The impact of the Oil price on Inflation rate in Canada

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Introduction

In this analysis we want to build a univariate ARMA model and multivariate VAR model to check if change in Oil price would affect CPI inflation in Canada. Our hypothesis is that change in Oil price positively and significantly affects CPI inflation in Canada. To test this hypothesis, we will build two models, and then interpret the results. We will also generate an Impulse Response Function to see whether CPI inflation is responsive to the shocks coming from the Oil price and vice versa. Finally, we will look at the results obtained from both models and discuss if our empirical results are aligned with our hypothesis.

Data Description

In order to build ARMA and VAR models we will use FRED online database where we can get data on CPI for Canada, Global price of Brent Crude Oil and data on Canadian Dollars to U.S. Dollar Spot Exchange Rate. Once we download all the necessary data, we make sure that they are all in time series form and if necessary, seasonally adjust them. We also adjust the frequency of all data to monthly frequency. Finally, we shorten all-time series to the same period. In our case all data start from **1990-01-01** and end in **2021-09-01.** We also need to use exchange rate data to convert oil price from USD**$** to CA$.

Unit Root Test

First, we plot our CPI and Oil time series, and we see that series in levels are likely to be non-stationary for CPI and Oil *(figure 1)*. Then we take the first difference of both time series to get their growth rates. When we plot these growth rates, we can see that upward trend disappears and series in growth rate is more stationary (see *figure 2)*. In order to check whether the data is non-stationary, we run a unit root test known as **Augmented Dicky Fuller Test** on the original CPI time series. Here we test the Null hypothesis Ho= *CPI is not trend stationary (it has a unit root) versus Ha=CPI* is *trend stationary*. In the result we can see that we have a very big *p-value* which is equal to 0.24 and therefore we fail to reject the Null which means that our CPI is not trend stationary. We can see it also visually in *the figure (1)*. In order to make CPI stationary, we take the first difference of the series and again run ADF test. Now, we get a very small p-*value* which is equal to 8.045424e-33 which means that we reject the Null. Now, our data is trend stationary. We do the same procedure with the Oil price and move on to build our ARMA model.

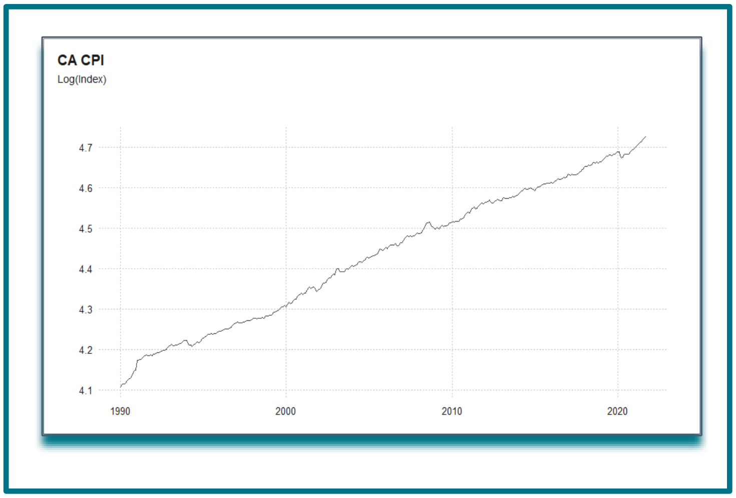


Figure (1)

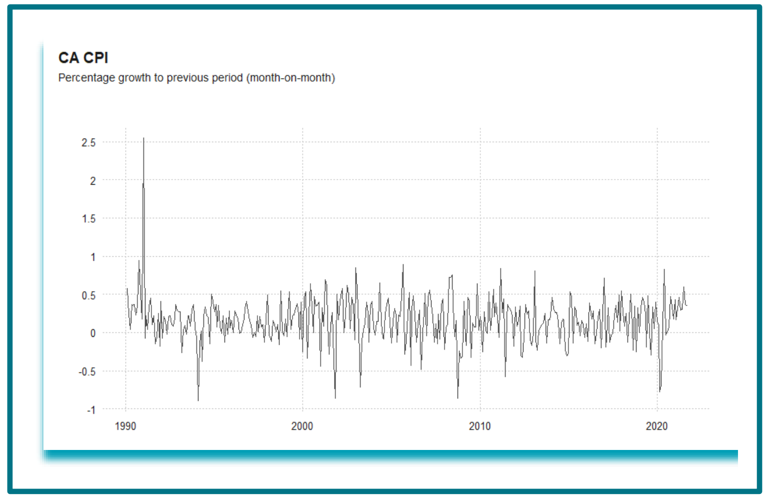


Figure (2)

Model Specification

In order to build our models, we need to select the lag order based on **information criteria** We select the number of lags that produce the smallest information criteria. According to AIC, we should favor an ARMA (0,1) and with BIC favor an ARMA (0,0). We proceed to estimate ARMA (0,1) based on AIC.

ARMA model

ARMA (0,1) model without Oil price:

First, we build an **ARMA (0,1)** model without including Oil price and we get the following results:

```
> summary(Model)
Series: difference_CPI
ARIMA(0,0,1) with non-zero mean

Coefficients:
         ma1     mean
      0.0918   0.0016
s.e.  0.0532   0.0002


t-stat     1.72        8.0
```

Figure (3)

Given these results in *figure (3)* we can see that MA (1) coefficient is only marginally significant at **10%**. Because t-statistics for MA(1) is 0.0918/0.0532 = **1.72** and the critical value for **10%** significance level is **1.64,** which means that MA (1) is significant at 10% level.

However, the coefficient for constant is highly statistically significant at **1%** level. Because t-statistics for constant is 0.0016/ 0.0002= 8.0 and the critical value for **1%** significance level is **2.58** which means that constant is statistically significant at 1% level. When we plot the residuals *figure (4)* we can see in ACF there is no sign of autocorrelation, and it seems MA (1) model fits our data well. We can also run **Box-Ljung test** and can see there is no significant autocorrelation. This model could be used to build a forecasting model later.

ARMAX (0,1) model with Oil price as exogenous regressor:

In this model we will incorporate **Oil price** as exogenous regressor and estimate an **ARMAX (0,1)** model and we get the following results:

```
> summary(ModelX)
Series: difference_CPI
Regression with ARIMA(0,0,1) errors

Coefficients:
         ma1   intercept   value
       0.036      0.0016  0.0095
s.e.   0.053      0.0002  0.0014


 t-stat   0.68       8.0       6.8
```

Figure (5)

Given these results in *figure (5)* we can see that for MA (1) and intercept we get almost the same results with similar marginal and statistical significance as in the previous model.

For Oil price, we can see that it's coefficient is highly statistically significant at 1% since the t-statistics is equal to 0.0095/0.0014= **6.8.** When we took first differences from CPI and OIL price, we transformed their unit value to a **%** value.

We can see that Oil price has a positive effect on CPI inflation which means that if Oil price would increase by **10%**, the CPI inflation would increase by **0.095%.** When we plot the residuals, we see similar results as in *figure (4)* where we see no sign of autocorrelation in the residuals. The **Box-Ljung test** also yields that there is no significant autocorrelation.

VAR model

In order to build our VAR multivariate model, we will do all the steps that we did in our previous ARMA and ARMAX models to prepare our time series for the process. Once we have a covariance stationary data, we will create a data set "**y**" and then we will move to select the optimal lag length and, in our case, AIC suggests estimating our model with lag =1. In this VAR model we will estimate the following two equations.

First equation: $CPI_t = CPI_{t-1} + Oil_{t-1} + \varepsilon_t$

Where CPI is dependent from its own 1 period lagged value, plus from 1 period lagged value of the Oil price and the error term.

Second equation: $Oil_t = CPI_{t-1} + Oil_{t-1} + \varepsilon_t$

Where Oil price is dependent from 1 period lagged value of the CPI, plus from its own 1 period lagged value and the error term.

We build these models and get the following results:

Figure (6)

	Dependent variable: y	
	(1)	(2)
dif_CPI.l1	0.174***	-4.034*
	(0.063)	(2.062)
dif_oil.l1	0.010***	0.371***
	(0.002)	(0.065)
Observations	259	259
R2	0.168	0.113
Adjusted R2	0.161	0.107
Residual Std. Error (df = 257)	0.003	0.103
F Statistic (df = 2; 257)	25.917***	16.450***
Note:	*p<0.1; **p<0.05; ***p<0.01	

First, let us look at our 1st model's result in *figure (6)*

We can see that the coefficients of both variables have a positive effect on CPI inflation rate. Plus, both are highly statistically significant at 1% level. When CPI in the previous period increases by **1%**, the current CPI inflation rate will increase by **0.17%.** Similarly, if Oil price in the previous period increases by **1%** the current

Now let us look at the second model. We can see that that Oil price's coefficient has a positive effect on the dependent variable, and it is highly statistically significant at 1% level whereas CPI has a negative effect, and it is marginally significant at 10% level. If, Oil price increased in the previous period by **1%** than in current period the Oil price will increase by **0.371%.** This is persistent, because if oil price has increased in previous month than it is very likely that it will continue to increase in the current month as well.

We can check if our model is stable using **root's** function. We except to get eigenvalues which is less than 1. When we run the test indeed, we get the results showing eigen values = to.3210543 and 0.3210543. And it means that our VAR model seems to be a stable model. Now this model can be used to build a forecasting model (fan chart in appendix for variable CPI (figure *(7)*). For example, in our case we build a VAR forecasting model for 36 months or in other words for 3 years.

Granger Causality test:

With VAR, we can also run a **Granger Causality test** to see whether Oil price causes CPI inflation or CPI inflation causes the Oil price.

We test the null hypothesis stating Ho: CPI does not Granger cause the OIL price. And our p-value is equal to 5.1 % therefore we fail to reject the null therefore, CPI inflation does not cause the Oil price.

Now we test the null stating Ho: Oil price does not Granger cause the CPI inflation. Since we obtained p-value = 1.785e-06 we reject the null therefore, the Oil price granger causes the CPI inflation.

Impulse Response Function

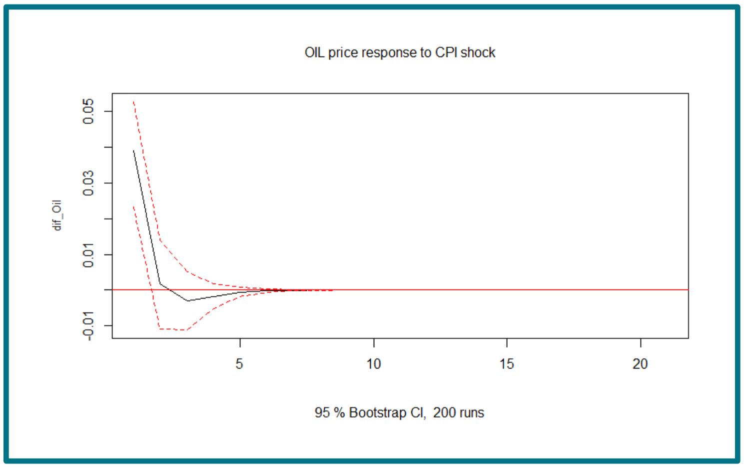


Figure (8)

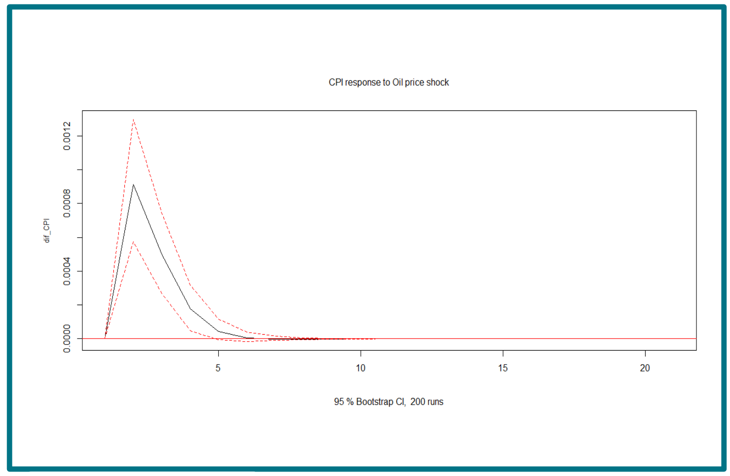


Figure (9)

We can also test whether one variable is responsive to the shock coming from another variable. For example, we can test the reaction of Oil price when impulse comes from CPI and similarly, we can test CPI inflation when the shock comes from the Oil price.

Oil price response to CPI shock (*figure 8*)**:** the initial one standard deviation shock of CPI on Oil price happens in the first period therefore it comes with a lag of one period. But this shock quickly dies out and already at lag 2, the impact starts to converge towards zero and at period 5 and afterwards, it is equal to zero.

CPI price response to Oil price shock: (*figure 9):* the initial one standard deviation shock of Oil price on CPI happens in the first period therefore it comes with a lag of one period. And this shock reaches its maximum at lag 2 and it converges to zero at lag 6 and afterwards.

Conclusion

In this analysis we tried to test whether Oil price has a positive effect on Inflation rate in Canada. With help of ARMA, VAR models and with various tools such as Impulse Response Function we could conclude that indeed Oil price has a positive effect on CPI inflation. When we build model estimation with ARMA, ARMAX and Var we tested whether our models fit the data well and all the tests showed that they do fit the data well. However, we could keep in mind when It comes to building a forecasting model with VAR models , the estimation error associated with it and coefficients of are often quite high and this is why univariate models actually often perform well for forecasting and VARs sometimes have trouble beating up simple univariate processes.

Appendix

Figure (4)

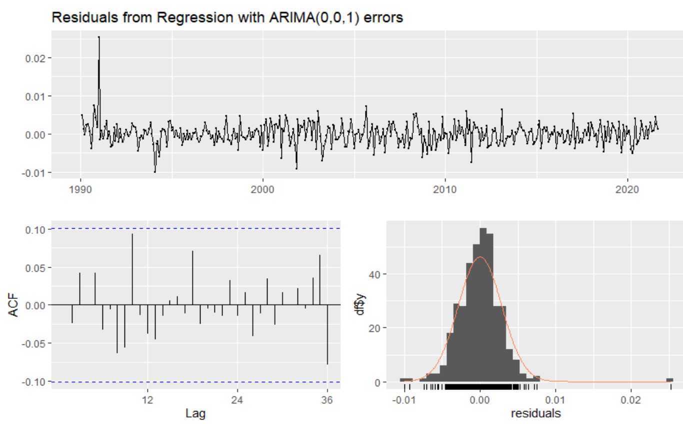
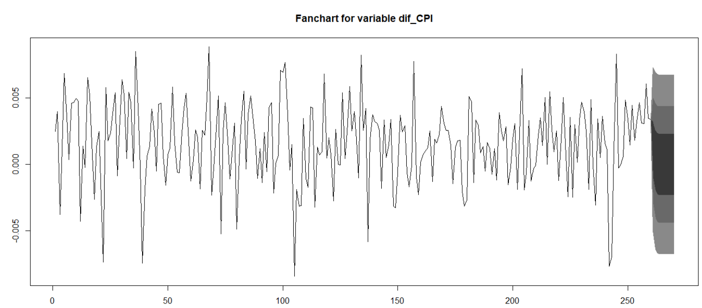


Figure (7)



References

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