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IN U.S. ENERGY INDUSTRIES

A DISSERTATION APPROVED FOR THE
DEPARTMENT OF ECONOMICS

BY

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ABSTRACT

This dissertation studies producer behavior and market dynamics in three important industries in the energy sector. The first essay, “Investment under Uncertainty: An Analysis of Capacity Adjustment in the Petroleum Refining Industry” investigates the effect of uncertainty on the investment decisions of petroleum refineries in the US. Uncertainty measures are constructed from commodity futures markets which capture the forward-looking nature of investment. Rather than relying on accounting information, data on actual capacity changes is used 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. This essay finds that an increase in uncertainty measures decreases the probability a refinery adjusts its capacity. The results are robust to various investment thresholds and uncertainty measures used in the analysis. Our findings lend support to theories emphasizing the role of irreversibility in investment decisions.

The second essay, “Weather, Storage, and Natural Gas Price Dynamics: Fundamentals and Volatility” examines how weather shocks impact asset return volatility in the U.S natural gas futures market. The results show that weather shocks have a significant impact on both the conditional mean and the conditional volatility of natural gas returns. The inclusion of the weather shock and inventory surprise variables in the variance equation reduces volatility persistence by approximately forty percent. Consistent with the literature, the volatility is considerably higher on Monday and the day when the natural gas storage report is released. Finally, this essay also provides

support for the "Samuelson effect" in the natural gas market that the volatility of commodity futures declines with the contract horizon.

The third essay, "Measuring Unilateral Market Power: An Application to the Texas Deregulated Electricity Market" analyzes the unilateral market power in the balancing electricity market in Texas. This essay follows the recent work of Wolak (2003) and develops measures of market power for the two largest firms based on the inverse of the *ex post* residual demand elasticities. The results indicate that the firm with the largest stake in the balancing market has consistently higher market power than the other firm even though both firms are about equally sized in terms of installed capacity. Further, most price spikes during the sample period are associated with at least one firm's exceptionally high market power. Finally, the lack of bids from smaller suppliers appears to contribute to the largest firms' market power and may exacerbate price spikes

CHAPTER I

INTRODUCTION

This dissertation studies producer behavior and market dynamics in three important industries in the energy sector, namely the petroleum refining, natural gas, and electric power industries. Because each industry faces its own challenges, this study covers a different research question for each industry. Since the removal of price controls in the 1980s, oil (including crude oil and refined products such as gasoline and heating oil) and gas prices have been rather volatile. As a result, oil and gas producers (including refiners) face a great deal of uncertainty. Chapter II of the dissertation constructs uncertainty measures from the commodity futures market and examines the role of uncertainty in petroleum refiners' investment decisions. In Chapter III, the determinants of volatilities are investigated. In particular, this chapter focuses on the impact of weather on the natural gas futures market. The electric power industry remained regulated until late 1990s. The deregulation in recent years raises concerns over the existence of market power. Chapter IV applies Wolak's (2003) method for measuring unilateral market power and analyzes the potential market power that each of the two largest firms had in the Texas deregulated wholesale electricity market from 2002 to 2004.

I.1. Investment in the Petroleum Refining Industry

An important feature of the petroleum refining industry since the mid 1980s is that the total refining capacity has increased while the number of refineries has declined. The number of refineries has steadily decreased from 225 at the end of 1984 to 149 at the end of 2003. The aggregate refining capacity has bumps and troughs. It was relatively flat from 1984 to 1991, declined in 1992, and recovered from 1993. As a result, the total refining capacity at the end of 2003 was 8 percent higher than it was at the end of 1984. Thus, while 76 refineries were shut down during this time period, surviving refineries have significantly expanded their capacities.[1] Chapter II of this dissertation describes the pattern of capacity changes in the refining industry and empirically examines factors driving the changes. In particular, we focus on the effect of uncertainty on refiners' capacity change and investment decisions.

The debate on investment under uncertainty and the nature of capital adjustment process is not limited to the petroleum refining industry. These are fundamental questions in the investment literature and have important policy implications. Because of its forward-looking and subjective nature, investment can be highly volatile and is often hard to predict (Bernanke, 2003). A better understanding of the relationship between investment and uncertainty and the cost of adjustment may help understand investment fluctuations. Depending on assumptions about the technology, the elasticity of demand, and the degree of irreversibility, theories about the impact of uncertainty on investment have both positive and negative predictions. While empirical studies using aggregate data generally find that uncertainty depresses investment, studies using micro data show a less consistent relationship.[2] The cost of capital adjustment is a separate yet related issue. If the cost of capital adjustment is convex as suggested by the neo-classical investment model, firms would smoothly adjust their capital stocks. On the

[1] No refinery has been built in US since year 1976.
[2] For a recent survey on the investment under uncertainty literature, see Carruth et al, (2000).

other hand, if the cost of adjustments is non-convex, the capital adjustment process would be lumpy.

Chapter II of the dissertation shed lights on both questions. There are two main innovations in this essay. First, we take advantage of the petroleum futures data to construct an uncertainty indicator that captures the forward-looking nature of investment and corresponds to firms' expected future return of capital. Second, rather than relying on accounting data, we use actual capacity changes in refineries as our measure of investment and disinvestment episodes. The accounting data on investment are often a mixture of expansionary investment, replacement investment which is driven by maintenance, and other mandatory investment such as environmental investment. The replacement investment and mandatory investment are likely irrelevant to the demand uncertainty and the optimal capital adjustment problems discussed in the literature. Thus, the use of physical capacity data mitigates, to some extent, capital measurement problems faced in the literature.

We find that capacity adjustments by refiners are very infrequent and lumpy. Over 74 percent of the year-to-year capacity changes are zero and only 2.4 percent of the investment episodes account for 50 percent of the total capacity additions in the industry. Given the lumpy nature of the data, we focus our analysis on the timing of the investment and disinvestment episodes. We find that an increase in uncertainty decreases the probability a refiner adjusts its capacity and the result is robust to a variety of adjustment thresholds and uncertainty measures.

I.2. Weather and Natural Gas Price Volatility

Because the intercontinental transportation of natural gas is still quantitatively limited, the natural gas market is generally considered a regional market that is confined in North America.[3] Chapter III studies the influence of weather changes in the US on daily natural gas price dynamics in the futures market. The Energy Information Administration, Department of Energy classifies the natural gas demand into four sectors: residential, commercial, industrial, and electric power. Weather has a direct impact on natural gas demand in all but the industrial sector. Because the demand from the industrial sector and natural gas production generally do not vary much in the short-time term, weather is likely the most important factor causing natural gas demand and supply imbalances. More importantly, unlike information about production and industrial demand, weather information reaches the market very frequently. Despite the fact that weather often makes headline news in trade publications, little effort has been devoted to understanding the impact of weather on short-term natural gas price dynamics.

Chapter III makes a first attempt in this area. We measure weather shocks as the deviation in heating degree days (HDD) and cooling degree days (CDD) from previous 30 years average. Under a GARCH framework, we show that the weather shock variable has a significant impact on both the conditional mean and conditional variance of natural gas futures returns. Consistent with the literature, the volatility is considerably higher on Monday and the day when the natural gas storage report is released. Both the "Monday effect" and the "storage announcement effect" can be

[3] Natural gas can be shipped by marine tans in the form of liquefied natural gas (LNG). An LNG trade requires both a liquefaction facility in the export terminal and a re-gasification facility in the import terminal, and typically involves long-term contracts to commit the investment.

driven by weather. Furthermore, the inclusion of weather shock and storage surprise variables in the GARCH model reduces volatility persistence by about forty percent. This later result corroborates the important influence of the weather but also demonstrates that a large portion of the volatility cannot be explained by these fundamental factors.

Chapter III contributes to our understanding of the determinants of price volatility in the natural gas market. It also sheds light on a broader debate centering on whether market fundamentals drive asset price volatilities. As volatility is a key element of many financial decisions, the findings from this chapter should be of interest to both academics and industry practitioners.

I.3. Market Power in Deregulated Electricity Markets

Traditionally, the electricity industry was characterized by vertically integrated, regulated natural monopolies. Power generation assets, transmission lines, and distribution systems were all owned by the same utility company. These utilities were regulated by state public utility commissions. Following the experience of UK, several states began to deregulate their electricity industries in the mid 1990s. Massachusetts, Rhode Island, and California were among the forerunners and about a dozen additional states implemented a deregulation program by the end of 2000 (Joskow, 2006). The deregulation process varies among states, but typically involves separating power generation assets from utilities, opening transmission lines to other power generators, and the creation of an independent system operator (ISO). The key functions of an ISO are to ensure the reliability of the power grid and to organize a spot electricity market. The initiative for such restructuring was to introduce competition into the electricity industry and lower prices and therefore benefit consumers. In the aftermath of California energy crisis, however, several states halted their plans for further restructuring. Texas is one of the few states that continued to deregulate the wholesale and retail markets after 2001.

Chapter IV analyzes market power in the balancing electricity market in Texas during peak hours from January 1, 2002 to December 31, 2004. Like many other deregulated electricity markets in the U.S., the Texas balancing market also adopts a multi-unit, uniform-pricing auction to clear the market. Suppliers bid a supply schedule specifying the prices and quantities at which they are willing to offer electricity to the market. Because the aggregate demand curve in real-time is essentially price-inelastic, the availability of individual firms' bids data allows us to compute the residual demand curves facing each of the two largest firms. As demonstrated by Wolak (2003), the inverse of the residual demand elasticity provides a measure of the firm's unilateral market power. This chapter examines the market power of the two largest electricity suppliers in Texas. There are two main findings. First, the firm with the largest stake (TXU) in the balancing market has consistently higher market power than the other firm even though both firms are about equally sized in terms of installed capacity. Second, most price spikes during the sample period are consistent with at least one firm's exercise of market power. The lack of bids from smaller suppliers appears to contribute to the largest firm's market power and may exacerbate price spikes.

CHAPTER II

INVESTMENT UNDER UNCERTAINTY: AN ANALYSIS OF CAPACITY ADJUSTMENT IN THE PETROLEUM REFINING INDUSTRY

II.1 Introduction

A fundamental question in the investment literature centers around the effect of uncertainty on investment. Does uncertainty encourage or discourage firms from making investments? From a theoretical standpoint, the impact of uncertainty is ambiguous. Abel (1983) shows that an increase in uncertainty in either output prices or input prices raises the expected returns on investment and thus leads to higher current investment. Alternatively, recent models that emphasize the irreversibility of investment decisions such as Dixit and Pindyck (1994) predict that uncertainty depresses current investment by increasing the option value of delaying the investment. The empirical literature presents mixed results. Studies using aggregate data generally report a negative relationship between uncertainty and investment, while studies using disaggregated industry data and producer-level data show a less consistent relationship.[4]

A second related but distinct question concerns the nature of the capital adjustment process. Is the adjustment process best characterized by a smooth adjustment process or a lumpy adjustment process? Recent empirical papers focusing on the micro-adjustment patterns of plants and firms show that producers often change their capital stocks in a lumpy fashion (Cooper, Haltiwanger and Power (hereafter CHP, 1999), Doms and Dunne (1998), and Nilsen and Schiantarelli (2003)). Episodes of high

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

investment activity are interspersed with episodes of low or zero investment activity. The presence of lumpy investment episodes has been interpreted as providing support for theories of investment that rely on the irreversibility of investment, the indivisibility of investment projects, and/or the presence of nonconvex costs of adjustment.[5]

In this chapter, we bring elements of both these literatures together by studying the relationship between uncertainty and investment in an industry characterized by infrequent capital adjustment -- the US petroleum refining industry. The chapter's main contributions stem from the way uncertainty and capital adjustments are measured. There are two main measurement challenges in this exercise. First, how should uncertainty be defined and measured? Most previous studies have used measures of macroeconomic uncertainty, stock market volatility, or model the uncertainty through a time series or an ARCH process. One of the drawbacks with these types of measures is that they often fail to capture the forward-looking nature of investment decisions. In this chapter, we take advantage of the petroleum futures data to construct forward-looking measures of uncertainty that are directly relevant to the capital adjustment decision of the refiner.

Second, inferring actual capital adjustment from nominal investment series raises some difficult measurement issues. The reported investment series are usually based on accounting data and these data series are plagued with measurement error and missing data items. In their discussion of shortcomings in the investment literature, Caballero, Engle, and Haltiwanger (CEH, 1995, p.1) state "Both right- and left-hand side variables are seldom measured properly." Rather than rely on accounting data, this study uses

[5] An early discussion of nonconvex adjustment costs is provided in Rothschild (1971). Dixit and Pindyck (1994) emphasize the role of irreversibilities along with uncertainty in the investment process.

actual capacity changes in refineries as our measure of investment and disinvestment episodes. Our data include annual observations on refining capacities for almost all US refineries in existence over the period 1985-2003. These capacity-based measures provide a number of distinct advantages over accounting-based data. The data measure only investment episodes that affect capacity expansion or contraction. These capacity-based data omit maintenance-driven investment and non-capacity changing investments such as investment in pollution control equipment.[6] 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. Using physical capacity measures avoids these types of measurement problems. We only know of two other studies using capacity changes to measure investment in the literature (Bell and Campa, 1997; Goolsbee and Gross, 2000).

The first part of our empirical analysis documents capital adjustment patterns in the petroleum refining industry. We find that capacity adjustments by refiners are very infrequent. Over 74 percent of the year-to-year changes in capacity are zero and only 2.4 percent of the investment episodes account for 50 percent of the total addition to capacity in the industry. The second part of the empirical analysis explores the relationship between price uncertainty and capacity adjustment. We use a hazard model of investment to estimate the effect of uncertainty on the probability a refinery adjusts its capacity. We find that uncertainty has a negative and statistically significant impact

[6] Caballero (2000) emphasizes the importance of distinguishing between maintenance-driven and expansion-driven investments.

on capacity adjustment and the result is robust to a variety of adjustment thresholds and uncertainty measures.

The remainder of this chapter proceeds as follows. Section II.2 describes some basic features of the refining industry and the data that we use in the chapter. In section II.3 we discuss our measures of uncertainty. Section II.4 provides a detailed statistical analysis and presents empirical findings. Section II.5 summarizes and concludes.

II.2 Investment in the Refining Industry

Constructing the capital stocks of firms and the changes in the capital stocks often involves difficult measurement issues.[7] Typically, authors use accounting data on the current dollar value of purchased plant and equipment and apply aggregate depreciation rates and capital price indices to construct a constant-dollar firm-level capital stock. These standard approaches to capital measurement at the micro level contain a number of drawbacks. On the one hand, many required data items for the creation of producer-level capital stocks are often missing at the micro level. For example, information on the economic depreciation of assets and the price of investment goods are typically unavailable at the producer level. On the other hand, accounting data on new investment contain a mix of capital expenditures that includes expansion-driven spending, maintenance-driven spending and non-capacity enhancing investments such as pollution control and occupational safety equipment. The latter investments may be mandated investments due to regulatory requirements. These mandated 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. Moreover,

[7] See CEH (1995) and Goolsbee and Gross (2000) for a detailed discussion of measurement issues.

these accounting based data are influenced by tax code issues and usually represent a mix of historical and current dollar data series. Economists prefer measures of the capital stock that are tied more directly to the physical capital stock or to the flow of services provided by the capital stock of the firm. In this chapter, we reduce some of the accounting-related problems by studying changes in actual capacities in refineries.

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 1995-1998 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)*.[8] 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 225 refineries with a total of 3,324 refinery-year observations.

As our basic measure of capital, we focus on the crude processing capacity (atmospheric distillation capacity) of refineries located in the 50 U.S. states.[9] Refining capacity is measured in two ways -- as the barrels per stream day (B/SD) and as the barrels per calendar day (B/CD). The former is "the maximum number of barrels of input (mainly crude oil) that a distillation facility can process within a 24-hour period

[8] The OGJ data only reports capacities measured in calendar days. We multiply the EIA 1994 data by the percentage change in OGJ data to obtain the 1995 data, and similarly for 1997 data.
[9] Crude distillation is the first and necessary procedure in a continuous refining process.

when running at full capacity under optimal crude and product slate conditions with no allowance for downtime.” The latter is “the amount of input that a distillation facility can process under usual operating conditions and allows limitations in downstream capability and downtime due to scheduled maintenance, turnaround, and slowdowns” (EIA, 2000, p 165-166). Throughout the analysis, we use refining capacities expressed as barrels per stream day in this study because changes in stream day capacities require a physical change in the actual processing units.

To investigate the investment-uncertainty relationship, we focus on the investment and disinvestment associated with refining capacity changes. We define capacity increases from year *t* to *t+1* as our measure of investment and capacity reductions from year *t* to *t+1* as our measured disinvestment. Refiners can increase their capacities through conventional project investments (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 usually termed "capacity creep." Capacity reductions typically result from the shutdown of either a refinery or a distillation unit in a multi-unit refinery. Given that the debottlenecking can be done at minimum costs, one might expect refineries to frequently adjust their capacities. However, as depicted below, this is not the case.

Figure II.1 shows the aggregate of capacity additions and the industry-level investment for petroleum refining (SIC code 2911 and NAICS code 32411) from the Annual Survey of Manufacturers (ASM) over the sample period. To accommodate construction lags, the ASM data is lagged for one year. It is striking to notice how the two series depart from each other. Clearly a substantial component of the dollar amount of investment is not driven by capacity changes. Indeed, anecdotal evidence suggests that a significant fraction of the investment in the refining industry is due to product specification changes and the adoption of pollution control equipment in response to changes in environmental regulations. In a comment about building new refineries in the U.S., Bill Greehey, the CEO of an independent refiner Valero Energy Corporation, told the press that Valero would spend $1.7 billion on meeting federal gasoline requirements in 2004 and 2005 (as reported in *San Antonio Express*, July 31, 2004). According to the Census Bureau's *Current Industrial Report*, pollution abatement capital expenditure accounts for 10-15 percent of the overall investment by the petroleum refining industry over the sample period. Investment in these mandated areas probably has little to do with the level of demand and demand uncertainty. Consequently, the use of accounting data on investment in this type of industry setting may be particularly misleading.

The micro-patterns of capacity changes in percentage terms are shown in Figure II.2. The underlying data represent changes in capacity between year t and t+1 at the refinery level. The large spike in the middle of the distribution indicates that 74 percent of the time refineries make no change to their capacity between two adjoining 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 Cooper, Haltiwanger and Power (1999), Doms and Dunne (1998), and Nilsen and Schiantarelli (2003). For example, Nilsen and Schiantarelli report only 20 percent of their investment episodes in Norwegian manufacturing as being zero 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 additional capacity added in the industry is highly concentrated in a few investment episodes. Only 2.4 percent of all investment episodes account for 50 percent of the addition to capacity in the industry. These additions all 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 closed during the 1985-2003 period and these closing refineries account for 63 percent of the overall reduction of capacity observed in the data.

While it is plausible that a refinery may increase its capacity by a small amount through debottlenecking and incremental investment activity, it is less likely that a refinery would disinvest its capacity by a small amount. We suspect that some of the small reductions 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.[10] To test the sensitivity of our results to the presence of these small adjustments in capacity, we employ three alternative thresholds to measure whether a change in capacity has occurred. The first one is the zero threshold: any capacity change above (below) zero is defined as investment (disinvestment). The second one is the 5 percent threshold: a capacity change greater than 5 percent is defined as investment and less than -5 percent is

[10] We owe this point to Stephen Patterson, Survey Manager at EIA and Sidney Gale, Managing Director of EPIC Inc.

defined as disinvestment. The third one is the 10 percent threshold which is similarly defined as the 5 percent threshold. Figure II.3 depicts the fraction of refineries experiencing investment and disinvestment according to the three criteria over the 1985-2003 period. Comparing Figure II.1 with Figure II.3, it is not surprising one finds a clear linkage between the fraction of refineries investing and disinvesting and the aggregate capacity change. When a large fraction of refineries invest (e.g. in 1994 and 1998), the aggregate capacity tends to rise; on the other hand, when a large fraction of refineries disinvest as in 1992, the aggregate capacity tends to fall. Doms and Dunne (1998) and CHP (1999) also document similar pattern using the Longitudinal Research Database (LRD).

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 capacity adjustments, Figure II.4 presents the distribution of durations between two investment/disinvestment episodes using the zero and five percent thresholds. The duration is defined as the length (in years) of inaction period between two adjacent investment or disinvestment episodes in the same refinery.[11] For instance, if a refinery invests in both year t and year $t+1$, the duration is zero. If it does nothing in year $t+1$ but invests in year t and $t+2$, the duration is one. Several points are worth making. First, consistent with the large number of zero observations in Figure II.2, the majority of the durations are above zero and the median duration for the 5 percent threshold series is 3 years. Second, the fraction of refineries with very long durations between investment episodes is quite small. Third, we do see a significant number of zero duration events.

[11] Here we do not distinguish between an investment and a disinvestment.

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 changes in capacity.

II.3 Measuring uncertainty

A major challenge in the empirical literature is how to measure uncertainty in the investment climate faced by firms. A measure of uncertainty should gauge producers' assessments of the distribution of future returns of investment. Attempts to construct uncertainty indicators generally fall into one of the three categories. The first is to construct an unconditional or conditional volatility from a macroeconomic aggregate (for example, exchange rate, inflation, and output growth) or price series in particular industries. This is the approach typically used in papers investigating macroeconomic uncertainty or industry-level uncertainty (see Huizinga (1993), Favero et al (1994), Bell and Campa (1997), Ghosal and Loungani (1996), Henley et al, (2003) among others). In microeconomics settings, two problems are associated with this approach. First, the volatility measure obtained from product prices can at best capture the uncertainty in one aspect of a firm's or an industry's business environment. For example, for a processing industry, the uncertainty in the cost of raw materials is probably equally important as the uncertainty in product prices. Second, the uncertainty measure often fails to capture the forward-looking nature of investment decisions. Some authors (e.g. Favero et al, (1994), Ghosal and Loungani (1996)) construct uncertainty measures from forecasting equations. Apart from the generated regressors' problem, this method implicitly assumes that all firms base their forecasts on the same model as the one used by the econometrician, which may be problematic.

The second approach, introduced by Leahy and Whited (1996), is to use the standard deviation of firms' daily stock returns. Using a panel of publicly listed U.S. companies, Leahy and Whited (1996) find that uncertainty measures (the variance of daily stock returns) negatively affects investment. Bloom et al. (2001) using UK data report a similar result. In contrast, Henley et al. (2003) find that the excess stock return volatility appears to stimulate investment, although the industry-wide uncertainty (measured as a moving standard deviation of sector producer index) depresses it. The advantage of a stock return based uncertainty measure is that it is forward-looking, firm-specific, and arguably should be able to capture all aspects of a firm's business environment that may influence investment decisions. The disadvantage is that these measures are *a priori* limited to publicly listed firms. In addition, stock price volatility may be influenced by not only fundamentals but also bubbles and fads, or "excess volatility" (see Shiller, 2003).

The third approach is to directly survey managers' expectations about future demand growth and to construct an uncertainty measure (typically standard deviation) from the subjective probability distribution based on the survey. We are only aware of a couple of papers that have used this approach. Building upon a survey of Italian firms, Guiso and Parigi (1999) find that higher demand uncertainty reduces investment and the negative effect is stronger for firms with substantial market power, a result consistent with Caballero (1991). Along the same line, Patillo (1998) finds uncertainty (also measured from survey data) raises the trigger value of investment in a panel of Ghanaian firms. Clearly, direct survey-based measures of the investment climate offer an attractive alternative to derived measures. The major problem is that the data are often costly and difficult to obtain.

In this study, we explore a novel approach by making use of commodity derivatives trading data. 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 indicator is based on a daily forward refining margin (or crack spread, denoted as *FRM*), which is defined as

$$FRM^t = 2*F_{GO}^{T,t} + 1*F_{HO}^{T,t} - 3*F_{CO}^{T,t} \tag{1}$$

where *GO, HO,* and *CO* stands for unleaded gasoline, heating oil, and crude oil respectively. $F_{(.)}^{T,t}$ denotes the price of the futures contract that is traded at time t and matures at month T.[12] 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. A recent EIA report (EIA, 2002, p. 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*.”

Theories on the price determination of storable commodities suggest that futures prices ($F^{T,t}$) can be viewed as market participants’ forecasts of spot prices based on all the information available at time t. Fama and French (1987, p.55) discuss two main

[12] The deliveries of all petroleum futures are ratable over the entire delivery month (NYMEX website).

interpretations of commodity futures prices. The theory of storage developed by Working (1949) models the future prices ($F^{T,t}$) as the sum of spot prices (S^{t}), foregone interest and storage costs from t to T, and a convenience yield from physically holding inventory.[13] An alternative view explains the futures price in terms of a forecast of future spot price and an expected risk premium. In a discussion about forecasting performance of commodity futures prices, Tomek (1997) points out that although futures prices may not accurately predict future spot prices, they do as well or better than econometric models. Specific to the petroleum futures market, Ma (1989) compares the forecasting performance of petroleum futures (crude oil, heating oil, and leaded gasoline) markets with a variety of widely-used time-series models including random walk, ARIMA, and VAR models. She finds that, on average, forecasts based on futures markets outperform econometric models for all the three commodities. Fujihara and Mougoue (1997) provide evidence that petroleum futures prices are unbiased predictors of the future spot prices. Given these findings, we believe that the forward refining margin defined in Equation (1) should proxy market participants' expected gross margin for the industry in T based on current information.

Analogous to papers using the standard deviation of stock returns, this essay 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 close prices of all the three commodity contracts with 6 months time-to-maturity. The 6-month maturity is chosen

[13] The convenience yield refers to a nonmonetary return to physical ownership of the commodity because physically holding an inventory provides insurance to producers against supply disruption. See McDonald (2003, p. 174).

because it is the longest time horizon with which we can obtain a consistent data series. The annual measures of forward refining margin (*Margin*) and the associated uncertainty measure (σ_{FRM})) are the mean and the standard deviation of daily forward margins as in (1) over a 12-month window and deflated with the implicit GDP deflator from the Bureau of Economic Analysis (BEA). Specifically,

$$Margin = (\textstyle\sum_{t=1}^{N} FRM^{t}) / N \tag{1.a}$$

$$\text{and } \sigma_{\text{FRM}} = \sqrt{\frac{\sum_{t-1}^{N} (FRM^{t} - MARGIN)^{2}}{N-1}} \tag{1.b}$$

where N is the number of trading days in a given year.

Figure II.5 plots the time series of the *Margin* and σ_{FRM}. The σ_{FRM} series appear to be heavily influenced by geopolitical events in the Middle East. The spike in 1990 is related to the first Gulf-War. Uncertainty 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 where war threatens important supply sources.

II.4 A Competing Risks Analysis

A. The Empirical Framework

The standard approach in the literature is to estimate a reduced form investment rate model. Given our data features episodes of investment and disinvestment interspersed with periods of investment inactivity, we make use of econometric techniques for survival analysis and estimate the effect of uncertainty on the timing capacity adjustment. The survival time variable measures the time that a refinery stays in an inaction regime. Investment and disinvestment are defined as two competing "failure" events. Most refineries have multiple investment or disinvestment episodes during the sample period and we reset an individual refinery's clock to zero after each episode.

Let T denote the length of survival time (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 will invest or disinvest in the interval of Δt after it stays in inaction until t. Following the notation in Kiefer (1988), the hazard function can be written as

$$\lambda(t) = \lim_{\Delta \to 0} \frac{pr(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}. \tag{2}$$

Using the hazard function, the survival function $S(t)$ is written as

$$S(t) = \exp[-\Lambda(t)] = \exp[-\int_0^t \lambda(s)ds] \tag{3}$$

where $\Lambda(t) = \int_0^t \lambda(s)ds$ is the integrated hazard function.

To distinguish between the two types of failure events (i.e. investment and disinvestment), we employ a competing risks framework. The competing risks approach allows for different estimates of the effects of the explanatory variables and different baseline hazard for each type of failure event. This is important in this application because we expect our explanatory variables to have very different effects on the probability a refiner exits the inactivity through an investment episode as opposed to a disinvestment episode. For example, an expected increase in future profitability should have a positive effect on the conditional probability of investment and a negative effect on disinvestment. Treatment of the two competing risks as a single risk of capacity change would blur the effect of explanatory variables.

Narendranathan and Stewart (1991) provide a detailed discussion of the competing risks approach. In our case, we have two competing risks, investment and disinvestment, denoted as i and d, respectively. Narendranathan and Stewart (1991) show that the aggregate hazard function can be written as the sum of the "cause-specific" hazards

$$\lambda(t)=\lambda_i(t)+\lambda_d(t) \tag{4}$$

and the survivor function can be written as

$$S(t) = \exp[-\Lambda(t)] = \exp[-(\Lambda_i(t)+\Lambda_d(t))] = \exp[-(\int_0^t \lambda_i(s)ds + \int_0^t \lambda_d(s)ds)]\,. \tag{5}$$

Under the assumption that the investment and disinvestment risks are independent, the model can be easily estimated and reduces down to estimating each of the "cause-specific" hazards separately and censoring the observations of the competing risk. For example, in our case we estimate a single risk hazard model for investment and treat all spells that end through disinvestment as censored observations. A similar procedure is done when examining the disinvestment hazard. In the competing risk framework, our cause-specific proportional hazards are

$$\lambda_i(t,x,\beta_i,\lambda_0) = \exp(x'\beta_i)\lambda_{i0}(t) \tag{6}$$

$$\lambda_d(t,x,\beta_d,\lambda_0) = \exp(x'\beta_d)\lambda_{d0}(t) \tag{7}$$

where λ_{i0} and λ_{d0} denote the "baseline" hazard functions corresponding to zero values of the explanatory variables for the investment and disinvestment hazards. β_i and β_d are the parameters to be estimated. x is a vector of explanatory variables that are the same across both equations. The effect of the *x's* on the conditional probability of ending an inactivity spell is to shift the baseline hazard proportionally (Kiefer, 1988).

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. [14] The variable *Urate* is the ratio of average daily input (crude) to average daily capacity. To avoid endogeneity problems, *Urate* enters equation (8) and (9) with one year's lag. We expect that if supply conditions are tight in an area this may increase (decrease) the probability of an investment (disinvestment) episode occurring. Since, Doms and Dunne (1998) find that smaller plants and plants undergoing ownership change have lumpier investment patterns, we control for these factors as well. *Ownchg* is a dummy variable that is equal to 1 within the first 2 years of ownership change and zero otherwise. *Small* is another dummy variable that is equal to 1 for refineries with capacity less than 50,000 B/SD and zero otherwise. Finally, a set of dummy variables for refining districts are also included to control for geographic and institutional differences across regions.

The recent literature on the cost of capital adjustments (CHP, 1999) suggests that positive duration dependence is consistent with non-convex forms of adjustment costs while convex adjustment costs implies no duration dependence. 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. In contrast, the best response to convex form of adjustment cost is to invest whenever there is a capital shortage. The Weibull model is a natural

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

choice for testing duration dependence. The baseline hazard for the Weibull model has the following form (the subscripts are dropped for ease of exposition):

$$\lambda_0(t) = \rho t^{\rho - 1} \tag{8}$$

When ρ=1, the Weibull model reduces to an exponential model with constant hazard. When ρ >1, the Weibull model has positive duration dependence — the hazard increases in the length of the duration. When ρ <1, the hazard has negative duration dependence.

In an attempt to account for the unobserved heterogeneity at the refinery level, we assume a multiplicative error term (frailty) v associated with each hazard specification

$$\lambda(t, x, \beta, \lambda_0) = \exp(x'\beta)\lambda_0(t)v \tag{9}$$

The frailty (v) is assumed to be gamma distributed with mean one and variance θ which is a standard assumption in this approach. Whether the unobserved heterogeneity is significant can be tested by testing whether the parameter θ is zero. When the null hypothesis is true, the model reduces to a model without frailty. We allow the frailties to be shared over the same refinery (a shared-frailty model).

Kiefer (1988, p 665) shows that equation (9) can be rewritten in the form of

$$-\rho \ln t = x'\beta + v . \tag{10}$$

Thus, the effect of x is to directly prolong or shorten the survival time t by a factor exp(-x'β/ρ) depending on whether the factor is greater or less than one.

B. Hazard Model Results

For the sake of robustness, we calculate three pairs of annual *Margin* and *Uncertainty* series by alternating the calculation window. The first pair (*Margin1* and $\sigma_{FRM}1$ shown in Figure II.5) is simply the mean and the standard deviation of daily margins in year *t*. To allow for construction lags, we build 6- and 3- month lags in the second (*Margin2* and $\sigma_{FRM}2$) and the third pairs (*Margin3* and $\sigma_{FRM}3$), respectively. *Margin2* and $\sigma_{FRM}2$ are the mean and standard deviation of daily margins from July of year *t-1* to June of year *t*, while *Margin3* and $\sigma_{FRM}3$ are similarly defined from October of year *t-1* to September of year *t*. All margins and uncertainty measures are deflated with the implicit GDP deflator from the Bureau of Economic Analysis (BEA).

The estimation results with the 5 percent investment threshold and alternative uncertainty measures are reported in Table II.2. In the investment column, the estimated coefficients for all three uncertainty measures are negative and significant at the 5 percent level. Take the estimated coefficient in Panel B as an example. A 10 percent increase in $\sigma_{FRM}2$ lowers the conditional probability of ending an inaction spell with an investment episode by approximately 5 percent, or increases the length of the no-investment spell by 4 percent.[15] As expected, the margin variable has a significantly positive effect on the investment hazard. A 10 percent increase in *Margin2* raises the estimated conditional probability of investment by 13 percent, which is equivalent to decreasing the length of no-investment spell by 10 percent. With respect to the other variables in the investment hazard, the estimated coefficient of *Urate* is not significant in the investment hazard nor do ownership changes appear to affect the investment hazard. The hazard is lower for smaller refineries indicating longer durations between investment episodes.

In the disinvestment hazard, the coefficients for uncertainty measures are also negative, although only significant at the 5 percent level in Panel A and at the 10 percent level in Panel B. The "real option" theory also implies a negative relationship

[15] The model predicted the median length of no-investment inaction spells to be 7.6 years.

between disinvestment and uncertainty. While the *Margin* coefficient becomes insignificant in the disinvestment hazard, the *Urate* coefficient is highly significant and negative as one would expect. When the utilization rate is high, refineries are less likely to disinvest. Not surprisingly, small refineries have a higher hazard of disinvestment.

The test of duration dependence indicates that ρ is significantly greater than 1 in both risks, thus providing evidence of positive duration dependence. Again, take the estimated ρ for the investment hazard in Panel B of Table II.2 as an example, after five years, a refinery is 40 percent more likely to invest than after 1 year. It is important to note that this result is obtained after controlling covariates that reflect overall market conditions and might influence the duration dependence (namely, margin, utilization rate, and uncertainty) and therefore is supportive of models with non-convex adjustment costs. Finally, the log likelihood ratio test for frailty suggests that there is a statistically significant level of unobserved heterogeneity and the frailty model specification is necessary.

To check whether the results are sensitive to our threshold definition of investment, we report a set of results using three different thresholds of investment in Table II.3. The top panel uses the zero threshold definition and this definition simply makes use of the raw changes in capacity to measure investment episodes. Recall the five and ten percent thresholds require a change of five and ten percent or more, respectively, to trigger an investment/disinvestment episode. All three panels in Table II.3 are consistent with the findings in Table II.2. The uncertainty measure is negative and statistically significant in the investment hazard across all three thresholds. Moreover, the results for the other variables in the model appear to have the same pattern across the alternative thresholds. Clearly, the results from Tables II.2 and II.3 indicate that hazard models differ markedly across the investments and disinvestments risks. Narendranathan and Stewart (1991, 1993) present a likelihood ratio test where one compares the likelihoods under the competing risks model to the likelihood under a single risk model. The test is effectively comparing the equality of the estimated parameters across the investment and disinvestment hazards. We perform this test and, not surprisingly, reject the null hypothesis of no difference in the parameters across competing risks hazards at the 1 percent significance level.

Throughout this analysis, we have used the standard deviation in the future refining margin as our measure of uncertainty. We think this appropriate as the refining margin is the principal determinant of profitability in the sector. However, our data allow us to compare the refining margin measure to the uncertainty measures constructed based on the specific forward markets for crude oil and gasoline products. Individually these measures reflect input price uncertainty (σ_{CO}) and output price uncertainty (σ_{GO}), respectively. The gasoline and crude price uncertainty variables in year *t* are the standard deviations of daily close prices of gasoline and crude futures calculated from July of year *t-1* to June of year *t*. These measures are constructed in a comparable fashion to our second definition of the refining margin used in Panel B of Table II.2. Table II.4 presents the results of the hazard model estimated with the individual measures of input and output price uncertainty. The first column reproduces the results from refining margin hazard model in Table II.3 and second two columns present the results from using uncertainty measures based on the forward markets for gasoline and crude oil, respectively. The results are clear. The individual measures of price uncertainty in the gasoline and crude markets do not have a statistically significant effect on either the investment or disinvestment hazards. Only when combined as a refining margin variable, do they matter in the investment decision.

The last column of Table II.4 presents the results of a model where we replace the refining margin measure of uncertainty with a stock market index based measure of uncertainty. We construct an uncertainty measures (σ_{OI}) based on a stock market index that is designed to measure the financial performance of publicly traded oil companies. The oil index (symbol: XOI) is comprised of 13 major oil companies (including independent refiners) and is price weighted. σ_{OI} is the annual standard deviation of the daily return of this oil index. Again, the results are clear. Across both the investment and disinvestment hazards and across the alternative thresholds, there is no statistically significant effect of stock market uncertainty on the investment decision.

The last exercise we perform presents some alternative specifications for our empirical model. We present two accelerated failure time models that allow for nonmontonic hazards – the lognormal and log-logistic models. The Weibull model presented throughout the analysis allows for increasing or decreasing hazards, however, it assumes the function is monotonically increasing or decreasing in time. In contrast, the hazard functions of the lognormal and log-logistic models can both first increase then decrease in time. The log-logistic hazard model can be monotonically decreasing only if the shape parameter is equal to 1. Table II.5 presents the results of these alternative accelerated failure time specifications. The coefficients in these models are interpreted quite differently than the proportional hazard models. A positive coefficient in an accelerated failure time models means that time to failure is delayed while a negative coefficient means that time to failure in accelerated. The results across both accelerated failure models are quite similar and consistent with the Weibull model (presented in column (1) of the table). Looking at the investment hazard, an increase in the uncertainty of the refining margin delays the ending of a spell while an increase in the margin accelerates the ending of a spell. With regard to disinvestment hazard, the effects of the uncertainty and the margin remain statistically not significant in the accelerated failure time models.[16] The results are consistent across all three investment episodes. The estimated hazard shape parameters in the log-logistic models are clearly less than 1, rejecting the possibility of negative duration dependence. Both the lognormal and log-logistic models suggest positive duration dependence followed by negative duration dependence. At face value, this seems to contradict with the results from the Weibull model. However, given the highly significant frailty effect in the Weibull model, it is possible that an individual refinery's investment (disinvestment) hazard continues to rise over time, but the frailty effect causes the population hazard to fall after some time. Evidently, although the frailty effects in the lognormal and log-logistic models are statistically significant, they are much stronger in the Weibull model.

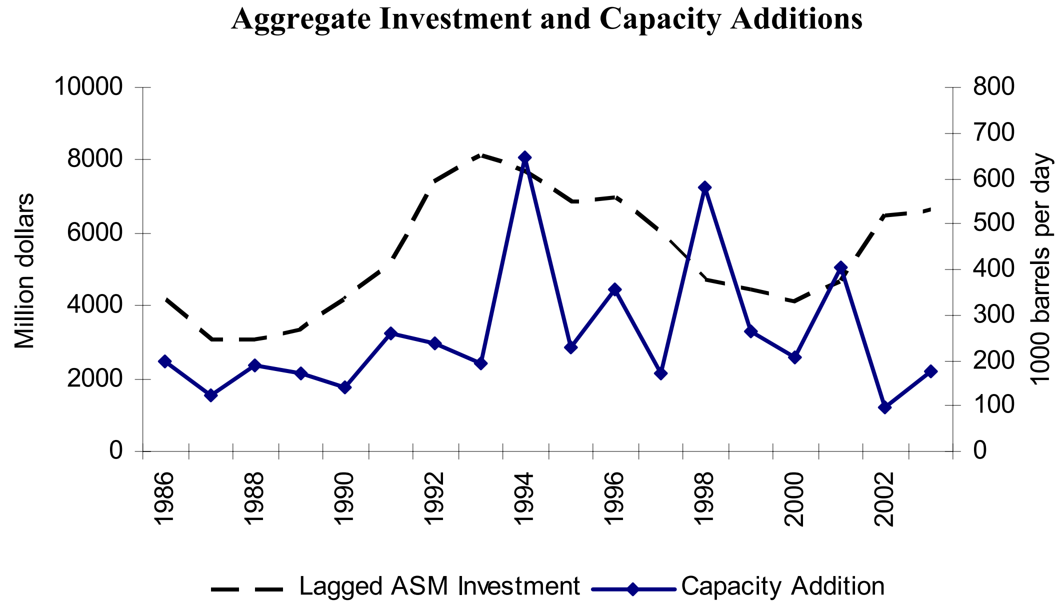
II.5 Conclusion

In this chapter, we have examined the role of uncertainty in the investment decisions of refineries in the United States. There are two main contributions of the essay. First, the essay 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.

[16] Although not reported, the coefficient of capacity utilization rate in the disinvestment hazard remains highly significant in the accelerated failure time models.

Refiners' decisions to make investments are clearly related to these measures of uncertainty. As uncertainty rises, refiners delay their investment decisions. This finding agrees with a number of papers that emphasize the option-value of waiting to invest. Second, we use data on changes in the actual capacity of refiners 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 type data. We also show that our results are very robust to investment threshold used in the analysis and model specifications. In addition, the data illustrate that investment episodes are quite lumpy in the refining industry and this type of pattern in the data in consistent with producers that face non-convex costs of adjustments. This last point, however, needs to be more fully developed as the focus of the essay has been on examining the relationship between uncertainty and investment and not on exploring the nature of adjustment costs in the industry.

Figure II.1

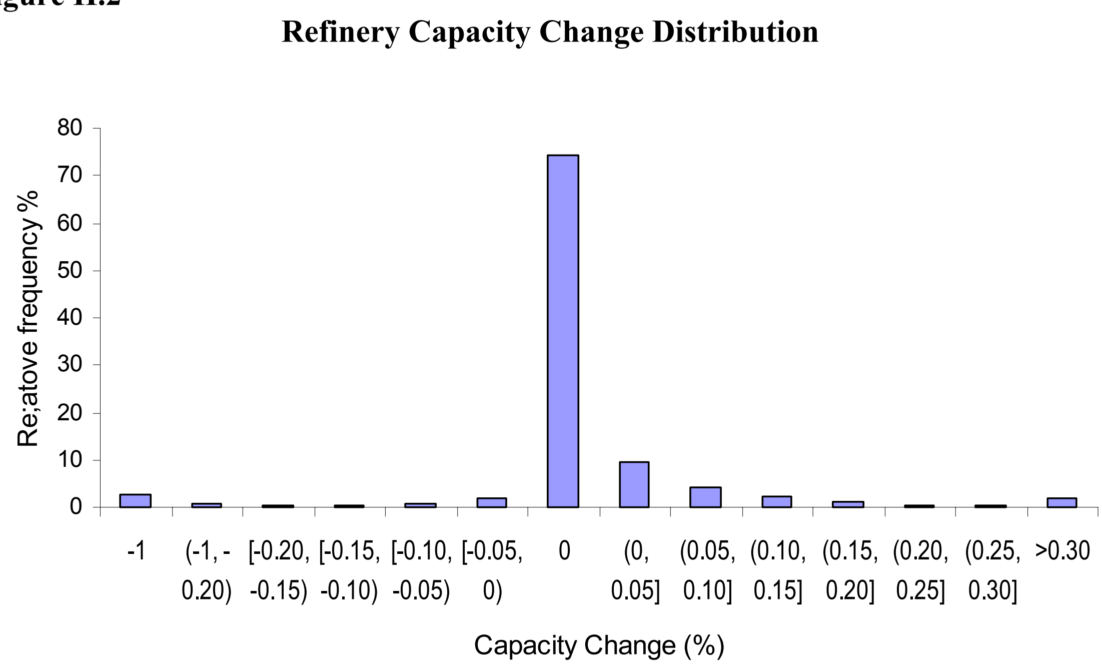


Data Source:

(1) Capacity addition is from Petroleum Supply Annual of EIA, various issues.

(2) ASM 1985-1996 investment is from NBER "Manufacturing Industry Productivity Database" collected by Bartelsman, Becker, Gray. 1997-2003 data is from the Annual Survey of Manufacturers, Census Bureau and is deflated the price index of private nonresidential structures investment in the Economic Report to the President.

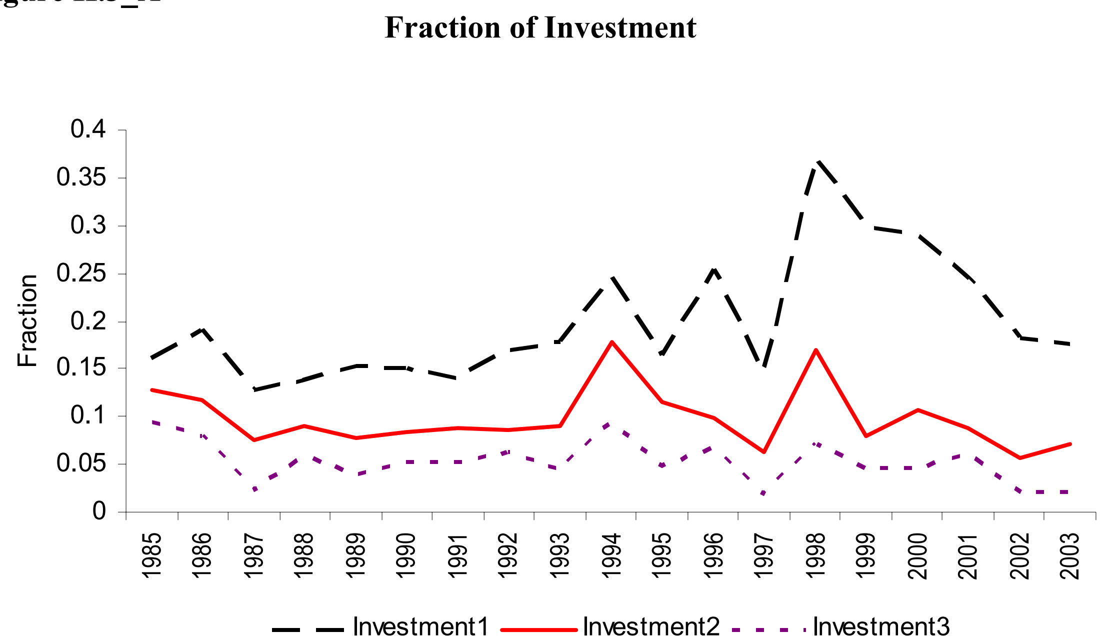
Figure II.2



Total number of observations: 3324.

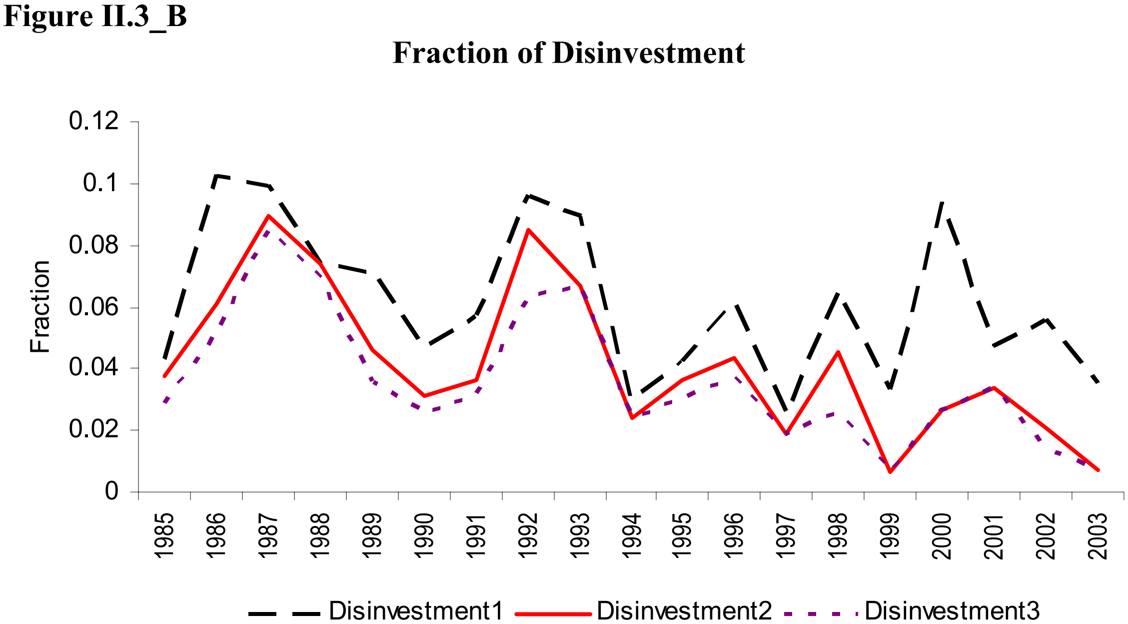
The far left bar (-1) represents complete shut-down refineries.

Figure II.3_A



Notes: Investment1 (Investment2, Investment3) is a capacity change greater than 0 (5%, 10%).

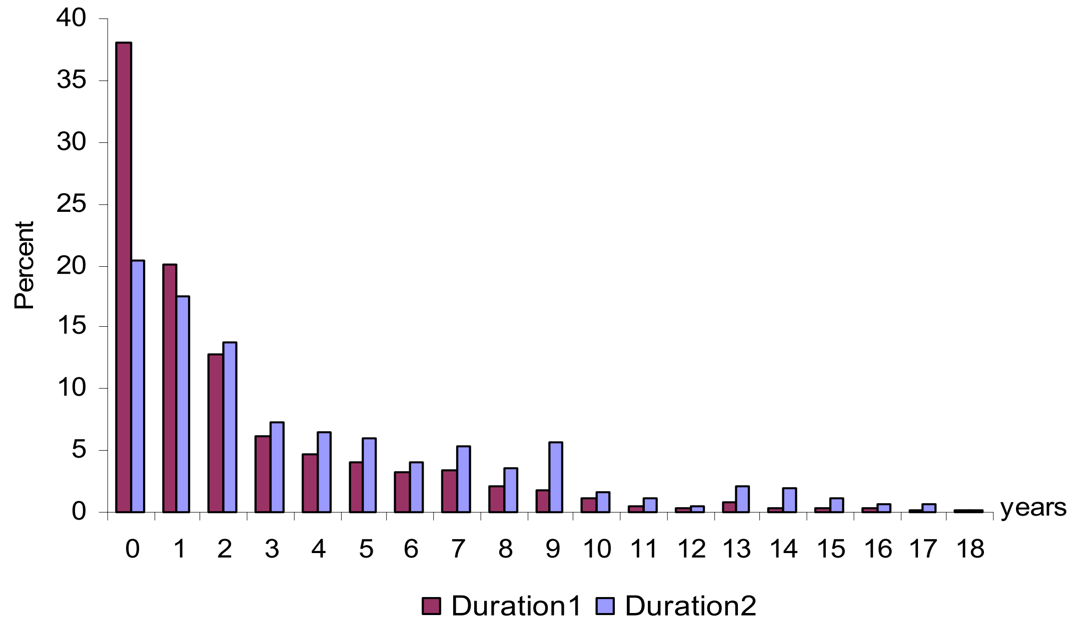
Figure II.3_B



Notes: Disinvestment1 (Disinvestment2, Disinvestment3) is a capacity change less than 0 (-5%, -10%).

Figure II.4

Distribution of Durations between Two Capacity Change Episodes



Notes
Duration 1: Years of duration between two capacity change episodes with zero threshold.
Duration2: Years of duration between two capacity change episodes with 5% threshold.

Figure II.5

Forward Refining Margin and Uncertainty Measure

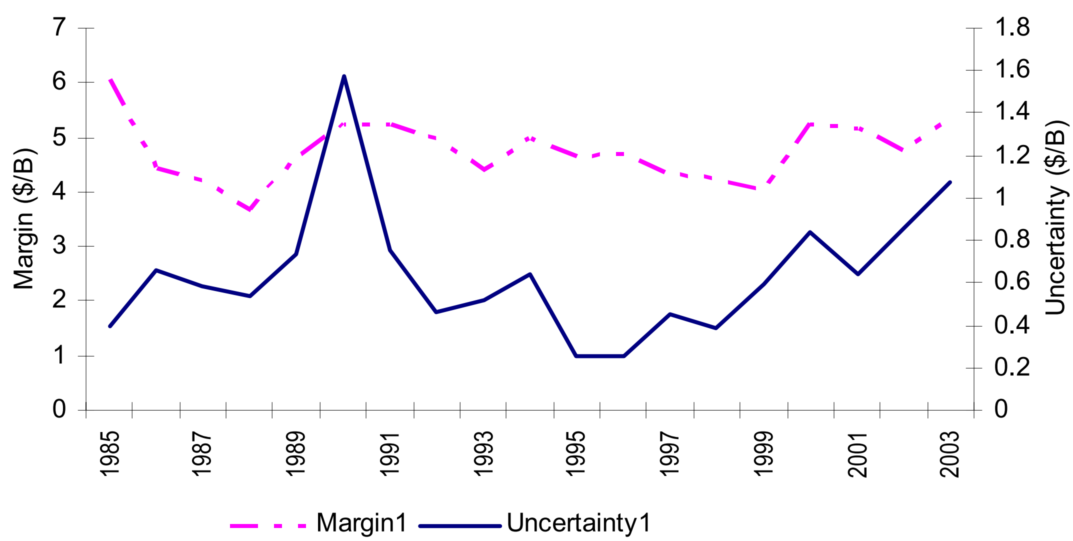


Table II.1

Summary Statistics

	Mean	Std. Deviation	Minimum	Maximum
Urate1 (%)	86.98	7.66	60.71	102.80
Margin1 ($/B)	4.75	0.57	3.66	6.03
Margin2 ($/B)	4.72	0.64	3.57	6.05
Margin3 ($/B)	4.72	0.58	3.48	5.96
$\sigma_{FRM}1$, ($/B)	0.64	0.30	0.25	1.57
$\sigma_{FRM}2$, ($/B)	0.59	0.24	0.22	1.24
$\sigma_{FRM}3$ ($/B)	0.62	0.24	0.21	1.15
σ_{GO} ($/Gallon)	0.063	0.049	0.017	0.213
σ_{CO} ($/B)	2.242	1.876	0.580	8.326
σ_{OI} (%)	1.15	0.39	0.62	2.14

Table II. 2 Estimation Result with 5% Threshold and Alternative Uncertainty Measures

	Investment	Disinvestment
	Panel A	
Margin1	0.187*	-0.192
	(0.104)	(0.148)
$\sigma_{FRM}1$	-0.543***	-0.707**
	(0.207)	(0.354)
Urate	-0.012	-0.069***
	(0.010)	(0.016)
Ownchg	-0.036	0.007
	(0.205)	(0.331)
Small	-0.406***	2.248***
	(0.157)	(0.299)
ρ (H_0: ρ=1)	1.187***	1.505***
	(0.060)	(0.116)
LR test (H_0: θ=0), χ^2	16.65***	12.03***
No of spells	546	288
Log likelihood	-694.48	-319.68
	Panel B	
Margin2	0.267***	0.025
	(0.102)	(0.143)
$\sigma_{FRM}2$	-0.822***	-0.679*
	(0.266)	(0.411)
Urate	-0.011	-0.067***
	(0.010)	(0.016)
Ownchg	-0.064	-0.030
	(0.205)	(0.331)
Small	-0.412***	2.312***
	(0.159)	(0.303)
ρ (H_0: ρ=1)	1.209**	1.521***
	(0.060)	(0.113)
LR test (H_0: θ=0): χ^2	18.23***	13.68***
No. of spells	546	288
Log likelihood	-692.91	-322.00
	Panel C	
Margin3	0.237**	0.085
	(0.106)	(0.149)
$\sigma_{FRM}3$	-0.631**	-0.467
	(0.251)	(0.384)
Urate	-0.013	-0.067***
	(0.010)	(0.016)
Ownchg	-0.051	-0.029
	(0.205)	(0.331)
Small	-0.401**	2.295***
	(0.158)	(0.303)
ρ (H_0: ρ=1)	1.192**	1.489***
	(0.060)	(0.114)
LR test (H_0: θ=0), χ^2	16.93***	12.78***
No. of spells	546	288
Log likelihood	-694.47	-322.19

Notes: (1) Regional dummies are included but not reported. (2) Standard errors are reported in parenthesis. (3) *** (**, *) denotes significance at the 1 (5, 10) percent level.

Table II.3 Estimation Result with Different Threshold Values of Investment

	Investment	Disinvestment
	Zero threshold	
Margin2	0.179**	0.043
	(0.077)	(0.125)
$\sigma_{FRM}2$	-0.699***	-0.300
	(0.193)	(0.329)
Urate	0.016**	-0.061***
	(0.007)	(0.013)
Ownchg	0.126	0.085
	(0.136)	(0.258)
Small	-0.957***	1.397***
	(-7.41)	(0.229)
ρ (H_0: ρ=1)	1.212***	1.528
	(0.041)	(0.096)
LR test (H_0: θ=0), χ^2	32.78***	14.65***
No. of spells	844	348
Log likelihood	-1095.75	-425.15
	5% threshold	
Margin2	0.267***	0.025
	(0.102)	(0.143)
$\sigma_{FRM}2$	-0.822***	-0.679*
	(0.266)	(0.411)
Urate	-0.011	-0.067***
	(0.010)	(0.016)
Ownchg	-0.064	-0.030
	(0.205)	(0.331)
Small	-0.412***	2.312***
	(0.159)	(0.303)
ρ (H_0: ρ=1)	1.209***	1.521***
	(0.060)	(0.113)
LR test (H_0: θ=0), χ^2	18.23***	13.68***
No. of spells	546	288
Log likelihood	-692.91	-322.00
	10% threshold	
Margin2	0.376***	-0.021
	(0.130)	(0.156)
$\sigma_{FRM}2$	-0.929***	-0.666
	(0.346)	(0.448)
Urate	-0.024*	-0.070***
	(0.013)	(0.017)
Ownchg	-0.021*	-0.250
	(0.266)	(0.386)
Small	0.015*	2.831***
	(0.216)	(0.354)
ρ (H_0: ρ=1)	1.177**	1.606***
	(0.074)	(0.128)
LR test (H_0: θ=0), χ^2	23.07***	13.80***
No. of spells	410	268
Log likelihood	-485.33	-273.97

Notes: (1) Regional dummies are included but not reported. (2) Standard errors are reported in parenthesis. (3) *** (**, *) denotes significance at the 1 (5, 10) percent level.

Table II.4 Estimation Results Using Gasoline, Crude, and Stock Price Volatilities

	Investment				Disinvestment			
	Margin ($\sigma_{FRM}2$)	Gasoline (σ_{GO})	Crude Oil (σ_{CO})	Stock Index (σ_{OI})	Margin ($\sigma_{FRM}2$)	Gasoline (σ_{GO})	Crude Oil (σ_{CO})	Stock Index (σ_{OI})
	Zero Threshold				**Zero Threshold**			
Margin2	0.179**	0.0289	0.019	0.068	0.043	-0.066	-0.062	0.012
	(0.077)	(0 .074)	(0.072)	(0.071)	(0.125)	(0.123)	(0.120)	(0.123)
Uncertainty	-0.699***	0.700	0.037	0.115	-0.300	1.991	0.057	0.086
	(0.193)	(1.046)	(0.026)	(0.110)	(0.329)	(1.566)	(0.038)	(0.194)
ρ (H_0: ρ=1)	1.212***	1.187***	1.188***	1.190***	1.525***	1.504***	1.506***	1.500***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.096)	(0.098)	(0.098)	(0.096)
Log Likelihood	-1095.75	-1102.11	-1101.33	-1100.79	-420.41	-424.75	-424.49	-425.46
	5% Threshold				**5% Threshold**			
Margin2	0.267***	0.131	0.120	0.089	0.025	-0.061	-0.071	-0.096
	(0.102)	(0.097)	(0.094)	(0.100)	(0.143)	(0.137)	(0.134)	(0.149)
Uncertainty	-0.822***	-0.400	0.003	-0.064	-0.679*	-0.957	-0.016	-0.044
	(0.266)	(1.318)	(0.033)	(0.072)	(0.411)	(1.847)	(0.046)	(0.237)
ρ (H_0: ρ=1)	1.209***	1.158***	1.157***	1.159***	1.530***	1.466***	1.466***	1.468***
	(0.06)	(0.060)	(0.06)	(0.06)	(0.113)	(0.113)	(0.113)	(0.114)
Log Likelihood	-691.82	-697.62	-697.66	-697.27	-312.41	-323.22	-323.30	-323.34
	10% Threshold				**10% Threshold**			
Margin2	0.376***	0.239	0.224	0.214*	-0.021	-0.113	-0.121	-0.129
	(0.130)	(0.123)	(0.122)	(0.127)	(0.156)	(0.150)	(0.147)	(0.163)
Uncertainty	-0.929***	-0.773	0.0002	-0.054	-0.666	-0.697	-0.012	0.006
	(0.346)	(1.602)	(0.039)	(0.216)	(0.448)	(2.023)	(0.050)	(0.255)
ρ (H_0: ρ=1)	1.177**	1.114	1.111	1.113	1.614***	1.553***	1.553***	1.553***
	(0.074)	(0.074)	(0.074)	(0.074)	(0.128)	(0.129)	(0.129)	(0.129)
Log Likelihood	-485.33	-488.78	-488.91	-488.88	-264.99	-275.01	-275.04	-275.07

Notes: (1) Standard errors are in parenthesis. (2) *** (**, *) denotes significance at the 1 (5, 10) percent level.

Table II.5 Empirical Result Using Alternative Models

	Investment			Disinvestment		
	Weibull	Log Normal	Log Logistic	Weibull	Log Normal	Log Logistic
	Zero Threshold			**Zero Threshold**		
Margin2	0.179** (0.077)	-0.203*** (.056)	-0.239*** (0.061)	0.043 (0.125)	-0.073 (0.099)	-0.052 (0.094)
$\sigma_{FRM}2$	-0.699*** (.193)	0.708*** (0.156)	0.795*** (0.167)	-0.300 (0.329)	0.224 (0.291)	0.253 (0.267)
Shape Parameters	1.212*** (0.041)	0.913*** (0.031)	0.549*** (0.020)	1.525*** (0.096)	1.077 (0.077)	0.583*** (0.048)
χ^2 (H_0: θ=0)	32.78***	18.88***	9.45***	14.65***	2.10*	4.31**
Log Likelihood	-1095.75	-1029.35	-1050.64	-425.15	-429.27	-429.95
	5% Threshold			**5% Threshold**		
Margin2	0.267*** (0.102)	-0.283*** (0.083)	-0.318*** (0.085)	0.025 (0.143)	0.040 (0.127)	0.021 (0.113)
$\sigma_{FRM}2$	-0.822*** (0.266)	0.793*** (0.240)	0.878*** (0.242)	-0.679* (0.411)	0.320 (0.376)	0.437 (0.325)
Shape Parameters	1.209*** (0.06)	1.121** (0.055)	0.658*** (0.037)	1.530*** (0.113)	1.208** (0.113)	0.601*** (0.063)
χ^2 (H_0: θ=0)	18.23***	7.27***	7.19***	13.68***	1.64	4.34**
Log Likelihood	-692.91	-675.19	-685.74	-322.00	-334.57	-330.42
	10% Threshold			**10% Threshold**		
Margin2	0.376*** (0.130)	-0.388*** (0.113)	-0.395*** (0.112)	-0.021 (0.156)	0.126 (0.135)	0.0762 (0.118)
$\sigma_{FRM}2$	-0.929*** (0.346)	0.897*** (0.334)	0.928*** (0.322)	-0.666 (0.448)	0.374 (0.393)	0.421 (0.334)
Shape Parameters	1.177** (0.074)	1.319*** (0.092)	0.739*** (0.058)	1.614*** (0.128)	1.167** (0.12)	0.565*** (0.064)
χ^2 (H_0: θ=0)	23.07***	13.15***	15.20***	13.80***	1.68*	4.50**
Log Likelihood	-485.33	-474.66	-481.03	-273.97	-288.29	-282.39

Notes: (1) Standard errors are in parenthesis. (2) *** (**, *) denotes significance at the 1 (5, 10) percent level. (3) The significance levels of ancillary parameters (ρ, δ, γ) are based on logarithm transformations.

CHAPTER III

WEATHER, STORAGE, AND NATURAL GAS PRICE DYNAMICS: FUNDAMENTALS AND VOLATILITY

III.1 Introduction

Why are asset prices volatile? There has been considerable discussion on whether market fundamentals drive asset price volatility. The efficient markets theory suggests that asset prices always incorporate the best information about fundamental values and the volatility is driven by news about these fundamentals. In contrast, the behavioral finance theory asserts that asset prices can change without fundamental reasons and the volatility is induced by anomalies such as "animal spirits" and mass psychology.[1]

This essay studies the short-term price dynamics of the natural gas futures market and examines how the prices and volatility are influenced by an important fundamental factor — weather, and to a lesser extent storage. Weather affects about fifty percent of the U.S. natural gas demand. This includes space heating in residential and commercial sectors, and those used by the electric power sector.[2] As shown in figure III.1, the industrial demand of natural gas does not vary much in the short-term and even if it does *de facto*, the information is not available to the market. Thus, weather is an extremely important factor that causes short-term natural gas demand variation and weather information reaches the market on a highly frequent basis (daily, even hourly). In a competitive commodity market where the demand is highly variable, storage is

[1] For a good survey of the literature about the evolvement from efficient markets theory to behavioral finance, see Shiller (2003). Some recent works in this area include Anderson et al. (2003), Boudoukh et al. (2003).
[2] According to data from the Energy Information Administration, Department of Energy, in 2001, the annual natural gas deliveries to residential, commercial, and electric power sectors are 4809 Bcf, 3037 Bcf, and 2686 Bcf respectively, accounting for 25%, 16%, and 14% of total natural gas consumption of that year.

crucial in balancing demand and supply conditions. The weekly natural gas storage report has been released since January 1994. Information about the weekly change of natural gas storage levels can shift the distribution of daily prices and for a given storage level, unexpected weather changes may cause price changes and create uncertainty about future supply conditions. Empirically, this implies that weather shocks may result in high conditional volatilities in both spot and futures markets.

Anecdotal evidence on the influence of weather on energy markets appears frequently in public media and industry publications such as Reuters' Financial news, Dow Jones Newswires. The following was reported in *USA Today* on Jan 14, 2005:

> "Prices for oil, **natural gas,** heating oil and other energy-related commodities all jumped Thursday as forecasts for colder weather in many parts of the USA this weekend led to predictions of greater energy demand…. Natural gas prices also soared Thursday, rising 50 cents, or 8.4%, to $6.445 for a million British thermal units."

The Existing academic literature generally focuses on the importance of weather changes to energy demand including the demand for natural gas (see Bower and Bower (1985), Elkhafif (1996), and Considine (2000)). Little effort has been devoted to quantifying the weather effect on short-term natural gas price dynamics. In particular, I could identify no studies examining how the volatility of natural gas prices is affected by weather. Although natural gas is one of the most heavily traded commodities in the U.S. futures market, academic studies on the determinants of price volatility in this market are rather limited. Pindyck (2004) has tested whether there is a significant trend in volatility and whether the demise of Enron increased volatility in natural gas and oil markets. He finds a statistically significant and positive time trend for natural gas. But the trend is too small to have any economic significance. The Enron event appears to have no significant impact on natural gas volatility. Murry and Zhu (2004) also study the impact of the EnronOnline (EOL) — Enron's online trading system — on the natural gas cash and futures market. They find no evidence that EOL reduced volatility in most of their price series data. Examining intraday volatility, Linn and Zhu (2004) show that natural gas price volatility is considerably greater around the time when the natural gas storage report is released. They attribute this phenomenon to the heterogeneity in the interpretation of key data describing the state of market. Rather than rely on commodity derivatives data, Ewing et al. (2002) examine the volatility transmission between two stock price indexes consisting of major companies in the oil and gas sectors. They find evidence of volatility persistence in both indexes and significant volatility transmission from the natural gas sector to the oil sector but not vice versa. Surprisingly, none of these studies have looked at the weather effect.

This chapter fills a gap in the literature by investigating the impact of weather shocks on daily natural gas price dynamics. The empirical results show that weather shocks have statistically significant and economically non-trivial effects on both the conditional mean and the conditional variance of natural gas futures returns. A one standard deviation increase in the weather shock variable would increase the average daily variance by 4-5%. Consistent with the literature, the conditional volatility is considerably higher on Monday and the day when the natural gas storage report is released. Both the "Monday effect" and the "storage announcement effect" can be driven by weather. In addition, the inclusion of the weather shock and storage surprise variables in the GARCH model reduces volatility persistence by approximately forty percent, which further corroborates the importance of the weather effect in volatility determination. Aside from these findings, I also provide support for Samuelson's (1965) hypothesis that commodity futures volatility declines with contract horizon.[3] To my knowledge, the "Samuelson effect" has never been documented in this market before.

This remainder of this chapter proceeds as follows. Section III.2 presents some stylized facts about natural gas demand, production, and storage. A brief discussion of natural gas futures market is also presented in this section. Section III.3 discusses the empirical strategy, defines the weather shock and storage surprise variables. Section III.4 reports the estimation results, and Section III.5 concludes.

III.2 Natural Gas Market

The Energy Information Administration (EIA) at the Department of Energy classifies natural gas consumption into four sectors: residential, commercial, industrial, and electric power.[4] Figure III.1 presents monthly natural gas production and consumption in the U.S. from January 1991 to December 2001. While the production and industrial use of natural gas are relatively stable over time, the total consumption is highly cyclical due to the obvious seasonality of demand in residential, commercial, and electric power sectors. The total consumption peaks in December and January arising from residential and commercial customers' space heating demand, troughs in summer when the space heating demand is low. In the summer, it has a "local peak" around July and August as cooling demand increases the electric power use of natural gas. Apparently, the heating and air-conditioning demand are driven by weather, and temperature in particular. Since industrial use of natural gas does not vary much in short

[3] The "Samuelson effect" has recently been elaborated and extended by Routledge et al. (2000).
[4] For a complete definition of these categories, see www.eia.doe.gov.

term (daily), weather variation provides a good instrument for the variability of natural gas demand.

In a competitive commodity market where the demand is highly seasonal such as the natural gas market, inventory plays a pivotal role in smoothing production and balancing demand-supply conditions. Total consumption of natural gas exceeds production in winter months but falls below it in summer months (Figure III.1). Consequently, as shown in Figure III.2, natural gas inventory displays a strong seasonal pattern: it builds up from April to October ("injection season"), while shrinks from November to March ("withdraw season"). The American Gas Association (AGA) conducted a weekly survey of inventory levels for working gas in storage facilities across the United States and released the weekly natural gas storage report from January 1994 to the end of April 2002, after which EIA has taken over this survey and prepared the report. The report tracks the overall natural gas inventory levels as well as the inventory levels in three regions — consuming east, consuming west, and producing region — as of 9:00 am each Friday. The report is released on Wednesday or Thursday of the subsequent week.[5]

Natural gas futures contracts began trading at the New York Mercantile Exchange (NYMEX) on Aril 3, 1990. The underlying asset of one contract is 10,000 million British thermal units (MMBtu) of natural gas delivered at Henry Hub, Louisiana. Trading terminates at the third-to-last business day of the month before the maturity month. The delivery period is over the course of the delivery month and "shall be made at as uniform as possible an hourly and daily rate of flow" (NYMEX website).

[5] The definition of each region can be found at http://tonto.eia.doe.gov/oog/info/ngs/notes.html. The storage report is now released on Thursday by EIA. When AGA was in charge, it was released on Wednesday.

The Henry Hub is the largest centralized natural gas trading hub in the United States. It interconnects nine interstate and four intrastate pipelines. Collectively, these pipelines provide access to markets throughout the U.S. East Coast, the Gulf Coast, the Midwest, and up to the Canadian border. Natural gas production from areas around the Henry Hub, including the Gulf of Mexico and the onshore Louisiana and Texas regions encircling the Gulf of Mexico, accounts for about 49 percent of total U.S. production in 2000 (Budzik, 2001).

The natural gas futures market is highly liquid with daily trading volumes of 30,000-50,000 contracts for the nearest month and 10,000-30,000 contracts for the second nearest month in recent years (Linn and Zhu, 2004). For example, on March 2, 2004 the trading volume of the April contract was 41,561 with a notional value of roughly $2.32 billion, while the trading volume of May contract was 18,300 with a notional value of about $1.04 billion.

III.3 Empirical Methodology and Data

A. An Initial Look at Daily Returns

In order to investigate the weather effect on natural gas price dynamics, I obtained daily trading data of natural gas futures from the Commodity Research Bureau (formerly Bridge). I use futures price rather than spot price data because the latter is generally not reliable. Spot prices are not *recorded* at a centralized exchange, but *reported* by such reporting agencies as Bloomberg, Platts, and Natural Gas Intelligence. Because the reporting agencies base their price estimates on informal polls of traders who have no obligation to report their real trading prices, and because each reporter has her/his own definition of "price",[6] it is not unusual to see discrepancies from different reporting agencies, and sometimes the difference can be large (EIA Report, 2002).

Returns are calculated as the daily change of the logarithm of the settlement prices of natural gas futures: $\ln(P_t/P_{t-1})$. Both to check the robustness of estimation and to test Samuelson's (1965) hypothesis that volatility declines with the time horizon of futures contracts, I compiled two return series (RET1 and RET2) from the nearest contract and the second nearest contract. As is typical of commodity futures markets, traders are often forced to cover their positions at the last trading day of a contract's life such that trading volume and open interest decline, while price volatility increases substantially. To avoid the "thin market" problem, I replaced the return of the nearest contract at the last trading day of each month with that of the second nearest contract in constructing the RET1 series. Figure III.3 plots the two return series.

The sample period is from January 2, 1997 to December 29, 2000. I start from January 2, 1997, because I estimate market expectations for the volume of weekly natural gas in storage in 1997 using data from December 31, 1993 through December 27, 1996. The end of sample period is limited by the availability of weather data. Table III.1 reports the autocorrelation coefficients for the two return series and the squared returns. While the returns do not display any significant serial correlation even at a large number of lags, the autocorrelation of squared returns are positive and significant, indicating the existence of time-varying volatility.

Table III.2 presents the mean returns and standard deviations of RET1 and RET2 over the entire time period as well as a breakdown by seasons and by weekdays. Several patterns in this table are noteworthy. First, in all cases, the standard deviations

[6] For example, spot price may include discounts and premiums.

are higher than the means, implying a rather high volatility in this market. Second, the standard deviation of RET1 is consistently higher than that of RET2; the difference between the two grand variances is significant at the 1% level using a one-sided F test. The "Samuelson (1965) effect" is evident. Third, while little can be said about the intraweek pattern of mean returns, the standard deviations on Monday are generally higher than other days. Roll (1984) found a similar pattern in the frozen orange juice market. Fourth, the standard deviations in winter are usually larger than other seasons, which is not surprising since natural gas demand peaks in winter and supply is tight.

B. Econometric Model

Theories of storable commodity prices (Deaton and Laroque (1992, 1996); Chambers and Bailey (1996), Routledge et al. (2000)) suggest that shocks to natural gas demand and supply conditions may result in mean price shifts or fluctuations around the mean in both spot and futures markets. While it seems obvious that the arrival of weather and inventory information will establish a new price equilibrium in the spot market, the rational for weather shocks to influence futures prices is more complicated. It stems from the nature of natural gas production and distribution. Limited by productive capacity, natural gas production is relatively price-inelastic in the short-term. While the productive capacity has generally tracked natural gas drilling activity, statistically there is a 1-3 months lag between the drilling activity and effective productive capacity due to well completions and wellhead infrastructure constructions (EIA report, 2003). Furthermore, when the pipeline utilization rate is high, the deliverability of pipeline network may be limited and natural gas in the producing region may not be transported to the consuming market. Therefore, a positive (negative) weather shock will lead to an unexpected decrease (increase) in natural gas inventory levels, which will in turn put upward (downward) pressure on futures price levels and increase the uncertainty about future supply conditions. To empirically assess how weather and inventory surprises affect the dynamics of natural gas futures returns, I estimate a generalized autoregressive conditional heteroskedastic (GARCH) model that allows exogenous variables to affect both the conditional mean and the conditional variance. The following exogenous variables are included:

Weather Shocks (W_t): this is a proxy for the demand shock. I defer a complete discussion of this variable to subsection III.C. It enters both the mean and the variance equation. In the mean equation, a positive (negative) demand shock is expected to increase (decrease) the returns.[7] In the variance equation, a quadratic form of this variable is used to capture the possible nonlinear effect of the demand shock on volatility — a greater demand shock might increase the volatility at an increasing rate. Alternatively, one can use the absolute value of the weather surprise ($|W_t|$) variable in the variance equation.[8]

Storage surprise ($STKERR_t$): the forecast error of the change of the amount of natural gas in storage. A detailed explanation about the construction of this variable is offered in subsection III.D. Storage affects both the mean and the variance. First, the commodity price is convex and inversely related to storage levels (Pindyck, 1994), so periodic information about the amount of natural gas in storage may shift the mean of returns to the extent that it surprises the market. The forecast error of the amount of

[7] I pre-tested whether W_t^2 should be included in the mean equation and find that it is not significant at conventional levels and the inclusion of this variable has little effect on the empirical results that follow.

[8] The empirical results using $|W_t|$ are qualitatively similar to those reported in section IV. However, the log likelihoods from the nonlinear specification are always larger than those from specifications with $|W_t|$.

natural gas in storage is expected to be negatively related to the conditional mean — the price will increase (decrease) when the actual amount of gas in storage falls below (exceeds) the market expectation. Second, just as the release of macroeconomic news will generate volatility in financial markets (Ederington and Lee, (1993); Anderson et al. (2003)), the release of the weekly natural gas storage report may increase volatiltiy in this market.

During the sample period, the AGA consistently compiled and released the natural gas storage report. It was announced after the close of NYMEX trading on Wednesday prior to March 2, 2000, after which it was released at the interval of 2:00-2:15 pm on Wednesday during NYMEX trading hours. Using intraday trading data from January 1, 1999 to May 3, 2002, Linn and Zhu (2004) find that the impact of storage announcement on volatility dissipates in 30 minutes. In other words, the price will be in a new equilibrium after 30 minutes of trading following the release of the storage report. Therefore, the storage surprise will shift the daily distribution of returns from week to week. I define the $STKERR_t$ as

$$STKERR_t = STKERR_\tau \text{ when } STKDAY_t = 1;$$
$$= 0 \text{ otherwise}$$

where $STKERR_\tau$ is the weekly forecasting error of the amount of gas in storage for week τ, and $STKDAY_t$ is a dummy variable equal to one on Thursday prior to March 2, 2000 and on Wednesday afterwards.[9] I include $STKDAY_t$ in the variance equation to test if there is a significant "storage announcement" effect on volatility.

[9] If Thursday is a holiday, then *STKERR* will influence the next trading day.

Crude oil is a close substitute of natural gas, and thus crude oil price fluctuations should have a direct impact on natural gas futures returns. *Crude oil return* ($CRET_t$), the continuously compounded return of first month crude oil (West Texas Intermediate) futures, is included in the mean equation. To account for possible volatility spillover from the crude oil market to the natural gas market, in the variance equation I include a *Crude oil return volatility* ($Voil_t$), which is the fitted conditional variance from an ARMA-GARCH model of *CRET*.[10] The crude oil price data are from the EIA website.

Other control variables in the mean equation include $TBILL_t$ and $SPRET_t$. $TBILL_t$ is the annual yield on 3-month Treasury bills on date *t* and represents the short-term risk-free interest rate. T-bill rates may affect natural gas returns because the interest rate is a significant component of the cost of carrying inventories (Pindyck, 2004a). $SPRET_t$ is the daily return on the S&P500 index and is a proxy for equity market return. Using monthly time-series data, Sadorsky (2002) finds that the T-Bill rate is a positive and significant predictor for gasoline futures returns and the excess equity market return is negative and statistically significant in predicting heating oil and gasoline futures returns.[11] Pindyck (2004a) finds that the T-bill rate is positive and significant in crude oil returns but not in natural gas returns. Gorton and Rouwenhorst (2004) show that commodity futures returns are negatively correlated with equity and bond returns and the negative correlation is stronger over a longer holding period. The data for the T-bill rates are obtained from the Federal Reserve Economic Data (FRED), and the returns on the S&P500 index are from the University of Chicago Center for Research in Security

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[10] Based on the SIC and diagnostic checks, AR(2)-GARCH(1,1) model fits the *CRET* data well. The details of the model are reported in the appendix.
[11] Sadorsky (2002) uses equally weighted return to CRSP value-weighted common stock price index and the Dow Jones Commodity Index in excess of the T-bill rate as market portfolio excess return.

Prices (CRSP) database. Finally, to test if the Monday and Winter effects hold for the conditional volatility, I include dummy variables for Monday (*MON*) and Winter (*WIN*) in the variance equation.

Since the exploratory data analysis suggests that there is no significant autocorrelation and seasonality in the mean returns but strong autocorrelation in the squared returns, I estimate the following model[12]

$$RET_t = a_0 + a_1 W_t + a_2 STKERR_t + a_3 CRET_t + a_4 TBILL_t + a_5 SPRET_t + \varepsilon_t \qquad (1)$$

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha + \sum_{i=1}^{p} \beta_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \gamma_j h_{t-j} + \phi_1 MON_t + \phi_2 WIN_t + \phi_3 STKDAY + \phi_4 Voil_t + \phi_5 W_t + \phi_6 W_t^2 \cdot \qquad (2)$$

where Ω_{t-1} is the information set available at time t-1 and h_t is the conditional variance of the ε_t.

C. Measuring Weather Shocks

Weather affects the natural gas industry on both the demand and supply side. Temperature is the main driver of heating and cooling demand. Hazardous weather conditions (e.g. a hurricane that hits Gulf Coast) may cause shut-downs of natural gas wells. Such severe weather situations may be good candidates for event-studies. In this study, I will concentrate on temperature shocks and examine their effect on volatility.

Weather shocks can be measured as the weather forecast error. In an influential paper, Roll (1984) examined the relationship between the returns of orange juice futures and the forecast error of temperatures in Florida and found a statistically significant relationship with a surprisingly low R^2. His findings are often cited as evidence of

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[12] In fitting the data, I find that the T-GARCH and GARCH-in-mean effects are not statistically significant at conventional significance levels.

excess volatility or noise trading.[13] Alternatively, weather shocks can be measured as "weather anomalies" i.e. the deviation of temperature on a given day from its normal level.[14] Because we were unable to obtain the historical weather forecast data from the National Weather Service (NWS), this chapter adopts the second approach. The temperature is expressed in degree days (DD), which is the sum of heating degree days (HDD) and cooling degree days (CDD).[15]

$$DD_t = CDD_t + HDD_t \tag{3}$$

$$CDD_t = Max\ (0,\ Tave_t - 65°F) \tag{3.a}$$

$$HDD_t = Max\ (0,\ 65°F - Tave_t) \tag{3.b}$$

where $Tave_t$ is the average of daily maximum temperature ($Tmax_t$) and daily minimum temperature ($Tmin_t$) on date *t*. For example, on a hot summer day when the Tave is 90°F, the CDD is 25 and the HDD is zero, hence the DD is 25. On a cold winter day when Tave is 40°F, the CDD is zero and HDD is 25, hence the DD is also 25. HDD measures heating demand while CDD measures cooling demand. Thus DD measures both the heating demand in the winter and the cooling demand in the summer. HDDs and CDDs are widely used in the energy industry and traded at the Chicago Mercantile Exchange (CME) as weather derivatives. The weather shock variable in equation (1) and (2) is then defined as

$$W_t = \frac{1}{m}\sum_{i=1}^{m}(DD_{t+i} - DDNORM_{t+i}) \tag{4}$$

where *m* is the weather forecast horizon. DD_{t+i} is the forecasted degree days on day $t+i$, $DDNORM_{t+i}$ is the normal degree days which is the average degree days of previous 30

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[13] See DeLong *et al*. (1990, p. 725) ; Hirshleifer (2001, p. 1560); and Daniel et al. (2002, p.172).
[14] Following the convention of National Weather Service, the normal temperature of day *t* is defined as the previous 30 years' average on day *t*.
[15] In section III.C, *t* denotes calendar day whereas in section III.B, it denotes trading day.

years on day $t+i$. I use realized temperature data for DD_{t+i} instead of weather forecast data in equation (4) and set $m=7$, because typically the 7-day forecast is the longest detailed weather forecast available from the public media. The empirical results that follow are not sensitive to the choice of m. Admittedly, the weather shock variable is a crude measure, but I believe it roughly captures the variation of the "true" shock. The more the temperature deviates from normal, the greater is the shock.

The temperature data are taken from the Lamb-Richman data set that is compiled by two meteorologists Peter Lamb and Mike Richman at the University of Oklahoma. The original data source is the National Climatic Data Center (NCDC), a division of the National Oceanographic and Atmospheric Administration (NOAA), Department of Commerce. Based on the analysis of weather station histories, the Lamb-Richman data set corrects erroneous measurements and discontinuities in the original data due to failures of recording equipment or changes of measurement equipment and station location. The data set consists of daily Tmin, Tmax measured from midnight to midnight (local time) in 766 weather reporting stations east of the Rocky Mountains from 1949 to 2000. A closer look at the data reveals that temperatures are highly correlated within a state, even within a Census region. For example, the correlation coefficients of daily Tmin series among the 38 weather reporting stations in the Great Lakes region range from 0.88 to 0.98. In the estimation that follows, I only use the data from weather reporting stations that are close to a large city in a natural gas consuming region.

The Lamb-Richman data set does not contain weather stations west of Rocky Mountains. While the Henry Hub is the main delivery point to the consuming east region, in an integrated market (Wall, 1994), weather in the west of the country may impact the Henry Hub price, particularly the futures price. Therefore, the use of east-of-Rocky-Mountains weather data may underestimate the weather impact, and hence provide a lower bound for the estimated effect on natural gas prices.

D. Modeling Storage Surprise

To form a measure of market expectations about the change of the volume of natural gas inventories, I estimate a time-series model augmented with a natural gas consumption weighted temperature variable (*TEMP*). The construction of the *TEMP* variable is given in the appendix. As shown in Figure III.2, the weekly natural gas inventory series displays a clear seasonal variation. Following Campbell and Diebold's (2002) method in modeling daily temperatures, I employ a Fourier series instead of weekly dummies to model the seasonality. The use of the Fourier series greatly reduces the number of parameters to be estimated and enhances numerical stability.

One might suspect that non-seasonal, non-temperature related factors may operate in the weekly storage series. For example, reporting errors in the natural gas storage survey may produce serial correlation. Therefore an autoregressive lag structure is used in the error term. Putting the various pieces together, I use the following model to obtain a forecast series:

$$E(\Delta I_{\tau}) = b_0 + b_1 TEMP_{\tau} + b_2 TEMP_{\tau}^2 + \sum_{k=1}^{K}[\lambda_k \sin(2\pi \frac{w(\tau)}{52}) + \theta_k \cos(2\pi \frac{w(\tau)}{52})] + \mu_{\tau} \quad (5)$$

[16]

[16] I compared the out-of-sample forecast performance of model (5) with a seasonal ARIMA model augmented by weekly temperature variables. Both the mean absolute error (MAE) and the root mean squared error (RMSE) from the Fourier series of model (5) are slightly smaller.

$$\mu_t = \sum_{l=1}^{L} (\rho_l \mu_{\tau-l}) + \eta_\tau \quad \text{where } \eta_t \sim \text{N}(0, 1) \tag{5.a}$$

where $E(\Delta I_\tau)$ is the market expected inventory change from the Friday of week τ*-1* to the Friday of week τ *;* $TEMP_\tau$ is the natural gas consumption weighted weekly (Friday to Friday) average temperature in week τ *;* $w(\tau)$ in the Fourier series is a repeating step function that cycles through 1,…,52 (i.e. each week of the year takes one value between 1 and 52). On the basis of Schwartz Information Criterion (SIC), I set the number of lags in the Fourier series $K=2$ and in the autoregressive series $L=1$. The resulting residuals η_t appear to be serially uncorrelated and the model fits the data well.

Based on model (5), each week's forecast $E(\Delta I_\tau)$ was made using all available storage data from January 1994 up through the prior week. The natural gas inventory data are downloaded from the EIA website. The storage surprise is then defined as the difference between the announced storage change and the expected storage change:

$$STKERR_\tau = \Delta I_\tau - E(\Delta I_\tau) \tag{6}$$

The weekly series $STKERR_\tau$ obtained from (6) is expanded to daily using the method outlined in subsection III.B and aligned to the return series in equation (1) for empirical estimation.

III.4 Estimation Results

The model outlined in the subsection of III.B was estimated using the method of maximum likelihood. The number of lags in equation (2) is determined to minimize the SIC and to ensure no serial correlation in both residuals and squared residuals. It turns out a parsimonious GARCH (1, 1) model fits the data well. For the weather shock variable (W_t and W_t^2), I start with Chicago's weather data as the Great Lakes region is the largest natural gas consuming area that is tied to the Henry Hub and often stressed by cold weather.[17] In the summer when the cooling demand is the main concern, the temperature deviation in Chicago probably does not provide a good measure for the real shock to the market, so I re-estimate the model with the average of the weather shock variables in Chicago and Atlanta.[18] Figure III.4 plots the weather shock variable over the time period.

The estimation results using the average of weather shocks in Chicago and Atlanta are reported in Table III.4, and those based on Chicago's weather data are reported in Table A.2. Both sets of results are very similar, but the models in Table III.4 yield slightly larger log likelihood values. In what follows, I base the discussion on Table III.4. In the mean equation, the estimated coefficient of the weather shock variable (W_t) is positive and significant at the 1% level. Price will increase (decrease) when the expected demand is high (low), that is, when the forecasted degree days are above (below) normal. The estimated coefficient of the storage surprise variable ($STKERR_t$) is negative and usually significant at the 5% or 10% level. When the announced storage level is above (below) the market expectation, price tends to decrease (increase). Consistent with the theory of the price of a substitute, the estimated coefficient of the crude oil return ($CRET_t$) variable is positive and significant at the 1% level. A one percentage point increase in crude oil return leads to 0.21-0.24 percentage

[17] Using natural gas spot price data in 1997, Bopp (2000, p.261) notes that the Henry Hub price is more closely related to Chicago's temperature than any other cities including New York, Boston, St. Louis, and Atlanta.

[18] I experimented the weather shock variable using a broader average of Chicago, New York, Atlanta, and Dallas. The results are similar with those reported in Table III.4. The EIA monitored the temperature of these cities in its weekly natural gas update in the summer.

point increase in natural gas return. The estimated coefficient of the T-bill (*TBILL*) rate and the market equity return (*SPRET*) variables are mostly insignificant, although the sign pattern is consistent with the literature (Sadorsky (2002), Gorton and Rouwenhorst (2004)).

In the variance equation, consistent with the literature (Murry and Zhu, 2004), the conditional volatility is higher on Monday and the day when the natural gas storage report is released. The Monday effect may reflect the weather influence as well. In Ederington and Lee (1993), the volatility of interest rate and foreign exchange futures on Monday is about the same as other weekdays when there is no macroeconomic news announcement. Fleming *et al*. (2004) find the differences between the variance ratios for weather-sensitive markets (natural gas is one of them) and those for equity market are more pronounced over the weekend than weekdays. They posit that this phenomenon is because the flow of weather information does not stop over the weekend whereas information flows for equity market are more concentrated during weekdays. The significantly positive $STKDAY_t$ coefficient indicates that the release of the weekly natural gas storage report generates considerable volatility and confirms the findings of Murry and Zhu (2004) and Linn and Zhu (2004). As for the volatility spillover effect, the result indicates the volatility in the natural gas market is not significantly affected by the crude oil market. There is also no evidence that the conditional volatility is higher in the winter than in other seasons.

The estimated coefficients of the weather shock variables (W_t *and* W_t^2) in the variance equation are statistically significant at the 1% level and economically non-trivial. In column (5) of Table III.4, I report a specification when insignificant variables are excluded. The estimated coefficients for W_t and W_t^2 are 0.046 and 0.008 in RET1 and 0.044 and 0.008 in RET2 respectively. A one standard deviation increase in W_t (5.39°F) would increase the variance of daily returns by 0.000048 and 0.000046, which is about 4-5% of the average daily variances of 0.0011 and 0.0009.[19] This result, together with the significant storage announcement effect and Monday effect, which is also potentially driven by weather, underpins the importance of fundamental factors in determining volatility. A log likelihood ratio test easily rejects the null hypothesis that the coefficients of *Monday, STKDAY*, and W_t *and* W_t^2 are jointly equal to zero at the 1% level across all model specifications.

The recent literature on volatility persistence suggests that the persistence in the conditional variance may be generated by an exogenous driving variable that is itself serially correlated. Hence the inclusion of such an exogenous variable in the conditional variance equation would reduce the observed volatility persistence (see Lamoureux and Lastrapes, 1990; Kalev et al., 2004). This implies the inclusion of the exogenous variables in equation (2) could reduce the observed volatility persistence. In a GARCH (1, 1) model, the sum ($\beta_1 + \gamma_1$) measures the degree of volatility persistence (Enders, 2004, p. 134). The half-life of a volatility shock measures the time it takes for a shock to fall to half of its initial value and is determined by (Pindyck, 2004a):

$$\text{Half-life time} = \log(.5) / \log(\beta_1 + \gamma_1) \qquad (7)$$

The estimated half-lives are reported in the last rows of Table III.5. When the exogenous variables are not included in the variance equation, the half-life is about 21 trading days for RET1, and 15 trading days for RET2. When the exogenous variables

[19] The returns are expressed in percent, so the unit of variance is 1/10000.

are included, the half-life time reduces to 13 trading days for RET1 and 8 trading days for RET2. This result further corroborates the importance of fundamental factors in volatility determination.

To shed light on whether the "Samuelson effect" holds for conditional volatility, I obtained the estimated conditional variances from RET1 and RET2 and denote them as h_{1t} and h_{2t} respectively (Figure III.5). The fitted values of h_{1t} are greater than those of h_{2t} in 961 of 998 cases, which is direct evidence of Samuelson's (1965) hypothesis that the closer-to-maturity contract is more volatile than those farther to maturity. Moreover, the estimated coefficients of the variance equation from RET1 always exceed those from RET2 regardless of which weather data are used. These results imply that a shock has a stronger impact on the nearest contract than it does on the second nearest contract.

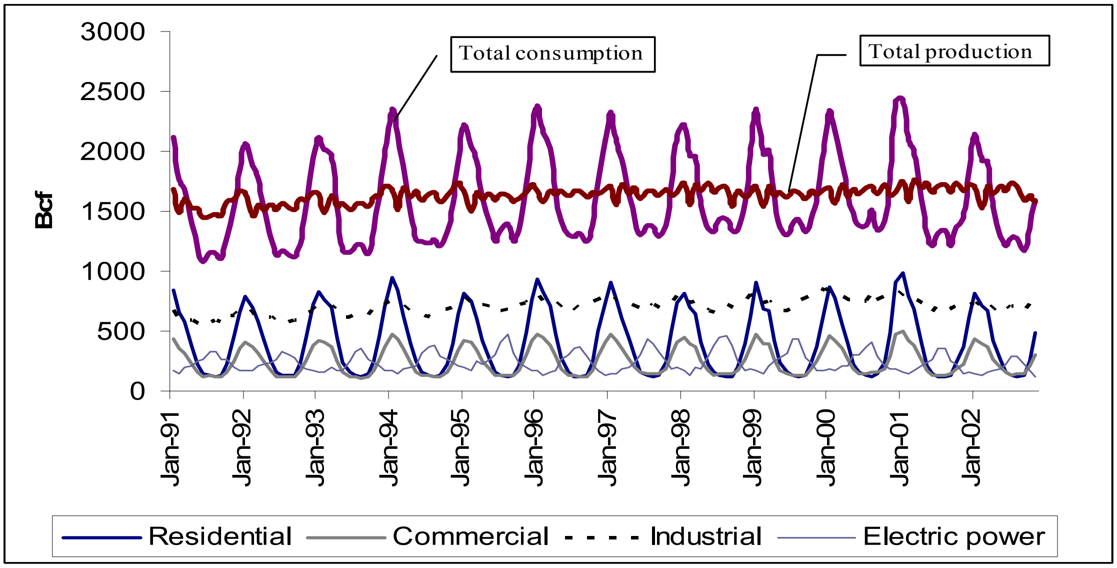
III.5 Summary and Conclusion

This chapter examines how weather shocks affect asset price dynamics in the U.S. natural gas futures market. The findings can be summarized as follows. First, the weather shock variable has a statistically significant and economically non-trivial effect on both the conditional mean and conditional volatility of natural gas futures returns. Second, consistent with the literature, the volatility is considerably higher on Monday and the day when the natural gas storage report is released. Both the "Monday effect" and the "storage announcement effect" can be driven by weather. Third, the inclusion of weather shock and storage surprise variables in the GARCH model reduces volatility persistence by about forty percent. This result, on the one hand, further corroborates the importance of these fundamental factors in determining volatility, on the other hand indicates that a large portion of volatility can not be explained by the fundamentals.

The findings of this chapter contribute to our understanding of what causes price volatilities in the natural gas market. Volatility is a key element of many financial decisions. For instance, the valuation of commodity-based options and risk-hedging decisions rely on assumptions about volatilities. Volatility can alter producers' perception about the opportunity cost of production and has a "feedback" to the supply-and-demand balance in the longer-term (Pindyck, 2004a). Thus, this study should be of interest to both academics and industry practitioners.

Figure III.1

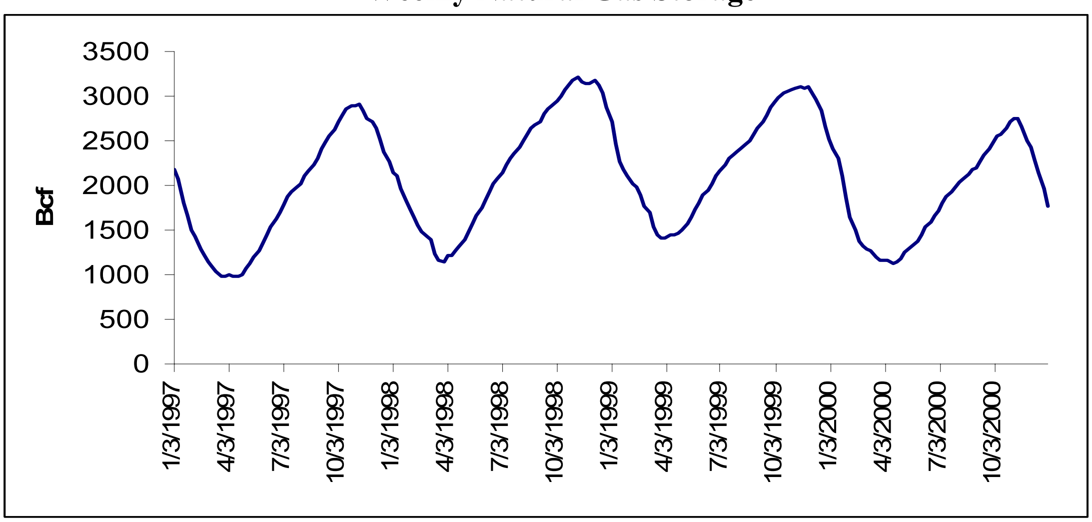
Monthly Natural Gas Production and Consumption



Data resource: www.eia.doe.gov

Figure III.2

Weekly Natural Gas Storage



Data resource: www.eia.doe.gov

Figure III.3_A

Daily Natural Gas Futures Returns (RET1)

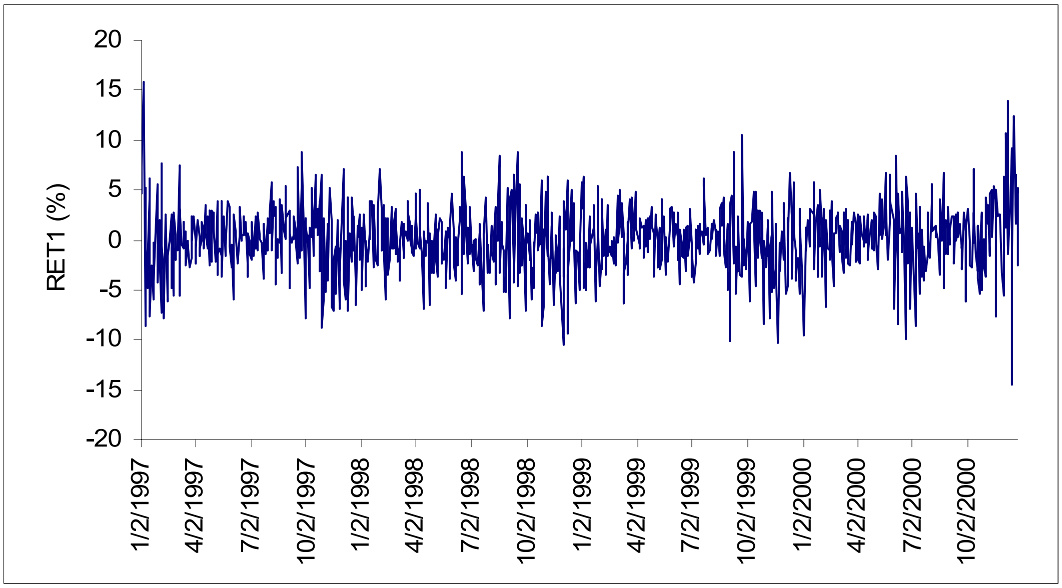


Figure III.3_B

Daily Natural Gas Futures Returns (RET2)

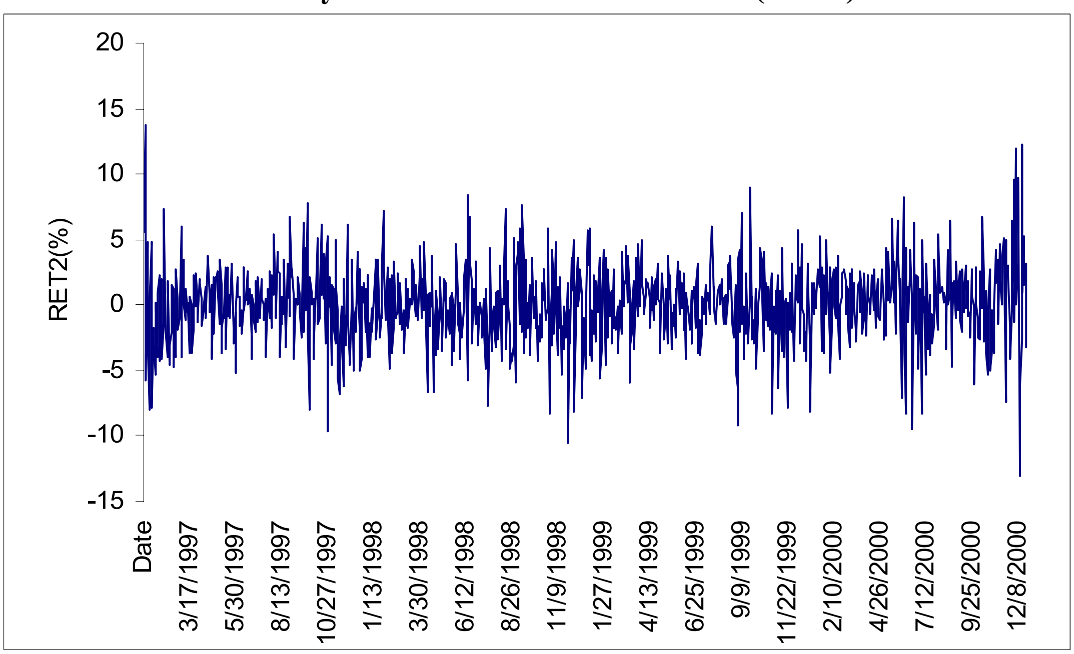
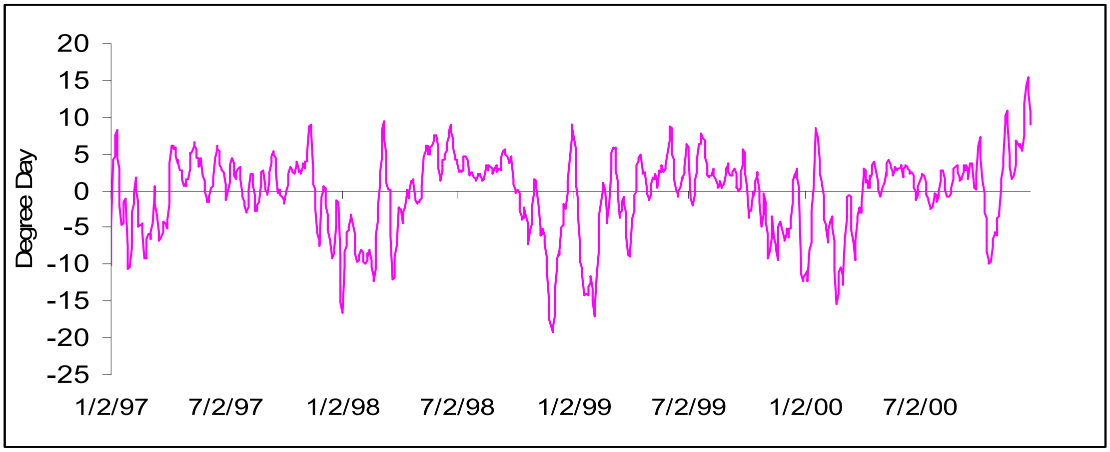


Figure III.4

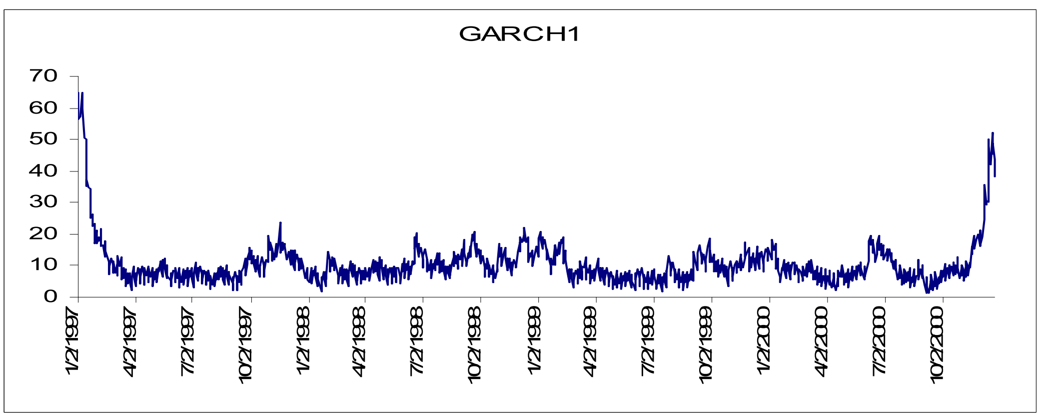
Weather Shock variable



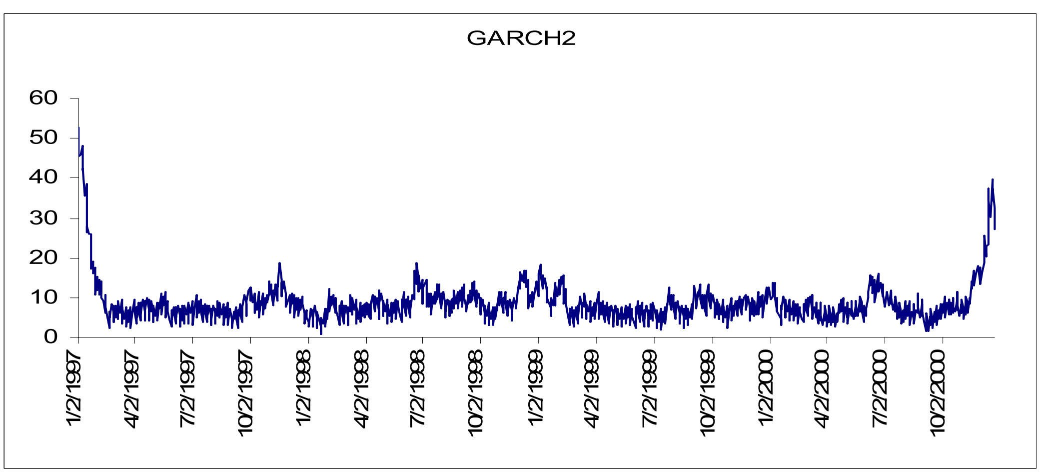
(This plot is based on the weather shock variable defined in Section III.C and the temperature data in Chicago and Atlanta)

Figure III.5

Fitted Conditional Variance of Natural Gas Returns



(This plot is based on Column (5) of Table III.5_A. The unit of Y-axis is 1/10000.)



(This plot is based on Column (5) of Table III.5_B. The unit of Y-axis is 1/10000.)

Table III.1

Autocorrelations of Natural Gas Futures Returns

Lag	RET1	$(RET1)^2$	RET2	$(RET2)^2$
1	-.012	.119***	-.000	.092***
2	-.013	.151***	-.028	.153***
3	.012	.122***	.012	.127***
4	.052	.173***	.047	.202***
5	-.013	.083***	-.001	.075***
6	-.017	.094***	-.021	.071***
7	.050	.186***	.057	.129***
8	.009	.075***	-.002	.077***
9	-.033	.084***	-.028	.075***
10	.018	.115***	.005	.082***
Q(12)	11.68	166.75***	10.52	140.08***

Note: The sample size is 1002.

Q(12) is the Ljung-Box statistic for the twelfth order autocorrelation, which is distributed χ^2 with 21 degrees of freedom. The 5% critical value is 21.

*** (**, *) denote significant at the 1% (5%, 10%) level.

Table III.2

Natural Gas Futures Daily Returns by Day of Week and By Season (1/2/1997-12/29/2000)

	Mean Returns			
	Winter	Summer	Shoulder	All Seasons
A. RET1 (N=1002)				
Monday	-0.43	0.23	-0.03	-0.12
	(4.72)	(3.45)	(3.26)	(3.96)
Tuesday	0.02	-0.51	0.16	-0.06
	(3.72)	(2.52)	(2.94)	(3.20)
Wednesday	-0.01	-0.25	-0.08	-0.09
	(3.30)	(3.33)	(2.95)	(3.18)
Thursday	0.01	0.08	0.22	0.10
	(3.47)	(2.77)	(3.88)	(3.44)
Friday	0.13	0.79	0.53	0.44
	(3.42)	(2.02)	(2.24)	(2.72)
All Days	-0.05	0.07	0.17	0.05
	(3.74)	(2.88)	(3.09)	(3.31)
B. RET2 (N=1002)				
Monday	-0.21	0.22	0.15	0.02
	(4.07)	(3.27)	(2.90)	(3.51)
Tuesday	0.12	-0.51	0.14	-0.03
	(3.28)	(2.51)	(2.76)	(2.93)
Wednesday	0.07	-0.23	-0.06	-0.05
	(2.83)	(3.16)	(2.68)	(2.86)
Thursday	-0.02	0.03	0.11	0.04
	(3.17)	(2.76)	(3.49)	(3.17)
Friday	0.14	0.86	0.44	0.43
	(3.26)	(2.06)	(1.96)	(2.58)
All Days	0.02	0.07	0.15	0.08
	(3.32)	(2.80)	(2.79)	(3.02)

Notes: 1). The returns are shown in percentage; standard deviations are shown in parentheses.
2). Winter is defined as November, December, January, February, and March. Summer includes June, July, and August. Shoulder months include April, May, September, and October.

Table III.3

Summary Statistics

	Mean	Std. Dev.	Skewness	Kurtosis
RET1 (percent)	0.0506	3.319	-0.028	4.47
RET2 (percent)	0.0787	3.019	-0.014	4.46
CRET (percent)	0.0010	2.481	-0.053	6.22
TBILL (annual yield)	5.07	0.53	0.34	2.69
SPRET(percent)	0.0628	1.246	-0.21	5.82
W (°F)	-0.44	5.39	-0.66	3.41

W: the weather surprise computed using Chicago and Atlanta data.

Table III.4_A

Estimation Result for RET1
(Using Chicago and Atlanta weather)

	(1)	(2)	(3)	(4)	(5)
Mean					
W	0.053***	0.055***	0.055***	0.052***	0.053***
	(0.017)	(0.015)	(0.015)	(0.017)	(0.017)
STKERR	-0.021**	-.020*	-0.021*	-0.019*	-0.020**
	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
CRET	0.22***	0.236***	0.234***	0.242***	0.241***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.038)
TBILL	0.240	0.201	0.201	0.234	
	(0.161)	(0.164)	(0.166)	(0.164)	
SPRET	-0.037	-0.022	-0.020	-0.034	
	(0.066)	(0.068)	(0.068)	(0.068)	
Constant	-1.124	-0.946	-0.948	-1.122	0.063
	(0.827)	(0.844)	(0.849)	(0.845)	(0.086)
Variance					
ARCH(1)	0.088***	0.084***	0.084***	0.077***	0.078***
	(0.018)	(0.019)	(0.018)	(0.017)	(0.017)
GARCH(1)	0.880***	0.868***	0.869***	0.870***	0.867***
	(0.026)	(0.030)	(0.030)	(0.029)	(0.029)
MON		4.73***	4.795***	5.930***	6.046***
		(0.964)	(1.052)	(1.114)	(1.082)
STKDAY		5.847***	5.769***	7.021***	6.860***
		(1.062)	(1.050)	(1.216)	(1.170)
WIN			-0.011	-0.119	
			(0.104)	(0.191)	
Voil			0.021	0.002	
			(0.028)	(0.028)	
W				0.041**	0.046***
				(0.020)	(0.017)
W^2				0.009***	0.008***
				(0.003)	(0.003)
Constant	0.333**	-1.632	-1.760***	-2.250***	-2.221***
	(0.132)	(0.324)	(0.376)	(0.407)	(0.380)
Log likelihood	-2528	-2511	-2511	-2504	-2505
Half-life time (days)	21.31	14.10	14.29	12.73	12.25

Notes:

(1) The adjusted R^2 ranges from 0.042 to 0.045. (2) Standard errors are reported in parentheses. (3) *** (**, *) denote significance at the 1% (5%, 10%) level.

Table III.4_B

Estimation Result for RET2
(Using Chicago and Atlanta weather)

	(1)	(2)	(3)	(4)	(5)
Mean					
W	0.043***	0.044***	0.045***	0.042***	0.043***
	(0.016)	(0.014)	(0.014)	(0.016)	(0.016)
STKERR	-0.020**	-0.019**	-0.019**	-0.017*	-0.018*
	(0.008)	(0.010)	(0.009)	(0.009)	(0.010)
CRET	0.213***	0.224***	0.222***	0.229***	0.228***
	(0.034)	(0.035)	(0.035)	(0.035)	(0.036)
TBILL	0.248	0.227	0.228	0.269*	
	(0.152)	(0.155)	(0.157)	(0.156)	
SPRET	-0.074	-0.066	-0.067	-0.077	
	(0.062)	(0.063)	(0.063)	(0.063)	
Constant	-1.165	-1.088	-1.094	-1.31	0.055
	(0.783)	(0.798)	(0.805)	(0.805)	(0.082)
Variance					
ARCH(1)	0.075***	0.072***	0.071***	0.065***	0.064***
	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
GARCH(1)	0.878***	0.864***	0.862***	0.854***	0.856***
	(0.030)	(0.031)	(0.031)	(0.031)	(0.030)
MON		4.31***	4.37***	5.65***	5.78***
		(0.848)	(0.920)	(1.009)	(0.940)
STKDAY		5.30***	5.227***	6.58***	6.45***
		(0.880)	(0.871)	(1.021)	(0.963)
WIN			0.015	-0.11	
			(0.085)	(0.161)	
Voil			0.027	0.012	
			(0.029)	(0.031)	
W				0.039**	0.044***
				(0.019)	(0.016)
W^2				0.009***	0.008***
				(0.003)	(0.002)
Constant	0.384**	-1.388***	-1.529***	-2.01***	-1.954***
	(0.155)	(0.285)	(0.322)	(0.357)	(0.320)
Log likelihood	-2447	-2430	-2429	-2422	-2425
Half-time (days)	14.40	10.51	10.03	8.24	8.30

Notes:

(1) The adjusted R^2 ranges from 0.042 to 0.045. (2) Standard errors are reported in parentheses. (3) *** (**, *) denote significance at the 1% (5%, 10%) level.

Appendix 1

Construction of Natural Gas Consumption Weighted Temperature Variable

The natural gas consumption weighted temperature (*TEMP*) variable is constructed from the following procedure. First, I calculate monthly averages for each of the daily temperature variables (*Tmin* and *Tmax*) of all weather stations in the Lamb-Richman dataset. This is necessary because the highest frequency for the natural gas consumption data is monthly. Second, as mentioned in the text, the temperature data are highly correlated within a state. From the many temperature variables in each sub-district of Petroleum Administrative Districts of Defense (PADDs), I choose the one that yields the highest correlation coefficient with the corresponding natural gas consumption data as the regional "representative" temperature variable.[36] Third, the daily regional "representative" temperature variables are weighted by the natural gas consumption of that region to get a daily weighted temperature series. Fourth, TEMP is the weekly average of the daily weighted temperature from Friday of week τ-1 to Thursday of week τ.

[36] The descriptions and maps of PADD can be found at the appendix of EIA's annual publication "Petroleum Supply Annual".

Appendix 2

Table A.1

Crude Oil Returns

Dependent Variable: CRET=log(P_t^c/P_{t-1}^c) where P_t^c is daily settlement price of the near month crude oil futures on NYMEX on date *t*.

	Coefficient
Mean	
CRET $_{t-1}$	0.047 (0.033)
CRET $_{t-2}$	-0.096*** (0.031)
Constant	0.014 (0.067)
Variance	
ARCH(1)	0.103*** (0.021)
GARCH(1)	0.719*** (0.062)
Constant	1.097*** (0.299)
Adjusted R^2	0.007

Standard errors are reported in parentheses.

Appendix 3

Table A.2 **Empirical Result Using Chicago's Weather Data**

	RET1		RET2	
Mean				
W	0.042***	0.043***	0.039***	0.037***
	(0.015)	(0.015)	(0.014)	(0.016)
STKERR	-0.022**	-0.022**	-0.019**	-0.020*
	(0.011)	(0.011)	(0.009)	(0.010)
CRET	0.238***	0.239***	0.227***	0.224***
	(0.038)	(0.037)	(0.036)	(0.036)
TBILL	0.249		0.287*	
	(0.172)		(0.162)	
SPRET	-0.021		-0.068	
	(0.068)		(0.062)	
Constant	-1.212	0.050	-1.417	0.040
	(0.878)	(0.088)	(0.828)	(0.082)
Variance				
ARCH(1)	0.078***	0.084***	0.063***	0.067***
	(0.018)	(0.020)	(0.014)	(0.017)
GARCH(1)	0.870***	0.853***	0.858***	0.841***
	(0.032)	(0.035)	(0.028)	(0.036)
MON	5.630***	5.547***	5.885***	5.461***
	(1.073)	(0.941)	(0.967)	(0.882)
STKDAY	6.483***	6.311***	6.406***	6.005***
	(1.069)	(1.024)	(0.885)	(0.919)
WIN	-0.177		-0.150	
	(0.145)		(0.106)	
Voil	0.026		0.038	
	(0.026)		(0.027)	
W	0.013	0.019	0.023*	0.030**
	(0.015)	(0.016)	(0.014)	(0.015)
W^2	0.005**	0.004**	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-2.146***	-1.954***	-2.126***	-1.675***
	(0.385)	(0.320)	(0.312)	(0.271)
Log likelihood	-2508	-2510	-2423	-2427

Notes:

(1) The adjusted R^2 ranges from 0.042 to 0.045. (2) Standard errors are reported in parentheses. (3) *** (**, *) denote significance at the 1% (5%, 10%) level.

CHAPTER IV

MEASURING UNILATERAL MARKET POWER: AN APPLICATION TO TEXAS WHOLESALE ELECTRICITY MARKET

IV.1 Introduction

A major development in the US electricity industry since mid 1990's is the divesture of power generation from vertically integrated utilities and the moving from a regulatory regime towards a competitive market mechanism. Policy makers were hoping that the introduction of competition would encourage investment and lower prices thereby benefiting consumers (Joskow, 2006 p.2). However, the California energy crisis of 2000-2001 raised numerous concerns about the exercise of market power in deregulated electricity markets and whether a competitive market can function well in the electricity industry. Empirical studies typically find that firms exercised some degree of market power in California and other deregulated electricity markets (see Wolfram (1999) for England and Wales, Borenstein, Bushnell and Wolak (2002), Joskow and Kahn (2002), Wolak (2003), and Puller (2005) for California). Consequently, several states have halted plans for further restructuring.[37] Texas is one of the few states that has continued to deregulate the wholesale and retail electricity markets after 2001.

The bulk of electric power in Texas is traded through bilateral transactions between buyers and sellers. To meet real-time changes in aggregate demand and to account for unforeseen supply losses due to equipment outages, the Electric Reliability

[37] For a detailed discussion on the status of state electric industry restructuring, see Energy Information Administration (2003).

Council of Texas (ERCOT) operates an hourly balancing market in which power generators bid a supply schedule to adjust their output levels relative to their day-ahead production plans. The market structure can be summarized as two equally-sized strategic firms (TXU and TexasGenco) plus a competitive fringe of about 30 smaller firms. Each of the two strategic firms controls about 25% of the total installed capacity in ERCOT. The purpose of this chapter is to empirically investigate whether the two strategic firms exercised market power and, if so, what factors contribute to the market power.

Because the aggregate demand in the real time electricity market is essentially price-irresponsive, it is possible to construct an *ex post* residual demand curve for each supplier from the observed bid data. Wolak (2003) shows that the inverse of the *ex post* residual demand elasticity (i.e., the Lerner index) measures a firm's unilateral market power. This chapter uses firm-level bid data from January 1, 2002 to December 31, 2004 and compute the elasticity of the residual demand curve faced by the two strategic suppliers in ERCOT. The major findings of this chapter can be summarized as follows. First, although both firms are about equally sized in terms of installed capacity, the firm with larger share of capacity in the balancing market has consistently higher market power. This is consistent with Hortacsu and Puller's (hereinafter "HP" 2005) finding that firms with large stakes in the market behave close to the *ex post* optimal model. Second, the price spikes observed during the fourth quarter of 2004 are consistent with the exercise of market power by the leading firm. Third, the lack of bids from smaller firms enhances the leading firm's market power. In particular, I find that the disclosure of a bidder's identity by ERCOT when the bid price is above $300/MWh appears to discourage firms from bidding in the market.

The remainder of this chapter proceeds as follows. Section IV.2 provides an overview of the deregulation process in Texas, and describes the market clearing process. Section IV.3 outlines the conceptual framework which draws heavily from Wolak (2003) and discusses the possible sources of bias of in the measurement of market power using this method. Section IV.4 presents empirical results using this method and an alternative measure of market power — the residual supplier index. Section IV.5 concludes.

IV. 2 ERCOT Market Overview

The Electric Reliability Council of Texas (ERCOT) is a not-for-profit Independent System Operator (ISO) that is responsible for the operations of the power grid in Texas. Historically, ERCOT's primary role was to ensure the reliable transmission and transfer of electric power among its member firms. Texas began to deregulate its wholesale generation market in 1995. In 1999, the Texas state legislature passed Senate Bill 7 (SB7) which initiated a series of further restructurings in the electricity market. Under SB7, all formerly regulated and integrated investor-owned utilities (IOUs) were required to unbundle their generation, transmission and/or distribution and retail functions into three separate entities: a power generation company, a transmission and/or distribution service provider (TDSP), and a retail electric provider. Under the new regime, the TDSP's continue to be regulated whereas the generation companies and retail electricity providers are open to competition.

The majority of transactions in the Texas wholesale electricity market are conducted through bilateral trades between buyers and sellers. To meet the real-time changes in demand, ERCOT began operating a balancing market on July 31, 2001. The trading volume in the balancing market amounted to 2-5% of total transactions during the first four years of the market operation. Although the total volume settled in the balancing market is relatively small, the influence of the price signal goes well beyond the balancing market. If we think of the balancing energy price as a spot price, the day-ahead price can be considered a forward price even though there is no centralized day-ahead market in ERCOT. In an efficient market without significant barriers to entry, arbitrage would equate the forward price and the spot price at the same delivery time. Indeed, there is evidence that the day-ahead price converges to the balancing market price (Potomac Economics, 2004 and 2005).

The balancing market is a "real-time" market to balance the actual demand and supply. The operations of the market can be summarized as follows. From 6:00am to 6:00pm on the day before the operating day of actual power flow, generators submit hourly balanced supply (generation) and demand (load) schedules through their qualified scheduling entities (QSEs).[38] A QSE is required to specify the amount of energy they plan to produce from each resource (unit) and the amount of energy they are selling to each consumer (buyer). In the day-ahead scheduling process, no auction mechanism is involved. In the balancing market, ERCOT adopts a multi-unit, uniform-price auction to clear the market. Bidders submit piecewise linear supply functions specifying the price and quantity pairs at which they are willing to increase (Upward

[38] All generators bidding and scheduling behavior are conducted through QSE's in ERCOT. In what follows, firms and bidders both refer to QSE and they will be used interchangeably. Large power generating companies such as TexasGenco and TXU are themselves QSEs.

Balancing Energy Service, or UBES) or decrease (Downward Balancing Energy Service, or DBES) from the day-ahead scheduled generation. The price of UBES is capped at $1,000/MWh and the price of DBES is capped at -$1,000/MWh. The supply functions (bid curves) apply to each of the four 15-minute intervals of the operating hour. UBES and DBES can each have up to 20 bid points and must be monotonically increasing. Figure IV.1 illustrates a sample bid curve.[39]

Depending on ERCOT's load forecast for the operating time interval and the scheduled generation, the balancing demand can be positive or negative. Because virtually no consumers can respond to price changes in real time, the demand in the balancing market is generally considered perfectly price-inelastic. ERCOT aggregates individual bid curves to a system-wide aggregate bid stack. When there is no congestion in transmission lines, the market clearing price for energy (MCPE) is determined by intersecting the 15-minute perfectly inelastic demand curve with the aggregate supply schedule.[40] The real-time market clears approximately 20 minutes ahead of each 15-minute operating interval. In the case of a positive demand for balancing energy, all bids with prices below the MCPE are deployed. A generator that is called to increase its output is paid MCPE for the amount of incremental sales. In the case of a negative balancing demand, ERCOT needs to decrease total generation to maintain system security.[41] A generator that is called to decrease its output from the scheduled level pays ERCOT the MCPE for the amount of electricity reduced. For example, a generator having submitted a balanced day-ahead schedule of 100 MWh generation and 100

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[39] Although UBES and DBES each must be monotonically increasing, the highest bid price DBES can be higher than the lowest bid price of UBES. This is called "Bid Overlap" (see Teng et al, 2004)
[40] The actual market clearance software considers other factors such as ramp rate, bid overlap as well.
[41] Because of the bid overlap, it is possible that one supplier is called to increase the output while another supplier is called to decrease the output. This is not a rare occurring.

MWh load obligation is called to decrease 10 MWh output. She can collect revenue for the 100 MWh load from her customer (her customer's demand will be satisfied by the pool), but she only generates 90 MWh. She pays MCPE for the decreased 10 MWh to ERCOT, and ERCOT transfers the payment to demand side bidders who reduce the load. Thus the DBES bid price can be interpreted as a generator's willingness to pay for the amount of electricity she purchases from the market.

To manage congestion in transmission lines, ERCOT divides its market into several zones. The number of zones has changed over time, from four in 2002-2003 to five in 2004. When the transmission lines between zones are not congested, ERCOT is a single market with uniform prices. When the transmission lines are congested, each zone has a different price because the additional megawatts (MW) of energy demanded in each zone can only be supplied from generating units in that zone. For this reason, bidders are required to separate their bid curves by zone and by hour of the day.

The market structure of ERCOT can be best characterized as two equally-sized strategic firms competing with a competitive fringe. Table IV.1 lists generating firms with installed capacity above 1000 MW. TXU and Texas Genco, the two formerly regulated utilities, together own more than 50 percent of total generating capacity in this market. The technology mix in ERCOT is primarily composed of coal and natural gas units with a small amount of nuclear, hydro, and wind generating units.

Firms in this market appear to have a great deal of information about the total demand, their own marginal cost, and the operating environment. ERCOT posts the aggregated bid curves on its website with a two-day lag. Individual bid curves and the day-ahead energy schedules are also made publicly available six months after the market clears. In addition, several private vendors provide proprietary information (surveys) on each generating unit's technology and fuel efficiency. The Energy Information Administration (EIA) also has monthly information on the input and output for a subset of power-plants in Texas.

IV.3 Conceptual Framework

Market power is typically defined as the ability to profitably raise prices above competitive levels (Twomey et al. p5) and measured as the price-cost markup, i.e. the proportional difference between prices and marginal costs. In the real-time electricity market, because the total demand is unresponsive to prices, the residual demand ($DR_t(p)$) faced by a firm at any interval is

(1) $$DR(p) = Q^{Total} - Q^{Other}(p)$$

where Q^{Total} is the total demand for that interval, and $Q^{Other}(p)$ is the aggregate bid curve from all other firms. The slope of the $DR(p)$ is determined by $Q^{Other}(p)$.

In Figure IV.2, $DR_1(p)$ and $DR_2(p)$ are two expected residual demand curves.[42] The firm does not know which residual demand curve will realize when it submits its bids. MC(q) is the marginal cost function. For an expected residual demand curve $DR_1(p)$, the profit-maximizing firm would bid at point A; and for an expected residual demand curve $DR_2(p)$, the firm would bid at point B. Wolak (2003) illustrates that because firms can submit a curve rather than a point, the optimal bid curve will pass through all profit maximizing points for various expected residual demand realizations. S(p) in Figure IV.2 is one such bidding strategy. Wolak (2003) further argues that the intersection of the *ex post* residual demand curve and the firm's supply schedule

[42] The discussion in this section draws heavily on Wolak (2003).

maximizes its profit given the other firms bids at that interval and the following equation holds:

(2) $$(P_t - MC_{it})/P_{it} = -1/\eta_{it}$$

where P_t is the market clearing price for interval *t*, MC_{it} is the firm *i*'s marginal cost at interval *t*, and η_{it} is the price elasticity of residual demand curve facing firm *i* at interval *t* evaluated at P_t. Define $L_{it} = -1/\eta_{it}$. L_{it} can be interpreted as the Lerner index and measures firm *i*'s market power at interval *t*.

Equation (2) holds if the firm can correctly forecast the slope of the residual demand curve (or the slope of the relevant section of a kinked demand curve). If the realized residual demand curve is steeper than expected, L_{it} overstates firm *i*'s market power. This is illustrated in Figure IV.3_a where $DR_1(p)$ and $DR_2(p)$ are the expected residual demand curves as before. I add the realized residual demand curve $DR_3(p)$ into the figure. $DR_3(p)$ crosses $DR_2(p)$ at point B. For $DR_3(p)$, equation (2) holds at point C. Because the absolute value of the residual demand elasticity at point C is greater than point B, L_{it} evaluated at point B would overestimate firm *i*'s market power. By the same logic, it is straightforward to show that L_{it} would understate firm *i*'s market power when the realized residual demand curve is flatter than expected, as shown in Figure IV.3_b. Despite the possible bias, I proceed to compute L_{it} because it provides a measure of potential market power that a firm would have if it can correctly forecast the slope of the residual demand, and therefore measures the competitiveness of the market.

Following Wolak (2003), I compute the arc elasticity evaluated at the market clearing price P_t using this formula

(3) $$\eta_{it} = \frac{DR_{it}(P_t^H) - DR_{it}(P_t^L)}{P_t^H - P_t^L} \times \frac{P_t^H + P_t^L}{DR_{it}(P_t^H) + DR_{it}(P_t^L)}$$

where $P_t^H = P_t + \text{d}$ and $P_t^L = P_t - \text{d}$. Since d is a pre-specified small value, the difference between P_t^H and P_t (i.e. 2d) measures the price change around P_t. $DR_{it}(P_t^H)$ and $DR_{it}(P_t^L)$ are the quantities on firm i's residual demand curve corresponding to P_t^H and P_t^L. $DR_{it}(P_t^H)$ is equal to the total demand on the balancing market minus the aggregate supply from all other firms at price P_t^H. $DR_{it}(P_t^L)$ is calculated using the same procedure. The following example illustrates the calculation of $DR_{it}(P_t^H)$ and $DR_{it}(P_t^L)$ for firm i. For simplicity, suppose there are only one zone and two other firms, firm 1 and firm 2. Further, suppose at an interval t the total quantity demanded Q_t^{Total} for the balancing market is 500MW, the market clearing price P_t is \$50/MWh, and d is \$1/MWh, such that P_t^H is \$51/MWh and P_t^L is \$49/MWh. Firm j ($j=1, 2$) has the following supply schedule:

Firm 1		Firm 2	
Price (\$/MWh)	Quantity (MW)	Price (\$/MWh)	Quantity (MW)
30	0	45	0
40	100	55	200
60	200	70	250
		90	260

Recall that the individual supply function is a piecewise linear function. By interpolation, it is easy to show that firm 1 is willing to supply 155MW and firm 2 is willing to supply 120MW when the price is \$51/MWh. Therefore, the total supply from all other firms $Q_t^{other}(P_t^H)$ is 275MW when the price P_t^H is \$51/MWh. Subtracting $Q_t^{other}(P_t^H)$ from Q_t^{total}, we have the residual demand for firm i $DR_{it}(P_t^H)$ is 225MW. Similarly, we can show that the $DR_{it}(P_t^L)$ is 275MW when P_t^L is \$49/MWh. Plugging these figures in equation (3), we have $\eta_{it} = -5$ and hence $L_{it} = 0.2$. Of course, the actual calculation of $Q_t^{other}(P_t^H)$ and $Q_t^{other}(P_t^L)$ involves the summation of all other firms' supply at prices P_t^H and P_t^L across zones. To mitigate the influence of extreme values, I set d equal to \$1, \$2, \$3, \$4, and \$5, and use the average of these calculated η's as the arc elasticity in equation (2).

To reduce the computational burden, I focus on the four time intervals of hour 18:00-19:00 from January 1, 2002 to December 31, 2004. The main reason for choosing this hour is that the ramp rate constraint is unlikely to bind during peak hours. A generating unit's ramp rate determines how fast a generator can increase or decrease its output in a short time period (e.g., 10-15 minutes). When the ramp rate constraint binds, the system operator may not be able to dispatch the least cost unit and hence the market clearing price may be higher than implied by the bid stacks. Because the residual demand quantities $DR_{it}(P_t^H)$ and $DR_{it}(P_t^L)$ are calculated from individual bid curves after observing P_t^L, ramp rate constraints can cause my calculation to be inaccurate if they are binding. During the peak hours when most units (including peak units) are online, the ramp rate constraint is less of a concern. In their study of individual firm's bidding behavior in ERCOT, HP(2005) focus on the time interval of 18:00-18:15.

When transmissions between zones are congested, an additional megawatt of power that is demanded in a zone can only be supplied from generating units within that zone. Therefore the market clearing price for each zone will be different and it is not straightforward to determine which units are can be used to meet the additional demand within a zone. Following Wolak (2003) and HP (2005), this chapter excluded congested time intervals from this analysis. During this time period, 85% of the intervals are not zonally-congested

The final issue before computing the residual demand elasticity is that the total demand as well as the residual demand in the balancing market can be negative. As discussed in HP (2005), firms have no incentives to inflate the price when the expected demand is negative. The reason is that when a firm is called to reduce its output relative to its day-ahead schedule it needs to buy power from the pool to serve its load obligations. So if a firm has market power, it would exercise the "monopsony power". Because the focus of this chapter is on monopoly market power, I also exclude these intervals.

IV.4 Empirical Results

A. Overall Market Performance

Table IV.2 presents the distribution of $L_{it} = -1/\eta_{it}$ for the two strategic firms (TXU and Texas Genco) from 2002 to 2004. Since I exclude the intervals when firm *i*'s residual demand is negative, it is not surprising the number of observations for the two firms generally do not coincide. Because there are a number of intervals during which the residual demand curve is too steep, the extremely large values of L_{it} make the mean and standard deviation for the full data set meaningless, I calculate the mean and the standard deviation for observations that are below the 90th percentile.

Two observations emerge from Table IV.2. First, TXU has higher market power than Texas Genco over the three-year period. This may be surprising because the two firms have nearly equal installed capacity. To further investigate this issue, I calculate the daily average of the installed capacity available for the balancing market. This is done by subtracting the day-ahead scheduled generation for firm *i* from the total capacity of that firm. If a firm commits more capacity day-ahead through bilateral transactions, it will have a smaller position and therefore limited market power in the balancing market. The result is reported in Table IV.3 and the pattern is clear that TXU relies more on the balancing market than Texas Genco. In 2002 the total capacity available owned by TXU for the balancing market is 44 percent more than the capacity owned by Texas Genco. In 2004 TXU's capacity available for the balancing market nearly doubles the capacity owned by Texas Genco. Thus the Lerner index computed from the residual demand curve appears to be consistent with the firms' positions in the balancing market. This result agrees with HP's (2005) finding that firms with larger stakes in the market bid closer to the *ex post* optimal strategy.

The second observation emerging from Table IV.2 is that TXU's market power is much higher in 2003 and 2004 than in 2002. Given the increase in TXU's total capacity available for the balancing market, this finding is also not too surprising. Another factor that may contribute to the increase in TXU's unilateral market power is the increase in the total demand for the real time market as shown in the last row of Table IV.3. Because the total demand Q^{total} in the real time market is perfectly inelastic, holding the supply from other firms ($Q^{other}(p)$) constant, an increase in the total demand shifts the residual demand to the right. As a result, the residual demand curve becomes less elastic and the Lerner index becomes larger.

To make an assessment about the overall competitiveness of the market, I compare the mean value of L for the lower 90 percent of observations in Table IV.2 with those reported in Table 1 of Wolak (2003). The mean values of L for both TXU and Texas Genco in 2002, and for Texas Genco in 2003 and 2004 are similar in magnitude with those in California in 1998 and 1999. Meanwhile, the index for TXU in 2003 and 2004 is similar to those in California in 2000.

B. Market Power and Price Spikes

During the sample period, particularly in the last two months of 2004, ERCOT experienced a number of exceptionally high-priced intervals or "price spikes" (see IV. 4). These price spikes were oftentimes not associated with generation outages, fuel price increases, or changes in the transmission network (Potomac, 2005). Therefore, it is natural to ask whether the price spikes resulted from the exercise of market power.

To investigate this issue, we first need to define price spikes. As mentioned above, the majority of marginal generating units in ERCOT are natural gas fired. Whether the electricity price is exceptionally high should be evaluated relative to natural gas prices. The standard approach to constructing marginal cost in the literature is to multiply fuel prices by a heat rate and to allow a variable operating, maintenance, and emissions cost.[43] Because I don't have data on unit-level heat rates, I can't construct the exact marginal cost in this way. Instead, I derive a plant-level heat rate from the Energy Information Administration's (EIA) Form 906 which reports the total electricity generation and the total fuel consumption at the plant level. I find the highest plant-level heat rate in ERCOT is about 26 MMBTU/MWh. To be conservative, I use a heat rate of 30 MMBTU/MWh and allow a $10/MW for operating, maintenance, and emissions cost. A price spike is defined as a time interval when the market clearing price (P_t) exceeds 30 times natural gas price (*Pgas*) for that day plus $10/MW, i.e.,

(4) $$P_t > 30*P_{gas} + \$10/MW.$$

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[43] Heat rate measures the efficiency of a power generating unit. It equals the heat content of the fuel input divided by the power output.

As such, I largely rule out the price spikes that are purely caused by a run-up in fuel prices and can relate them to the market power indices calculated from the residual demand curve.

The result is reported in Table IV.4. The second column of Table IV.4 indexes the interval of the day. For example, the first interval in hour 18:00-19:00 is 73, the second interval is 74, and so on. MCPE is the market clearing price for energy. Gas Price is the natural gas spot price at Houston Katy hub. *L_TXU* is the Lerner index calculated for TXU, and *L_Genco* is the Lerner index for Texas Genco. Given that TXU has higher market power in the balancing market, it is perhaps not surprising that the majority of the price spikes are associated with rather high values of *L_TXU*. In fact, only 4 out of the 52 price spikes occur when *L_TXU* is below one. In other words, more than 90 percent of price spikes occur when TXU faces an inelastic demand curve. As an example, Figure IV.5 produces the two residual demand curves facing TXU at two intervals on November 29, 2004 along with its bid curve. The two residual demand curves are perfectly inelastic at the market clearing quantity, which implies that the market clearing price could have been higher (up to the cap of $1000/MWh). I examined other price spikes in 2004 and this pattern is fairly common.

The lack of bids from smaller suppliers appears to contribute to the price spikes during this period. In a discussion about the price spikes in the fourth quarter of 2004, the independent market monitor of ERCOT states "we also identified a relatively large quantity of available energy that could have been produced from on-line and quick-start resources by rival suppliers that was not offered in the balancing energy market. If all of this energy had been offered, the price spikes would not have occurred" (Potomac

Economics, 2005). Notice that when *L* is greater than one, it overstates a firm's market power (see Section III and Figure IV.3_a) and cannot be interpreted as the price-cost markup. This occurs because *L* is calculated from the *ex post* residual demand curve and equation (2) is based on *ex ante* calculation. If the firm incorrectly forecasts either the slope or the intercept of the residual demand curve, the *ex post* calculated *L* would be different from the *ex ante* price-cost markup.

If we further restrict price spikes to include only intervals when the MCPE is above \$300/MWh, the elasticity of the residual demand facing TXU is virtually zero for all intervals in 2003 and 2004. It has some slope albeit in the inelastic range in 2002 when the price reached \$990/MWh. I suspect this has to do with a provisional change in ERCOT Protocol. In June 2002, the ERCOT Protocol added a provision calling for the disclosure of QSEs identities when their bid prices are greater than \$300/MWh for UBES bids or less than -\$300/MWh for DBES bids. In discussions with ERCOT staff, I learned that companies call this a "Shame Cap". Despite having no penalty for bidding above \$300/MWh, this provision appears to discourage smaller firms from offering electricity at the high-price range. This can be clearly seen in Figure IV.6 which displays the frequency of maximum bid prices when they are over \$200/MWh. In Figure IV.6_A when all bids are included, about 24 percent of the maximum bid prices are in the range of \$290-300/MWh. If we exclude TXU's bids, the pattern is more pronounced (Figure IV.6_B) — more than 60 percent of maximum bid prices are in the range of \$290-300/MWh and these bids are submitted by four different smaller firms on different days. It is hard to believe the marginal cost of the most expensive units for these suppliers are uniformly in the range of \$290-300/MWh, but not in the range of \$300-\$400.

C. Measuring Market Power with Alternative Tools

The last exercise I do is to analyze market power with alternative market monitoring tools and compare the result with those reported in Table IV.2. One such measure that is currently used by market monitor and regulators is the Residual Supply Index (RSI) (Twomey et al). The RSI was developed by the California Independent System Operator (CAISO).[44] The RSI for firm *i* measures the ratio of residual supply capacity (the total capacity in the market subtracting firm *i*'s capacity) to total demand, and hence it is a capacity-based measure.

(5) $$RSI_{it} = (TotCap_t - Cap_{it})/Q_t^{total}$$

where $TotCap_t$ is the total capacity available for providing energy at time *t*, Cap_{it} is firm *i*'s capacity available at *t*, and Q_t^{total} is the total market demand.

When RSI is greater than 1, other suppliers have enough capacity to meet the total demand, so firm *i* should have less influence on market clearing price. On the other hand, if the RSI is less than 1, firm *i*'s capacity is needed and becomes a pivotal player according to the definition of the Federal Energy Regulatory Commission. Since RSI is a capacity measure, it is inversely related to the price-cost margin. The higher the RSI, the lower is the firm's market power. A limitation of this measure is that it does not discern the bidding strategies for a given capacity (the slope of the bid curve). To see this, consider a generator who commits a unit with the capacity of 100 MW. He has two bidding strategies: one is to bid at marginal costs and the other is to bid with markups. If every firm has the same choices, the residual demand curve facing any firm will have

[44] See Sheffrin (2002)

different slopes depending upon the bidding behavior of the other firms but the RSI will be the same.

The empirical results using this measure are reported in Table IV.5. Overall the patterns are consistent with Table IV.2. The RSI is lower for TXU than for Texas Genco, and it is substantially lower in the 2003-2004 period compared with 2002. This indicates TXU has higher market power than Texas Genco and the market was more competitive in 2002.

IV.5 Conclusion

This chapter studies the ability of the largest two firms, TXU and Texas Genco, to raise prices above competitive levels in the Texas wholesale electricity balancing market. Market power is measured as the inverse of the residual demand elasticity faced by the two firms. The main findings can be summarized as follows. First, TXU has higher market power than Texas Genco and its market power rises over time. This pattern is consistent with the result using an alternative measure of market power – Residual Supply Index. The plausible explanation is that TXU relies more on the balancing market and its relative position in the balancing market has increased over this time period. Second, the majority of price spikes occur when the residual demand curves facing TXU are price-inelastic. The lack of bids from smaller firms contributes to the strategic firm’s market power. Finally, I find evidence that the disclosure of a bidder’s identity by ERCOT when the bid price is above $300/MWh discourages firms from bidding into the market and may have exacerbated price spikes.

Figure IV.1

A Sample Bid Curve

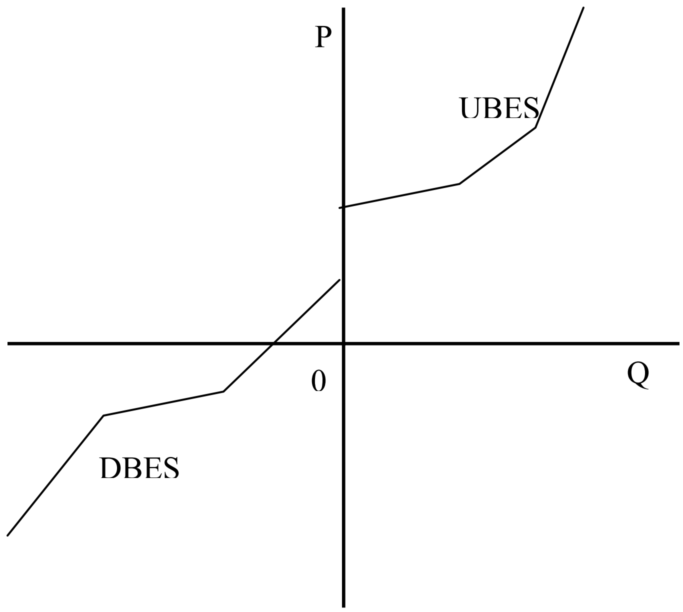


Figure IV.2

Firm's Profit-Maximizing Bidding Strategy (Adapted from Wolak, 2003)

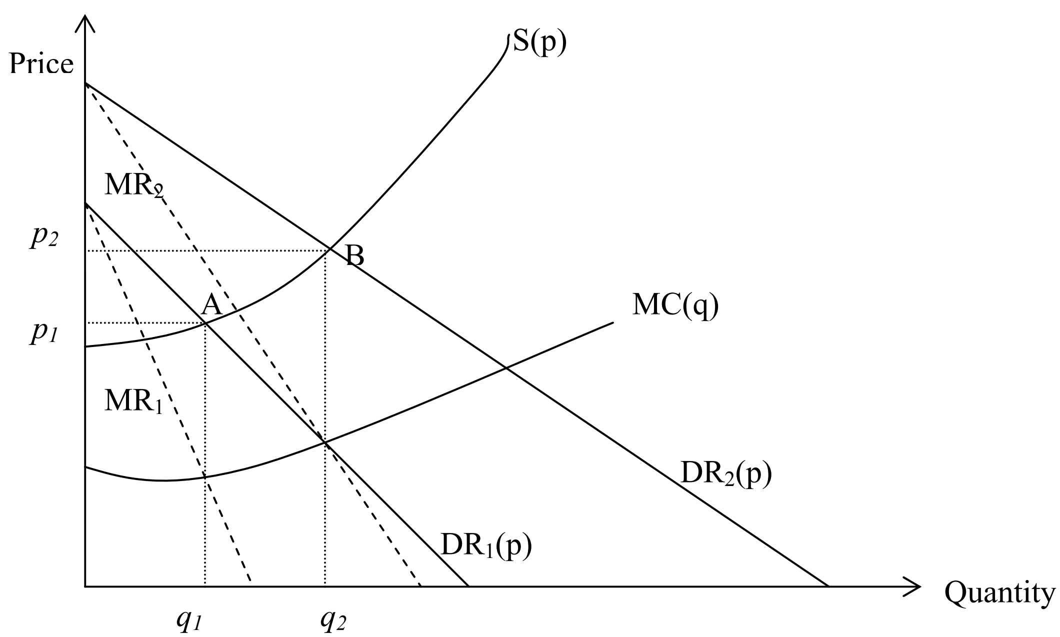


Figure IV.3 **Profit - Maximisation (*ex ante* vs. *ex post*)**

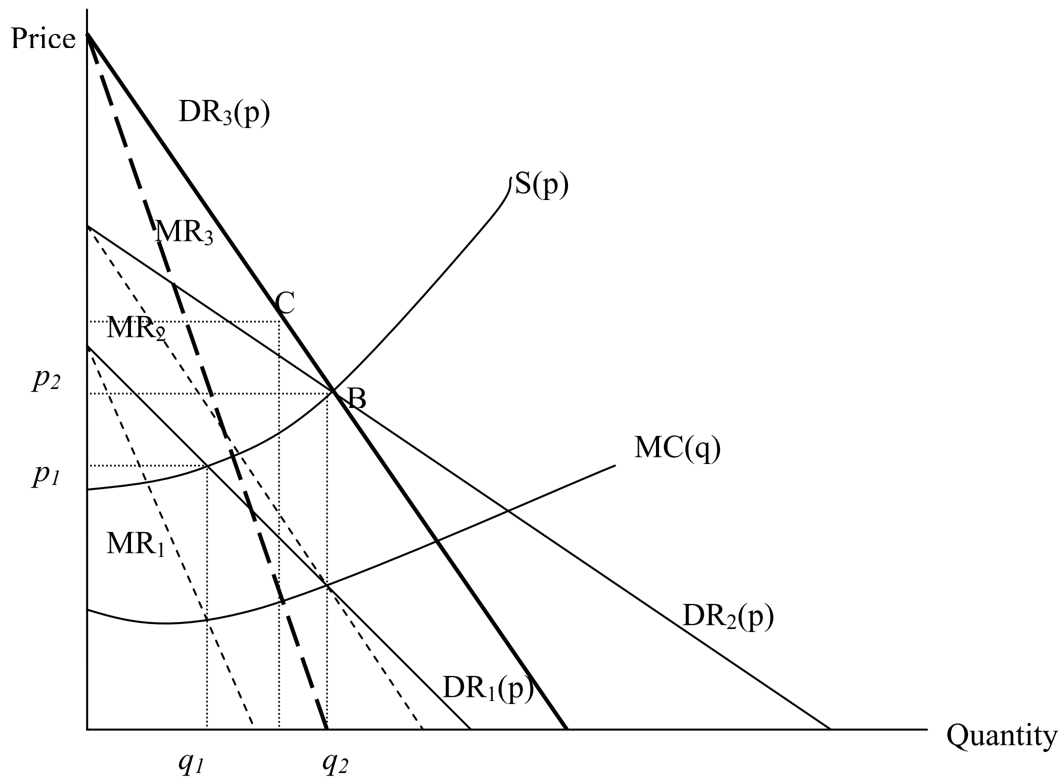


Figure IV.3_a

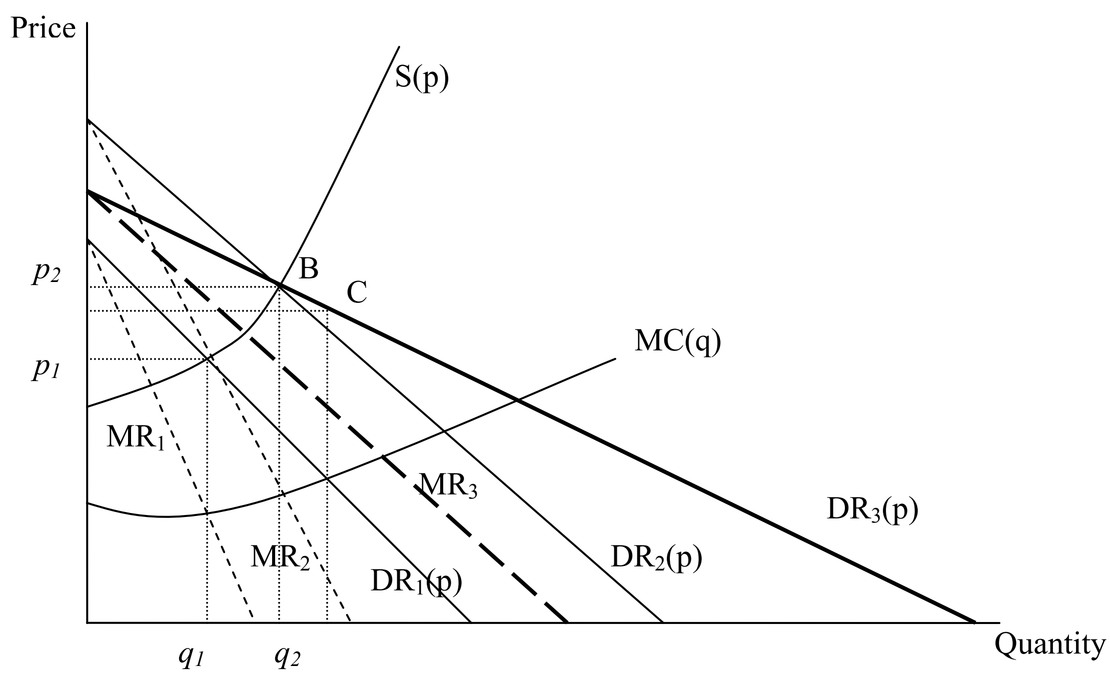


Figure IV.3_b

Figure IV.4

Electricity and Natural Gas Prices

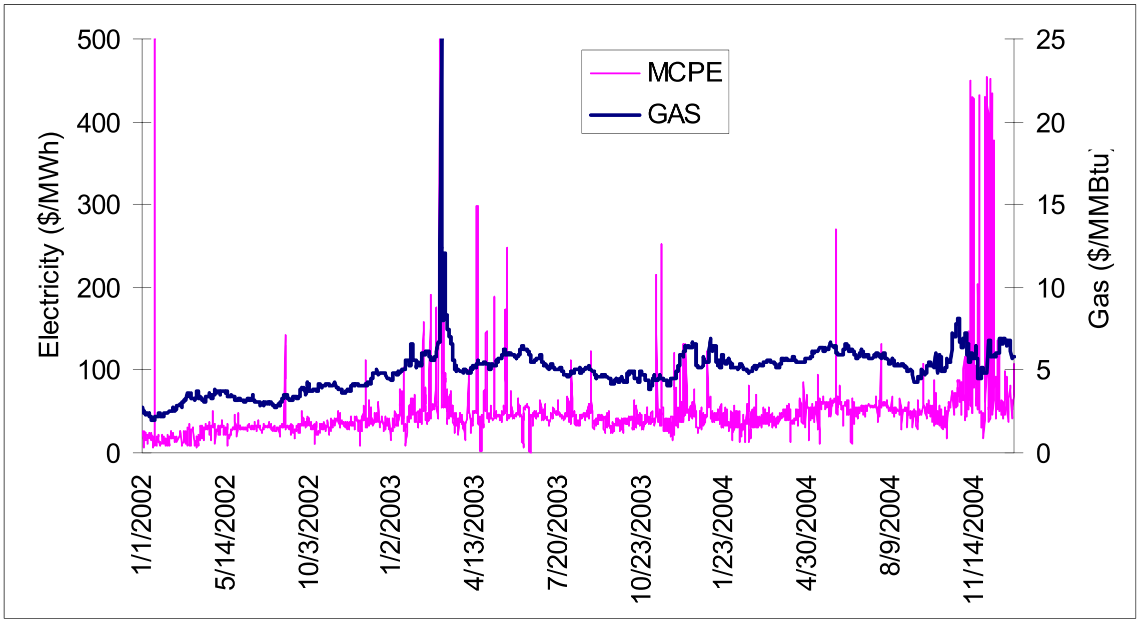


Figure IV.5

TXU's Residual Demand and Bid Curves on 11/29/2004

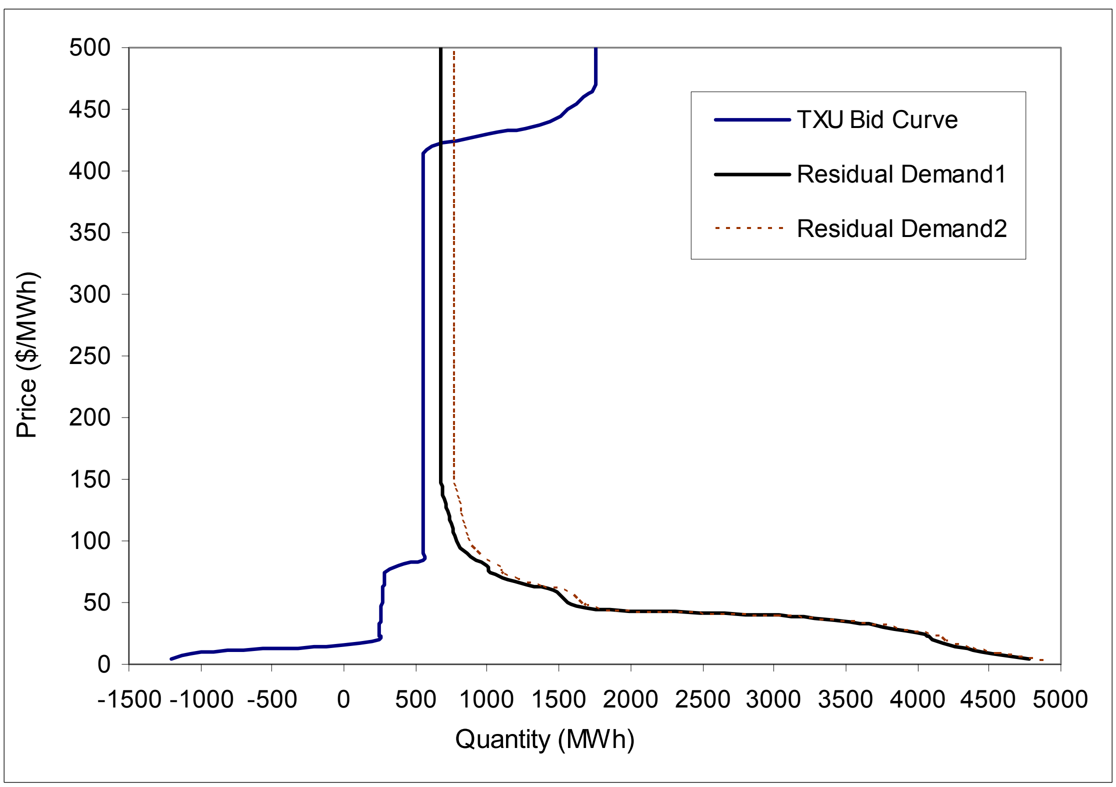


Figure IV.6_A

Relative Frequency of Max Bid Prices from All Firms (1/1/2004—12/31/2004)

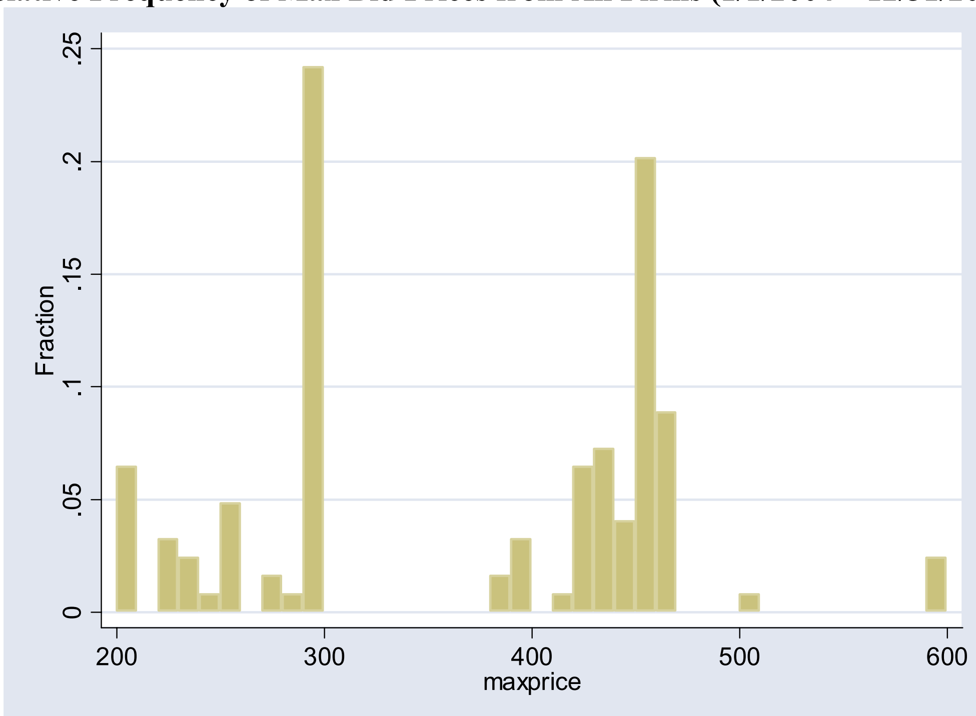
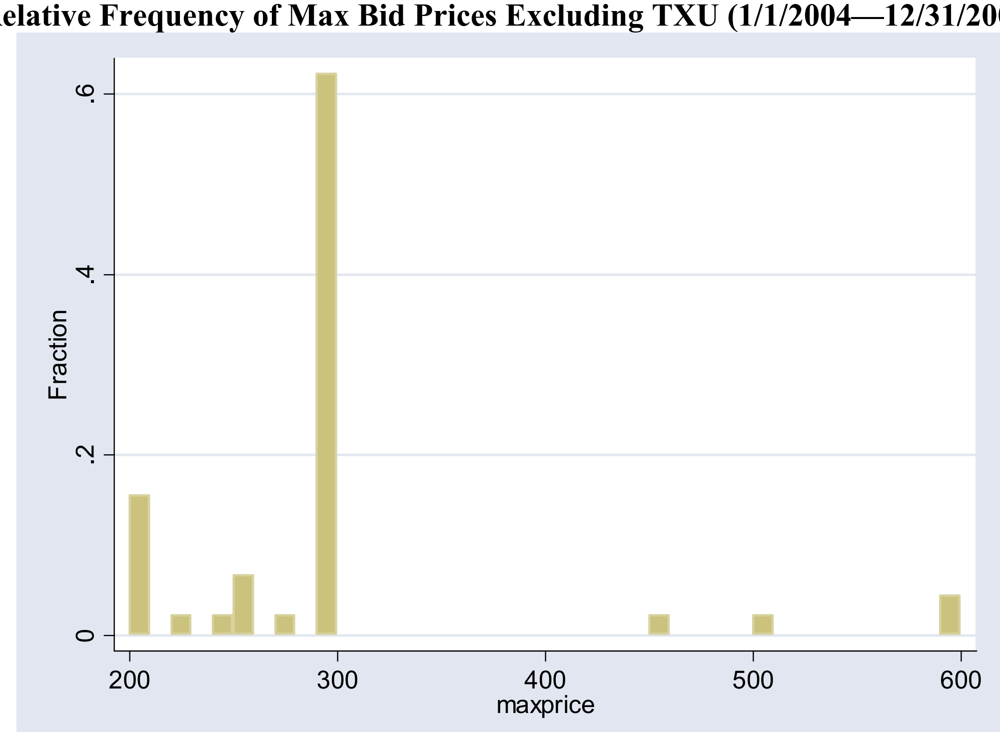


Figure IV.6_B

Relative Frequency of Max Bid Prices Excluding TXU (1/1/2004—12/31/2004)



(The width of each bin is $10/MWh)

Table IV.1 Market Structure of ERCOT

Firm (QSE)	Capacity(MW)	Percentage
TXU Portfolio Management Company	20524	26.7%
Texas Genco. LP	19097	24.9%
Calpine Power Management LP	6016	7.8%
American Electric Power Service Corp.	3548	4.6%
Lower Colorado River Authority	2929	3.8%
City of Austin DBA Austin Energy	2910	3.8%
Exelon Power Team	2410	3.1%
ANP Funding I LLC	2363	3.1%
BPTX (SQ1)	2001	2.6%
FPL Energy Power Marketing	1422	1.9%
Coral Power LLC (SQ2)	1194	1.6%
Brazos Electric Power Co.	1183	1.5%
Others	11222	14.6%
Total	76829	100%

Table IV.2

Distribution of Inverse Residual Demand Elasticity

	N. Obs.	25th Pctile	Median	75th Pctile	90th Pctile	Max	Mean for 90th Pctl	Std for 90th Pctl
TXU								
2002	532	0.017	0.044	0.102	0.246	47.763	0.055	0.053
2003	868	0.065	0.185	0.398	0.748	3293.99	0.209	0.185
2004	857	0.017	0.078	0.253	0.996	Infinity	0.166	0.216
Texas Genco								
2002	488	0.010	0.026	0.065	0.132	1.059	0.032	0.030
2003	855	0.009	0.026	0.100	0.312	1851.36	0.050	0.065
2004	688	0.006	0.014	0.029	0.103	97.697	0.017	0.017

Table IV.3

Daily Average of Capacity Available for Balancing Market and Average Balancing Demand

	2002	%	2003	%	2004	%
Capacity						
TXU	6309	26%	7987	33%	8841	33%
Texas Genco	4391	18%	4523	19%	4520	17%
Others	13554	56%	11484	48%	13082	49%
Sum	24254	100%	23994	100%	26443	100%
Balancing Demand	933		1330		1225	

Table IV.4

Price Spikes

Date	Interval	MCPE	GAS Price	L_TXU	L_TxGenco
2/5/2002	74	990.01	2.16	8.82	1.06
2/5/2002	75	990.01	2.16	8.82	1.06
2/5/2002	76	990.01	2.16	8.82	1.06
8/26/2002	74	142.44	3.49	3.00	0.83
8/26/2002	76	130.33	3.49	3.27	0.91
2/13/2003	75	189.94	5.87	2.69	0.73
2/24/2003	73	990.00	6.68	3293.99	949.71
2/24/2003	74	990.00	6.68	3293.99	949.71
2/24/2003	75	990.00	6.68	3293.99	949.71
2/24/2003	76	990.00	6.68	3293.99	949.71
2/25/2003	73	496.68	12.56	1835.26	0.01
2/25/2003	74	496.91	12.56	2091.82	0.01
2/25/2003	75	497.67	12.56	2367.48	0.02
2/25/2003	76	497.89	12.56	2383.90	0.02
4/16/2003	74	299.00	5.38	8.23	37.64
4/16/2003	75	299.00	5.38	8.23	37.64
5/5/2003	73	188.13	5.25	2.44	2.87
5/19/2003	74	211.20	5.93	23.21	3.85
11/10/2003	73	153.92	4.44	0.31	0.36
11/10/2003	74	214.42	4.44	0.65	0.50
11/10/2003	75	173.77	4.44	0.39	0.41
11/10/2003	76	162.12	4.44	0.34	0.39
11/16/2003	73	252.08	4.49	2.00	1.15
6/4/2004	73	269.09	6.39	2.45	1.36
11/11/2004	74	450.65	6.01	Infinity	0.06
11/14/2004	73	430.92	5.74	Infinity	0.03
11/14/2004	74	427.76	5.74	Infinity	0.05
11/20/2004	73	204.87	4.47	Infinity	8.74
11/21/2004	73	432.08	4.47	Infinity	0.01
11/21/2004	74	428.71	4.47	Infinity	0.01
11/27/2004	74	426.96	4.85	Infinity	0.07
11/27/2004	75	429.83	4.85	Infinity	0.03
11/28/2004	74	443.45	4.85	Infinity	0.03
11/28/2004	75	454.36	4.85	Infinity	0.02

(Table IV.4 Continued)

Date	Interval	MCPE	GAS Price	L_TXU	L_TxGenco
11/28/2004	76	451.97	4.85	Infinity	0.02
11/29/2004	73	428.43	4.85	Infinity	0.01
11/29/2004	74	430.47	4.85	Infinity	0.01
11/29/2004	75	427.51	4.85	Infinity	0.01
11/29/2004	76	419.98	4.85	Infinity	0.03
11/30/2004	74	409.11	6.67	Infinity	0.02
12/3/2004	74	452.58	6.57	Infinity	0.00
12/4/2004	74	439.75	5.85	Infinity	0.00
12/4/2004	75	434.36	5.85	Infinity	0.00
12/5/2004	73	434.83	5.85	Infinity	0.00
12/5/2004	74	434.83	5.85	Infinity	0.00
12/5/2004	75	434.83	5.85	Infinity	0.00
12/5/2004	76	434.83	5.85	Infinity	0.00
12/8/2004	73	377.56	5.85	Infinity	0.00
12/8/2004	74	373.78	5.85	Infinity	0.00
12/8/2004	75	360.87	5.85	Infinity	0.00
12/8/2004	76	360.87	5.85	Infinity	0.00

Table IV.5

Distribution of Residual Supply Index

	N. Obs.	Minimum	25th Percentile	Median	75th Percentile	90th Percentile	Max-imum	Mean for 90th Pctl	Std for 90th Pctl
TXU									
2002	573	1.015	4.94	8.41	17.93	35.5	379.98	10.337	7.504
2003	886	1.061	3.33	5.43	11.18	22.78	3877.45	6.594	4.819
2004	975	1.485	4.09	6.18	11.94	36.08	7933.93	7.831	6.087
Texas Genco									
2002	573	2.105	5.9	9.93	21.15	41.88	525.02	12.165	8.949
2003	886	1.79	4.46	7.16	14.55	28.36	5437.2	8.605	6.023
2004	975	1.609	4.57	6.91	13.37	42.18	8015.87	8.912	7.083

CHAPTER V

CONCLUSION

V.1 Study Summary

This dissertation is composed of three essays on producer behavior and market dynamics in US energy industries. Chapter II examines the impact of uncertainty on the investment decisions of petroleum refineries from 1985 to 2003. Using a hazard model, we find that uncertainty has a negative effect on the probability of a refinery adjusting its capacity. As uncertainty rises, refiners delay their investment decisions. This finding agrees with theories that emphasize the role of irreversibility in investment decisions. The essay also shows that investment episodes are quite lumpy in the refining industry, which is consistent with non-convex costs of capital adjustments. This last point, however, needs to be more fully developed as the focus of the essay has been on examining the relationship between uncertainty and investment and not on exploring the nature of adjustment costs in the industry.

Chapter III studies how weather shocks affect asset price dynamics in the natural gas futures market. Under a GARCH framework, I show that the weather shock variable has a statistically significant and economically non-trivial effect on both the conditional mean and conditional volatility of natural gas futures returns. Consistent with the literature, I find that the volatility is considerably higher on Monday and the day when the natural gas storage report is released. Both the “Monday effect” and the “storage announcement effect” can be driven by weather. Furthermore, the inclusion of weather shock and storage surprise variables in the GARCH model reduces volatility persistence by about forty percent. This later result further corroborates the importance of these fundamental factors in determining volatility but also indicates that a large portion of volatility remains unexplained by the fundamentals.

Chapter IV analyzes market power issues in a deregulated electricity market ---- the balancing energy market in Texas. I compute the inverse of the residual demand elasticity for the largest two firms during the peak hour of 18:00-19:00 from 2002 to 2004. There are two main findings. First, the firm with a higher stake in the balancing market has higher market power. Second, the majority of price spikes occur when the residual demand curves facing one of the two largest firms are price-inelastic. The lack of bids from smaller firms appears to contribute to the larger firms' market power. In particular, I find evidence that the disclosure of a bidder's identity by ERCOT when the bid price is above $300/MWh discourages firms from bidding into the market and may have exacerbated price spikes.

V.2 Extensions for Future Research

There are clear avenues to extend the research presented in all three essays in this dissertation. The first essay on investment in the petroleum refining industry can be extended in two distinct directions. The first is to examine how the sign of investment-uncertainty relationship varies with the degree of market power. Under the assumption of constant return to scale, Caballero (1991) shows that the impact of uncertainty on investment depends on the individual firm's demand elasticity. The irreversibility of investment creates an option value only if a firm has market power. A firm facing an infinitely elastic demand curve would never "regret" that it had invested too much in the previous period because its profitability is independent of the capital stock. Hence the option value of “wait-and-see” diminishes and the positive effect of uncertainty dominates. Using our refining data, we can test whether the uncertainty effect differs between larger firms, which presumably have higher market power, and smaller firms which are more likely to operate as a competitive fringe. A second direction for future research is to empirically investigate how environmental regulations affect the capital adjustment process in the refining industry. Petroleum refining is one of the heavy polluting industries that are strictly monitored by the Environmental Protection Agency (EPA). According to a ranking of 18 air emitting industries by the EPA, petroleum refining was the first for volatile organic compounds (VOC), first for sulfur dioxides (SO2), second for nitrogen oxides (NOx), and fourth for carbon monoxide (CO). How the costs of complying with the environmental regulations alter the capital adjustment process is an interesting empirical question.

A natural extension to the second essay “Weather, Storage, and Natural Gas Price Dynamics: Fundamentals and Volatility” is to perform an out-of-sample forecast using data beyond 2000. The incorporation of weather information into a volatility model should lead to an improvement in forecasting performance.

The third essay on Texas electricity market can have a number of extensions. The first is to construct firm-level marginal cost data and perform a neo-empirical industrial organization type analysis. The purpose here is to test whether firms’ joint behavior is consistent with perfect competition, Cournot competition, or tacit collusion. The second is to investigate firms’ pricing and bidding behavior in ancillary service markets. Ancillary services in electricity markets usually refer to four types of capacity reserves: regulation-up, regulation-down, spinning reserve, and non-spinning reserve. These services are necessary for the reliability of electric power network. Typically a firm bidding in the energy (power) market has obligations to either self-provide or procure ancillary services from the market. Because providing ancillary services represents an opportunity cost of producing energy for a power generator, understanding firms' bidding behavior in the ancillary service markets could also provide useful insight to understanding the bidding behavior in energy market. To date, the literature in this area has focused on strategic bidding and market power issues in the energy market, but little research has been done in the ancillary service markets.

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