Chapter 4. Empirical Results to Responses to Oil Price Changes

4.1. Empirical Results: Unit Root, Order of Integration and Cointegration Tests

This chapter presents the results for macroeconomic responses to changes in oil price. The analyses are based on a VAR model, which is to be used as suggested by the results of some pre-tests. The results for these pre-tests are also discussed in detail.

To recapitulate, the key variables are represented by:

lnppi	=	natural log of Producer Price Index
lnipi	=	natural log of Industrial Production Index
lntbill	=	natural log of the 3-month Treasury Bill
rsr	=	real stock return

All the variables employed in this study are tested for presence of unit roots. The variables *lnppi, lnipi, lntbill* and *rsr* at levels are subjected to the Augmented Dickey-Fuller (ADF) test for lags m = 0, 1, 3, 6, and 12 with its trend and intercepts. The initial results show that the test for *lnppi, lnipi, lntbill* could not be rejected in their levels as the test statistics are smaller than the critical values in absolute terms. The results are presented in table 4.1.

The ADF test is conducted again on the four variables at first differences. Overall results indicate rejection of the null hypothesis for all the variables.

Table 4.1. The Augmented Dickey–Fuller (ADF) test statistics for lnppi, lnipi, lntbill and rsr

(a) lag m = 0

Variable	ADF test statistics
In levels	
lnppi	- 1. 2393
lnipi	- 5.1178 ***
lntbill	- 1. 9053
rsr	-10. 3747***
In first difference	
Δlnppi	- 6.9645***
Δlnipi	- 19.8622***
Δlntbill	- 8. 1999***
Δrsr	- 21..2976***

(b) lag m = 1

Variable	ADF test statistics
In levels	
lnppi	- 2.6171
lnipi	- 3.3618
lntbill	- 2.5582
rsr	- 6.1876***
In first differences	
Δlnppi	- 6.7171***
Δlnipi	- 13.1295***
Δlntbill	- 7.5056***
Δrsr	- 10.7347***

(c) lag m = 3

Variable	ADF test statistics
In levels	
lnppi	- 1.9773
lnipi	- 2.6700
lntbill	- 1.9534
rsr	- 6.5850***
In first differences	
Δlnppi	- 6.6901***
Δlnipi	- 6.3986***
Δlntbill	- 5.8611***
Δrsr	- 9.2388***

(d) lag m = 6

Variable	ADF test statistics
In levels	
lnppi	- 1.3267
lnipi	- 2.6700
lntbill	- 2.0237
rsr	- 3.6952**
In first differences	
Δlnppi	- 5.0588***
Δlnipi	- 4.7898***
Δlntbill	- 3.6338**
Δrsr	- 8.4088***

(e) lag m = 12

Variable	ADF test statistics
In levels	
lnppi	- 1.6422
lnipi	- 2.6956
lntbill	- 2.3451
rsr	- 2.4834
In first differences	
Δlnppi	- 3.2465***
Δlnipi	- 2.1029
Δlntbill	- 3.2489*
Δrsr	- 4.3812***

The above tables follows the Dickey-Fuller critical values are - 3.1468, -3.4445, -4.0303 for 10%, 5% and 1% levels of significance, respectively.
* significant at 10% level
** significant at 5% level
*** significant at 1% level

Tables 4.1. shows that the *lnppi, lnipi* and *lntbill* are stationary in first difference which means that they are of integration order I(1). The variable *rsr* exhibit stationarity in levels i.e. its order of integration is I(0). Consequently, we can proceed by using these findings in stationarity.

Since, *lnppi, lnipi* and *lntbill* are intergrated of the same order, and are not stationary, they are then tested for cointegration. The results of the Johansen and Juselius cointegration tests are presented in Table 4.2.

Table 4.2. Johansen test for Cointegration for lnppi, lnipi and lntbill.

Lags	$H_0 : r = 0$ $H_1 : r > 0$	$H_0 : r = 1$ $H_1 : r > 1$	$H_0 : r = 2$ $H_1 : r > 2$
	Likelihood ratio Trace statistics	*Likelihood ratio Trace statistics*	*Likelihood ratio Trace statistics*
1	21.56	7.07	0.40
2	18.54	5.53	0.41
3	15.80	4.97	0.20
4	12.81	3.49	0.45
5	16.20	2.68	0.12
6	13.25	2.78	0.05

r indicates the number of cointegrating relationships. The critical values are 29.68 and 35.65 for 5% and 1% levels of significance, respectively for r = 0, 15.41and 20.04 for 5% and 1% levels of significance, respectively for r = 1; and 3.76 and 6.65 for 5% and 1% levels of significance for r = 2.

All trace statistics show that none of the likelihood ratio trace statisitcs exceed the critical values prescribed by Johansen (1991). The tests above cannot provide evidence to reject the null hypothesis of zero cointegrating vectors at both 5% and 1% levels. On the basis of these results, there is no statistical support for presence of long-run relationships over the period under examination for Malaysia, among the oil price, industrial activity and interest rate. The robustness of the cointegrating tests is checked by performing the test using 1 to 6 lags. In all cases, no cointegration is found.

4.2. The Estimated Vector Autoregression (VAR)

Consequently, the four variables, *Δlnppi, Δlnipi, Δlntbill* and *rsr* may be modelled as an unrestricted vector autoregression. The next step is to choose the VAR with the optimal lag using the Akaike Information Criterion (AIC) and the Bayesian Schwarz Criterion (BIC).

Table 4.3. Akaike Information Criterion (AIC) and the Bayesian Schwarz Criterion (BIC) for the VAR(p) model.

Lag (p)	AIC	BIC
1	- 11.2158	- 10.7747*
2	- 11.2675*	- 10.4694
3	- 11.2318	- 10.0732
4	- 11.0996	- 9.57675
5	- 11.1521	- 9.26130
6	- 11.1517	- 8.88905

* minimum value

The AIC selection criterion shows that the short-run dynamics of this structure is best described by VAR(2). Although the BIC results tend to choose lag 1 instead, we feel that a period of one lag in the model may be too short a time to observe the paths of innovations in the variables. Also, BIC has the tendency to choose a more parsimonious model than the AIC as the former imposes a heavier penalty on the increase of number of explanatory variable. The unrestricted VAR(2) model is thus estimated and the results are presented in Table 4.4.

Table 4.4. Unrestricted VAR(2)

	$\Delta lnppi$	$\Delta lnipi$	$\Delta lntbill$	rsr
$\Delta lnppi_{t-1}$	0.4324*** (4.4547)	0.1117 (1.0350)	- 0.4584 ** (-2.2715)	- 0.0026 (-0.0113)
$\Delta lnppi_{t-2}$	-0.1187 (-1.2357)	- 0.0620 (-0.5811)	0.2569 (1.2863)	0.2308 (1.0021)
$\Delta lnipi_{t-1}$	0.1297* (1.6516)	- 0.6127*** (-7.0156)	- 0.0116 (- 0.0711)	- 0.0405 (1.0021)
$\Delta lnipi_{t-2}$	0.0574 (0.7544)	- 0.3120*** (-3.6867)	- 0.1482 (- 0.9364)	0.3121* (1.7107)
$\Delta lntbill_{t-1}$	0.0111 (0.2626)	0.0774 (1.6382)	0.3874*** (4.3823)	0.0969 (-0.8896)
$\Delta lntbill_{t-2}$	- 0.2436 (- 0.5886)	- 0.0197 (-0.4289)	- 0.1442* (-1.6759)	- 0.0788 (- 0.7948)
rsr_{t-1}	- 0.0260 (-0.6809)	0.0037 (0.0892)	- 0.2621*** (-3.2961)	0.0608 (0.6634)
rsr_{t-2}	- 0.0135 (-0.3478)	- 0.01179 (-0.2728)	0.1617** (2.0002)	0.2055*** (2.2052)
intercept	0.0006 (0.1834)	0.0152*** (3.8877)	- 0.0012 (-0.1702)	- 0.0052 (- 0.6148)
R- squared	0.2144	0.3093	0.2321	0.1107
F -Statistics	4.0941**	6.7173***	4.5361**	1.8677

Akaike Information Criterion = - 11.2675

t-statistics in parentheses.
* significant at 10% level
** significant at 5% level
*** significant at 1% level

Not all the estimated coefficients are statistically significant. The equations *Δlnppi, Δlnipi* and *Δlntbill* are statistically significant. The impulse response functions (IRF) can provide dynamic simulations of responses of an endogenous variable over n-periods, in reaction to a given shock in oil prices

($\Delta lnppi$). Variance decomposition (VDC) is also useful in providing information of the contributions of source of each shock to the variance forecast error of n-periods ahead for each endogenous variable.

Prior to examining the IRF and VDC, the variance-covariance and the correlation matrices of the residuals from the unrestricted VAR (2) are computed.

Table 4.5. Variance-covariance matrix of the residuals of VAR(2)

	Δlnppi	**Δlnipi**	**Δlntbill**	**rsr**
Δlnppi	0.0013	0.0003	0.0002	- 0.0008
Δlnipi	0.0003	0.0017	0.0000	- 0.0002
Δlntbill	0.0002	0.0000	0.0058	- 0.0008
rsr	- 0.0008	- 0.0002	0.0008	0.0077

Table 4.6.Correlation matrix of the residuals of the residuals of VAR(2)

	Δlnppi	**Δlnipi**	**Δlntbill**	**rsr**
Δlnppi	1.0000	0.2262	0.0831	- 0.2448
Δlnipi	0.2262	1.0000	0.0109	- 0.0561
Δlntbill	0.0831	0.0089	1.0000	- 0.1271
rsr	- 0.2448	- 0.0561	- 0.1271	1.0000

Both Tables 4.5. and 4.6. show that the correlation between the residuals are fairly weak and hence, the ordering of the variables should not affect the results of the IRF and VDC significantly. However, there is an anomaly suggested by the results; a weak positive correlation between the Producer

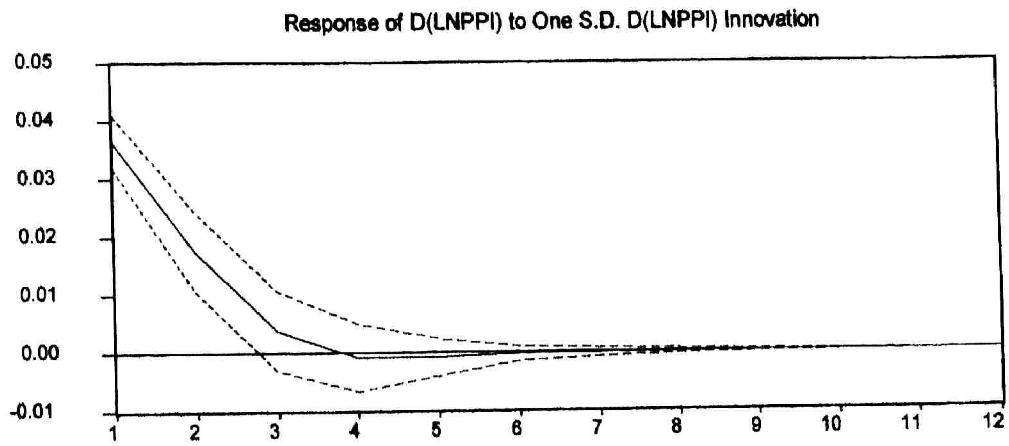
Price Index (PPI) and the Industrial Production Index (IPI). It does seem to suggest that an increase in price of oil is accompanied by an increase in output. This could be explained by the fact that the PPI measures the price of domestic petroleum, which is a controlled item in Malaysia. Being a controlled item, a hike in the domestic petroleum prices is usually allowed only if a change in the world oil is significant and persistent. Since the PPI for Malaysia is lagged, producers would anticipate a future hike in domestic fuel prices ahead and increase production in the current period. However, a clearer picture of the relationship between oil prices and industrial is better revealed using IRF. IRF results are reported in the next section.

As expected, there is a negative correlation between price of oil, interest rates and real stock returns. The stock market generally views a rise in interest rates negatively for three reasons. Firstly, higher interest rates raise the cost of borrowing for corporations thus, reducing profit margins. Secondly, higher interest rates make other interest-related financial instruments more attractive compared to the stock market. Thirdly, as most stocks are purchased on margins, it makes it costlier for investors to invest in equities thereby, reducing their return on investment.

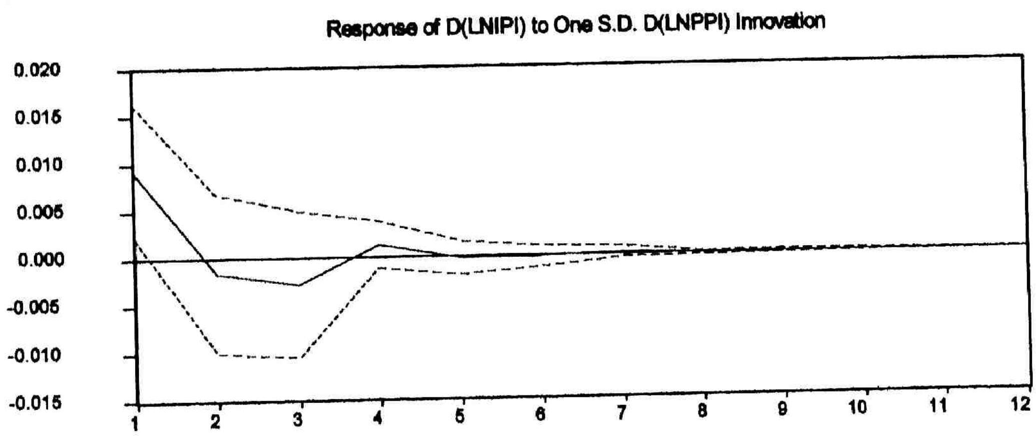
Hikes in oil prices are expected to reduce production activities and thus, create a dampening effect on the economy. This may lead to a more pessimistic

Figure 4.1. The responses due to one standard deviation shock to oil price changes.
Ordering: Δlntbill, Δlnppi, Δlnipi, rsr

(a)



(b)

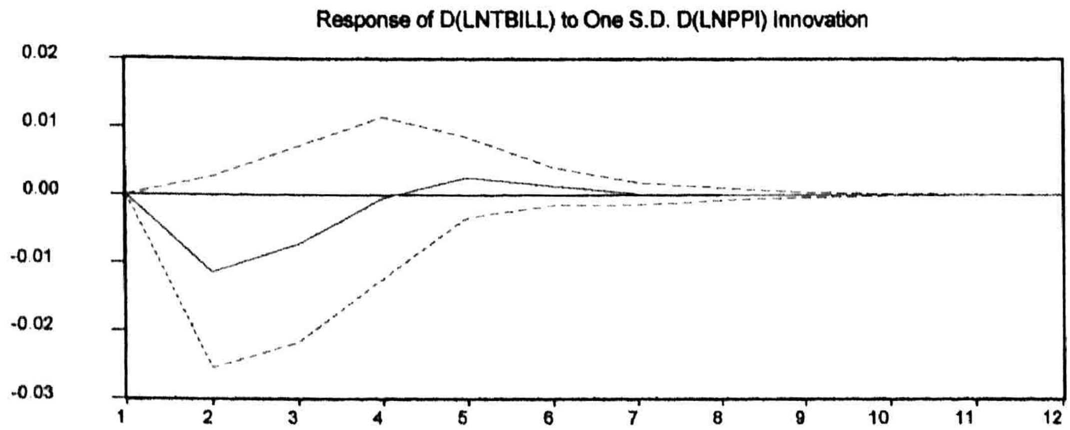


outlook in the stock market and therefore, the negative correlation between *Δlnppi* and *rsr*. All these results are bivariate results and do not control the effect of other variables in the system. To take the entire system of four variables into consideration, we move to the analysis of IRF and VDC.

4.2.1. Empirical Results: Impulse Response Function

Oil prices, industrial production, interest rates and stock returns are subjected to one standard innovation in oil price changes and their reactions are mapped over 12 months. The graph is presented in Figure 4.1. The order of the variables replicates that of Sadorsky (1999): *Δlntbill, Δlnppi, Δlnipi, rsr.* His rationale is that one would assume that changes in interest rates are contemporaneously independent of disturbances to other variables. Further testing by using different orderings (presented in the Appendix I) confirms this assumption of order does not make any difference to the implication of the results.

(c)



(d)

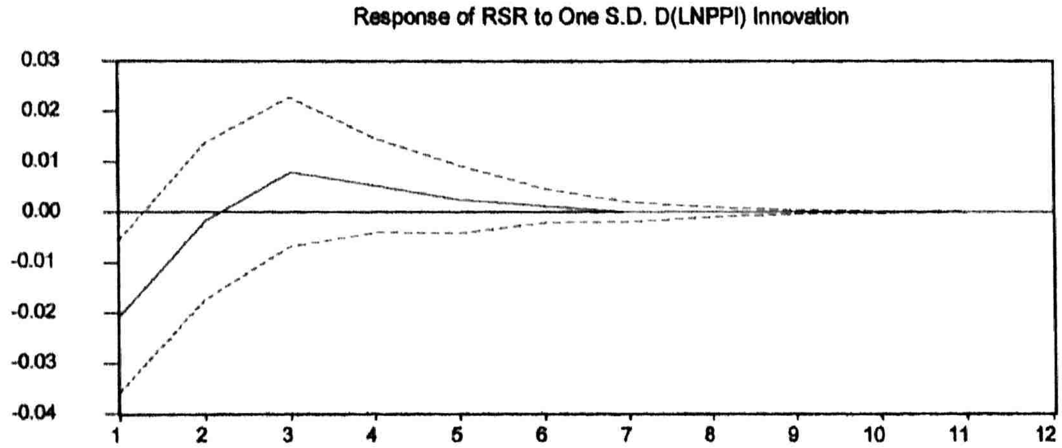


Figure 4.1(a) shows that oil prices would experience a positive response following a positive shock in oil prices in the first period of about 3.5%. This declines slowly and the reaction stabilizes in about 6 months.

Figure 4.1(b) shows that a shock in oil price has a negative impact on industrial production or, economic activity. However, this does not happen immediately as plans for production continues for at least 2 months before falling to a negative growth rate. Industrial production re-adjusts itself to oil price shocks in about 5 months.

Figure 4.1(c) shows no initial reaction in interest rates but a negative impact can be expected only after the second period. Such a reaction is presumably due to monetary stimulation to counter the depressing effects on economic activity due to the oil shock. This is expected to stabilize after about 6 months, but the main adjustment period is within the first 3 months after the shock.

Sadorsky's (1999) mentions that how fast the stock market reacts to the oil price shocks reflects the efficiency of the market. Figure 4.1 (d) we see an immediate negative response to oil shocks. Here, the IRF seems to suggest that the Malaysian stock market is indeed efficient in responding to changes in oil prices. By the second month, the responses returns to zero level and any effect of oil shocks are dampened out by the fifth month.

4.2.2. Empirical Results: Variance Decomposition

The reported numbers in Table 4.7. indicate the percentage of the variance of forecast error in each variable that can be attributed to innovations in other variables for 1-month, 6-months and 1-year ahead forecasts.

Table 4.7. Variance Decomposition Analysis due to an innovations in oil prices, industrial production, interest rates and stock returns.
Ordering: Δlntbill, Δlnppi, Δlnipi, rsr

Period (months)	Oil Price Shock	Industrial Production Shock	Interest Rates Shock	Stock Returns Shock
Variance decomposition of:				
Δlnppi (oil price growth)				
1	100.0000	0.0000	0.0000	0.0000
6	97.4152	1.7723	0.0882	0.7274
12	97.4037	1.7755	0.0915	0.7293
Δlnipi (industrial production growth)				
1	5.1146	94.8854	0.0000	0.0000
6	4.0787	93.4510	1.7729	0.7074
12	4.0872	93.4440	1.7735	0.7127
Δlntbill (interest rate growth)				
1	0.6913	0.0066	99.3021	0.0000
6	2.3485	1.1290	89.6284	6.8940
12	2.3487	1.1326	89.6245	6.8942
rsr (real stock returns)				
1	5.9937	0.0000	1.1475	92.8588
6	6.3550	2.6308	3.3883	87.6359
12	6.3542	2.6423	3.3894	87.6141

In the first month, variance in forecast errors for oil price changes comes from its own movements (100%) and does not seem to change very much even after a year (97%), while very little comes from the other variables even after a year.

For industrial production, its own movements account for 95% of the forecast error variance in the first month and this does not change significantly even after 12 months. Some 4% of the variation can be explained by oil shocks, while 2% by interest rate movements.

As for interest rates, in the first month, 99% variability is accounted for in its own movements. This decays to about 90% by the end of the 12 month period while, 2%, 1% and 7% is explained by innovations in oil prices, industrial production and stock returns, respectively, after 12 months.

Finally, the variance decomposition of real stock returns shows that in the first month, 93% of the real stock returns variability inherits shocks in itself while, 6% and 1% from shocks in oil prices and interest rates, respectively. In the longer run, the variations in real stock returns are still mainly due to its own changes (88%), while 6%, 3%, 3% are attributed to oil price rates changes, industrial output growth and real returns on the stock market.

In all cases, the results seem to suggest that the variance in the forecast error in the variances of each of the variable stems mainly from innovations in itself. This is consistent with the findings by Sadorsky (1999) and Papapetrou (2001). The VDC results also imply that the explained variability in the macroeconomic variables remain pretty much the same after one year the shocks in oil prices have taken place.