Oil Price Uncertainty and Business Fixed Investment: A Real Options Approach*

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Abstract

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Abstract

Using longitudinal plant-level data we investigate whether the decision to invest is affected by oil price uncertainty. The theoretical background is given by models emphasizing the role of embedded real options creating the possibility that investment inaction might be optimal in the presence of increased uncertainty. According to our results oil price uncertainty increases the likelihood of investment inaction and moreover this effect is non-uniformly distributed across decisions makers with different attributes. Essentially, oil price uncertainty increases the probability of investment inaction more for small plants and this effect is further amplified for plants exhibiting high oil dependence in production.

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1 Introduction

Oil price can affect business fixed investment mainly through two direct and an indirect channel. First, increases in oil price may reduce investment via the increase in the marginal cost of production and/or through reduced demand for the firm's output, as consumer expenditures fall in response to rising oil prices (Hamilton (1983), Hamilton (1988); Edelstein and Killian (2007)). Second, changes in oil prices are thought to create uncertainty about future oil prices, causing firms to postpone irreversible investment decisions (Bernanke (1983); Pindyck and Rotemberg (1983); Pindyck (1991); Ferderer (1996)).

The existing literature has thoroughly explored most of the potential oil effects on output (either GDP or industrial production), providing evidence for oil price's adverse effect. The effects of oil price on business fixed investment have received considerable less attention in the empirical literature, with the evidence pointing in the direction of symmetric effects of energy price increases and decreases (Edelstein and Killian (2007)). However, the hypothesized effect of oil price uncertainty on investment deferral has not been explicitly investigated so far. This is exactly the gap that the present study attempts to fill. In other words, we will explore whether oil price driven uncertainty leads to a deferral of investment decisions and, consequently, whether it increases the likelihood of investment inactivity.

In order for uncertainty to generate investment inactivity, capital decisions must be characterized by irreversibility or, in general, non-convex adjustment costs (Abel and Eberly (1994), Abel and Eberly (1996); Caballero and Engel (1999)). Irreversibility implies that one cannot fully reverse capital deployment decisions due to sunkness of capital or due to the inability to recover the value of undepreciated installed capital. Similarly, asymmetric costs suggest that the upward adjustment of capital (positive investment) is less costly than downward adjustment (disinvestment). In such contexts, investment deferral might emerge as an optimal choice in uncertain environments, when the decision maker prefers to wait until part of uncertainty is resolved. In contrast to the frictionless investment benchmark models that predict smooth investment paths, deferral generates inaction zones that result in an investment behavior that is discontinuous and persistent. The underlying theoretical rationale can be accommodated in a real options setting where higher uncertainty discourages investment (McDonald and Siegel (1986); Pindyck (1988); Dixit and Pindyck (1994)). Essentially, the embedded options lead to a modification of the standard Jorgensonian investment rule so as to take into account the values of the real options. Effectively, unless returns are high enough to surpass the cost of capital and the options' values or are low enough to justify disinvestment, inactivity is the optimal choice.

We construct reduced-form econometric models utilizing longitudinal plant level data in order to investigate whether oil-driven uncertainty results in intermittent investment behavior. The distinct advantage of micro-level data is the alleviation of the inherent difficulties associated with aggregate data, that usually mask investment discontinuity. The variable under scrutiny is dichotomous in nature and contrasts investment inactivity (neither positive nor negative investment) to investment activity (either positive or negative investment). Applying random effects Probit models, and after controlling for a wide set of plant-specific attributes, we examine the effects of oil-price uncertainty on the probability of investment inaction.

Our main finding is that oil price uncertainty results in substantial declines in the probability of investment for the average plant in the Greek manufacturing sector. However the magnitude of this effect varies considerably with plant size and its degree of oil dependence in production. Essentially, we find that this type of uncertainty affects most small plants, and plants that have a high degree of oil dependence in their production structure. Furthermore, oil price uncertainty impacts the most – and more robustly – on small plants that are also characterized by high oil dependence.

The remainder of the paper is organized as follows. Section 2 reviews the literature and section 3 describes the dataset used. Section 4 discusses the adopted econometric methodology and section 5 presents our empirical results. The last section concludes.

2 Literature Review

2.1 Oil and Investment

The price of energy is one of the many prices faced by firms (and households), yet in many cases is considered "special", perceiving energy price increases as fundamentally different from increases in the prices of other goods – characterized by sustained increases not typical in other goods. For instance, Hamilton (2005) notes that energy price shocks are transmitted, on the one hand through shifts and reductions in consumption expenditure, and on the other hand, through adjustments in firms' investment expenditures. As such, changes in firms' investment spending are considered one of the main channels through which energy price changes are transmitted to the macro-economy.[1]

There are two main (direct) channels through which energy shocks impact on physical investment. First, the increase of the price of energy represents an increase in the marginal cost of production, and its effects depend on the cost share of energy, usually considered to be small (Edelstein and Killian (2007); Kilian (2008b)). The second channel operates by reducing demand for firms' output, because of cutbacks in consumer spending in response to rising energy prices. In this vein, Herrera (2007) studies an inventory model that links shifts in consumer demand in response to energy price shocks to real economic activity. In addition, Edelstein and Killian (2007) argue that there is also a direct link from lower demand to reductions in investment in equipment and structures.

Furthermore, the response of fixed investment to energy price changes might be asymmetric. The usual argument is that changes in energy prices tend to create uncertainty about future energy prices, causing firms to postpone irreversible investment decisions (Bernanke (1983); Pindyck (1991)).[2] This type of uncertainty has implications for both the supply–side and demand–side effects of energy-price shocks, indicating an extra (indirect), of equal or greater importance, channel through which changes in energy prices affect investment spending. Specifically, firms may respond to uncertainty about future production costs and/or to uncertainty about future sales and revenue. When energy prices rise, the uncertainty effect will reinforce the decline in firms' investment spending.[3] In contrast, when energy prices fall, the uncertainty effect counteracts the increase in investment expenditures driven by lower costs and increased consumer demand, dampening the increase in investment spending. The evidence in Edelstein and Killian (2007), indicate that there is no compelling evidence of asymmetries in the responses of investment expenditures, at the sectoral level for the US.

The existing empirical literature, however, has not allowed for an explicit role of oil price uncertainty. With the notable exception of Ferderer (1996), that employs a measure of oil price uncertainty,[4] the rest of empirical literature refers to the effects of uncertainty to justify the finding of asymmetric response of investment spending to energy price changes. Additionally, the existing literature usually examines whether investment spending responds to oil price changes, looking only the direct effects these changes have.

2.2 Investment Under Uncertainty

The intermittent behavior of investment decisions has been widely documented in the empirical literature (Doms and Dunne (1998); Barnett and Sakellaris (1999); Gelos and Isgut (2001); Nilsen and Schiantarelli (2003); Bontempi et al. (2004); Sakelaris (2004); Wilson (2004); Cooper and Haltiwanger (2006)). Moreover, as the level of desegregation decreases the episodes of investment inactivity tend to become more frequent.

Recent investment models deviating from the frictionless benchmark (Jorgenson (1963); Brainard and Tobin (1968); Tobin (1969)) provide the theoretical background for such behavior by explicitly allowing for fixed adjustment costs, and (partial) irreversibility (Abel and Eberly (1994), Abel and Eberly (1996); Caballero and Engel (1999)).[5] The introduction of these frictions generates a wedge between the marginal revenue product of capital and the Jorgensonian user cost.

Another strand of the literature has led to the development of the so-called Real Options Theory which suggests that a firm with an opportunity to invest possesses an option similar to a financial call option. Provided that the firm proceedes with the irreversible investment, it exercises ('kills') its option. Consequently the lost option value is an opportunity cost that must be reflected in the cost of investment (McDonald and Siegel (1986); Pindyck (1988); Dixit and Pindyck (1994)).

Abel et al. (1996) present a flexible model of investment allowing for arbitrary degrees of reversibility and expandability that generate two embedded options: an option to disinvest (put option) since investment is at least partially reversible; and an option to invest (call option) given the ability of costly expandability.

If we let b, b_L and b_H denote the standard user-cost of capital, the resale and purchase prices of capital respectively, with $b_L \leq b_H$, then the relationship between b_L, b_H and b determines the degrees of reversibility and expandability and can nest various investment models. For instance, in the case that $b = b_H = b_L$, investment is fully reversible and expandable, corresponding to the Jorgensonian environment. The other extreme case of full irreversibility and unexpandability would emerge if $b_L = 0$ and $b_H \rightarrow +\infty$, where the former suggests that the resale price of capital is zero and therefore investment is sunk and the latter that capital expansion requires infinite cost and therefore is impossible to implement. Of greater interest are cases that either lead to a single trigger investment policy, when investment is fully irreversible ($b_L = 0$) but partially expandable ($b_H > b > 0$) or to a two trigger policy in which both reversibility and expandability are costly (i.e. $b_L < b$ and $b_H > b$). Investment inactivity (zero investment) is optimal when the marginal product of capital falls short of the trigger for the single trigger case; or when it lies between the two thresholds in the two trigger case.

In such contexts, the standard optimal investment rule has to be modified in order to take into account the two embedded options. Essentially, if investment is initiated (option exercised) the marginal call option is lost and therefore this foregone value must be added to the standard cost of capital. In other words, the investment trigger threshold is higher compared to the Neoclassical investment model. In contrast, the value of the marginal put option has to be subtracted from the cost of capital and consequently tends to decrease the investment trigger threshold. The magnitude of the so-called option value multiple (ϕ) depends on the relative degrees of irreversibility and expandability of capital. For instance, if capital is completely irreversible but at least partially expandable then $\phi \geq 1$ — because the put option does not exist, while the call option has some positive value. In general, as the degree of irreversibility and/or the degree of expandability increase, so does the value of the option multiple, which implies that returns to capital, must clear a higher threshold to render investment optimal. Uncertainty increases the values of both options like in standard financial contracts and therefore if capital is fully irreversible, then higher uncertainty unequivocally raises the investment trigger threshold. The intuition is that in volatile and ambivalent environments it is worthwhile keeping options 'alive' until uncertainty resolves, tactic known as 'wait and see'. Hence, the size of the wedge between the return and cost of capital captures the values of options and is a function of the level of uncertainty and the degree of irreversibility. Two points are in order here: first, the option value may create sizeable inaction zones generating intermittent investment behavior and second, the size of the inaction zone is affected by uncertainty. Along similar lines Abel and Eberly (1994), Abel and Eberly (1996) have shown that irreversibility and fixed adjustment costs lead to a non-continuous investment policy that includes an inaction zone.

3 Data Issues

We utilize plant-level data from the Annual Industrial Survey (AIS) for Greece provided by the National Statistical Service of Greece. The dataset corresponds to 12 AIS's for the period 1994 to 2005 covering 4,323 plants on average belonging to firms with more than 10 employees across 21 manufacturing industries. The number of plants has not been constant over time, leading to an unbalanced panel with a total of 51881 plant-year observations. Table 1 reports the number of observations per industry.

[Insert Table 1 about here]

The AIS provides (gross) values for capital acquisitions $(ACQ_{i,t})$ and disposals $(DISP_{i,t})$ by plant, based on which we construct gross investment expenditure as $GINV_{i,t} = ACQ_{i,t} - DISP_{i,t}$. Table 2 gives the sample distribution of plants across investment regimes (positive investment, negative investment, inaction) by year. Positive investment $(GINV_{i,t} > 0)$ represents on average the 69.42 percent of the sample distribution, followed by investment inaction $(GINV_{i,t} = 0)$ with 26.03 percent and disinvestment ($GINV_{i,t} < 0$) which accounts on average for about 4.54 percent. Based on these figures one may draw two conclusions: *(i)* investment inaction is not a rare phenomenon and therefore the intermittent behavior of investment is apparent, and *(ii)* the ability to sell capital seems rather limited implying that a substantial degree of irreversibility is present. Similar evidence has been reported in Caballero et al. (1995), Barnett and Sakellaris (1999), Doms and Dunne (1998), Gelos and Isgut (2001), Nilsen and Schiantarelli (2003), Sakelaris (2004) and Wilson (2004).

[Insert Table 2 about here]

In Table 3 we provide a more detailed picture of zero investment episodes (inaction) by year and industry.[6]

[Insert Table 3 about here]

The reduced-form models that will follow, apart from a set of industry dummies,[7] will also condition on a set of covariates capturing important plant-specific characteristics defined as follows:[8] the ratio of sales to value added (SL), the ratio of cash flow (gross operating profit) to value added (CF), the ratio of equity to value added (EQ), the ratio of bank loans to value added (LO), and finally the logarithm of the number of employees (EMP).[9] Table 4 reports the summary statistics for the control variables.

[Insert Table 4 about here]

In order to obtain measures of oil price uncertainty, we resort to daily data on Europe Brent Spot Price FOB (Dollars per Barrel) which were obtained from the website of Energy Information Administration: Official Energy Statistics from the US Government (http://www.eia.doe.gov). The data were converted into euros employing daily data on the euro exchange rate from Global Financial Data.[10] Figure 1 displays the evolution of the level of oil price (€ per barrel) as well as its daily percentage change (log difference).

[Insert Figure 1 about here]

The first thing to note is that for the period under study the oil price shows a clear upward trend. In particular, the price varies smoothly between €12 and €20 per barrel, from 1994 to 1998, increases sharply during the following three years – reaching a peak at roughly €43 per barrel – and fluctuates between €20 and €55 per barrel, over the period 2002-2005. On the other hand, the daily percentage price change indicates time-varying volatility and also displays significant clustering, something we model and take advantage below, in order to obtain measures of oil price uncertainty.

4 Econometric Methodology

4.1 Measuring Oil Price Uncertainty

In many applications the variance of the error term varies over time, depending on past volatility. This volatility clustering is apparent in Figure 1, where we report the daily price of Brent crude oil (in levels and log-differenced). The implication of volatility clustering is that volatility shocks today influence the expectation of volatility in the future (see Figure 1b).

ARCH models have been developed to model time-varying conditional variances (Engle (1982); Bollerslev (1986); Bollerslev et al. (1994)). The specification for the conditional variance may allow for threshold or asymmetric effects, of positive and negative errors (Glosten et al. (1993); Zakoian (1994)). Letting $\Delta p_{d,t}$ denote the daily price (log) change of oil prices in year t, we estimate models of the form:

$$\Delta p_{d,t} = \mathbf{x}'_{d,t}\boldsymbol{\pi} + v_{d,t}; \quad v_{d,t}|\,\mathcal{F}_{d-1,t} \sim N\left(0, h^2_{d,t}\right) \tag{1}$$

and

$$h_{d,t}^2 = \omega + \sum_{i=1}^{p} a_i v_{d-i,t}^2 + \sum_{j=1}^{k} \kappa_j h_{d-j,t}^2 + \sum_{l=1}^{r} c_l \mathbf{1}_{d-l,t} v_{d-l,t}^2 \tag{2}$$

where $\mathbf{x}_{d,t}$ denotes an appropriately chosen vector contained in information set $\mathcal{F}_{d-1,t}$, $\boldsymbol{\pi}$ is a vector of parameters, d denotes the specific day in year t, so $h_{d,t}^2$ denotes the conditional variance in day d in year t, and $\mathbf{1}_{d-l,t} = 1$ when $v_{d-l,t} < 0$ and zero otherwise. The above model is usually described as a Threshold GARCH (T-GARCH) model, in which imposing the restriction $c_l = 0, \forall l$, one obtains the GARCH(p, k) model of Bollerslev (1986).[11]

To account for the possibility that the conditional variance may also be time varying in the long run, Engle and Lee (1999) introduce the following specification:[12]

$$h_{d,t}^2 = q_{d,t}^2 + a\left(v_{d-1,t}^2 - q_{d-1,t}^2\right) + \kappa\left(h_{d-1,t}^2 - q_{d-1,t}^2\right) + c\mathbf{1}_{d-1,t}\left(v_{d-1,t}^2 - q_{d-1,t}^2\right), \tag{3}$$

$$q_{d,t}^2 = \omega + \gamma\left(v_{d-1,t}^2 - h_{d-1,t}^2\right) + \zeta\left(q_{d-1,t}^2 - \omega\right), \tag{4}$$

where $\mathbf{1}_{d-1,t}$ is defined as above. With this specification, the conditional variance $h_{d,t}^2$ is mean-reverting around the *permanent component* $q_{d,t}^2$, with the speed of mean-reversion determined by the parameters a and κ. The speed of mean reversion of the permanent component is determined by γ and ζ. As long as $\zeta > a + \kappa$, $q_{d,t}^2$ represents the component of the variance with the longer memory. The difference between the conditional variance and its *trend*, $h_{d,t}^2 - q_{d,t}^2$, is the zero-mean, *transitory* component of the conditional variance.[13]

Estimating the above models, we may generate daily conditional standard deviations. These measures can then be used to compute measures of oil price uncertainty on an annual basis that will be employed below in our analysis. One option is to follow Ferderer (1996) and compute the annual oil price volatility as the average of the daily conditional standard deviations:[14]

$$\sigma_t^{oil} = \frac{1}{D} \sum_{d=1}^{D} h_{d,t}, \tag{5}$$

where D denote the total number of days in a year. The alternative would be to use the within-year high-low range of the conditional standard deviations (see Bollerslev et al. (1994), p. 3012), since it is likely that the higher the uncertainty, the higher the high-low range within a year will be. That is, we may use

$$\sigma_t^{oil} = \max_{d \in [1,D]} h_{d,t} - \min_{d \in [1,D]} h_{d,t}, \tag{6}$$

as the measure of yearly oil price uncertainty.

4.2 Oil-Driven Uncertainty and Investment Inaction

In order to explore the potential effect of oil price uncertainty, σ_t^{oil}, on the probability of investment action, $\Pr(INV_{i,t} = 1)$, we assume the following latent random variable (see Wooldridge (2002)):

$$INV_{i,t}^{*} = \alpha_0 + \alpha_1 \sigma_t^{oil} + \mathbf{y}_{i,t}' \boldsymbol{\beta} + e_{i,t}, \tag{7}$$

where the α_0 and $\alpha_1$are unknown estimable scalars; the vector $\mathbf{y}_{i,t}$ contains a set of control variables, which apart from industry dummies, includes the following plant-specific variables: $(SL_{i,t-1}, CF_{i,t-1}, EMP_{i,t-1}, EQ_{i,t-1}, LO_{i,t-1})'$; $\boldsymbol{\beta}$ is a vector of coefficients, and finally $e_{i,t}$ denotes a normally distributed random disturbance uncorrelated with the members of $\mathbf{y}_{i,t}$ and σ_t^{oil}. However instead of $INV_{i,t}^{*}$, we only observe the binary variable:

$$INVDUM_{i,t} = \begin{cases} 1 & \text{if } INV_{i,t}^{*} > 0 \text{ or } INV_{i,t}^{*} < 0 \\ 0 & \text{if } INV_{i,t}^{*} = 0 \end{cases}. \tag{8}$$

Note that we contrast investment inaction with any sort of action (positive investment or disinvestment). Given the panel dimension of the sample (repeated observations over time for plants) one may condition on plant heterogeneity by augmenting equation (7) with an unobserved effect μ_i, treated as random, assuming that $\mathrm{E}\left(\mathbf{y}_{i,t}' \mu_i\right) = 0$

and $\mathrm{E}\left(\sigma_t^{oil}\mu_i\right) = 0$, $\forall i, t$, leading to a model of the following specification:

$$\begin{aligned}\Pr\left(INVDUM_{i,t} = 1 | \, \sigma_t^{oil}, \mathbf{y}_{i,t}\right) &= \alpha_0 + \alpha_1\sigma_t^{oil} + \beta_1 SL_{i,t-1} + \beta_2 CF_{i,t-1} + \beta_3 EMP_{i,t-1} \\ &\quad + \beta_4 EQ_{i,t-1} + \beta_5 LO_{i,t-1} + \mu_i + e_{i,t}. \qquad (9)\end{aligned}$$

The parameters of (9) are estimated by Maximum Likelihood (MIL) further assuming that $\mathrm{E}\left(\mathbf{y}_{i,t}' e_{i,t}\right) = 0$.

We also consider an alternative specification which essentially augments equation (9) by a dynamic component where we control for last period's investment activity or inactivity. If state-dependence in investment decisions exists, we expect last period's decision to significantly affect the status of current investment and more importantly in terms of the properties of the estimated model it would considerably increase the value of the maximized likelihood function and also reduce unobserved heterogeneity (lower rho). Thus the model takes the following form:

$$\begin{aligned}\Pr\left(INVDUM_{i,t} = 1 | \, \sigma_t^{oil}, \mathbf{y}_{i,t}\right) &= \alpha_0 + \alpha_1\sigma_t^{oil} + \beta_1 SL_{i,t-1} + \beta_2 CF_{i,t-1} + \beta_3 EMP_{i,t-1} \\ &\quad + \beta_4 EQ_{i,t-1} + \beta_5 LO_{i,t-1} + \beta_6 INVDUM_{i,t-1} + \mu_i + e_{i,t}. \qquad (10)\end{aligned}$$

The parameter α_1 captures the effect of the oil price uncertainty on the likelihood of investment activity, and is expected to be negative since, the probability of hitting the trigger thresholds is, *ceteris paribus*, lower. So, we expect that:

$$\frac{\partial\left\{\Pr\left(INVDUM_{i,t} = 1 | \, \mathbf{y}_{i,t}\right)\right\}}{\partial\sigma_t^{oil}} = \alpha_1 < 0.$$

4.3 Asymmetric Response: Sample Splits by Plant Size and Oil Dependence

We extend the econometric analysis by exploring the possibility of asymmetric effects of oil uncertainty across plants. In particular, we consider two dimensions in which this asymmetry may manifest namely size and oil intensity in production.

Firm size may be an important moderator of the relationship between investment and uncertainty. The general perception is that smaller firms' investment decisions are more susceptible to uncertainty (Campa (1994); Lensink et al. (2001); Ghosal and Loungani (2000)). Potential explanations of this might be that large firms have a greater ability in dealing with uncertainty either because they have the expertise or the necessary know-how. Apart from ability, they may also have either more financial resources or access to hedge against risk. It is conceivable that large firms may also have access to more and enhanced information (Koetse et al. (2006)). Finally, another explanation may be based on the severity of financing constraints, which tends to be inversely related to firm size (Peeters (2001)). Plant size is proxied by employment level, defining an indicator variable, that splits the sample at the mean employment level, between small and large plants as follows:

$$SMALL_{i,t} = \begin{cases} 1 & \text{if } EMP_{i,t} \leq 50 \\ 0 & \text{if } EMP_{i,t} > 50 \end{cases} . \tag{11}$$

As far as oil dependence is concerned, it should come as no surprise that not all industries are equal consumers of energy and as Bohi (1989) and Bohi (1991) argued oil shocks effects' are expected to be diverse across industries, with energy intensive sectors being affected more severely. More recently, Lee and Ni (2002) found that for oil-intensive industries (in production) both demand and supply of industries are affected by oil price shocks. We measure oil intensity by the share of plant petrol expenditures to total energy expenditures, where the latter is the sum of expenditures on petrol, natural gas, coal and lignite:

$$DEP_{i,t} = \left[\frac{\text{Petrol Expenditure}}{\text{Expenditure on Petrol + Coal + Lignite + Natural Gas}} \right]_{i,t} \tag{12}$$

The whole sample average oil intensity is 8.6 percent with a standard deviation of 39 percent. Moreover a closer inspection of the data reveals that oil intensity differs quite dramatically both between as well as within industries. The substantial between industries variation becomes apparent when one compares the mean levels of oil intensities across industries which range from 0 percent to 62 percent. However, if oil intensity was uniform within industries and only varying between industries, inclusion of industry dummies would suffice to capture the underlying variation. Note that simple fixed or random effects models of oil intensity on industry dummies are able to explain 5 and 11 percent of total variation across plants respectively.[15] Nevertheless, this is not the case since considerable variation is present also within industries, which can easily be seen by examining the coefficient of variation for each industry, which ranges from 0 to 24 (see Figure 2).

[Insert Figure 2 about here]

Note that the Annual Industrial Survey does not include expenditures on fuel for vehicles or heating since respondents are asked only to report expenditures related to the production process. As a consequence the non-zero values of $DEP_{i,t}$ account for only approximately 22 percent of plant-year observations. Then, we define $HDEP_{i,t}$ as an indicator variable that splits the sample between plants with zero oil expenditures (low dependence) and plants with positive oil expenditures (high dependence) as follows:

$$HDEP_{i,t} = \begin{cases} 1 & \text{if } DEP_{i,t} > 0 \\ 0 & \text{if } DEP_{i,t} = 0 \end{cases} \tag{13}$$

Thus, we estimate eight variants of the baseline specification where each one corresponds to a different sample split with reference to plant size and oil dependence as follows: *(i)* small plants; *(ii)* large plants; *(iii)* plants with high oil dependence; *(iv)* plants with low oil dependence; *(v)* small plants with low oil dependence; *(vi)* small plants with high oil dependence; *(vii)* large plants with low oil dependence; and finally *(viii)* large plants with high oil dependence. Our priors are, that the impact of oil price uncertainty on the probability of investment activity will be mitigated by plant size and oil dependence.

5 Empirical Results

Estimating various T-GARCH models for $p = 1, 2$, $k = 1, 2$ and $r = 1, 2$, the Schwarz Information Criterion suggests that $p = 1$, $k = 1$ and $r = 1$. Table 5 summarizes the estimation results from time series T-GARCH(1,1) & T-CGARCH(1,1) models on the daily price of Brent.[16] Our results clearly indicate that – on a daily basis – the volatility process itself is asymmetric, since the parameters that capture threshold effects are in both specifications statistically significant.

`[Insert Table 5 about here]`

Using these estimates, it is possible to produce in-sample estimates of the conditional standard deviations, which are in fact time-varying. These estimates are further used in constructing measures of annual oil price uncertainty according to equations (5) and (6).[17]

In our baseline specification the measure of oil price uncertainty corresponds to the annual average of the daily conditional standard deviations estimated from the T-GARCH(1,1) model of Table 5.[18] The estimation results of the baseline specification and its eight variants are reported in Table 6, while Table 7 corresponds to the models augmented by the lagged of investment dummy. A comparison of the two alternative versions (static *vs.* dynamic) indicates that across all nine models, the value of rho is always lower and also the value of the maximized likelihood function is considerably higher qualifying the dynamic specification as the one fitting more adequately the data. The implication of this finding is that the decision to invest (or stay put) is highly persistent and coupled with the large positive coefficient of lagged investment dummy suggests the existence of strong positive state-dependence for the average plant. Hence, we proceed our analysis employing the dynamic specification.

`[Insert Tables 6 and 7 about here]`

Now we focus on the estimated parameters reported in Table 7 and for brevity restrict the discussion to the parameters of oil-price uncertainty. In seven out of nine models the coefficient of oil price uncertainty carries a negative sign as expected. Starting with the whole sample we find that oil price uncertainty exerts a significantly negative impact on the probability of investment activity, implying that higher uncertainty increases the probability of investment inaction.

Moving to sample splits allows exploring potential differences across plants of different characteristics. In particular, when we split the sample by size, we uncover substantially diverse responses of investment to oil price uncertainty. The probability of investment activity for large plants is found to be unaffected by oil price uncertainty while for small plants is significantly reduced. This finding supports an asymmetric oil price uncertainty effect across plants of different size. The higher adverse impact on small plants may be explained either by their lower ability to substitute oil with other energy sources due to technological constraints or higher exposure to oil uncertainty's effects (uncertainty about demand conditions, uncertainty about marginal cost, etc).

When we split the sample according to oil dependence we find that both groups' probability of investment activity is reduced by oil price uncertainty. The point estimates indicate that the effect for highly oil dependent plants is approximately twice as large as that for less oil dependent, with both coefficients being statistically significant. The latter implies that heterogeneity in terms of oil dependence per se is not a major determinant of the manner in which investment responds to oil price uncertainty.

Then we consider potential differences across plants of different size and different oil dependence, to allow for the possibility that the two reinforce each other. According to our results, conditioning on oil dependence does not alter our previous finding for an insignificant response of investment to oil price uncertainty for large plants. However, when we consider small plants we uncover a negative effect of oil price uncertainty on investment activity both for plants with high and low oil dependence. Moreover, inspection of the point estimates shows that the group of small plants with high oil dependence exhibits considerably higher sensitivity to oil price uncertainty compared to that of small plants with low oil dependence. This finding suggests a second asymmetric effect of oil price uncertainty. Hence, our results indicate that oil price uncertainty significantly increases the probability of investment inactivity for small plants and also the probability of inactivity is further increased by oil dependence. Thus, the adverse oil price effect is present for small plants and accentuated by dependence to oil.

All in all, our empirical findings support significant asymmetric effects of oil price uncertainty across plants. In other words, the adverse effect of oil price uncertainty on the probability of investment inactivity is non-uniformly distributed across plants. Small plants are hit harder by oil uncertainty and this effect is exacerbated as dependence on oil is increased.

5.1 Sensitivity Analysis: Revenue-based Uncertainty and Extensions

Recall that the oil uncertainty variable is only time varying and common to all cross-sectional units and in essence captures economy-wide effects. However, it might be plausible that the used oil uncertainty metric is correlated with other sources of uncertainty and the previously presented model erroneously attributed the estimated impact to oil. To tackle this eventuality, the model must incorporate another uncertainty metric not directly related to oil, that would allow us to conduct a more stringent test for oil price uncertainty effects.

The existing literature has modelled uncertainty as stemming from demand, product / input prices, profits, or sales (e.g. Ghosal and Loungani (1996); Guiso and Parigi (1999); Kalckreuth (1999); Peeters (2001); Cassimon et al. (2004); Fedderke (2004);

Drakos and Goulas (2006)), while another approach is to base uncertainty measures on stock return volatility (e.g. Leahy and Whited (1996); Böhm et al. (1999); Bulan (2005); Bloom et al. (2007)).

Since the unit of our analysis is the plant we resort to plant-specific conditional uncertainty stemming from revenue. Thus we construct plant-specific uncertainty, $\sigma_{i,t} = \sqrt{\sigma^2_{i,t}}$, estimating a Pooled Panel GARCH (PP-GARCH hereafter) model for the conditional volatility of total revenue as a ratio to value added $R_{i,t}$. The the mean–equation is given by the following autoregressive model:

$$R_{i,t} = \theta_0 + \theta_1 R_{i,t-1} + u_{i,t}. \tag{14}$$

For the disturbance term, assuming that $u_{i,t} \sim N(0, \Sigma_{i,t})$, i.e. are multivariate normal error terms with a time-varying conditional variance-covariance matrix, produces a PP-GARCH model (Cermeno and Grier (2005)). The variance-covariance matrix $\Sigma_{i,t}$ is time-dependent and its diagonal and off-diagonal elements are given by the following equations:

$$\begin{aligned} \sigma^2_{i,t} &= \phi_0 + \sum_{n=1}^{p} \phi_n \sigma^s_{i,t-n} + \sum_{m=1}^{k} \eta_m u^2_{i,t-m}, \text{ for } i = 1, ..., I & (15) \\ \sigma_{i,j,t} &= \psi_0 + \sum_{n=1}^{p} \psi_n \sigma_{i,j,t-n} + \sum_{m=1}^{k} \rho_m u_{i,t-m} u_{j,t-m}, \text{ for } i \neq j & (16) \end{aligned}$$

where the ϕ's, ψ's, η's and ρ's denote unknown constant parameters to be estimated.

Although multivariate GARCH models are also available, they are not practical for most panel applications, because they require the estimation of a large number of parameters which consumes degrees of freedom rapidly. In contrast, PP-GARCH estimation by imposing common dynamics on the variance-covariance process across cross-sectional units reduces the number of parameters dramatically ensuring parsimony. Furthermore, the PP-GARCH model does not imply constant cross-sectional correlation over time.

[Insert Table 8 about here]

Then, we extend the previous model by including plant-specific uncertainty as follows:

$$\Pr\left(INVDUM_{i,t} = 1 | \, \sigma_t^{oil}, \hat{\sigma}_{i,t}, \mathbf{y}_{i,t}\right) = \alpha_0 + \alpha_1 \sigma_t^{oil} + \alpha_2 \hat{\sigma}_{i,t} + \beta_1 SL_{i,t-1} + \beta_2 CF_{i,t-1}$$
$$+\beta_3 EMP_{i,t-1} + \beta_4 EQ_{i,t-1} + \beta_5 LO_{i,t-1} + \beta_6 INVDUM_{i,t-1} + \mu_i + e_{i,t}. \quad (17)$$

For completeness and comparison purposes we estimate all nine versions of the model and the results are reported in Table 9. The inclusion of another uncertainty metric provides a more stringent framework within which oil price uncertainty's potential impacts are tested. According to our estimation results oil price uncertainty continues to exert a negative effect on the probability of investment activity when all plants are considered. In addition, the asymmetric effect across plants of different size is again present suggesting that small plants' investment decision is adversely affected by oil price uncertainty even after controlling for revenue-based plant-specific uncertainty. The asymmetric effect of oil price uncertainty across plants with different oil dependence is again verified where plants' investment with high oil dependence shows a negative response to oil uncertainty, while for those with low oil dependence the response is effectively zero. When we condition both on plant size and oil dependence the negative impact of oil price uncertainty on small plants is deepened by oil dependence. In particular, small plants with high oil dependence exhibit twice as large sensitivity to oil price uncertainty compared to small plants with low oil dependence. All in all, the sensitivity analysis conducted supports robustness of our main empirical results.

[Insert Table 9 about here]

Thus far, all our results regarding the effects of oil price uncertainty are based on a measure that has been constructed as yearly average of daily conditional standard deviation from a T-GARCH(1,1) model. To further explore the robustness of our results to using alternative measures of annual oil price uncertainty, we have re-estimated all model specifications reported in Tables 7 and 9. In general, we find that our main findings remain unaltered. First, regardless of the measure employed, oil price uncertainty exerts a negative impact on the decision to invest. Second, this is particularly so for small plants, plants with high oil dependence and small plants with high oil dependence. We may therefore conclude that the particular measure of oil price uncertainty employed is immaterial for our results.[19]

6 Conclusions

In this paper, we have examined the effects of oil price uncertainty on the decision to invest, providing evidence for various manufacturing industries. The theoretical background was given by models of investment that emphasize the role of frictions especially in the form of capital irreversibility. In this context, the embedded real options create the possibility that investment inaction is optimal in the presence of increased uncertainty.

Using longitudinal plant-level data, that enabled us to correct for various sources of aggregation bias embedded in aggregate measurements of the effects of oil price changes on investment, we have investigated whether the decision to invest is affected by oil price uncertainty. In particular, our models explicitly examined whether and in which direction oil price uncertainty affects the probability of investment inactivity. In our analysis we differentiated between small and large plants as well as plants with high and low dependence on oil, and we also controlled for a set of plant-specific attributes, and showed how the latter interact with oil price uncertainty, determining the decision to invest or not.

We find that oil price uncertainty indeed increases the likelihood of investment inaction, a finding which is in line with the predictions of economic theory. Moreover, the analysis supports that the effect of oil price uncertainty is non-uniformly distributed across decisions makers. In fact, we find that oil price uncertainty increases the probability of investment inaction more for small plants and this effect is further amplified for plants exhibiting high oil dependence.

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Notes

[1]The bulk of the existing literature focuses on the effects of oil price increases at the aggregate level (see e.g. Ferderer (1996); Hamilton (1983), Hamilton (1996); Hamilton and Herrera (2004); Hooker (1996), Hooker (2002); Kilian (2008a); Kilian (2008b); Lee et al. (1995); Mork (1989)). Another strand using data at the level of individual industries, firms, or workers examines the effects of oil price shocks on output, employment, or wages (Davis and Haltiwanger (2001); Edelstein and Killian (2007); Herrera (2007); Keane and Prasad (1996); Lee and Ni (2002)).

[2]As Pindyck (1991) puts it: "...But energy shocks also raised uncertainty about future economic conditions; it was unclear whether energy prices would fall or keep rising, what impact higher energy prices would have on the marginal products of various types of capital, how long-lived the inflationary impact of the shock would be, and so on... This may have contributed to the decline in investment spending that occurred."(p.1142).

[3]Bernanke (1983) has demonstrated that it is optimal to postpone irreversible investment spending when firms are faced with increased uncertainty about the future price of oil.

[4]Ferderer (1996) uses the within-month standard deviation of daily oil prices, neglecting the fact that standard deviations of daily oil prices are clustered. In addition, he focuses on industrial output and does not explicitly model investment, at the aggregate or sectoral level.

[5]Fixed costs of investment are nonnegative costs independent of the level of investment and are incurred at each point in time when investment is nonzero. Thus, fixed costs can be avoided only during periods of investment inactivity.

In this paper, we employ the transactions-based notion of partial irreversibility, which describes a situation where, the resale price of capital, although positive, is strictly less than the purchase price of capital.

[6]Zero gross investment may also be the outcome of acquisitions being of equal value with disposals. However, in our sample zero gross investment is always the outcome of pure inaction (i.e. both acquisitions and disposals are equal to zero).

[7]Following Bond et al. (2003) industry effects are included to capture variations in the user-cost of capital for which direct information is not available.

[8]Division by value added is done for normalization purposes.

[9]Sales are included in order to proxy the investment opportunity set motivated by the Sales-Accelerator model (Abel and Blanchard (1986)). Cash flow is intended to capture any additional information not embodied in Sales and is motivated by the capital market imperfections literature (Fazzari et al. (1988)). Equity and Bank Loans are proxies for financing mix and credit availability. Finally, employment level is used as a proxy for plant size.

[10]Global Financial Data reports synthetic Euro exchange rates prior to January 1, 1999. We employ closing euro exchange rates at each date for the conversion.

[11]Note that this specification, good news, $v_{d-l,t} > 0$, and bad news, $v_{d-l,t} < 0$, have differential effects on the conditional variance: good news has an impact of a_l, while bad news has an impact of $a_l + c_l$, so if $c_l > 0$, bad news increases volatility. More generally, if $c_l \neq 0$, the news impact is asymmetric.

[12]See also Ding and Granger (1996) for a similar specification.

[13]Note that the CGARCH model reduces to the classical GARCH(1,1) if the long-run variance is constant. Bollerslev et al. (1992)(p. 10 and p. 20) argue in favor of low-order GARCH modeling, and especially for GARCH(1,1).

[14]In fact Ferderer (1996) computes the unconditional (sample) standard deviations

on a quarterly basis from daily data.

[15]Estimation results are available by the authors upon request.

[16]Since the innovations are not Gaussian, the usual standard errors are not consistent, and the quasi-maximum likelihood robust standard errors described in Bollerslev and Wooldridge (1992) are employed.

[17]Plots of the daily conditional standard deviations as well as the estimated annual measures of oil price uncertainty are not reported for the sake of brevity but are available upon request.

[18]This does not impact seriously on the reported results, which are robust to using different measures of oil price uncertainty. We return to this issue below.

[19]Results are available from the authors upon request.

Tables

Table 1. Sample Size by Industry

Industry	**NACE Code**	**Plant-Year Observations**
Food and Beverages	15	9,582
Tobacco	16	63
Textiles	17	4,044
Clothing	18	6,215
Leather and Footwear	19	1,778
Wood and Cork	20	1,494
Paper and Paper Products	21	1,212
Printing and Publishing	22	2,581
Petroleum and Coal Products	23	110
Chemicals	24	2,546
Rubber Articles and Plastics	25	2,590
None-Metallic Minerals	26	4,978
Basic Metals	27	1,143
Manufacture of Final Metallic Products	28	3,639
Machines and Equipment Articles	29	3,158
Electrical Machines, Apparatus etc	31	1,090
Radio, TV, Communications Appliances	32	269
Medical and Accuracy Instruments	33	276
Transport Equipment	34	450
Other Transport Equipment	35	1,114
Furniture and Other Industries	36	3,549
Total		51,881

Notes: Data for the industries Office Accounting and Computing Machinery and Recycling were not available due to confidentiality.

Table 2. Pooled Distribution of $GINV$ **by investment regime**

Year	$GINV > 0$	$GINV < 0$	$GINV = 0$
1994	61.94	3.78	34.26
1995	65.86	4.71	29.41
1996	65.78	4.05	30.16
1997	64.06	4.09	31.83
1998	67.36	4.28	28.35
1999	68.41	4.11	27.47
2000	69.18	4.12	26.69
2001	75.55	4.39	20.05
2002	74.27	5.23	20.48
2003	77.15	5.10	17.74
2004	77.98	5.78	16.22
2005	78.60	6.30	15.09
All years	69.42	4.54	26.03

Table 3. Percentages of Inactivity Episodes by Year and Industry

	Year											
NACE	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**
15	33.06	27.71	30.04	31.62	28.54	27.65	26.94	19.85	20.76	18.64	15.08	15.40
16	0.00	16.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	27.18	21.63	23.24	27.18	25.83	25.21	23.75	25.47	16.54	20.85	21.24	13.92
18	41.90	39.64	39.86	41.44	36.71	34.50	33.40	28.01	23.95	19.49	17.60	20.00
19	44.21	37.72	41.20	33.88	35.20	38.46	40.99	23.16	27.37	26.67	25.68	25.00
20	46.15	33.55	32.89	33.10	35.00	41.54	33.86	21.88	34.74	27.36	22.64	17.89
21	22.22	22.41	21.19	26.32	18.92	23.00	18.63	14.29	15.22	17.24	15.19	12.82
22	29.82	25.11	29.28	23.85	23.64	23.95	20.97	10.34	15.61	14.93	17.20	13.51
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	16.73	11.89	10.50	16.10	13.48	15.35	14.88	10.70	11.98	10.27	9.39	8.43
25	22.09	18.04	16.25	18.91	17.52	15.45	15.60	11.92	10.82	12.57	9.89	10.80
26	40.12	32.70	33.26	35.89	33.12	28.38	27.13	24.46	21.97	11.68	15.58	10.29
27	15.69	10.68	11.65	12.00	14.00	18.56	18.18	9.47	10.75	7.78	8.33	5.19
28	30.95	24.29	22.55	25.07	15.66	19.50	22.84	16.18	15.44	13.31	12.10	15.06
29	33.64	32.70	32.79	36.61	33.45	28.77	27.15	20.55	20.74	19.91	17.56	17.41
31	20.00	20.59	23.71	31.58	27.37	17.98	16.30	8.99	15.29	17.86	15.00	15.58
32	33.33	28.57	37.04	42.31	32.00	24.00	23.08	30.00	22.22	5.88	6.67	16.67
33	37.93	41.38	60.00	66.67	53.57	56.00	50.00	50.00	52.94	37.50	26.67	28.57
34	32.61	15.22	22.73	26.83	25.00	25.64	28.21	20.00	26.67	33.33	31.25	26.67
35	52.85	46.77	46.90	48.04	39.00	34.04	45.26	41.10	48.68	41.56	28.36	31.43
36	44.44	40.53	39.02	40.92	34.10	35.19	33.02	22.03	29.69	21.23	19.89	18.23

Table 4. (Pooled) Sample Descriptive Statistics[(a)]

Variable	Mean	Standard Deviation	Minimum	Maximum
SL [(b)]	0.23	0.53	0.00	3.98
CF [(c)]	-0.05	0.66	-5.99	1.07
EMP [(d)]	3.24	1.04	0.00	8.29
EQ [(e)]	0.71	1.36	0.00	10.99
LO [(f)]	0.89	1.50	0.00	8.99

Notes: (a) Outliers corresponding to values above the 99th percentile were excluded from the sample, (b) ratio of sales to value added, (c) ratio of gross operating profit to value added, (d) logarithm of number of employees, (e) ratio of equity to value added, (f) ratio of bank loans to value added.

Table 5. Maximum Likelihood Estimates of GARCH models for Brent Oil Price

Coefficient	Point Estimate [*t*-statistic]	
	T–GARCH(1,1)	T–CGARCH(1,1)
Panel A: Maximum Likelihood Estimates		
A.1: Mean Equation		
π_0	0.0007	0.0007
	[1.62]	[0.99]
A.2: Variance Equation		
ω	2.55×10^{-5} ***	0.0005 ***
	[3.86]	[6.15]
ζ	-	0.990 ***
		[157.35]
γ	-	0.025 **
		[2.07]
a	0.050 ***	0.010
	[2.87]	[0.44]
b	0.878 ***	0.844 ***
	[37.10]	[15.46]
c	0.056 **	0.072 *
	[1.99]	[1.81]
Panel B: Diagnostics		
	Test Statistic [p-value]	Test Statistic [p-value]
Wald Test: $a+b=1$	1132.21 ***	6.26
	[0.00]	[0.01]
ARCH LM $\sim\chi^2(40)$	41.99	42.371
	[0.38]	[0.36]
Q $\sim\chi^2(40)$	26.34	44.53
	[0.88]	[0.28]

Notes: The *t*-statistics for the parameter estimates reported are based on robust standard errors (Bollerslev and Wooldridge, 1992). The Wald test statistic (also using robust standard errors) examines the null that the conditional variance is an integrated process (IGARCH), against the alternative that it is mean-reverting. The ARCH LM test examines the null of no remaining ARCH effects in the estimated residuals up to order 40. The *Q* statistic is the Ljung-Box test of no autocorrelation in the squared residuals up to order 40, also providing indications as to whether there are ARCH effects that remain unmodeled by the specifications employed.

Table 6. Random Effects Probit Model for Investment Activity; $\Pr\left(INVDUM_{i,t}=1\,|\,\sigma_t^{oil},\mathbf{y}_{i,t}\right)$

Covariate[(a)]	**All plants**	**Small plants** $(SMALL)=1$	**Large plants** $(SMALL)=0$	**High oil dependence** $(HDEP_{i,t})=1$	**Low oil dependence** $(HDEP_{i,t})=0$	**Small plants & low oil dependence** $(SMALL)=1$ & $(HDEP_{i,t})=0$	**Large plants & low oil dependence** $(SMALL)=0$ & $(HDEP_{i,t})=0$	**Small plants & high oil dependence** $(SMALL)=1$ & $(HDEP_{i,t})=1$	**Large plants & high oil dependence** $(SMALL)=0$ & $(HDEP_{i,t})=1$
	Estimated coefficient[(b)] **[z-score]**								
σ_t^{oil}	**-0.067**** **[-2.10]**	**-0.123***** **[-3.69]**	-0.082 [-0.72]	**-0.144*** **[-1.91]**	**-0.061*** **[-1.69]**	**-0.103***** **[-2.76]**	-0.109 [-0.74]	**-0.249***** **[-3.00]**	-0.110 [-0.53]
$SL_{i,t-1}$	0.199*** [8.36]	0.181*** [7.21]	0.508*** [4.68]	0.184*** [3.56]	0.198*** [7.26]	0.177*** [6.24]	0.573*** [3.75]	0.185*** [3.26]	0.289* [1.81]
$CF_{i,t-1}$	0.080*** [4.97]	0.073*** [4.22]	0.229*** [4.17]	0.143*** [4.49]	0.075*** [3.89]	0.073*** [3.61]	0.205*** [2.61]	0.132*** [3.71]	0.235*** [2.90]
$EMP_{i,t}$	0.685*** [39.39]	-	-	0.689*** [19.62]	0.697*** [34.63]	-	-	-	-
$EQ_{i,t-1}$	0.170*** [15.74]	0.165*** [14.37]	0.178*** [4.71]	0.134*** [5.84]	0.201*** [15.85]	0.196*** [14.65]	0.273*** [5.09]	0.131*** [5.14]	0.170** [2.55]
$LO_{i,t-1}$	0.232*** [4.27]	0.396*** [6.58]	-0.048 [-0.33]	0.206* [1.70]	0.271*** [4.30]	0.444*** [6.39]	-0.088 [-0.48]	0.396*** [2.81]	0.007 [0.02]
Industry dummies	included	Included	included	Included	Included	Included	Included	included	included
Diagnostics									
rho[(c)]	0.571***	0.611***	0.739***	0.592***	0.576***	0.613***	0.752***	0.628***	0.727***
Log-Likelihood	-19385.28	-17953.62	-1939.98	-3867.12	-15621.90	-14766.19	-1270.01	-3288.47	-680.54
Obs.	48000	37942	10158	10664	37336	30943	6461	6999	6697

Notes: (a) the list of covariates includes full set of industry dummies, (b) *, **, and *** indicate statistical significance at the 10, 5 and 1 percent level, (c) overall significance test.

Table 7. Random Effects Probit Model for Investment Activity; $\Pr\left(INVDUM_{i,t}=1 \mid \sigma_t^{oil}, INVDUM_{i,t-1}, \mathbf{y}_{i,t}\right)$

Covariate[a]	**Estimated coefficient**[b] **[z-score]**								
	All plants	**Small plants** $(SMALL)=1$	**Large plants** $(SMALL)=0$	**High oil dependence** $(HDEP_{i,t})=1$	**Low oil dependence** $(HDEP_{i,t})=0$	**Small plants & low oil dependence** $(SMALL)=1$ & $(HDEP_{i,t})=0$	**Large plants & low oil dependence** $(SMALL)=0$ & $(HDEP_{i,t})=0$	**Small plants & high oil dependence** $(SMALL)=1$ & $(HDEP_{i,t})=1$	**Large plants & high oil dependence** $(SMALL)=0$ & $(HDEP_{i,t})=1$
σ_t^{oil}	**-0.091***** **[-2.87]**	**-0.133***** **[-4.05]**	0.049 [0.47]	**-0.140**** **[-1.98]**	**-0.081**** **[-2.31]**	**-0.114***** **[-3.16]**	0.098 [0.75]	**-0.212***** **[-2.76]**	-0.042 [-0.26]
$INVDUM_{i,t-1}$	1.108*** [45.82]	1.145*** [44.51]	1.932*** [23.82]	1.328*** [25.48]	1.121*** [42.29]	1.170*** [41.97]	1.936*** [20.58]	1.329*** [23.81]	2.094*** [19.82]
$SL_{i,t-1}$	0.154*** [6.96]	0.135*** [5.95]	0.271*** [3.25]	0.073* [1.71]	0.164*** [6.57]	0.142*** [5.62]	0.432*** [3.66]	0.064 [1.39]	0.003 [0.03]
$CF_{i,t-1}$	0.081*** [5.14]	0.077*** [4.70]	0.122*** [2.72]	0.139*** [4.80]	0.068*** [3.73]	0.068*** [3.63]	0.098 [1.62]	0.135*** [4.26]	0.139** [2.33]
$EMP_{i,t-1}$	0.478*** [31.83]	-	-	0.415*** [15.09]	0.471*** [27.53]	-	-	-	-
$EQ_{i,t-1}$	0.147*** [14.39]	0.155*** [14.35]	0.139*** [4.46]	0.123*** [6.09]	0.164*** [14.07]	0.171*** [14.04]	0.174*** [4.30]	0.131*** [5.96]	0.108** [2.19]
$LO_{i,t-1}$	0.161*** [3.12]	0.323*** [5.67]	-0.118 [-1.04]	0.080 [0.75]	0.208*** [3.55]	0.365*** [5.71]	-0.057 [-0.40]	0.262** [2.11]	-0.210 [-1.20]
Industry dummies	included	Included	Included	Included	Included	Included	Included	Included	Included
					Diagnostics				
$rho^{(c)}$	0.281***	0.278***	0.206***	0.204***	0.274***	0.263***	0.246***	0.213***	0.000
Log-Likelihood	-15849.05	-14691.35	-1500.25	-2999.64	-12860.17	-12130.28	-1003.32	-2563.87	-481.72
Observations	42794	33642	9240	9279	33515	27584	5992	6058	3248

Notes: (a) the list of covariates includes full set of industry dummies, (b) *, **, and *** indicate statistical significance at the 10, 5 and 1 percent level, (c) overall significance test.

Table 8. Pooled Panel GARCH for Revenue[(a)]

Covariate	Estimated Coefficient (z-score)[(b)]
Level Equation[(c)] (AR-1)	
Constant	0.408*** (95.80)
$R_{i,t-1}$	0.841*** (582.70)
Conditional Variance Equation[(d)] (GARCH 1-1)	
Constant	0.187*** (186.04)
$\sigma^2_{i,t-1}$	0.772*** (166.18)
$u^2_{i,t-1}$	0.428*** (244.30)

Notes: (a) ratio of total revenue to industrial value added. (b) one, two and three asterisks indicate statistical significance at the 10, 5, and 1 percent level. (c) the mean equation models the level of variable. (d) the conditional variance equation models the volatility of the error term.

Table 9. Sensitivity Analysis, Random Effects Probit Model for Investment Activity; $\Pr\left(INVDUM_{i,t}=1 \mid \sigma_t^{oil}, INVDUM_{i,t-1}, \hat{\sigma}_{i,t}, \mathbf{y}_{i,t}\right)$

Covariate[a]	**Estimated coefficient**[b] **[z-score]**								
	All plants	**Small plants** $(SIZE)=1$	**Large plants** $(SIZE)=0$	**High oil dependence** $(HDEP_{i,t})=1$	**Low oil dependence** $(HDEP_{i,t})=0$	**Small plants & low oil dependence** $(SIZE)=1$ $\&(HDEP_{i,t})=0$	**Large plants & low oil dependence** $(SIZE)=0$ $\&(HDEP_{i,t})=0$	**Small plants & high oil dependence** $(SIZE)=1$ $\&(HDEP_{i,t})=1$	**Large plants & high oil dependence** $(SIZE)=0$ $\&(HDEP_{i,t})=1$
σ_t^{oil}	**-0.084**** **[-2.54]**	**-0.145***** **[-4.27]**	-0.008 [-0.07]	**-0.150**** **[-2.04]**	**-0.070*** **[-1.91]**	**-0.126***** **[-3.34]**	0.031 [0.23]	**-0.238***** **[-3.00]**	-0.070 [-0.40]
$INVDUM_{i,t-1}$	1.119*** [45.86]	1.159*** [44.81]	1.936*** [23.62]	1.340*** [25.52]	1.132*** [42.41]	1.181*** [42.27]	1.947*** [20.51]	1.344*** [23.99]	2.078*** [17.23]
$\hat{\sigma}_{i,t}$	0.006 [0.27]	-0.048** [-2.20]	-0.122* [-1.93]	-0.043 [-1.01]	0.019 [0.81]	-0.045* [-1.89]	-0.107 [-1.36]	-0.068 [-1.46]	-0.140 [-1.43]
$SL_{i,t-1}$	0.158*** [6.75]	0.152*** [6.34]	0.282*** [3.28]	0.069 [1.53]	0.172*** [6.47]	0.164*** [6.13]	0.468*** [3.77]	0.063 [1.32]	0.015 [0.13]
$CF_{i,t-1}$	0.085*** [5.13]	0.076*** [4.36]	0.083* [1.73]	0.140*** [4.50]	0.072*** [3.77]	0.062*** [3.18]	0.089 [1.41]	0.142*** [4.15]	0.066 [0.96]
$EMP_{i,t-1}$	0.479*** [31.46]	-	-	0.419*** [14.98]	0.471*** [27.15]	-	-	-	-
$EQ_{i,t-1}$	0.147*** [14.17]	0.155*** [14.20]	0.133*** [4.25]	0.125*** [6.04]	0.162*** [13.71]	0.168*** [13.71]	0.164*** [4.08]	0.134*** [5.99]	0.107** [2.10]
$LO_{i,t-1}$	0.140*** [2.70]	0.300*** [5.24]	-0.131 [-1.16]	0.050 [0.47]	0.191*** [3.24]	0.344*** [5.36]	-0.058 [-0.41]	0.234* [1.88]	-0.246 [-1.40]
Industry dummies	Included	Included	Included	included	Included	Included	Included	included	Included
					Diagnostics				
rho [(c)]	0.278***	0.272***	0.203***	0.193***	0.270***	0.257***	0.231***	0.201***	0.011
Log-Likelihood	-15529.83	-14400.20	-1462.44	-2909.76	-12630.54	-11910.02	-983.35	-2490.75	-464.79
Observations	42007	32977	9114	9048	32959	27095	5921	5882	3193

Notes: (a) the list of covariates includes full set of industry dummies, (b) *, **, and *** indicate statistical significance at the 10, 5 and 1 percent level, (c) overall significance test.

Figures

Figure 1a: (Level) Daily Prices of Brent Crude (euros per barrel)

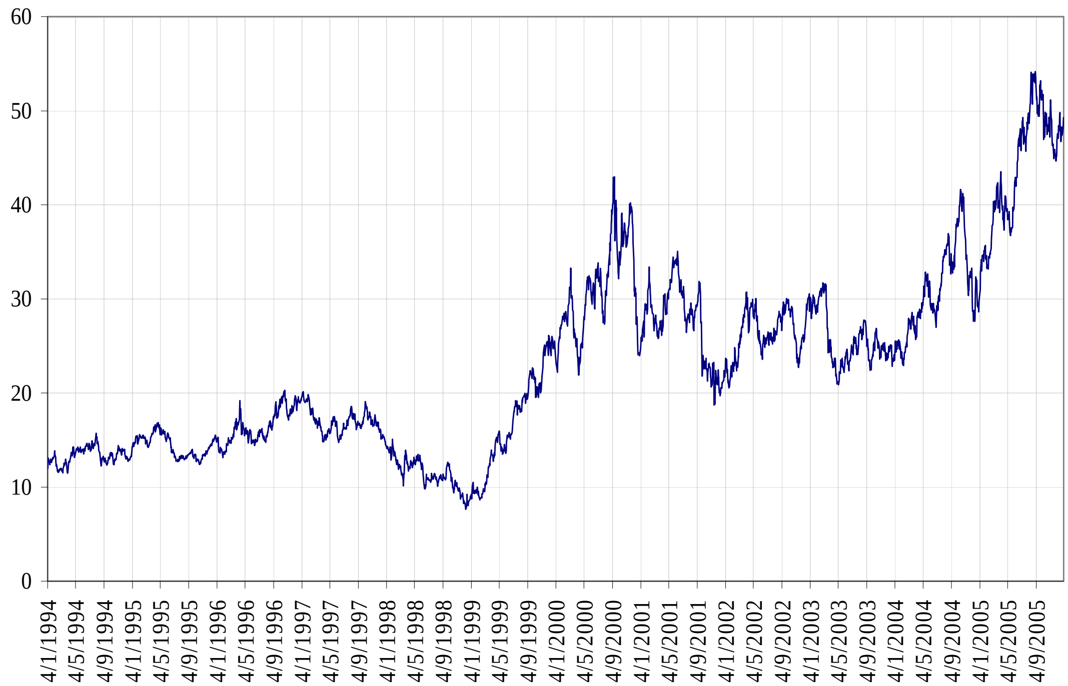


Figure 1b: Daily Percentage (log-difference) Change of Prices of Brent Crude (euros per barrel)

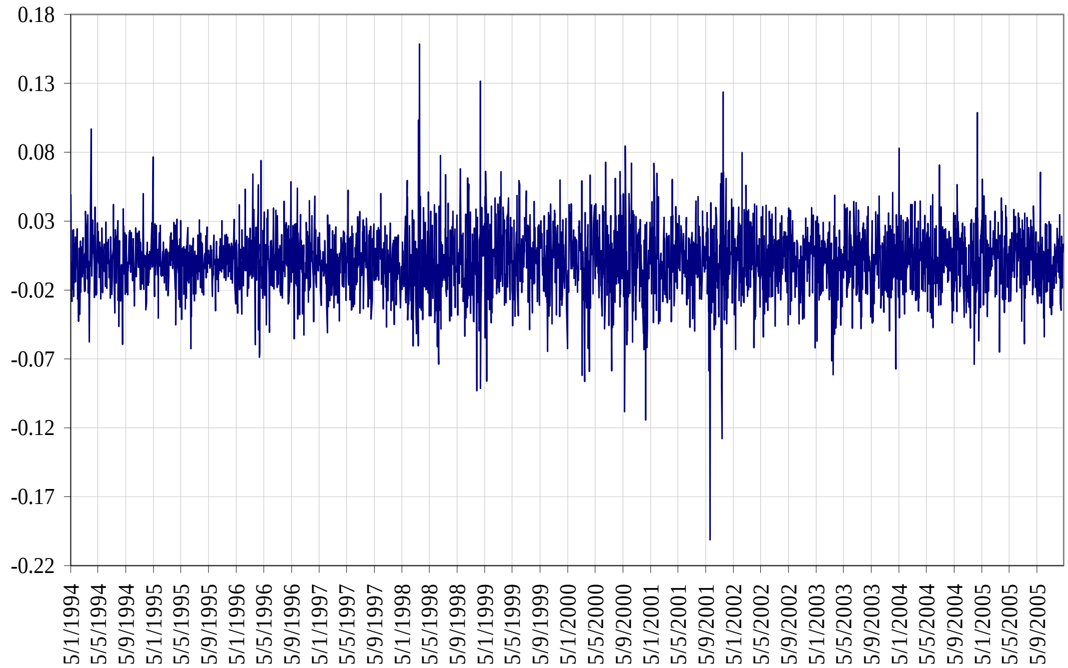
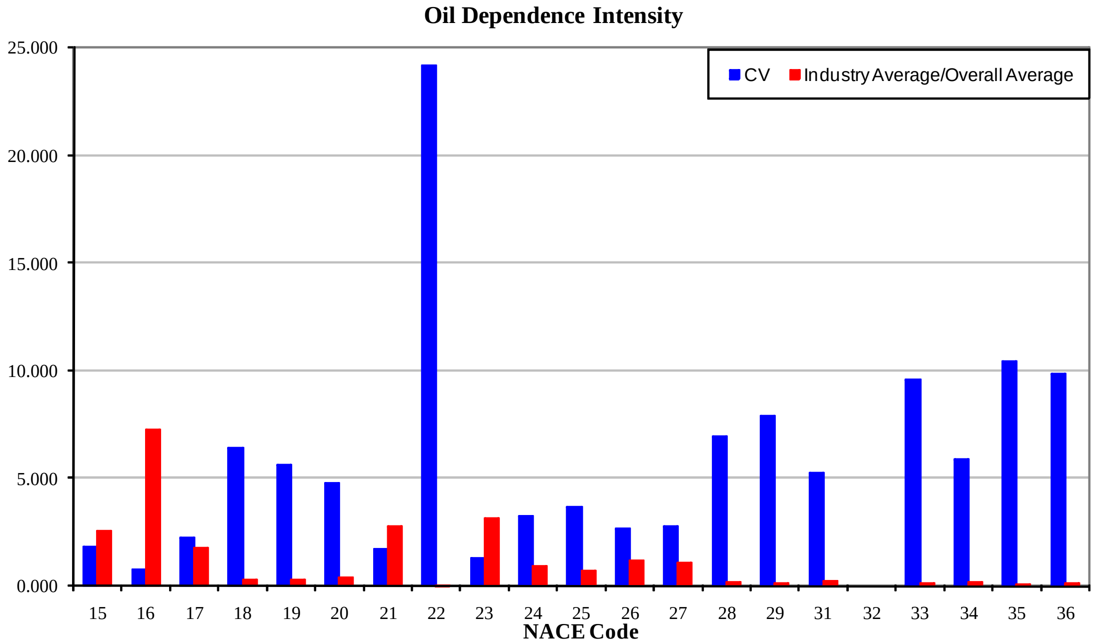


Figure 2. Measures of Oil Dependence Intensity Within and Across Industries



Notes: CV denotes the coefficient of variation i.e. the ratio of the industry average relative to the industry standard deviation.