# The lead-lag relationship between PPI, CPI and oil price: Malaysian evidence

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25 November 2017

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## Abstract

A considerable body of economic literature shows the impact of oil-price shocks on commodities and inflation especially for the developed countries. However, there has been a relative lack of empirical study of this kind on the developing countries. The focus of this paper is to discern the lead-lag relationship between the producer price index (PPI), CPI and the oil price. We used the standard time-series techniques for the analysis and Malaysia as a case study. The findings tend to indicate that it is the PPI that leads the Oil price rather than the other way around. The results have strong policy implications at least in the context of developing countries like Malaysia.

**Keywords**: PPI, CPI, oil price, VECM, VDC, Malaysia

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## INTRODUCTION : ISSUE MOTIVATING THE PAPER

Between mid-1999 to 2008, the price of crude oil has increased substantially in the world market. For example, the West Texas Intermediate (WTI, a reference price used in the United States and globally) increased from US$19 per barrel in 1993 to US$31 in 2003. In October 2004, it reached US$51 and in 2005 it went up to US$67 per barrel, and continued increasing exceeding US$70 in April 2006 and finally recorded its highest of US$102.08 a barrel in April, 2008. Factors like depletion in oil supply, increasing oil consumption, particularly from emerging industry in third world nations like China and India and political instability in oil producing countries are being blamed as the main causes for these increases. These events have triggered global panic that caused many countries to review and restructure their economic policies to offset the negative impacts.

Moreover, the inflation that results from higher oil prices will reduce the monetary value and adversely affect their expenditures and demand for goods and services. On the producer's side, a higher oil price is associated with higher input price. Production at higher cost will not only cause reduction in quantity of output produced but also push the price of output sold in the market to be higher.

Producer and consumer price are measured by the producer price index (PPI) and consumer price index (CPI), respectively. The PPI collectively refers to three different indexes, one for crude materials, one for intermediate goods, and one for finished goods. The CPI refers to a single index, covering the prices of a typical basket of goods and services purchased by the typical consumer. More specialized indexes of consumer prices are also available. For example, the so-called core CPI measures the prices of non-food and non-energy goods and services purchased by consumers. The producer and consumer price indexes are often viewed as prices of different goods along a chain of production. Typically, producer prices are seen as prices of input goods, which are used to produce final goods. Consumer prices are seen as prices of the final goods, which are sold to consumers.

Economic reasoning also suggests there are important links between the prices of different goods along the chain of production. In theory, a firm sets its price as a markup over production cost, where cost is defined in the broad sense used by economists to include a normal return or profit for investors and firm owners. Given the markup, a change in cost will cause the price to change. For instance, if a drill manufacturer suffers an increase in production cost, the firm will pass through the higher cost to the price of a drill. Consequently, an increase in the price of an input material will push cost up, causing a firm to raise its price. Thus, simple theory suggests the chain of production should link movements in the PPI to subsequent movements in the CPI. Changes in producer prices at earlier stages of production should pass through to producer prices at later stages of production, and ultimately, to consumer prices.

The price of oil and CPI are often seen as being connected in a cause and effect relationship. As oil prices move up or down, inflation follows in the same direction. The reason why this happens is that oil is a major input in the economy, it is used in critical activities such as fueling transportation and heating homes and if input costs rise, so should the cost of end products.

In the case of Malaysia, oil price is set by the government through government subsidy. Despite the fact that Malaysia is exporting oil, the country also imports oil from other countries. The surplus of exporting value over the importing value makes Malaysia a net oil exporting country. Despite these facts, the repercussions from price increase in the world market could not be avoided from spill-over to the local market, and forces the Malaysian government to slowly liberalize the domestic oil price. The implementation of oil price increase in the local market has triggered mixed responses from the public, particularly households and business units. This is because, being a major energy resource to Malaysia's industries, the increase in oil prices is likely to push the overall price level, and adversely affect the economy. In particular, to the household, higher oil prices directly means taking a bigger percent of their income for gasoline expenses.

In relation to those facts, the event of oil price increase and the public's reaction to it has raised an important question of the impact of oil price on the economy. However, we are more interested to look at which factor that actually gives greater impact to oil price movement as this is more important to policy makers.

Therefore, the motivation of this study are, besides we want to determine the effect of global oil price shock on Malaysia, we also want to validate the public perceptions which say "oil price hike does essentially because of **mainly** the increase in commodities price" as we believe it is vice versa. Our study is unique to previous research done because we consider both PPI and CPI in Malaysia that would give impact to oil price movement. As previous studies gave the result which shows oil price and CPI is interrelated, we tried to include PPI to see the impact on CPI and oil prices.

## LITERATURE REVIEW

A large empirical research has been done on the impact of oil prices with inflation (CPI) and commodity prices. However, there are still little studies done on PPI and how does it affect oil prices. As we believe PPI will give rise to oil price and CPI, therefore we tried to test the theory. Previous researches done mainly focused on certain commodities which they believe it will directly give impact to oil prices. According to a report by the Food and Agricultural Organization of the United Nations, food prices increased by almost 40% in 2007 and continued increasing sharply in 2008 (Rosegrant, 2008). Taheripour and Tyner (2008) showed that a large share of the corn price hikes is the result of the increase in the oil prices.

While Braun et al. (2008) found high energy prices have increased the costs of transportation and agricultural inputs such as fertilizer and pesticides, making agricultural production more expensive. All of these studies reported direct relationship with certain commodities specifically agricultural products with the rise of oil prices.

Moreover, when determining the relationship between PPI and CPI, there are numerous studies examining the relationship between PPI and CPI in many countries over periods of time. Ghazali, Yee and Muhammed (2008) examined the relationship between PPI and CPI using monthly data from January 1986 to April 2007 in Malaysia. The authors employed both Engle-Granger and Vector Error Correction Model (VECM). The results reveals that there is no direct relationship between PPI and CPI in Malaysia.

## METHODOLOGY

This study employs a time-series technique, in particular, cointegration, error correction modeling and variance decomposition, in order to find empirical evidence of the nature of relations between PPI, oil prices and CPI as being introduced in previous sections. This method is favored over the traditional regression method for the following reasons.

Firstly, all the variables are non-stationary. This means that performing ordinary regression on the variables will render the results misleading, as statistical tests like t-ratios and F-statistics are not statistically valid when applied to non-stationary variables. Performing regressions on the differenced form of these variables will solve one problem, at the expense of committing an arguably even graver mistake. When variables are regressed in their difference form, the long term trend is effectively removed. Thus, the regression is not really testing long term (theoretical) relationships.

Secondly, in traditional regression, the endogeneity and exogeneity of variables is pre-determined by the researcher, usually on the basis of prevailing of a priori theories. Cointegration techniques are advantageous in that it does not presume variable endogeneity and exogeneity. In the final analysis, the data will determine which variables are in fact exogenous, and which are endogenous. In other words, with regression, causality is presumed whereas in cointegration, it is empirically proven with the data.

Thirdly, cointegration techniques embrace the dynamic interaction between variables whereas traditional regression methods, by definition, exclude or discriminate against interaction between variables. Economic intuition tells us that the interaction between PPI, oil prices and CPI is dynamic in nature.

The data used here are monthly data from January 2001 until September 2013. A total of 153 observations were obtained. The data of Producer Price Index (PPI) and Consumer Price Index (CPI) are taken in the case of Malaysia but we are using crude-brent oil (US$) for oil-price as we cannot take Malaysian oil price because it has been subsidized. The source of data was DataStream.

**TESTING STATIONARITY OF VARIABLES**

We begin our empirical testing by determining the stationarity of the variables used. In order to proceed with the testing of the cointegration and other steps later, ideally, our variables should be I(1) in that, in their original level form, they are non-stationary and in their first differenced form, they are stationary. The differenced form for each variable used is created by taking the difference of their log forms. For example, DPPI = LPPI – LPPIt-1. We then computed the

| Augmented Dickey-Fuller (ADF) test on each variable (in both level and differenced form). The table below summarizes the results. Variables in Level Form | | | |
|---|---|---|---|
| Variable | Test Statistic | Critical Value | Implication |
| LPPI | -2.1234 | -3.4409 | Variable is non-stationary |
| LOIL | -2.8710 (SBC) | -3.4409 | Variable is non-stationary |
| | -3.2082(AIC) | -3.4409 | Variable is non-stationary |
| LCPI | -3.1369 | -3.4409 | Variable is non-stationary |
| | | | |
| Variables in Differenced Form | | | |
| DPPI | -5.6852 (SBC) | -2.8812 | Variable is stationary |
| | -4.5747 (AIC) | -2.8812 | Variable is stationary |
| DOIL | -7.2111 | -2.8812 | Variable is stationary |
| DCPI | -6.8045 (SBC) | -2.8812 | Variable is stationary |
| | -6.3305 (AIC) | -2.8812 | Variable is stationary |

Relying primarily on the AIC and SBC criteria, the conclusion that can be made from the above results is that all the variables we are using for this analysis are I(1), and thus we may proceed with testing of cointegration. Note that in determining which test statistic to compare with the 95% critical value for the ADF statistic, we have selected the ADF regression order based on the highest computed value for the AIC and SBC. In some instances, AIC and SBC give different orders and in that case, we have taken different orders and compared both (for example, this applies to the variable LOIL, DPPI and DCPI, see the table above). This is not an issue as the implications are consistent.

Another alternative test for a unit root was Phillips-Perron Test. Unlike the ADF test, there are no lagged difference terms. Below, the result reported by Phillips-Perron :

| Variables in Level Form | | |
|---|---|---|
| Variable | P-value | Implication |
| LPPI | 0.472 | Variable is non- stationary |
| LOIL | 0.199 | Variable is non- stationary |
| LCPI | 0.739 | Variable non- stationary |
| | | |
| Variables in Differenced Form | | |
| DPPI | 0.000 | Variable is stationary |
| DOIL | 0.000 | Variable is stationary |
| DCPI | 0.000 | Variable is stationary |

In the case of Phillips-Perron Test, the p-value in the level form must be larger than 0.05 and for differenced form, it must be smaller than 0.05. Thus, as indicates in both test (ADF and PP), the implications are still consistent, (the result should give I(1)) and we shall proceed to next step.

**DETERMINATION OF ORDER OF THE VAR MODEL**

| Before proceeding with test of cointegration, we need to first determine the order of the vector auto regression (VAR) that is the number of lags to be used. As per table below, results show that AIC recommends order of 6 whereas SBC favours 1 lag ( | Choice Criteria | |
|---|---|---|
| | AIC | SBC |
| Optimal Order | 6 | 1 |

Given this apparent conflict between recommendation of AIC and SBC, we address this in the following manner. First we checked for serial correlation for each variable and obtained the following results.

| Variable | Chi-Square p-value | Implication (at 5%) |
|---|---|---|
| DPPI | 0.356 | There is no serial correlation |
| DOIL | 0.215 | There is no serial correlation |
| DCPI | 0.847 | There is no serial correlation |

As evident from the above results, there is no autocorrelation in all variables. For vector auto regression (VAR), in the case we adopted a lower order; we may encounter the effects of serial correlation. The disadvantage of taking a higher order is that we risk over-parameterization. However, in our case, given that we have no serial correlation, thus, considering the trade off of lower and higher orders, we decided to choose the VAR order of 2.

**TESTING COINTEGRATION**

Once we have established that the variables are I(1) and determined the optimal VAR order as 2, we are ready to test for cointegration. As depicted in the table below, the maximal Eigenvalue, Trace, AIC and SBC all of the criteria report the same results which are 3 cointegrating vectors.

| Criteria | Number of cointegrating vectors |
|---|---|

| | |
|---|---|
| Maximum Eigenvalue | 3 |
| Trace | 3 |
| AIC | 3 |
| SBC | 3 |

The cointegration result reported the same theory that we believe the variables have cointegration with each other. Based on the above statistical result as well as our insight which we are more interested on the relationship between PPI and oil price, for the purpose of this study, we shall assume that there is one cointegrating vector, or relationship.

Statistically, the above results indicate that the variables are theoretically related, in that they tend to move together, in the long term. In other words, the 3 variables are cointegrated, that is their relations to one another are not merely by chances. This conclusion has an important implication for policy makers as well as consumers. Given that there is increase in PPI, the consumers can expect that the oil prices will increase. Thus, the policy makers should do something such as make a good monetary policy to control the situation in order to avoid high inflation (CPI). However, the E-G test shows that there is no cointegration between the variables. But as we intuitively believe that they are cointegrated, we proceed with Johansen test results.

**LONG RUN STRUCTURAL MODELLING (LRSM)**

Next, we attempt to quantify this apparent theoretical relationship among the variables. We do this in order to compare our statistical findings with theoretical (or intuitive) expectations. Relying in the Long Run Structural Modeling (LRSM), component of Microfit, and normalizing our variable, the Producer Price Index (PPI), we initially obtained the results in the following table (see Appendix 4A). Calculating the t-ratios manually, we found the other two variables become insignificant which are DOIL and DCPI.

| Variable | Coefficient | Standard Error | T-Ratio | Implication |
|---|---|---|---|---|
| DPPI | -Normalize- | | | |
| DOIL | -1.4308 | 5.6463 | 0.25 | Variable is insignificant |
| DCPI | 22.7552 | 102.3101 | 0.22 | Variable is insignificant |

These initial results were generally intuitively not appealing to our mind. Driven by the curiosity and our intuition which the variables should be significant, we decided to verify the results by subjecting the estimates to over-identifying restrictions. We did this for all variables (making one over-identifying restriction at a time) and the results show in table below.

| Variable | Chi-Square P-Value | Implication |
|---|---|---|
| LPPI | -Normalize- | |
| LOIL | 0.020 | Variable is insignificant |
| LCPI | 0.036 | Variable is insignificant |

However, interestingly, when we made the over-identifying restrictions all at once, that is, testing the null hypothesis, the null hypothesis is rejected, or in other words, that set of restrictions is incorrect (see Appendix 4B to 4C). This latest observation confirmed our earlier hunch, that OIL and CPI was actually a significant variable, despite its earlier computed t-ratio of less than two. Applying our intuition, we are more inclined to believe that both of the variables are significant.

**VECTOR ERROR CORRECTION MODEL (VECM)**

From our analysis thus far, we have found the cointegration and the significance of the relationships between variables. However, the cointegrating result reveals nothing about causality, that is, which variable is the leading variable and which is the laggard variable. Information on direction of Granger-causation can be particularly useful for policy makers and consumers. By knowing which variable is exogenous and endogenous, they can better forecast or predict expected results of the price movements. Thus, the previous assumption made by most people who said the rise in oil price will give hike to commodities price are probably not really correct.

In light of this, the next part of our analysis involves the Vector Error Correction Model (VECM). Here, in addition to decomposing the change in each variable to short-term and long-term components, we are able to ascertain which variables are in fact exogenous and which are endogenous. The principle in action here is that of Granger-causality, a form of temporal causality where we determine the extent to which the change in one variable is caused by another variable in a previous period. By examining the error correction term, $e_{t-1}$, for each variable, and checking whether it is significant, we found that there is only one endogenous variable which is OIL, as depicted in the table below. The other variables were found to be exogenous

| Variable | ECM(-1) t-ratio p-value | Implication |
|---|---|---|
| LPPI | 0.180 | Variable is exogenous |
| LOIL | 0.000 | Variable is endogenous |
| LCPI | 0.922 | Variable is exogenous |

The implication of this result is that, as far as the analyzed economy are concerned, the PPI and CPI would receive economy shocks, and transmit the effect of those shocks to other factor which is OIL. In addition, the VECM produces a statistic that may be of interest to the consumers and policy makers. The coefficient of e t-1 tells us how long it will take to get back to long term equilibrium if that variable is shocked.

**VARIANCE DECOMPOSITION (VDC)**

Whilst we have established that the PPI and CPI are the exogenous variables and OIL is endogenous variable, we have not been able to say anything about the relative exogeneity of the variables. In other words, which is the most laggard variable compared to others, or, the least laggard? As the VECM is not able to assist us in this regard, we turn our attention to variance decomposition (VDC). Relative exogeneity can be ascertained in the following way. VDC decomposes the variance of system, including its own. The least exogenous variable is thus the variable whose variation is explained mostly by its own past variations.

We started out applying orthogonalized VDCs and obtained the following results

| | DPPI | DOIL | DCPI |
|---|---|---|---|
| DPPI | 95.12% | 4.85% | 0.03% |
| DOIL | 21.81% | 57.46% | 20.74% |

| | | | |
|---|---|---|---|
| DCPI | 13.11% | 54.38% | 32.52% |

Forecast At Horizon 24 Months

Forecast At Horizon 48 Months

| | DPPI | DOIL | DCPI |
|---|---|---|---|
| DPPI | 95.3% | 44.3% | 3.5% |
| DOIL | 13.6% | 69.5% | 61.6% |
| DCPI | 21.5% | 77.3% | 51.9% |

For the above two tables, rows read as the percentage of the variance of forecast error of each variable into proportions attributable to shocks from other variables (in column), including its own. The columns read as the percentage in which that variable contributes to other variables in explaining observed changes. The diagonal line of the matrix (highlighted) represents the relative exogeneity. According to these results, the ranking of indices by degree of exogeneity (extent to which variation is explained by its own past variations) is as per table below:

| No. | Variable Relative Exogeneity | |
|---|---|---|
| | At Horizon = 24 months | At Horizon = 48 months |
| 1 | DPPI | DPPI |
| 2 | DOIL | DOIL |
| 3 | DCPI | DCPI |

We found this result shows that PPI is the most exogenous variable whether in the 24 or 48 months time horizon. However, there are two important limitations in orthogonalized VDCs. Firstly; it assumes that when a particular variable is shocked, all other variables are "switched off". Secondly, orthogonalized VDCs do not produce a unique solution. The generated numbers are dependent upon the ordering of variables in the VAR. Typically, the first variable would report the highest percentage and thus would likely to be specified as the most exogenous variable. To confirm the result in Orthogonalized VDCs, we also test the variables into Generalized VDCs.

We obtained results.. In interpreting the numbers generated by the Generalized VDCs, we need to perform additional computations. This is because the numbers do not add up to 100% as in the case of orthogonalized VDCs. For a given variable, at a specified horizon, we total up the numbers of the given row and we then divide the number for that variable (representing magnitude of variance explained by its own past) by the computed total. In this way, the numbers in a row will now add up to 1.0 or 100%. The tables below show the result.

Forecast At Horizon 24 Months

| | DPPI | DOIL | DCPI |
|---|---|---|---|
| DPPI | 66.8% | 30.76% | 2.22% |
| DOIL | 14.6% | 52.9% | 32.6% |
| DCPI | 9.1% | 46.8% | 44.0% |

Forecast At Horizon 48 Months

| | DPPI | DOIL | DCPI |
|---|---|---|---|
| DPPI | 66.6% | 31.0% | 28.2% |
| DOIL | 14.3% | 51.3% | 34.4% |
| DCPI | 9.4% | 48.0% | 42.6% |

We can now more reliably rank the variables by relative exogeneity, as depicted in the table below:

Generalized Ranking Of Indices By Degree Of Exogeneity

| No. | Variable Relative Exogeneity | |
|---|---|---|
| | At Horizon = 24 months | At Horizon = 48 months |
| 1 | DPPI | DPPI |
| 2 | DOIL | DOIL |
| 3 | DCPI | DCPI |

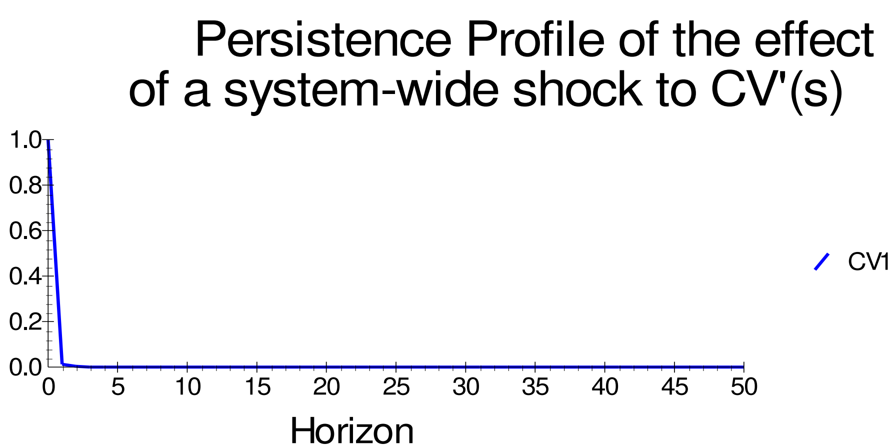
From the above two results (Orthogonalized and Generalized VDCs) both reported that PPI is the most exogenous variable followed by OIL and CPI.

## IMPULSE RESPONSE FUNCTIONS (IRFs)

The Impulse Response Functions (IRFs) essentially produce the same information as the VDCs, except that they can be presented in graphical form. For the sake of completeness, we have included the various graphs of IRFs .

**PERSISTENCE PROFILE**

The persistence profile illustrates the situation when the entire cointegrating equation is shocked, and indicates the time it would take for the relationship to get back to equilibrium. Here the effect of a system-wide shock on the long-run relations is the focus (instead of variable-specific shocks as in the case of IRFs. The chart below shows the persistence profile for the cointegrating equation of this study.




The chart indicates that it would take approximately 1 month for the cointegrating relationship to return to equilibrium following a system-wide shock.

**CONCLUSION**

The results presented in this study provide the evidence of the relationship between Producer Price Index (PPI), oil-price, and Inflation (CPI). Producer Price Index has both the long-term and short-term effects on OIL and CPI. Equally important is, by looking at the VDC results, it clearly indicates that PPI is the most exogenous variable compared to others while OIL has been reported in the test as only the endogenous variable. That means, the increase in PPI will lead to increase in OIL price. However, this result is applicable to developing countries specifically, Malaysia. We expect difference in results when testing with different countries either developed or developing as the variables may also be related to other core factors such as monetary policies.

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