# Risk Management and Firm Value:

# Evidence from Weather Derivatives [*]

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This paper examines the impact of financial innovation on firm value, investment, and financing decisions. More specifically, we examine the effect of the introduction of weather derivatives on electric and gas utilities, arguably some of the most weather-exposed businesses in the economy. Weather derivatives were introduced in 1997 to help firms manage their weather-related risk exposure. We derive instruments for weather derivative use based on historical (pre-1997) weather exposure. Intuitively, firms whose cash flows have historically fluctuated with changing weather conditions are, relative to other firms, more likely to use weather derivatives once they become available, irrespective of their investment opportunities. Using data from U.S. energy firms, we find that weather derivatives lead to higher market valuations, investments, and leverage. Overall, our results demonstrate that financial innovation can significantly affect firm outcomes and that risk management meaningfully affects valuation, investments, and financing decisions.

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*"Mother Nature is business's biggest saboteur"*[1]

*"Whatever the weather, it's no excuse to lose money"*[2]

A distinctive feature of modern societies is their ability to understand and control risks (Bernstein, 1996). Progress, however, does not necessarily eliminate risk exposure. As argued by Arrow (1965), "nothing is more obvious than the universality of risks in the economic system." Economic development has, nonetheless, eased the process of shifting or trading risks. From the forward contracts in the Bible to exotic financial derivatives, financial innovation has facilitated risk management.[3]

The relevance of risk management to firm value is, nevertheless, suspect. While investors are exposed to uncertain payoffs, portfolio formation á la Markowitz (1952) allows them to diversify all but market-wide risks. As Modigliani and Miller (1958) (henceforth MM) have long stressed, investors assign higher valuations to firms with positive net present value (NPV) projects but do not assign a premium for hedged profits that they can themselves, replicate through trading. Hedging, a pure financial transaction is – at best – a zero NPV project. This logic suggests that managers should focus on pursuing valuable investments and not on managing risks.

This invariance result, however, stands in sharp contrast to the prominence of risk management in practice and the rapid growth in financial innovation (Miller, 1986; Tufano, 2003). According to the Wharton-Chase Derivative Survey, nearly 60 percent of large firms hedge with derivatives (Bodnar, Hayt, and Marston, 1996). Furthermore, derivative markets are larger than the U.S. stock market capitalization (Office of the Comptroller of the Currency, 2007).

The MM intuition is nonetheless helpful in evaluating hedging decisions. That is, in order to affect value, firms need to be facing market frictions, such as, transaction costs, informational asymmetries, or distorting taxes that are alleviated by hedging (Mayers and Smith, 1982; Stulz, 1984; Smith and Stulz, 1985; Froot, Scharfstein, and Stein, 1993; DeMarzo and Duffie, 1995; Leland, 1998; Graham and Rogers, 2002; among others). Consistent with these ideas, recent empirical evidence highlights the importance of risk management for firm value. Allayannis and Weston (2001), Carter, Rogers, and Simkins (2006), MacKay and Moeller (2007), Berrospide, Purnanandam, and Rajan (2007), and Bartram, Brown, and Conrad (2009), among others, show that hedging is correlated with higher market valuations.[4]

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[1] *CFO Magazine*, April 1st, 2005.
[2] *Financial Times*, September 17th, 2003.
[3] The book of Genesis, Chapter 29 describes a forward transaction between Jacob and Laban, his eventual father-in-law (Chance, 1998). Similarly, Swan (2000) traces the use of derivatives to forward transactions in Ancient Mesopotamia, circa 1750 B. C.
[4] Guay and Kothari (2003), in contrast, find evidence that questions the relevance of hedging for firm value, and Jin and Jorion (2006) document insignificant effects of risk management on valuation.

The main objective of this paper is to estimate the direct effect of risk management on firm value, investment, and capital structure decisions. Identifying such effects is empirically challenging because firms do not randomly select their hedging policies. To overcome those inference constraints, we examine the impact of risk management on firms' behavior using a financial innovation approach. More specifically, we test whether firm value, investment, and capital structure decisions change with the introduction of weather derivatives.

Weather derivatives are financial instruments whose payoffs are contingent on weather conditions. Changing weather conditions are a textbook example of a risk-exposure that is both significant and largely outside management's control (Stulz, 2003). Yet, until recently formal markets for weather exposure did not exist.[5] Weather derivatives were introduced in 1997 to help firms manage such weather-related exposures.

To test whether completing the weather exposure market affected decision making, we focus on electric and gas utilities, some of the most weather-sensitive businesses in the economy. Heating and cooling demand variation is tightly linked to changes in weather conditions. Moreover, medium and long term weather predictions are difficult to make.[6] Not surprisingly, energy firms widely recognize the weather as an important risk factor.[7] Similarly, survey data indicates that nearly 70 percent of the end users of weather derivatives are energy firms.[8]

To identify the effect of weather derivatives, we rank utilities as a function of their pre-1997 weather exposure. Intuitively, while all firms potentially benefit from hedging, we expect that those firms whose cash flows have historically fluctuated with changing weather conditions will be prone to using weather derivatives after 1997, irrespective of their investment opportunities. Econometrically, we use pre-1997 weather exposure rankings as instrumental variables (IVs) for the use of weather derivatives in the post-1997 period. Furthermore, such variation is likely to isolate the insurance, as opposed to the speculative, demand for derivatives.[9]

To pursue our empirical tests, we use financial data from COMPUSTAT, weather information from the National Oceanic and Atmospheric Administration (NOAA), and hand-collected information on the use of financial derivatives since 1997. Our sample includes information on 203 U.S. utilities.

[5] See Roll (1984), for a description of a market that pre-dates weather derivatives, and that closely tracks weather surprises in a single U.S. location.

[6] Einstein's (1941) famous quote, "one need only think of the weather, in which case prediction even for a few days ahead is impossible," which refers to the complexity of meteorological events, illustrates the point.

[7] Over 95 percent of our sample firms state that changing weather conditions are an important factor influencing their annual or quarterly results.

[8] Weather Risk Management Association (2005).

[9] For evidence on speculation with derivatives, see for example, Géczy, Minton, and Schrand (2007).

The key weather variables of interest in the energy sector are cooling, heating, and energy degree days (CDD, HDD, and EDD, respectively). CDD and HDD values track temperature deviations above and below 65°F, respectively.[10] CDD (HDD) values seek to capture cooling (heating) demand. EDD is the sum of CDD plus HDD, and proxies for total energy demand.

We begin our analysis by verifying that for our sample firms, moderate weather realizations significantly affect operating results. We find that mild relative to normal weather levels are correlated with significantly lower revenues and profits. Interestingly, when we divide our sample firms into equal-sized quartiles based on proxies for weather exposure, we uncover substantial heterogeneity in response to mild weather shocks. In particular, while most firms are unaffected by mild weather realizations, firms in the top weather-exposure quartiles exhibit dramatic declines in revenue.

The proxies for pre-1997 weather exposure that we use are based on (i) revenue volatility or (ii) weather-induced volatility. Weather-induced volatility is defined as the product of the sensitivity of revenue to changes in weather variables (CDD, HDD, and EDD) and its standard deviation. Using those weather exposure measures, we test for (a) the effect of weather risk on value, investment, and financing decisions in the absence of weather derivatives, and (b) the impact of weather derivatives on these outcome variables. We find four main results.

First, in the absence of weather derivatives, weather-exposed firms exhibit significantly lower valuations and pursue more conservative operating and financing policies than other firms. Our estimates suggest a value gap for firms in the highest weather-exposure quartiles of around four percent. Also, we find that weather-exposed firms use less operating and financial leverage. Specifically, they rarely use nuclear facilities to generate electricity; they rely less on debt financing and pay fewer dividends than other firms.

Second, we show that pre-1997 weather exposure is a strong predictor of weather derivative use after 1997. Firms in the top weather exposure quartile are two to three times more likely to use weather derivatives after 1997 than the least weather-exposed firms. In other words, we provide evidence that those firms that we would expect to use derivatives for hedging reasons are indeed more likely to rely on weather derivatives.

[10] More specifically, a cooling degree day is given for each degree that the daily mean temperature exceeds 65°F; CDD is zero if the daily mean temperature is below 65°F. The reference value of 65°F is used because historically, when the outside temperature is equal to this value, cooling (electricity) demand is low. Demand increases as daily temperatures exceed 65°F. Similarly, a heating degree day is given for each degree that the daily mean temperature falls below 65°F; HDD is zero if the daily mean temperature is above 65°F. Demand for heating (natural gas) declines above 65°F and increases as daily temperatures fall below this value. Energy degree days are the sum of cooling degree days and heating degree days, and measure all deviation from 65°F to capture extreme hot and cold weather conditions.

Third, we show that the introduction of weather derivatives led to a substantial increase in firm value. The impact of hedging on market-to-book ratios is economically large and statistically robust. While the IV estimates are at least 20 percent, we cannot reject that the causal effect of risk-management on market-to-book ratios is in the 5 to 10 percent level, as previously reported in the literature. We also assess if the reported results can be alternatively explained by global warming trends, deregulation, or the use of other risk management tools, such as interest rate or natural gas derivatives. Yet, after controlling for those effects, we find robust evidence that weather hedging led to higher market valuations.

Fourth, we find that hedging allows firms to increase investment and to use more aggressive financing policies. Such results are consistent with the idea that smooth cash flows allow firms to invest more, either by relaxing borrowing constraints or by allowing firms to pursue valuable investment projects in low cash flow states. Similarly, they provide evidence that left-tail cash flow realizations can limit debt capacity due to distress costs or other frictions.

Overall, our results demonstrate that risk management has a meaningful impact on valuation, investments, and financing decisions. Our estimates on the value of risk management, both based on cross-sectional and in time-series tests, are consistent with those reported by Allayannis and Weston (2001). Our results on hedging and debt capacity are also in line with Smith and Stulz (1985) and Leland (1998). Moreover, the investment effects reported are consistent with Froot, Scharfstein, and Stein (1993).

Finally, our focus on financial innovation to identify the value of risk management is, to the best of our knowledge, new in corporate finance literature.[11] This approach is potentially promising for a number of reasons. First, it provides an arguably exogenous variation in the cost of hedging. Second, it tightens the link between *specific* risk exposures and hedging instruments, allowing researchers to understand which specific policies are affected by risk management. Finally, the results provide a rough estimate of the value of financial innovation, which is an important and controversial topic in the literature.

The rest of the paper is organized as follows. Section I describes the weather exposure of energy firms and the various operating and financial policies that can help them mitigate such risks. Section II presents our empirical strategy and predictions. Section III describes the data. Section IV examines the impact of mild weather realizations on operating results. Section V examines the importance of weather risk exposure in the absence of weather derivatives. Section VI presents the main results of the paper. Section VII concludes.

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[11] Our approach is closest to Conrad (1989), who examines the effect of the introduction of option contracts on the returns of the underlying securities. She, however, does not analyze a market-wide innovation, nor she examines the consequence of completing a market on capital structure decisions.

## I. *Risk Management and Energy Utilities*

### *I. A. Weather Risk Management and Energy Utilities*

According to the National Research Council (NCR), 25 percent of the U.S. gross domestic product is weather- and climate-sensitive (NCR, 2003). In their report, the NCR identifies the energy industry as one of the most sensitive sectors in the economy.

Within the energy industry, electric and natural gas utilities are subject to substantial weather exposure. Heating and cooling demands are tightly linked to changes in weather conditions.[12] Furthermore, regulated utilities are often required to serve such changing demand at fixed prices. As a result, it is not surprising that weather events have been frequently reported to significantly affect the cash flows of energy firms.[13] In lieu of weather exposure, energy utilities face the dilemma of determining whether to engage in active risk management and if so, deciding which hedging tools are appropriate to mitigate their weather exposures.

Prior studies have stressed several rationales for risk management. Smith and Stulz (1985) and Leland (1998) emphasize the tax benefits from hedging. Froot, Scharfstein, and Stein (1993) show that risk management can alleviate investment distortions when external financing is costly. Adam, Dasgupta, and Titman (2007) demonstrate the value of hedging as a strategic tool in competitive settings. Stulz (1984), in contrast, shows that risk-averse managers with substantial holdings in their own firm may prefer to hedge firm value.

In terms of tools, utilities can rely on a long array of hedging instruments. Several widely available tools, however, are effective at hedging price or cost risks, but not volumetric risk exposure (Brockett, Wang, and Yang, 2005). Such concerns, limit the list of admissible risk management tools as variation in the weather is primarily a quantity risk exposure.

On the operational side, firms can, for example, diversify their weather exposure by investing in several geographic regions that differ in their weather patterns. While this approach is potentially attractive for hedging weather risks, it faces an important tradeoff. Economies of scale are usually achieved by expanding business activities in nearby communities, which by construction tend to exhibit similar weather conditions.

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[12] In this paper, we focus on non-catastrophic weather exposure that result from frequent but relatively low impact events, such as heat waves or extreme cold conditions, rather than on catastrophic but infrequent events.

[13] Abnormally high (low) cooling degree days have, for example, been reported to boost (harm) the cash flows of the Florida Power and Light Group (Midwest Resources Inc). Source: *The Palm Beach Post*, July 16, 1998 (*The Omaha World-Herald*, November 3, 1992). On the other end, high (low) heating degree days have been reported to strengthen (weaken) the cash-flows of Dominion Resources Inc. (Atmos Energy Corp). Source: *Dow Jones News* Service, April 15, 1994 (*The Dallas Morning News*, May 11, 1989).

Utilities on the other hand, may participate simultaneously in the provision of electricity and natural gas services. Electricity sales tend to be positively correlated with warm temperatures, while natural gas sales tend to be negatively correlated with them, providing firms with a natural hedge. Such strategy, however, may be at least partially ineffective in settings where the negative correlation between electricity and natural gas sales is less than perfect. Other operating strategies include the use of flexible generation technologies or the ability to store or trade energy using for example, long-term contracts. There are, however, some barriers to such approaches. For example, electricity cannot be efficiently stored. Natural gas can be stored, but the weather related risk-shifting opportunities are limited by two important forces. First, transportation costs make natural gas a regional North American market. Second, even in the U.S., monopolistic and congested gas pipelines lead to a collection of imperfectly integrated regional markets (Energy Information Administration, 2002)

Energy utilities may alternatively use their capital structure to manage their weather exposure. Firms that are significantly exposed to weather risks may limit their leverage or hold higher levels of cash to limit their earnings volatility and protect their valuable investments. Lower leverage or higher cash holdings, however, may limit the firm's ability to capture the tax or the disciplining benefits of debt, leading to significant value effects.

Utilities may also use energy derivatives to manage their weather exposure. For example, energy derivatives allow firms to sell production forward, potentially alleviating the negative consequences of low energy demand. In the U.S., natural gas futures are widely used among utilities. These contracts, however, face an important drawback: they are not contingent on the weather, and as a result, provide only imperfect hedges against weather risks. Electricity derivatives are, in contrast, virtually nonexistent. [14]

Energy utilities can alternatively hedge their climate risk using weather derivatives. Weather derivatives are financial instruments whose payoffs are contingent on weather conditions. Given the interest of energy utilities in tracking energy demand, it is revealing that the majority of weather derivatives are, in fact, linked to HDD or CDD values.[15] That is, they track deviations in temperatures from a reference value of 65 degrees Fahrenheit (°F) rather than mean temperatures. Such reference is used because at 65°F, both cooling and heating demand is low, yet cooling and heating demand are tightly linked to CDD and HDD values, respectively. [16]

[14] See Energy Information Administration (2002) for a review on these risk management tools.

[15] Garman, Blanco, and Erickson (2000).

[16] $CDD = \max\,[0, \frac{T_{max}+T_{min}}{2} - 65°]$ and $HDD = \max\,[0, 65° - \frac{T_{max}+T_{min}}{2}]$. As an example, if the average temperature is 75°F, the corresponding CDD value for the day is 10. If a months' average daily temperature is consistently 75°F, the corresponding monthly CDD value is 300.

Weather derivatives specify five characteristics: (1) the underlying weather index, i.e. HDD, etc; (2) the period of time over which the index accumulates, i.e. month, season; (3) the weather station, which is typically located in a major city; (4) the dollar value of each tick size, i.e., the amount to be paid per unit of cooling or heating degree days; and (5) the strike price, which is indexed as the number of degree days in a period of time.

The first weather derivative transaction occurred in 1997.[17] Since then, weather derivatives have been traded over-the-counter (OTC) and starting in 1999, the CME has offered exchange-traded futures and options. The CME offers monthly and seasonal CDD and HDD contracts for 42 cities around the world. According to the exchange, weather derivatives are one of the fastest growing derivative sectors (CME, 2005). The OTC market, in contrast, offers options and swap contracts that are tailored to the needs of individual firms (Considine, 2000).

While weather derivatives are ideally suited to hedge weather risks, they also face important tradeoffs (Brockett, *et. al.*, 2005). Exchanged-based contracts are attractive because they entail lower transaction costs and counterparty default risks. Yet, hedging energy firms may be subject to basis risks, as the traded weather indexes may not perfectly track the firms' weather exposure. OTC derivatives, in contrast, minimize basis risk but lead to higher transaction costs and credit risk exposures.

*I. B. Weather Derivatives: Example*

We illustrate the type of contracts that energy firms can write in the presence of weather risks with the following example from KeySpan Corp's 2006 annual report:

> "In 2006, we entered into heating-degree day put options to mitigate the effect of fluctuations from normal weather on KEDNE's financial position and cash flows for the 2006/2007 winter heating season - November 2006 through March 2007. These put options will pay KeySpan up to $37,500 per heating degree day when the actual temperature is below 4,159 heating degree days, or approximately 5 percent warmer than normal, based on the most recent 20-year average for normal weather. The maximum amount KeySpan will receive on these purchased put options is $15 million. The net premium cost for these options is $1.7 million and will be amortized over the heating season. Since weather was warmer than normal during the fourth quarter of 2006, KeySpan recorded a $9.1 million benefit to earnings associated with the weather derivative."

KeySpan Corp, now National Grid, provides gas and electric services in the New York area. In this contract, the weather variable is HDD, the accumulation period is November 2006 to March 2007, the tick size is $37,000, and the settlement level is 4,159 (seasonal cumulative HDD). The realized HDD value for the year was 3,913, which gave the contract a payoff at maturity date of $9.1 million.

[17] *Houston Chronicle*, November 7th, 1997.

Following this example, the strategic use of weather derivatives allows energy firms to eliminate left tail events that are triggered by specific weather realizations. To the extent that negative cash flow events distort investment or financing decisions, hedging using weather derivatives can help firms overcome market frictions and potentially enhance firm value.

### *I. C. Quantity Risk and Informational Problems*

As previously stressed, weather derivatives are unique in helping firms manage their weather related quantity risk exposure. Beyond utilities, quantity risk may, in some settings, be more relevant for a hedging program than managing price risk. However, a major practical barrier to insuring and therefore testing for the importance of volumetric risk insurance results from information asymmetries. Firms tend to buy insurance whenever they expect a low-quantity realization, leading to significant adverse selection problems. Similarly, insured firms may change their behavior, generating moral hazard concerns. Given that firms typically possess superior information with regard to quantity exposures, volumetric insurance contracts are rare.[18]

A clear advantage of weather-based insurance contracts is that information asymmetry concerns are a minor obstacle for their development. First, it is difficult to argue that a given energy utility has superior weather forecasting abilities relative to other market participants. Likewise, the actions of energy firms are unlikely to affect weather realizations. As a result, weather derivatives provide a near ideal laboratory to test for the importance of quantity risk on firm outcomes.

In sum, electric and gas utilities with significant weather-related volumetric risk exposure can mitigate those risks using a long list of real and financial tools. Hedging weather exposure with weather derivatives is a relatively new practice that results from financial innovation in the late nineties. Interestingly, these derivatives are ideally designed to address the volumetric risk facing energy utilities. Furthermore, unlike other insurance products, weather derivatives face minor information asymmetry concerns. In the following sections, we empirically test whether the introduction of weather derivatives had a meaningful impact on firm outcomes.

## *II. EMPIRICAL STRATEGY*

In this section, we describe the empirical challenges faced when identifying the causal effect of derivatives, and explain our empirical strategy to overcome such inference problems.

[18] Not surprisingly, cost-related contracts (based on interest rate, exchange rates, etc) are relatively more common than those based on volumetric risks.

*II. A. Empirical Challenges*

A common approach to examining the effect of risk management on firms' outcomes is to use cross-sectional specifications that compare valuation, investment, or capital structure decisions as a function of hedging decisions. For example:

$$y_{it} = \alpha + \beta * hedge_{it} + \psi_{\chi} X_{it} + \varepsilon_{it} \qquad (1)$$

where $y_{it}$ is the outcome variable of interest for firm $i$ at time $t$. $hedge_{it}$ is an indicator variable that is equal to one if the firm uses derivatives and zero otherwise. If hedging is valuable for firms' outcomes, $\beta$ would be expected to be positive and statistically different from zero.

In terms of inference, (1) provides an unbiased estimate of the effect of hedging whenever the use of derivatives is uncorrelated with other determinants of the key outcome variable $y_{it}$. Yet, a large number of studies starting with Nance, Smith, and Smithson (1993) have, for example, reported a positive and robust link between firm size and the use of derivatives. Perhaps, more problematic is the correlation between derivative use and firms' risk or investment profile, which has been documented in the literature. For example, Haushalter (2000) and Geczy et al. (2006) show that firms with high leverage, low bond ratings and low dividend yields are more likely to hedge than otherwise similar firms. Similarly, Geczy et al. (1997) show that firms with better growth opportunities rely more on derivatives than other firms.

Whenever hedging decisions are not random and the econometrician can only rely on imperfect controls, cross-sectional OLS or propensity score based estimates are subject to inference concerns. In consequence, finding that $\beta$ is significantly different from zero may be alternatively explained by: (a) the direct effect of derivatives, (b) the fact that higher valued firms may hedge even if risk management does not affect outcomes (ex. due to fixed costs in hedging), (c) difficult to control for variables (ex. omitted) that drive, for example, both higher valuations and the use of derivatives, or (d) a combination of (a) to (c). In all cases other than (a), it is difficult to interpret $\beta$ as a direct estimate of the effect of hedging on real or financial outcomes.

An alternative way to describe the identification challenges described above is that when hedging is not random, we implicitly require a rationale for why two otherwise identical firms would differ in their hedging decisions, even when risk management can meaningfully affect their businesses. Furthermore, we need such an argument to be unrelated to the firms' investment opportunities. Those assumptions, however, are difficult to meet in practice.

*II. B. Identification Strategy*

To identify the effect of derivatives on firm outcomes, an arguably exogenous source of variation in hedging decisions is required. In this paper, we focus on the effect of weather derivatives on utility firms and exploit variation in weather derivative use that results from both time-series and cross-sectional sources as explained below:

<ins>Time Series Variation</ins>

Because weather derivatives were introduced in 1997, they provide us with time-series variation in the use of derivatives. Such variation is attractive because it allows us to use *within-firm* specifications to test for the effect of risk management on value. Formally, we can estimate:

$$y_{it} = \alpha + \beta * hedge_{it} + \eta_i + \psi_\chi X_{it} + \varepsilon_{it} \qquad (2)$$

where $\eta_i$ are firm-fixed effects. Given that (2) captures within-firm variation, $\beta$ is no longer affected by time-invariant firm characteristics, even if omitted. $\beta$ is, however, subject to time-varying omitted variable and endogeneity concerns. For example, firms with deteriorating business conditions may be inclined to hedge. To the extent that the econometrician cannot ascertain why it is that some firms decide to change their hedging strategies over time while others remain exposed to weather risk, the estimates of $\beta$ remain difficult to interpret as causal.

<ins>Time Series - Cross Sectional Variation: Pre-1997 Weather Exposure (“Reduced Form”)</ins>

An alternative test for the effect of weather derivatives is to focus, not on actual or endogenous hedging decisions, but instead on those firms who from an *ex-ante* perspective might be expected to benefit from financial innovation. Weather derivatives are, in principle, beneficial for *weather-exposed* firms. Weather derivatives allow weather-sensitive firms to manage their weather exposure, leaving other, non-weather exposed firms unaffected.

In an ideal setting, the econometrician would anticipate which firms face future exposures to weather risks and would therefore use such information in her empirical tests. In the absence of such data, however, we can rely on a number of proxy variables that are based on historical exposure information. We then use such proxies in our empirical tests.

Formally, we estimate the following specification:

$$y_{it} = \alpha + \gamma * weatherexp_i * post_t + \delta * post_t + \eta_i + \psi_\chi X_{it} + \varepsilon_{it} \qquad (3)$$

where $weatherexp_i$ captures ex-ante (pre-1997) or historical sensitivity to weather fluctuations. $weatherexp_i$ also proxies for the potential gains from hedging with weather derivatives after 1997. $post_t$ is an indicator variable that is equal to one after 1997 and zero otherwise. The coefficient of interest is $\gamma$. If weather derivatives benefit weather-exposed firms, $\gamma$ would be expected to be positive and significant. Note that to estimate (3), we do not require information on actual weather derivatives usage. Yet this formulation implicitly assumes that weather-exposed firms are more likely to use weather derivatives relative to their peers.

In terms of inference, there are two key identifying assumptions in (3). First, weather exposure predicts weather derivative usage. Second, other than through the effect of hedging, weather-exposed firms have similar investment opportunities as other businesses. If those assumptions are met, $\gamma$ is no longer subject to endogeneity or omitted variables concerns. In such a case, $\gamma$ captures the "reduced form" estimate of the effect of weather derivatives on outcomes.

Instrumental Variables

To obtain the causal effect of weather derivatives, we need to scale the magnitude of the reduced form coefficient by the variation in weather derivative use that is generated by the ex-ante weather exposure variables. This two-stage least-squares (2SLS) procedure is, essentially, an instrumental variables (IV) estimation where the ex-ante weather exposure control acts as an instrument for weather derivative use. The first-state specification is:

$$wderiv_{it} = b * weatherexp_i * post + d * post + \eta_i + a_\chi X_{it} + e_{it}. \tag{4}$$

From (4), we predict the use of weather derivatives using *only* information about this ex-ante weather exposure variable, i.e. $\widehat{wderiv}_{it}$. Note that $wderiv_{it}$ is zero for the pre-1997 period for all firms; thereafter, it takes the value of one for weather derivative users. Also, even though $wderiv_{it}$ is a dichotomous variable, we estimate (4) using an OLS specification, since a probit or a logit first-stage can harm the consistency of the IV estimates (Angrist and Krueger, 2001).

We then use $\widehat{wderiv}_{it}$ to test for the effect of weather derivatives on firm value, investment, or capital structure decisions. Formally:

$$y_{it} = \alpha + \beta_{wderiv} * \widehat{wderiv}_{it} + \psi_\chi X_{it} + \delta * post_t + \eta_i + \varepsilon_{it} \tag{5}$$

In a value specification, for example, the estimated coefficient $\beta_{wderiv}$ captures the impact of weather derivatives on firm value. Under the above-described assumptions, $\beta_{wderiv}$ provides an unbiased estimate of the effect of hedging on firm outcomes.

*II. C. Implementation: Estimating Weather Exposure before 1997*

Electric and natural gas utilities provide a near-ideal setting to estimate the impact of weather derivatives. The cash flows of these energy firms are significantly exposed to variation in climate conditions. Weather data is readily available. Furthermore, energy rates were historically regulated. In consequence, a significant fraction of within-year variation in revenue reflects *quantity* rather than price fluctuations. To the extent that energy sales respond to temperature variation, quantity risk is closely tracked by weather derivatives.

As previously discussed, energy firms may engage in various operational, capital structure, or other financial strategies to manage their weather risk exposure. Yet any residual exposure would translate into potentially detrimental revenue volatility. We, therefore, measure the potential gains from using weather derivatives based on the following proxies for weather-exposure:

(a) <u>Volatility (quarterly) of revenue to assets before 1997</u>. If changing weather conditions are the primary determinant of the quantity (units) of energy sold and rates are relatively stable over time, quarterly (seasonal) weather would tend to be a primary determinant of revenue volatility. As a result, pre-1997 revenue volatility would be a relevant predictor of the use of weather derivatives after 1997. Revenue volatility is attractive because it is straightforward to compute, and also because it captures the total potential to hedge. However, it includes variation in cash flows that may reflect other confounding variables, such as the quality of the management team or the intensity of the firms' investment program, etc., which may not provide us with predictive power in the post-1997 use of weather derivatives.

(b) <u>Weather-induced volatility (quarterly) of revenue to assets before 1997</u>. To specifically focus on weather volatility, we follow two steps:

First, for each firm, we estimate the sensitivity of revenue to the quarterly level of cooling, heating, or energy degree days before 1997 using the following specification:

$$revassets_{it} = \alpha_i + \beta_i * DD_{it} + \gamma_i * ln(assets_{it}) + \varepsilon_t \qquad (6)$$

where $revassets_{it}$ is the quarterly revenue to assets ratio. $DD_{it}$ is the relevant weather measure of energy, cooling, or heating degree days (EDD, CDD, and HDD, respectively) measured at the firm level. We control for the level of assets to isolate weather-driven effects. To avoid multi-collinearity concerns, we estimate separate regressions for each of the weather-related variables. $\beta_i^{EDD}, \beta_i^{HDD},$ and $\beta_i^{CDD}$ measure, respectively, the sensitivity of revenue to variation in EDD, CDD, and HDD, respectively. We herein refer to those estimates as "weather betas." Notice that energy firms can potentially gain from hedging weather risks irrespective of the sign of those weather betas. In consequence, the absolute value of weather betas is informative about the firms' hedging opportunities.

Second, to obtain an estimate of the relevant revenue volatility that is attributable to weather fluctuations, we multiply the estimated weather betas by the relevant historical standard deviation. For hedging purposes, the meaningful weather exposure is the product of the absolute value of weather betas ($|\beta_i^{EDD}|,$ etc) and the degree of variation in each variable ($\sigma_i^{EDD}$, etc).

When estimated before 1997, $|\beta_i^{EDD}| * \sigma_i^{EDD}$, for example, captures the historical weather-induced volatility of revenue that results from EDD. A crucial assumption in this paper is that this pre-1997 weather-induced energy, cooling, and heating degree day volatility predicts the relevant post-1997 weather exposures. We anticipate that such exposure would induce firms to use derivatives as they become available, irrespective of their post-1997 investment opportunities.

### *II. D. Predictions*

Based on the above-described specifications, we test four predictions:

**1. Annual weather variation affects the operating results of energy firms, particularly those that are classified as weather exposed.** If the cash flows of energy firms are subject to weather-induced quantity risk, deviations from normal weather conditions are expected to affect revenue and operating margins. Furthermore, to the extent that weather-exposure measures provide useful rankings of actual weather risk exposure, we would expect the effect of extreme weather realizations to be larger (in absolute value) for those firms with higher weather exposure rankings.

**2. In the absence of weather derivatives, weather exposed firms are less valuable and more conservative in their investment and capital structure decisions than other firms.** Weather exposure may affect firm value whenever those risks are not fully diversifiable or if their presence limits the firms' ability to overcome market imperfections. For example, idiosyncratic weather-induced variation in cash flows can limit debt capacity (Smith and Stulz, 1985; Leland, 1998) or prevent valuable investments (Froot et al., 1993).

**3. After the introduction of weather derivatives, weather exposed firms are more likely to use weather derivatives.** Firms whose pre-1997 cash-flows were subject to weather fluctuations are more likely to benefit from hedging. As a result, they are expected to be more likely to use weather derivatives relative to other firms.

**4. The introduction of weather derivatives leads to a decline in weather-driven differences in value.** To the extent that left tail weather-driven cash flow realizations limit debt capacity or prevent firms from undertaking valuable investment projects, we expect weather-related value differences to decline as hedging allows firms to manage their weather exposure. In other words, risk sharing gains are expected to be larger for firms with greater weather exposure.

The data used for testing these hypotheses are described next.

## *III. Data Description*

### *III.A. Financial and Market Information*

To test for the effect of weather risk on energy utilities, we use data from COMPUSTAT firms whose primary business is in the distribution and generation of electricity and natural gas services (Standard Industrial Classification (SIC) codes 4911, 4923 4924, 4931, and 4932). Because of the availability of weather data, we focus on U.S. firms. Given our interest in estimating pre-1997 volatility and weather exposure measures, we focus on those firms with matching quarterly data for at least 10 years before the introduction of weather derivatives. We arrive at a final sample of 203 firms and up-to 8,161 firm-year observations.[19]

Summary statistics are presented in Table I, Panel A. To facilitate comparison across years, we report information in constant 2008 dollars (Consumer Price Index, adjusted, 2008=100). Average (median) total assets are $5.2 (2.7) billion. Mean (median) revenue is $2 ($1.1) billion. The mean (median) market capitalization (common shares outstanding times their closing price) is $2.3 ($1.1) billion. As expected, utilities are larger than the average COMPUSTAT firm.

We follow the pre-existing literature in using market-to-book (M-B) ratios as a measure of firm value. M-B ratios are a proxy for Tobin's Q (Tobin, 1969), the market value of assets relative to their replacement costs. M-B ratios are calculated as the ratio of the sum of the book value of assets, plus the market value of common equity, minus the sum of the book value of common equity and deferred taxes all divided by the book value of assets. The average market-to-book of sample firms is 1.08, with a standard deviation of 0.21.

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[19] Selected variables such as market capitalization or deferred taxes are not available for all firm-years.

Utilities are the textbook example of firms with tangible assets and stable cash flows. As a result, it is unsurprising that they use substantial amounts of leverage. In Table I, Panel A, we report that mean and median book leverage (sum of long-term debt plus debt in current liabilities) relative to assets for sample firms are both 0.41, with a standard deviation of 0.09. Net debt to assets ratios (book leverage minus cash and short-term investments) are on average 0.38 (median 0.37). The average and median operating profitability (operating income before depreciation) to total assets ratio (OROA) is 0.12. OROA's standard deviation is 2.6 percent, which is relatively low and consistent with the fact that utilities have historically been regulated.

Table I, Panel A also includes information on investment and dividend decisions. The mean (median) ratio of capital expenditures to assets is 0.074 (0.067). However, capital expenditure information is not available for all firm-year observations. The growth rate of assets or net investment rate is, in contrast, consistently available, with an average (median) value of 0.072 (0.061). The fraction of energy firms with nuclear plants is 0.37. This indicator variable is constructed using the COMPUSTAT industry-specific files. This information is only consistently reported until 1994. Lastly, the average ratio of dividends (common) over assets is 0.03.

*III.B. Weather Data*

We obtain weather data for all 344 climate divisions in the contiguous U.S. from the National Oceanic and Atmospheric Administration (NOAA). NOAA has monthly temperatures, cooling and heating degree day data from 1895 to the present. We also compute energy degree days as the sum of CDD and HDD values. To match firms with weather sites, we use latitude and longitude information on the location of the firms' main business, and of each of the weather stations. For each firm, we find the closest climate division in terms of their geodesic distance and use its weather information.[20] NOAA reports the latitude and longitude data of all climate divisions. COMPUSTAT reports the firms' zip codes. To determine the approximate latitude and longitude location of each zip code, we rely on data from the U.S. Census Bureau.[21]

The annual weather information is summarized in Table I, Panel A. The annual mean (median) CDD value is 1,040 (809), with substantial variation around this average (standard variation of 809 degree days). The mean (median) annual HDD level for the firms in the sample is 5,170 (5,577) with a standard variation of 1,965. Average (median) annual EDD values are 6,210 (6,386) and the EDD standard deviation is 1,381.

[20] See Vincenty (1975) for computing geodesic distances between locations.
[21] http://www.census.gov/geo/www/gazetteer/places2k.html#counties.

*III.C. Information on the Use of Financial Derivatives After 1997*

The final source of data used pertains to the use of financial derivatives in the post-1997 period. We hand-collect data from Securities and Exchange Commission (SEC) filings using the *LexisNexis Academic* application. We use keywords to identify those firms that rely on weather derivatives, as well as those that use natural gas and interest-rate hedging instruments.[22]

While we do not have data on actual derivative exposure by firm, we use indicator variables to classify them as derivative "users" whenever their SEC filings described their exposure or reliance on such contracts. Table I, Panel B reports information for the post-1997 sample or 1,633 firm-year observations. Weather derivatives were used by one quarter of the sample firms (0.249). This usage level suggests that weather derivatives are unlikely to be beneficial for all sample firms and that, following the logic described in the previous section, we can potentially focus on differential exposure to estimate the likely gains from their usage. Natural gas derivatives were used by 57 percent of the sample firms. The fraction of interest rate derivatives users was 0.87. The fact that the latter ratio is the largest is not surprising given the magnitude of the interest-rate swaps markets.

*III.D. Weather Conditions and Energy Units: Average and Regional Variation*

As a first pass on the link between weather conditions and monthly energy sales, Figure 1 plots the 2005 sales of electricity (Panel A) and natural gas (Panel B), and their corresponding average temperatures. To emphasize quantity variation, we report electricity in gigawatts per hour (GWh) and natural gas in million cubic feet (MMcf).

Figure 1, Panel A shows that electricity sales peak during the summer, reflecting the seasonal demand for air conditioning. Panel B shows that natural gas sales peak during the winter months, with a maximum volume in January, reflecting the seasonal heating demand. Figure 1, in Panels A and B, shows a strong correlation between monthly average temperatures and energy sales in units. The correlation is 0.56 and -0.8 for electricity and natural gas, respectively.

Figure 2 provides a graphical justification for the widespread use of CDD and HDD values to proxy for electricity and natural gas demand, respectively. Panel A plots monthly electricity sales relative to the peak August value (August units=100) and the corresponding monthly CDD levels. Beyond the already stressed seasonality of electricity sales, it shows a tight

[22] For each of the weather, natural gas, and interest-rate contracts, we use the following accompanying keywords: derivatives, forwards, futures, hedging, options, and swaps. For example, for interest-rate derivatives, we used "interest-rate derivatives," "interest-rate forwards," "interest-rate futures," "interest-rate hedging" "interest-rate options," and "interest-rate swaps."

correlation between electricity units and CDD values of 0.82. Similarly, the correlation between natural gas units sold (January units=100) and HDD values is 0.88, which is also very high.

In Figure 3, we use data from three non-random states, California, Louisiana, and Montana, to highlight the existence of regional differences in terms of the seasonality of energy sales. Panel A shows that Louisiana's electricity units are highly seasonal. Summer electricity volumes are over 40 percent higher than those in March, which occurs in more than half a dozen states, including, for example, Kansas and Texas. In contrast, Panel B shows that Louisiana's monthly natural gas sales are relatively stable. Figure 3 also shows that Montana energy sales display contrasting patterns: monthly electricity sales are relatively stable while natural gas sales are remarkably seasonal. January natural gas sales were 50 percent higher than those in March and four times July's sales. Other states where summer natural gas sales are less than half than their winter levels include Ohio, Minnesota, Vermont, among others. Lastly, California's energy sales reveal a moderate level of seasonality both for electricity and natural gas sales.

Overall, Figures 1-3 suggest four issues. First, weather variation and energy demand are tightly linked. Second, CDD and HDD values track energy demand more closely than average temperatures. Third, some regions may be more subject to weather-induced variation than others. Finally, the relevant weather and energy sales variables differ around the U.S.

## *IV. Changing weather Conditions and Cash Flow Effects*

To formally test for the effect of changing weather conditions on operating performance, in Table II, we examine the effect of abnormally low energy degree days or "weather shocks" on revenue, profits, investment and payout decisions. The weather shock indicator variable is firm-specific and is set to be one for the lowest quintile of annual EDD observations per firm and zero otherwise (i.e. each firm has one "shock" per five observations). We focus on the effect of mild EDD values to provide a single and simple test that is meaningful independent of a firm's main weather exposures (CDD or HDD). In Table II, we use fixed-effects specifications where we control for year effects and for firm size using the natural logarithm of lagged assets.

Table II, Column I shows that mild weather realizations lead to lower levels of revenue. The effect is statistically significant at the five percent level but modest in economic terms: mild weather leads to a decline of two percent in revenue. Table II, Columns II and III confirm that mild weather negatively affects cash flows in a significant way. Both operating return on assets and the level of operating profits decline when the weather is mild. The effect on profits is also modest. Table II, Columns IV and V, in contrast, cast doubt on the notion that mild weather conditions meaningfully affect dividend or investment decisions.

To explore whether the results reported in Table II are evidence that changing weather conditions have moderate effect on cash flows, or, alternatively, reflect heterogeneous effects across firms, we turn to the weather exposure variables described in Section II, which seek to capture the *un-hedged* volumetric exposure faced by energy firms.

Table III, Panel A provides summary statistics for various measures of weather exposure. The risk measures include (a) revenue volatility (standard deviation of quarterly revenue to assets), (b) CDD, HDD, and EDD betas (absolute value of the estimated coefficient of CDD, HDD, and EDD on revenue to assets) or "weather betas," and (c) CDD, HDD, and EDD weather-induced volatility (weather betas times the relevant historical standard deviation). All measures are estimated using pre-1997 data.

Table III, Panel A provides consistent evidence that the reported exposure measures tend to vary substantially. Mean revenue to assets volatility is 0.024, but it is 0.01 (0.11) in the $10^{th}$ ($90^{th}$) percentile. Weather betas also exhibit substantial dispersion. Average CDD or EDD betas, for example, are 0.9 and 0.3, respectively. Yet the $10^{th}$ and $90^{th}$ ranges are 0.06 and 3.2 for CDD betas and 0.01 to 0.94 for EDD betas. Similarly, weather-induced volatility varies greatly. The $10^{th}$ and $90^{th}$ percentiles are 0.17 and 30.6 for CDDs, 1.62 and 160.7 for HDDs, and 2.3 and 162.4 for EDDs, respectively. While these weather exposure numbers may be difficult to interpret in isolation, the relative ranks that they generate are intuitive: they are orderings of risk exposure.

Interestingly, Table III, Panel B shows that revenue and weather-induced volatility measures are highly correlated. For example, the correlation between revenue and weather volatility is 0.79, 0.93, or 0.90 depending on the weather measure CDD, HDD, or EDD, respectively. Moreover, the CDD-HDD (HDD-EDD) volatility correlation is 0.84 (0.97). Such correlations corroborate that these volatility measures capture weather-induced variation.

In Table IV, we formally test whether the risk exposure measures reported in Table III provide useful information about the weather exposure that energy firms face. In each column, we analyze the effect of one weather risk measure at a time, but we refer to them generically as "quantity risk" measures. In each case, we (a) divide our sample firms in four equally sized groups (quartiles) based on each risk measure, (b) interact each quartile with the firm-specific "shock" variable developed in Table II, and (c) test which quartile exhibits the largest decline in revenue in the presence of a weather shock. As in Table II, all specifications provide fixed-effects estimates and include year and size controls.

Table IV, Column I examines the revenue consequences of mild EDD values for the different quartiles sorted by revenue volatility. The estimated coefficients show that weather shocks generate economically and statistically insignificant effects on the sales of all but the most volatile quartile. For firms in the most volatile quartile, however, weather shocks lead to a drastic decline in revenue of 9.1 percent, significant at the one percent level. Columns II, III, and IV show that ranking weather exposure based on weather betas generates similar results. In each case, the most exposed quartile drives the entire decline in revenue. The estimated coefficients on quartile 4 firms are -6.4, -11.2, and -10.6 for CDD, HDD, and EDD betas, respectively. All are significant at conventional levels.

Table IV, Columns V, VI, and VII show the results of moderate EDD values on firms when we sort them by CDD, HDD, and EDD weather-induced volatility, respectively. As before, the most weather sensitive group exhibits consistently large and robust declines in revenue. Mild EDD values lead to a 9 to 12 percent decline in revenue for the most weather-sensitive firms. These effects are significant at the one percent level.

The results of Table IV show that irrespective of the risk measure used, firms in the highest weather exposure quartile exhibits high cash flow sensitivity to changes in weather conditions. Moreover, the fact that weather variation can have such large effects on energy firms' cash flows confirms the numerous media reports linking abnormally low levels of energy, cooling and heating degree days to significant cash flow variation.

In sum, the results from Tables II and IV provide robust empirical support for prediction 1. Namely, that changing weather conditions meaningfully affect the operating results of utilities. Further, the correlations in Table III and the results in Table IV show that weather exposure can be measured by using revenue or weather-induced volatilities. Finally, the results also suggest that firms with mild weather exposure are able to hedge it even in the absence of weather derivatives. In other words, the fact that only a fraction of firms are subject to cash flow volatility provides information on which firms are expected to be subject to the largest distortions, if any, in terms of value, or investment and capital structure decisions. We turn to those tests next.

## *V. PRE-1997 WEATHER EXPOSURE: VALUE, INVESTMENT, AND CAPITAL STRUCTURE EFFECTS*

### *V. A. Weather Risk in the Absence of Weather Derivatives: Market-to-Book Analysis*

Table V examines the effect of weather exposure on market valuations before 1997. Market value is measured using market-to-book ratios (Columns I to VI) and the natural logarithm of the market value of equity (Columns VII to VIII.)

Given that our measures of weather exposure are time-invariant, we cannot rely on fixed-effects specifications and instead use an array of controls to account for the heterogeneity in firm characteristics. In every specification, we control for firm size (lagged log of total assets), profitability (OROA), and investment opportunities (investment rate). In addition, to account for economy-wide shocks, in Columns II to VIII, we control for year effects. To isolate region-wide effects, we control for regional (Columns III and V) or state (Columns IV and VI to VIII) dummies. Further, to recognize the potential lack of independence in the error terms across observations by the same company, standard errors are clustered at the firm level.

Table V, Column I shows that firms in volatility quartiles 3 and 4 trade at a discount, with a value gap of 5 and 10 percent, respectively, relative to other firms. Such a difference is significant at the one percent level. Column II shows that a portion of the weather discount may be driven by common weather shocks as introducing year dummies reduces the estimated effects. As a result, only those firms in quartile 4 robustly underperform. Table IV, Columns III and IV present results controlling for regional and state dummies, respectively. The estimated discounts fall to the 3-4 percent range, but remain statistically significant. The correlation between size, profitability, and investment opportunities controls and M-B ratios are as expected: negative for assets, positive for OROA and for investment rates. Lastly, the number of observations relative to previous tables reflects the fact that some firm-year observations have missing M-B ratios. [23]

The effect of weather exposure as captured by EDD weather volatility confirms that high risk exposure affects value. The estimated effect for quartile 4 firms is roughly four percentage points lower relative to their peers, significant at the one percent level. In economic terms, such effects are equivalent to a value difference in the four percent range. In results not shown, we examine the linear impact of revenue volatility and EDD, CDD, and HDD volatility. In every case, we obtain estimates that are indicative of statistically significant weather exposure effects on valuation. Yet, given the shock and M-B results, we favor the quartile specifications as they highlight the observations that are indeed driving the relevant effects.

Lastly, in Table V, Columns VII and VIII, we provide further evidence that weather exposure correlates with lower valuations using the natural logarithm of market capitalization as an outcome variable. The estimated coefficients indicate that firms in the top quartile in terms of weather exposure trade at a discount of 7 to 10 percentage points, significant at conventional levels.

[23] The results presented in Table IV are robust to only focusing on the subset of firms with non-missing market-to-book ratios.

*V. B. Weather Risk in the Absence of Weather Derivatives: Investment and Financing Decisions*

To assess if the market value differences reported above reflect distortions in operating or financial decisions, Table VI examines the effect of weather exposure on capital spending decisions and the type of technology used, as well as on financing and dividends policies. In every specification, we use year-specific dummies to control for time trends, state dummies to control for systematic differences in regional characteristics, and assets, OROA, and M-B ratios, to control for size, profitability, and investment opportunities, respectively.

The results in Table VI, Columns I and II cast doubt on the idea that weather exposure affects firms' investment decisions. The estimated effect of weather risk on the ratio of capital expenditures to assets is not different from zero at conventional levels and is relatively small in economic terms. Such investment results, however, do not necessarily imply that risk management is irrelevant for investment decisions. The results may alternatively be a reflection of the empirical setting, which is characterized by high levels of asset tangibility and lower external financing costs relative to those faced by firms in other industries.

To further test for the effect of weather risk exposure on investments, we examine the use of nuclear plants for electricity generation. Nuclear plants exhibit low fuel costs relative to other alternatives. However, they are relatively inflexible in terms of output and they are characterized by high operating leverage. Nuclear plants are interesting as a technology choice because weather exposure would, holding other factors constant, make them unattractive. Their inflexibility and high operating leverage would tend to magnify weather shocks. Consistent with this notion, Table VI, Columns III and IV show that weather exposure is linked to a dramatic effect on the choice of technology: firms in the top exposure quartile are 57 percentage points less likely to rely on nuclear generation, which is significant at the one percent level. The results provide striking evidence that weather exposure distorts investments against inflexible production technologies.

The effect of weather exposure on capital structure and payout policy is reported in Table VI, Columns V to VI and VII and VIII, respectively. Columns V and VI examine the impact of weather risk exposure on net debt (debt minus cash) to asset ratios, which captures the net level of indebtedness relative to fixed assets. As previously discussed, if the weather affects cash flow volatility and creditors care about left tail events, we would expect a negative correlation between weather exposure and leverage. Columns V and VI (Columns VII and VIII) show that firms in the most weather exposed quartile have debt ratios that are 2 to 4 percentage points lower than their peers. Economically, such estimates are equivalent to 6 to 11 percent of average leverage ratios.

Table VI, Columns VII and VIII examine the impact of weather volatility on dividend decisions. In them, we assess if common stock dividends to asset ratios differ as a function of weather volatility. Using revenue volatility (Column V) as a proxy for weather exposure, we find that dividend payments decline as we move across volatility quartiles. Using weather-induced volatility, we confirm that quartile 4 firms tend to pay less dividends relative to other firms. The estimated coefficient is -0.0023, significant at the five percent level. These estimates suggest that firms in the most volatile group pay 8 to 10 percent less dividends than other firms.

The results from Table VI show that investment and financial distortions may be central to understanding the negative effects of weather exposure on value. While utilities with high weather exposure have investment levels that are comparable to those of their competitors, their types of investments are distorted towards technologies with less operating leverage. Similarly, the presence of substantial weather risk induces firms to use less aggressive financial structures, which may prevent the firm from seizing important tax or incentive-based benefits. The impact of weather exposure on investment, technology use, and financing decisions is, as before, robust to the use of a linear specification instead of quartiles (results not shown).

Overall, Tables V and VI provide robust empirical support for prediction 2: absent weather derivatives, highly weather-exposed firms are less valuable than their peers, and weather-induced volumetric risk is meaningful for operating and financing decisions. We now turn to testing whether these distortions were relaxed by financial innovation.

## *VI. MAIN RESULTS*

### *VI.A. Derivative Use and Firm Value: Within Variation*

Before implementing our main empirical tests, we provide a benchmark estimate of the effect of weather derivatives on value using the within-firm variation specification described in specification (2) of Section II. More specifically, we test whether the M-B ratio of those firms that endogenously decided to use weather derivatives after they were introduced increased relative to the pre-1997 period. To test for this hypothesis, we use a weather derivative indicator variable that is equal to one if the firm used weather derivatives after 1997, and is zero otherwise. Naturally, this variable is set to zero for all observations before 1997. The variable of interest is the interaction between this indicator variable and the post variable, which is set to one after 1997. As in previous specifications, we control for time, size, profitability, and investment effects and we report firm-clustered standard errors.

Table VII, Column I shows that weather derivative users experienced an average increase in value of 5.2 percentage points, which is significant at the five percent level. This estimated coefficient is not driven by time-invariant firm characteristics. Yet, as outlined in Section II, it is potentially subject to time-varying endogeneity or omitted variables concerns.

To partially assess the severity of such concerns, in Table VII, Columns II to V, we test whether those firms that use other financial derivatives after 1997 gain in terms of value relative to their peers. If the use of derivatives is a symptom of superior business prospects, we would expect any hedging strategy to be correlated with higher valuations. However, in Columns II, III, and VI, we fail to find significant economic or statistical effects for the use of interest rate derivatives. In Columns IV to VI, we show that natural gas derivatives led to higher M-B ratios in the 3-4 percent range, but this effect is not robustly significant. Interestingly, the effect of weather derivatives is unaffected by those added controls; it is statistically significant at the five or ten percent level across specifications. Finally, the estimated coefficients on size, profitability, and investments carry the previously reported and expected signs.

Using the natural logarithm of market valuations as an outcome variable, in Table VII, Column VII, we confirm that weather derivatives correlate with significantly higher market valuations and that the results shown in Columns I to VI are not driven by variation in the denominator of the M-B ratios. Surprisingly, we report that the use of interest rate derivatives is correlated with significantly lower M-B ratios. Such a result is arguably reflective of omitted variables concerns, as firms are unlikely to voluntarily use derivatives to lower their firm value. In contrast, natural gas derivatives are correlated with higher firm values.

The results shown in Table VII suggest that financial innovation targeted at the specific risks facing energy firms was conducive to higher valuations. Furthermore, the estimates on the value of hedging are consistent with those reported by Allayannis and Weston (2001). Lastly, those specifications highlight the inference concerns of using endogenous hedging variation. To address those shortcomings, we turn to our main empirical tests.

*VI.B. Weather Exposure and Firm Value ("Reduced Form")*

The central idea of this paper is that financial innovation and, more specifically, the introduction of weather derivatives allowed weather-exposed firms to shield a portion of their weather risk. The empirical evidence presented in Tables IV, V, and VI robustly supports the idea that meaningful weather exposure is concentrated in those firms in the top quartile of weather volatility. To the extent that weather exposure rankings do not change over time, we would expect those firms to increase in value as weather hedging contracts become available.

To test for this hypothesis, we interact the historical weather exposure measures of Table III with a post-1997 dummy. As in Table IV, we refer to weather exposure variables collectively as “quantity risk” measures. In each Column I through V, we report a different proxy and each variable is described at the top of each column.

Table VIII, Columns I and II present results for the two main measures of weather exposure: revenue and EDD weather-induced volatility, respectively. The results show that quartile 4 firms, which were reported to underperform before 1997, do indeed gain following the introduction of weather derivatives. The estimated effect is economically large and statistically significant: M-B ratios increase by 10 percentage points, which is significant at the one percent level. As in the pre-1997 period, firms in weather-exposure quartiles 2 and 3 do not exhibit differential patterns in terms of value, which may confirm that moderate levels of exposure are relatively easy to hedge using other operating and financial tools. The post-1997 indicator variable shows that all energy firms as a group were more valuable than in the past. Other controls are robustly significant and exhibit the expected signs.

Table VIII, Columns II to IV show that firms whose cash flows and market valuation were affected by weather exposure before 1997, gain as weather derivatives are introduced, irrespective of the proxy for weather exposure used: EDD, CDD, or HDD weather-induced volatility. The estimated coefficients are in the 0.10 to 0.13 range and always significant at the one percent level.

An alternative but arguably noisier measure of weather exposure is using an indicator variable equal to one if variation in energy degree days had a bearing on explaining revenue volatility, irrespective of the sign of this relationship. Table VIII, Column V confirms that while such a weather beta does not account for the total variation in EDD over time, it still does corroborate that weather-exposed firms gained in the post-1997 period.

The estimates of Table VIII provide robust evidence that the weather risk discount reported in Table V disappeared after 1997. Under our baseline assumptions, these reduced-form estimates are not subject to endogeneity or omitted variables concerns, and as such provide causal evidence that risk management affects firm value.

*VI.C. Weather Derivatives and Firm Value: Instrumental Variables*

The idea of the 2SLS-IV approach is to establish a direct link between weather derivatives and firm value. If weather derivatives are used to hedge weather risks, their usage would be expected to be more prominent among weather-exposed firms. If that were the case, we could exploit the differential variation in weather derivative use that results from this ex-ante exposure to assess the causal effect of weather derivatives on value. We proceed with this test by first testing whether pre-1997 weather exposure variables predict weather derivative use after these financial derivates were introduced.

First Stage: Ex-Ante Weather Exposure and Weather Derivative Use

Table IX examines the effect of the previously described measures of weather exposure on the use of derivatives after 1997. In all specifications, the dependent variable is an indicator variable that in the post-1997 period takes the value of one for firms using weather derivatives and is zero for both non-users and all pre-1997 observations.

Table IX shows that the use of weather derivatives increases with weather exposure, irrespective of how such exposure is measured. Using revenue volatility as proxy for weather exposure, we report, in Table IX, Column I, that firms in quartiles 3 and 4 are 18 and 22 percentage points, respectively, more likely to use weather derivatives than the least weather exposed quartile of firms, a difference that is significant at the five percent level.

A tighter test on the effects of weather exposure on weather derivative use is to focus on weather-induced volatility, which captures the portion of revenue volatility that is attributable to the weather. In Table IX, Column II, we show that EDD weather-induced volatility quartiles 3 and 4 are 19 and 22 percent, respectively, more likely to use weather derivatives than quartile 1. This difference is statistically significant at the five and one percent levels, respectively. Economically, these results show that firms in the most weather-sensitive quartile are over 2.5 times more likely to use weather derivatives than those in quartile one.

Table IX, Columns III and IV confirm that weather exposure does in fact predict weather derivative use. Specifically, firms in the top two CDD and HDD quartiles exhibit higher rates of weather derivative use after 1997 than the energy firms in the bottom two groupings. The rate of weather derivative use among firms in the top weather exposure quartile is the 0.32-0.35 range, while the equivalent rate for firms in the bottom quartile is only 0.13-0.14. Table IX, Columns V and VI show that even a rough proxy for historical weather exposure, such as having a statistically significant EDD weather beta, provides large variation in weather derivative use. In particular, those firms with significant weather betas in the pre-1997 period are 26 percent more likely to use weather derivatives than other firms, also significant at the one percent level.

Consistent with prediction 3, Table IX provides robust evidence that pre-1997 weather exposure rankings are important determinants of weather derivative use after 1997. As such, we are able to confirm that those firms that from an ex-ante perspective would be expected to benefit from "completing" the weather exposure market are indeed using these financial instruments more frequently than other firms. Having shown that weather exposure begets usage of weather derivatives, we now examine the consequences of risk management for firm value.

Second Stage: Weather Derivative Use and Firm Value

Table X presents the main results of this paper. Across specifications, we use market-to-book ratios as benchmarks for firm value. We exploit variation in weather derivative usage resulting from (a) the introduction of weather derivatives in 1997 and (b) the pre-1997 weather exposure measures described earlier. We use fixed-effects specifications, with controls for size, profitability, and investment opportunities, as well as time effects.

Table X, Columns I and II present the effects of weather derivatives on firm value using EDD weather-induced volatility quartiles as instruments, our benchmark specification. The results show a positive and arguably causal effect of financial derivatives on value. The point estimates are 0.39 and 0.36, depending on whether we include the firms' concurrent investment rate as a control, and both are significant at the five percent level. As it is common with IV estimates, the standard errors are large since they rely on fewer observations to estimate the effect of derivatives. As a result, we cannot reject the possibility that the true causal effect of weather derivatives is, for example, in the 5 to 10 percent range as previously reported in the literature.

While we have stressed the potential advantages of using EDD weather-induced quartiles as a benchmark proxy for quantity risk exposure, we also report the results using revenue-based volatility quartiles (Columns III and IV) and EDD weather betas (Columns V and VI) as instruments. Depending on the source of variation used, the estimated effect of derivatives ranges from 0.22 (revenue volatility) to 0.31 (EDD weather beta) percentage points, significant at the five percent level. These findings show that there are substantial risk-sharing gains that result from targeted financial innovation. Also, across specifications, firm size, profitability, and investment rate controls exhibit the expected signs and significance. Size is negatively related to M-B ratios. Higher profitability and investment rates robustly relate to higher valuation.

The results in Table X provide empirical support for prediction 4, which anticipates that weather derivatives lead to economically large and statistically significant effects on value.

A potential challenge to reported effects of weather derivatives on firm value is that the pre-1997 weather exposure rankings may affect post-1997 M-B ratios through other channels. For example, inference may be challenged by a combination of changing climate conditions due to global warming, variation in business opportunities due to deregulation, or a reduction in risk exposure due to other hedging technologies, among others.

In Table XI, we examine the robustness of our results against alternative hypotheses. Throughout our specifications, we provide 2SLS estimates where the IVs are EDD weather-induced volatility quartiles. However, all the results are robust to using, for example, historical revenue volatility quartiles as alternative instruments. In Table XI, Columns I and II, we examine whether the reported effect may be driven by differential cooling or heating degree day conditions. To test for this effect, we use the natural logarithm of CDD and HDD values, respectively. The estimated coefficient of CDD on M-B ratios is positive and significant, suggesting that higher cooling demand lead to higher market valuations. Yet the effect of weather derivatives on value is unaffected. The effect of HDD is, in contrast, insignificant. In any event, we continue to report a robust effect of weather derivatives on value.

We also use information from the Energy Information Administration (EIA) to test whether state level deregulation of electricity and natural gas markets drives the reported effects on market valuation.[24] Table XI, Column III includes indicator variables that are equal to one for the observations where the relevant state-year has experienced deregulation in electricity and natural gas markets, respectively, and are zero otherwise. The results show that deregulation by itself does not affect firm value and, more importantly, it does not affect the estimated coefficient of weather derivatives on value.

To further control for differences in the structure of deregulation, in Column IV, we include indicator variables associated with specific events in electricity (Fabrizio, Rose, and Wolfram, 2007) and natural gas deregulation. These include having access to retail, industrial, or all consumers in electricity or having a pilot, partial, or comprehensive choice program in natural gas. Each dummy is set to one for the observations where, according to the EIA, the relevant state-year has experienced deregulation. While we find that complete access to all consumers in electricity led to a significant increase in M-B ratios of 7 percentage points (other effects are insignificant), we do not find that such deregulation indicator variables affect the estimated coefficients of interest.

In Table XI, Columns V to VIII, we empirically assess if hedging through other financial contracts affects the impact of weather derivatives on value. In Columns V and VI, respectively, we separately investigate the effect of interest rate and natural gas derivatives, while in Column VII, we control for the use of both risk management tools. Across specifications, we do not find that interest rate or natural gas derivatives have a differential effect on valuation. Moreover, the effect of weather derivatives on value remains economically large and statistically significant.

[24] Information on electricity and natural gas deregulation was obtained from the following EIA websites:
http://www.eia.doe.gov/cneaf/electricity/page/restructuring/restructure_elect.html
http://www.eia.doe.gov/natural_gas/restructure/restructure.html.

Finally, in Table XI, Column VIII, we concurrently control for weather variables, deregulation characteristics, and hedging technologies. Despite the wide standard errors, the effect of weather derivatives on firm value is robust to the inclusion of this long array of controls.

A potential interpretation of these results in Tables X and XI is that financial derivatives are particularly valuable when they are first introduced, helping firms and investors hedge existing exposures. Firm hedging may, at the margin, be less relevant whenever investors can, themselves, easily hedge their exposures as shown by Jin and Jorion (2006). To explore if, in contrast, these value effects reflect meaningful changes inside firms, we also investigate the effect of derivatives on operating and financing decisions.

Specific Channels

The evidence presented thus far demonstrates that weather-exposed firms use weather derivatives more frequently than other firms, and that weather derivatives lead to significantly large gains in terms of value. But what exactly changes with weather derivatives? Previous studies have emphasized the role of hedging for investment and capital structure decisions. Furthermore, investment and financing policies were shown to be at least partially distorted by weather exposure before weather derivatives were available. We examine those and several other alternative channels in Table XII.

Following the empirical methodology outlined before, we report both reduced-form (Panel A) and 2SLS-IV estimates (Panel B), where the IVs are EDD weather exposure quartiles. We investigate whether revenue, investments, financing, and dividend policies responded differentially for firms in distinct weather quartiles and in response to weather derivative use.

The impact on revenue is presented in Table XII, Column I. We do not find systematic evidence that revenue increased in a differential manner for weather exposed firms. Not surprisingly, the IV estimates on the effect of weather derivatives on revenue are also insignificant. Such results are inconsistent with the hypothesis that global warming or deregulation may be driving the effects on value, as those factors would tend to affect revenue in weather sensitive regions differentially.

Table XII, Column II examines the effect of risk management on the level of capital expenditures relative to asset values (nuclear plant information is not available in COMPUSTAT after 1994). The reduced form estimates of Panel A indicate that firms in quartile 4 increased their investments by one percentage point of assets, which is significant at the five percent level. The resulting IV estimates in Panel B show that weather derivatives led to a positive and significant effect on investment. The IV estimate is 0.047, which is significant at the five percent level. As before, the standard errors in the IV specifications are large.

The fact that investments respond to risk management is consistent with Froot, Scharfstein, and Stein (1993). Higher investment is, however, potentially consistent with overinvestment stories due to agency concerns. Yet, the fact that higher investment rates are tied to increases in firm value, suggests that the former hypothesis may be more empirically relevant.

The risk management consequences for financing decisions are investigated in Table XII, Columns III (net debt), IV (book leverage), and V (cash to assets). Irrespective of the measure used, reduced form estimates (Panel A) indicate that quartile 4 firms increase their reliance on debt financing after 1997. Book leverage increases by 2.85 percentage points and cash to assets declines 0.73 percentage points. The combined effect on net debt is 3.58, which is significant at the five percent level. Consistent with tradeoff theories of capital structure, we find that weather exposed firms were, as a result, able to use more debt and hold less cash than prior to 1997.

The IV estimates on the effect of weather derivatives in Table XII, Panel B reflect the same signs as the reduced form correlations in Panel A. However, the standard errors are large and, as a result, the effect of weather hedging on net debt and book leverage is only significant at the 12 and 19 percent level, respectively. Despite the increased noise in the IV estimates, Column V shows that hedging led to lower cash holdings. The estimated coefficient is -2.66, significant at the 10 percent level.

An alternative test for the effect of risk management on leverage is to test in the cross-section whether weather risk characteristics matter for capital structure after 1997. In unreported results, we find that the across group differences in leverage, such as those reported in Table VI, are no longer statistically different from zero at conventional levels after 1997.

Lastly, Table XII, Column VI examines the effect of weather derivatives on dividend ratios. We do not find evidence that hedging led to significant effects on dividend decisions.

## *VII. CONCLUSIONS*

Financial derivatives lie at the heart of Miller's (1986) "revolution" in financial innovation. Derivatives are increasingly important and controversial securities. They are powerful tools for shifting or hedging risks. On the other hand, they also reduce the cost of engaging in speculative transactions. The controversial feature of derivatives is exacerbated by their prominent role in recent financial crises. Yet, establishing the risk management benefits of financial derivatives is empirically difficult.

This paper provides direct evidence of the insurance benefits of financial derivatives on firms' valuation and financial policies. We seek to overcome the empirical challenges faced when determining whether agents are hedging or speculating with derivatives by using a financial innovation approach. More specifically, we use the introduction of weather derivatives as an exogenous source of variation to firms' hedging costs. To further identify the effect of weather derivatives, we exploit variation in weather exposure prior to the introduction of these financial contracts. Intuitively, we anticipate that those firms whose cash flows have historically fluctuated with changing weather conditions are, relative to other firms, more likely to benefit from the insurance feature of these contracts.

Using data from U.S. electric and gas utilities, two highly weather-sensitive sectors, we find four main results. First, in the absence of weather derivatives, weather-exposed firms exhibit significantly lower valuations and pursue more conservative operating and financing policies than other firms. Second, measures of weather exposure that predate the introduction of weather derivatives are strong predictors of weather derivative use upon innovation. Third, weather derivatives led to a substantial increase in firm value. Fourth, hedging allows firms to increase investment and to use more aggressive financing structures.

Overall, our results demonstrate that financial innovation that is targeted to meaningful economic risks can significantly affect firm decisions. Our empirical approach isolates the use of derivatives as risk management instruments. As a result, we show that hedging allows firms to overcome market frictions, and that investment and financing policies respond to low cash flow realizations.

Finally, whether our results extend to other industries or to alternative financial products are fascinating areas for further research.

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## TABLE I. SUMMARY STATISTICS

This table shows summary statistics for 203 U.S. electric and gas firms (SIC codes 4911, 4923, 4924, 4931, and 4932) with matching (a) financial information from COMPUSTAT for at least 10 years prior to 1997 and (b) weather data from the National Oceanic and Atmospheric Administration (NOAA). Panel A. presents financial and weather variables. Total assets, revenue, and market value of equity are in thousands of constant 2008 dollars (Consumer Price Index, adjusted, 2008=100). *OROA* is the ratio of operating income before depreciation to assets. *Book leverage / assets* is the ratio of the sum of long-term debt plus existing debt in current liabilities to total assets. *Market value of equity* is the price (close) times the number of common shares outstanding. *M-B ratio or market-to-book ratio* is the book value of assets plus market value of common equity minus book value of common equity and deferred taxes divided by total assets. *Net debt / assets* is the ratio of book leverage minus cash and marketable securities to total assets. *CAPEX / assets* is the ratio of capital expenditures to total assets. *Investment rate* is the growth rate of total assets. *Nuclear plant generation* is an indicator variable equal to one if a utility has nuclear-powered generating plants, zero otherwise. *Common dividends / assets* is the ratio of common dividends over total assets. Weather variables reported are cooling, heating and energy degree days. A heating (cooling) degree day reflects the number of degrees that a daily average temperature is below (above) 65°F, zero otherwise. *Energy degree days* are the sum of heating and cooling degree days. Cooling, heating, and energy degree days seek to capture cooling, heating, and cooling and heating energy demand, respectively. *Heating (cooling) degree days, annual* is sum of daily heating (cooling) degree days in a year in the firms' main location. In Panel B, *weather (natural gas, interest derivative) user* is an indicator variable equal to one if a firm used weather, natural gas, or interest rate derivatives in the post-1997 period, zero otherwise.

| Variables | Number Obs | Mean | Std Dev. | Min | p10 | Median | p90 | Max |
|---|---|---|---|---|---|---|---|---|
| ***Panel A. Firm and Weather Information*** | | | | | | | | |
| *Total assets* | 8,161 | 5,152 | 6,723 | 62 | 500 | 2,702 | 13,662 | 73,370 |
| *Revenue* | 8,161 | 1,994 | 2,712 | 39 | 265 | 1,070 | 4,865 | 72,339 |
| *OROA* | 8,161 | 0.117 | 0.026 | 0.030 | 0.084 | 0.117 | 0.150 | 0.199 |
| *Book leverage/ assets* | 8,161 | 0.411 | 0.087 | 0.001 | 0.306 | 0.410 | 0.516 | 0.888 |
| *Market value of equity* | 5,630 | 2,290 | 3,345 | 0.031 | 176 | 1,128 | 5,750 | 56,052 |
| *M-B ratio* | 5,532 | 1.075 | 0.207 | 0.733 | 0.862 | 1.027 | 1.370 | 1.950 |
| *Net debt / assets* | 6,353 | 0.376 | 0.084 | (0.125) | 0.278 | 0.372 | 0.478 | 0.821 |
| *CAPEX / assets* | 6,353 | 0.074 | 0.035 | 0.015 | 0.035 | 0.067 | 0.124 | 0.212 |
| *Investment rate* | 8,161 | 0.072 | 0.082 | (0.204) | (0.006) | 0.061 | 0.159 | 0.716 |
| *Nuclear plant generation* | 4,056 | 0.366 | 0.482 | 0 | 0 | 0 | 1 | 1 |
| *Common dividends / assets* | 8,161 | 0.030 | 0.011 | 0.000 | 0.016 | 0.030 | 0.041 | 0.267 |
| *Cooling degree days, annual* | 8,161 | 1,040 | 809 | 5 | 295 | 809 | 2,246 | 4,443 |
| *Heating degree days, annual* | 8,161 | 5,170 | 1,965 | 85 | 2,131 | 5,577 | 7,408 | 10,244 |
| *Energy degree days, annual* | 8,161 | 6,210 | 1,381 | 2,056 | 4,311 | 6,386 | 7,842 | 10,684 |
| ***Panel B. Use of Derivatives After 1997*** | | | | | | | | |
| *Weather derivative user* | 1,733 | 0.249 | 0.433 | 0 | 0 | 0 | 1 | 1 |
| *Natural gas derivative user* | 1,733 | 0.574 | 0.495 | 0 | 0 | 1 | 1 | 1 |
| *Interest rate derivative user* | 1,733 | 0.866 | 0.341 | 0 | 0 | 1 | 1 | 1 |

## TABLE II. WEATHER SHOCKS AND OPERATING PERFORMANCE

This table presents the impact of mild temperatures (low energy degree days (EDDs)) on measures of operating performance. The dependent variables are (a) *ln revenue*, the natural logarithm of revenue in constant 2008 dollars (Column I), (b) *OROA*, the operating profitability on assets (Column II), (c) *ln operating income*, the natural logarithm of operating income in constant dollars (Column III), (d) *dividends/assets*, the ratio of common stock dividends to assets (Column IV), and (e) *investment rate*, the growth rate of total assets (Column V). EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. Heating (cooling) degree days reflects the number of degrees that a daily average temperature is below (above) 65°F. *Weather shock* is an indicator variable equal to one if the annual EDD values are in the lowest quintile for each sample firm, zero otherwise. Each column shows the results of a fixed-effects (firm) regression that also includes the natural logarithm of lagged total assets and year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| | Dependent Variables | | | | |
|---|---|---|---|---|---|
| | ***Ln Revenue*** | ***OROA*** | ***Ln Operating Income*** | ***Dividends / Assets*** | ***Investment Rate*** |
| ***Variable*** | (I) | (II) | (III) | (IV) | (V) |
| *Weather shock* | -0.0160 ** | -0.0023 ** | -0.0196 *** | 0.00004 | 0.0029 |
| | *(0.0074)* | *(0.0009)* | *(0.0075)* | *(0.0003)* | *(0.0027)* |
| Year controls | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,743 | 7,743 | 7,743 | 7,743 | 7,743 |
| R-squared | 0.9672 | 0.4005 | 0.9774 | 0.3240 | 0.1736 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE III. MEASURES OF WEATHER EXPOSURE

This table shows summary statistics (Panel A) and correlations (Panel B) of various measures of weather exposure. Risk measures include (a) revenue volatility (standard deviation of quarterly revenue to assets), (b) CDD, HDD, and EDD betas (absolute value of the estimated coefficient of CDD, HDD, and EDD, respectively, on quarterly revenue to assets) or "weather betas", (c) CDD, HDD, and EDD historical standard deviation, and (d) CDD, HDD, and EDD weather induced volatility, which is the product of CDD, HDD, and EDD weather betas times their relevant historical standard deviation. All measures are estimated using pre-1997 data.

***Panel A. Measures of Pre-1997 Weather Exposure***

| Variables | N | Mean | Std Dev. | Min | p10 | Median | p90 | Max |
|---|---|---|---|---|---|---|---|---|
| *Revenue volatility* | 203 | 0.043 | 0.040 | 0.007 | 0.013 | 0.024 | 0.111 | 0.191 |
| *CDD beta* $(\lvert\beta_i^{CDD}\rvert)$ | 203 | 0.897 | 1.397 | 0.001 | 0.056 | 0.291 | 3.172 | 9.802 |
| *HDD beta* $(\lvert\beta_i^{HDD}\rvert)$ | 203 | 0.251 | 0.356 | 0.000 | 0.008 | 0.095 | 0.815 | 2.144 |
| *EDD beta* $(\lvert\beta_i^{EDD}\rvert)$ | 203 | 0.296 | 0.441 | 0.001 | 0.012 | 0.107 | 0.935 | 3.358 |
| *CDD standard deviation* | 203 | 19.522 | 23.755 | 0.000 | 1.343 | 10.365 | 56.634 | 102.937 |
| *HDD standard deviation* | 203 | 186.973 | 42.739 | 38.845 | 125.150 | 196.674 | 228.701 | 311.516 |
| *EDD standard deviation* | 203 | 179.623 | 47.227 | 63.971 | 99.612 | 190.604 | 225.859 | 311.107 |
| *CDD weather induced volatility* $(\lvert\beta_i^{CDD}\rvert)*\sigma_i^{CDD}$ | 203 | 10.474 | 17.289 | 0.000 | 0.169 | 3.905 | 30.612 | 123.921 |
| *HDD weather induced volatility* $(\lvert\beta_i^{HDD}\rvert)*\sigma_i^{HDD}$ | 203 | 43.414 | 60.401 | 0.011 | 1.623 | 17.147 | 150.677 | 347.004 |
| *EDD weather induced volatility* $(\lvert\beta_i^{EDD}\rvert)*\sigma_i^{EDD}$ | 203 | 49.133 | 71.791 | 0.236 | 2.261 | 20.373 | 162.406 | 470.043 |

***Panel B. Correlation Table***

| | Revenue Volatility | CDD Weather Ind. Volatility | HDD Weather Ind. Volatility | EDD Weather Ind. Volatility |
|---|---|---|---|---|
| *Revenue volatility* | 1.000 | | | |
| *CDD weather induced volatility* | 0.788 | 1.000 | | |
| *HDD weather induced volatility* | 0.927 | 0.837 | 1.000 | |
| *EDD weather induced volatility* | 0.896 | 0.802 | 0.970 | 1.000 |

## TABLE IV. REVENUE CONSEQUENCES OF WEATHER SHOCKS: BY MEASURES OF WEATHER EXPOSURE

This table presents the impact of mild temperatures (low energy degree days (EDDs)) on the revenue of firms sorted by their estimated weather exposure. The dependent variable is *ln revenue*, the natural logarithm of revenue in constant 2008 dollars. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. Heating (cooling) degree days reflects the number of degrees that a daily average temperature is below (above) 65°F. *Weather shock* is an indicator variable equal to one if the annual EDD values are in the lowest quintile for each firm, zero otherwise. Measures of weather exposure are (a) *Revenue / Assets* quartiles, equal-sized groupings based on the historical standard deviation of quarterly revenue divided by assets (Column I), (b) *weather beta* quartiles, equal sized-groupings based on the absolute value of the sensitivity of revenue to CDD (Column II), HDD (Column III), and EDD (Column IV) values, and (c) *weather induced volatility* quartiles, equal-sized groupings based on the product of CDD (Column V), HDD (Column VI), and EDD (Column VII) weather betas, respectively and their historical standard deviation. Each column shows the results of a fixed-effects (firm) regression that also includes the natural logarithm of lagged total assets and year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| | Dependent Variable: *Ln Revenue* | | | | | | |
|---|---|---|---|---|---|---|---|
| | Proxies for Weather-Based Quantity Risk | | | | | | |
| | ***Volatility of Revenue / Assets*** | ***\|β CDD\|*** | ***\|β HDD\|*** | ***\|β EDD\|*** | ***CDD Weather Ind. Vol.*** | ***HDD Weather Ind. Vol.*** | ***EDD Weather Ind. Vol.*** |
| ***Variable*** | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) |
| *Weather shock* | 0.0071 | 0.0026 | 0.0155 | 0.0094 | 0.0306 | 0.0215 | 0.0088 |
| | *(0.0119)* | *(0.0146)* | *(0.0158)* | *(0.0148)* | *(0.0190)* | *(0.0172)* | *(0.0159)* |
| *Quantity Risk Quartile 2* | 0.0044 | 0.0216 | -0.0016 | 0.0087 | -0.0256 | -0.0124 | 0.0074 |
| ** Weather shock* | *(0.0209)* | *(0.0236)* | *(0.0228)* | *(0.0211)* | *(0.0251)* | *(0.0208)* | *(0.0211)* |
| *Quantity Risk Quartile 3* | -0.0013 | -0.0311 | -0.0058 | -0.0005 | -0.0455 * | -0.0256 | -0.0111 |
| ** Weather shock* | *(0.0193)* | *(0.0220)* | *(0.0238)* | *(0.0245)* | *(0.0251)* | *(0.0258)* | *(0.0230)* |
| ***Quantity Risk Quartile 4*** | **-0.0909 ***** | **-0.0642 **** | **-0.1124 ***** | **-0.1056 ***** | **-0.1157 ***** | **-0.1056 ***** | **-0.0866 ***** |
| **** Weather shock*** | ***(0.0237)*** | ***(0.0253)*** | ***(0.0233)*** | ***(0.0230)*** | ***(0.0267)*** | ***(0.0261)*** | ***'(0.0260)*** |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sub- Sample | All firms | All firms | All firms | All firms | All firms | All firms | All firms |
| Observations | 7,743 | 7,743 | 7,743 | 7,743 | 7,743 | 7,743 | 7,743 |
| R-squared | 0.9674 | 0.9673 | 0.9675 | 0.9675 | 0.9674 | 0.9674 | 0.9674 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE V. WEATHER EXPOSURE AND MARKET VALUATION BEFORE 1997

This table examines the impact of weather risk exposure on firm value before weather derivatives were introduced. Weather exposure is measured using, alternatively, (a) *Revenue / Assets* quartiles, equal-sized groupings based on the historical standard deviation of quarterly revenue divided by assets (Columns I to IV, and VII), (b) *weather induced volatility* quartiles, equal-sized groupings based on the product of energy degree days (EDD) *weather beta* times the historical standard deviation of EDD values (Columns V, VI, and VIII). EDD weather beta measures the sensitivity of revenue to EDD variation. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. The dependent variables are the market-to-book ratio (Columns I-VI) and the natural logarithm of market value of equity (VII and VIII). *Market-to-book* is defined as the value of total assets plus the market value of common equity (stock price times the number of common shares outstanding) minus book value of common equity and deferred taxes divided by total assets. *Market value of equity* is the price (close) times the number of common shares outstanding. Other controls include: *Ln assets*, the natural logarithm of total assets; *OROA*, the ratio of operating income to total assets; *Investment rate*, the rate of growth of total assets. Standard errors are clustered at the firm level and are shown in parentheses.

| | ***Market to Book Ratio, pre- 1997*** | | | | | | ***Ln Market Value, pre-1997*** | |
|---|---|---|---|---|---|---|---|---|
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) | (VIII) |
| ***Revenue/Asset volatility, quartile 4*** | **-0.1026** *** | **-0.0401** ** | **-0.0388** ** | **-0.0287** ** | | | -0.0671 ** | |
| | ***(0.0192)*** | ***(0.0166)*** | ***(0.0152)*** | ***(0.0130)*** | | | *(0.0310)* | |
| *Revenue/Asset volatility, quartile 3* | -0.0521 *** | -0.0216 | -0.0156 | -0.0037 | | | -0.0149 | |
| | *(0.0169)* | *(0.0145)* | *(0.0134)* | *(0.0129)* | | | *(0.0271)* | |
| *Revenue/Asset volatility, quartile 2* | -0.0199 | -0.0076 | -0.0012 | -0.0060 | | | -0.0178 | |
| | *(0.0143)* | *(0.0131)* | *(0.0134)* | *(0.0099)* | | | *(0.0219)* | |
| ***Weather induced volatility, quartile 4*** | | | | | **-0.0444** *** | **-0.0420** *** | | **-0.0924** *** |
| | | | | | ***(0.0151)*** | ***(0.0135)*** | | ***(0.0328)*** |
| *Weather induced volatility, quartile 3* | | | | | -0.0080 | -0.0067 | | -0.0425 * |
| | | | | | *(0.0135)* | *(0.0121)* | | *(0.0248)* |
| *Weather induced volatility, quartile 2* | | | | | -0.0161 | 0.0039 | | -0.0328 |
| | | | | | *(0.0124)* | *(0.0127)* | | *(0.0275)* |
| *Ln assets* | -0.0272 *** | -0.0004 | -0.0025 | -0.0089 * | -0.0031 | -0.0134 *** | 0.9906 *** | 0.9869 *** |
| | *(0.0069)* | *(0.0048)* | *(0.0045)* | *(0.0053)* | *(0.0045)* | *(0.0051)* | *(0.0110)* | *(0.0106)* |
| *OROA* | 1.9970 *** | 2.0008 *** | 1.902 *** | 1.8566 *** | 1.8842 *** | 1.8484 *** | 7.3920 *** | 7.3823 *** |
| | *(0.2881)* | *(0.1739)* | *(0.1697)* | *(0.1683)* | *(0.1682)* | *(0.1682)* | *(0.6035)* | *(0.5982)* |
| *Investment rate* | -0.0196 | 0.4467 *** | 0.4108 *** | 0.3496 *** | 0.4113 *** | 0.3476 *** | 1.8776 *** | 1.8784 *** |
| | *(0.0555)* | *(0.0585)* | *(0.0525)* | *(0.0431)* | *(0.0532)* | *(0.0432)* | *(0.1436)* | *(0.1443)* |
| Year Controls | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Electricity Division Controls | No | No | Yes | No | Yes | No | No | No |
| State Controls | No | No | No | Yes | No | Yes | Yes | Yes |
| Observations | 4,490 | 4,490 | 4,490 | 4,490 | 4,490 | 4,490 | 4,576 | 4,576 |
| R-squared | 0.0870 | 0.7185 | 0.7323 | 0.7606 | 0.7332 | 0.7626 | 0.9527 | 0.953 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE VI. WEATHER EXPOSURE, AND INVESTMENT AND FINANCIAL DECISIONS BEFORE 1997

This table examines the impact of weather exposure on investment, production choice, financing, and dividend policies before weather derivatives were introduced. The dependent variables are (a) *CAPEX / Assets*: the ratio of capital expenditures to total assets (Columns I and II), (b) *Nuclear Plant Generation*: an indicator variable equal to one if a utility has nuclear-powered generating plants, zero otherwise (Columns III and IV), (c) *Net Debt / Assets*: is the ratio of the book value of debt minus cash and marketable securities over total assets (Columns V and VI), and (d) *Dividend / Assets*: is the ratio of common dividends over total assets (Columns VII and VIII). Weather exposure is measured using, alternatively, (i) *Revenue / Assets* quartiles (Columns I, III, V, and VII), equal-sized groupings based on the historical standard deviation of quarterly revenue divided by assets, (ii) *EDD weather induced volatility* quartiles (Columns II, IV, VI, VIII), equal-sized groupings based on the product of energy degree days (EDD) *weather beta* times the historical standard deviation of EDD values. EDD weather beta measures the sensitivity of revenue to EDD variation. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. *Ln assets* is the natural logarithm of total assets. *OROA* is the ratio of operating income to total assets. *M-B ratio* is defined as the value of total assets plus the market value of common equity (stock price times the number of common shares outstanding) minus book value of common equity and deferred taxes divided by total assets. Columns I, II, and V to VIII are linear specifications, and Columns III and IV are probit models. Each regression also includes state and year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| | **CAPEX / Assets** | | **Nuclear Plant Generation** | | **Net Debt / Assets** | | **Dividend / Assets** | |
|---|---|---|---|---|---|---|---|---|
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) | (VIII) |
| ***Revenue/Asset volatility, quartile 4*** | **-0.0019** | | **-0.5684** *** | | **-0.0414** *** | | **-0.0031** *** | |
| | ***(0.0036)*** | | ***(0.0469)*** | | ***(0.0106)*** | | ***(0.0012)*** | |
| *Revenue/Asset volatility, quartile 3* | 0.0011 | | -0.0331 | | -0.0073 | | -0.0020 ** | |
| | *(0.0029)* | | *(0.1381)* | | *(0.0072)* | | *(0.0009)* | |
| *Revenue/Asset volatility, quartile 2* | 0.0015 | | -0.0443 | | -0.0122 * | | -0.0019 *** | |
| | *(0.0029)* | | *(0.1392)* | | *(0.0071)* | | *(0.0006)* | |
| ***Weather induced volatility, quartile 4*** | | **-0.0012** | | **-0.5767** *** | | **-0.0214** * | | **-0.0023** ** |
| | | ***(0.0033)*** | | ***(0.0462)*** | | ***(0.0115)*** | | ***(0.0012)*** |
| *Weather induced volatility, quartile 3* | | -0.0008 | | -0.0218 | | -0.0085 | | -0.0014 |
| | | *(0.0026)* | | *(0.1041)* | | *(0.0072)* | | *(0.0009)* |
| *Weather induced volatility, quartile 2* | | 0.0043 | | 0.1084 | | 0.0104 | | 0.0001 |
| | | *(0.0032)* | | *(0.1309)* | | *(0.0096)* | | *(0.0010)* |
| *Ln assets* | -0.0026 *** | -0.0030 *** | 0.3678 *** | 0.3410 *** | -0.0025 | -0.0009 | 0.00004 | 0.00002 |
| | *(0.0011)* | *(0.0012)* | *(0.0648)* | *(0.0685)* | *(0.0032)* | *(0.0035)* | *(0.0003)* | *(0.0003)* |
| *OROA* | -0.3379 *** | -0.3359 *** | 0.9453 | 0.6045 | -0.8447 *** | -0.8545 *** | 0.0480 *** | 0.0466 *** |
| | *(0.0524)* | *(0.0523)* | *(0.9474)* | *(1.0623)* | *(0.1248)* | *(0.1237)* | *(0.0085)* | *(0.0088)* |
| *M-B ratio* | 0.1009 *** | 0.1001 *** | -0.3012 | -0.4031 | -0.0279 | -0.0342 | 0.0225 *** | 0.0219 *** |
| | *(0.0179)* | *(0.0174)* | *(0.2659)* | *(0.2745)* | *(0.0438)* | *(0.0415)* | *(0.0076)* | *(0.0075)* |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,080 | 3,080 | 2,394 | 2,394 | 3,080 | 3,080 | 3,080 | 3,080 |
| R-squared / Pseudo R-squared | 0.3599 | 0.3609 | 0.5669 | 0.5604 | 0.5468 | 0.5376 | 0.4369 | 0.4350 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE VII. DERIVATIVE USE AND FIRM VALUE AROUND 1997

This table presents the impact of financial derivatives on firm value. The dependent variables are (a) the market-to-book ratio (Columns I to VI) and (b) the natural logarithm of market value of equity (Column VII). *Market-to-book* is defined as the value of total assets plus the market value of common equity (stock price times the number of common shares outstanding) minus book value of common equity and deferred taxes divided by total assets. *Market value of equity* is the price (close) times the number of common shares outstanding. *Weather (interest rate, natural gas) derivative* is an indicator variable equal to one if a firm used weather (interest rate, natural gas) derivatives after 1997, and zero otherwise. *Post* is an indicator variable equal to one in the post-1997 period, zero otherwise. *Ln assets* is the natural logarithm of total assets. *OROA* is the ratio of operating income to total assets. *Investment rate* is the growth rate of total assets. Each specification also includes year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| | *Market to Book Ratio* | | | | | | *Ln MV* |
|---|---|---|---|---|---|---|---|
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) |
| ***Weather derivatives * post*** | **0.0523** ** | | **0.0540** ** | | **0.0463** * | **0.0482** * | **0.1203** ** |
| | ***(0.0259)*** | | ***(0.0258)*** | | ***(0.0264)*** | ***(0.0262)*** | ***(0.0593)*** |
| *Interest rate derivatives * post* | | -0.0089 | -0.0176 | | | -0.0279 | -0.1240 ** |
| | | *(0.0396)* | *(0.0395)* | | | *(0.0401)* | *(0.0594)* |
| *Natural gas derivatives * post* | | | | 0.0397 * | 0.0324 | 0.0365 | 0.0991 * |
| | | | | *(0.0230)* | *(0.0234)* | *(0.0250)* | *(0.0546)* |
| *Post* | 0.1697 *** | 0.0799 ** | 0.0733 * | 0.1635 *** | 0.1534 *** | 0.0645 * | 0.4113 *** |
| | *(0.0282)* | *(0.0381)* | *(0.0386)* | *(0.0296)* | *(0.0298)* | *(0.0369)* | *(0.0596)* |
| *Ln assets* | -0.0539 *** | -0.0522 *** | -0.0527 *** | -0.0563 *** | -0.0566 *** | -0.0549 *** | 0.7714 *** |
| | *(0.0163)* | *(0.0178)* | *(0.0173)* | *(0.0166)* | *(0.0162)* | *(0.0169)* | *(0.0421)* |
| *OROA* | 1.8754 *** | 1.854 *** | 1.8784 *** | 1.8527 *** | 1.8727 *** | 1.8770 *** | 6.4444 *** |
| | *(0.1784)* | *(0.1814)* | *(0.1787)* | *(0.1768)* | *(0.1756)* | *(0.1747)* | *(0.3922)* |
| *Investment rate* | 0.2501 *** | 0.2515 *** | 0.2513 *** | 0.2438 *** | 0.2443 *** | 0.2455 *** | 1.4926 *** |
| | *(0.0357)* | *(0.0359)* | *(0.0363)* | *(0.0338)* | *(0.0343)* | *(0.0345)* | *(0.1007)* |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 | 5,336 |
| R-squared | 0.7609 | 0.7594 | 0.7610 | 0.7604 | 0.7616 | 0.7619 | 0.9593 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE VIII. WEATHER EXPOSURE AND FIRM VALUE ("REDUCED FORM")

This table reports post-1997 valuation effects as a function of alternative measures of pre-1997 weather exposure. The dependent variable is the *market-to-book* ratio, the value of total assets plus the market value of common equity minus book value of common equity and deferred taxes divided by total assets. Measures of weather exposure are (a) *Revenue / Assets* quartiles (Column I), equal-sized groupings based on the historical standard deviation of quarterly revenue divided by assets, (b) EDD (Column II), CDD (Column III), and HDD (Column IV) *weather induced volatility* quartiles, equal-sized groupings based on the product of energy, cooling and heating degree days (EDD, HDD, and CDD, respectively) *weather beta* times the historical standard deviation of each of those variables. EDD, HDD, and CDD weather betas measure the sensitivity of revenue to EDD, HDD, and CDD variation, respectively. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. (c) $|\beta_{EDD}|$ *significant*, is an indicator variable equal to one if the EDD weather beta is statistically significant at the five-percent level, zero otherwise (Column V). *Post* is an indicator variable equal to one in the post-1997 period, zero otherwise. *Ln assets* is the natural logarithm of total assets. *OROA* is the ratio of operating income to total assets. *Investment rate* is the growth rate of total assets. Each specification also includes year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| ***Dependent Variable: Market to Book Ratio*** | | | | | |
|---|---|---|---|---|---|
| | ***Proxies for Weather-Based Quantity Risk*** | | | | |
| | ***Volatility of Revenue / Assets*** | ***EDD Weather Ind. Vol.*** | ***CDD Weather Ind. Vol.*** | ***HDD Weather Ind. Vol.*** | ***\|β EDD\| Stats. Significant*** |
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) |
| ***Weather-Based Quantity Risk Quartile 4 * Post*** | **0.1079 *****<br>***(0.0324)*** | **0.1044 *****<br>***(0.0303)*** | **0.1317 *****<br>***(0.0290)*** | **0.1002 *****<br>***(0.0348)*** | |
| *Weather-Based Quantity Risk Quartile 3 * Post* | 0.0277<br>*(0.0334)* | -0.0211<br>*(0.0291)* | -0.0023<br>*(0.0298)* | 0.0033<br>*(0.0309)* | |
| *Weather-Based Quantity Risk Quartile 2 * Post* | -0.0174<br>*(0.0303)* | -0.0387<br>*(0.0280)* | 0.0096<br>*(0.0297)* | -0.0089<br>*(0.0284)* | |
| ***Weather-Based Quantity Risk Indicator * Post*** | | | | | **0.0697 *****<br>***(0.0243)*** |
| *Post* | 0.1624 ***<br>*(0.0381)* | 0.1737 ***<br>*(0.0339)* | 0.1502 ***<br>*(0.0291)* | 0.1667 ***<br>*(0.0337)* | 0.1376 ***<br>*(0.0296)* |
| *Ln assets* | -0.0672 ***<br>*(0.0159)* | -0.0683 ***<br>*(0.0157)* | -0.0656 ***<br>*(0.0162)* | -0.0637 ***<br>*(0.0167)* | -0.0539 ***<br>*(0.0166)* |
| *OROA* | 1.8645 ***<br>*(0.1758)* | 1.7686 ***<br>*(0.1780)* | 1.7844 ***<br>*(0.1755)* | 1.8186 ***<br>*(0.1792)* | 1.8537 ***<br>*(0.1762)* |
| *Investment rate* | 0.2357 ***<br>*(0.0334)* | 0.2272 ***<br>*(0.0324)* | 0.2292 ***<br>*(0.0323)* | 0.2367 ***<br>*(0.0336)* | 0.2438 ***<br>*(0.0345)* |
| Year controls | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 |
| R-squared | 0.7662 | 0.7692 | 0.7696 | 0.7651 | 0.762 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE IX. WEATHER EXPOSURE AND WEATHER DERIVATIVE USE (FIRST STAGE)

This table examines the effect of pre-1997 weather exposure measures on post-1997 weather derivative use. The dependent variable is *weather derivative use*, an indicator variable equal to one if a firm used weather derivatives in the post-1997 period, zero otherwise. Measures of weather exposure are (a) *Revenue / Assets* quartiles (Column I), equal-sized groupings based on the historical standard deviation of quarterly revenue divided by assets, (b) EDD (Column II), CDD (Column III), and HDD (Column IV) *weather induced volatility* quartiles, equal-sized groupings based on the product of energy, cooling and heating degree days (EDD, HDD, and CDD, respectively) *weather beta* times the historical standard deviation of each of those variables. EDD, HDD, and CDD weather betas measure the sensitivity of revenue to EDD, HDD, and CDD variation, respectively. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. (c) $|\beta_{EDD}|$ *significant*, is an indicator equal to one if the EDD weather beta is statistically significant at the five-percent level, zero otherwise (Column V). *Post* is an indicator variable equal to one in the post-1997 period, zero otherwise. Standard errors are clustered at the firm level and are shown in parentheses.

| *Dependent Variable: Weather Derivative Use, Post 1997* | | | | | |
|---|---|---|---|---|---|
| | *Proxies for Weather-Based Quantity Risk* | | | | |
| | *Volatility of Revenue / Assets* | *EDD Weather Ind. Vol.* | *CDD Weather Ind. Vol.* | *HDD Weather Ind. Vol.* | *\|β EDD\| Stats. Significant* |
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) |
| ***Weather-Based Quantity Risk Quartile 4 * Post*** | **0.2175** ** | **0.2201** *** | **0.2163** ** | **0.1820** ** | |
| | **(0.0855)** | **(0.0842)** | **(0.0847)** | **(0.0839)** | |
| *Weather-Based Quantity Risk Quartile 3 * Post* | 0.1790 ** | 0.1932 ** | 0.1373 * | 0.1841 ** | |
| | (0.0878) | (0.0853) | (0.0829) | (0.0869) | |
| *Weather-Based Quantity Risk Quartile 2 * Post* | 0.0368 | 0.0766 | 0.0992 | 0.0655 | |
| | (0.0768) | (0.0778) | (0.0822) | (0.0794) | |
| ***Weather-Based Quantity Risk Indicator * Post*** | | | | | **0.2004** *** |
| | | | | | (0.0584) |
| *Post* | 0.1418 *** | 0.1255 ** | 0.1320 *** | 0.1405 *** | 0.1064 ** |
| | (0.0505) | (0.0487) | (0.0506) | (0.0502) | (0.0419) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,161 | 8,161 | 8,161 | 8,161 | 8,161 |
| F-statistic | 16.13 | 15.96 | 15.67 | 15.75 | 31.66 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE X. WEATHER DERIVATIVES AND FIRM VALUE (2SLS)

This table presents 2SLS-IV estimates on the impact of weather derivatives on firm value. The dependent variable is the market-to-book ratio. Market-to-book ratios are defined as the value of total assets plus the market value of common equity (stock price times the number of common shares outstanding) minus book value of common equity and deferred taxes divided by total assets. *Weather derivatives*, is an indicator variable equal to one if a firm used weather derivatives in the post-1997 period, zero otherwise. The instruments for weather derivatives are based on measures of pre-1997 weather exposure, and are, alternatively: (a) *EDD weather induced volatility* quartiles (Columns I and II), equal-sized groupings based on the product of energy degree days (EDD) *weather beta* times the historical standard deviation of EDD values. EDD weather beta measures the sensitivity of revenue to EDD variation. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. (b) *Revenue / Assets* quartiles (Columns III and IV), equal-sized groupings based on the historical standard deviation of quarterly revenue divided by assets. (c) $|\beta_{EDD}|$ *significant* (Columns V and VI), an indicator equal to one if the EDD weather beta is statistically significant at the five-percent level, zero otherwise. Weather derivatives were introduced in 1997. *Ln assets* is the natural logarithm of total assets. *OROA* is the ratio of operating income to total assets. *Investment rate* is the growth rate of total assets. Each specification also includes year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| ***Dependent Variable: Market to Book Ratio, Post 1997*** | | | | | | |
|---|---|---|---|---|---|---|
| | ***Instrumental Variables*** | | | | | |
| | ***EDD Weather Induced Volatility*** | | ***Volatility of Revenue / Assets*** | | **\|βEDD\| Significant** | |
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) | (VI) |
| ***Weather derivatives*** | **0.3943** ** | **0.3610** ** | **0.2298** ** | **0.2163** ** | **0.3067** ** | **0.2856** ** |
| | ***(0.1859)*** | ***(0.1714)*** | ***(0.1138)*** | ***(0.1058)*** | ***(0.1294)*** | ***(0.1221)*** |
| *Ln assets* | -0.0724 *** | -0.0603 *** | -0.0691 *** | -0.0573 *** | -0.0707 *** | -0.0587 *** |
| | *(0.0197)* | *(0.0190)* | *(0.0167)* | *(0.0164)* | *(0.0177)* | *(0.0173)* |
| *OROA* | 1.7489 *** | 2.0086 *** | 1.6749 *** | 1.9462 *** | 1.7095 *** | 1.9761 *** |
| | *(0.2100)* | *(0.2146)* | *(0.1697)* | *(0.1793)* | *(0.1891)* | *(0.1967)* |
| *Investment rate* | | 0.2452 *** | | 0.2475 *** | | 0.2464 *** |
| | | *(0.0412)* | | *(0.0376)* | | *(0.0392)* |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE XI. WEATHER DERIVATIVES AND FIRM VALUE (2SLS): ALTERNATIVE HYPOTHESES

This table presents 2SLS-IV estimates on the impact of weather derivatives on firm value. The dependent variable is the market-to-book ratio. Market-to-book ratios are defined as the value of total assets plus the market value of common equity (stock price times the number of common shares outstanding) minus book value of common equity and deferred taxes divided by total assets. *Weather derivatives*, is an indicator variable equal to one if a firm used weather derivatives in the post-1997 period, zero otherwise. The instrumental variable for weather derivatives use in the post-1997 period is based on pre-1997 weather exposure or *weather induced volatility*. EDD weather induced volatility quartiles, are equal-sized groupings based on the product of energy degree days (EDD) *weather beta* times the historical standard deviation of EDD values. EDD weather beta measures the sensitivity of revenue to EDD variation. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. Weather derivatives were introduced in 1997. *Ln CDD* (*Ln HDD*) is the natural logarithm of CDD (HDD). *Deregulation electricity (natural gas)* is an indicator variable equal to one for the observations where the relevant state-year has experienced deregulation in electricity (natural gas) markets, respectively, zero otherwise. *Deregulation access to retail, industry and all consumers* are indicator variables equal to one for the observations where the relevant state-year has experienced deregulation to access to retail, industry and all consumers, respectively, and zero otherwise. *Dereg. NG pilot, partial and all consumers* are indicator variables equal to one for the observations where the relevant state-year has experienced natural gas deregulation for pilot, partial and all consumers, respectively, and zero otherwise. *Interest rate (natural gas) derivatives* is an indicator variables equal to one if a firm used interest rate (natural gas) derivatives in the post-1997 period, zero otherwise. *Ln assets* is the natural logarithm of total assets. *OROA* is the ratio of operating income to total assets. *Investment rate* is the growth rate of total assets. Each specification also includes year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

| *Dependent Variable: Market to Book Ratio* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***Variables*** | (I) | (II) | (III) | (IV) | (V) | (VI) | (VII) | (VIII) |
| ***Weather derivatives*** | **0.3654** ** | **0.3605** ** | **0.3330** ** | **0.3216** ** | **0.4053** ** | **0.2875** * | **0.3365** * | **0.300** * |
| | ***(0.1730)*** | ***(0.1711)*** | ***(0.1643)*** | ***(0.1535)*** | ***(0.1948)*** | ***(0.1632)*** | ***(0.1855)*** | ***(0.1618)*** |
| *Ln CDD* | 0.0314 *** | | 0.0303 *** | 0.0292 *** | | | | 0.0287 *** |
| | *(0.0100)* | | *(0.0094)* | *(0.0088)* | | | | *(0.0088)* |
| *Ln HDD* | | -0.0197 | -0.0032 | -0.0048 | | | | -0.0056 |
| | | *(0.0238)* | *(0.0227)* | *(0.0225)* | | | | *(0.0228)* |
| *Deregulation electricity* | | | -0.0128 | -0.0452 | | | | -0.0565 * |
| | | | *(0.0394)* | *(0.0329)* | | | | *(0.0315)* |
| *Deregulation natural gas* | | | 0.0024 | -0.0118 | | | | -0.0067 |
| | | | *(0.0374)* | *(0.0510)* | | | | *(0.0513)* |
| *Dereg. retail consumers* | | | | -0.0648 | | | | -0.0757 |
| | | | | *(0.0549)* | | | | *(0.0572)* |
| *Dereg. indust. consumers* | | | | 0.0352 | | | | 0.0414 |
| | | | | *(0.0527)* | | | | *(0.0550)* |
| *Dereg. all consumers* | | | | 0.0658 ** | | | | 0.0665 ** |
| | | | | *(0.0331)* | | | | *(0.0318)* |
| *Dereg. NG pilot* | | | | -0.0184 | | | | -0.0113 |
| | | | | *(0.0484)* | | | | *(0.0474)* |
| *Dereg. NG partial* | | | | 0.0610 | | | | 0.0592 |
| | | | | *(0.0543)* | | | | *(0.0520)* |
| *Dereg. NG all consumers* | | | | -0.0057 | | | | -0.0080 |
| | | | | *(0.0684)* | | | | *(0.0661)* |
| *Interest rate derivatives* | | | | | -0.0744 | | -0.0621 | -0.0624 |
| | | | | | *(0.0659)* | | *(0.0593)* | *(0.0522)* |
| *Natural gas derivatives* | | | | | | -0.0058 | -0.0038 | -0.0033 |
| | | | | | | *(0.0387)* | *(0.0418)* | *(0.0375)* |
| *Ln assets* | 2.0039 *** | 2.0086 *** | 1.9937 *** | 1.9789 *** | 2.0371 *** | 1.9769 *** | 2.0058 *** | 1.9813 *** |
| | *(0.2149)* | *(0.2146)* | *(0.2016)* | *(0.1985)* | *(0.2225)* | *(0.2028)* | *(0.2099)* | *(0.1919)* |
| *OROA* | -0.0608 *** | -0.0606 *** | -0.0608 *** | -0.0586 *** | -0.0556 *** | -0.0583 *** | -0.0548 *** | -0.054 *** |
| | *(0.0190)* | *(0.0190)* | *(0.0182)* | *(0.0185)* | *(0.0197)* | *(0.0170)* | *(0.0178)* | *(0.0175)* |
| *Investment rate* | 0.2451 *** | 0.2451 *** | 0.2432 *** | 0.2416 *** | 0.2496 *** | 0.2474 *** | 0.2506 *** | 0.2444 *** |
| | *(0.0412)* | *(0.0411)* | *(0.0410)* | *(0.0405)* | *(0.0427)* | *(0.0389)* | *(0.0403)* | *(0.0384)* |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 | 5,244 |

***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

## TABLE XII. WEATHER DERIVATIVES: REVENUE, INVESTMENT, FINANCING AND DIVIDEND POLICIES

This table examines the effect of weather derivatives on (a) revenue (natural logarithm of revenue) (Column I), (b) investment (CAPEX/Assets) (Column II), (c) financing (Net debt/Assets (Column III), Book Leverage/Assets (Column IV) and Cash/Assets (Column V)) and (d) Dividends (Dividend/Assets) (Column VI). Panel A presents estimates on the effect of EDD weather-induced volatility quartiles on each of the outcome variables in the post-1997 period. Panel B presents 2SLS-IV estimates on the effect of weather derivatives on revenue, investment, financing and dividend policies. The instrumental variable for weather derivatives use in the post-1997 period is based on pre-1997 weather exposure or *weather induced volatility*. EDD weather induced volatility quartiles, are equal-sized groupings based on the product of energy degree days (EDD) *weather beta* times the historical standard deviation of EDD values. EDD weather beta measures the sensitivity of revenue to EDD variation. EDDs are defined as the sum of the annual heating and cooling degree day values, temperatures indexes that seek to capture the energy demand for heating and cooling services. Quartile 1 is the omitted category. *Post* is an indicator variable equal to one in the post-1997 period, zero otherwise. *Weather exposure quartiles * post*, capture the differential evolution of each outcome variable for each quartile of firms after 1997. Weather derivatives were introduced in 1997. *Weather derivatives* is an indicator variable equal to one if the energy firm used weather derivatives after 1997, zero otherwise. Each specification also includes year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses.

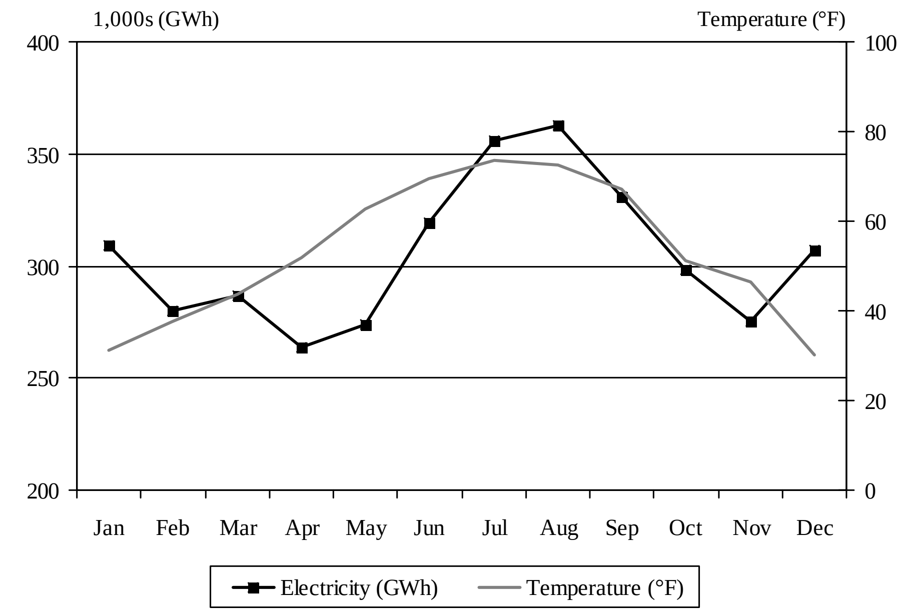
| | *Dependent Variables:* | | | | | |
|---|---|---|---|---|---|---|
| | ***Ln Revenue*** | **CAPEX / Assets** | **Net Debt / Assets** | **Book leverage / Assets** | **Cash / Assets** | **Dividends / Assets** |
| | (I) | (II) | (III) | (IV) | (V) | (VI) |
| ***Panel A. Reduced Form*** | | | | | | |
| ***Weather induced volatility, quartile 4 * Post*** | **0.0190** | **0.0099 **** | **0.0358 **** | **0.0285 *** | **-0.0073 **** | **-0.0009** |
| | ***(0.1006)*** | ***(0.0043)*** | ***(0.0147)*** | ***(0.0146)*** | ***(0.0032)*** | ***(0.0018)*** |
| *Weather induced volatility, quartile 3 * Post* | 0.0770 | 0.0062 * | -0.0086 | -0.0093 | -0.0007 | 0.0021 |
| | *(0.0781)* | *(0.0035)* | *(0.0142)* | *(0.0139)* | *(0.0033)* | *(0.0019)* |
| *Weather induced volatility, quartile 2 * Post* | 0.0330 | -0.0011 | -0.0126 | -0.0114 | 0.0012 | -0.0016 |
| | *(0.0768)* | *(0.0036)* | *(0.0145)* | *(0.0142)* | *(0.0034)* | *(0.0016)* |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,343 | 6,343 | 6,343 | 6,343 | 6,343 | 6,343 |
| ***Panel B. Instrumental Variables: EDD Weather-Induced Volatility Quartiles*** | | | | | | |
| ***Weather derivatives*** | **0.1771** | **0.0469 **** | **0.1149** | **0.0883** | **-0.0266 *** | **0.0043** |
| | ***(0.3717)*** | ***(0.0219)*** | ***(0.0738)*** | ***(0.0673)*** | ***(0.0161)*** | ***(0.0075)*** |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,343 | 6,343 | 6,343 | 6,343 | 6,343 | 6,343 |

$^{***}$, $^{**}$ and $^{*}$ denote significance at the 1, 5 and 10 percent level, respectively.

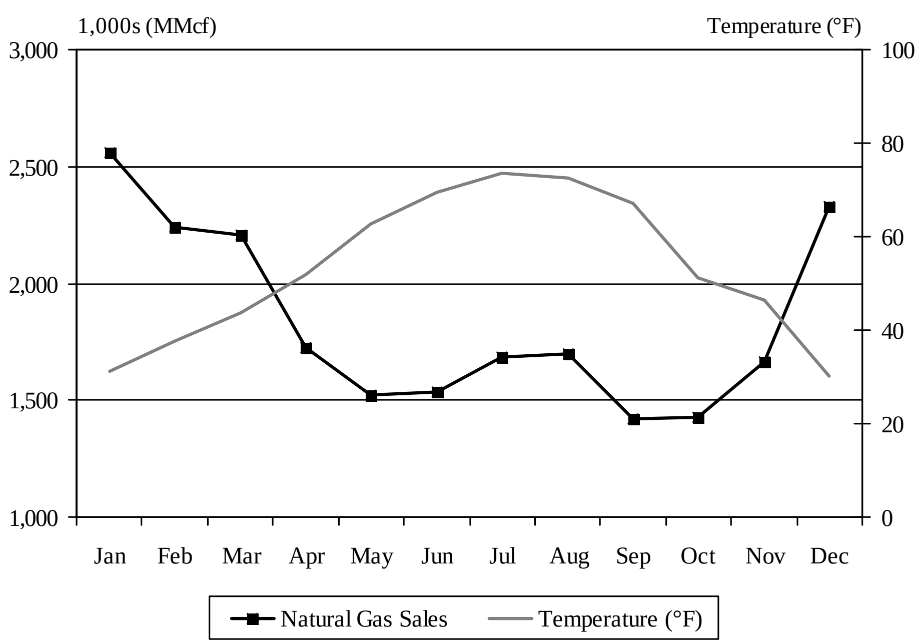
**FIGURE 1. MONTHLY ELECTRICITY AND NATURAL GAS UNITS AND AVERAGE TEMPERATURES, 2005**

Figure A shows the 2005 monthly electricity sales in the United States (thousands of gigawatts per hour or GWh) and the corresponding average monthly temperature (°F). Figure B shows the 2005 monthly natural gas sales in the United States (thousands of million cubic feet or MMcf) and the corresponding average monthly temperature (°F). Data on electricity and natural gas sales are from the Energy Information Administration (EIA), forms 826 and 857, respectively. Data on monthly temperatures are from the National Oceanic and Atmospheric Administration (NOAA).

A. Monthly Electricity Sales (Units: GWh) and Average Temperatures



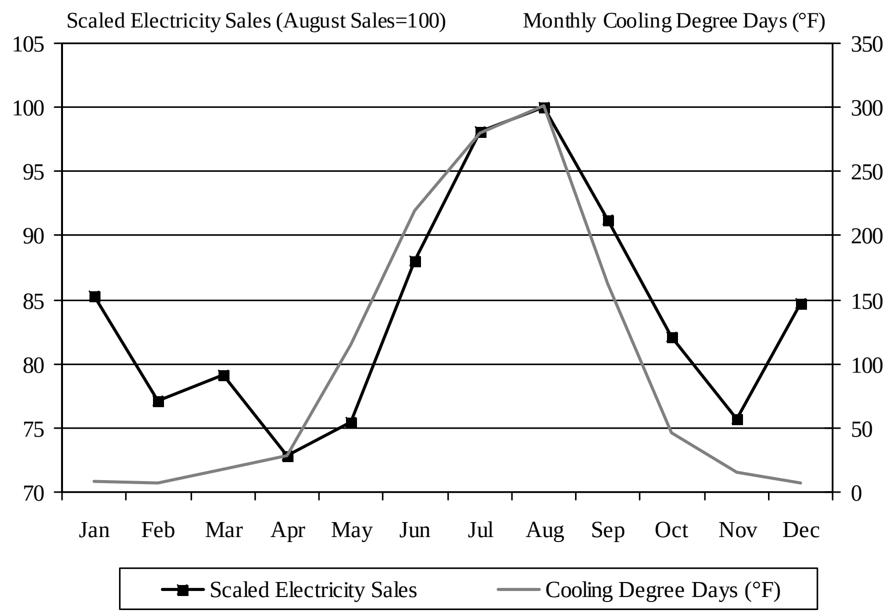

B. Monthly Natural Gas Sales (Units: MMcf) and Average Temperatures



## FIGURE 2. MONTHLY ELECTRICITY AND NATURAL GAS UNITS, AND MONTHLY COOLING AND HEATING DEGREE DAYS, 2005

Figure A shows the *scaled* (August sales=100) monthly electricity sales in the United States in 2005 (thousands of gigawatts per hour or GWh), and the monthly cooling degree days (CDD) (°F). Figure B shows the scaled (January sales=100) monthly natural gas sales in the United States (thousands of million cubic feet or MMcf) and the monthly heating degree days (HDD). Heating and cooling degree day values seek to capture the energy demand for heating and cooling services, respectively. A heating (cooling) degree day reflects the number of degrees that a daily average temperature is below (above) 65° F. Data on electricity and natural gas sales are from the Energy Information Administration (EIA), forms 826 and 857, respectively. CDD and HDD data are from the National Oceanic and Atmospheric Administration (NOAA).

A. Monthly Electricity Sales (Scaled, August=100), and Cooling Degree Days




B. Monthly Natural Gas Sales (Scaled, Jan=100), and Heating Degree Days

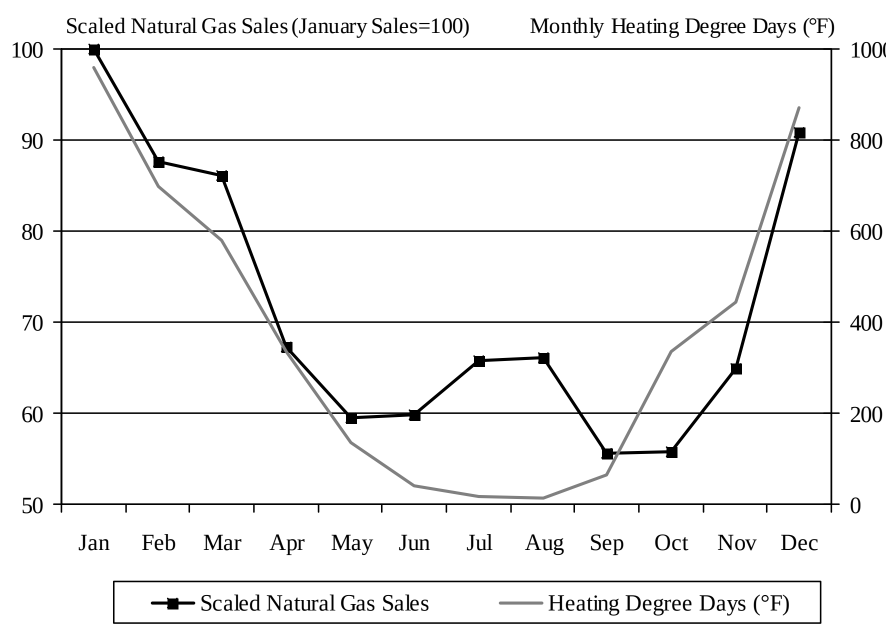
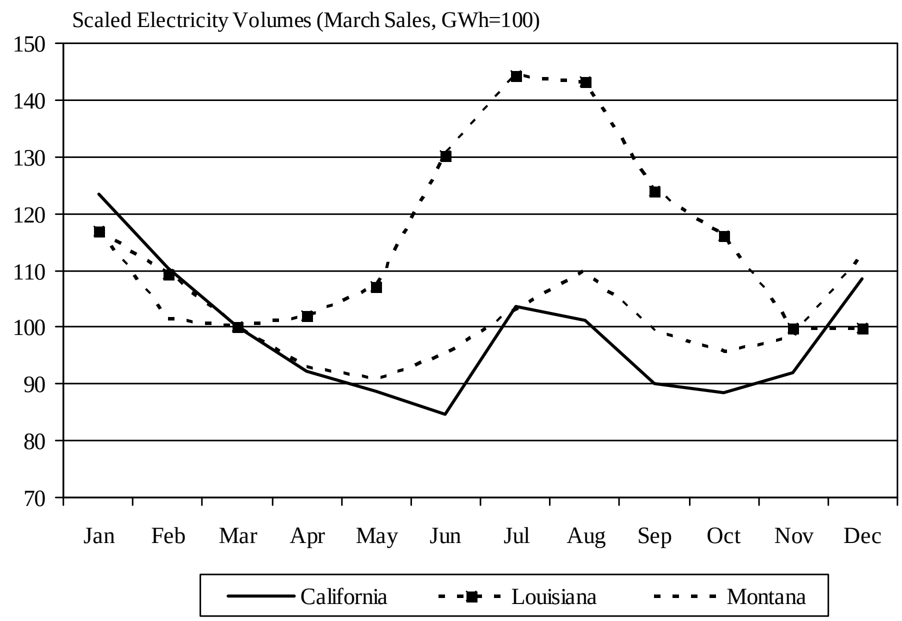


**FIGURE 3. REGIONAL DIFFERENCES IN ENERGY VOLUME VARIATION, 2005**

Figure A shows the *scaled* (March sales=100) monthly electricity sales in Louisiana and Montana in 2005 (thousands of gigawatts per hour or GWh). Figure B shows the scaled (March sales=100) monthly natural gas sales in Louisiana and Montana (thousands of million cubic feet or MMcf). Data on electricity and natural gas sales are from the Energy Information Administration (EIA), forms 826 and 895, respectively.

A. Monthly Electricity Sales (Scaled, March=100)




B. Monthly Natural Gas Sales (Scaled, March=100)