The investment-uncertainty relationship in the oil and gas industry

Maryam Ahmadi a,*, Matteo Manera b, Mehdi Sadeghzadeh c

a University of Milan-Bicocca, Italy
b University of Milan-Bicocca and Fondazione Eni Enrico Mattei (FEEM), Italy
c Institute for Management and Planning Studies (IMPS), Iran

ARTICLE INFO

Keywords:
Oil market
Investment
Uncertainty
SVAR-GARCH

JEL classification:
C3
G11
Q41
Q43

ABSTRACT

Recent studies of the oil market demonstrate endogeneity of the oil price by modelling it as a function of consumption and precautionary demands and producers’ supply. However, studies analysing the effect of oil price uncertainty on investment do not disentangle uncertainties raised by underlying components which play a role in the oil market. Accordingly, this study uses a new approach to investigate the relationship between investment and uncertainty for a panel of U.S. firms operating in the oil and gas industry. We decompose oil price volatility to be driven by structural shocks that are recognized in the oil market literature, over and above other determinants, in order to study whether the investment uncertainty relationship depends on the drivers of uncertainty. Our findings suggest that oil market uncertainty lowers investment only when it is caused by global (consumption) oil demand shock. Stock market uncertainty is found to have a negative effect on investment with a year of delay. The results suggest no positive relationship between irreversible investment and uncertainty, but interestingly, a positive relation exists for reversible investment. This finding is in line with the option theory of investment and implies that the irreversibility effect of increased uncertainty dominates the traditional convexity effect.

1. Introduction

Investment decisions have three characteristics: first, the cost of investment is at least partially irreversible; second, there is uncertainty over future profits; and, third, investors can postpone their decisions to get additional information and reduce uncertainty (Dixit and Pindyck (1994)). The orthodox theory of investment, based on the assumption of reversible investment, is built upon net present value of future income of the investment. Postulated on reversible investment and convexity of marginal product of capital, this theory claims that an increase in uncertainty may raise investment (Abel (1983) and Hartman (1972)). The option theory of investment, on the other hand, builds on the assumption of irreversible investment. Taking into account the role of uncertainty in the timing of investment, this theory finds a negative effect of uncertainty on investment.

There are various sources for uncertainty, which are different across industries. Examples are: exchange rate uncertainty; output price uncertainty; and input price uncertainty. One important source of uncertainty in the oil and gas industry is about the price of oil. The effects of oil price changes on investment are analysed in many studies (e.g. Glass and Cahn (1987) and Uri (1980)). The general finding is that oil price fluctuations are important for investment decisions at the aggregate level, as well as for single firms operating in the oil and gas sector. Some studies which relate oil price volatility to investment find that increases in oil price uncertainty raise the value of waiting. Hence, firms postpone their investment decisions when they face increased uncertainty (e.g. Bernanke (1983), Mohn and Misund (2009), Ratti and Yoon (2011) and Kellogg (2014)). However, the cited studies, as well as other contributions which investigate the relationship between oil price uncertainty and investment, consider the price of oil exogenous with respect to the macroeconomic variables. Based on this assumption, the construction of oil price variance estimates by averaging the squared residuals obtained from modelling the oil price conditional mean is an approach widely employed in empirical studies to measure uncertainty (e.g. Sadorsky (2008) and Henriques and Sadorsky (2011)). Conversely, there is a consensus in recent studies to consider the oil price as endogenous (see, e.g. Hamilton (2009), Kilian (2009), Dvir and Rogoff (2010), Alquist and Kilian (2010) and Kilian and Murphy (2014)). For instance, Hamilton (2009), Kilian (2009) and Baumeister and Kilian (2017) argue that the endogeneity of the price of oil with respect to the

https://doi.org/10.1016/j.resourpol.2019.101439

Received 13 May 2019; Received in revised form 21 June 2019; Accepted 26 June 2019

© 2019 Elsevier Ltd. All rights reserved.
This structural model of the global oil market has been widely used in the literature, for example, Baumeister and Kilian (2015), Baumeister and Kilian (2016), Kilian and Lee (2014), Kilian (2017) and Herrera and Rangaraju (2018).

2 For a full structural model specification, refer to the methodological section of this paper.

3 This ratio is called Tobin's Q and captures the firm's opportunity cost of capital investment.

4 See e.g. Charles and Gautam (1996), Sadorsky (1999), Park and Ratti (2008), Oudsami (2009) and Singhal and Ghosh (2016).

5 Abel (2018), in a study of the relationship between investment, Q and cash flow, shows that cash flow has explanatory power for investment and this effect is even larger for faster growing firms that are likely to be financially constrained.

uncertainty for U.S. firms. A few examples of these proxies are: volatility of exogenous variables such as output prices and wages (Huizinga (1993) and Ghosal and Loungani (1996)); exchange rate (Campa (1993)) and stock market return (Bulan (2005)); as well as endogenous variables such as: sale growth rates (Ogawa and Suzuki (2010)); future profits (Bond and Cummins (2004)); and expected volatility of the future price (Kellogg (2014)). However, some authors report that the significance of the negative relationship is not robust when Tobin’s Q or other important factors, such as cash flow, are included. This finding may be due to a negative correlation between Tobin’s Q and a given measure of uncertainty (Leahy and Whited (1996)). Hayashi (1982) shows that, for the case of perfectly competitive markets and constant returns to scale technology, average Q, the ratio of the maximised value of the firm to the replacement cost of its capital stock, would be a sufficient statistic for investment rates. Tobin’s Q, however, measures the maximised value of the firm by its stock market valuation, and assumes that the stock market valuation captures all information about expected future profitability. However, as Bond et al. (2004) show, if the Hayashi conditions are not satisfied, or if stock market valuations are influenced by factors other than the present discounted value of expected profits, Tobin’s Q would not capture all relevant information about the expected future profitability of current investment. This motivates some empirical studies based on the Q model augmented with other explanatory variables of interest.⁷

Several studies assess the importance of energy price fluctuations in investment decisions. Uri (1980) develops a simple model and finds that the price of energy is important in explaining investment decisions at the aggregate level and, more importantly, for energy intensive industries. Bernanke (1983) shows that, when oil price uncertainty increases, firms postpone their irreversible investment when they have to choose between energy-efficient and energy-inefficient capital. Ratti and Yoon (2011) estimate an error correction model of capital stock adjustment with data on U.S. manufacturing firms. Their results suggest that stability in energy prices would be conducive to greater stability in firm-level investment. Rafiq et al. (2009), in a study of Thai economy and by using a vector auto-regression model, show that oil price volatility has negative effect on investment. Similar result found by Wang et al. (2017) in a study of the effects of oil price uncertainty on China’s economy and Phan et al. (2019) in a global level. Using a large set of data, which spans a wide range of countries, Phan et al. (2019) also find that the negative effect is stronger in the crude oil producers group than for crude consumers.

The relationship between uncertainty and investment in the oil and gas industry, as a special case, has attracted academic interest at both micro and aggregate levels. However, the number of studies working on the effects of uncertainty on investment in oil and gas fields is rather small, and the empirical findings are mixed. At the aggregate level, Favero et al. (1992) develop a theoretical model and derive the determinants of the decision to develop an oil field. They evaluate the importance of the variables suggested by theory to explain the length of development lags of U.K. oil and gas fields. Their results imply that the volatility of prices positively(negatively) affects the duration of

---

⁷See, e.g., Mohn and Misund (2009), Henriques and Sadorsky (2011) and Abel (2018).
investment appraisal when prices are low (high). Hurn and Wright (1994), using data from oil fields of the North Sea, analyse the effects of expected oil price, variance of oil price and the level of reserves, on the lag between discovery of a field and the decision to develop the field.

They find that the expected oil price and the level of reserves are important in influencing the appraisal duration, while the variance is not. At the micro-level, Mohn and Misund (2009) estimate the effect of oil price volatility on investment in the international oil and gas industry. Their results show that Tobin’s Q is a poor investment indicator, but uncertainty measures contribute significantly to the explanation of investment. Elder and Serletis (2010) apply a bi-variate GARCH model to study how oil price uncertainty affects investment for the U.S. economy, and find that increases in oil price volatility reduce aggregate investment. Similar results are found for Canada. Lee et al. (2011) apply a standard investment model to analyse the joint effects of an oil price shock and firm-specific uncertainty on investment, using firm-level panel data. They conclude that an oil price shock has a greater effect on delaying a firm’s investment, the greater the uncertainty faced by that firm. Abel (2018) uses a tractable stochastic model to analyse investment, Q and cash flow and shows that Q is not a sufficient statistic for investment and other variables, in particular, cash flow, have additional explanatory power for investment behavior of firms.

This paper analyses the relation between investment and different sources of uncertainty that are identified by their underlying causes for the firms operating in the U.S. oil and gas industry. We consider two sources for uncertainty, oil and stock market uncertainties, and employ a Structural Vector Autoregressive with a time-varying conditional variances (SVAR-GARCH) model to describe the oil and stock markets. By using this model, we depart from the literature in three ways. First, we take into account the fact that the uncertainty of financial time series, as measured by their variances, is time varying. Second, we take into account, for the first time, the endogeneity of the oil price in the investment-uncertainty relationship, and estimate the oil price uncertainty driven by each of the oil market structural shocks. Third, we identify the stock market uncertainty from which the effects of oil market shocks are excluded.

Our focus is on the oil and gas industry, since uncertainty about the price of oil is one of the most important sources of uncertainty in this industry, which connects the oil and stock markets. We believe that, since the oil price is not exogenous with respect to oil market participants and macroeconomic fundamentals, the oil and gas industry represents a natural laboratory for the application of our new approach to the analysis of the investment-uncertainty relationship.

3. Data

Our data are in the form of an unbalanced panel of U.S. oil and gas companies (t = 1, ..., N) for the period 1974 to 2018 (t = 1, ..., T) drawn from COMPUSTAT. It includes the following annual variables: market value of equity, long-term debt, total assets, capital expenditure, short-term liabilities, short-term assets, income before extraordinary items, depreciation, and amortization. Firm investment is proxied by capital expenditure on property, plant, and equipment. Following the literature, the Tobin’s Q is measured as the sum of market value and long-term debt, divided by lagged total assets:

\[ Q_t = \frac{\text{market value of equity + preferred stock + debt}_t}{\text{total assets}_{t-1}} - 1. \]

Our firm investment measure is constructed as the ratio of capital expenditure to capital stock, and capital stock is measured by total assets (Mohn and Misund (2009)). Cash flow is measured as the sum of income before extraordinary items and depreciation over capital stock, written as:

\[ \text{Cashflow}_{it} = \frac{(\text{income before extraordinary items} + \text{depreciation})_{it}}{\text{total assets}_{i,t-1}} - 1. \]

We clean our data using a number of sample selection rules. First, observations with Tobin’s Q values out of the 99% confidence interval are dropped. Second, any observation for which there is one or more variable/s missing is screened. At the end, we keep firms with at least five observations in our sample. After this procedure, our sample is left with N = 985 firms.

Global oil market variables include global crude oil production, an updated measure of cyclical fluctuations in global real economic activity\(^6\), real price, and above-ground inventory of oil, which are all available in monthly frequency. Data on global oil production are from the Monthly Energy Review of the Energy Information Administration (EIA). The real price of oil, proxied by the U.S. refiners’ acquisition cost for imported crude oil, is also available from the EIA. The price of oil is deflated by the U.S. consumer price index. Since data on oil inventories for all countries are not available, we follow Hamilton (2009), Kilian and Murphy (2014), and Kilian (2017) to construct global oil inventory data. The series is constructed by scaling total U.S. oil inventories by the

---

\(^6\) This measure of global real economic activity, introduced by Kilian (2009) and updated by Kilian (2019), captures the global business cycle, and is used to measure consumption demand for oil and all industrial commodities.
ratio of the OECD petroleum stocks to the U.S. petroleum stocks, which are available from the EIA.

The U.S. aggregate stock market returns are obtained from the Center for Research in Security Prices (CRSP), and are related to a value-weighted market portfolio including NYSE, AMEX and NASDAQ stocks. The real stock returns are constructed by subtracting the Consumer Price Index (CPI) inflation from the log of aggregate stock returns.

The oil market variables, in addition to the stock market returns, form the vector of variables for the SVAR-GARCH analysis. The volatility series extracted from estimating the SVAR-GARCH model (see Fig. 2) are annualised by averaging monthly volatilities prior to each year. Table 1 presents the descriptive statistics for the whole data set.

The graph in Fig. 3 shows the annual mean of the investment capital ratio of all firms versus demand and supply shocks volatilities. The patterns of variability associated with these series suggest a more pronounced negative correlation of the investment measure with the volatility of the demand shock, especially after 2000. The correlation of the mean investment capital ratio with the demand shock volatility is −0.46, while the value of the correlation coefficient with the supply shock volatility is 0.27.

4. Methodology

Our empirical methodology follows a two-step procedure. First, we estimate the volatility series of the oil market and stock market shocks within a time-varying volatility Structural VAR (SVAR-GARCH) framework. Since the firm-level data are annual, volatility series are annualised, such that each annual volatility is the average of the monthly volatilities. Second, an augmented Tobin’s Q model of investment is estimated using firm-level data and annualised volatility series.

4.1. Measures of uncertainty

A SVAR-GARCH model is employed to estimate the oil price uncertainty driven by each of the oil market structural shocks as well as by the stock market shocks. SVAR-GARCH models have been widely applied by researchers for the identification of structural shocks or for testing over-identification in a VAR context.12 The assumption of conditional heteroskedasticity allows for statistical identification without the need for conventional exclusion restrictions. However, this purely statistical identification procedure may not provide the researcher with economically interpretable results, which makes it difficult to interpret the shocks as being structural VAR shocks. Our methodology addresses this issue by applying a SVAR-GARCH framework which uses a set of identifying restrictions generally adopted in the literature, and departs from the conventional framework by assuming time-varying variances of structural shocks.

Our baseline SVAR specification is taken from Kilian and Murphy (2014). We depart from this specification in two ways. First, following Ahmadi et al. (2016), we include stock market returns in our structural model to account for the effects of stock market uncertainty on the firm-level investment. The advantage of this approach is that we identify the

\[\text{Fig. 3. Firm investment capital ratio versus annualized supply shock and demand shock volatilities.}\]
stock market shocks from which the effects of oil market shocks are excluded. Second, we estimate the model under the assumption that the structural shocks have time-varying volatility. Our specification is.\(^{13}\)

\[
A_0 y_t = \alpha + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t
\]

\[
E(\varepsilon_t) = 0, \quad E(\varepsilon_t^2) = \mu_t, \quad E(\varepsilon_t \varepsilon_s) = 0, \quad t \neq s
\]

\[
h_{tt} = \delta_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}
\]

(1)

where \(y_t\) is the vector of endogenous variables including the percentage change in global oil production, the global real economic activity, the first difference of oil inventory, the first difference of real oil price and real stock market returns; \(\varepsilon_t\) is the vector of structural shocks, namely, oil supply shocks, global demand shocks, oil speculative demand shocks, other oil market shocks and stock market shocks. The \(i\) - \(th\) structural shock has a GARCH(1,1) conditional variance, \(h_{tt}\), which is the \(i\) - \(th\) diagonal element of the conditional covariance matrix \(H_t\). The structural shocks are estimated from the analogous reduced form VAR model:

\[
y_t = \beta + \sum_{i=1}^{24} B_i y_{t-i} + \varepsilon_t
\]

(2)

\[
B_i = A^{-1}_i \Lambda_i, \quad \forall i,
\]

\[
\varepsilon_t = A^{-1}_0 \varepsilon_t
\]

The VAR residuals have the following time-varying covariance matrix:

\[
E(\varepsilon_t^2) = E(A_1 \varepsilon_t^2 A_1^{-1}) = A_2^{-1} E(\varepsilon_t^2) A_2^{-1} = A_2^{-1} D_t A_2^{-1} = S_t S_t^\prime = \nu_t
\]

The structural shocks are identified from the reduced form VAR model, \(\varepsilon_t = A_0^{-1} \varepsilon_t\), by imposing short-run restriction on \(A_0\). Following Kilian (2009) and Ahmadi et al. (2016), the matrix of short-run restrictions is:

\[
\begin{pmatrix}
\varepsilon_{it}^\text{global oil production} \\
\varepsilon_{it}^\text{global real activity} \\
\varepsilon_{it}^\text{real price of oil} \\
\varepsilon_{it}^\text{global oil inventory} \\
\varepsilon_{it}^\text{real stock return}
\end{pmatrix}
= \begin{pmatrix}
\alpha_{11} & 0 & 0 & 0 & 0 \\
\alpha_{21} & \alpha_{22} & 0 & 0 & 0 \\
\alpha_{31} & \alpha_{32} & \alpha_{33} & 0 & 0 \\
\alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & 0 \\
\alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55}
\end{pmatrix}
\begin{pmatrix}
\varepsilon_{it}^\text{oil supply shock} \\
\varepsilon_{it}^\text{global demand shock} \\
\varepsilon_{it}^\text{speculative shock} \\
\varepsilon_{it}^\text{other oil shocks} \\
\varepsilon_{it}^\text{stock market shock}
\end{pmatrix}
\]

(3)

The identifying restrictions are based on four assumptions. Within, a month changes in global oil production do not respond to oil demand shocks. This assumption is made because adjustment in oil production plans is very costly. Second, when the increase in the oil price is caused by speculative demand or other oil market shocks, it affects global real economic activity with at least one month of delay. Third, within a month, the real price of oil responds to oil supply, consumption demand, and speculative demand shocks. Finally, oil market variables are predetermined with respect to stock market returns, while stock returns are affected by different oil price shocks.

\(^{13}\) Applying 24 months of lags is consistent with Hamilton and Herrera (2004) and Kilian and Park (2009) who argue that allowing for a high lag order is crucial to capture the transmission of the structural shocks in the oil market. They provide evidence that moving cycles in the oil market are very slow and a low number of lags would fail to capture the whole dynamics of the cycle. The alternative way of setting the lag order is by testing the goodness of fit using information criteria. However, some researchers (see, e.g., Leeb and Potscher (2006), and Ivanov and Kilian (2005)) argue against the validity of such methods especially when there is a prior on the number of lags. However, according to Hamilton and Herrera (2004), there are strong claims about the value of lag order in the oil market based on prior studies, and the AIC estimates would make a lower bound (Ahmadi et al. 2016).

4.2. The investment model

The effects of uncertainty on firm-level investment are estimated using an augmented Tobin's Q model (Tobin 1969). This model relates investment to the firm's stock market valuation, which reflects the present discounted value of expected future profits. The Q-model of investment is represented by the following relationship:\(^{14}\):

\[
\left( \frac{1}{K} \right)_{it} = a + \frac{1}{b} Q_{it} + \nu_{it}.
\]

(4)

where \(Q_{it}\) is the ratio of the market value of the \(i\)th firm to the replacement value of its assets; \(I_t\) is the firm's gross investment; \(K_{it}\) is the firm's net capital stock; \(\nu_{it}\) is a random error term; and \(a\) and \(b\) are the structural parameters of the adjustment cost function. To take into account the factors reported in the literature which affect investment, we augment Tobin's Q model with additional explanatory variables, including stock market uncertainty (\(\sigma_{stock}\)) and oil market uncertainty, driven by oil supply shocks (\(\sigma_{supply}\)); global demand shocks (\(\sigma_{demand}\)); speculative demand shocks (\(\sigma_{spec}\)); and other oil market shocks (\(\sigma_{other}\)). These variables are included in the model to capture and compare local (i.e. industry) and global (i.e. market) risks brought about by different sources of uncertainty. Following Henriques and Sadorisky (2011) and Abel (2018), firms’ cash flow is also included among the explanatory factors. In order to avoid serial correlation in the error terms, \(\nu_{it}\) is assumed to follow an AR(1) process (see Mohn and Misund (2009)):

\[
\nu_{it} = \rho \nu_{i(t-1)} + \nu_{it},
\]

(5)

with \(\nu_{it}\) representing a white noise error term. Substituting the additional variables in equation (4) and incorporating (5), we obtain the following dynamic investment model:

\[
\left( \frac{1}{K} \right)_{it} = a(1 - \rho) + \rho \left( \frac{1}{K} \right)_{i(t-1)} + \frac{1}{b} Q_{it} + \frac{1}{b} \rho Q_{i(t-1)} + \chi_{it} CF_{it} + \rho \chi_{i(t-1)} CF_{i(t-1)} + B_{it} X_{it} + \rho B_{i(t-1)} X_{i(t-1)} + \xi_{it},
\]

(6)

where \(X_{it}\) is a vector of variables including \(\sigma_{supply}, \sigma_{demand}, \sigma_{spec}, \sigma_{other}\) and \(\sigma_{stock}\). However, it is more convenient to estimate the unrestricted version of (8), represented as:

\[
\left( \frac{1}{K} \right)_{it} = b_0 + b_1 \left( \frac{1}{K} \right)_{i(t-1)} + b_2 Q_{it} + b_3 Q_{i(t-1)} + b_4 CF_{it} + b_5 CF_{i(t-1)} + B_{it} X_{it} + B_{i(t-1)} X_{i(t-1)} + \xi_{it},
\]

(7)

The empirical specification (7) relates the firms’ investment capital ratio to its one-period lag, Tobin’s Q, cash flow, oil price volatility series, and stock market volatility.

4.2.1. Panel unit root tests

To determine the order of integration of the variables involved in the investment model, two panel unit root tests were carried out. The reason to choose panel unit root tests is that these statistics have a higher power to reject the null hypothesis of a unit root than traditional tests such as the Augmented Dickey-Fuller (ADF) test, especially in shorter time spans. The Levine et al. (2002)’s panel unit root test postulates that the unit roots among the cross-sections are homogeneous. This assumption allows for different lag orders across cross sections. Hence, the null hypothesis is that each individual time series has a unit root, and the alternative is that at least one time series is stationary. Conversely, the Im et al. (2003) test allows for heterogeneity across cross-sectional unit roots and specifies an ADF regression for each cross section. The null hypothesis is that there is a unit root, while the alternative is that the fraction of individual units following stationary processes is non-zero.

The results of the tests are presented in Table 2 and suggest strong
Since both the Im et al. (2003) and Levine et al. (2002) tests require a
fluenced by past disturbances. Second, when some series in the model
gressors that are independent of current disturbances, but can be in-
effect and the two-step System Generalized Method of Moments
stock market uncertainty. The model uses a panel data of
latest ratio of investment to a firm’s capital to its own one-period lag,
4.2.2. Model estimation
The augmented Tobin’s Q model of investment in equation (7) re-
lates the ratio of investment to a firm’s capital to its own one-period lag,
Tobin’s Q, and cash flow, as well as to our measures of oil price and
levels, respectively.
Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10%
levels, respectively.
evidence against the presence of unit root in our panel data set, meaning that all variables are stationary in levels. Accordingly, we do
not need to apply the cointegration test, and our data are appropriate to
adopt the System GMM (SGMM) methodology.

<table>
<thead>
<tr>
<th>IPS</th>
<th>LL</th>
<th>IPS</th>
<th>LL</th>
</tr>
</thead>
<tbody>
<tr>
<td>−1.989**</td>
<td>−11.012***</td>
<td>−5.518*</td>
<td>−19.340***</td>
</tr>
<tr>
<td>−9.217***</td>
<td>−21.689***</td>
<td>5.862</td>
<td>−8.389***</td>
</tr>
<tr>
<td>−2.621***</td>
<td>−3.385***</td>
<td>0.827</td>
<td>4.199</td>
</tr>
<tr>
<td>−10.091***</td>
<td>−14.266*</td>
<td>−8.649***</td>
<td>−16.591***</td>
</tr>
<tr>
<td>−7.763***</td>
<td>−10.561***</td>
<td>−5.840***</td>
<td>−11.527***</td>
</tr>
<tr>
<td>−6.3028***</td>
<td>−16.5863***</td>
<td>−8.4223***</td>
<td>−5.2720***</td>
</tr>
</tbody>
</table>

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10%
levels, respectively.

5. Estimation results
We report two sets of estimation results. Table 4 presents the results
of a set of linear models, where the average firm investment capital
ratio is the dependent variable. Similarly, cash flows and Tobin’s Q are
averaged annually and treated as explanatory variables. Averaging
variables across firms cancels out the noise among firms in making
investments decisions, and could serve as an aggregate measure in
analysis.

The first three columns report estimation results based on conven-
tional Tobin’s Q specifications. The last columns report the results for
the specification augmented with volatility measures. The empirical
findings suggest a high explanatory power for the lagged Tobin’s Q.
Most important, out of five volatility measures, only the volatility of
global demand shock negatively affects the aggregate investment cap-
ital ratio. This result is robust to the inclusion of lag dependent vari-
able and is in line with the oil market literature, where demand shock is
reported as the main driver of the oil price. In other words, investors
mainly monitor demand shifts when deciding about new investment
projects.

The results from estimating investment model (10) are reported in
Table 5. The first column refers to panel estimation, where robust
standard errors are reported, and firm fixed effects are controlled for.
The last two columns present the results obtained with the SGMM
method. For both SGMM specifications, robust standard errors are re-
ported and all volatility measures are treated as instrument variables.
In the second column, the lagged dependent variable, cash flow and the
Tobin’s Q are treated as endogenous, and in the last column the lagged
Tobin’s Q and cash flow are also assumed to be endogenous.

Evidence on the sign and the significance of the coefficient of the
lagged investment-capital ratio, reported in the first row of Table 5,
confirms a positive and significant impact of lag dependent variable.
The contemporaneous cash flow significantly raises investment only in
the third specification of the model, while a positive significant re-
spone of investment to the lagged cash flow is robust with larger
coefficients in the all specifications. This result supports the finding in
Chen (2016), suggesting that when firms face investment frictions such
as high adjustment cost and investment planning lag, their capital ex-
penditures are more sensitive to the lagged cash holdings than to the
contemporaneous cash flows. The results show that Tobin’s Q and its
lag positively affect investment.

The estimated coefficients of different uncertainty measures, re-
ported in Table 5, show that investment-uncertainty relationship
greatly depends on the cause of uncertainty. When uncertainty is driven
by shocks to oil supply, speculative demand, or oil market-specific
demand, there is no significant effect of uncertainty on investment. On
the contrary, when uncertainty is brought about by global

---

15 Since both the Im et al. (2003) and Levine et al. (2002) tests require a
balanced panel dataset, we restrict our analysis to the sample period starting
from 1998.
16 The lagged dependent variable and the Tobin’s Q ratio are both considered
to be endogenous in the model. There is a consensus among researchers on the
endogeneity bias for the lagged dependent variable in panel data models (see,
e.g., Arellano (2003)). Moreover, our Tobin’s Q measure may not be strictly
exogenous since it incorporates market valuation in the numerator (Mohn and
Misund (2009)).
17 The Arellano-Bond GMM estimators can be implemented as one- and two-
step estimators. The two-step estimator is asymptotically more efficient, but the
standard errors are downward-biased (Blundell and Bond (1998)). A finite-
sample correction of the covariance matrix of two-step GMM estimators pro-
posed by Windmeijer (2005) is adopted in our paper, which results in larger
standard errors that are much more reliable in finite samples.
18 Aggregation is carried out by averaging firm level values across each year.
19 They argue that by making investments with realized cash holdings, firms
avoid the costs that are incurred when investing with uncertain cash flows.
For more detailed discussion, refer to section 2.

Table 3
Results from regressing each variable on its one-period lag.

<table>
<thead>
<tr>
<th></th>
<th>$\pi$</th>
<th>$Q$</th>
<th>CashF</th>
<th>$\delta_{\text{supply}}$</th>
<th>$\delta_{\text{demand}}$</th>
<th>$\delta_{\text{oil specific}}$</th>
<th>$\delta_{\text{stock}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q(-1)$</td>
<td>.515*** (.030)</td>
<td>.399*** (.022)</td>
<td>0.15*** (0.011)</td>
<td>.864*** (.004)</td>
<td>.560*** (.030)</td>
<td>.510*** (.0354)</td>
<td>.605*** (.030)</td>
</tr>
</tbody>
</table>

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard error are reported in parentheses.

Table 4
Results of the regression of the aggregate level equation This table presents the results of a set of linear models, where the average firm investment capital ratio is the dependent variable. Similarly, cash flows and Tobin’s Q are averaged annually and treated as explanatory variables. The first three columns report estimation results based on conventional Tobin’s Q specifications. The last columns report the results for the specification augmented with volatility measures.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CashFw</td>
<td>-0.0156***</td>
<td>-0.0148***</td>
<td>-0.0170***</td>
<td>-0.0184***</td>
<td>-0.0178***</td>
<td>-0.0189***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Q</td>
<td>0.0132</td>
<td>0.0131</td>
<td>-0.0159</td>
<td>0.00828</td>
<td>0.00731</td>
<td>-0.0155</td>
</tr>
<tr>
<td>(0.088)</td>
<td>(0.083)</td>
<td>(0.000)</td>
<td>(0.323)</td>
<td>(0.386)</td>
<td>(0.222)</td>
<td>(0.439)**</td>
</tr>
<tr>
<td>Q(1)</td>
<td>0.0489***</td>
<td>0.0489***</td>
<td>0.0489***</td>
<td>0.0489***</td>
<td>0.0489***</td>
<td>0.0489***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.188***</td>
<td>0.135***</td>
<td>0.147***</td>
<td>0.183***</td>
<td>0.145</td>
<td>0.166**</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.051)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
</tbody>
</table>

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. p-values are reported in parentheses.

For more detailed discussion, refer to section 2.
Table 5 Results of estimating the investment model 10 This table reports the results from estimating investment model (10). The first column refers to panel estimation. The last two columns present the results obtained with the SGMM method. For both SGMM specifications, all volatility measures are treated as instrument variables. In the second column, the lagged dependent variable, cash flow, and the Tobin’s Q are treated as endogenous, and in the last column, the lagged Tobin’s Q and cash flow are also assumed to be endogenous. 

<table>
<thead>
<tr>
<th>Panel with fixed effect</th>
<th>System GMM(1)</th>
<th>System GMM(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cashflow</td>
<td>0.133***</td>
<td>0.131***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Cashflow(-1)</td>
<td>0.000119</td>
<td>0.000298</td>
</tr>
<tr>
<td>(0.829)</td>
<td>(0.281)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Q</td>
<td>0.00169</td>
<td>0.0130**</td>
</tr>
<tr>
<td>(0.018)</td>
<td>(0.020)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Q(-1)</td>
<td>0.00933***</td>
<td>0.00409</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.371)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>σ2_Sply(1)</td>
<td>0.000629</td>
<td>0.00142</td>
</tr>
<tr>
<td>(0.252)</td>
<td>(0.928)</td>
<td>(0.092)</td>
</tr>
<tr>
<td>σ2_Dmnnd(-1)</td>
<td>0.00700***</td>
<td>0.00790***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>σ2_Spec(-1)</td>
<td>0.00333***</td>
<td>0.0538**</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>σ2_Other(-1)</td>
<td>0.00431</td>
<td>0.00525</td>
</tr>
<tr>
<td>(0.144)</td>
<td>(0.359)</td>
<td>(0.326)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00441</td>
<td>0.009984</td>
</tr>
<tr>
<td>(0.132)</td>
<td>(0.304)</td>
<td>(0.760)</td>
</tr>
<tr>
<td>AR(1)</td>
<td>-0.000768</td>
<td>-0.00467</td>
</tr>
<tr>
<td>(0.751)</td>
<td>(0.186)</td>
<td>(0.607)</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.00357</td>
<td>0.00826</td>
</tr>
<tr>
<td>(0.885)</td>
<td>(0.316)</td>
<td>(0.505)</td>
</tr>
<tr>
<td>Hansen</td>
<td>0.194***</td>
<td>0.208***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>10379</td>
<td>10379</td>
</tr>
</tbody>
</table>

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. p-values are reported in parentheses.

the endogeneity of the oil price in the investment-uncertainty relationship and proxy oil market uncertainty by considering the underlying causes behind oil price fluctuations. Third, we identify the stock market uncertainty from which the effects of oil market shocks are excluded.

The results show that the impact of oil market uncertainty on investment largely depends on the causes behind uncertainty. When uncertainty results from shocks to oil supply, speculative demand, or other oil market-specific demands, there is no significant impact on firms’ investment decisions. If oil price uncertainty is driven by global (consumption) demand shock, current investment responds negatively to oil price uncertainty. Therefore, the consumption demand component of the oil price is the main oil market variable which affects investment in the oil and gas industry. Stock market uncertainty has a positive and significant impact on firms’ investment decisions. However, the effect becomes negative for the lagged stock market uncertainty. We interpret this finding by assuming that firms increase their diversified investment in the non-oil sectors, where investment is not sunk by increased stock market uncertainty. Our main results are robust across different estimation techniques. We confirm the view that Tobin’s Q is not a sufficient factor to explain firms’ investment behaviour. Conversely, there is an important role for uncertainty in the investment decision-making process of a firm, which is consistent with the option theory of investment.

The policy makers in governments or industries can apply the findings of this paper when there is uncertainty about the price of oil and the price is not stable. According to the findings of this paper, in order to take the right and relevant policy, they should take into account the reason behind this situation. In other words, government should mainly monitor demand shifts to pursue its policy to boost investment and growth in the economy. This is very important also for investors when they decide to invest in the oil sector or to diversify their investment in non-oil sector.

Acknowledgments

The first and third authors acknowledge financial support from the Department of Economics, Management and Statistics of the University of Milan-Bicocca, Italy. Previous versions of the paper have been presented in seminars organized by: the Department of Economics, Management and Statistics, University of Milano-Bicocca, Italy; EEME 2018, 11th International Workshop on “Empirical Methods in Energy Economics”, Fondazione Eni Enrico Mattei, Milano, Italy; the Department of Environmental Science and Policy, University of Milan, Italy; and SIS 2018, 49th Scientific meeting of the Italian Statistical Society, University of Palermo, Italy. The authors are indebted to seminar participants for insightful comments and suggestions.

References


