel-VAR regression and its results. Finally,in section 4 we test whether the effects are consistent with different specifications of the test model using an OLS panel regression.

## 2. THE EMPIRICAL MODEL SPECIFICATIONS

Prior studies have found relationships between oil prices and real economic variables. An empirical macro model has to include measures that account for these relationships(see Hamilton

(1996), Lee, *et al.*, (1995), Bernanke, *et al.*, (1997), Hamilton and Herrera (2004), Kilian (2008), and Elder and Serletis (2010)). Therefore, we include a measurement for the aggregate price level (CPI), real industrial output (Industry Value as percentage of GDP), and a short term interest rate. The data comes from the World Bank dataset and includes yearly observations from 1960 to 2010 for all OPEC members (Qatar was dropped from the sample because there were not enough data points[2]). Since industrial production is measured as percentage of GDP, we calculate the numerical value of the industrial production. The short term interest rate is difficult to estimate for many of the OPEC members. Although the Arabic countries issue bonds, it is still difficult to estimate the actual short term interest rates, since the markets for bonds are not fully developed (Espinoza, *et al.*, (2010)). For this reason, we use the bank deposit rates as a proxy for short term interest rates in the hope that these rates will capture the same movements as the short term rates, and thus providing the same explanatory power. Deposit rates are preferred to lending rates because of higher data availability.

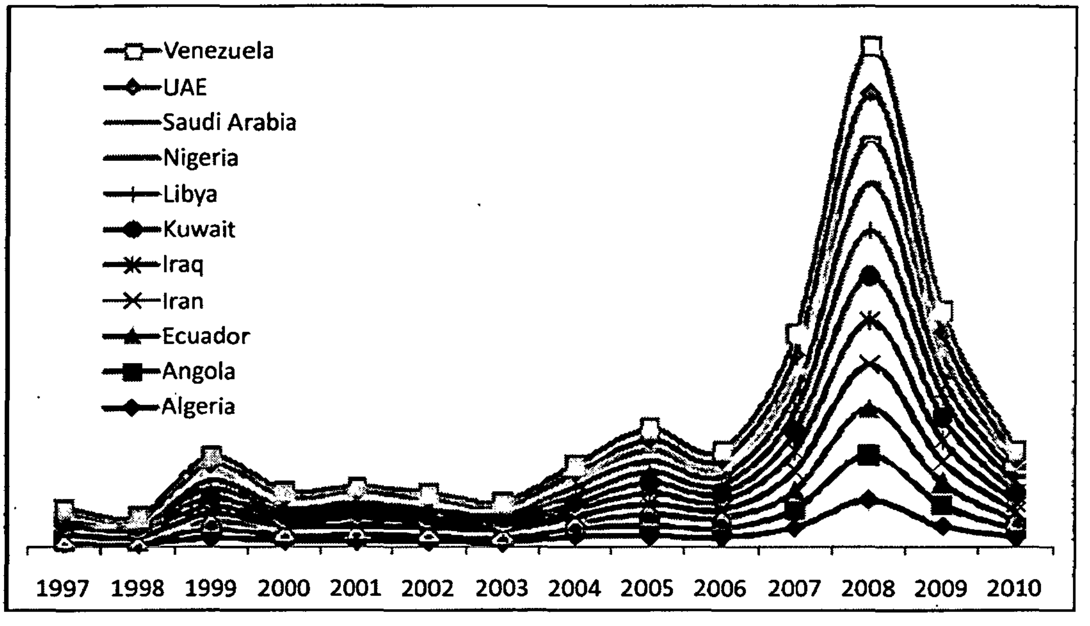
**Figure 1: Industrial Production Time Trend**




We collected a comprehensive dataset of weekly oil prices, from the Energy Information Administration (EIA)[3] for all the cartel members. The dataset includes weekly spot prices from 1987 to 2011. Based on this, we calculated the standard deviation of the oil prices conditioned on years. Only post-1997 data was used in this calculation., as the conditional standard deviation could not be calculated for themany yearsfor which there was only one observation. Thus the total sample includesonlyobservations from 11cross-sectional countries,with 14 years of time series.

Figure 1 shows a plot of the industrial production series of the OPEC members. Saudi Arabia has been omitted, since it has the largest industrial production, andits inclusionwould dwarf the graphical representation of the other countries. By simple inspection, it appears the actual oil price hike encouraged production. This wasto be expected, since most of the wealth of these countries depends on oil production. For instance, in 2008, the lowest industrial production, as a GDP percentage, was 40.99% for Ecuador, while the largest was 78.19% for Libya. After 2008, however, it appearsthat the sudden price drop in oil caused a decrease (or a delay) in production. Ecuador's industrial production decreased to 26.35%, and Libya's decreased to 76%.

**Figure 2: Oil Price Volatility**




On the other hand, Figure 2, which displays a stacked plot of oil price volatility, shows that this drop in industrial production comes after the highest point of oil price volatility in 2008. The remainder of the paper focuses on testing this implication empirically. Weuse an unrestricted Vector Autoregression model, adjusted for panel data to incorporate all countries simultaneously,in order to test this hypothesis empirically(Holtz-Eakin, 1988). The Panel-VAR process is of the form:

$$y_{t,i} = \beta_0 + \beta_1 y_{t-1,i} + \beta_2 y_{t-2,i} + \cdots + \beta_n y_{t-n,i} + \varepsilon_{t,i} \tag{1}$$

where the lags are chosen to minimize the Schwartz Information Criterion (SIC). Also, $y_{t,i}$ is a vector of the form:

$$y_{t,i} = \begin{bmatrix} CPI_{t,i} \\ IP_{t,i} \\ \sigma_{oil_{t,i}} \\ R_{t,i} \end{bmatrix} \tag{2}$$

Table I summarizes the unit root tests and the Schwartz information Criterion needed to estimate equation (1). Panel A shows the test for a common unit root process based on the Levin, Lin, and Chu test. Panel B shows the ADF - Fisher test of a unit root for individual unit root processes. As expected, CPI, industrial production, and the measurement for yearly oil price volatility have a unit roots. These results are robust to whether the whole sample is considered (Panel A) or the individual cross-sections are considered (Panel B).The null hypothesis of a unit root cannot be rejected, even at the 1% level, in all cases except for the interest rate, which agrees with previous studies and theory. Column (c) shows the number of cross-sectional observations used for each test. It should be noted that ofthe whole sample of 11 countries (cross-sections), someobservations were ignored as unsuitable due to singularity of the data.For example, the oil price volatility unit root test was performed usingonly 6 cross-sections. Finally, column (d) shows the maximum number of lags based on the minimumSIC. Except for interest rates, all variables follow an AR(2) process. In other words, SIC is minimized for the autoregressive regression with two lags as exogenous variables.

**Table I**
**Unit Root Tests**

Table I reports Panel Unit Root tests for the relevant variables of the system. Panel A shows the test for a common unit root process based on the Levin, Lin, and Chu test. Panel B shows the ADF - Fisher test of a unit root for individual unit root processes. Column (d) shows the maximum number of lags based on the SIC. The null hypothesis of a unit root cannot be rejected, even at the 1% level, for all cases except for the interest rate

PANEL A
Unit Root of a common unit root process

| *Variable* | *t-statistic* (*a*) | *p-value* (*b*) | *Cross-sections* (*c*) | *Max Lags* (*d*) |
|---|---|---|---|---|
| Industrial Production | 2,855 | 0.9979 | 8 | 2 |
| CPI | 9.279 | 1.0000 | 10 | 2 |
| Oil Price Volatility | 5.193 | 1.0000 | 6 | 2 |
| Interest Rate | -26.931 | 0.0000 | 10 | 1 |

PANEL B
Unit Root of an individual unit root process

| *Variable* | *Chi-square* (*a*) | *p-value* (*b*) | *Cross-sections* (*c*) | *Max Lags* (*d*) |
|---|---|---|---|---|
| Industrial Production | 2,259 | 1.0000 | 8 | 2 |
| CPI | 1.118 | 1.0000 | 10 | 2 |
| Oil Price Volatility | 0.266 | 1.0000 | 6 | 2 |
| Interest Rate | 53.502 | 0.0000 | 10 | 1 |

Before proceeding to the Panel VAR, weperformed the Engel-Granger Cointegration test and the Granger Causality test to check if the variables are indeed cointegrated: in the absence of cointegration, it is pointless to develop a VAR model. Thecointegration tests were adjusted for panel datastructures following Pedroni (1999, 2004). Under the null hypothesis, the residuals of a regression of integrated order one parameters should follow anAR(1) process. Results for the test are presented in Table II. The null hypothesis of no cointegration is rejected at the 1%

level (the test statistic not shown). Panel A shows coefficients estimators of the AR(1) process for the residuals. The conclusion of cointegration is robust to different specifications of the test. Panel B then shows the Engel-Granger causality test. The null hypothesis that oil price volatility does not Granger-cause industrial production is rejected at the 1% level, showing that there is causation between thesevariables.

**Table II**
**Cointegration Tests**

Table II reports the Engle-Granger cointegration test extended for panel data by Pedroni. The hypothesis of no cointegration is rejected at the 1% level for the whole panel (test-statistic not shown). Panel A presents the coefficient estimates of the residual regression AR(1) process. Panel B shows the Granger causality test. Results are consistent with the hypothesis that oil price volatility has an influence on industrial production.

PANEL A
PedroniCointegration Test

| *Phillips-Peron Results* | | *ADF Results* | |
|---|---|---|---|
| *Country* | *AR(1)* | *Country* | *AR(1)* |
| Algeria | -0.277 | Algeria | -0.444 |
| Angola | 0.207 | Angola | 0.025 |
| Ecuador | 0.508 | Ecuador | 0.306 |
| Iran | -0.306 | Iran | -0.948 |
| Iraq | -0.389 | Iraq | -0.585 |
| Kuwait | -0.215 | Kuwait | -0.618 |
| Libya | 0.085 | Libya | -0.067 |
| Nigeria | -0.387 | Nigeria | -1.236 |
| Saudi Arabia | -0.084 | Saudi Arabia | -0.268 |
| UAE | 0.106 | UAE | -0.464 |
| Venezuela | N/A | Venezuela | N/A |

PANEL B
Granger Causality Test

| *Hypothesis* | *F-statistic* | *p-value* |
|---|---|---|
| Industrial Production does not granger-cause CPI | 0.54153 | 0.5833 |
| CPI does not granger-cause Industrial Production | 0.90353 | 0.408 |
| Oil price volatility does not granger-cause CPI | 3.26356 | 0.0418 |
| CPI does not granger-cause Oil price volatility | 0.21717 | 0.8051 |
| R does not granger-cause CPI | 7.57007 | 0.0008 |
| CPI does not granger-cause R | 8.27265 | 0.0004 |
| Oil price volatility does not granger-cause Industrial Production* | 7.7553 | 0.0007 |
| Industrial Production does not granger-cause Oil price volatility | 12.5181 | 0 |
| R does not granger-cause Industrial Production | 2.72598 | 0.0697 |
| Industrial Production does not granger-cause R | 0.29297 | 0.7466 |
| R does not granger-cause Oil price volatility | 0.79166 | 0.4555 |
| Oil price volatility does not granger-cause R | 0.04034 | 0.9605 |

* From this paper's perspective, the important relation is between oil price volatility and industrial production. The null hypothesis that oil price volatility does not Granger-cause industrial production is rejected at the 1% level.

## 3. THE PANEL VAR MODEL

Having concluded that there is a cointegrated relationship between oil price volatility and industrial production, we estimate equations (1) and (2) with the following correction to both minimize SIC and to control for non-stationarity of the data:

$$\Delta y_{t,i} = \beta_0 + \beta_1 \Delta y_{t-1,i} + \beta_2 \Delta y_{t-2,i} + \varepsilon_{t,i} \tag{3}$$

where $y_t$ is a the log first difference vector:

$$\Delta y_{t,i} = \begin{bmatrix} \Delta CPI_{t,i} \\ \Delta IP_{t,i} \\ \Delta \sigma_{oil_{t,i}} \\ \Delta R_{t,i} \end{bmatrix} \tag{4}$$

Equation (3) yields 4 models to account for each of the components of the vector $\Delta y_t$:

$$\Delta CPI_{t,i} = \beta_0 + \beta_1 \Delta CPI_{t-1,i} + \beta_2 \Delta CPI_{t-2,i} + \beta_3 \Delta IP_{t-1,i} + \beta_4 \Delta IP_{t-2,i} + \beta_5 \Delta \sigma_{oil_{t-1,i}} + \beta_6 \Delta \sigma_{oil_{t-2,i}} + \beta_7 R_{t-1,i} + \beta_8 R_{t-2,i} + \varepsilon_{t,i} \tag{3-1}$$

$$\Delta IP_{t,i} = \beta_0 + \beta_1 \Delta CPI_{t-1,i} + \beta_2 \Delta CPI_{t-2,i} + \beta_3 \Delta IP_{t-1,i} + \beta_4 \Delta IP_{t-2,i} + \beta_5 \Delta \sigma_{oil_{t-1,i}} + \beta_6 \Delta \sigma_{oil_{t-2,i}} + \beta_7 R_{t-1,i} + \beta_8 R_{t-2,i} + \varepsilon_{t,i} \tag{3-2}$$

$$\Delta \sigma_{oil_{t,i}} = \beta_0 + \beta_1 \Delta CPI_{t-1,i} + \beta_2 \Delta CPI_{t-2,i} + \beta_3 \Delta IP_{t-1,i} + \beta_4 \Delta IP_{t-2,i} + \beta_5 \Delta \sigma_{oil_{t-1,i}} + \beta_6 \Delta \sigma_{oil_{t-2,i}} + \beta_7 R_{t-1,i} + \beta_8 R_{t-2,i} + \varepsilon_{t,i} \tag{3-3}$$

$$\Delta R_{t,i} = \beta_0 + \beta_1 \Delta CPI_{t-1,i} + \beta_2 \Delta CPI_{t-2,i} + \beta_3 \Delta IP_{t-1,i} + \beta_4 \Delta IP_{t-2,i} + \beta_5 \Delta \sigma_{oil_{t-1,i}} + \beta_6 \Delta \sigma_{oil_{t-2,i}} + \beta_7 R_{t-1,i} + \beta_8 R_{t-2,i} + \varepsilon_{t,i} \tag{3-4}$$

The VAR Panel is estimated with only 121 observations: 11 cross-sectional countries with 11 years of time series data each. That is, taking the log first difference deletes the first observation, 1997; using two year lags further deletes 1998-1999, leaving the time series from 2000 to 2010, and hence the small sample bias for each individual cross-section. Although modeling panel data can overcome the limitation of small data samples, results are not significant for most coefficients at the usual levels, as t-statistics are larger for small samples. This will cause rejection rules to penalize significant coefficients more often. A Monte-Carlo simulation could be used to infer the true t-statistics for the small samples, entailingless stringent rejection rules. However, that is beyond the scope of the presentpaper. Inthis study, we found evidence supporting the hypothesis that the two year lag of oil volatility has a negative effect on industrial production. Even if statistical significance is not obtained, these results are of economic significance.

**Table III**

**VAR Model**

Table III shows the Unrestricted VAR Model estimation of equation (3). The panel consists of 11 OPEC country members with time series from 1997 to 2010. The t-statistics and standard errors are reported.

Empirical Model

$$\Delta IP_{t,i} = \beta_0 + \beta_1 \Delta CPI_{t-1,i} + \beta_2 \Delta CPI_{t-2,i} + \beta_3 \Delta IP_{t-1,i} + \beta_4 \Delta IP_{t-2,i} + \beta_5 \Delta\sigma_{oil_{t-1,i}} + \beta_6 \Delta\sigma_{oil_{t-2,i}} + \beta_7 R_{t-1,i} + \beta_8 R_{t-2,i} + \varepsilon_{t,i}$$

$R^2 = 0.1691$

| *Parameter* | *Estimator* | *t-statistic* | *S.E.* |
|---|---|---|---|
| $\beta_0$ | 0.1042*** | 3.3364 | 0.0312 |
| $\beta_1$ | –0.0712 | -0.446 | 0.1597 |
| $\beta_2$ | 0.0560 | 0.3503 | 0.16 |
| $\beta_3$ | 0.1357 | 1.5834 | 0.0857 |
| $\beta_4$ | –0.0073 | -1.0389 | 0.0882 |
| $\beta_5$ | –0.0240 | -0.7998 | 0.03 |
| $\beta_6$ | -0.1097*** | -3.3383 | 0.0328 |
| $\beta_7$ | –0.0050 | -1.1058 | 0.0045 |
| $\beta_8$ | 0.0066* | 1.7673 | 0.0375 |

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

Results for equation (3-1) are summarized in Table III[4]. The model has 8 coefficient estimators plus a constant, of which only three are statistically significant. As expected, the results are consistent with Bredin, *et al.*,(2011). The variable of interest, $\Delta\sigma_{oil_t}$, is negative and significant at the 1% level for the second lag, although it is not significant at the first lag. $R^2$ values are also shown in Table III. The fit of the model suggested by equation (3-2) is 16.91%, and the adjusted $R^2$ is only 0.1098. It is worth noting that the fit for equations (3-1), (3-3), and (3-4) is impressively higher, with $R^2$ greater than 0.80. This suggests that although equation (3-2) is a poor fit, the Panel-VAR does capture the movements of the different time series, allowing us to make meaningful inferences.

Despite the low statistical significance,these resultsprovide interesting insights and are consistent with trends noted in previous studies. In fact, the results show economic significance. The model shows that a 1% growth on volatility at $t$–1 will imply a 2.4 basis points reduction in industrial production, and a 1% growth on volatility at $t$–2 will yield a larger reduction of 10.9 basis points. The evidencesuggests that further lags on oil volatility have an even stronger effect on today's production.

It is worthwhileto mention that the coefficient estimate for interest rates is puzzling. There is no economic significance in the fact that the coefficient on the two years lag of interest rates, $\beta_8$, is positive and significant even at the 10% level, since this implies that an interest rate increase will lead to an increase in production. The one year lag coefficient makes more economic sense, although it lacks statistical significance.

How oil price volatility affects each country remains an important question. With this in mind, were-estimatedthePanel-VAR with dummy variables for each countryin order to capture the effect of oil volatility on each cross-section. The dummies are generated as follows:

$$Dummy_{i,t} = \begin{cases} \Delta\sigma_{oil_t} & \forall i = country \\ 0 & otherwise \end{cases} \quad (5)$$

where represents each individual cross-sectional country.

Table IV summarizes the results.Consistent with the original model specification of equation (3), the two year lag coefficients are larger than the one year lag coefficients for most countries. Aside from Ecuador, with a -31.11 basis points, neither of the one lag coefficients surpasses a value of 7.14 basis points, whereas the two lags coefficients are always larger than -6.86 basis points — except for Iran, with -2.59 basis points. Yet most of the coefficients are not significant at the usual levels. When considering the first lag, only Libya and Venezuela are significant at the 10% and 5% level, respectively. Moreover, not all coefficients show consistent effects. While Angola, Iraq, Kuwait, Libya, and the United Arabic Emirates have positive coefficients, suggesting that production has slightly risenin the presence of increasing oil price volatility, Algeria, Ecuador, Iran, Nigeria, Saudi Arabia, and Venezuela have negative coefficients, suggesting the opposite.

Overall, the data suggest that oil price volatility does have an effect in industrial production for the members of the OPEC. It is remarkable that industrial production does not react as strongly to one year lags as it does to higher order lags. However, we recommend caution with this conclusion, because we have included data for 2007-2010 oil prices, which show significantly larger volatility than normal periods. The two lags higher dependence might be completely attributed to the above time period. Further studies with a larger data set might prove this to be true. The consideration of that possibility is beyond the scope of the present paper[5].

## 4. ROBUSTNESS

For robustness, wecheck if the two years lags significance is persistent to other regression specifications. Weturn ourattentionto a Panel Data regression. Wefirst take logs of all variables, except the deposit rate, in order to remove any exponential (or othertype of non-linear) trend. The estimating equations are:

$$\ln(IP_{i,t}) = \beta_0 + \beta_1 Ln(CPI_{i,t-2}) + \beta_2 \ln(R_{i,t-2}) + \beta_3 \ln\left(\sigma_{oil_{i,t-2}}\right) + \beta_4 \ln(IP_{i,t-2}) + \varepsilon_{i,t} \quad (6)$$

$$\ln(IP_{i,t}) = \beta_0 + \beta_1 Ln(CPI_{i,t-2}) + \beta_2 \ln(R_{i,t-2}) + \beta_3 \ln(IP_{i,t-2}) + \sum_{i=1}^{11} \beta_i \ln(Dummy\sigma_{i,t-2}) + \varepsilon_{i,t} \quad (7)$$

where the dummies are estimated following equation (5). While equation (6) captures the overall effect of oil price volatility, equation (7) has the power to capture each country's coefficient estimates. Both equations can be estimated by ordinary least squares. Following Hsiao (1986), we start with the assumption that the panel structure is not needed, and so we use a pooled

**Table IV**
**VAR Model**

Table IV shows an adjustment of equation (3) to incorporate equation (5). Equation (5) captures individual cross-sectional effects due to oil volatility.The t-statistics are shown in parenthesis.

Empirical Model

$$\Delta IP_t = \beta_0 + \beta_1 \Delta CPI_{t-1} + \beta_2 \Delta CPI_{t-2} + \beta_3 \Delta IP_{t-1} + \beta_4 \Delta IP_{t-2} + \sum_{i=5}^{16} \beta_i \Delta \sigma_{oil_{t-1}} + \sum_{i=17}^{28} \beta_6 \Delta \sigma_{oil_{t-2}} + \beta_{29} R_{t-1} + \beta_{30} R_{t-2}$$

| *Parameter* | *t – 1* | *t – 2* |
|---|---|---|
| Algeria | -0.0319 | -0.1864 |
| | (-0.3552) | (-1.8994)* |
| Angola | 0.0493 | -0.1383 |
| | -0.5156 | (-1.2859) |
| Ecuador | -0.3111 | -0.1628 |
| | (-3.1380) | (-1.5702) |
| Iran | -0.0605 | -0.0259 |
| | (-0.7238) | (-0.2987) |
| Iraq | 0.0164 | -0.09 |
| | -0.1589 | (-0.7758) |
| Kuwait | 0.0197 | -0.1374 |
| | -0.2437 | (-1.6465)* |
| Libya | 0.008 | -0.0805 |
| | -0.0879 | (-1.6465)* |
| Nigeria | -0.0176 | -0.0702 |
| | (-0.2014) | (-0.7347) |
| Saudi Arabia | -0.0438 | -0.1755 |
| | (-0.5100) | (-2.0062)** |
| UAE | 0.0714 | -0.0686 |
| | -0.8986 | (-0.8167) |
| Venezuela | -0.057 | -0.1281 |
| | (-0.6126) | (-1.3125) |

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

regression, or plain OLS, assuming all observations are just one large cross-section and that no individual country can be differentiated. If, however, a panel structure exists, then we proceed to estimate a correction of the models incorporating both Fixed Effects and Random Effects.

The fixed effects model assumes that none of the individual countries has any independent effect differentiatingit from the others — and thus the variances are also equal throughout the panel. The model requires a specification correction to capture the individual effect; this is done by demeaning all variables. Equations (6) and (7) can be rewritten to account for fixed effects as:

**Table V**
**Panel Data Model for the Total Effect**

Table V reports a Panel Data regression. There are 11 cross-sections representing the OPEC members except Qatar; each has times series for 14 years. The t-statistics are shown in parenthesis. The estimation equation is

$$\ln(IP_{i,t}) = \beta_0 + \beta_1 Ln(CPI_{i,t-2}) + \beta_2 \ln(R_{i,t-2}) + \beta_3 \ln\left(\sigma_{oil_{i,t-2}}\right) + \beta_4 \ln(IP_{i,t-2}) + \varepsilon_{i,t}$$

| | *Plain OLS* (a)* | *Fixed Effects* (b) | *Random Effects* (a) |
|---|---|---|---|
| *Regressor* | $R^2 = 0.9129$ | $R^2 = 0.8649$ | $R^2 = 0.7301$ |
| *Constant* | 01246 | | 0.1604 |
| | (1.0722) | | (0.8790) |
| $Ln(CPI_{t-2})$ | 0.0529* | 0.0928* | 0.0723** |
| | (1.6878) | (2.6049) | (2.0875) |
| $\ln(R_{t-2})$ | 0.0057 | 0.0015 | 0.0044 |
| | (1.4314) | (0.3677) | (1.2178) |
| $\ln(\sigma_{oil_{t-2}})$ | -0.1017*** | -0.0737* | -0.0990*** |
| | (-6.1131) | (1.7158) | (-3.0342) |
| $\ln(IP_{t-2})$ | 0.9800 | 0.8574*** | 0.9482*** |
| | (26.8968) | (7.6675) | (22.4335) |

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

$$\ln(IP_{i,t}) - \ln(\overline{IP_i}) = \beta_0 + \beta_1[Ln(CPI_{i,t-2}) - Ln(\overline{CPI_i})] + \beta_2[\ln(R_{i,t-2}) - \ln(\bar{R}_i)] + \beta_3\left[\ln\left(\sigma_{oil_{i,t-2}}\right) - \ln(\overline{\sigma_{oil_i}})\right] + \beta_4[\ln(IP_{i,t-2}) - \ln(\overline{IP_i})] + \varepsilon_{i,t} - \bar{\varepsilon}_i \quad (8)$$

$$\ln(IP_{i,t}) - \ln(\overline{IP_i}) = \beta_0 + \beta_1[Ln(CPI_{i,t-2}) - Ln(\overline{CPI_i})] + \beta_2[\ln(R_{i,t-2}) - \ln(\bar{R}_i)] + \beta_3[\ln(IP_{i,t-2}) - \ln(\overline{IP_i})] + \sum_{i=1}^{11} \beta_i [\ln(Dummy\sigma_{i,t-2}) - \ln(\overline{Dummy\sigma_i})] + \varepsilon_{i,t} - \bar{\varepsilon}_i \quad (9)$$

On the other hand, the random effects model assumes that each cross-section has an individual effect; in other words, there is a country specific effect. This model is preferred, *ex-ante*, as it is expected that each country will have different economic and political realities, giving rise to individual effects.We expect no two countries to be the same. Equations (6) and (7) are, therefore, estimated as:

$$\ln(IP_{i,t}) = \beta_0 + \beta_1 Ln(CPI_{i,t-2}) + \beta_2 \ln(R_{i,t-2}) + \beta_3 \ln\left(\sigma_{oil_{i,t-2}}\right) + \beta_4 \ln(IP_{i,t-2}) + U_i + \varepsilon_{i,t} \quad (10)$$

$$\ln(IP_{i,t}) = \beta_0 + \beta_1 Ln(CPI_{i,t-2}) + \beta_2 \ln(R_{i,t-2}) + \beta_3 \ln(IP_{i,t-2}) + \sum_{i=1}^{11} \beta_i \ln(Dummy\sigma_{i,t}) + U_i + \varepsilon_{i,t} \quad (11)$$

where $U_i$ is the country specific effect (random effect).

Table V summarizes the results for equations (6), (8), and (10), the total effects of oil volatility on industrial production. Column (a) shows the pooled regression, column (b) shows the fixed effects estimation, and finally column (c) estimates the random effects. The standard errors are adjusted for heteroscedasticity.By simple inspection, the panel regression shows that the coefficients are more significant than the Panel-VAR suggested. In fact, indicates a better fit for all models, the best being plain OLS(equation (6)).

Overall, the results are consistent with the main hypothesis that oil price volatility has a negative impact on industrial production. Some coefficients from the pooled regression and the Random Effects regression are significant at the 1% level, while those for the Fixed Effects regression are only significant at the 10% level. The evidence suggests that the oil price volatility has an overall impact on industrial production approaching10 basis points, which stillindicates economic significance.

Following Housman (1978), we test whether Random Effects or Fixed Effects should be used. Under the null hypothesis, both are consistent, but Random Effects is more efficient. The null is rejected at the 5% significance level,[6] suggesting that Fixed Effects are the only consistent estimators. However, when considering the SIC that minimizes the log likelihood, plain OLS results in a better model than Fixed Effects: $SIC = 21.399$ for the pooled regression, while $SIC = 31.405$ for the Fixed Effects model.

Wenow estimate the individual impact for each countryfollowing equations (7), (9) and (11). The results are consistent with the overall effects. When compared to the VAR Panel in equation (3), these estimatesimply that for the two year lag all countries show a negative impact on industrial production.Angola, Iraq, Kuwait, Libya, and the United Arabic Emirates no longer show positive coefficients as before. Table VI summarizes the results. Houseman's test does not show significance forthe individual coefficients, even at the 10% confidence level, suggesting that Random Effects is the most efficient estimator. Yet the log likelihood that minimizes SIC is still attributed tothe pooled regression,with a value of 36.792. Once again, the OLS regression is preferred to the panel structured regressions.

Perhaps the pooled regression is to be preferred because there are only ten years of time series data after taking the log first difference and two year lags for each individual cross-section,[7]diminishing the fit of the Fixed Effects and Random Effects models. Together with the small sample bias for t-statistics, this may explain why,in terms of minimizing the SIC, the pooled regression is preferred to the panel structured regressions.

When the pooled regression is used, the largest impact on industrial production is for Ecuador with a decrease of 21.52for every 1% increase in volatility, significant at the 1% level.When Fixed Effects are considered, Angola is the country with the greatest decrease in industrial production, accounting for 26.31 basis points, significant at the 5% level, whereas the Random Effects model also suggests that Ecuador's production is most impacted, also significant at the 1% level. It is worthwhile noting that Ecuador is the only country with a significant coefficient throughout all the regressions. What is surprising is the overall failure of statistical significance.Yet our results are in general consistent with the prior literature..

Finally, it should be noted that the *ex-ante*assumption of a Random Effects process has been rejected because of the overall superiorityof the pooled regression. This remains a puzzle, since it is not plausiblethat all countries are exactly the same (the assumption of the pooled regression model — all cross-sections made identical). Perhaps one explanation of this is the

**Table VI**

**Panel Data Model for the Total Effect**

Table VI reports individual country coefficients only for the Panel regression. There are 11 cross-sections representing the OPEC members except Qatar; each has time series for 14 years. The t-statistics are shown in parenthesis. The estimation equation is

$$\ln(IP_{i,t}) = \beta_0 + \beta_1 Ln(CPI_{i,t-2}) + \beta_2 \ln(R_{i,t-2}) + \beta_3 \ln(IP_{i,t-2}) + \sum_{i=1}^{11} \beta_i \ln(Dummy\sigma_{i,t-2}) + \varepsilon_{i,t}$$

| Regressor | *Plain OLS* *(a)** $R^2 = 0.9240$ | *Fixed Effects* *(b)* $R^2 = 0.9333$ | *Random Effects* *(a)* $R^2 = 0.9238$ |
|---|---|---|---|
| Algeria | -0.0632 | -0.0747 | -0.0655 |
| | (-1.1023) | (-0.6892) | (-1.0557) |
| Angola | -0.0029 | -0.2631** | -0.0164 |
| | (-0.0545) | (-1.9395) | (-0.2866) |
| Ecuador | -0.2152*** | -0.1691* | -0.2058*** |
| | (-4.0577) | (-1.6341) | (-3.5518) |
| Iran | -0.0378 | -0.047 | -0.0386 |
| | (-0.5732) | (-0.4867) | (-0.5603) |
| Iraq | -0.1463*** | -0.0745 | -0.1422*** |
| | (-2.8326) | (-0.6157) | (-2.4857) |
| Kuwait | -0.1724*** | -0.0637 | -0.1606*** |
| | (-3.1065) | (-0.7417) | (-2.7206) |
| Libya | -0.0431 | 0.0815 | -0.0383 |
| | (-0.7977) | -0.708 | (-0.653) |
| Nigeria | -0.0698 | -0.0299 | -0.0675 |
| | (-1.2793) | (-0.2806) | (-1.134) |
| Saudi Arabia | -0.0109 | -0.0527 | -0.0172 |
| | (-0.1350) | (-0.5332) | (-0.2123) |
| UAE | -0.0321 | -0.0352 | -0.0358 |
| | (-0.5080) | (-0.3583) | (-0.5377) |
| Venezuela | -0.1087* | -0.1555 | -0.1062 |
| | (-1.6919) | (-1.5416) | (-1.5927) |

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

high dependence of the cartel members on the production of oil. In this sense, OPEC members tend to react only to shocks from oil production, and hence individual economic and political shocks can be disregarded,since thesedo not affect industrial production performance. This hypothesis is left for future research.

## 5. CONCLUSIONS

Prior studies have found a link between oil price volatility and industrial production. Today the global economy has come to rely heavilyon all types of oil derivatives, and so it is to be expected that price volatility will have an impact on world-wide production,as firms try to adjust to price changes. However, when price changes occur too often, i.e., increased volatility, companies find it hard to successfully adjust to thesechanges. Therefore it isimportant to assess how this oil volatility has affected production world-wide. In this paper weassess the impact of these shocks on the cartel of the largest oil exporting countries.

We have constructed panel data with yearly observations for OPEC members comprisedof industrial production, CPI, an oil volatility measure, and a benchmark interest rate. Forthe oil volatility measurement, weused weekly data to compute the oil volatility as the conditional yearly standard deviation. The real variable series, taken from the World Bank database, had several missing values on industrial production and/or CPI. The missing values for a particular variable were manually computedby inputting data-points from plots of the given series. The finalpanel consists of 11 cross-sectional countries, with a 14-year time series for each.

Despite the small sample constraint, the results provide insight. A Panel-VAR model showsa cointegrating relationship between industrial production and a measurement of oil volatility. Furthermore, this relationship is negative, suggesting that increasing oil volatility will have a negative impact on industrial production innet oil-exporting countries.This relationship becomes stronger with longer lags. In fact, the two year lag of oil volatility has a total impact estimated to be 10 basis points for every 1 percent increase in oil volatility— farlarger than the effect of the one year lag.This is a verystrong impact, one having economic significance, considering that industrial production is in the billions of dollars.

When we measured the individual country effects, however, theresults are rather disappointing. Although the data suggest that all the individual countries consistently face a reduction in industrial production between 2 and 18 basis points for the two year lag in oil volatility (for a 1 percent increase in oil volatility), the results are not statistically significant at the conventional levels for 7 out of the 11 countries. Weconjecture that the small sample bias may be largely responsible for this lack of significance.

Nevertheless, the results are consistently robust. When using a least squares regression for panel data structures, we found that the two year lag of oil volatility gives consistent results. Indeed, the effect is negative for all individual countries, butstatistically significant for only 3 of the 11 OPEC members.The parameter for Ecuador is the only coefficient which is significant regardless the specification of the empirical model. In summary, wefound evidence that the net oil exporting countries face reductions in production levels due to volatility in oil prices.These resultsimply that volatility does affect particular industries,such as mining, manufacturing, and utilities, in those OPEC countries for which energy is a major input or output.Even though the net oil exporting countries benefited from the 2007-2011 record high oil prices, they also suffered from setbacksin industrial production. We suggest, however, some caution with these results because the data sample size is small and because of the bias introduced by the 2007-2008 period of abnormal oil volatility. In our opinion, this abnormal period of volatility may account for the larger impact observed for the two year lag.

## *Notes*

1. All figures are taken from the OPEC's Annual Statistical Bulletin. 2008 figures are taken from the 2009 bulleting, while 2009 and 2010 figures are taken from the 2010 bulletin.
2. As a matter of fact, many countries had missing data on CPI, GDP, Industrial production, or interest rates. To overcome this, we had to manually complete the dataset. The main problem with completing

the dataset was that historical data is not freely available to download, and the only website that we could find a comprehensive dataset, *http://www.tradingeconomics.com*, had a charge of $49 for the first month, followed by $249 thereafter. Still, the site allowed us to see graphs and plots of the different series. We therefore handpicked the estimated value of the missing points from the plots. Off course, this probably induced some bias into our dataset. All data comes from ?????

3. The EIA has discontinued this data set since we collected the data in October, 2011.

4. Estimations for equations (3-1), (3-3), and (3-4) can be requested. The results are beyond the scope of this paper.

5. Although we proposed an initial dataset to account a larger period of time, due to high missing data and lack of a larger series on industrial production, we cannot test this alternative hypothesis, thus leaving it for future research.

6. The actual value of the chi test statistic is with a p-value??of 0.0505.

7. Taking log first difference deletes the first observation, 1997. Using two year lags further deletes 1998-1999, leaving the time series from 2000 to 2010.

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