Oil Price Volatility and Stock Price Fluctuations in an Emerging Market: Evidence from South Korea

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Abstract

How important are oil price fluctuations and oil price volatility on equity market performance? We assess this issue for Korea using a VEC model including interest rates, economic activity, real stock returns, real oil prices and oil price volatility. Results indicate the dominance of oil price volatility on real stock returns and emphasize how this has increased over time. This increase in dependency has been found in other net oil importing emerging equity markets. We test the relationship between oil price movements and economic activity by using modern time series techniques in a cointegrating framework. We expand the standard error correction model by examining the dynamics of out of sample causality through the variance decomposition and impulse response function techniques. The evidence from persistence profiles also gives important guidelines based on how fast the entire system adjusts back to equilibrium.

1.0 Introduction

Since the oil price shocks of 1973-74 and 1979-80, dozens of academics and practitioners have explored the relationships between oil price shocks and the Macroeconomy. Both shocks were followed by worldwide recessions, and the earlier shock by a several-year period of inflation as well. The coincident timing of oil supply shocks and the periods of macroeconomic disturbance was too close for possible causal links to be ignored, and considerable attention was devoted in studying the macroeconomics of these events.

We must remember that monetary and fiscal policies in several countries were parts of pre-existing campaigns against inflation, so on that score, the oil price shocks were not ripples in a completely calm pool. The Korean government, to some degree managed to combat the oil price hikes by having favourable policies which increased industrial production and thus led to an increase in export revenue. To maintain high industrial production levels, investment had to be high which in turn meant that interest rates had to be kept at a low level. This was easier said than done given the inflationary effects of higher oil prices which inturn had to be controlled by increasing interest rates. Amongst all these complementary and conflicting goals there was also the stock market to consider. It is interesting to note that it was only the 1990s that researchers seriously looked at the impacts of oil price shocks on stock markets. Macroeconomics and financial dynamics have not been captured together in one model when subjected to oil price shocks, especially for a net oil importing and emerging economy such as South Korea.

The Republic of Korea (South Korea) is important to the world energy markets as the fourth largest oil importer. Korea relies entirely on oil imports as there are no oil reserves in the country or surrounding areas. Being a net importer of oil, the movements in oil prices are very important in making crucial decisions that affect the macro economy. We define the macro variables as ones consisting of economic and financial markets. With the close dynamics between economic indicators and financial markets many studies have used various proxies to illustrate the degree and direction of causality in a cointegrating VAR framework. To our knowledge these dynamics have not been observed together with exogenous oil price movements and oil price volatilities.

The paper tries to answer the following questions. What is the long-run relationship between oil price movements and stock markets in an emerging market like South Korea? Did the stochastic trends between industrial production, interest rates, stock markets and oil price change during the financial crises and oil price hikes in the early 1990s? What is the direction of causality between these variables and what are the implications for the transmission mechanisms of shocks? Can the domestic stock market be isolated from oil price movement? Answers to these questions will have serious fiscal and monetary policy implications.

The paper is structured as follows. Section 2 discusses the literature review surrounding the dynamics between stock markets and economic markets, together with impacts from energy and oil price movements. In Section 3 we econometric concepts and methodology surrounding multivariate cointegration analysis and the out-of sample testing framework. The application and estimation results are presented in Section 4 and in Section 5 we draw some important policy conclusion with respect monetary policy and policies designed for stock markets to withstand oil price movements.

2.0 Literature Review

James Hamilton's (1983) study of the role of oil price shocks in United States business cycles has had considerable influence on research on the macroeconomics of oil price shocks. As Mork's (1994) review paper outlines, economists worked for nearly a decade on methods of incorporating oil price shocks in to macroeconomic models before a synergy developed with real business cycle (RBC) models and oil price shocks. This theoretical relationship between macroeconomics and oil price movements has been applied and tested using various econometric techniques. The literature shows that prior to 1986 the main focus was on the impact of oil price increases on macroeconomic variables. The oil price increase in the 70s has severe impacts on most economies and the major focus of research was on the negative impact of oil price increases. Numerous studies using data from this era have using the 1973-74 oil price increase as a structural break on their series.

There is some debate as to the degree of impact of these oil price shocks, as to whether they have been overemphasized because they haven't taken into account other macro dynamics in the economies. The other debate has evolved around the asymmetric effects of oil price shocks. It was until the decline in oil prices in 1985 and beyond that provided the data for testing whether oil price shocks were symmetric. Numerous papers have come about that try to test whether oil price declines are as beneficial in magnitude in comparison to the detrimental effects of oil price increases. In this paper we discuss some of the more recent articles testing the oil macro relationship using modern time series techniques. Hamilton (1983) was one of the first to introduce the concept of Granger causality and seriously look at the supply side effects of oil price shocks rather than the demand side.

Chaudhuri and Daniel (1998) use cointegration and causality to demonstrate that nonstationary behaviour of the US dollar real exchange rate is explained by nonstationary behaviour of real oil prices. Since exchange rates are constructed using prices of different commodities, real exchange rates are relative prices. The authors use this basis and state that real shocks can have long-run effects on real exchange rates even if perfect markets exist in the long run. The increase in a countries exchange will be evident depending on whether it is a oil producing country. Since oil is a crucial commodity it will be included in the producer price index which inturn will be reflected in the countries exchange rate. The authors also show evidence that non-stationarity of oil prices and real exchange rate is only evident in the post Bretton wood era and the direction of causality running from real oil prices to real exchange rates.

Greene (1998) assesses the impact of cartels like OPEC on the U.S. economy. He finds that the oil cost as a share of GDP has risen and fallen with oil prices, but in recent years stood at the same level as in 1972, immediately prior to the first oil price shock. He states that the evidence from various econometric studies show that sensitivity of US GDP to oil prices has changed little in the past 20 years. Green identifies three main separate and additive type of economic losses resulting from oil prices increases. The loss of the potential to produce, macroeconomic adjustment losses and the transfer of wealth from US oil consumers to foreign oil exporters. The transfer of wealth is exactly equal to the quantity of oil the country imports times the difference between the monopoly price and the competitive market price of oil.

Kaneko, T., and Lee, B.S., (1995) use an eight variable VAR model to test the pricing influence of economic factors on U.S. and Japanese stock market returns and in identifying their relative importance in a dynamic context. The eight variables used in this study include, risk premium, term premium, growth rate in industrial production, rate of inflation, changes in terms of trade, changes in oil prices, change in exchange rates and excess stock returns. They find the average values of excess stock returns, rates of inflation, risk premiums and term premiums to be higher for the United States than for Japan. The average growth rate

Papaetrou (2001) uses the latest advancements in econometric time series to explain the short and long run (dynamic) relationship among oil prices, stock returns, interest rates, economic activity and employment in Greece. The main focus of the paper is to test the dynamic linkage between crude oil price and employment in Greece. The paper uses industrial production and industrial employment as alternative measures of economic activity. The study is modelled in a cointegrated VAR framework and extends out by looking at the generalised variance decomposition and impulse response functions. This is very encouraging at most studies have not gone beyond cointegration and error corrections modelling. The use of variance decomposition analysis is particularly important in determining the endogeneity or exogeneity of variables. The generalised impulse response functions show the response in one variable when innovations and induced in other variables.

3.0 Data

The data consists of monthly observations of the Korean stock market index, industrial production, interest rates and oil prices. The data are from International Financial Statistics of the International Monetary Fund. The sample period runs from May 1988 to January 2000. From these data we calculate the real stock returns and calculate the volatility of oil prices. In the results we report industrial production as *ip,* real stock returns as *rsr*, interest rates as *r,* oil prices as *lo*, and oil price volatility as *rvol.*

4.0 Econometric Concepts, Methodology and Results

In this paper we use a VAR model to explain the impacts of oil price changes and volatility and its affects on real stock returns, industrial production and interest rates. The methodology will let us test the endogeneity of all remainder variables when oil price shocks are introduced as exogenous variables. We use two models to test our dynamics. One model introduces oil prices in level form in the other model we introduce oil prices in a volatility context. We are testing the magnitude of reactions of industrial production, real stock returns and interest rates when actual price movements or percentage gains or drops in oil price are introduced in the model. The following section is set out as follows. We first conduct unit root test to test the order of integration. We use different procedures unlike the standard tests in most models. We then discuss the cointegration VAR

4.0.1 Unit Root Test

To verify the order of integration of the variables we test for unit root based on the Perron (1988), Phillips (1987) and Phillips and Perron (1988) and Kwiatkowski (KPSS) et al. (1992).

The semi-parametric Phillips-Peron (PP) type tests developed by Phillips (1987), Phillips and Perron (1988), and Peron (1988) are convenient testing procedures, both based on the null hypothesis that a unit root exists in the autoregressive representation of the time series. The null hypothesis for the KPSS is based on the opposite, i.e., that a unit root does not exist. We recommend our readers to read further in Kwiatkowski et al. (1992). The Dickey-Fuller tests (Dickey and Fuller 1981), attempt to account for temporally dependent and heterogeneously distributed errors by including lagged sequences of first differences of the variable in its set of regressors. The PP tests try to account for dependent and IID processes through adopting a non-parametric adjustment, hence eliminating any nuisance parameters. Recently these tests have been shown, by Schwert (1987) and DeJong et al (1992), to suffer from lack of power as they often tend to accept the null of a unit root too frequently against a stationary alternative. Therefore, the failure to reject a unit root may be simply due to standard unit root tests having low power against stable autoregressive alternatives with roots near unity. Furthermore, Stock (1995) stresses that nuisance parameters such as the largest autoregressive root are quite typical of economic as well as financial time series. In particular, this knife-edge assumption of an exact unit root could lead to substantial biases which are clearly conditional upon this property to hold, even in large samples.

4.0.2 Modified DF-GLS $^{\tau}$ Test

In this paper, instead of the standard ADF test we use the modified Dickey –Fuller test (DF-GLS $^{\tau}$) due to Elliot, Rothenberg and Stock (1995). This test is conducted using the following regression:

$$(1-L)y_{t-1}^{\tau} = a_0 y_{t-1}^{\tau} + \sum_{j=1}^{p} a_j (1-L) y_{t-j}^{\tau} + \mu_t$$

where μ_t is a white noise error term; and y_t^{τ} is locally detrended data process under local alternative of $\bar{\alpha}$ as given by:

$$y_t^{\tau} = y_t - \overline{\beta'}' z_t$$

where $z_t = (1-t)'$ and $\overline{\beta}$ is the regression coefficient of $\bar{y}_t$ and $\bar{z}_t$ for which:

$$(\bar{y}_1, \bar{y}_2, \ldots, \bar{y}_T) = (y_1, (1-\bar{\alpha}L)y_2, \ldots, (1-\bar{\alpha}L)y_T)$$

$$(\bar{z}_1, \bar{z}_2, \ldots, \bar{z}_T) = (z_1, (1-\bar{\alpha}L)z_2, \ldots, (1-\bar{\alpha}L)z_T)$$

The t - test testing the hypothesis of $H_0 : a_0 = 0$ against $H_0 : a_0 < 0$ gives the ADF - GLS$^{\tau}$ test statistic. Elliot et al (1992) recommend that the parameter $\bar{c}$, which defines the local alternative by :

$$\bar{\alpha} = 1 + \frac{\bar{c}}{T}$$

be set equal to –13.5. This test can attain a significant gain in power over the traditional unit root tests. The critical values are computed by Elliot et al (1995, Table 1) using Monte Carlo simulations. For finite sample correlations, Cheung and Lai (1995) provide approximate critical values. In the non-deterministic case, the use of $\bar{c} = -7$ is recommended where the test DF-GLS$^{\mu}$ basically involves the same procedure as computing the DF-GLS$^{\tau}$ test, apart from the exception that the locally detrended process series (y_t^{τ}) is replaced by the locally demeaned series (y_t^{μ}) and $z_t = 1$. The asymptotic distribution of the DF-GLS$^{\mu}$ test is the same as that of the conventional DF test.

4.0.3 Confidence Interval for the Largest Autoregressive Root

ADF test indicate the presence of a unit root in each series since for no series can the null of non-stationarity be rejected. To allow us to measure how persistent the unit root in the process is, we also calculate a confidence interval (CI) due to Stock (1995) suggests that reporting CIs may provide useful information regarding sampling uncertainty. The confidence interval estimates, tend to suggest that the unit root is quite persistent with all lower bounds quite clearly above 0.80 for both ADF (μ) and ADF(τ). We also supplement these results from Sims Bayesian unit root procedure which seem to be suggestive of a unit root with high value of a. Furthermore, GPH tests for fractional integration, also quite uniformly suggest that most estimates of d fall significantly in the neighbourhood of 1. To check that these series are not integrated of higher orders, we also repeat these tests using first differences of each series. These results are not reported here but suggest that they are all stationary after applying the difference filter only once[1].

[1] As a means of investigating the robustness of these results derived from conducting tests for the total sample, we also undertake a sub-sample analysis of these tests taking the October 1987 crash as the break

Given the consistency and un ambiguity of results from all these testing approaches, we conclude that our variables are integrated at most order one. This provides a requisite for the forthcoming multiple cointegration analysis.

4.0.4 Multivariate Cointegration Analysis

As OLS estimates of cointegrating vectors, particularly in small samples, may be severely biased, in this analysis we employ the well known Johansen and Juselius (JJ) procedure of testing for the presence of multiple cointegrating vectors

It is demonstrated in Johansen (1991) that the procedure involves the identification of the rank of the *m* by *n* matrix $\prod$ in the specification given by:

$$\Delta x_t = \delta + \sum_{i=1}^{k-1} \Gamma_i \Delta x_{t-1} + \prod x_{t-k} + \varepsilon_t$$

where, x_t is a column vector of the *m* variables,

Results of cointegration rank by the JJ procedure appear in Table 2. Evidence from both trace and maximal eigenvalue tests suggests that there is at most a single cointegrating vector or analogously 7 independent common stochastic trends within this four-variable system[2]. This finding is consistent with studies by Corhay et al (1993), Leachman and Francis (1995) and Jeon and Chiang (1991) who, among others, find that equity markets

point. In order to save space, these results have been reported in Appendix Table A1 for pre- and post-crash samples. Results, in general, indicate that the unit root approximation seems to be quite robust to the October 1987 crash, since these sub-sample results do not change our conclusion from conducting the tests over the full sample that these variables are integrated of at most order one. Once again, it is important to warn readers that such results are very much vulnerable to low power due to poor performance in small samples.

[2] Due to one of the biases of the JJ procedure being the sensitivity of cointegration rank to the order of the lag length used in the VAR, We chose the lag subject to the Akaikes FPE criterion. In addition, results of a unique cointegrating vector were insensitive to slight modifications to lag length. Furthermore, there has been much recent work documenting the potential for severe small sample bias in Johansen tests [see Cheung and Lai (1993)].The scaling-up factor on the asymptotic critical values suggested by Cheung and Lai''s study does not alter our conclusion of cointegration rank. Furthermore, their study favours the trace test in that: ``it shows little bias in the presence of either skewness or excess kurtosis, and is found to be more robust to both skewness and kurtosis than the maximal eigenvalue test. [Cheung and Lai (1993, p. 324)]. In the light of this statement, the trace statistic of 215.64, further confirms our initial conclusion of r equal to at most 1.

of countries belonging to the G-7 countries possess at least one cointegrating vector. It is worth noting that an implicit assumption underlying these tests are that events over this period such as the Asian financial crises did not significantly affect the stability of this system in terms of altering the number of common stochastic trends between the macro and financial variables. This issue may now be tested using procedures advocated by in the literature by Hansen and Johansen (1993), and Quintos and Phillips (1993). However, based on evidence using similar techniques on a system of five OECD equity markets, Masih and Masih (1996c) find evidence that the crash did not affect the number of common stochastic trends within this particular system. In this study we find that the Asian financial and banking crises had very little effect on the stochastic trends between interest rates, industrial production, oil prices, oil price volatility and real stock returns. Besides observing these variables we have seen that South Korea was one of better economies that withstood the pressures of currency meltdowns in Thailand and Indonesia and the severe banking crises in Japan in the early nineties.

In order to assess the relative strength of the long run relationship, Johansen and Juselius (1993) point out that larger eigenvalues are associated with the cointegrating vector being more correlated with the stationary component of the process. To gain some insight into the robustness of results for all five variables, we also conducted cointegration tests revealing r=1 at the 95% confidence level for both models. Eigenvalues, presented in Table 2 are in descending order; indicate the cointegration relationship between the variables.

Finally in order to test that each of the variables enters the cointegrating vector significantly, we test for zero restrictions upon each of the coefficients derived by the Johansen procedure. Having established the presence of a single cointegrating vector, the Johansen procedure allows us to test several hypotheses on the coefficients by way of imposing restrictions and likelihood ratio tests which are, asymptotically, chi-square distributed with one degree of freedom. Scrutinising the cointegration vector in each model, presents us with a measure of the most important component, in terms of its relative weight, in comparison to the remaining components. Coefficient estimates and significance levels associated with the tests of zero-loading restrictions appear in Table 3. Normalising on interest rates in Korea provide evidence of each of these restrictions being rejected, for most at least at the 10 per cent level. This implies that most of the variables enter into the cointegrating vector at a statistically significant level. However, although the weights of some of the variables are not statistically significant, we cannot exclude this from the cointegrating vector as it forms a part of the long-run relationship. In general, these results indicate that almost all variables adjust in a significant fashion to clear any short-run disequilibrium.

4.0.5 Short-Run Dynamics and Long-Run Relations: Vector Error-Correction Modelling (VECM)

Given the presence of a unique cointegrating vector in the nine-dimensional VAR used in the JJ cointegration tests, this then provides us with one error-correction term for constructing our models. Analogously, we may also extract (n-r) or four common trends, [for such an approach see Kasa (1992), Chung and Lui (1994)].

Summary results based on the VECM are presented in Table 4 and 5 provide some interesting results. For each of the variables, at least one channel of Granger causality is active: either the short-run through joint tests of lagged-differences or a statistically significant ECT. This latter channel is a novelty of the VECM formulation but it is noteworthy of significance only in the GE equation. The economic intuition arising from this finding implies that when there is a deviation from the equilibrium cointegrating relationships as measured by the ECTs, it is mainly changes in the real stock returns that adjust to clear the disequilibrium i.e. bears the brunt of short-run adjustment to long-run equilibrium. This leaves changes in interest rates and oil production, which appear to be statistically exogenous in both models and thus represents the initial receptor of any exogenous shocks to their long-term equilibrium relationships.

Although the ECT's are not statistically significant for variables other than real stock returns, one cannot assume that all other variables are non-causal since the short-run channels are still active. For example, fluctuations in interest rates seem to explain movements in industrial production, and the exogenous oil price shocks seem to cause the biggest fluctuations in real stock returns. These short-run causalities are explained by the significance of lagged differences in Table 4 and Table 5.

4.0.6 Generalized Variance Decomposition Analysis

Inference from using vector autoregressions, in the way of *F*-and *t*-tests may be interpreted as within-sample causality tests. They can indicate only the Granger causality of the dependent variable within the sample period, but do not provide an indication of the dynamic properties of the system, nor do they allow us to gauge the relative strength of the Granger-causal chain or strength of causality amongst the variables beyond the sample period.

Variance decompositions (VDCs), which may be termed as out-of-sample causality tests, by partitioning the variance of the forecast error of a certain variable intro proportions attributable to shocks in each variable in the system including its own, can provide an indication of these relativities. Placed under an alternative context, VDCs provide a literal breakdown of the change in value of the variable in a given period arising from changes in the same variable in addition to other variables in previous periods. A variable that is optimally forecast from its own lagged values will have all its forecast error variance accounted for by its own disturbances (Sims 1982).

The variance decompositions presented in table 6 indicate that 80.55% of shocks to interest rates are self explained in the first month. This weighting stays at around 79% for 6, 12 and 24 months, suggesting that interest are relatively exogenous but the 20% difference calls for some investigation in finding out what other variable influences interest rates. We find that stock returns and oil prices have a greater influence on the variance of interest rates than industrial production. Economic theory makes the link between industrial production and interest rates through an increase in investment. An increase in investment results in an increase in industrial production and then puts an increasing pressure on interest rates. In South Korea's case industrial production has minimal impact on interest rates and perhaps this indicates the country's capability to enjoy high industrial growth and not worry too much about inflation. This explains why South Korea had double digit growth in the 1980s and in early 1990s.

In table 6 we also find that industrial production is strongly exogenous with only small influences from interest rates and real stock returns. The brunt of the variance in endogenous real stock return variable is explained by movements in interest rates. In the first month, 11.04% of variance and in six months 16.48% variance in real stock return is explained by innovation in interest rates. This influence establishes a link between instruments of monetary policy and the stock market. Movements in interest are indicative of the state of the economy and this embeds expectations among investors. An increase in variance of interest rates could suggest the direction of inflation in the economy which inturn reflects whether economic activity has picked up or slowed down. If interest rates are on the increase than investors are likely to go easy on the stock market as the risk return trade off in the bond market will become more attractive.

In table 7 we get similar results except that oil price volatility explains a greater proportion of variation in industrial production than the level series of the oil price. Industrial production appears to be less exogenous compared to table 6 mainly because of the uncertainty caused by oil price volatility. After 6 horizons only 82.50% of shock is self explained compared to 92.28 in table 6. Oil price volatility explains 10.60%, while interest rates explain 6.57% of the innovations in industrial production. The endogeneity of the real stock returns are illustrated by the strong causal links between interest rates and oil price volatility, with 14.45% and 12.36% of shocks in stock returns being explained by the former and later.

4.0.7 Impulse Response Functions

The information contained in the VDCs can be equivalently represented by graphs of the impulse response functions (IRFs). Both are obtained from the moving average (MA) representation of the original VAR model. IRFs essentially map out the dynamic response path of a variable due to a one-period standard deviation shock to another variable. The IRFs become crucial in our analysis of oil price shocks, as VDCs cannot be generated for exogenous variables.

The results based on VDCs and IRFs are generally found to be sensitive to the lag length used and the ordering of the variables. By construction, the errors in any equation in a VAR are usually serially uncorrelated. However, there could be contemporaneous correlations across errors of different equations. In the case where there is more than one common trend, alternative orderings of the trend may affect the results of VDCs and IRFs if the common trends are themselves not absolutely uncorrelated. In the standard applications of VDCs and IRFs, these errors are orthogonalized through Choleski decomposition, which is not unique, since the number of MA representations for any given VAR is not finite. In order to circumvent this problem, in this study we apply the generalised impulse response analysis provided and applied in Lee, Pesaran and Pierse (1992), Pesaran, Pierse and Lee (1993) and Lee and Pesaran (1993). Unlike standard IRFs, generalised IRFs are not subject to any arbitrary orthogonalisations of innovations in the system. If the shocks do not explain any of the forecast error variance of one macroeconomic variable Y_t in all forecast horizons, then Y_t is an exogenous variable. At the opposite end if shocks can explain all or a major part of the forecast error variance of Y_t at all forecast horizons then Y_t is an entirely endogenous variable.

Information from application of these tools should provide some further evidence on the patterns of linkages amongst stock markets and oil price shocks, as well as contribute to enhancing our insights upon how other macroeconomic variables react to system wide shocks and how these responses propagate over time. It is important to note, however, that although derivation of GIRFs does not suffer from the arbitrary orthogonalizations of innovations, GIRFs should not be strictly used to isolate responses of a particular shock, assuming that all other shocks are not present, or not also running in conjunction with the particular shock in question. In this respect, one should not attribute the shock, as in traditional IRF analysis, to sole variables in the system, and thereby practice caution when interpreting such results.

Generalised IRFs from one-standard deviation shocks to the model using log of oil price and oil price volatility in Korea are traced out for each individual variable in Figures 1 to 4 (including the own shock to each market). In general the responses show long-lasting effects and the variables take about 6 to 7 months to return to a new equilibrium level. Of all the variables interest rates seem to act positively in responding to their own shocks and shocks to oil price and oil price volatility. Shocks to industrial production and real stock returns seem to have no upward pressure on interest rates. This shows that interest rates in South Korea are purely driven up by expectations embedded in interest rates (perhaps long-term interest rates) and through shocks in oil prices. We can see that industrial production is more susceptible to shocks in the stock market and it takes about 11 months to reach to a new equilibrium state. The self reactionary profile of oil price and oil price volatility seem to settle back to their pre-shock levels the quickest which is not surprising given the conclusions from the within-sample causality VECM and VAR results. Responses of the stock market are interesting when interest rates and oil prices are shocked. In both instances the stock market increases and then reverts back in the negative territory to its long-run level after about 9 months. This shows the lag effect of interest rates and oil price have on stock market activity and thus shows that the Korean stock markets is of strong character in the short term. The identical reactionary profiles of real stock returns in Figure 1 also suggest that inflationary expectation are evident through oil prices and through movements in short term interest rates. .

In summary, impulse responses of the two models are very similar in nature indications that volatility of oil price and log of oil price have the same impact on the Korean economy. The IRFs show that the Korean economy is not affected adversely by oil price shocks any differently to normal oil price movements. The long-run time path of real stock returns in figure 1 and figure 3 when ROLV and ROL are shocked indicate a bigger impact from oil price volatility then from the level series. The new equilibrium for the stock market settles at a higher negative standard deviation level (-1.2) then through the impacts of the level of oil prices

5.0 Conclusion

From this study we have tried to capture the stochastic properties and long run dynamics between the macro economy, the stock markets, instruments of monetary policy and oil price movements and oil volatilities. There have been a few studies that have looked at net importing countries of oil and how movements in oil prices influence the economic and financial variables. The influence of oil prices on stock market activity is one of the significant findings in the paper as sharp oil price movements show a direct effect on decreasing the profitability of firms. Investors see this and act accordingly by selling off on the stock market.

Results

Table 1: Modified DF-GLS Tests and Confidence Intervals for the Largest Autoregressive Root

	Modified DF Tests		90% Confidence Intervals		KPSS
Variable	ADF-GLS$^{\mu}$	ADF-GLS$^{\tau}$	ADF(μ)	ADF(τ)	μ
R	-1.656	-1.043	(1.023,0.879)	(0.977,0.854)	0.884
Ip	-0.404	-0.315	(0.978,0.857)	(1.112,0.901)	1.115
rsr	-0.871	-0.117	(0.988,1.054)	(1.078,0.954)	0.973
rol	-0.214	-0.907	(0.914,1.116)	(1.110,0.938)	0.917
rolv	-0.437	-0.012	(0.897,1.047)	(0.965,0.802)	0.873

Notes: The modified Dickey [DF-GLS] test is performed on logs of industrial production and real oil price. The test is associated with a null hypothesis of a unit root against the alternative of no unit root. The finite sample critical values are used in accordance to the response surface equations due to Cheung and Lai (1995). The 90% confidence intervals are constructed using Stock's (1991) technique for the largest autoregressive root; indicates that the calculation is not available from Stock's tables. ADF and PP test are associated with a null hypothesis of no unit root. KPSS tests are associated with a null hypothesis of mean stationarity against an alternative hypothesis of nonstationarity.

Table 2: Tests for Multiple Cointegrating Vectors

Interest Rate, Log of Oil, Log of Industrial Production, Real Stock Return

Eigenvalues	Hypothesis		Max Eigenvalue		Trace	
	H_0	H_1	Λ_{max}	95% CV	λ_{trace}	95% CV
0.3286	$r = 0$	$r \geq 1$	56.19	31.79	92.20	63.00
0.1024	$r \leq 1$	$r \geq 2$	15.24	25.42	36.01	42.34
0.0867	$r \leq 2$	$r \geq 3$	12.79	19.22	20.77	25.77
0.0550	$r \leq 3$	$r \geq 4$	7.98	12.39	7.98	12.39

Interest Rate, Oil Price Volatility, Log of Industrial Production, Real Stock Return

Eigenvalues	Hypothesis		Max Eigenvalue		Trace	
	H_0	H_1	Λ_{max}	95% CV	Λ_{trace}	95% CV
0.3342	$r = 0$	$r \geq 1$	55.74	31.79	116.82	63.00
0.2384	$r \leq 1$	$r \geq 2$	27.32	25.42	41.08	42.34
0.1111	$r \leq 2$	$r \geq 3$	16.13	19.22	23.77	25.77
0.0542	$r \leq 3$	$r \geq 4$	7.64	12.39	7.64	12.39

Notes: λ_{max} and λ_{trace} are the maximum eigenvalue and trace statistics respectively. The VAR is estimated using a VAR (3) model with unrestricted intercepts and a restricted trend. The optimal lag structure for seach of the VAR model is selected by minimising the Akaike's Information Criteria. In the final analysis we use a lag of 3. Results based on slight alterations of lag-depth were absolutely insensitive to the conclusion of 3 cointegrating vectors. Critical values used are sourced from Osterwald-Lenum (1992) and a comparison is made to that reported by Cheung and Lai (1993) for small sample bias (see text for details)

Table 3: Tests for Restrictions on Cointegrating Vectors

Vector Including	r_t	ip_t	rsr_t	rol_t	$rolv_t$	Trend	χ^2 test
Real Oil Price	1	0	0	-0.991 (0.098)		-0.002 (0.0004)	
	0	1	0	-1.145 (0.214)		0.094 (0.002)	
	0	0	1	-1.258 (0.141)		0.005 (0.0007)	----
Real Oil Price Vol.	1	0	0	-1.025 (0.354)		0	
	0	1	0	-1.150 (0.278)		0	
	0	0	1	-1.117 (0.554)		0	5.028 (0.121)

Notes: Tests were based on the 1 cointegrating vectors found in the Johansen procedure in Table 2. Figures reported below in parenthesis are standard errors.

Table 4: VEC Model Estimates Using Real Oil Prices

Equation	Δr_t	Δrol_t	Δlip_t	Δrst_t
$\xi_{1,t-1}$	-0.019 (0.019)	-0.004 (0.001)	-0.000 (0.000)	-1.019 (0.160)
α	0.899 (0.913)	0.216 (0.068)	0.041 (0.052)	47.990 (7.55)
Δr_{t-1}	0.296 (0.092)	0.011 (0.007)	0.001 (0.005)	-0.579 (0.759)
Δr_{t-2}	-0.084 (0.088)	-0.003 (0.007)	-0.003 (0.005)	0.440 (0.729)
Δrol_{t-1}	1.096 (1.215)	0.064 (0.090)	-0.141 (0.069)	15.303 (10.043)
Δrol_{t-2}	-1.183 (1.208)	0.132 (0.090)	0.000 (0.000)	14.406 (9.992)
Δlip_{t-1}	-0.924 (1.514)	-0.005 (0.113)	-0.280 (0.085)	17.004 (12.516)
Δlip_{t-2}	0.643 (1.472)	0.171 (0.109)	-0.208 (0.083)	-4.130 (12.151)
Δrsr_{t-1}	0.005 (0.015)	0.002 (0.001)	0.000 (0.000)	0.116 (0.122)
Δrsr_{t-2}	0.012 (0.011)	0.000 (0.000)	0.000 (0.000)	0.098 (0.094)
$\overline{R}$	0.13	0.17	0.15	0.43
$\hat{\sigma}$	0.66	0.05	0.04	6.75
RSS	0.53	0.29	0.17	3638.8
$\chi^2_{SC}[12]$	21.42	16.56	14.67	4.82
$\chi^2_{FF}[1]$	0.56	0.49	5.13	0.06
$\chi^2_{NOR}[2]$	344.02	6336.9	32.30	0.71
$\chi^2_{HET}[1]$	0.03	10.38	30.02	4.46

Notes: The underlying VAR model is of order 3 and contains unrestricted intercepts and restricted trend coefficients. Lag order was selected by Schwarz Bayesian Criterion (SBC). Standard errors are given in parenthesis. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels. The diagnostics are chi-squared χ^2 [degrees of freedom] statistics for serial correlation (*SC)*, functional form misspecification *(FF)*, non-normal error terms *(NOR)* and heteroskedastic error variances *(HET)*.

Table 5: VEC Model Estimates Using Real Oil Volatility

Equation	Δr_t	$\Delta rolv_t$	Δlip_t	Δrst_t
$\xi_{1,t-1}$	-0.013 (0.012)	-0.001 (0.000)	-0.001 (0.001)	-0.626 (0.108)
α	2.035 (1.983)	0.212 (0.054)	0.239 (0.108)	99.474 (17.030)
Δr_{t-1}	0.303 (0.094)	0.007 (0.003)	0.001 (0.005)	-0.388 (0.807)
Δr_{t-2}	-0.110 (0.092)	0.000 (0.003)	-0.000 (0.005)	0.910 (0.791)
$\Delta rolv_{t-1}$	-0.225 (3.195)	0.356 (0.087)	-0.503 (0.174)	65.539 (27.441)
$\Delta rolv_{t-2}$	3.032 (3.342)	-0.076 (0.091)	0.129 (0.182)	10.258 (28.707)
Δlip_{t-1}	-0.408 (1.600)	-0.029 (0.043)	-0.307 (0.087)	19.242 (13.747)
Δlip_{t-2}	0.456 (1.526)	0.011 (0.041)	-0.233 (0.083)	-5.077 (13.108)
Δrsr_{t-1}	0.002 (0.014)	0.001 (0.000)	0.001 (0.000)	0.055 (0.117)
Δrsr_{t-2}	0.010 (0.011)	0.000 (0.000)	0.001 (0.001)	0.085 (0.095)
$\overline{R}$	0.12	0.32	0.21	0.39
$\hat{\sigma}$	0.66	0.02	0.04	6.83
RSS	52.23	0.04	0.15	3854.2
$\chi^2_{SC}[12]$	19.67	28.08	21.21	3.26
$\chi^2_{FF}[1]$	0.67	2.43	4.85	1.51
$\chi^2_{NOR}[2]$	366.33	7507.4	32.05	0.37
$\chi^2_{HET}[1]$	0.611	1.59	25.13	1.79

Notes: The underlying VAR model is of order 3 and contains unrestricted intercepts and restricted trend coefficients. Lag order was selected by Schwarz Bayesian Criterion (SBC). Standard errors are given in parenthesis. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent levels. The diagnostics are chi-squared χ^2 [degrees of freedom] statistics for serial correlation (*SC)*, functional form misspecification *(FF)*, non-normal error terms *(NOR)* and heteroskedastic error variances *(HET)*.

Table 6: Generalised Variance Decompositions (Using Oil Price)

Horizon	Interest Rate	Oil Price	Industrial. Prod	Real Stock Returns
Shock to Interest Rate *(r_t)* Explained by Innovations in:				
1	80.55	8.30	0.83	10.31
6	79.27	6.34	1.01	13.38
12	79.57	5.73	1.07	13.63
24	79.68	5.40	1.11	13.82
Shock to Economic Activity *(lip_t)* Explained by Innovations in:				
1	0.64	1.44	96.81	1.11
6	3.00	1.61	92.28	3.11
12	3.45	1.51	91.52	3.52
24	3.73	1.45	91.01	3.80
Shock to Real Stock Return *(rsr_t)* Explained by Innovation in:				
1	11.04	2.69	2.27	84.00
6	16.48	3.65	2.50	77.37
12	24.09	3.67	2.32	69.92
24	34.97	3.71	2.10	59.23

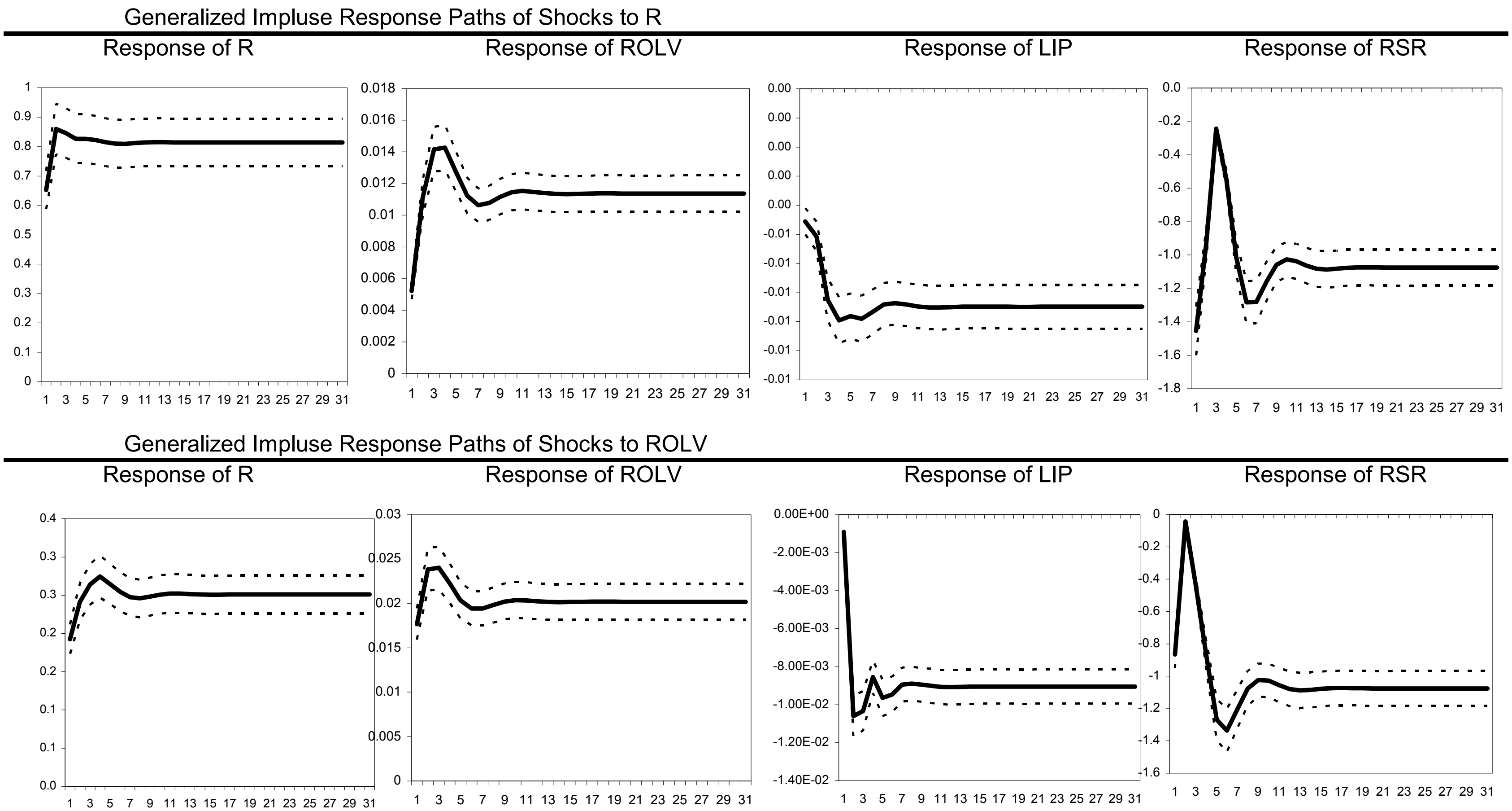
Notes: The underlying cointegrated VAR model is of order 3 and contains unrestricted intercepts and restricted trend coefficients. Lag order was selected using Schwarz Bayesian Criterion (SBC). Standard errors generated from 10,000 replications are presented in parenthesis. We cannot obtain VDCs for oil price because it is introduced as an exogenous variable.

Table 7: Generalised Variance Decompositions (Using oil Price Volatility)

Horizon	Interest Rate	Oil Price Vol	Industrial. Prod	Real Stock Returns
Shock to Interest Rate *(r_t)* Explained by Innovations in:				
1	82.84	6.79	1.97	8.39
6	78.92	7.52	2.14	11.43
12	78.28	7.44	2.15	12.13
24	77.89	7.41	2.17	12.53
Shock to Economic Activity *(lip_t)* Explained by Innovations in:				
1	2.39	5.83	91.37	0.41
6	6.57	10.60	82.50	0.33
12	7.34	11.30	81.07	0.29
24	7.84	11.75	80.14	0.27
Shock to Real Stock Return *(rsr_t)* Explained by Innovation in:				
1	7.87	1.98	0.44	89.71
6	14.45	12.36	2.87	70.33
12	19.60	17.87	2.64	59.88
24	24.43	23.32	2.45	49.81

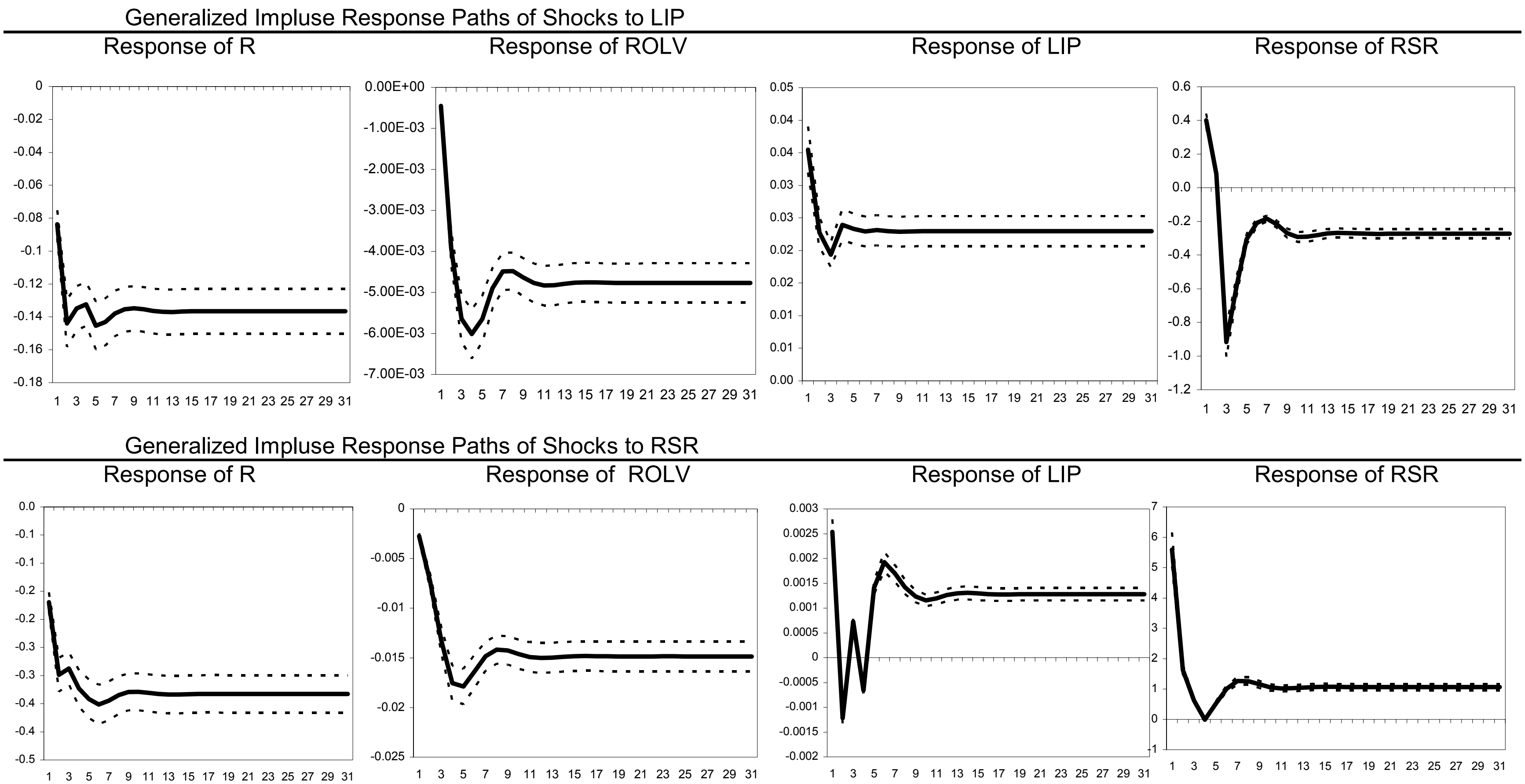
Notes: The underlying cointegrated VAR model is of order 3 and contains unrestricted intercepts and restricted trend coefficients. Lag order was selected using Schwarz Bayesian Criterion (SBC). Standard errors generated from 10,000 replications are presented in parenthesis. We cannot obtain VDCs for oil price volatility as it is introduced as an exogenous variables. We do capture the out of sample dynamics in the subsequent impulse responses.

Figure 1



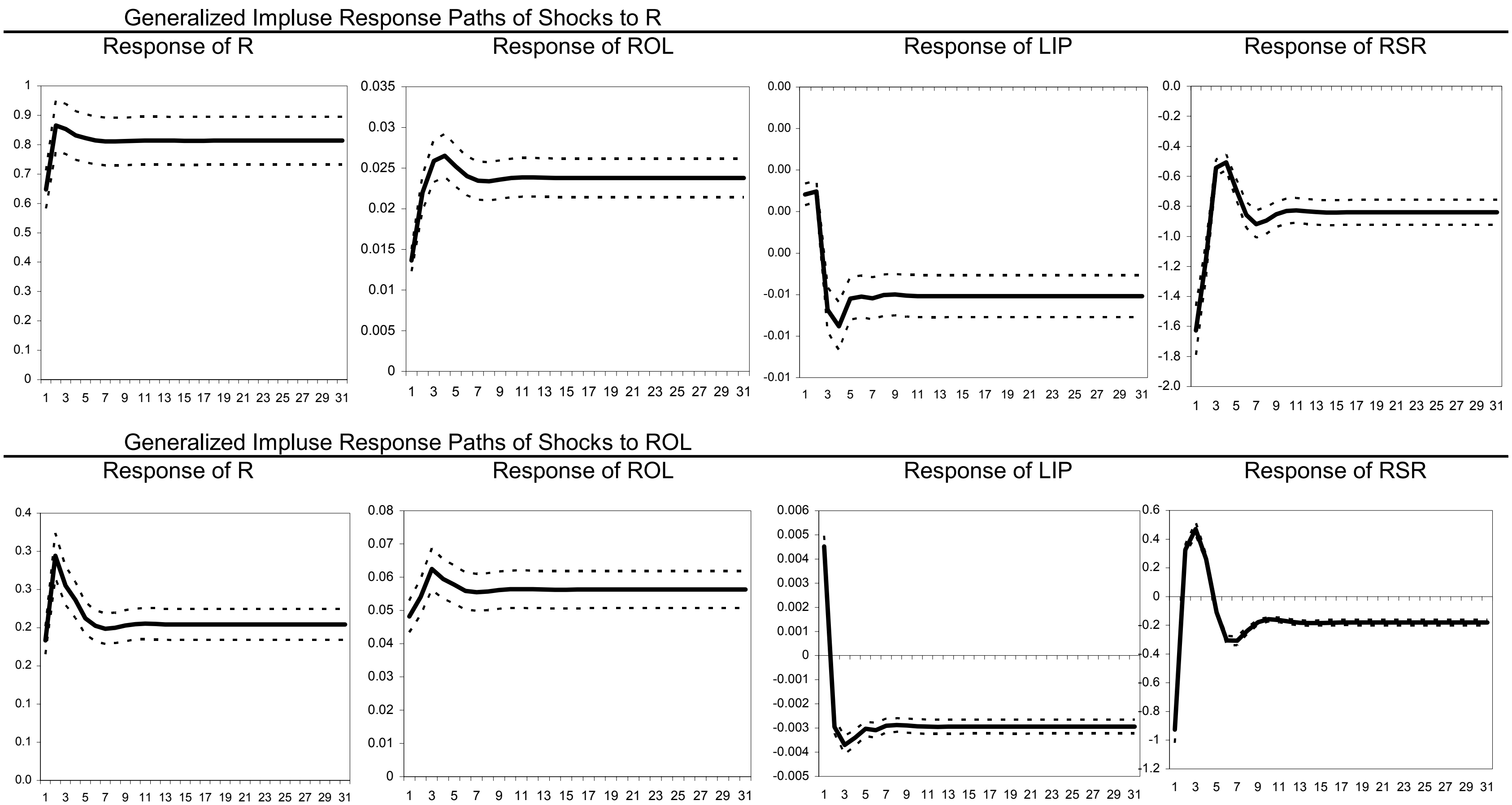
Notes: The horizontal axis refers to months after shock. The vertical axis refers to standard deviations. Charts provide generalized impulse response functions (GIRF) or reactionary profiles for the response of all the variables in our model when interest rates (R) and oil Volatility (ROLV) are shocked. Dashed lines represent single standard error bounds around the point estimates. GIRFs are based on a procedure developed by Koop, Pesaran and Potter (1996), Impulse response analysis in nonlinear multivariate models, Journal of Econometrics, 74, 119-147. These IRFs are generated after normalising (R=1) on interest rates (R). We compare these to results presented in Figure 3.

Figure 2



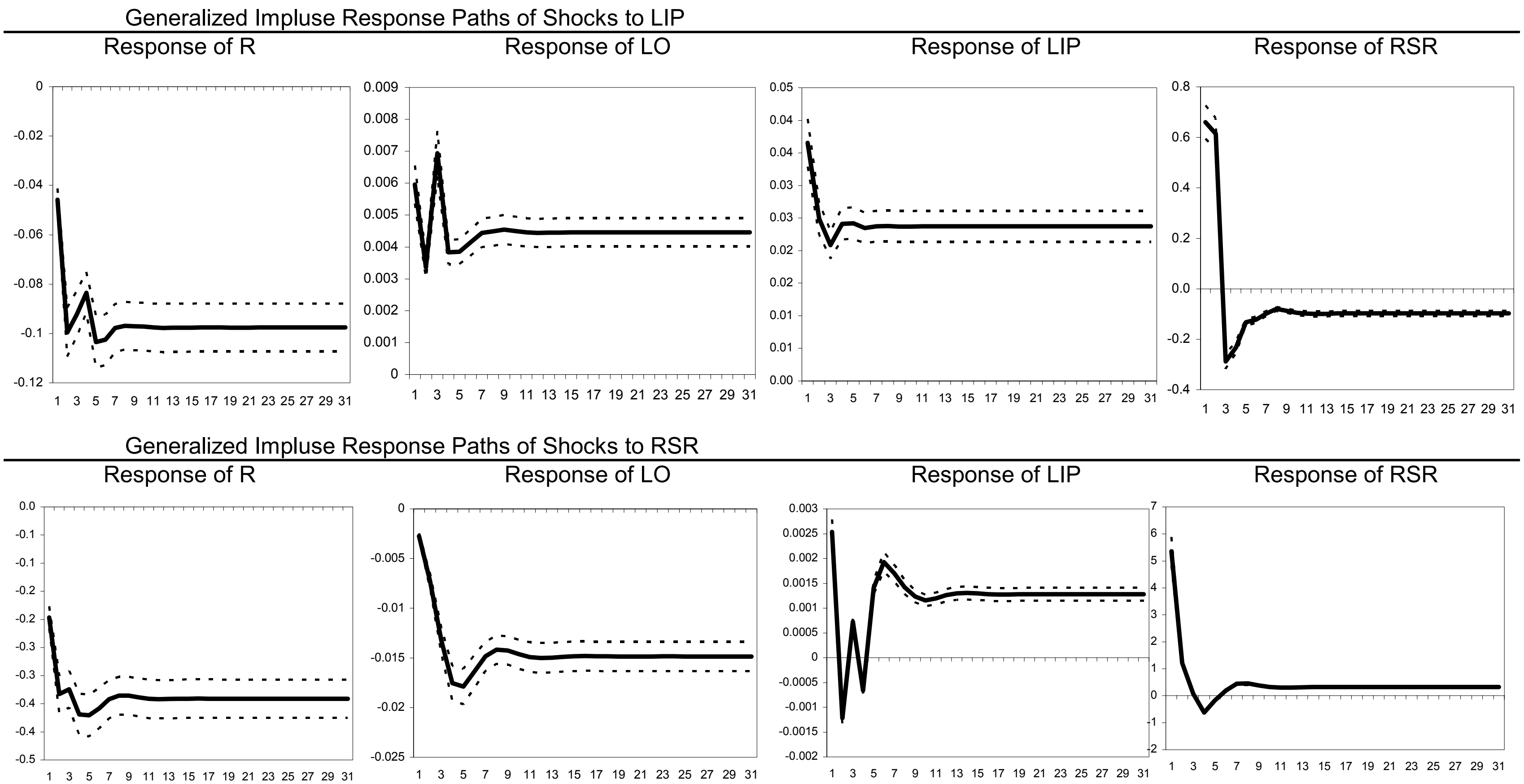
Notes: The horizontal axis refers to months after shock. The vertical axis refers to standard deviations. Charts provide generalized impulse response functions (GIRF) or reactionary profiles for the response of all the variables in our model when industrial production (IP) and real stock returns (RSR) are shocked. Dashed lines represent single standard error bounds around the point estimates. GIRFs are based on a procedure developed by Koop, Pesaran and Potter (1996), Impulse response analysis in nonlinear multivariate models, Journal of Econometrics, 74, 119-147. These IRFs are generated after normalising (R=1) on interest rates (R). We compare these to results presented in Figure 4.

Figure 3



Notes: The horizontal axis refers to months after shock. The vertical axis refers to standard deviations. Charts provide generalized impulse response functions (GIRF) or reactionary profiles for the response of all the variables in our model when interest rates (R) and oil prices (LO) are shocked. Dashed lines represent single standard error bounds around the point estimates. GIRFs are based on a procedure developed by Koop, Pesaran and Potter (1996), Impulse response analysis in nonlinear multivariate models, Journal of Econometrics, 74, 119-147. These IRFs are generated before normalising on interest rates (R). We compare these to results presented in Figure 1.

Figure 4



Notes: The horizontal axis refers to months after shock. The vertical axis refers to standard deviations. Charts provide generalized impulse response functions (GIRF) or reactionary profiles for the response of all the variables in our model when industrial production (IP) and real stock prices (RSR) are shocked. Dashed lines represent single standard error bounds around the point estimates. GIRFs are based on a procedure developed by Koop, Pesaran and Potter (1996), Impulse response analysis in nonlinear multivariate models, Journal of Econometrics, 74, 119-147. These IRFs are generated before normalising on interest rates (R). We compare these to results presented in Figure 2.

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