A VAR Model to Investigate the Volatility of Line-Pipe Steel Prices using Oil Price as a Referred Currency

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Abstract

The volatility of steel prices and international currency is an element that affects actual project costs. This situation can be mitigated by considering risk contingency as a fixed percentage of the total budget and/or by inputting an inflation factor into the cost estimation. These methods have not overcome the root problem, however, which is the volatility and declining trend of US dollar purchasing power as base currency. As a result, an alternative currency with more reliable value as a cost reference is needed as a comparison of using gold equivalency as an alternative currency for cost estimation (Asmoro, 2013).

This paper will explore the potential for oil as a referred currency to be used in investigating the price volatility of selected steels, i.e. hot rolled coil (HRC) and billet as main material components in oil and gas pipeline projects. The reliability of oil in terms of purchasing power compared to the US dollar and inflation will be discussed along with how oil equivalency can be applied for selected steels to develop an oil-based forecasting model using a statistical VAR (Vector Auto-Regressive) model. VAR model is widely used to analyse multivariate time series data such as domestic product and oil price.

These methods might change the paradigm for estimating the material costs of pipeline projects and could be developed for and applied to other projects since steels are heavily used in all major construction projects.

Keywords: Line-pipe steel prices, oil price, VAR model, multivariate time series data, US dollar, purchasing power, oil equivalency, cost estimation, pipeline project

1. Introduction

Project cost overruns have become a major issue for project management in recent years. The volatility of steel prices and international currencies are two of many elements that affect actual project costs. Project costs are also affected by the discrepancy between local currencies and the US dollar, the base currency. Furthermore, market volatility and quantitative actions by major governments have led to large fluctuations in the value of the US dollar in terms of purchasing power. Although the US dollar has been widely accepted and used as the international currency in most countries, using the US dollar as a basis for forecasting prices and cost estimation for future projects might be more risky now, thus it requires further evaluation.

1.1. Steel and Oil Prices

Steel is a cornerstone and key driver for the world's economy and is used as an essential material for key equipment in most oil and gas projects. Hence, oil price is intuitively considered as one of key drivers in determining the steel prices. The volatility of the steel price could therefore be result in project cost overruns. Figure 1 shows that the oil and steel price has shown a similar pattern of movement during the last decades.

It is also broadly known that when oil price goes down, number of executing oil gas projects will decrease, so that demand of steel for oil gas projects will also be reduced (IHS, 2016). Consequently, the steel prices will adjust accordingly based on new equilibrium of steel's supply and demand.

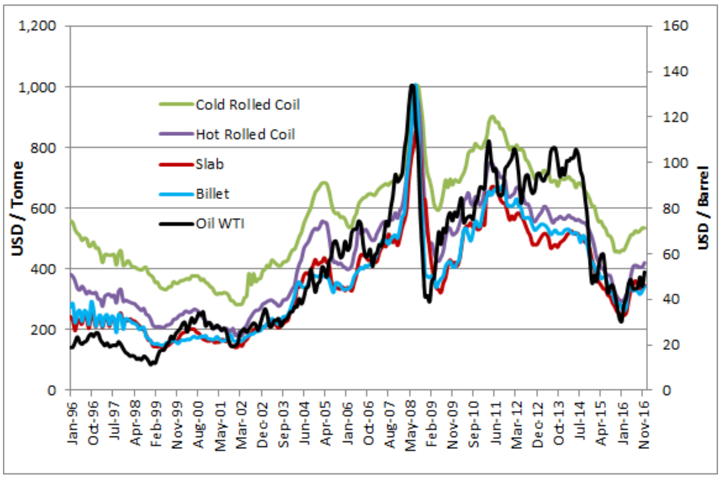

Figure 1 World Average Steel Prices and Oil Price WTI

1.2. Consumer Price Index (CPI) and Purchasing Power (PP)

CPI represents the changes in price of a selected basket of household goods and services. CPI was considered as a measurement to quantify the purchasing power (PP) of a certain amount of money by answering the question of how much income is required today to purchase the same bag of goods and services that were purchased in the base period (Australian Bureau of Statistics, 2009). Therefore, comparing PP of the US dollar and oil will give an alternative comparison against inflation.

Using USD 1,000 in year 1986 as the base value, Figure 2 shows that PP of USD 1,000 has decreased by 119% when benchmarked CPI (Inflation Data, 2017). Conversely, PP oil over the US dollar has increased by 65.1% according to the value of USD 1,000. In other words, USD 1,000 can buy 66.4 barrel oil in 1986 where the oil price was averagely USD 15 per barrel, while the same amount of money can only buy 23.1 barrel oil in 2016 where the oil price was averagely USD 43 per barrel. This shows that oil has maintained its value compared to the US dollar for many years.

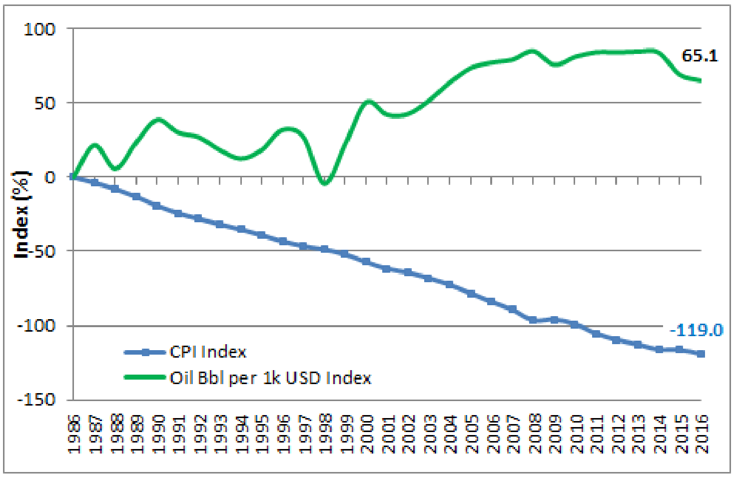

Figure 2 CPI US Dollar and PP Oil

In fact, the CPI released from the Government might not reflect the real inflation figure of the market. Therefore, applying the real inflation figure into PP USD will make the CPI look even worse compared to that shown in Figure 2. In addition, it shows the US dollar (along with other paper currencies) has eroded in terms of PP oil over years. As a result, any future cost estimation based on the US Dollar is not reliable, and runs a high risk of cost overrun. Conversely, the PP of oil over the US dollar has been seen more reliable which makes it superior compared to the US dollar for future project cost estimation.

2. Pipeline Project Cost Component

The total pipeline project cost represents the sum of the four major categories: material, labor, right-of-way (ROW) and others. Labor and material costs make up around 80 percent of the total cost of onshore pipelines and around 84 percent of the total cost of offshore pipelines, as shown in Figure 3.

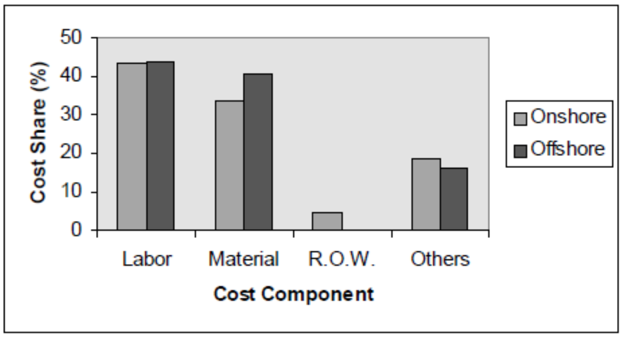

Figure 3 Cost Components in Pipeline Projects (Zhao, 2000)

Offshore pipelines use seamless pipelines as the main component, whereas onshore pipelines use welded pipeline. Based on the price in 2016 (Steel on the net, 2017a & 2018b), the proportion of cost components for seamless and welded pipeline using data in 2016 is shown in tables below. Table 1 show that billet is about 62.5% of the cost of seamless pipe, and HRC is about 82.5% of the cost of welded line pipe.

Table 1 Proportion of Pipe Mill Conversion Costs for Pipe

Item $/unit	Line Pipe Cost ($)	Portion in Line Pipe Cost
Typical Seamless Pipe		
Billet	298.38	62.5%
Billet transport	5.43	1.1%
Manpower	50	10.5%
Energy	13.13	2.8%
Electricity	7.7	1.6%
Consumables	75	15.7%
Yield loss	12.86	2.7%
Scrap credit	-12.58	-2.6%
Depreciation & other	20	4.2%
Packaging	2.5	0.5%
Sales, G&A costs	5	1.0%
Pipe cost $/t (Seamless Pipe)	**477**	**100.0%**

Item $/unit	Line Pipe Cost ($)	Portion in Line Pipe Cost
Typical Welded Pipe		
Hot rolled coil	339.63	82.5%
HRC transport	5.23	1.3%
Manpower	35	8.5%
Electricity	8.4	2.0%
Welding consumables	2.5	0.6%
Other consumables	7.5	1.8%
Yield loss	2.64	0.6%
Scrap credit	-6.66	-1.6%
Depreciation & other	10	2.4%
Packaging	2.5	0.6%
Sales, G&A costs	5	1.2%
Pipe cost $/t (Welded Pipe)	**412**	**100.0%**

Referring to the tables above, billet and HRC steel are the main components of line pipe material, where material contributes 25-35% to the cost of pipeline projects. It actually varies depending upon the steel prices, in which material contributed 35-45% to the cost of projects in 2012 (Asmoro, 2013). Therefore, investigating the price volatility and forecasting the price of such steels is very important for improving project cost estimations.

3. Model Development Using Oil Value

Steel is a primary material for pipeline projects, thus the cost of steel must be monitored in order to make a better project cost estimation. Using the value of oil has proved to be the more reliable and sustainable way to understand and develop the forecast model for steel prices, i.e. billet and hot rolled coil (HRC). Statistic-based approach using software Eviews will be used to analyse the time series data of billet, HRC and steel prices, as well as their further relationship.

3.1. Theory Overview

VAR (Vector Auto-Regressive) model is built to analyse multivariate time series data. It is chosen to understand the volatility of line-pipe steel and oil price as well as investigating their relationship. A VAR is a systems regression model of multiple autoregressive equations that fit with requirement of analysing the time series data (the number of time periods of the data), i.e. HRC price, billet price and oil price. The simplest is a bivariate VAR which is produced from two variables as follows (and it can be easily generalized to more than two variables).

$$
\begin{aligned}
y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \dots + \beta_{1k} y_{1t-k} \\
+ \alpha_{11} y_{2t-1} + \dots + \alpha_{1k} y_{2t-k} + u_{1t} \\
y_{2t} = \beta_{20} + \beta_{21} y_{1t-1} + \dots + \beta_{2k} y_{1t-k} \\
+ \alpha_{21} y_{2t-1} + \dots + \alpha_{2k} y_{2t-k} + u_{2t}
\end{aligned}
$$

VAR modelling has some advantages, such as possibility of having all variables are endogenous and allowing the variables to depend on not just their own lags. However, it has also disadvantages, such as a-theoretical issue (not relying on a theory or a common knowledge/practice), data stationarity issue (two variables that trends over time may look correlated even if they are totally unrelated), appropriate lag lengths, and possibility to have too many parameters/variables (Brooks, 2008).

3.2. Data Gathering and Pre-Treatment

Data are taken from January 1986 until December 2016 using monthly average price because oil price tends to have seasonal monthly trend rather than daily trend. Spot FOB Price of crude oil WTI is used (EIA, 2017), while steel prices describe average monthly world export FOB prices which originate from national customs statistics of larger exporting countries (Steel on the net, 2017).

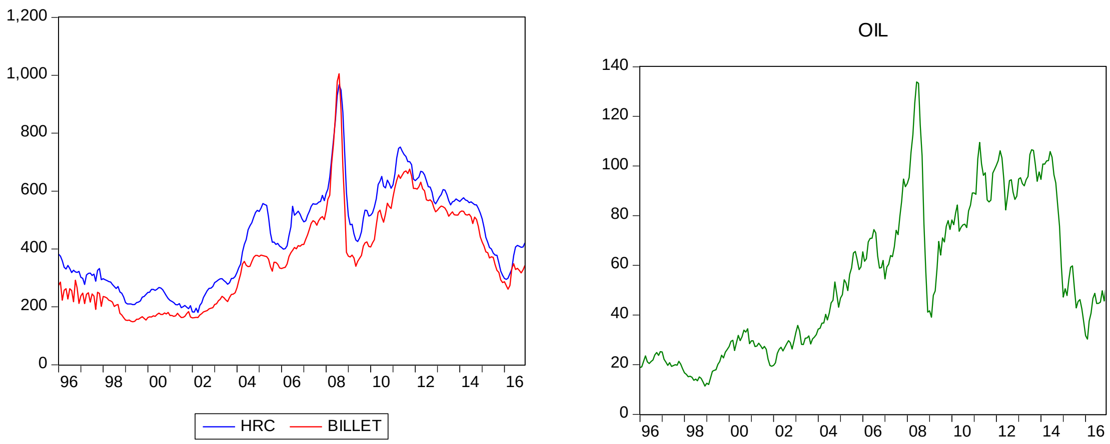

Figure 4 HRC, Billet and Oil Price (1996 – 2016)

It looks both graphs of HRC, billet and oil prices likely move together in the same pattern, and will be considered in testing stationarity and constructing the model. Hence, unit root test is required to test stationarity because non-stationarity data can lead to spurious regressions; two variables that trends over time looks correlated even if they are totally unrelated (Brooks, 2008). Hypothesis statistical test is as follows.

H0: a unit root exists (non-stationary data), and
Hα: stationary data

Based on t-statistic of Augmented Dickey-Fuller (ADF) test with lag 12 (monthly basis) for three time series data (HRC, billet, oil), null cannot statistically be rejected. Taking HRC price as an example, summary of ADF t-statistic is described below.

Null Hypothesis: HRC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic based on SIC, MAXLAG=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.152556	0.0967
Test critical values:	1% level	-3.995189	
	5% level	-3.427902	
	10% level	-3.137310	

*MacKinnon (1996) one-sided p-values.

As a result, the null cannot be rejected at 10% significance level/SL (t-statistic -3.152 greater than 10% critical values -3.137), even though the null can be rejected at 1% and 5% SL (t-statistic -3.152 smaller than 1% and 5% critical values/CV). This confirms that there is unit root in the raw data, or the data is non-stationary at level (raw) condition. Therefore, first difference (delta/growth/return) is taken for HRC price (DHRC) with summary result of ADF testing as follows.

Null Hypothesis: DHRC has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.888361	0.0000
Test critical values:	1% level	-3.456514	
	5% level	-2.872950	
	10% level	-2.572925	

*MacKinnon (1996) one-sided p-values.

It can then be concluded that null can statistically be rejected at any SL (t-statistic -6.888 greater than 1%, 5% and 10% CV), so that DHRC has no unit root. In other words, the data (DHRC) is stationary at first difference condition. Hence, HRC, billet and oil price data should be converted to first difference (delta) in constructing the model to make the data stationary. Although they likely have a similar pattern, the changes in oil price may explain steel price need to be tested afterward.

3.3. VAR Model

Since it is the objective to see whether the steel prices are explained by the oil price, we arrange the equation in VAR model in order: steel price (dhrc or dbillet), then oil price (doil). This arrangement sometimes matters, but in this case it doesn't even when using three variables straight in one VAR model (dhrc doil dbillet). Eviews calculation using two and three variables are shown below, set using VAR lag 3 taken from a 3-month lag assumption.

Table 2 VAR Model of HRC, Billet and Oil Price at First Difference Condition

Vector Autoregression Estimates
Date: 05/09/17 Time: 21:24
Sample (adjusted): 1996M05 2016M12
Included observations: 248 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DHRC	DOIL	DBILLET
DHRC(-1)	0.048262	0.205117	0.259594
	(0.07906)	(0.17252)	(0.11815)
	[0.61046]	[1.18896]	[2.19709]
DHRC(-2)	-0.016148	-0.264833	-0.144822
	(0.07573)	(0.16525)	(0.11317)
	[-0.21323]	[-1.60264]	[-1.27963]
DHRC(-3)	0.014969	-0.075514	-0.286633
	(0.06597)	(0.14397)	(0.09860)
	[0.22689]	[-0.52453]	[-2.90705]
DOIL(-1)	0.065085	0.226454	0.153170
	(0.03090)	(0.06742)	(0.04618)
	[2.10645]	[3.35863]	[3.31697]
DOIL(-2)	0.056408	0.058182	0.123183
	(0.03179)	(0.06937)	(0.04751)
	[1.77454]	[0.83878]	[2.59294]
DOIL(-3)	0.053446	-0.094751	0.067304
	(0.03205)	(0.06995)	(0.04791)
	[1.66737]	[-1.35459]	[1.40493]
DBILLET(-1)	0.229808	0.024070	-0.041254
	(0.04994)	(0.10898)	(0.07464)
	[4.60144]	[0.22086]	[-0.55271]
DBILLET(-2)	0.118302	0.175232	-0.156981
	(0.04992)	(0.10893)	(0.07460)
	[2.36998]	[1.60871]	[-2.10425]
DBILLET(-3)	0.120336	-0.020205	0.445979
	(0.04935)	(0.10769)	(0.07375)
	[2.43847]	[-0.18762]	[6.04693]
C	-0.021643	0.251786	-0.021150
	(0.24575)	(0.53628)	(0.36728)
	[-0.08807]	[0.46951]	[-0.05758]
R-squared	0.371039	0.109863	0.326820
Adj. R-squared	0.347255	0.076203	0.301364
Sum sq. resids	3551.206	16910.30	7931.917
S.E. equation	3.862775	8.429215	5.772987
F-statistic	15.60021	3.263853	12.83844
Log likelihood	-681.9369	-875.4557	-781.5842
Akaike AIC	5.580136	7.140771	6.383743
Schwarz SC	5.721807	7.282442	6.525414
Mean dependent	0.090352	0.320027	0.115401
S.D. dependent	4.781098	8.769984	6.906771

Vector Autoregression Estimates
Date: 05/09/17 Time: 21:26
Sample (adjusted): 1996M05 2016M12
Included observations: 248 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DHRC	DOIL
DHRC(-1)	0.264471	0.287839
	(0.06522)	(0.13722)
	[4.05496]	[2.09759]
DHRC(-2)	0.090637	-0.158661
	(0.06582)	(0.13848)
	[1.37706]	[-1.14572]
DHRC(-3)	0.041260	-0.120131
	(0.06226)	(0.13098)
	[0.66275]	[-0.91714]
DOIL(-1)	0.086113	0.216081
	(0.03149)	(0.06625)
	[2.73470]	[3.26153]
DOIL(-2)	0.084528	0.072939
	(0.03216)	(0.06767)
	[2.62798]	[1.07782]
DOIL(-3)	0.076676	-0.079316
	(0.03239)	(0.06815)
	[2.36720]	[-1.16386]
C	-0.013025	0.247332
	(0.25513)	(0.53678)
	[-0.05105]	[0.46077]
R-squared	0.313529	0.096865
Adj. R-squared	0.296438	0.074380
Sum sq. resids	3875.916	17157.23
S.E. equation	4.010317	8.437525
F-statistic	18.34515	4.308040
Log likelihood	-692.7862	-877.2533
Akaike AIC	5.643437	7.131075
Schwarz SC	5.742607	7.230244
Mean dependent	0.090352	0.320027
S.D. dependent	4.781098	8.769984

Based on comparison of two tables above, three parameters will be chosen, because the three-parameter model has higher adjusted r-squared than the other. In addition, it is more plausible to explain that, beside of oil price, the price of particular steel such as HRC is also affected by the other steel price such as billet.

3.4. Lag Criteria Test

As mentioned above that one of disadvantages of VAR model is to determine the optimal lag length, in which usually theory has little to say about the appropriate one. Using a tool in Eviews to show the lag order criteria for the three-variable VAR model resulting in as shown below:

VAR Lag Order Selection Criteria
Endogenous variables: DHRC DOIL DBILLET
Exogenous variables: C
Date: 05/09/17 Time: 22:03
Sample: 1996M01 2016M12
Included observations: 239

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2264.402	NA	34907.01	18.97407	19.01771	18.99166
1	-2210.186	106.6178	23910.51	18.59570	18.77025*	18.66603
2	-2188.938	41.25024	21582.22	18.49321	18.79867	18.61630
3	-2169.513	37.22540	19781.04	18.40596	18.84234	18.58181*
4	-2157.078	23.51715	19223.92*	18.37722*	18.94451	18.60582
5	-2153.319	7.013344	20091.53	18.42108	19.11928	18.70244
6	-2145.733	13.96753	20338.80	18.43291	19.26202	18.76702
7	-2143.171	4.650733	21476.76	18.48679	19.44682	18.87365
8	-2134.808	14.97796	21607.30	18.49211	19.58305	18.93173
9	-2132.109	4.764329	22798.70	18.54485	19.76670	19.03722
10	-2127.075	8.763289	23595.42	18.57803	19.93080	19.12316
11	-2124.008	5.261480	24831.69	18.62768	20.11136	19.22556
12	-2106.303	29.92745*	23126.49	18.55484	20.16943	19.20547

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Referring to the table, there are several options of selecting lag length, i.e. lag 1, 3, 4 or 12. In this case, lag 4 is selected because it is from two criterions (FPE and AIC), and may intuitively explain that the price of a particular steel is statistically influenced by oil price and other steel price(s) in 4 months before. Meanwhile, lag 1, 3, 4 and 12 months of oil price and other steel price(s) might jointly explain today's such particular steel price that is plausible in practices. Therefore, a 4-lag VAR model will be used for further analysis.

3.5. Granger Causality

Furthermore, granger causality test is performed to see whether changes in variable 1 cause changes in other variables (Brooks, 2008). Granger causality uses null and alpha hypothesis as follows:

H0: no causality
Hα: causality exists

Using 4-lag VAR model with DHRC as dependant variable, Eviews result is shown below. It shows that the null hypothesis cannot fully be rejected since prob-value (0.0102) only exceeds SL at 1% (0.01), or the null hypothesis (no causality) can be rejected implying that there is causality at SL 5% (0.05) and 10% (0.1). Thus, based on granger test, oil price in the 4-month past causes today's hrc and billet prices at 5% and 10% significance level.

From granger tests, it can also be revealed statistically that oil price movement (doil) influences the movement of steel prices (dhrc and dbillet), not conversely. Meanwhile, HRC price and billet price are more inter-correlated statistically in their price movement. These results are plausible and help explain the common knowledge/practices of relationship between oil price and steel prices.

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 05/10/17 Time: 08:14
Sample: 1996M01 2016M12
Included observations: 247

Dependent variable: DHRC

Excluded	Chi-sq	df	Prob.
DOIL	13.23200	4	0.0102
DBILLET	26.45827	4	0.0000
All	54.30463	8	0.0000

Dependent variable: DOIL

Excluded	Chi-sq	df	Prob.
DHRC	4.469408	4	0.3462
DBILLET	2.048430	4	0.7269
All	9.416816	8	0.3084

Dependent variable: DBILLET

Excluded	Chi-sq	df	Prob.
DHRC	7.720265	4	0.1024
DOIL	23.69582	4	0.0001
All	32.20240	8	0.0001

4. Conclusion

Steel is key driver for the world's economy, and widely used as an essential material for key equipment in most oil and gas projects. Therefore, the volatility of steel prices considerably affects the actual project costs. In fact, steel material contributes 25-45% to the cost of pipeline projects which varies depending upon the steel prices (Asmoro, 2013). Moreover, the volatility and declining trend of US dollar purchasing power as base currency in most of estimation methods has affected the actual project costs.

Using VAR model that fits the multivariate time series data analysis, this paper has explored the potential for oil as a referred currency to be used in investigating the price volatility of selected steels, i.e. hot rolled coil (HRC) and billet. After developing a VAR model and doing granger causality test, it is concluded that oil price in the 4-month past causes today's hrc and billet prices at 5% and 10% significance level. In addition, prices of HRC and billet steel are statistically inter-correlated in their price movement. The VAR model of HRC price at first difference level (delta/growth) using 4-month lag is then presented as follows.

DHRC = 0.0363*DHRC(-1) + 0.0498*DHRC(-2) + 0.1239*DHRC(-3) - 0.0264*DHRC(-4) + 0.0586*DOIL(-1) + 0.0592*DOIL(-2) + 0.0494*DOIL(-3) + 0.0404*DOIL(-4) + 0.2737*DBILLET(-1) + 0.05599*DBILLET(-2) + 0.0687*DBILLET(-3) - 0.1322*DBILLET(-4) - 0.00696

DBILLET = 0.2198*DHRC(-1) - 0.0246*DHRC(-2) - 0.0925*DHRC(-3) + 0.1658*DHRC(-4) + 0.1275*DOIL(-1) + 0.1395*DOIL(-2) + 0.0629*DOIL(-3) - 0.0018*DOIL(-4) + 0.097*DBILLET(-1) - 0.2722*DBILLET(-2) + 0.3627*DBILLET(-3) - 0.344*DBILLET(-4) + 0.02295

These results help explain the common knowledge/practices of relationship between oil price and steel prices. Then, these methods could be elaborated for estimating the material costs of pipeline projects using historical oil prices. It could also be developed for and applied to other projects since steels are heavily used in all major construction projects.

Note

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