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Investment Spikes and Uncertainty in the Petroleum Refining Industry

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This paper investigates the effect of uncertainty on the investment decisions of petroleum refineries in the US. We construct uncertainty measures from commodity futures market and use data on actual capacity changes to measure investment episodes. Capacity changes in US refineries occur infrequently and a small number of investment spikes account for a large fraction of the change in industry capacity. Given the lumpy nature of investment adjustment in this industry, we empirically model the investment process using hazard models. An increase in uncertainty decreases the probability a refinery adjusts its capacity. The results are robust to various investment thresholds. Our findings lend support to theories that emphasize the role of irreversibility in investment decisions.

Key words: Investment,Uncertainty, Irreversibility, Discrete Hazard Models.

JEL code: L0, L6 and Q4

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I. Introduction

How uncertainty influences the decisions of firms to undertake investment projects is a fundamental issue in the investment literature. Theory offers models that predict increases in uncertainty can either raise or lower investment with a particularly influential line of research being the real options theory.[1] Specifically, Dixit and Pindyck [1994] describe a theory of investment that focuses on the irreversibility inherent in many capital projects and the effect of uncertainty on the timing of irreversible investment projects. In their model, uncertainty in the future profitability of an investment project that is irreversible, or partially irreversible, may cause a firm to delay the investment in order to obtain additional information on the profitability of the project. Dixit and Pindyck [1994] refer to this as 'the option value of waiting to invest' and firms consider this 'option' when making investment decisions. Increases in uncertainty, increase the option value of waiting in this environment. The result of which is a delay in investment. In this paper, we empirically examine the uncertainty-investment relationship by investigating how the timing of capital projects responds to changes in the volatility of input and output prices.[2]

Although there exists a large empirical literature looking at the uncertainty-investment relationship, relatively few studies have investigated the effect of uncertainty on the timing of specific investment projects (Favero et al [1994], Hurn and Wright [1994] and Bulan, Mayer and Somerville [2006]). This paper examines uncertainty and the timing of investment projects at individual US oil refineries. We believe this is a good testing ground of the uncertainty-investment relationship for three reasons. First, investments that involve refinery expansion will include a significant fraction of sunk costs. The investment in capacity expansion in refineries is largely composed of structures that are usually engineered and integrated into an existing production facility. Once in place a refinery cannot easily divest itself of such a capacity

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[1] Hartmann [1972] and Abel [1983] develop models where greater uncertainty in input or output prices actually increases the likelihood a firm invests.

[2] For a complete survey on recent development in the investment under uncertainty literature, see Carruth et al. [2000].

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expansion project without bearing significant costs. Thus, it is reasonable to believe that a significant fraction of such investment is irreversible. Second, firms in the industry change their capacity in discrete investment and disinvestment bursts. Episodes of high investment activity are interspersed with episodes of zero investment activity. This pattern in US refineries is similar, though more stark, to those found in recent empirical papers that document the lumpy nature of plant and firm-level investment (Cooper, Haltiwanger and Power (hereafter CHP [1999], Doms and Dunne [1998], and Nilsen and Schiantarelli [2003]).[3] The discrete nature of investment in this industry allows us to look at the timing of capital projects and thus we will be able to see if firms delay investment when uncertainty rises. Third, the industry has well developed commodity future markets for its main input, crude oil, and its main outputs, heating oil and gasoline. We compute a forward refining margin from these futures prices and use the volatility of the forward refining margin to proxy for uncertainty in the economic environment in which refiners must make investment decisions.

Our data include annual observations on refining capacities for almost all US refineries in existence over the period 1985-2003. We use year-to-year changes in capacities to identify when firms undertake capital projects. The data measure only investment activities that affect refinery capacity. These capacity-based data omit maintenance-driven investment and non-capacity changing investments such as investment in pollution control equipment. In the case of environmental investments which are important in this industry, the timing of these kinds of investment is likely to be quite unrelated to the firm's optimal capital adjustment problem discussed in the literature. By using physical capacity measures, we reduce these types of measurement problems and improve our ability to measure the timing of capital projects.[4]

The first part of our empirical analysis documents capital adjustment patterns in the US petroleum refining industry. We find that capacity adjustments by refiners are very infrequent.

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[3] An early discussion of nonconvex adjustment costs is provided in Rothschild [1971].
[4] Two other recent studies use capacity changes to measure investment in the literature, Bell and Campa [1997] and Goolsbee and Gross [2000].

Approximately three-quarters of the year-to-year changes in capacity are zero. This pattern of inactivity in the investment data is consistent with models of irreversibility, as well as models that stress the presence of fixed adjustment costs (CHP [1999] and Cooper and Haltiwanger (hereafter CH [2006])). The second part of the empirical analysis explores the relationship between uncertainty in oil markets and capacity adjustment. We estimate a hazard model to examine the relationship between uncertainty, as measured by the volatility of forward refining margins, and the probability a refinery undertakes an investment project. We find that increases in uncertainty are associated with delays in capital investment projects. Our results are robust to a variety of adjustment thresholds and hazard specifications.

The remainder of this paper proceeds as follows. Section II describes some basic features of the refining industry and the data that we use in the paper. In section III we discuss our measures of uncertainty. Section IV provides a description of the empirical methods used and presents our findings. Section V concludes the paper.

II. Investment in the Refining Industry

In order to examine how uncertainty affects the timing of investment, we utilize data on changes in capacity at US refineries to identify when investment projects are undertaken. Typically, studies use accounting data on investment expenditures as the basis of their empirical analyses. However, relying on such accounting data is not without drawbacks. Accounting data on new investment contain a mix of capital expenditures that include expansion-driven spending, maintenance-driven spending and non-capacity enhancing investments such as pollution control and occupational safety equipment. In the latter case, these may be mandated investments due to regulatory requirements – a situation common in the refining sector. Mandated investments and maintenance-driven investments are driven by forces distinct from the firm's decision to expand or contract its capacity to produce output. Accounting data rarely allow the researcher to discriminate among these alternative investment categories. Caballero [2000] emphasizes the

importance of distinguishing between maintenance-driven and expansion-driven investments when modeling investment dynamics. In addition, accounting data on firm- and plant-level investments almost always show that producers make investments in every time period, even if at a very low level. Investment spikes are often surrounded by periods of positive but low levels of investment activity. This makes measuring the timing of the investment spike more difficult and potentially obscures the discrete nature of the investment process. In this work, we reduce some of these problems by studying changes in actual capacities.

We use the petroleum refinery capacity data from the 'Petroleum Supply Annual' published by the Energy Information Administration (EIA), Department of Energy. Beginning in 1980, the EIA implemented a mandatory annual survey of refinery capacities except for the period of 1995-1997 during which the survey was done biennially. It surveys both crude oil processing (distillation) capacity and downstream capacities for all operable refineries located in the 50 U.S. states, Puerto Rico, the Virgin Islands, Guam and other U.S. possessions. To fill in the missing data in 1995 and 1997, we supplement the EIA data by a private survey of refining capacities in 1995 and 1997 from the *Oil & Gas Journal (OGJ)*.[5] Because our primary uncertainty measure is derived from commodity futures market and unleaded gasoline futures markets did not exist before December 1984, our time period of analysis runs from 1985 to 2003. The final data set contains 224 refineries with a total of 3307 refinery-year observations.

Refining capacity (atmospheric distillation capacity) is measured as the 'the maximum number of barrels of input (mainly crude oil) that a distillation facility can process within a 24-hour period when running at full capacity under optimal crude and product slate conditions with no allowance for downtime' (EIA [2000], pp 165-166). Under this definition, a refiner's capacity is measured as barrels per stream day (B/SD). Figure 1 presents the total refining capacity and the number of refineries in the US from 1985 to 2004. The number of refineries falls steadily

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[5] The OGJ data only reports capacities measured in calendar days (barrels per calendar day or B/CD). We multiply the EIA 1994 data (B/SD) by the percentage change in OGJ data to obtain the 1995 data, and similarly for 1997 data.

while the overall US refining capacity increases by 8%. Smaller refineries have closed while larger refiners have, on average, expanded their size over time.

Year-to-year changes in refinery capacity are used to define our investment events. Refiners increase their capacities through conventional capital project (e.g., adding a catalytic cracking unit) and through debottlenecking investments which are smaller investments that increase refining capacities but do not alter the number of processing units (EIA Staff report, [1999]). Debottlenecking is usually accomplished at the same time as maintenance and repair. The additional capacity gained through debottlenecking is termed 'capacity creep' in the industry. Given that debottlenecking can be done at small cost, one might expect refineries to frequently adjust their capacities. However, as depicted below, this is not the case. Capacity reductions at ongoing refineries also occur in our data but at a much lower frequency than capacity expansions with a significant number of such events being refinery closures. In the empirical work that follows we focus primarily on the decision of a refinery to expand capacity.[6]

The distribution of refinery-level capacity changes are shown in Figure 2. The underlying data represent the percentage change in capacity between two years in the data. The large spike in the middle of the distribution indicates that 74 percent of the time refineries make no change in capacity between years. In addition, a significant number (11 percent) of non-zero observations are in the interval of (-0.05, +0.05). These patterns in capacity adjustment are even 'lumpier' than those reported in CHP [1999], Doms and Dunne [1998], and Nilsen and Schiantarelli [2003]. For example, Nilsen and Schiantarelli [2003] report zero investment episodes in Norwegian manufacturing account for 21 percent of total observations for equipment and 61 percent for buildings and Doms and Dunne [1998] state "…while a significant portion of investment occurs in a relatively small number of episodes, plants still invest in every period." Moreover, the

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[6] We also estimate hazard models that use two-sided changes in capacity to identify the end of an investment inactivity spell. The results on uncertainty carry through to that analysis as well and are reported in Table IV below. However, using capacity expansion episodes to define the end of a spell is more line with the recent work reported in CHP [1999] and Nilsen and Schiantarelli [2003].

additional capacity added in the industry is concentrated in a few investment episodes. Thirty-three projects account for roughly 30 percent of the total addition to capacity that occurred in the industry throughout the period of study. These additions occur in ongoing refineries since no new refineries have been built in the US during our period of analysis. Alternatively, the large reductions in capacity observed in the data are due largely to the closure of refineries — 83 refineries shut down during the 1985-2003 period.

While it is plausible that a refinery may increase its capacity by a small amount through debottlenecking and incremental investment activity, we suspect that some of the small changes in capacities might be a result of either reporting errors or may reflect the fact that refinery engineers adjust the estimates of the capacity levels at their refinery based upon their ongoing review of the data.[7]   To test the sensitivity of our results to the presence of these small adjustments in capacity, we employ two sets of alternative thresholds to identify whether an investment episode has occurred. The first set includes three relative thresholds based on the annual percent change in capacity at a refinery: a zero percent threshold, a five percent threshold, and a ten percent threshold. The second set includes two absolute capacity change thresholds: a 2000 B/SD threshold and a 4000 B/SD threshold.[8]   Investment episodes are then identified as investments events that cross these thresholds. For example, under the zero percent threshold there are 835 investment episodes in our data, while under the more restrictive ten percent threshold, there are only 400 investment episodes.

Theories emphasizing the role of irreversibility imply that a refiner will put off investment decisions at times of high uncertainty. To shed light on the timing of investments, Figure 3 presents a histogram of durations from completed investment spells using the zero and the five

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[7] We owe this point to Stephen Patterson, Survey Manager at EIA and Sidney Gale, Managing Director of EPIC Inc.
[8] While somewhat arbitrary, the 2000 B/SD and 4000 B/SD thresholds correspond roughly to a five percent and ten percent investment in the median sized refinery in 1985 – the first year of our sample. Moreover, it's unlikely that a capacity increase over 2000 B/SD would simply due to reporting errors while a 4000 B/SD capacity change would represent a substantial investment.

percent thresholds.[9] The duration is defined as the length of time, in years, between investment episodes in a refinery. If a refinery invests in both year k and year $k+1$, the duration is zero. If it does not invest in year $k+1$ but invests in year k and $k+2$, the duration is one. Several points are worth making. First, consistent with the large number of zero observations in Figure 2, the majority of the durations are above zero and the median duration for the five percent threshold series is 3.5 years. Second, there are a significant number of zero duration events. This may be due to the fact that refinery investment episodes may span calendar years in the data. In this case, refiners would report back-to-back years of capacity expansions. These back-to-back capacity additions represent a substantially lower fraction of durations under the five percent definition perhaps indicating that refineries may undergo some additional capacity fine-tuning in the wake of an initial capacity expansion. These additional fine-tunings in capacity would appear under a zero percent threshold definition but not register as a capacity expansion episode under the five percent threshold.

III. Measuring Uncertainty

A measure of uncertainty should gauge agents' assessments of the distribution of future returns. Prior industry-level studies have often used information on the volatility of industry-level input and output prices to measure uncertainty in the economic environment (Ghosal and Loungani [1996] and Bell and Campa [1997]). Alternatively, firm-level studies often rely on stock price volatility as a measure of the uncertainty facing the firm (Leahy and Whited [1996], Henly et al [2003], Bloom et al [2007]). Our approach will focus on industry-level uncertainty using data on inputs and outputs that are related specifically to the future profitability of the refining sector.

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[9] Here we dropped the 'censored' observations. For example, if the last investment episode was observed in 2000, then the observations of 2001-2003 are dropped.

The refining process involves distillation which 'cracks' crude oil into different components to make petroleum products such as gasoline and heating oil. Crude oil, gasoline and heating oil are all actively traded in the futures market in the New York Mercantile Exchange (NYMEX). Our uncertainty measure is based on a daily forward refining margin (or crack spread, denoted as *FRM*), which is defined as

(1) $FRM^d = 2*F_{GO}^{M,d} + 1*F_{HO}^{M,d} - 3*F_{CO}^{M,d}$

where *GO, HO,* and *CO* stands for unleaded gasoline, heating oil, and crude oil respectively. $F_{()}^{M,d}$ denotes the price of the futures contract that is traded at day *d* and matures at month M.[10] The 3-2-1 refining margin reflects the gross profit from processing three barrels of crude oil into two barrels of unleaded gasoline and one barrel of heating oil. Because the 3:2:1 ratio approximates the real-world ratio of refinery output, it is commonly used in the oil industry to construct the refining margin. An EIA report (EIA [2002], pp. 21-22) notes that "Refinery managers are more concerned about the difference between their input and output prices than about the level of prices. Refiners' profits are tied directly to the spread, or difference, between the price of crude oil and the prices of refined products. Because refiners can reliably predict their costs other than crude oil, *the spread is their major uncertainty*."

A common interpretation of commodity futures prices describes the futures prices as a forecast of the future spot price of a commodity that incorporates a risk premium (Fama and French [1987]). In a recent study about predictive ability of commodity futures prices, Chinn, LeBlanc and Coibion [2005] show that futures prices for crude oil, gasoline and heating oil are unbiased predictors of future spot prices and outperform time-series models.[11] These findings agree with earlier analysis by Ma [1989], Tomek [1997] and Fujihara and Mougoue [1997]. For this reason, the futures prices are generally considered as a benchmark price forecast by many industry observers and risk managers rely on these petroleum futures to hedge their price risks

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[10] The deliveries of all petroleum futures are ratable over the entire delivery month (NYMEX website).
[11] However, they also show that futures prices are not very accurate predictors of future spot prices.

(EIA [2002], pp. 20). Thus, we believe an uncertainty measure constructed from the forward refining margins is a reasonable proxy for the uncertainty faced by refiners in forecasting future profitability.

Analogous to papers using the standard deviation of stock returns, this paper uses the annual standard deviation of the daily forward refining margin as our uncertainty indicator. The NYMEX began trading crude oil futures in March 1983, unleaded gasoline futures in December 1984, and heating oil futures in January 1980. The daily forward refining margin of (1) is calculated using daily closing prices of all the three commodity contracts with six months time-to-maturity. The six-month maturity is chosen because it is the longest time horizon with which we can obtain a consistent data series. The annual measures of forward refining margin and the associated uncertainty measure are the mean and the standard deviation, respectively, of daily forward margins as defined in (1) over a 12-month window and deflated with the implicit GDP deflator from the Bureau of Economic Analysis (BEA).

To allow for construction lags and to check the robustness of our empirical results, we construct three alternative measures of the mean and standard deviation of the forward refining margin by varying the calculation window. The first definition is based on the mean and the standard deviation of daily margins in the contemporary year y. The second and the third definitions build in six- and three- month lags, respectively. Throughout the analysis below we report the results from the six-month lag definition but the findings are generally robust across the alternative windows.

Figure 4 plots the mean and standard deviation of the forward refining margin according to the six-month lag definition for the period 1985-2003. The uncertainty series appears to be heavily influenced by geopolitical events in the Middle East. The spike in 1991 which is the standard deviation of the *FRM* from July 1, 1990 to June 30, 1991 is related to the first Gulf-War. It rises again in 2003 surrounding the second Gulf War. Given the importance of Persian Gulf in

the world oil supply, it is not surprising that investors are less certain about future refining margins during periods when war threatens important supply sources.

IV. Investment and Uncertainty

The Empirical Framework

Given our data features discrete bursts of investment interspersed with periods of inactivity, we make use of econometric techniques for survival analysis and estimate the effect of uncertainty on the timing of investment projects. Following the empirical approach of CHP [1999], Gelos and Isgut [2001] and Nilsen and Schiantarelli [2003], we estimate a discrete hazard model. Let T denote the length of a spell that a refinery stays in an inaction regime with the cumulative probability distribution function $F(t)$. The probability that a refinery stays in an inaction regime longer than T is given by the survival function $S(t)=1-F(t)=Pr(T>t)$. The hazard function gives the conditional probability that a refinery increases its capacity by more than the threshold value in the interval of Δt after it stays in inaction until t. Using the notation of Kiefer [1988], the hazard function can be written as

$$(2) \qquad \lambda(t) = \lim_{\Delta \to 0} \frac{pr(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}$$

And the survival function $S(t)$ is given by

$$(3) \qquad S(t) = \Pr(T \geq t \mid x) = \prod_{s=1}^{t-1}(1 - \lambda(t)) \ .$$

In our application, an inaction spell is exited by an investment episode exceeding the relevant threshold. Spells that end through refinery closures are censored and capacity reductions of ongoing operations do not result in the exit of a spell. Most refineries have multiple investment episodes during the sample period and we reset an individual refinery's clock to zero after each episode. Some refineries were in an ongoing inaction spell at the start of the sample period. For

these refineries, we identify their last investment episode before 1985 and use this information to initialize the current spell length in 1985.

The recent literature on the cost of capital adjustments (CHP [1999], CH [2006]) argues that positive duration dependence is consistent with non-convex forms of adjustment costs. The reason is that under the assumption of non-convex costs of adjustment (say, a fixed cost), the likelihood of net gains from a new investment being able to justify the fixed cost increases in the time since the last investment. This is due to the fact that in the CHP [1999] model the difference in the productivity of a firm's existing capital stock and new investment grows in time since the last investment. When the productivity difference between the new capital and the firm's existing vintage of capital becomes large enough, firms invest. In contrast, under convex adjustment costs, the best response is to invest whenever there is a capital shortage. This yields positive correlation in producer-level investment series and the prediction of negative duration dependence in the hazard, though one should not observe lumpy investment. Models with irreversibility also yield positive correlations in investment and the prediction of negative duration dependence in the hazard (Bigsten et al [2005]). However, there is a key difference between the irreversibility and convex adjustment cost models. Models of irreversibility imply episodes of investment inactivity interspersed with periods of investment and this is not the case in convex adjustment cost models where firms smooth investment across periods.

The discrete hazard is parameterized using a complementary log-log function:

$$(4) \qquad \lambda(t, x, \beta) = \Pr(T = t \mid t > t - 1, x) = 1 - \exp(-\exp(\varphi + \sum_{t=2}^{S} \gamma_t D_{tiy} + x_{iy}' \beta))$$

where φ is the intercept. γ's and β's are the coefficients to be estimated. D_{tiy} is a set of duration dummies, equal to 1 if year y is the tth year from the last investment episode for refinery i.[12] S denotes the longest spell duration. D_{1iy} is the omitted category. From the estimated γ's, one can construct a non-parametric estimation of the baseline hazard. If the γ's are increasing, then the

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[12] For example, if an investment episode occurs in year y, then t is equal to 1 in year $y+1$.

baseline hazard has positive duration dependence. That is, the probability of exiting a spell increases as the time elapsed from the last investment episode increases. On the other hand, declining γ's indicate negative duration dependence, meaning the probability of undertaking an investment project decreases as the duration of the inactivity spell rises. x_{iy} is a vector of explanatory variables. The marginal effect of x on the hazard is $exp(-exp(x'\beta))·exp(x'\beta)\beta$, so the sign of the estimated β gives the directional effect of the x variable on the hazard function. A positive β means the hazard increases in x, and *vice versa*.

The variables contained in x include both the margin and uncertainty variables discussed above and a number of additional variables. We control for the overall capacity utilization rate in the refining district to proxy for supply conditions in an area.[13] The variable is measured as the ratio of average daily input (crude) to average daily capacity in a refining district and enters the empirical specification with a one year lag.. We expect that if supply conditions are tight in an area this may increase the probability that a refinery expands capacity. Since, Doms and Dunne [1998] find that smaller plants tend to have lumpier investment patterns than larger plants, a dummy variable that is equal to one for refineries with capacities less than 50,000 B/SD and zero otherwise is included in the model.[14] To control for geographic and institutional differences across regions, a set of dummy variables for refining districts is also included in the model.[15]

The refining industry is one of the most heavily polluting industries and is subject to a number of environmental regulations. Using plant data from the Longitudinal Research Database, Becker and Henderson [2000] find that the differential air quality regulations reduce new plant

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[13] A complete description and map for refining districts can be found in EIA's annual publication *Petroleum Supply Annual*.

[14] 50,000 B/SD is a standard industry definition for small refinery and is used by Kerr and Newell [2003].

[15] Doms and Dunne [1998] find that plants undergoing ownership change have lumpier investment patterns. However, we didn't find the ownership change to have a significant effect on the hazard in our data. We also investigated the possible effect of business cycle on the hazard shape by including yearly dummies for the two recession years (1990 and 2001) during this period and find no evidence that the hazard in recession years differs significantly from other years.

births in ozone-nonattainment areas.[16] Similarly, Greenstone [2002] finds that nonattainment counties have a lower plant-level growth rate relative to attainment counties. To control for the potential regulatory effect on refinery investments, we also make use of the data on air quality attainment status, and in particular, focus on the ozone attainment status. Ozone is a major component of smog and is formed by the reaction of volatile organic compounds (VOC) and nitrogen oxides (NOx). The refining industry emits both VOC and NOx and is ranked first and second, respectively, among 18 air polluting industries by the EPA [2004]. A dummy variable is constructed that is equal to 1 if a refinery is located in an ozone-nonattainment county in a particular year and zero otherwise. Since refineries located in ozone nonattainment areas are subject to stricter regulations which may require extra investment in pollution abatement associated with a capacity expansion project or a longer time to get a permit for their expansion plans, we expect the ozone-nonattainment variable to have a negative sign in the estimated hazard.

To control for the unobserved heterogeneity, we also applied Heckman and Singer's [1984] approach by allowing the intercept term φ in the hazard function (4) to differ. We model the distribution of the φ by a discrete distribution of Z mass points. Each mass point has probability α_z. The hazard function for a spell belonging to type z is:

$$(5) \qquad \lambda(t, x, \beta) = 1 - \exp(-\exp(\varphi_z + \sum_{s=2}^{S} \gamma_s D_{siy} + x_{iy}' \beta))$$

Equations (4) and (5) are estimated using maximum likelihood methods.

Empirical Results

Table I reports the estimation result of equation (4) using the second definition (six months lag) of refining margin and uncertainty measures. The results using the first and third definitions

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[16] According to the Clean Air Act and its amendments, the Environmental Protection Agency (EPA) uses four criteria pollutants -- carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), and particulate matter – as indicator of air quality and establishes national air quality standards for each of them. A county is designated 'nonattainment' if its air pollution level of a particular pollutant persistently exceeds the relevant national standards.

of margin and uncertainty measures are very similar and therefore not reported for brevity's sake. The first three columns in Table I present the results from the investment hazard using the relative thresholds (0%, 5% and 10%) while the remaining two columns provide the estimates using the absolute thresholds (2000 B/D and 4000 B/D). Across all five investment hazards, the estimated coefficient on the uncertainty variable is negative and statistically significant, indicating increases in uncertainty decrease the probability refiners make new investment. As with any nonlinear model, the magnitude of the marginal effect in a complementary log-log model varies with the point of evaluation. Using the five percent threshold as an example, when the other control variables are evaluated at their mean values a one standard deviation increase in margin uncertainty lowers the hazard rate by about 11 percent. Alternatively, a one standard deviation in uncertainty lowers the hazard by 18 percent when the 4000 B/SD threshold is used. Figures 5A and 5B show the shift in the hazard for this one standard deviation change in uncertainty for the five percent and 4000 B/SD thresholds. Comparing the hazard results based on relative thresholds to the absolute thresholds, uncertainty has a stronger impact when the absolute thresholds are used and for projects that cross the ten percent threshold. This suggests that initiation of larger projects is more sensitive to increased uncertainty. These results on uncertainty are consistent with the predications from the 'real option' theory that firms delay investment when uncertainty is high.

Looking at the other variables in the hazard, both the refining margin and utilization rate variables are generally positive though not always statistically significant in the hazard. The hazard is generally lower for smaller refineries indicating longer durations between investment episodes and this is especially true under the absolute thresholds. For example, when other explanatory variables are evaluated at their mean values a small refinery is 67 percent less likely to exit an investment inactivity spell with 2000 B/D investment than a large refinery. This reflects the fact that under the absolute definition an investment of 2000 B/D is quite large for small refineries but represents a relatively small investment for large refineries. This illustrates

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the key difference between using an absolute and a relative definition. It changes the distribution of spells systematically across the size distribution of refineries -- lengthening the spells of small refineries. The variable that identifies whether a refinery is in an ozone nonattainment area has the expected sign although is only statistically significant under the five percent threshold.

The duration dummies in Table I indicate that the hazard falls for the first three years following an investment episode, it then remains relatively flat, although there is some variation across thresholds. For example, in the 2000 B/SD case, the hazard bumps in the eighth year after an investment, but the overall shape after the third year is essentially flat. The pattern can also be seen in Figures 5A and 5B for the five percent and 4000 B/SD thresholds. A likelihood ratio test of the restriction that sets all the duration dummies equal to zero in each of the five models presented in Table I rejects the null hypothesis that all the duration dummies are jointly zero for all five models.

However, the previous literature (e.g., CHP [1999]) has noted that the shape of the hazard can be quite sensitive to the modeling of the unobserved heterogeneity in the data. Table II presents the estimation results of equation (5) when the unobserved heterogeneity is controlled for by allowing the intercept term to vary with a discrete distribution of mass points. The effect of uncertainty on the hazard is somewhat weaker in these models both in terms of magnitude and statistical significance. In addition, the shape of the hazards generated from the model with heterogeneity varies more across models. Three out of the five models have a downward slope but the remaining two (ten percent and 4000 B/SD thresholds) are essentially flat. In Figure 6A and 6B we plot the hazard curves for the five percent and 4000 B/SD cases allowing the intercepts to vary by our estimates of the mass points. For the five percent case, the shape of the hazard (Figure 6A) clearly mirrors the shape in Figure 5. In the case of 4000 B/SD threshold, the hazard rate for the first three years is not significantly higher than other years. It flattens out almost immediately after an investment. The estimated coefficients for other variables are largely consistent with Table I. Comparing the log likelihoods in Table I and Table II, the log likelihood

improves little with the inclusion of the mass points. This may be due to the fact that the heterogeneity is less prominent in a well-defined industry like oil refining and that the inclusion of explanatory variables already controls for refinery-level heterogeneity. Cameron and Trivedi [2005] suggest the use of a penalized likelihood criterion for model selection, with a high penalty for more parameters.[17] We report the Bayesian Information Criterion (BIC) in the last rows of Table I & 2. A lower BIC indicates a preferred specification. Based on this test, the model with discrete heterogeneity is clearly favored only in the 4000 B/SD case.

Our data and the results in Tables I and II appear to be largely consistent with an environment where irreversibility is an important characteristic of the investment process.[18] First, the timing of investment is affected by uncertainty as predicted by the Dixit and Pindyck [1994] model. This framework emphasizes the importance of the irreversibility in the investment process. Second, the lumpy pattern of investment observed in the refining industry is also in line with the irreversibility story. Finally, the shape of the hazard, while sensitive to the choice of specification, is generally consistent with irreversibility. A declining hazard could arise in models where either irreversibility or convex adjustment cost are present. However, given the large number of inaction spells and the significant uncertainty-investment relationship, we believe it is irreversibility rather than a convex cost story that best explains our data. In models that incorporate heterogeneity through the estimation of mass points, the results regarding the shape of the hazard are less clear. In specifications where the threshold is high (ten percent or 4000 B/SD thresholds), the hazard is essentially flat. Perhaps one interpretation is that a refiner may need to bear significant fixed costs, especially in terms of lost output, when undertaking a larger investment project. The flat hazards could be consistent with a model that incorporates both the

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[17] Cameron and Trivedi [2005] report on work by Baker and Melino [2000] that examines the issue of overparameterization in discrete duration models with unobserved heterogeneity. Baker and Melino [2000] show that overparameterization of the unobserved heterogeneity leads to bias in the estimated coefficients for the explanatory variables and spurious duration dependence.

[18] Bloom [2007] estimates a dynamic model of investment and finds an important role for irreversibility in explaining the patterns of capital adjustment in Compustat data.

irreversibility (a downward sloping hazard) and fixed cost components (an upward sloping hazard).[19] The two competing forces could yield a flat hazard.

In addition to our main results presented above, we also estimate a model with an alternative measure of aggregate industry investment uncertainty. Table III present the results of a model where we replace the refining margin measure of uncertainty with a stock market index based measure of uncertainty (XOI uncertainty). The XOI uncertainty is constructed from the oil index (symbol: XOI) which is designed to represent the financial performance of publicly traded oil companies. XOI is comprised of 13 major oil companies (including independent refiners) and traded at the American Stock Exchange (AMEX). Similar to the refining margin uncertainty, XOI uncertainty is the annual standard deviation of the daily return of this oil index. Across alternative thresholds, there is no statistically significant effect of stock market uncertainty on the capacity expansion decision. One interpretation of this weak correlation is that the share of an oil company's profits derived from refinery operations is relatively small and that the majority of the fluctuations in the XOI are due to fluctuations in the profitability of the explorations and production divisions of the integrated oil companies. Moreover, the XOI only reflects the large producers but many of our refineries are owned by smaller public and nonpublic companies.

Our last set of estimates replaces the capacity expansion definition of an event with a capacity change definition. Under this definition a spell can end because of a capacity expansion event that exceeds the threshold or a contraction event that exceeds the negative of the threshold. Table IV reports these results using the same empirical specifications used in Table I. The main results hold from Table I. The likelihood of making a capacity change falls as uncertainty increases and the shape of the hazard is downward sloping. The uncertainty results are robust across the different thresholds. Most of the other variables are not statistically significant with the exception of the indicator variable on refining size. The small refinery indicator now becomes

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[19] The presence of a mix of fixed and convex adjustment costs is explored in CH [2006] and they find evidence that a model that incorporates both types of adjustments fit the data best.

positive and statistically significant under the five percent and ten percent thresholds, but remains negative under absolute thresholds. This contrasts dramatically to the results in Table I to III where the small refinery dummy had a negative effect in all the estimated models. This varying pattern in the size effects is likely due to the treatment of refinery closures. In the analysis presented in Tables I to III, refinery closings were treated as censored observations. In the models presented in Table IV, refinery closings now end inactivity spells. Figure 2 shows the spike of refinery closings in the data on the far left side of the chart. This leftmost bar represents largely small refineries. The implication is that small refinery closings make up a larger fraction of the five percent and ten percent spells compared to the 2000 B/SD and 4000 B/SD definitions where there are a larger number of spells. However, even under the 2000 B/SD and 4000 B/SD thresholds, the magnitude of the refinery size parameter is greatly reduced in comparison to the results presented in Table I.

V. Conclusion

There are two main measurement contributions of the paper. First, the paper uses data on changes in the actual capacity of refineries to measure investment episodes. We believe that these data offer a cleaner assessment of the capital stock changes of producers than those based on accounting data. Second, the paper uses forward measures from financial markets on commodities to construct estimates of market uncertainty. These measures of commodity price uncertainty reflect uncertainties in both input and output prices faced by the refiner.

Using these data, we examine how refiners' investment decisions are influenced by market-level uncertainty. Empirically, a one standard deviation increase in the margin uncertainty measure reduces the probability of investment by 11% under the 5% investment threshold (Table I). This finding, along with capital adjustment patterns that are present in the data, appears most consistent with an environment where irreversibility is important. Our results generally conform to the predications that arise from the real-options approach developed by Dixit and Pindyck

[1994] where both irreversibility and uncertainty play key roles. In particular, as uncertainty in the refining margin rises, refiners delay their investment decisions. The paper, therefore, provides evidence of the *wait-and-see* response of investment to a rise in uncertainty in a setting where the timing of investment projects is measured in a relatively clean fashion.

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Figure 1

The Number of Refineries and Total Refining Capacity 1985-2003
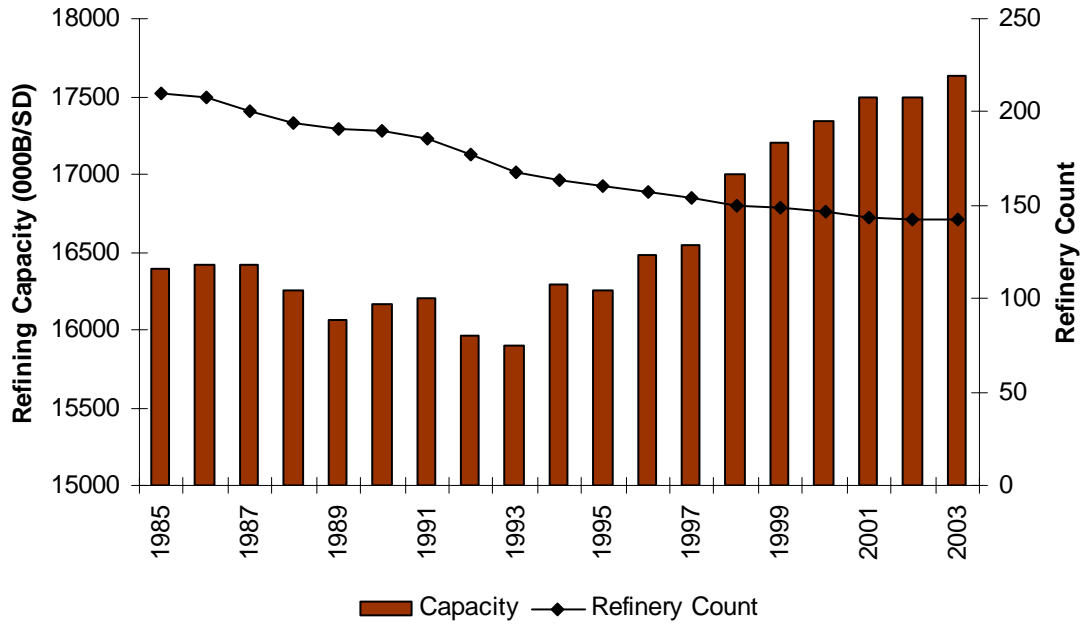
Data Source: Petroleum Supply Annual of EIA, various issues. This figure depicts the number of refineries and total refining capacity at the end of each year.

Figure 2

Refinery Capacity Change Distribution
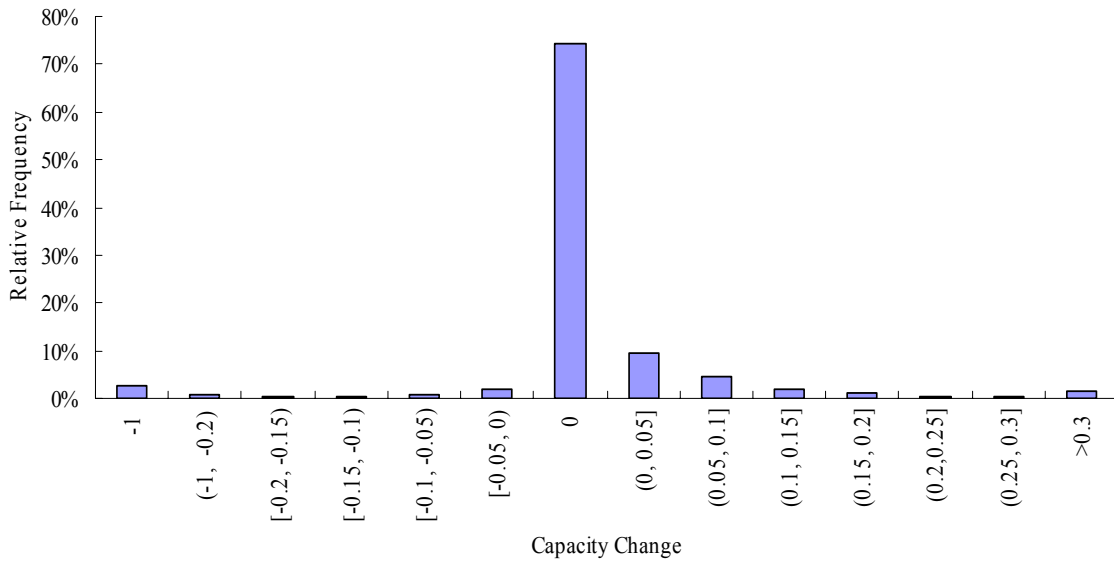
Note: The capacity change variable on the horizontal axis is defined as the capacity change relative to each refinery's capacity at the end of last year. Each bar shows the percent of refinery-year observations with the depicted capacity change rate. The far left bar (-1) represents refinery closures.

Figure 3
Distribution of Duration Lengths (Years) between Two Investment Episodes
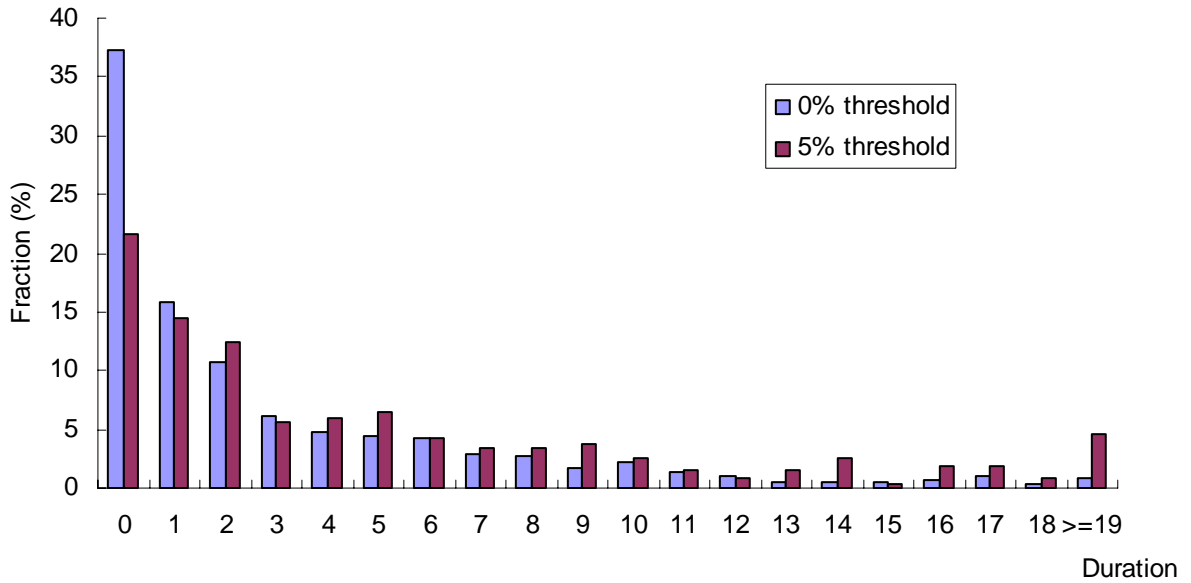
Note: Only completed investment spells are used to construct this figure.

Figure 4
Forward Refining Margin and Uncertainty Measure
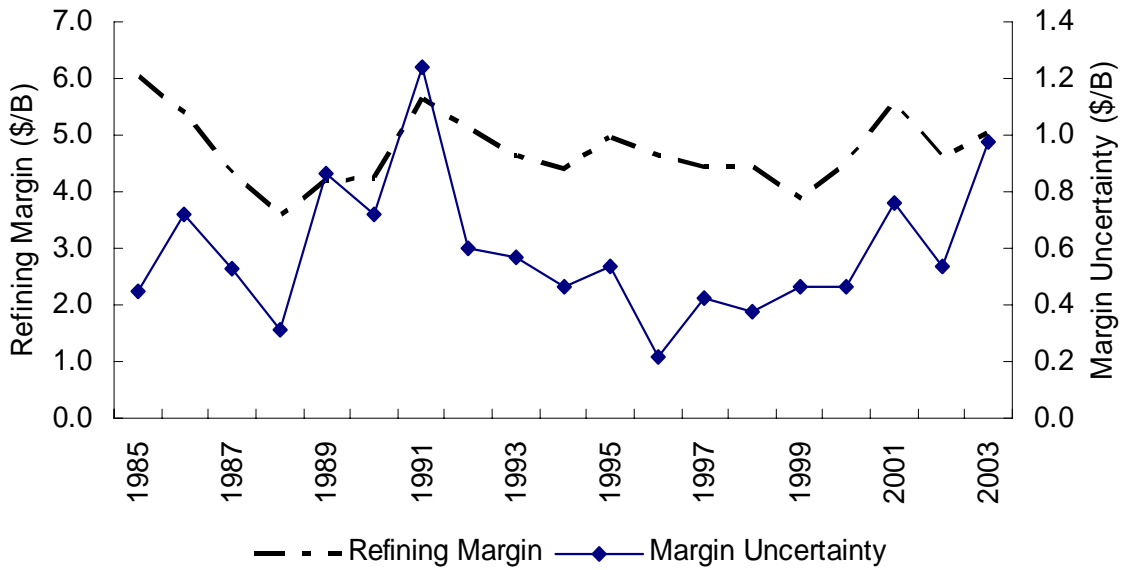
Note: The refining margin and margin uncertainty in this figure are, respectively, the mean and standard deviation of the daily forward refining margin of equation (1) from July 1 of year *t-1* to June 30 of year *t*. The underlying futures price data are obtained from the Commodity Research Bureau.

Figure 5A

Impact of Uncertainty on Investment Hazard
(5% Threshold)

Figure 5B

Impact of Uncertainty on Investment Hazard
(4000 b/sd threshold)
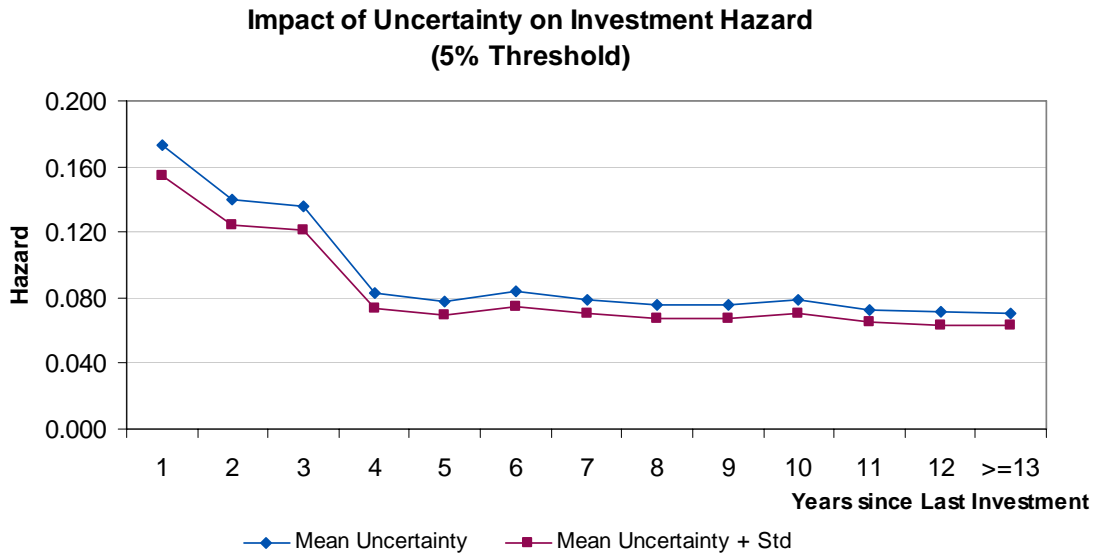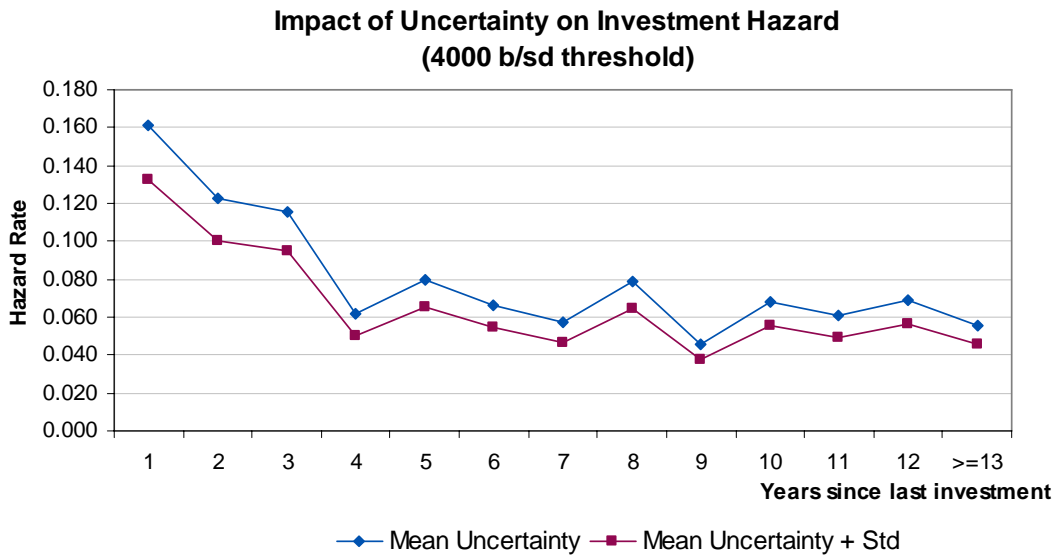
Note: This figure depicts the investment hazard rates at mean uncertainty and at mean plus one standard deviation of the uncertainty measure. Other control variables are set at their mean values.

Figure 6A

Discrete Hazard with Heterogeneity for 5% Threshold

Figure 6B

Discrete Hazard with Heterogeneity for 4000 b/d Threshold

Note: This graph depicts the hazard curve estimated from equation (5) with two mass points. Type 1 and type 2 correspond to φ_1 and φ_2 respectively.

Table I   Investment Hazard Results

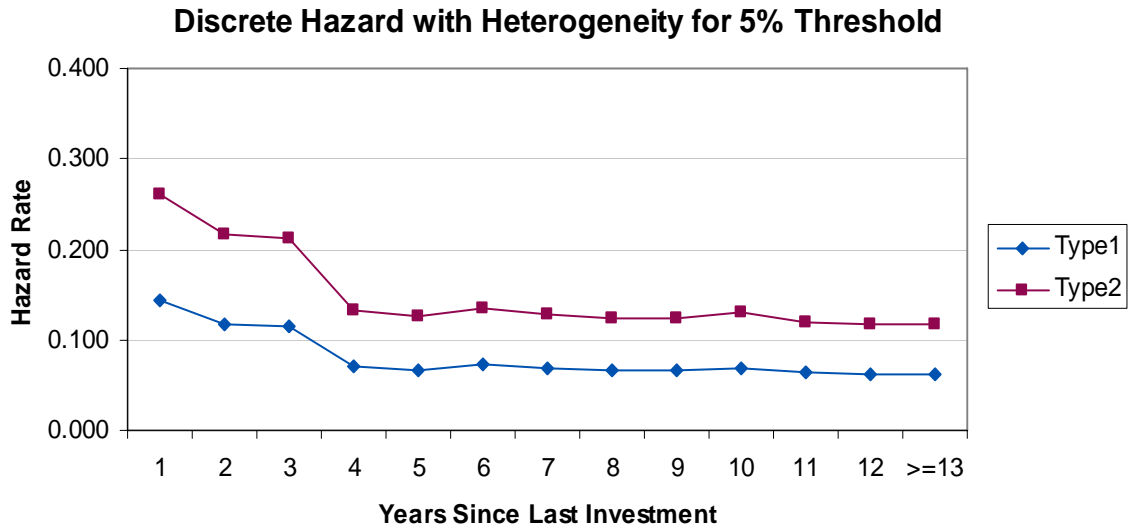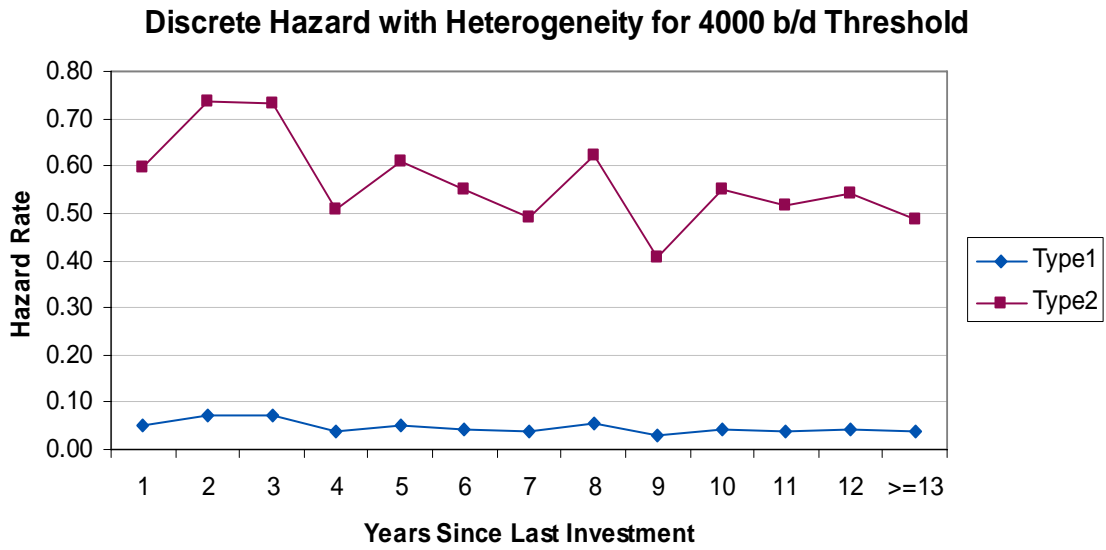|	Relative Thresholds (%)			Absolute Size Thresholds	
	0%	**5%**	**10%**	**2000 B/D Threshold**	**4000 B/D Threshold**
Margin Uncertainty	-0.560***	-0.508*	-0.690*	-0.694***	-0.886***
	(0.199)	(0.268)	(0.36)	(0.224)	(0.271)
Refining Margin	0.057	0.125	0.220*	0.166*	0.130
	(0.076)	(0.101)	(0.131)	(0.086)	(0.101)
Utilization rate	0.029***	0.002*	0.004	0.021**	0.014
	(0.007)	(0.01)	(0.013)	(0.008)	(0.010)
Small Refinery Dummy	-0.800***	-0.418***	-0.068	-1.168***	-1.634***
	(0.105)	(0.13)	(0.168)	(0.134)	(0.189)
Ozone Nonattainment	-0.134	-0.251*	-0.289	-0.093	-0.082
	(0.094)	(0.131)	(0.175)	(0.106)	(0.126)
D2	-0.435***	-0.234	-0.228	-0.279**	-0.301*
	(0.121)	(0.198)	(0.294)	(0.138)	(0.167)
D3	-0.430***	-0.267	-0.567*	-0.409***	-0.362*
	(0.136)	(0.207)	(0.328)	(0.16)	(0.186)
D4	-0.855***	-0.788***	-0.768**	-0.781***	-1.021***
	(0.176)	(0.257)	(0.357)	(0.201)	(0.263)
D5	-1.021***	-0.854***	-0.980**	-0.854***	-0.751***
	(0.202)	(0.268)	(0.384)	(0.222)	(0.252)
D6	-1.203***	-0.778***	-0.571*	-1.036***	-0.938***
	(0.235)	(0.274)	(0.337)	(0.258)	(0.287)
D7	-0.950***	-0.837***	-0.868**	-0.924***	-1.098***
	(0.226)	(0.297)	(0.385)	(0.265)	(0.334)
D8	-0.743***	-0.885***	-0.821**	-0.369*	-0.758**
	(0.221)	(0.316)	(0.385)	(0.223)	(0.297)
D9	-0.904***	-0.885***	-1.627***	-0.697**	-1.320***
	(0.253)	(0.328)	(0.536)	(0.273)	(0.393)
D10	-1.351***	-0.836**	-1.316***	-1.115***	-0.918***
	(0.341)	(0.342)	(0.487)	(0.365)	(0.351)
D11	-0.701***	-0.919***	-1.150**	-0.695**	-1.035***
	(0.261)	(0.357)	(0.451)	(0.303)	(0.37)
D12	-0.696**	-0.943***	-1.057**	-0.761**	-0.906***
	(0.278)	(0.357)	(0.423)	(0.316)	(0.351)
D13 & above	-1.327***	-0.953***	-1.426***	-1.13***	-1.120***
	(0.179)	(0.185)	(0.247)	(0.172)	(0.179)
φ	-2.089***	-1.734	-2.729*	-2.866***	-2.238**
	(0.801)	(1.094)	(1.471)	(0.923)	(1.081)
Log L	-1457.84	-1016.53	-665.82	-1237.02	-971.205
BIC	3126.38	2243.76	1542.34	2684.74	2153.11
No. Spells	835	537	400	700	571

Notes: (1) The model is estimated using a complementary log-log function. (2) n=3307. (3) Standard errors are in parenthesis. (4)*** (**, *) denotes significance at the 1 (5, 10) percent level. (5) D2-D13 are indicator variables that measure spell length in years. (6) Controls for refining districts are not reported.

Table II   Investment Hazard Results with Heterogeneity

	Relative Thresholds (%)			Absolute Size Thresholds	
	0%	**5%**	**10%**	**2000 B/D Threshold**	**4000 B/D Threshold**
Margin Uncertainty	-0.392*	-0.516*	-0.993***	-0.529**	-0.801**
	(0.233)	(0.271)	(0.384)	(0.261)	(0.324)
Refining Margin	-0.038	0.131	0.381***	0.082	0.057
	(0.098)	(0.104)	(0.142)	(0.106)	(0.128)
Utilization rate	0.029***	0.005	0.046**	0.033***	0.040***
	(0.01)	(0.014)	(0.020)	(0.012)	(0.016)
Small Refinery Dummy	-0.910***	-0.440***	-0.663**	-1.378***	-2.486***
	(0.132)	(0.157)	(0.306)	(0.189)	(0.399)
Ozone Nonattainment	-0.139	-0.264*	-0.602**	-0.100	-0.098
	(0.107)	(0.142)	(0.270)	(0.122)	(0.156)
D2	-0.222	-0.217	-0.033	0.019	0.394
	(0.187)	(0.209)	(0.301)	(0.248)	(0.299)
D3	-0.192	-0.235	-0.204	-0.073	0.379
	(0.207)	(0.242)	(0.348)	(0.273)	(0.336)
D4	-0.614***	-0.746**	-0.280	-0.429	-0.238
	(0.243)	(0.305)	(0.389)	(0.307)	(0.389)
D5	-0.822***	-0.814***	-0.494	-0.527	0.044
	(0.268)	(0.311)	(0.417)	(0.328)	(0.391)
D6	-1.002***	-0.728**	0.062	-0.691*	-0.118
	(0.293)	(0.334)	(0.387)	(0.358)	(0.417)
D7	-0.763***	-0.783**	-0.112	-0.611*	-0.294
	(0.284)	(0.359)	(0.453)	(0.363)	(0.455)
D8	-0.532*	-0.828**	-0.076	-0.034	0.071
	(0.275)	(0.382)	(0.456)	(0.328)	(0.431)
D9	-0.671**	-0.826**	-0.848	-0.360	-0.544
	(0.301)	(0.394)	(0.607)	(0.367)	(0.502)
D10	-1.086***	-0.774*	-0.581	-0.732*	-0.124
	(0.381)	(0.412)	(0.553)	(0.443)	(0.469)
D11	-0.479	-0.857**	-0.521	-0.365	-0.222
	(0.312)	(0.425)	(0.504)	(0.402)	(0.493)
D12	-0.492	-0.883**	-0.400	-0.461	-0.148
	(0.329)	(0.423)	(0.501)	(0.405)	(0.468)
D13 & above	-1.079***	-0.89***	-0.735*	-0.746**	-0.301
	(0.243)	(0.301)	(0.430)	(0.301)	(0.347)
φ_1	-2.785***	-2.154	-8.926***	-4.013***	-5.107***
	(1.021)	(1.656)	(2.288)	(1.308)	(1.742)
φ_2	0.376	-1.493	-5.722	-0.932	-2.227
$[\alpha_2]$	[0.092]	[0.241]	[0.494]	[0.104]	[0.211]
Log L	-1455.03	-1016.49	-661.60	-1234.11	-965.14
BIC	3128.86	2251.78	1542.00	2687.02	2149.08
No. of Spells	835	537	400	700	571

Notes: (1) The hazard model is estimated using the Heckman-Singer approach including two mass points (φ's). (2) n=3307. (2) Standard errors are in parenthesis. (3)*** (**, *) denotes significance at the 1 (5, 10) percent level. (4) D2-D13 are indicator variables that measure spell length in years. (5) Controls for refining districts are not reported.

Table III   **Investment Hazard Results with XOI Uncertainty**

	Relative Thresholds (%)			Absolute Size Thresholds	
	0%	**5%**	**10%**	**2000 B/D Threshold**	**4000 B/D Threshold**
XOI Uncertainty	0.023 (0.097)	-0.174 (0.162)	-0.017 (0.23)	-0.095 (0.112)	-0.195 (0.132)
Refining Margin	-0.035 (0.067)	0.011 (0.095)	0.121 (0.126)	0.028 (0.072)	-0.054 (0.085)
Utilization rate	0.020** (0.009)	0.001 (0.010)	0.002 (0.013)	0.020 (0.010)	0.013 (0.012)
Small Refinery Dummy	-0.796*** (0.117)	-0.424*** (0.141)	-0.067 (0.176)	-1.163*** (0.140)	-1.628*** (0.21)
Ozone Nonattainment	-0.138 (0.100)	-0.262** (0.125)	-0.289* (0.171)	-0.105 (0.111)	-0.101 (0.129)
D2	-0.428*** (0.122)	-0.218 (0.197)	-0.214 (0.294)	-0.265* (0.143)	-0.288 (0.167)
D3	-0.425*** (0.151)	-0.254 (0.219)	-0.556* (0.305)	-0.398** (0.176)	-0.361 (0.204)
D4	-0.850*** (0.193)	-0.771*** (0.239)	-0.751** (0.329)	-0.779*** (0.201)	-1.030*** (0.261)
D5	-1.022*** (0.200)	-0.849*** (0.239)	-0.980*** (0.375)	-0.859*** (0.205)	-0.767*** (0.244)
D6	-1.186*** (0.231)	-0.763*** (0.276)	-0.564 (0.356)	-1.021*** (0.247)	-0.932*** (0.258)
D7	-0.970*** (0.239)	-0.856*** (0.282)	-0.900** (0.400)	-0.951*** (0.272)	-1.160*** (0.320)
D8	-0.765*** (0.23)	-0.902*** (0.314)	-0.851** (0.389)	-0.392* (0.228)	-0.800** (0.327)
D9	-0.937*** (0.259)	-0.915*** (0.324)	-1.665*** (0.536)	-0.736*** (0.278)	-1.355*** (0.401)
D10	-1.384*** (0.343)	-0.889** (0.355)	-1.363*** (0.501)	-1.185*** (0.366)	-1.015*** (0.348)
D11	-0.695** (0.259)	-0.937*** (0.341)	-1.179** (0.462)	-0.707** (0.305)	-1.074*** (0.358)
D12	-0.683** (0.281)	-0.947*** (0.355)	-1.056** (0.439)	-0.769** (0.313)	-0.926*** (0.339)
D13 & above	-1.318*** (0.187)	-0.950*** (0.18)	-1.416*** (0.239)	-1.129*** (0.171)	-1.132*** (0.191)
φ	-2.015** (0.950)	-1.126*** (1.229)	-2.436 (1.605)	-2.469** (1.072)	-1.571 (1.234)
Log L	-1461.8951	-1017.78	-667.723	-1241.69	-975.93
BIC	3134.49	2246.26	1546.14	2694.08	2162.56
No. of Spells	835	537	400	700	571

Notes: (1) The model is estimated using a complementary log-log function. (2) n=3307. (3) Standard errors are in parenthesis. (4)*** (**, *) denotes significance at the 1 (5, 10) percent level. (5) D2-D13 are indicator variables that measure spell length in years. (6) Controls for refining districts are not reported.

Table IV   Hazard Results with Capacity Change Definition

	Relative Thresholds (%)			Absolute Size Thresholds	
	0%	**5%**	**10%**	**2000 B/D Threshold**	**4000 B/D Threshold**
Margin Uncertainty	-0.462***	-0.516**	-0.561**	-0.538***	-0.627***
	(0.169)	(0.222)	(0.275)	(0.190)	(0.219)
Refining Margin	0.047	0.069	0.067	0.117	0.086
	(0.064)	(0.081)	(0.098)	(0.072)	(0.081)
Utilization rate	0.011*	-0.008	-0.008	0.008	0.007
	(0.006)	(0.008)	(0.01)	(0.007)	(0.008)
Small Refinery Dummy	-0.315***	0.239**	0.754***	-0.462***	-0.447***
	(0.083)	(0.104)	(0.133)	(0.100)	(0.117)
Ozone Nonattainment	-0.091	-0.136	-0.127	-0.055	-0.028
	(0.081)	(0.108)	(0.134)	(0.091)	(0.103)
D2	-0.42***	-0.222	-0.226	-0.261**	-0.296**
	(0.105)	(0.164)	(0.23)	(0.121)	(0.145)
D3	-0.480***	-0.310*	-0.626**	-0.39***	-0.429***
	(0.120)	(0.177)	(0.268)	(0.139)	(0.166)
D4	-0.793***	-0.781***	-0.641**	-0.692***	-0.827***
	(0.151)	(0.216)	(0.273)	(0.171)	(0.209)
D5	-0.903***	-0.773***	-0.764***	-0.942***	-0.632***
	(0.170)	(0.219)	(0.284)	(0.201)	(0.204)
D6	-0.770***	-0.525**	-0.352	-0.896***	-0.734***
	(0.174)	(0.21)	(0.252)	(0.211)	(0.224)
D7	-0.614***	-0.584**	-0.546**	-0.635***	-0.715***
	(0.178)	(0.23)	(0.278)	(0.204)	(0.237)
D8	-0.788***	-0.944***	-1.068***	-0.574***	-1.024***
	(0.209)	(0.279)	(0.349)	(0.215)	(0.283)
D9	-0.729***	-0.739***	-0.957***	-0.442**	-0.837***
	(0.218)	(0.264)	(0.336)	(0.215)	(0.267)
D10	-0.896***	-0.359	-0.667**	-0.845***	-0.895***
	(0.266)	(0.248)	(0.315)	(0.289)	(0.294)
D11	-0.545**	-0.588**	-0.816**	-0.471*	-0.873***
	(0.239)	(0.279)	(0.336)	(0.250)	(0.294)
D12	-0.955***	-1.381***	-1.045***	-1.164***	-1.352***
	(0.309)	(0.393)	(0.365)	(0.344)	(0.367)
D13 & above	-1.177***	-0.741***	-1.069***	-0.961***	-1.066***
	(0.161)	(0.157)	(0.194)	(0.149)	(0.152)
φ	-1.296*	-0.628	-1.232	-1.628**	-1.508*
	(0.675)	(0.878)	(1.096)	(0.766)	(0.876)
Log L	-1773.17	-1306.36	-961.29	-1549.73	-961.29
BIC	3757.04	2823.42	2133.28	3310.16	2133.28
No. of Spells	957	600	443	781	635

Notes: (1) The model is estimated using a complementary log-log function. (2) n=3307. (3) Standard errors are in parenthesis. (4)*** (**, *) denotes significance at the 1 (5, 10) percent level. (5) D2-D13 are indicator variables that measure spell length in years. (6) Controls for refining districts are not reported.

Appendix

Summary Statistics

	Mean	Std. Deviation	Minimum	Maximum
Utilization Rate (%)	86.98	7.66	60.71	102.80
Refining Margin ($/B)	4.723	0.637	3.570	6.046
Refining Margin Uncertainty, ($/B)	0.594	0.239	0.220	1.237
XOI Uncertainty (%)	1.137	0.381	0.621	2.142