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# Investment-Uncertainty Relationship in the Oil and Gas Industry

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**Abstract**

Recent studies on oil market demonstrate endogeneity of oil price by modeling 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 playing a role in oil market. Accordingly, this study investigates the relationship between investment and uncertainty for a panel of U.S. firms operating in oil and gas industry with a new approach. We decompose oil price volatility to be driven by structural shocks that are recognized in oil market literature, over and above other determinants, to study whether 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 demand shocks. Stock market uncertainty is found to have a negative effect on investment with a year of delay. The results suggest no positive relation between irreversible investment and uncertainty, but interestingly, positive relation exists for reversible investment. This finding is in line with the option theory of investment and implies that irreversibility effect of increased uncertainty dominates the traditional convexity effect.



**Keywords:** Oil Market, Investment, Uncertainty, SVAR-GARCH.

**Classification:** C3, G11, Q41, Q43.

# 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, investment decisions can be postponed by investors who need additional information to reduce uncertainty (Dixit and Pindyck [1994]). The orthodox theory of investment, based on the assumption of reversible investment expenditure, 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 to the timing of investment decisions, this theory finds a negative effect of uncertainty on investment.

There are various sources for uncertainty, which are different for different 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 analyzed 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 relating 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], Misund and Mohn [2009] Ratti and Yoon [2011]). However, the cited studies, as well as other contributions which investigate the relation between oil price uncertainty and investment, consider the price of oil exogenous with respect to the macroeconomic variables. Based on this assumption, construction of oil price variance estimates by averaging the squared residuals obtained from modeling 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 [2009a], Dvir and Rogoff [2010], Alquist and Kilian [2010] and Kilian and Murphy [2014]). For instance, Kilian and Park [2009], Hamilton [2009] and Kilian [2009a] argue that the endogeneity of the price of oil with respect to the macro-economy is essential to appropriately study the effects of the oil price on key economic variables. Along this line, Kilian and Murphy [2014] propose a structural decomposition of oil price shocks into their underlying components, among which shocks to oil supply, global demand, and oil demand.

Figure 1 represents the historical decomposition of real oil price changes driven by relevant structural shocks [1]. The figure conveys the idea which supports our study: oil price dynamics is historically driven by a combination of aggregate demand and speculative shocks, which dominate the oil supply shocks. Accordingly, investors would react more significantly to shocks from the demand side of the oil market when deciding about irreversible investment.

[Figure 1 here]

The aim of this paper is to analyze the relationship between uncertainty and investment in oil and gas industry, taking into account the underlying factors that drive oil price changes, along with other factors represented in the literature as determinants of firm investment. Stock market volatility is also incorporated to the analysis to control for the effects of stock market uncertainty, which is an additional source of uncertainty af-

[1] Refer to the methodological section of this paper for a full structural model specification.

fecting firms' investment decision. A Structural Vector Autoregressive with time-varying conditional variances (SVAR-GARCH) model is employed to describe the global market for crude oil and the stock market. We employ the same structural model as Ahmadi et al. [2016], although we depart from the assumption of time-invariant variances of the structural shocks.

It has been recognized by researchers that the uncertainty of financial time series, as measured by their variances, is changing through time. One of the most popular tools that has emerged to model non-constant variances is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and its various extensions (see, for a review, Bollerslev et al. [1992]). Our SVAR-GARCH model identifies five structural shocks, namely oil supply shocks, global demand shocks, speculative demand shocks, other oil market-specific shocks and stock market shocks. Accordingly, we measure uncertainty by estimating time varying volatilities of each structural shock. We then feed the (annualized) estimated volatility series into a Tobin's Q model of investment, which relates investment of a firm to it's stock market valuation, measured as the ratio of the market value of a firm to the replacement value of its assets (the Tobin's Q), and captures the firm's opportunity cost of capital investment.

One advantage of our approach is that it accounts for two different sources of uncertainty affecting firm's investment: uncertainty brought about by the oil market and uncertainty related to the stock market. Although some studies have reported a connection between these two markets, yet there is no consensus about the direction of their casual relation. Oil price changes are known as an important factor that contributes to describe fluctuations in stock market. Moreover, according to Kilian and Park [2009], it is widely accepted by researchers that, since the 1970s, oil prices have been responding to the same economic factors that affect the stock market. Our framework allows to address this issue by relating the U.S. stock returns to the global crude oil market, within our SVAR-GARCH model. Consequently, stock market uncertainty is measured by the volatility of aggregate stock market return shocks which are uncorrelated with oil market-related shocks.

Many empirical studies augment the Tobin's Q model for investment with additional explanatory variables, such as different measures of uncertainty (see, for example, Henriques and Sadorsky [2011]). In this paper, the Tobin's Q model is augmented by the firm's cashflow and oil price uncertainty driven by structural shocks to the price of oil, as well as by aggregate stock market uncertainty.

The rest of the paper proceeds as follows. Section 2 offers a brief review of the relevant literature. In Section 3 the data are described. The Structural VAR model and the augmented Tobin's Q model of investment are presented in Section 4. Section 5 illustrates and discusses the estimation results. Section 6 concludes.

## 2 Literature review

The relationship between investment and uncertainty has been analyzed in numerous studies. A number of theoretical studies apply the standard neoclassical investment model that predicts a positive relationship between uncertainty and investment. According to this model, a firm invests when the present value of the project's expected cash flows is at least as large as its costs. Oi [1961], Hartman [1972] and Abel [1983], under the assumptions of risk neutrality, perfect competition and constant returns to scale, find a positive effect on investment of the uncertainty related to the price of output. This result, however, depends on the convexity of the expected profits in the output price.

Some studies follow the option theory of investment and show that, when investment is irreversible, firms have the option to postpone investment (e.g., Cukierman [1980], Bernanke [1983], McDonald and Sigel [1986], Pindyck [1991] and Dixit and Pindyck [1994]). The underlying idea of the option theory of investment is that firms invest if the net present value of investment is greater than the option value of waiting. According to Favero et al. [1992], for instance, an investment project is adopted if the expected payoff is greater than the cost of investment plus the value of the waiting option. Hence, since the value of the waiting option raises with uncertainty, the implication is that firms may decide to postpone investment when there is uncertainty about future prices (see e.g. Carruth et al. [1998] and Bond and Cummins [2004]). Therefore, according to this approach, investment responds negatively to higher uncertainty.

The empirical studies on the investment-uncertainty relationship for U.S. firms are numerous. Employing various proxies for uncertainty, several authors report negative and significant effects. 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 as sale growth rates (Ogawa and Suzuki [2010]) and future profits (Bond and Cummins [2004]) are only a few examples of how researchers deal with measuring uncertainty. However, some authors report that the significance of the negative relation is not robust to the inclusion in their empirical applications of Tobin's Q or other important factors, such as cash flows. This finding may be due to a strong negative correlation between Tobin's Q and a given measure of uncertainty (see, for example, Leahy and Whited [1996]). While studies indirectly analysing the relationship are not many, these contributions generally report the same result. For example, Shaanan [2005] finds that irreversibility reduces investment for the

U.S. listed firms.

Several studies assess the importance of energy prices fluctuations in explaining investment decisions. Glass and Cahn [1987] explore the relationship between energy price changes and investment. They find that energy price increases retard aggregate investment. However, they do not examine whether there is a role for uncertainty as a channel to transmit this effect. Uri [1980] develops a simple model to study the role of energy price changes as a determinant of investment behavior. He finds that the price of energy is an important factor in explaining investment decisions at the aggregate level, and more importantly, for energy intensive industries. Bernanke [1983] shows that, when uncertainty about the future price of oil increases, firms postpone their irreversible investment when they have to choose between energy-efficient or energy-inefficient capital. Ratti and Yoon [2011] estimate an error correction model of capital stock adjustment with data on U.S. manufacturing firms. They find that higher energy price uncertainty declines the responsiveness of investment to sales growth. Their results suggest that stability in energy prices would be conducive to greater stability in firm-level investment.

The relation 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 decision to develop an oil field. They evaluate the importance of the variables suggested by theory to explain the length of development lags on the U.K. oil and gas fields. Their results imply that the effect of uncertainty is a function of the expected price level: the volatility of prices has a positive(negative) impact on the duration of investment appraisal when prices are low(high). Hurn and Wright [1994], using data from operations in the 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, Misund and Mohn [2009] estimate the effect of oil price volatility on investment in the oil and gas sector. Their results show that Tobin's Q is a poor investment indicator for the international oil and gas industry, 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 and economic growth for the U.S. economy. They 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 analyze 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.

This paper analyses the effects of uncertainty on investment of firms operating in the oil and gas industry with a new approach. We contributes to the literature by taking into account the endogeneity of the price of oil in the relation between investment and uncertainty. Our paper answers the question of whether and how this relationship depend on the causes which drive uncertainty.

Our focus is on 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 oil price is not exogenous with respect to oil market participants and macroeconomic fundamentals[2], the oil and gas industry represents the natural laboratory for the application of our new approach to the analysis of the investment-uncertainty relation.

# 3 Data

Our data are in the form of an unbalanced panel of U.S. oil and gas companies ($i = 1, ..., N$) for the period 1976 to 2016 ($t = 1, ..., T$) 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 proxies 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:[3]

$$Q_{it} = \frac{(market\ value\ of\ equity + preferred\ stock + debt)_{it}}{total\ assets_{it-1}} - 1$$

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

$$Cashflow_{it} = \frac{(income\ before\ extraordinary\ items\ +\ depreciation)_{it}}{total\ assets_{it-1}} - 1$$

[2]See, for example, Hamilton [2009], Kilian [2009a] and Kilian [2008].
[3]In terms of COMPUSTAT item labels, the relation is:

$$Q = (PRCC\_C * CSHO + PSTKL + (LCT - ACT) + DLTT)/AT(-1) - 1$$

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 and $NT$=11865 firms$x$years observations.

Global oil market variables include global crude oil production, a measure for global trade that captures the global (consumption) demand for oil and other industrial commodities[4], 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, proxies 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] and Kilian and Murphy [2014] to construct global oil inventory data. The series is constructed by scaling data for total U.S. oil inventories by the ratio of the OECD petroleum stocks over 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 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 Figure 2) are annualized by averaging monthly volatilities

[4]The measure of global real economic activity, introduced by Kilian [2009a], is based on the global dry cargo shipping rates that capture the global business cycle and is used to measure consumption demand for oil and all industrial commodities.

prior to each year.[5]. Table 1 presents the descriptive statistics for the whole dataset.

[Figure 2 here] [Table 1 here]

Figure 3 graphs the annual mean of the investment capital ratio of all firms versus demand and supply shock 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 0.27 is the value of the correlation coefficient with the supply shock volatility for the period 2000-2016.

[Figure 3 here]

# 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 annualized, 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 annualized volatility series.

[5]To match the frequency of volatility series with firm-level data we aggregate monthly series to obtain annual series. We are aware of the information we lose when aggregating the monthly volatilities. To cope with this problem, we have applied quarterly firm-level data to reduce the information loss of data aggregation. Although quarterly firm-level data are highly seasonal, our results do not change overall. Another possibility for avoiding data aggregation is to apply the Mixed Data Sampling (MiDaS) approach which allows for estimation where regressors have different frequencies. Unfortunately, we are not aware of a consistent MiDaS estimator that incorporates the Two-step System GMM methodology.

## 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 along with the stock market shocks.

SVAR-GARCH models have been widely applied by researchers for identification of structural shocks or for testing over-identification in a VAR context. 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 to 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 can identify the stock market shocks from which the effects of oil market shocks are excluded. Second, the SVAR model is estimated under the assumption that the structural shocks have time-varying volatility. Our specification is:[6]

$$
\begin{aligned}
A_0 y_t &= \alpha + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t \\
E(\varepsilon_t) = 0, \quad E(\varepsilon_t \varepsilon_t^{'}) &= H_t, \quad E(\varepsilon_t \varepsilon_s^{'}) = 0, t \neq s \\
h_{i,t} &= \delta_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}
\end{aligned}
\tag{1}
$$

where $y_t$ is the vector of endogenous variables including the percentage change in global oil production, the global real economic activity, 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, $h_{i,t}$, 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:

$$
y_t = \beta + \sum_{i=1}^{24} B_i y_{t-i} + e_t \tag{2}
$$

$$
B_i = A_0^{-1} A_i, \ \forall i,
$$

$$
e_t = A_0^{-1} \varepsilon_t = A_0^{-1} D_t^{\frac{1}{2}} z_t = S_t z_t,
$$

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

$$
E(e_t e_t^{'}) = E(A_0^{-1} \varepsilon_t \varepsilon_t^{'} A_0^{-1}) = A_0^{-1} E(\varepsilon_t \varepsilon_t^{'}) A_0^{-1'} = A_0^{-1} D_t A_0^{-1'} = S_t S_t^{'} = V_t
$$

[6]Applying 24 months of lags is consistent with Hamilton and Herrera [2004] and Kilian and Park [2009] who argue that allowing for high lag order is crucial in capturing 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 lag would fail to capture the whole dynamics of the cycle. The alternative way of setting the lag order is 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 specially 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])

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

$$\begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{4t}^{real\ price\ of\ oil} \\ e_{3t}^{\Delta global\ oil\ inventory} \\ e_{5t}^{real\ stock\ return} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ supply\ shock} \\ \varepsilon_{2t}^{global\ demand\ shock} \\ \varepsilon_{3t}^{speculative\ shock} \\ \varepsilon_{4t}^{other\ oil\ shocks} \\ \varepsilon_{5t}^{stock\ market\ shock} \end{pmatrix} \tag{3}$$

The identifying restrictions are based on the following assumptions. First, within a month, changes in global oil production do not respond to different oil demand shocks. This assumption is due to the fact that 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 at least with one month of delay. Third, the real price of oil responses to oil supply shocks, consumption demand and speculative demand shocks and other oil market shocks will affect the price of oil with at least one month delay. Finally, oil market variables are all predetermined with respect to stock market returns, while stock market returns are affected by different shocks to the price of oil.

## 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:

$$(\frac{I}{K})_{it} = a + \frac{1}{b}Q_{it} + \upsilon_{it} \tag{4}$$

where $Q_{it}$ is the ratio of the market value of the $i-th$ firm to the replacement value of its assets; $I_{it}$ is the firm's gross investment, $K_{it}$ is the firm's net capital stock and $\upsilon_{it}$ is a random error term; $a$ and $b$ are the structural parameters of the adjustment cost function. To take into account the factors reported in the literature which affect investment, it is common practice in the literature to augment the Tobin's Q model of investment with additional variables. In this paper, the additional explanatory variables include 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 Sadorsky [2011], firms' cash-flow is also included among the explanatory factors.

In order to avoid serial correlation in the error terms, $\varepsilon_t$ is assumed to follow an AR(1) process (see Misund and Mohn [2009]):

$$\upsilon_{it} = \rho\upsilon_{it-1} + \nu_{it} \tag{5}$$

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

$$
\begin{aligned}
(\frac{I}{K})_{it} = a(1-\rho) + \rho(\frac{I}{K})_{it-1} + \frac{1}{b}Q_{it} + \frac{\rho}{b}Q_{it-1} + \gamma_1 CF_{it} + \rho\gamma_1 CF_{it-1} \\
+ B_1 X_t + \rho B_1 X_{t-1} + \xi_{it}
\end{aligned}
\tag{6}
$$

where $X_t$ 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 equation (6), which is represented as:

$$
\begin{aligned}
(\frac{I}{K})_{it} = b_0 + b_1(\frac{I}{K})_{it-1} + b_2 Q_{it} + b_3 Q_{it-1} + b_3 CF_{it} + b_4 CF_{it-1} \\
+ B_1 X_t + B_2 X_{t-1} + \xi_{it}
\end{aligned}
\tag{7}
$$

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 are carried out. The reason to choose panel unit root tests is that these statistics have higher power to reject the null hypothesis of a unit root than the 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 hypothesis is that at least one time series is stationary.

Conversely, the Im et al. [2003] test allows for heterogeneity across cross sectional unit roots, each cross section having an individual unit root process, and specifies an ADF regression for each cross section. The null hypothesis is that there is a unit root, while the alternative hypothesis is that the fraction of individual units following stationary processes is nonzero.

The results of the tests are presented in Table 2 and suggest strong evidence against the presence of unit root in our panel data set[7], meaning that all variables are stationary in levels, that is, their order of integration is zero. Accordingly, we do not need to apply the cointegration test and our data are appropriate to adopt the System GMM (SGMM) methodology.

[Table 2 here]

#### 4.2.2 Model Estimation

The augmented Tobin's Q model of investment in equation (7) relates the ratio of investment to firms capital to its own one-period lag, Tobin's Q, cash flow, as well as our measures of oil price and stock market uncertainty. The model uses a panel data of $N$=985 U.S. firms in the oil and gas industry over a period of $T$=41 years. The model is estimated with two methods, that is panel estimation with firm fixed effect, and the two-step System Generalized Method of Moments (SGMM) proposed by Blundell and Bond [1998]. The motivation to apply SGMM is four-fold. First, it allows to control for possible endogeneity between the model's variables and the predetermined regressors that are independent of current disturbances, but can be influenced by past disturbances.[8] Second, when some

[7] Since both Im et al. [2003] and Levine et al. [2002] tests require a balanced panel data, we restrict our analysis to the sample period covering 1998 to 2016.

[8] The lagged dependent variable and the Tobin's Q ratio are both considered as being 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 (Misund and Mohn [2009]).

series in the model have near unit root properties, according to Bond and Cummins [2004] and Blundell and Bond [1998], the lagged levels of the regressors, used in the difference GMM model, may be poor instruments for the first-differenced regressors. The level of persistence of the variables in our model is shown in Table 3.

[Table 3 here]

The SGMM method includes level equations in the estimated system of equations. This method applies lags of both first-differences and levels of the dependent and predetermined variables as instruments to improve efficiency, compared to the Arellano and Bond [1991]'s difference GMM estimator (Misund and Mohn [2009]). Third, the two-step estimator is asymptotically more efficient than the one-step estimator and the standard covariance matrix is robust to panel-specific autocorrelation and heteroskedasticity.[9] Forth, since our model incorporates a generated vector of variances among the regressors, inference based on standard $t$ tests is generally biased (see Pagan [1984] and Pagan [1986]. On the contrary, the SGMM approach avoids the inferential issues raised by the generated risk regressors (Pagan and Ullah [1988]).

It is very important to test for autocorrelation when the GMM method is applied on panels and lags are treated as instruments. Arellano and Bond [1991] suggest an appropriate test for first- and second- order autocorrelation in first-differenced errors. If the residuals are independent and identically distributed, the first-order test statistic is significant, meaning that the first-differenced errors are first-order serially correlated. The higher-order serial correlations should be insignificant. To test for over-identifying

[9] 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]). However, a finite-sample correction of the covariance matrix of two-step GMM estimators proposed by Windmeijer [2005] is adopted in our paper, which results in larger standard errors that are much more reliable in finite samples.

restrictions, the Arellano and Bond [1991]'s version of the Sargan test could incorrectly reject the null hypothesis in presence of heteroskedasticity. Hence, following Rodman [2005], we use the Hansen statistic to test for over identifying-restrictions.

## 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 analysing the relation between uncertainty and investment.[10]

[Table 4 here]

Table 4 has six columns. 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. The empirical findings suggest a high explanatory power for the lagged Tobin's Q measure. The coefficient associated with the Tobin's Q measure is positive and significant, unless its lagged value enters the regression. Most important, out of five volatility measures, only the volatility of demand shocks does affect negatively the aggregate investment capital ratio. This result is in line with the oil market literature, where demand shocks are reported as the main explanatory determinant of oil price movements. In other terms, investors monitor more carefully demand shifts when deciding about new investment projects.

[10] Aggregation is carried out by averaging firm level values across each year.

The results from estimating investment model (7) 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 reported and all volatility measures are treated as instrument variables. In the second column, the lagged dependent variable, cash flow and the Tobin's Q measure are treated as endogenous, while in the last column the lagged Tobin's Q measure and cash flow are assumed to be endogenous.

[Table 5 here]

The results show that the investment-uncertainty relationship depends largely on the causes of uncertainty. When uncertainty is driven by shocks to oil supply, speculative demand or oil market-specific demand, there is no significant relationship between investment and uncertainty. On the contrary, when uncertainty is brought about by global (consumption) demand shocks, investment significantly decreases. Stock market uncertainty is found to negatively affect investment decisions in the oil and gas industry with one-year lag, although the concurrent effect is positive. This finding could be due to diversified firm investment in non-oil sectors, where investment is at least partially reversible. (see Lamont [1997] for further discussion).

However, the negative response of investment to uncertainty raised by the oil market is dampened over time. As we can see in Table 5, the effects of lagged oil price uncertainty caused by global demand shock are insignificantly positive in three out of four specifications. The temporary significant effect suggests that any change in uncertainty is taken by oil companies as being transitory. However, the results indicate that there is no significant positive relationship between uncertainty and investment in the oil and gas industry. This is in line with the option theory of investment and the irreversibility effect of increased uncertainty, which dominates the traditional convexity effect.

Evidence on the sign and the significance of the coefficient for the lagged investment-capital ratio, reported in the first row of Table 5, is not conclusive. Lagged Tobin's Q positively impacts current investment, but no significant relation is found between current Tobin's Q measure and investment. Our findings are in line with the previous literature, according to which Tobin's Q is not a sufficient statistic to explain investment. Consistent with the option theory of investment, we have found that there is an important role for uncertainty in investment decisions of the firms.

The results from Arellano and Bond [1991] postestimation specification tests are presented in the last rows of Table 5. There is no significant evidence of serial correlation at second order in the first-differenced errors. According to the results of the Hansen test, the validity of the over-identifying restrictions is not rejected.

# 6 Conclusions

In this paper we study the relationship between investment and uncertainty in a panel of U.S. firms operating in the oil and gas industry. To analyze this relation, a Tobin's Q model of investment, augmented with measures of industry-level and aggregate stock market uncertainty from a SVAR-GARCH model of the global oil market, is estimated. We contribute to the literature in at least two ways. First, in order to capture industry-level uncertainty, we proxy oil market uncertainty by taking into account the underlying causes behind oil price fluctuations. We found that considering the causes of oil price changes is very important to investigate how investment depends on oil market uncertainty. Second, oil market effects are excluded from aggregate stock market uncertainty to capture the net effects of stock market uncertainty in our investment model.

The results show that the impact of oil market uncertainty on investment largely depends on the causes behind uncertainty. When uncertainty is derived by 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, investment responds negatively to oil price uncertainty. Therefore, the consumption demand component of oil price is the main oil market variable affecting investment in the oil and gas industry. Stock market uncertainty has a positive and significant impact on the 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 results do not signal any significant positive relationship between uncertainty and irreversible investment in the oil and gas industry. This evidence is in line with the view that Tobin's Q is not a sufficient factor to explain firms' investment behavior. 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.

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Table 1: Summary statistics of data

| | mean | SD | min | max |
|---|---|---|---|---|
| $\frac{I}{K}$ | 0.213 | 0.453 | -0.242 | 36.968 |
| Q | 0.585 | 1.878 | -0.945 | 18.306 |
| CashF | -0.007 | 1.791 | -62.977 | 170.881 |
| Number of Observations | 11865 | | | |
| $\sigma^2\_Supply$ | 1.101 | 0.351 | 0.638 | 2.165 |
| $\sigma^2\_Demand$ | 0.959 | 0.406 | 0.504 | 2.376 |
| $\sigma^2\_Speculation$ | 1.991 | 0.814 | 0.846 | 3.755 |
| $\sigma^2\_Other\ shocks$ | 2.844 | 0.522 | 1.854 | 4.813 |
| $\sigma^2\_Stock\ market$ | 2.475 | 0.557 | 1.483 | 3.806 |
| Number of Observations | 41 | | | |

Table 2: Panel unit root tests.

| | without trend | | with trend | |
|---|---|---|---|---|
| | IPS | LL | IPS | LL |
| $\sigma_{demand}$ | -1.989** | -11.012*** | -5.518* | -19.340*** |
| $\sigma_{supply}$ | -9.217*** | -21.689*** | 5.862 | -8.388*** |
| $\sigma_{oil-specific}$ | 7.607 | 7.362 | -16.083*** | -21.193*** |
| $\sigma_{stock\ market}$ | -2.621*** | -3.385*** | 0.827 | 4.199 |
| $\frac{I}{K}$ | -10.091*** | -14.266* | -8.649*** | -16.591*** |
| $Q$ | -7.763*** | -10.561*** | -5.640*** | -11.527*** |
| $CashF$ | -6.3028*** | -16.5863*** | -8.4223*** | -5.2720*** |

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

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

| | $\frac{I}{K}$ | $Q$ | $CashF$ | $\sigma_{supply}$ | $\sigma_{demand}$ | $\sigma_{oil-specific}$ | $\sigma_{stock}$ |
|---|---|---|---|---|---|---|---|
| $\frac{I}{K}(-1)$ | .515*** | | | | | | |
| | (.030) | | | | | | |
| $Q(-1)$ | | .399*** | | | | | |
| | | (.022) | | | | | |
| $CashF(-1)$ | | | 0.15*** | | | | |
| | | | (0.011) | | | | |
| $\sigma_{supply}(-1)$ | | | | .864*** | | | |
| | | | | (.004) | | | |
| $\sigma_{demand}(-1)$ | | | | | .560*** | | |
| | | | | | (.030) | | |
| $\sigma_{oil-specific}(-1)$ | | | | | | .510*** | |
| | | | | | | (.0354) | |
| $\sigma_{stock}(-1)$ | | | | | | | .605*** |
| | | | | | | | (.030) |

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.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $\frac{I}{K}(-1)$ | | 0.410 | 0.254 | | 0.336 | 0.230 |
| | | (0.098) | (0.177) | | (0.133) | (0.176) |
| $CashF$ | -0.0491 | -0.00985 | -0.00427 | -0.0102 | 0.0121 | -0.000471 |
| | (0.519) | (0.891) | (0.947) | (0.865) | (0.834) | (0.993) |
| $Q$ | 0.0263** | 0.0214* | -0.00308 | 0.0219* | 0.0182* | -0.00250 |
| | (0.004) | (0.019) | (0.797) | (0.011) | (0.038) | (0.828) |
| $Q(-1)$ | | | 0.0512** | | | 0.0448** |
| | | | (0.003) | | | (0.002) |
| $\sigma^2\_Sply$ | | | | -0.0188 | -0.0173 | -0.0124 |
| | | | | (0.320) | (0.338) | (0.461) |
| $\sigma^2\_Dmnd$ | | | | -0.0735** | -0.0660** | -0.0509* |
| | | | | (0.001) | (0.009) | (0.028) |
| $\sigma^2\_Spec$ | | | | 0.0200 | 0.0155 | 0.00694 |
| | | | | (0.227) | (0.360) | (0.689) |
| $\sigma^2\_Other$ | | | | 0.00383 | 0.00433 | -0.000793 |
| | | | | (0.698) | (0.614) | (0.922) |
| $\sigma^2\_Stck$ | | | | 0.00490 | -0.000122 | -0.00405 |
| | | | | (0.741) | (0.993) | (0.677) |
| $Const.$ | 0.195*** | 0.110* | 0.128*** | 0.227*** | 0.169* | 0.198** |
| | (0.000) | (0.019) | (0.001) | (0.000) | (0.045) | (0.001) |
| # of Obs. | 41 | 40 | 40 | 41 | 40 | 40 |
| $R^2$ | 0.106 | 0.238 | 0.498 | 0.345 | 0.429 | 0.608 |

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

Table 5: Results of estimating the investment model 7.

| | Panel with fixed effect | System GMM(1) | System GMM(2) |
|---|---|---|---|
| $\frac{I}{K}(-1)$ | -0.387*** | 0.131*** | 0.0144 |
| | (0.000) | (0.000) | (0.330) |
| $CashF$ | 0.00977 | 0.0159 | 0.0129 |
| | (0.515) | (0.493) | (0.534) |
| $CashF(-1)$ | 0.00433 | 0.0127 | 0.00558* |
| | (0.377) | (0.147) | (0.011) |
| $Q$ | 0.00239 | 0.0138 | 0.0102 |
| | (0.554) | (0.308) | (0.117) |
| $Q(-1)$ | 0.0169*** | 0.0151** | 0.0154*** |
| | (0.000) | (0.001) | (0.000) |
| $\sigma^2\_Sply$ | 0.00970 | 0.0174 | -0.00659 |
| | (0.154) | (0.340) | (0.449) |
| $\sigma^2\_Sply(-1)$ | -0.0133 | -0.0604 | -0.0163 |
| | (0.068) | (0.075) | (0.060) |
| $\sigma^2\_Dmnd$ | -0.104*** | -0.0874*** | -0.0829*** |
| | (0.000) | (0.000) | (0.000) |
| $\sigma^2\_Dmnd(-1)$ | 0.0217 | 0.0291 | 0.0211 |
| | (0.296) | (0.184) | (0.052) |
| $\sigma^2\_Spec$ | 0.00354 | 0.00800 | 0.00223 |
| | (0.573) | (0.722) | (0.831) |
| $\sigma^2\_Spec(-1)$ | 0.0186** | 0.00743 | 0.00585 |
| | (0.004) | (0.710) | (0.451) |
| $\sigma^2\_Other$ | -0.00334 | -0.00286 | -0.00539 |
| | (0.436) | (0.612) | (0.181) |
| $\sigma^2\_Other(-1)$ | -0.0146 | -0.00285 | -0.0109 |
| | (0.069) | (0.845) | (0.173) |
| $\sigma^2\_Stck$ | 0.0309** | 0.0202** | 0.0267*** |
| | (0.009) | (0.010) | (0.000) |
| $\sigma^2\_Stck$(-1) | -0.0394** | -0.0189 | -0.0387*** |
| | (0.002) | (0.244) | (0.000) |
| Const. | 0.389*** | 0.246*** | 0.328*** |
| | (0.000) | (0.000) | (0.000) |
| AR(1) | | -9.75 | -10.09 |
| | | (0.000) | (0.000) |
| AR(2) | | -0.73 | -1.19 |
| | | (0.465) | (0.235) |
| Hansen | | 5.94 | 4.53 |
| | | 0.312 | 0.467 |
| # of Obs. | 10929 | 10929 | 10929 |

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

Figure 1: Historical decomposition of real oil price change

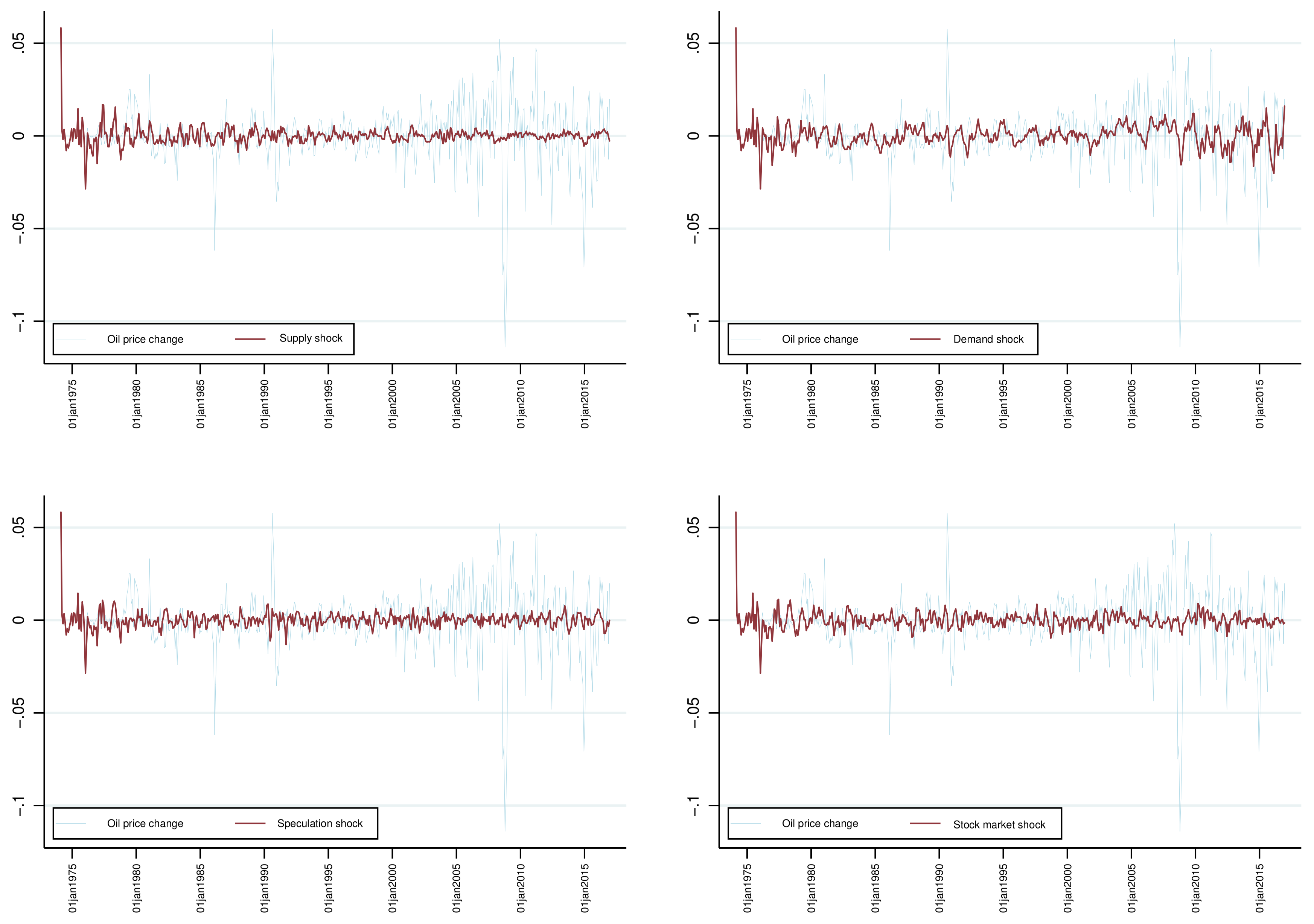

Figure 2: Monthly volatility of structural shocks

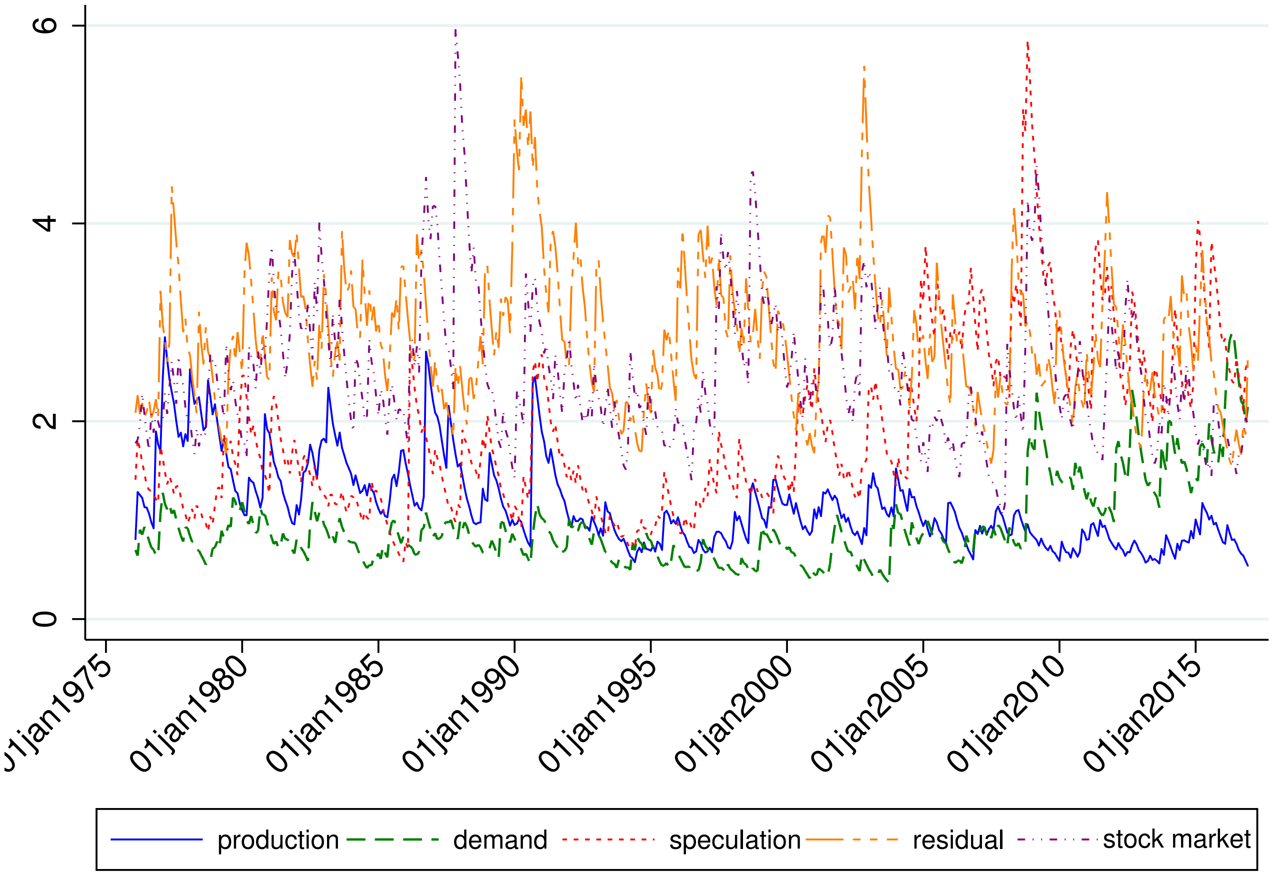

Figure 3: Firm investment capital ratio versus annualized supply shock and demand shock volatilities