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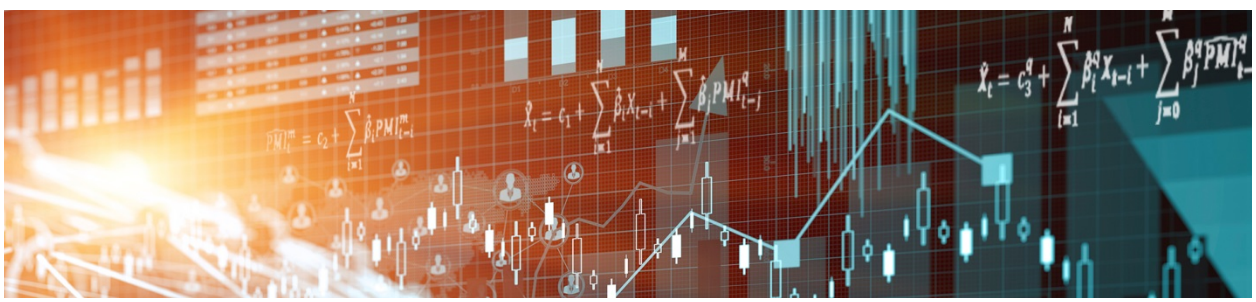

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Crude Oil Prices and Fixed-Asset Cash Spending in the Oil and Gas Industry: Findings from VAR Models

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Abstract

This note investigates the relationship between crude oil prices and investment in the energy sector. We employ a set of vector autoregression (VAR) models (unconstrained VAR, vector error-correction and Bayesian VAR) to formalize the relationship between the West Texas Intermediate (WTI) benchmark and fixed-asset cash spending in the oil and gas extraction and support activities sector of the Canadian economy. Using data from Statistics Canada's Quarterly Financial Statistics for the period 1999Q2–2015Q4, we report that, for example, an average WTI of $50 in 2016 would yield a 27.1 to 31.4 per cent (year over year) decline in fixed-asset cash spending in the sector relative to 2015.

JEL classification: Q43, Q47, E22, E27
Bank classification: Econometric and statistical methods; Domestic demand and components

Résumé

Cette note examine la relation entre les prix du pétrole brut et les investissements dans le secteur de l'énergie. Nous utilisons un groupe de modèles vectoriels autorégressifs (VAR) (modèle VAR non contraint, modèle vectoriel à correction d'erreurs et modèle VAR bayésien) pour formaliser la relation entre le prix du brut de référence West Texas Intermediate (WTI) et les investissements en immobilisations dans le secteur de l'extraction gazière et pétrolière et les activités de soutien au sein de l'économie canadienne. En nous fondant sur les données des *Statistiques financières trimestrielles des entreprises* publiées par Statistique Canada pour la période 1999T2-2015T4, nous constatons, par exemple, qu'un prix moyen du baril WTI à 50 $ induirait un recul de 27,1 % à 31,4 % (en glissement annuel) des investissements en immobilisations par rapport à 2015.

Classification JEL : Q43, Q47, E22, E27
Classification de la Banque : Méthodes économétriques et statistiques; Demande intérieure et composantes

Introduction

While it is certain that the current slump in oil prices has slowed investment in the energy sector, the magnitude of the impact remains an open question. The existing literature offers little guidance for understanding the extent to which investment in the sector is sensitive to fluctuations in crude oil benchmarks. Although the analysis of the macroeconomic impact of oil price shocks has long been the subject of a vast and growing literature (e.g., Berument, Ceylan and Dogan 2010; Blanchard and Gali 2007; Blanchard and Riggi 2011; Filis 2010; Hamilton 2011; Kilian 2009; and Schubert and Turnovsky 2011), very few studies have focused on the impact of oil price changes at an industry level. Among the few are Bohi (1990), Lee and Ni (2002), and Yoon and Ratti (2011) who carried out industry-level analyses focused on output in manufacturing industries. The second somewhat relevant stream of literature deals with the changes in valuation, driven by energy prices, of oil and gas firms. Sadorsky (2001) reports that an increase in crude prices leads to a hike in the return to Canadian oil and gas stock prices. Similarly, Boyer and Filion (2007) find that the returns for Canadian energy stocks are positively associated with the appreciation of crude oil and natural gas prices. That being said, none of the reviewed studies directly measure the sign and strength of the relationship between crude oil prices and investment for firms in the Canadian oil patch.

Given the scarcity of parameter estimates in the literature, we first proceed with building a set of VAR models. We then discuss our data and empirical approach and analyze the out-of-sample forecasting performance of the estimated systems. These models are part of a large set of tools, including consultations with energy sector firms and the tracking of publicly released capital expenditure plans used by the Bank of Canada to analyze and forecast investment in the oil and gas sector. In the final section, we provide a range of estimates for changes in fixed-asset cash spending in the oil and gas industry under various scenarios of WTI evolution in 2015 and 2016.

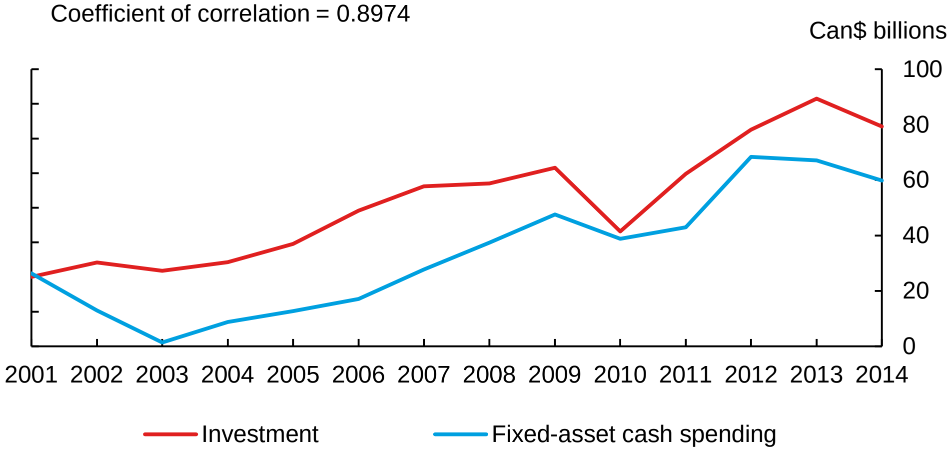
Data and Estimation Framework

Investment and investment intentions are reported annually by Statistics Canada (Table 029-0005: Capital and repair expenditures, by sector and province). The low frequency of the data prevents its real-time use in modelling and forecasting. Similarly, the recently established Quarterly Survey of Capital Expenditures – Oil and Gas Activities (Table 029-0052) has insufficient data points for regression analysis at this point, with the first round of the survey in the first quarter of 2013. Unfortunately, no other quarterly, or more frequent, information about capital expenditures by sector or industry in Canada is publicly available.

An alternative source of related and more frequent information is available through the Quarterly Financial Statistics for Enterprises summarized by Statistics Canada. These data are based on a survey and represent the activities of all corporations in Canada, except those that are government-controlled or not-for-profit. Under the survey's section on total applications of available cash, firms are asked about fixed-asset cash spending, which is usually derived from cash-flow statements. As opposed to capital expenditures, the construct of fixed-asset cash spending does not capture non-cash capital expenditure transactions. For instance, depreciation, amortization and other non-cash investment spending would not be reflected as cash applied to fixed assets. The data for the period 1999Q2–2015Q4 are available through CANSIM at the national level for 22 industry groupings (Tables 187-0001 and 187-0002).

Chart 1: Investment and fixed-asset cash spending for oil and gas extraction

Coefficient of correlation = 0.8974



Source: Statistics Canada

Last observation: 2014

Chart 1 illustrates the correlation between annual capital spending on machinery, equipment and construction in the mining and oil and gas extraction sector (from Table 029-0005) and the annualized fixed-asset cash spending (Table 187-0002). With a Pearson's coefficient of correlation of 0.8974, the dynamics of the illustrated constructs are largely in tandem. Based on this evidence, we believe that fixed-asset cash spending may be considered as a fair proxy for capital expenditures. As such, findings on the dynamics of fixed-asset cash spending may provide meaningful inferences about the trends in investment in the sector.

A theoretical framework for the relationship between fixed-asset cash spending and crude oil prices can be derived from several models, including the investment–cash-flow sensitivity model pioneered by Fazzari et al. (1988). According to this model, the interpretation of investment–cash-flow sensitivity stems from financial constraints. The authors suggest that, when a firm faces financial constraints, external financing in the form of new debt or equity is not often readily available or comes at a greater cost. Therefore, investment by a financially constrained firm depends heavily on the availability of internal funds, which, in turn, is a function of cash flow from sales or other activities. Subsequent studies offering a detailed discussion on the intuition behind the investment–cash-flow sensitivity model include Hoshi, Kashyap and Scharfstein (1991); Hubbard (1998); Fazzari, Hubbard and Petersen (2000); and more recently, Biddle and Hilary (2006); Almeida and Campello (2007); and Beatty, Liao and Weber (2010).

To estimate the relationship between fixed-asset cash spending and crude oil prices, we employ a set of three VAR models—an unconstrained VAR, a vector error-correction model (VECM) and a Bayesian VAR. The choice of the VAR models can be justified on two grounds. First, VAR models allow for some variables in the system to be treated as endogenous a priori. VAR modelling does not require as much knowledge about the forces affecting a variable as do structural models with simultaneous equations. This is a proper feature for our system of equations since the exogeneity assumption for some of the variables is questionable and not backed by a developed theory. The set-up of a VAR model is such that current values of variables are partly explained by past values of the variables. Second, the endogeneity of variables in the system comes in handy at the forecasting stage. The system will generate the future values for these variables based on their past patterns. No assumption is required for these variables; therefore, to forecast the level of fixed-asset cash spending ($cashfa_t$), we only have to introduce the level of the exogenous variable: the WTI price benchmark. Overall, the VAR model has proven to be particularly useful for describing the dynamic behaviour of economic and financial time series and forecasting.

We start off with an unconstrained VAR model, a vector-autoregressive system of equation with no assumption about short- or long-run constraints on the resulting impulse-response functions. Empirical representation of the unconstrained VAR model used in the study could be written as

$$y_t = \mu + \sum_i^p \Gamma_i \, y_{t-i} + \sum_i^p \Psi_i \, WTI_{t-i} + \epsilon_t \qquad [1]$$

where y is a $7 \text{ x } 1$ vector of endogenous, industry-level and time-specific variables:[1]

$$y_t = \begin{bmatrix} cashfa_t \\ cf_t \\ assets_t \\ de_t \\ r_t \\ e_t \\ png_t \end{bmatrix}$$

The inclusion of cash flow (cf_t), total assets *($assets_t$)*, debt-to-equity ratio (de_t) and interest rate *(r_t)* in the specification is a common practice in the existing empirical literature on the determinants of investment. The Can$/US$ exchange rate (e_t) in the model reflects the fact that output prices for the industry are frequently denominated in US dollars. Finally, the price for natural gas (png_t) captures the evolution of the natural gas market in North America. Natural gas prices are represented by the Henry Hub benchmark.

Further, in equation [1], μ is a $7 \text{ x } 1$ vector of intercepts; Γ_i denotes a *7* x *p* matrix of coefficients on the lags of endogenous variables; WTI_t is an exogenous price for crude oil; Ψ_i represents a 7 x *p* matrix of coefficients on the lags of WTI; p is the number of lags in the system; and ϵ_t is a $7 \text{ x } 1$ vector of error terms that are assumed to follow a white-noise process with mean zero ($\text{E}_{\epsilon_\text{t}} = 0$) and no autocorrelation ($\text{E}_{\epsilon_\text{t}\epsilon'_\text{t-s}} = 0$ for all $s \neq 0$).

Then, to check the robustness of our results and explore the long-run equilibrium of the variables, we turn to the VECM, which explores the cointegration of variables. A set of time-series variables is thought to be cointegrated if they are integrated in the same order and a linear combination of them is stationary. The linear combinations (cointegrating equations) would then point to the existence of a long-term

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[1] Fixed-asset cash spending ($cashfa_t$), cash flow (cf_t) and total assets ($assets_t$) are expressed in logarithmic terms.

relationship among the variables (Johansen and Juselius 1990). An advantage of cointegration analysis and VECM is the possibility of examining the dynamic co-movement among variables and the adjustment process towards a long-term equilibrium. In vector-matrix notation, our VECM is

$$y_t = \mu + \alpha(\beta' y_{t-1}) + \sum_i^p \Gamma_i \, y_{t-i} + \sum_i^p \Psi_i \, WTI_{t-i} + \epsilon_t \qquad [2]$$

where notation follows [1] and $\alpha(\beta' y_{t-i})$ represents the force driving y_t to its long-run equilibrium. More specifically, $(\beta' y_{t-i})$ is a vector containing the error-correction terms, whereas α indicates the speed of adjustment to the long-run equilibrium.

Both the unconstrained VAR model and the VECM tend to be susceptible to the problem of overfitting when the data set is short and the number of parameters is relatively large. In-sample overfitting typically translates into poor forecasting performance. Bayesian methods can solve these problems; they can make in-sample fitting less volatile and improve out-of-sample performance (Canova and Ciccarelli, 2004). Bayesian VAR models diminish the risk of overfitting by imposing some simple restrictions on the VAR parameters that are incorporated through their prior probability distribution functions. We use a well-known Minnesota prior method developed by Doan, Litterman and Sims (1984). The Minnesota prior assumes that most of the economic series can be defined by a random walk with a drift. Similar to other Bayesian models, a broad data-generating process is selected and it is assumed that the prior distributions for the VAR parameters are independent normal probability distribution functions, with its means set by random walk parameters' values (Félix and Nunes 2002). Following a well-established literature on the Bayesian VAR,[2] we assign the prior variances of these probability distribution functions as fixed by a second set of parameters, known as hyperparameters that control the probability of each parameter of the VAR model by assuming values farther or closer to the random walk prior mean.

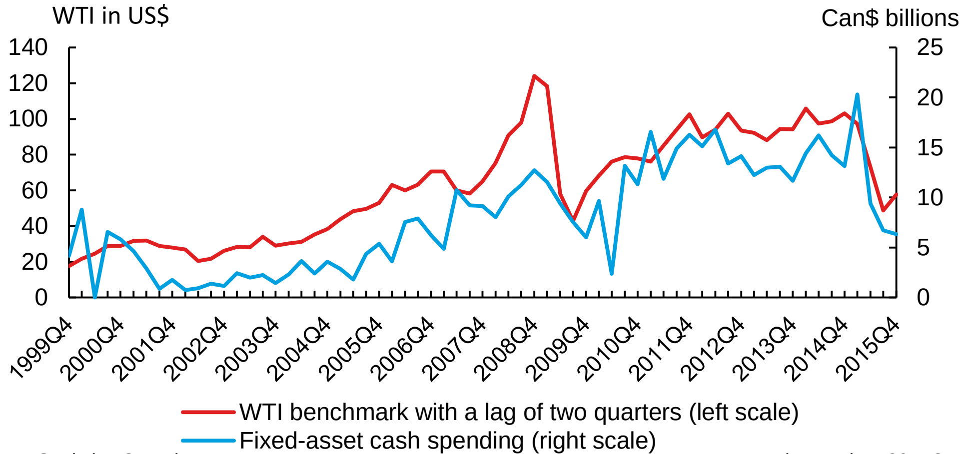
Estimation and Results

Chart 2 points to a strong explanatory power of WTI with respect to movements of fixed-asset cash spending of firms in oil and gas extraction and support activities sector. This is particularly true for two- and three-quarter lagged WTI. With a Pearson's coefficient of correlation of 0.8505, the chart shows a significant strength and direction of the linear relationship between two variables. In fact, regressing $cashfa_t$ solely on WTI benchmark with a lag of two quarters (WTI_{t-2}) using OLS produces strong statistical significance of parameter estimates and an R-squared of 0.72.

[2] Detailed descriptions of the Minnesota prior and other Bayesian VAR models can be found in Banbura, Giannone and Reichlin (2010), among others.

Chart 2: Fixed-asset cash spending in the oil and gas sector and WTI

Coefficient of correlation = 0.8505



Source: Statistics Canada Last observation: 2015Q4

As a first step in the empirical analysis, we perform unit-root tests to check the stationarity of all variables in equation [1]. The augmented Dickey-Fuller (ADF) test confirms the existence of non-stationary processes for fixed-asset cash spending ($cashfa_t$), cash flow (cf_t) and total assets ($assets_t$) estimated in levels. However, when we subject the first difference of these three variables to unit-root tests, we are able to reject the unit-root null hypothesis at the 1 per cent level of significance. The implication of this finding is that both the unconstrained VAR and Bayesian VAR models need to be estimated in first differences for all the variables in the system of equations [1]. Furthermore, this points to a possible cointegration (long-run) relationship between endogenous variables in the system. To test for a long-run relationship among the variables, we apply the Johansen (1988) cointegration test. Both trace and eigenvalue criteria point to the existence of two cointegrating relationships between $cashfa_t$ and other endogenous variables in the system.

The optimal lag lengths are selected using the Akaike criterion separately for each model. As a result, the unconstrained VAR model employs three lags, the VECM four lags and the Bayesian VAR two lags.

We find that the unconstrained VAR and VECM models generate a better fit of fixed-asset cash spending with R-squares of 0.543 and 0.893, respectively.[3] The Bayesian VAR model generates a somewhat weaker fit with an R-squared of 0.393 for the fixed-asset cash spending equation. Parameter estimates for most of the lagged values of WTI are positive, indicating that a decline in the value of WTI benchmark would lead to cuts in fixed-asset cash spending with a certain lag. Due to a limited number of observations, parameter estimates for WTI are not statistically significant at the conventional levels. However, Wald

[3] In the interest of brevity, we do not display system estimates in this note. The regressions are available upon request.

tests for equality of lagged WTI parameter estimates to zero are rejected in each model. We also find no significant evidence of serial correlation and heteroscedasticity in the error terms at the 5 per cent significance level.

Out-of-sample forecasting performance is presented in Table 1. We calculate the root-mean-square error (RMSE) using the model forecasts for the period of 2010Q1–2014Q4 for eight quarters forward. Next, we compare derived RMSEs with the RMSE from the AR(4) equation that is used as a benchmark model. In other words, in Table 1, lower numbers suggest a better forecasting performance.

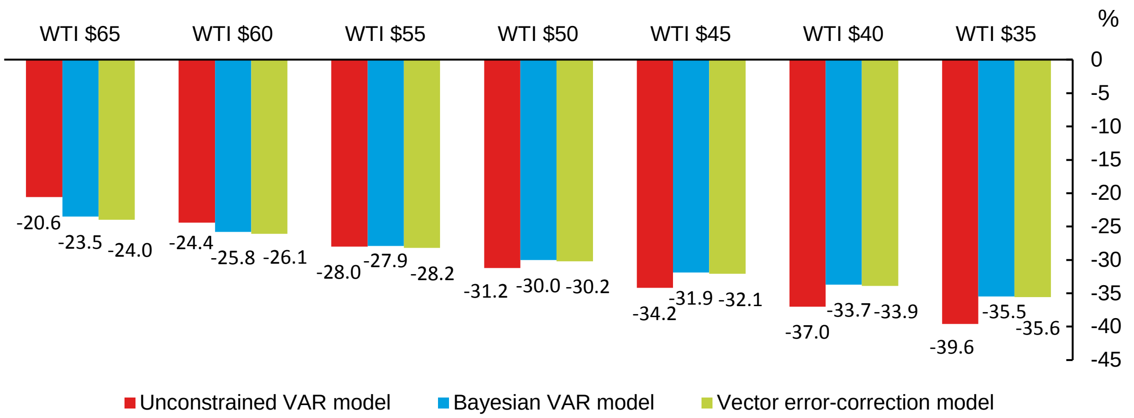
Table 1: Forecasting performance: ratios of model RMSEs to RMSE of the AR(4) model

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
Bayesian VAR	0.94	0.86	0.72	0.69	0.61	0.60	0.60	0.61
VECM	0.67	0.52	0.58	0.50	0.49	0.53	0.49	0.56
Unconstrained VAR	0.56	0.48	0.51	0.48	0.49	0.51	0.50	0.54

All three models outperform the AR(4) model by significant margins. That said, it seems that the Bayesian VAR falls somewhat short of the two other estimated models, especially in the first year of the forecasted horizon. While the performance of VECM lags that of the unconstrained VAR models in Q1–Q4 of the forecasting horizon, it catches up in performance in the longer term as one would expect from the error-correction models.

Next, we use the estimated models to forecast $cashfa_t$, for a set of predefined values of the WTI benchmark in 2015. Chart 3 shows these results. They are reasonably robust to changes in the choice of the empirical framework. While the Bayesian VAR model underperformed in terms of the fit indicators, it still generates forecasts comparable to the outcome from the unconstrained VAR and VECM.

Chart 3: WTI and fixed-asset cash spending in the oil and gas sector in 2015 (y/y)



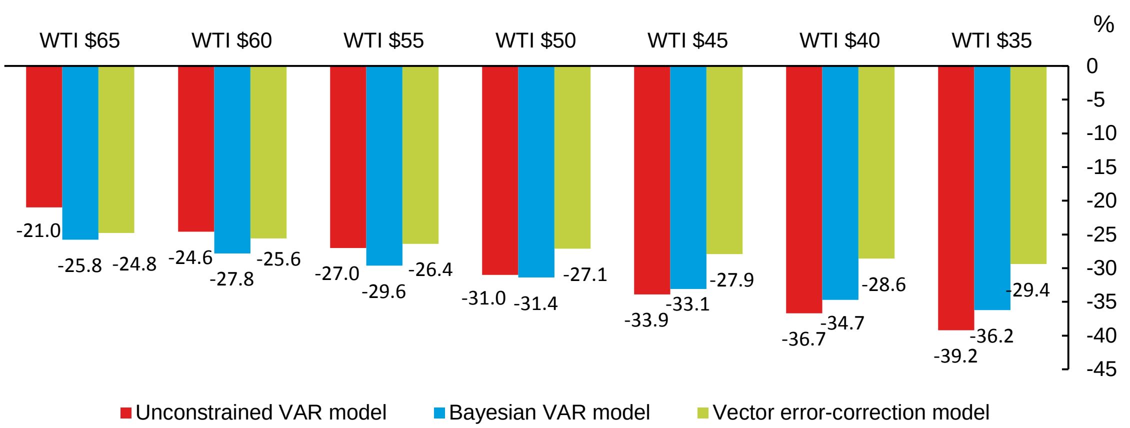
Source: Authors' calculations

Last observation: 2014Q4

For an average WTI of $50 in 2015, the expected decline rates of cash spending on fixed assets are within the range of 30.0 to 31.2 per cent (y/y) in 2015. Under a more optimistic scenario of WTI at $65, the decline rates are between 20.6 and 24.0 per cent. In contrast, for WTI at $35, the drop in fixed-asset cash spending in the oil and gas extraction and support activities sector is estimated at 35.5 to 39.6 per cent.

For 2016, all models forecast another year of significant cuts in investment (see Chart 4). At a WTI of $50 on average during 2016, investment is expected to be slashed by another 27.1 to 31.4 per cent. At a more optimistic price of WTI at $65 on average in 2016, the models suggest a reduction in the range of 21.0 to 25.8 per cent. On the other hand, with the WTI at $35, the sector is forecast to experience a decline in the range of 29.4 to 39.2 per cent. The unconstrained VAR model seems to be more elastic to changes in oil prices with the range of estimates between –21.0 and –39.2 per cent. Taken together, the analysis predicts two consecutive years of significant declines in investment, the first such development since the 1986 oil price downturn.

Chart 4: WTI and fixed-asset cash spending in the oil and gas sector in 2016 (y/y)



Source: Authors' calculations Last observation: 2015Q4

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