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Risk Management and Firm Value: Evidence from Weather Derivatives

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ABSTRACT

This paper shows that active risk management policies lead to an increase in firm value. To identify the effect of hedging and to overcome endogeneity concerns, we exploit the introduction of weather derivatives as an exogenous shock to firms' ability to hedge weather risks. This innovation disproportionately benefits weather-sensitive firms, irrespective of their future investment opportunities. Using this natural experiment and data from energy firms, we find that derivatives lead to higher valuations, investments, and leverage. Overall, our results demonstrate that risk management has real consequences on firm outcomes.

AN IMPORTANT AND HIGHLY debated topic in corporate finance is whether active risk management policies affect firm value. Conceptually, the seminal work of Modigliani and Miller (1958) shows that, in a frictionless setting, hedging is irrelevant for value.[1] 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)).

Despite the relevance of risk management, we know surprisingly little about the causal effect of risk management on value. An important challenge with preexisting empirical studies examining the impact of hedging on firm value

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[1] Subsequent analyses stress that hedging can affect value in the presence of market frictions, such as transaction costs, informational asymmetries, taxes, etc. See Mayers and Smith (1982), Stulz (1984), Smith and Stulz (1985), Froot, Scharfstein, and Stein (1993), DeMarzo and Duffie (1995), and Leland (1998), among others.

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is that they rely on endogenous variation in risk management policies.[2] Given that firms do not randomize their hedging decisions, it has been difficult to establish whether hedging does in fact lead to an increase in firm value.

The objective of this paper is to estimate the effect of risk management policies on value. To this end, we exploit the introduction of weather derivatives as a natural experiment. Weather derivatives are financial contracts whose payoffs are contingent on weather conditions. Because these derivatives were introduced in 1997, they provide arguably exogenous variation in the cost of hedging weather risks, which we use empirically. To further identify the effect of weather derivatives, we exploit the historical weather exposure of firms. Intuitively, we expect that firms whose cash flows have historically fluctuated with changing weather conditions are more prone to use weather derivatives once these contracts are introduced, irrespective of their investment opportunities. Econometrically, we use *pre*-1997 weather exposure rankings as instrumental variables (IVs) for the use of weather derivatives *after* 1997.

To test for the importance of weather derivatives, we focus on electric and gas utilities. These firms provide a near ideal laboratory for determining the importance of weather risk exposures because heating and cooling demands are tightly linked to changes in weather conditions. Furthermore, if regulated utilities are able to pass along their costs to consumers, the main exposure they face is quantity risk, which weather variables closely track. Not surprisingly, nearly 70% of the end-users of weather derivatives are from the energy industry (Weather Risk Management Association (WRMA, 2005)). 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 data on 203 U.S. firms. Using these data, we report four main findings.

First, in the absence of weather derivatives, firms that are highly exposed to weather volatility exhibit significantly lower valuations and pursue more conservative financing policies. Our estimates show value differences of around 4% for firms in the highest weather exposure quartiles. Also, weather-exposed firms use less debt financing and pay fewer dividends than other firms.

Second, we show that historical (pre-1997) weather exposure is a strong predictor of weather derivative use after 1997. Firms that are historically highly weather exposed are two to three times more likely to use weather hedges after 1997 than other utilities. This evidence shows that an important fraction of firms use derivatives for hedging reasons.

Third, we show that weather derivatives lead to an economically important and statistically robust increase in firm value. Using IVs specifications, we show that hedging leads to an increase in market-to-book (M–B) ratios of at

[2] 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 valuations. Cornaggia (2013) examines the relation between hedging and productivity. Jin and Jorion (2006) document insignificant risk management effects. Guay and Kothari (2003) question the empirical relevance of hedging for firm value.

least 6%. We investigate whether the reported results can alternatively be explained by weather trends, deregulation, or the use of other risk management tools. After controlling for those effects, we find robust evidence for the causal interpretation of the link between hedging and value.

Fourth, we find that hedging leads to more aggressive financing policies and higher investment levels. These results are consistent with the idea that left-tail cash flow realizations can limit debt capacity because of distress costs or other frictions. Similarly, they provide evidence that smooth cash flows may allow firms to relax their borrowing constraints or to pursue valuable investments in low cash flow scenarios.

Overall, our results demonstrate that active risk management policies have real consequences. The estimates of the value of risk management, based on both cross-sectional and time-series tests, are consistent with those reported by Allayannis and Weston (2001) and Carter, Rogers, and Simkins (2006). Our results on hedging and debt capacity are also in line with Smith and Stulz (1985) and Leland (1998). Moreover, the reported investment effects are consistent with Froot, Scharfstein, and Stein (1993).

An attractive feature of our analysis is that it provides unique insights on the value of quantity risk insurance. Quantity risk may in some cases be more relevant for firm value than price risk exposures. Information asymmetries, however, provide an important barrier to the development of quantity-based insurance contracts. A clear advantage of weather derivatives relative to other contracts is that information asymmetry concerns are minor because it is difficult to argue that a given utility has superior weather forecasting abilities relative to other market participants, or that the actions of energy firms affect weather outcomes.

To the best of our knowledge, our focus on financial innovation to identify the value of hedging is new in the literature.[3] This approach is promising for a number of reasons. First, it provides exogenous variation in the cost of hedging. Second, it tightens the link between *specific* risk exposures and hedging instruments, allowing researchers to understand which policies are directly affected by risk management. Finally, the results provide rough estimates of the value of financial innovation, which is an important topic in the literature.

The rest of the paper is organized as follows. Section I describes the weather exposure of utilities and the tools used to mitigate those risks. Sections II and III present the empirical strategy and data, respectively. Section IV examines the impact of weather shocks on operating results whereas Section V tests for the effect of weather exposure on value in the absence of weather derivatives. Section VI presents the main results of the paper, examining the impact of weather derivatives on value as well as the potential channels through which hedging can affect firm valuation. Section VII concludes.

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

I. Risk Management and Energy Utilities

According to the National Research Council (2003), energy is one of the most weather-sensitive sectors in the economy. Heating and cooling demands are tightly linked to changes in weather conditions.[4] Furthermore, utilities are often required to serve such changing demands at fixed prices. As a result, it is not surprising that weather events have often been reported to affect the profits of energy firms.[5] Given this risk, utilities face the dilemma of determining whether to hedge their weather exposure and, if they choose to do so, deciding which tools to use.

Prior studies stress several rationales for risk management. Smith and Stulz (1985), Leland (1998), and Graham and Rogers (2002) 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. Stulz (1984), in contrast, shows that risk-averse managers may prefer to hedge firm value.

A challenge in selecting risk management tools is that several standard mechanisms are effective at hedging price or cost risk, but not quantity risk (Brockett, Wang, and Yang (2005)).[6] On the operational side, firms can diversify weather risks by investing in several geographic regions or by offering several product lines; economies of scale, however, are often higher in nearby communities, which exhibit similar weather conditions. Bundling several product lines is effective when individual product risks exactly offset each other. Other operating strategies to offset risk include using flexible operating technologies, storing or trading energy, and using long-term contracts. There are, however, some barriers to such hedging strategies. For example, electricity cannot be efficiently stored, and while natural gas can be stored, risk-sharing opportunities are limited by the lack of integration of regional markets (Energy Information Administration (2002)).

Firms can alternatively use their capital structure or other financial tools. Higher cash or lower debt levels reduce earnings volatility and protect investments. Lower leverage, however, limits the tax or disciplining benefits of debt, affecting valuation. Firms can also use energy derivatives to sell output forward, potentially alleviating the negative consequences of low energy demand.

[4] We focus on frequent but relatively low-impact weather events, rather than on catastrophic insurance.

[5] Abnormally high (low) CDDs have, for example, been reported to boost (harm) the cash flows of the Florida Power and Light Group (Midwest Resources Inc). Sources: FPL Income Soars with the Heat, *The Palm Beach Post*, July 16, 1998, and Utility: Cool Weather Is Why Earnings Fell, *The Omaha World-Herald*, November 3, 1992, respectively. On the other end, high (low) HDDs have been reported to strengthen (weaken) the cash flows of Dominion Resources Inc. (Atmos Energy Corp). Sources: Dominion Resources 1Q, *Dow Jones News* Service, April 15, 1994, and Mild Winter Diminishes Profits at Dallas-Based Atmos Energy, *The Dallas Morning News*, May 11, 1989, respectively.

[6] See Petersen and Thiagarajan (2000) for a detailed analysis of the alternative hedging strategies of two firms in the gold industry.

Although natural gas futures are widely used among utilities, electricity futures, in contrast, are virtually nonexistent.[7] However, these contracts provide imperfect hedges against weather risks. The lack of regional integration of energy markets highlighted above makes it extremely difficult to find counterparties for the entire exposure facing large utilities. An alternative potential hedging strategy relies on agricultural derivatives. Although under some circumstances commodity prices may correlate with local weather conditions (Roll (1984)), these instruments are likely to expose utilities to substantial basis risk.

Utilities may use regulatory measures to minimize the impact of the weather. Weather normalization adjustments (WNA) allow utilities to transfer weather risk to consumers by increasing (decreasing) energy bills in mild (extreme) weather seasons. However, WNA clauses have shortcomings. First, their coverage is limited—they do not cover the unregulated portion of energy firms' business and they are not available in every state.[8] Second, cash flow recovery may lag weather shocks, particularly in extreme cases (Jenkin and Ives (2002)), which may be important for increasing debt capacity or funding a growing investment program. Third, recovery is subject to regulatory and political risk.

Since the late 1990s, energy firms have also used weather derivatives to manage their weather exposures. The first over-the-counter (OTC) weather derivative contract was introduced in 1997.[9] The weather insurance market developed in response to severe and unexpected weather conditions caused by the 1997 to 1998 El Niño-Southern Oscillation (ENSO) event.[10] The expectation of record warm winter temperatures triggered utilities' (in particular, natural gas firms') interest in weather hedging tools and helped jump start the development of the market.

Since the inception of weather derivatives, energy firms have been the biggest end-users of these contracts. Over 90% of transactions in this market are set in terms of cooling and heating degree days (CDD and HDD, respectively), which are temperature-based measures that seek to capture the energy demand for cooling and heating services.[11] More specifically, CDD (HDD) values capture

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

[8] See http://www.aga.org/SiteCollectionDocuments/RatesReg/0708WEANORM.PDF for a list of states with natural gas WNA clauses.

[9] For the first publicly reported weather derivative contact, see Enron Contract Hedges against Weather, *Houston Chronicle*, November 7, 1997, which describes the first OTC weather derivative between Enron and a consortium of utility companies. The WRMA traces the origin of the weather derivatives market to three OTC transactions that took place in the autumn of 1997 involving Koch Industries, Enron, and PXRe (source: www.wrma.org). In Table IA.I of the Internet Appendix, available in the online version of this article, we provide a detailed account of the early development of the weather derivatives market as reported by the news media.

[10] Before the development of the 1997 to 1998 ENSO, NOAA reported near-normal climate conditions. By mid-1997, however, weather forecasts predicted unseasonably mild winter conditions in the northern United States, comparable to the warmest in the preceding 50 years. The 1997 to 1998 ENSO was eventually classified by the World Meteorological Organization (1999) as the strongest ENSO event of the century. See Table IA.I in the Internet Appendix for a chronological account of the weather advisory reports released by NOAA in 1997.

[11] WRMA (2009).

deviations in mean temperatures above (below) 65°F, the benchmark at which energy demand is low.[12]

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

Although the Chicago Mercantile Exchange (CME) has offered exchange-traded futures and options since 1999, most transactions in this market are OTC (Golden, Wang, and Yang (2007)).[13] OTC transactions allow firms to tailor the contracts to their individual needs (Considine (2000)). OTC contracts, however, are less likely to be liquid, have higher transaction costs, and are subject to credit risk exposures.

Although systematic data on this market do not exist at the firm level, corporate filings and anecdotal evidence indicate the use of puts, collars, and swaps to hedge weather exposures. Puts allow firms to retain the upside potential of high weather-driven demand at the cost of a premium. Strike values are typically set at or slightly below historical (10–20 year) HDD or CDD values. Collars and swaps are often preferred by firms because they do not require upfront premiums, even though protection comes at the cost of lower profits in high weather-driven demand scenarios. Finally, these derivatives often have maximum payouts associated with them.

We illustrate the type of contracts that energy firms can use 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% 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.

In this contract, the weather variable is HDD, the accumulation period is November 2006 to March 2007, the tick size is \$37,500, and the seasonal strike price is 4,159. With this transaction, the firm obtains protection against low

[12] $\text{CDD} = \max[0, \frac{T_{\max}+T_{\min}}{2} - 65^\circ]$ and $\text{HDD} = \max[0, 65^\circ - \frac{T_{\max}+T_{\min}}{2}]$. As an example, if the average temperature is 75°F, the corresponding CDD value for the day is 10.

[13] The CME offers 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)).

heating demand scenarios. Specifically, if winter temperatures are 5% milder than normal (cumulative HDD values are below 4,159) then the company will receive $37,500 per HDD below this threshold.[14] The realized HDD value for the year was 3,916, which gave the contract a payoff at maturity of $9.1 million.

Beyond energy companies seeking weather protection, other market participants include dedicated brokers and market makers, investment banks, insurance and reinsurance firms, and hedge funds. As stressed above, the magnitude of utility transactions is unlikely to involve other end-users with identical but opposite exposures. As a result, market makers provide the key risk capital in this market.

Based on survey data, the average notional value of this market between 2006 and 2008 was $32.2 billion per year, significantly larger than the average annual level of $4.4 billion between 2001 and 2004 (WRMA (2009)). Although small in scale and mostly dedicated on one industry, this market is likely to be extremely important for the most weather-exposed utilities. As we discuss in subsequent sections, we find that only a fraction of utilities use derivatives, but those firms that use them reduce their weather exposure and improve their valuations.

II. Empirical Strategy and Predictions

A common approach to examining the effect of derivatives on firms' outcomes is to use cross-sectional tests that compare firm value as a function of hedging decisions. For example,

$$y_{it} = \alpha + \beta * hedge_{it} + \psi_x X_{it} + \varepsilon_{it}, \tag{1}$$

where y_{it} is firm value, $hedge_{it}$ is a dummy equal to one if the firm uses derivatives and zero otherwise, and X_{it} consists of other control variables of interest. If hedging is valuable, we expect β to be positive and significant.

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 firm value. However, a large number of studies, starting with Nance, Smith, and Smithson (1993), show that hedging decisions are correlated with size, investment opportunities, and leverage.[15] Whenever hedging is endogenously determined, OLS or propensity score-based estimates are subject to inference concerns—it is difficult to interpret β as an estimate of the causal effect of derivatives.

In this paper, we exploit both time-series and cross-sectional variation in the use of weather derivatives to overcome these inference concerns. Because weather derivatives were introduced in 1997, they provide arguably exogenous

[14] The average of 4,159 HDDs corresponds to average daily temperatures of 37.5°F (65 − HDD/n days) for the 151 days in the season, and the realized value of 3,916 corresponds to an average temperature of 39.1°F.

[15] See, for example, Geczy, Minton, and Schrand (1997), Haushalter (2000), and Geczy, Minton, and Schrand (2006).

time-series variation in the cost of hedging weather risks. Before this date, firms with local weather exposures did not have access to financial contracts that would allow them to directly hedge their weather positions. Furthermore, we expect weather derivative contracts to disproportionately benefit those firms that, from a historical (pre-1997) perspective, were most subject to local weather shocks, irrespective of their post-1997 investment opportunities. This second layer of analysis is important because it provides cross-sectional predictions on the effect of weather risk exposure, both before and after weather derivatives were introduced, and because it allows the econometrician to control for other concurrent aggregate trends.

Using these sources of variation, we test the following two hypotheses:

HYPOTHESIS 1: *Weather-exposed firms are more likely to use weather derivatives.* Although all firms potentially benefit from hedging, we expect that those firms whose cash flows have historically fluctuated with changing weather conditions will be more likely to use weather derivatives after 1997, irrespective of their investment opportunities.

HYPOTHESIS 2: *The introduction of weather derivatives leads to an increase in firm value.* To the extent that left-tail weather-driven cash flow realizations limit debt capacity or investments, we expect weather-exposed firms to increase in value as weather derivatives allow them to insure against those negative weather realizations.

Hypothesis 1, although intuitive, is critical for our empirical tests, as it provides variation in weather derivative use that is likely to be orthogonal to future investment opportunities. Together with the time-series variation that results from the introduction of weather derivatives, Hypothesis 1 provides the arguably exogenous variation that we use to investigate Hypothesis 2.

To test Hypothesis 2, we alternatively rely on (1) fixed effects IVs (FE-2SLS-IV) and (2) lagged dependent variables 2SLS-IV (LD-2SLS-IV) specifications. FE-2SLS-IV models are attractive tests that allow us to overcome unobserved time-invariant firm heterogeneity, but they may exaggerate (underestimate) the effect of risk management when hedging is negatively (positively) correlated with lagged M–B ratios.[16] LD-2SLS-IV specifications, in contrast, are attractive in settings where the key omitted variables are time varying. In the results section, we discuss the robustness of the results to these alternative tests.

Formally, the first-stage FE-2SLS-IV specification is given by

$$wderiv_{it} = b * weatherexp_i * post + d * post + \eta_i + a_\chi X_{it} + e_{it}, \tag{2}$$

where $weatherexp_i$ captures historical (pre-1997) sensitivity to weather fluctuations. This variable proxies for the potential gains from hedging with weather

[16] See Angrist and Pischke (2009), pp. 243–247, for a discussion on the relative merits of these alternative models, as well as on the challenges of including lagged dependent variables in fixed effects specifications. The use of lagged dependent variable FE-2SLS models, however, does not affect the results (see Table IA.II in the Internet Appendix).

derivatives after 1997. The variable $post_t$ is an indicator that is equal to one after 1997, and η_i are firm fixed effects. Note that $wderiv_{it}$ is zero for the pre-1997 period and one for firms that used weather derivatives in the post-1997 period.[17]

We next use $\widehat{wderiv}_{it}$ to test for the effect of weather derivatives on value using the following second-stage specification:

$$y_{it} = \alpha + \beta_{wderiv} * \widehat{wderiv}_{it} + \psi_{\chi} X_{it} + \eta_i + \varepsilon_{it,} \tag{3}$$

where β_{wderiv} provides the FE-2SLS-IV estimate of the value of hedging. In (3), β_{wderiv} captures the causal effect of weather derivatives on value, in which the empirical counterfactuals are the same firm without derivatives in a period in which these contracts were not available and other firms without derivatives after 1997. LD-2SLS-IV specifications are analogously defined, with the exception that lagged M–B ratios are used instead of firm fixed effects. We expect β_{wderiv} to be positive and significant.

Finally, to take specifications (2) and (3) to the data, we require an estimate of $weatherexp_i$. We estimate pre-1997 weather exposures using the following two measures:

(1) Volatility (quarterly) of revenue to assets before 1997. Revenue volatility is attractive because it is straightforward to compute, and also because it captures the total hedging potential available to firms. However, it includes variation that results from other nonweather sources, which may be irrelevant for weather derivative use. An additional concern with this measure is that it is likely to be largest for relatively smaller firms, which may complicate inference.[18] As a result, our main specification focuses on a weather-based measure that we describe next.

(2) Weather-induced revenue-assets volatility (quarterly) before 1997. To focus on revenue volatility driven by weather fluctuations, we proceed in two steps. First, we estimate the sensitivity of revenue to weather conditions before 1997 using the following specification:

$$revassets_{it} = \alpha_i + \beta_i * DD_{it} + \gamma_i * \ln(assets_{it}) + \varepsilon_t, \tag{4}$$

where $revassets_{it}$ is the quarterly revenue-to-assets ratio, and DD_{it} is the relevant "degree day" weather measured at the firm level. We use cooling, heating, and energy degree days (CDD, HDD, and EDD, respectively) as controls. EDD is the sum of CDD plus HDD, and proxies for total energy demand. In (4), we also control for the level of assets. To avoid multicollinearity concerns,

[17] Even though $wderiv_{it}$ is a dichotomous variable, we estimate (2) using OLS, since a probit or a logit first stage can harm the consistency of the IV estimates (Angrist and Krueger (2001)). Using alternative specifications, however, does not affect the results of this paper (see Table IA.III in the Internet Appendix).

[18] In Tables IA.V and IA.VI, Columns I to III, in the Internet Appendix, we assess the potential consequences of size on the results of the paper.

we estimate separate regressions for each weather-related variable. The estimated coefficients β_i^{EDD}, β_i^{HDD}, and β_i^{CDD} capture the sensitivity of revenue to variation in EDD, CDD, and HDD, respectively. We refer to these estimates as "weather betas." Utilities can potentially gain from hedging weather risks irrespective of the sign of these betas. For example, some firms may benefit from abnormally cold seasons, whereas others may be negatively affected by cold weather conditions. As a result, the absolute value of these betas is informative about firms' hedging opportunities as a function of each variable.[19]

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 of the corresponding weather variable. For hedging purposes, the meaningful weather exposure is the product of the absolute value of weather betas ($|\hat{\beta}_i^{\text{EDD}}|$, etc.) and the degree of variation in each variable (σ_i^{EDD}, etc.). As such, $|\hat{\beta}_i^{\text{EDD}}|^* \sigma_i^{\text{EDD}}$, for example, captures the historical weather-induced volatility that results from changing EDD values.

We use the two historical weather exposure measures above to investigate the importance of weather distortions. In our empirical tests, we emphasize the importance of EDD weather-induced volatility for valuation, both with and without weather derivatives.

Note that, although the introduction of weather derivatives is plausibly exogenous to the investment opportunities of individual firms, other concurrent events can potentially complicate inference. The introduction of weather derivatives coincided with rapid growth in financial innovation affecting other financial contracts, concerns about global warming, and important deregulation events in the energy industry. In analyzing the effect of weather derivatives, we investigate and test for the implications of these concurrent effects.

III. Data Description

We use data from COMPUSTAT firms engaged in the distribution and generation of electricity and natural gas (Standard Industrial Classification codes 4911, 4923, 4924, 4931, and 4932). Given our interest in estimating pre-1997 weather exposure measures, we focus on U.S. firms with matching quarterly data for at least 10 years before 1997.[20] We arrive at a sample of 203 firms with up to 8,161 firm-year observations between 1960 and 2007.[21]

[19] Alternatively, we can concurrently estimate weather betas for both HDD and CDD variables. Using this alternative approach to rank firms in terms of their weather exposures does not affect the results of the paper. See Table IA.VII in the Internet Appendix.

[20] COMPUSTAT quarterly data are available since 1962. We require that the sample firms have at least 10 years of data prior to 1997 to allow us to estimate firms' exposure to weather variation before weather derivatives were introduced. Relaxing this assumption does not affect the main results of the paper. See Table IA.VI in the Internet Appendix.

[21] Selected variables such as market capitalization or deferred taxes are not available for all firm years. The balance sheet and cash flow statement variables as a percentage of assets are trimmed to remove the most extreme 0.50% in either tail of the distribution.

Table I

Summary Statistics

This table shows summary statistics for 203 U.S. electric and gas firms with matching financial information from COMPUSTAT before 1997 and weather data from NOAA. Panel A presents financial and weather variables. Total assets, revenue, and market value of equity are in thousands of constant 2008 dollars. *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 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 the market value of common equity minus the 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. *Dividends/assets* is the ratio of total dividends over total assets. Weather variables reported are CDD, HDD and EDD. HDD (CDD) reflects the number of degrees that a daily average temperature is below (above) 65°F, zero otherwise. EDD reflects the sum of HDD and CDD values. *Heating (cooling, energy) degree days, annual* is the sum of daily HDD (CDD, EDD) 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, interest rate) derivatives in the post-1997 period, and 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
Dividends/assets	8,161	0.030	0.011	0.000	0.016	0.030	0.041	0.267
Heating degree days, annual	8,161	5,170	1,965	85	2,131	5,577	7,408	10,244
Cooling degree days, annual	8,161	1,040	809	5	295	809	2,246	4,443
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	1,731	0.249	0.433	0	0	0	1	1
Natural gas derivative user	1,731	0.574	0.495	0	0	1	1	1
Interest rate derivative user	1,731	0.866	0.341	0	0	1	1	1

Summary statistics are presented in Table I, Panel A. To facilitate comparison over time, we report information in constant 2008 dollars. Average (median) total assets are \$5.2 (\$2.7) billion. Mean (median) revenue is \$2 (\$1.1) billion. The mean (median) market capitalization is \$2.3 (\$1.1) billion. We follow preexisting literature in using M–Bs as a measure of value. The average M–B is 1.075, with a standard deviation of 0.21.

Weather data are from NOAA. NOAA reports monthly temperatures as well as CDD and HDD data from 1895 to the present for 344 climate divisions in the

United States. Again, we compute EDD as the sum of CDD and HDD values. To match firms with weather sites, we use latitude and longitude information on firms' main business and each of the weather stations. For each firm, we find the closest climate division and use its weather information.[22] The annual weather information is summarized in Table I, Panel A. The mean (median) annual HDD level is 5,170 (5,577). The annual mean (median) CDD value is 1,040 (809). Similarly, the average (median) annual EDD value is 6,210 (6,386).

Data on the use of financial derivatives in the post-1997 period is hand-collected from Securities and Exchange Commission (SEC) filings using the LexisNexis Academic application. We use a list of related keywords to identify firms that relied on weather derivatives, natural gas, and interest rate hedging instruments at least once in the post-1997 period.[23]

Although we do not have data on actual derivative exposure by firm, we use indicator variables to classify firms as derivative users whenever SEC filings describe such contracts in the post-1997 period. Table I, Panel B reports information for the post-1997 sample, or 1,731 firm-year observations. Weather derivatives are used by 25% of the sample firms. This percentage contrasts with survey data from the CME that show that the percentage of firms using weather hedges in this industry is 35% (CME (2008)). The difference between these numbers may indicate that we are underreporting derivatives usage, which may reflect the fact that OTC weather derivative transactions are generally exempt from disclosure rules under the guidelines of the Financial Accounting Standards No. 133 statement.[24] Both percentages, however, suggest that weather derivatives are unlikely to be beneficial for all firms in the sample, reinforcing the importance of focusing on those utilities with significant weather exposures. Moreover, these percentages raise the concern that the estimated results from the paper may not be representative of the value of hedging in other settings.

In terms of other derivative use in the post-1997 period, natural gas and interest rate derivatives were used by 57% and 87% of the sample firms, respectively. The fact that the latter percentage is the largest is not surprising given the importance of interest rate swaps markets.

Table II, Panels A and B show the variables that we use to capture the historical weather exposure faced by utilities. These include: (1) revenue volatility (volatility of quarterly sales to assets), (2) CDD, HDD, and EDD weather betas (absolute value of the estimated coefficient of CDD, HDD, and EDD on

[22] NOAA reports the latitude and longitude data of all climate divisions. COMPUSTAT reports firms' zip codes and we rely on data from the U.S. Census Bureau to approximate the latitude and longitude location of each zip code. See http://www.census.gov/geo/www/gazetteer/places2k.html#counties for zip code location information, and Vincenty (1975) for computing geodesic distances between locations.

[23] 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."

[24] See http://www.fasb.org.

Table II

Measures of Weather Exposure

This table shows summary statistics (Panel A) and correlations (Panel B) for various measures of weather risk exposure. Panel C shows firm and hedging characteristics for four groups of firms based on EDD weather-induced volatility ranks. 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 at the quarterly level, 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 weather risk exposure measures are estimated using pre-1997 data. Revenue is the average pre-1997 value of revenue in thousands of constant 2008 dollars. In Panel C, firm-clustered standard errors are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

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	0.006	0.013	0.024	0.111	0.193
CDD beta ($\lvert\beta_i^{\mathrm{CDD}}\rvert$)	203	0.908	1.419	0.003	0.059	0.310	2.972	10.508
HDD beta ($\lvert\beta_i^{\mathrm{HDD}}\rvert$)	203	0.255	0.360	0.000	0.008	0.099	0.823	2.209
EDD beta ($\lvert\beta_i^{\mathrm{EDD}}\rvert$)	203	0.300	0.449	0.000	0.013	0.114	0.930	3.480
CDD standard deviation	203	0.027	0.015	0.005	0.009	0.024	0.048	0.078
HDD standard deviation	203	0.102	0.033	0.009	0.047	0.112	0.135	0.165
EDD standard deviation	203	0.085	0.033	0.020	0.031	0.096	0.121	0.150
CDD weather-induced volatility ($\lvert\beta_i^{\mathrm{CDD}}\rvert) * \sigma_i^{\mathrm{CDD}}$	203	0.019	0.026	0.000	0.001	0.008	0.066	0.123
HDD weather-induced volatility ($\lvert\beta_i^{\mathrm{CHDD}}\rvert) * \sigma_i^{\mathrm{HDD}}$	203	0.024	0.033	0.000	0.001	0.009	0.088	0.152
EDD weather-induced volatility ($\lvert\beta_i^{\mathrm{CEDD}}\rvert) * \sigma_i^{\mathrm{EDD}}$	203	0.022	0.031	0.000	0.001	0.009	0.086	0.131

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	0.921	1.000		
HDD weather-induced volatility	0.916	0.991	1.000	
EDD weather-induced volatility	0.863	0.957	0.977	1.000

(Continued)

Table II—*Continued*

Panel C. EDD Weather-Induced Volatility Groupings, Firm, and Hedging Characteristics						
	Group 1	Group 2	Group 3	Group 4	Diff 4 vs. 1	Diff 3&4 vs. 1&2
Number of firms	49	50	49	55		
Revenue volatility	0.0178	0.0208	0.0323	0.0943	0.077***	0.046***
	(0.001)	(0.002)	(0.003)	(0.005)	(0.006)	(0.005)
Revenue	3,453.2	2,424.1	2,608.8	1,959.8	−1,493.4**	−667.916*
	(548.5)	(263.9)	(350.3)	(322.5)	(636.1)	(387.3)
M–B ratio	1.586	1.520	1.497	1.373	−0.2121***	−0.1207***
	(0.030)	(0.038)	(0.038)	(0.033)	(0.044)	(0.003)
Net debt	0.523	0.512	0.503	0.482	−0.0413***	−0.0253***
	(0.012)	(0.006)	(0.008)	(0.008)	(0.014)	(0.009)
Weather derivative user	0.122	0.160	0.306	0.346	0.223***	0.186***
	(0.047)	(0.052)	(0.067)	(0.065)	(0.080)	(0.058)
Natural gas derivatives user	0.367	0.640	0.612	0.527	0.160	0.062
	(0.070)	(0.069)	(0.070)	(0.068)	(0.097)	(0.070)
Interest rate derivative user	0.776	0.860	0.898	0.691	−0.085	−0.030
	(0.060)	(0.050)	(0.044)	(0.063)	(0.087)	(0.056)

the revenue-to-assets ratio), and (3) CDD, HDD, and EDD weather-induced volatility (weather betas times the relevant historical standard deviation). All measures are estimated using pre-1997 quarterly data.

Table II, Panel A provides consistent evidence that the reported weather exposure measures tend to vary substantially. The mean of revenue-to-assets volatility is 0.043, but the 10^{th} and 90^{th} percentiles are 0.01 and 0.11, respectively. Weather betas also exhibit substantial dispersion. The averages of 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 for CDD and 0.01 to 0.93 for EDD betas. Similarly, weather-induced volatility measures vary greatly. Although these weather exposure numbers are difficult to interpret in isolation, the relative ranks that they generate are intuitive: they are orderings of weather risk exposure, which is what we use in the paper.

Table II, Panel B shows that the correlation coefficient between revenue and weather-induced volatility is 0.92, 0.92, and 0.86 for weather measures CDD, HDD, and EDD, respectively, and that the CDD–HDD (HDD–EDD) volatility correlation is 0.99 (0.98).[25] The fact that, holding revenue-weather correlations constant, weather betas are (by construction) increasing in revenue volatility implies that this correlation should be interpreted with caution.[26]

In this paper, we are primarily interested in exploring the consequences of weather exposure rankings rather than revenue volatility groupings because the latter may include revenue variation from other sources, which is irrelevant for weather derivative use.

In Table II, Panel C, we sort the sample firms into four groupings based on their estimated EDD weather-induced volatility measures, and present firm and hedging characteristics for each subsample. Firm characteristics are pre-1997 averages collapsed at the firm level. Firms in group 1 (4) exhibit the lowest (highest) EDD weather exposures. Consistent with Panel B, weather exposure and revenue volatility measures are tightly linked. Panel C also indicates that firms with larger weather exposures are significantly smaller in terms of revenue than other firms. The average revenue differences between firms in groups 1 and 4 is \$1.5 billion, significant at the 5% level. Interestingly, despite the fact that high weather exposure firms are smaller, their average M–B ratios are lower, which is consistent with the idea that weather risk can potentially harm firm value. M–B ratios are consistently lower for firms with

[25] Similar correlations are obtained if the pre-1997 sample is divided into two equal-sized periods and we compute: (a) firm-level revenue volatility using pre-1980 data, and (b) weather exposure measures using 1980 to 1997 data. Using these nonoverlapping period measures, we obtain correlations between revenue volatility and EDD, HDD, and CDD weather exposure measures of 0.89, 0.91, and 0.90, respectively.

[26] More generally, whether firms with higher revenue volatility have a higher covariance between weather and revenue variables is determined by whether higher revenue volatility is driven by weather or other factors. For example, higher revenue volatility that is explained by nonweather-related variables leads to unchanged weather betas and lower revenue-weather correlations. Intuitively, higher revenue volatility does not necessarily imply higher gains from hedging weather exposures as measured by the weather betas.

higher weather exposures: they are 1.59, 1.52, 1.50, and 1.37 for firms in groups 1–4, respectively. The difference between firms in groups 1 and 4 is 0.2, significant at the 1% level. In addition, net debt is monotonically decreasing in weather exposure. Net debt is 0.52, 0.51, 0.50, and 0.48 for firms in weather exposure groups 1–4, respectively. The leverage difference for firms in groups 1 and 4 is 0.04, significant at the 1% level.

The last three rows in Table II, Panel C show the usage of weather, natural gas, and interest rate derivatives in the post-1997 period as a function of weather exposure. Noticeably, firms with higher weather exposure before 1997 are monotonically more likely to use weather derivatives after 1997. The ratio of derivative users is 0.12, 0.16, 0.31, and 0.35 across weather exposure groups 1–4. The difference between firms in groups 4 and 1 is 0.22, significant at the 1% level. These ratios indicate that only 6 and 8 firms in groups 1 and 2, respectively, used weather derivatives, whereas 15 and 19 firms, respectively, used them in the top two weather exposure categories. In the empirical tests, we exploit both the time-series and the cross-sectional (group) variation in weather derivative use. Interestingly, there are no significant differences across weather exposure groups in terms of the use of natural gas and interest rate derivatives.

Although the summary statistics suggest that weather risk exposure may limit debt capacity and hurt firm value, other confounding factors can potentially account for these correlations. To explore the direct consequences of weather variables, we next investigate the impact of changing weather conditions on firms' cash flows using fixed effects specifications.

IV. Changing Weather Conditions and Cash Flow Effects

To test for the effect of changing weather conditions on operating performance, we investigate whether relatively clement weather seasons relative to historical averages, or weather "shocks" for utilities, affect firm results. More specifically, we test whether relatively low EDD values affect firm outcomes. To this end, we introduce a firm-specific weather shock variable that is set to one for the lowest quintile of annual EDD values per firm (i.e., each firm has one shock per five observations) and zero otherwise. We focus on the effect of mild EDD values to provide a single and simple test that captures the importance of weather variation on cash flows independent of a firm's main seasonal exposures (CDD or HDD). We control for year effects using indicator variables, and we control for time-varying firm characteristics using the natural logarithm of lagged assets, and lagged profitability in those specifications in which the dependent variable is not profit itself. These within-firm tests are attractive because they allow us to control for time-invariant characteristics that would otherwise complicate inference.

The results are presented in Table III. Column I shows that mild weather realizations are correlated with lower revenue. The effect is statistically significant but economically modest; weather shocks lead to average declines of 2% in revenue. Columns II and III confirm that weather shocks lead to lower

Table III

Revenue Consequences of Weather Shocks: By Measures of Weather Exposure

This table presents the impact of mild weather conditions (low EDDs), or weather shocks for utilities, on measures of operating performance both for all sample firms (Columns I through V) and for subsamples sorted into quartiles based on their pre-1997 estimated weather exposure, or quantity risk quartiles (Columns VI through X). The dependent variables are (a) *Ln Revenue* (Columns I, VI, VII, VIII, and IX), (b) *OROA* (Columns II and X), (c) *Ln Operating Income* (Column III), (d) *Dividends/Assets* (Column IV), and (e) *Investment Rate* (Column V). *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. Measures of weather exposure are (a) *Revenue/Assets* volatility quartiles, groupings based on the historical standard deviation of quarterly revenue divided by assets (Column VI), (b) *Weather-induced volatility* quartiles, groupings based on the product of EDD (Columns VII and X), CDD (Column VIII), and HDD (Column IX) weather betas in the pre-1997 period, and the relevant historical standard deviation. Each column shows the results of a fixed effects (firm) regression that also includes the following controls: the natural logarithm of lagged total assets, lagged *OROA* (except Columns II, III, and X, where it is omitted), and year dummies (estimated coefficients not reported). Standard errors are clustered at the firm level and are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables									
	Ln Rev. (I)	OROA (II)	Ln. Op. Inc (III)	Div./ Assets (IV)	Inv. Rate (V)	Ln Rev. (VI)	Ln Rev. (VII)	Ln Rev. (VIII)	Ln Rev. (IX)	OROA (X)
Weather shock	−0.0161**	−0.0023**	−0.0196***	0.00004	0.0029	0.0092	0.0003	0.0172	0.0144	−0.0001
	(0.007)	(0.001)	(0.008)	(0.0014)	(0.003)	(0.012)	(0.015)	(0.016)	(0.016)	(0.001)
Quantity risk quartile 2						−0.0048	0.0243	−0.0092	−0.0016	−0.0009
*Weather shock						(0.019)	(0.018)	(0.020)	(0.019)	(0.002)
Quantity risk quartile 3						−0.0048	−0.0117	−0.0128	−0.0269	−0.0031
*Weather shock						(0.019)	(0.027)	(0.024)	(0.027)	(0.002)
Quantity risk quartile 4						−0.0872***	−0.0775***	−0.1041***	−0.0906***	−0.0050**
*Weather shock						(0.024)	(0.022)	(0.024)	(0.023)	(0.002)
Weather-based quantity risk quartiles						Vol. of Rev/Assets	EDD Weather Ind. Vol.	CDD Weather Ind. Vol.	HDD Weather Ind. Vol.	EDD Weather Ind. Vol.
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,743	7,743	7,743	7,743	7,743	7,743	7,743	7,743	7,743	7,743
R^2	0.970	0.400	0.977	0.370	0.175	0.970	0.970	0.970	0.970	0.401

operating return-on-assets and operating profits. Columns IV and V, in contrast, cast doubt on the notion that moderate weather conditions affect dividend or investment decisions. The large R^2s in Table III are mostly driven by the firm fixed effects controls and the significant degree of persistence in the relevant outcome variables.

To explore whether the results in Table III, Columns I–V are evidence of small weather effects across the board, or whether they reflect heterogeneous consequences across firms, we rely on the weather exposure variables described in Table II. For each weather exposure measure, we (1) divide the sample firms into quartiles, which are referred to as "quantity risk" quartiles, (2) interact each quartile with the firm-specific weather shock variable, and (3) test which quartile exhibits the largest effects. By construction, we expect firms with higher weather exposures to be most sensitive. We are interested, however, in testing whether those rankings provide significant economic and statistical differences across groups of firms.

The results are reported in Table III, Columns VI–X. Column VI shows that weather shocks lead to insignificant effects on all but the most volatile quartile of firms; firms in quartile 4 exhibit a drastic decline in revenue of 9%, significant at the 1% level. Columns VII, VIII, and IX show that alternative weather exposure proxies (EDD, CDD, or HDD weather volatilities) obtain similar results: firms in weather exposure group 4 suffer large and significant declines in revenue. Lastly, using profitability as an alternative outcome variable in Column X, we confirm that the negative effects of weather shocks are concentrated on quartile 4 firms.

Taken together, the results from Table III show that weather conditions affect operating profitability. Furthermore, they demonstrate that mild weather events are relevant for a subset of high weather exposure firms. In other words, the fact that only a fraction of utilities are subject to cash flow volatility provides information on which firms are likely to be subject to the largest distortions in terms of value, investment, and financing policies. We turn to these tests next.

V. Weather Exposure without Derivatives: Value, Investment, and Financing Effects

In this section, we investigate the value, investment, and financing effects of weather risk exposure before the introduction of weather derivatives.

In Table IV, Columns I and II, we examine the effect of weather risk on M–B ratios before 1997. Given that weather exposure variables are time-invariant, we rely on regional indicator variables and firm controls to account for heterogeneity across firms.[27] The results show that firms in the fourth quartile

[27] We include dummies for each of the U.S. Census divisions (see http://www.census.gov). Furthermore, the number of observations in Table IV declines relative to Table III because M–B ratios are not available for all firms. Also, the number of observations in Columns III–VI in Table IV declines because capital expenditures and cash data are available for fewer firm years than other variables.

Table IV

Weather Risk Exposure without Weather Derivatives: Pre-1997 Evidence

This table examines the impact of weather risk exposure on firm value, investment, financing, and dividend policies before weather derivatives were introduced in 1997. The dependent variables are: (a) the market-to-book ratio (Columns I and II), (b) *CAPEX/Assets* (Columns III and IV), (c) *Net Debt/Assets* (Columns V and VI), and (d) *Dividend/Assets* (Columns VII and VIII). Weather-based quantity risk exposure is measured using, alternatively, (i) *Revenue/Assets* volatility quartiles (Columns I, III, V, and VII), and (ii) *EDD weather-induced volatility* quartiles (Columns II, IV, VI, VIII). Each regression also includes regional indicator variables for each of the U.S. Census divisions, and year dummies as controls (estimated coefficients are omitted). Standard errors are clustered at the firm level and are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Market-to-Book Ratio		CAPEX/Assets		Net Debt/Assets		Dividends/Assets	
Dependent variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Quantity risk quartile 4	−0.0415***	−0.0330**	−0.0001	0.0019	−0.0430***	−0.0240**	−0.0044***	−0.0030***
	(0.014)	(0.013)	(0.003)	(0.003)	(0.012)	(0.012)	(0.001)	(0.001)
Quantity risk quartile 3	−0.0206*	−0.0177	0.0006	−0.0008	−0.0222**	−0.0065	−0.0018**	0.0002
	(0.012)	(0.012)	(0.003)	(0.003)	(0.010)	(0.009)	(0.001)	(0.001)
Quantity risk quartile 2	−0.0098	−0.0129	−0.0001	0.0031	−0.0186**	0.0032	−0.0004	0.0008
	(0.011)	(0.011)	(0.003)	(0.002)	(0.009)	(0.009)	(0.001)	(0.001)
Ln Assets	−0.0078*	−0.0056	−0.0001	0.0001	−0.0032	−0.0009	0.0003	0.0005*
	(0.004)	(0.004)	(0.001)	(0.001)	(0.003)	(0.003)	(0.0003)	(0.0003)
OROA	1.5851***	1.5446***	−0.0648	−0.0624	−0.9376***	−0.9980***	0.0613***	0.0556***
	(0.155)	(0.152)	(0.043)	(0.043)	(0.129)	(0.127)	(0.010)	(0.010)
Investment rate	0.2380***	0.2393***						
	(0.041)	(0.042)						
Market-to-book ratio			0.0902***	0.0898***	−0.0298	−0.0212	0.0152***	0.0158***
			(0.015)	(0.015)	(0.044)	(0.042)	(0.004)	(0.004)
Weather-based quantity risk quartiles	Vol. of Rev/assets	EDD weather Ind. vol	Vol. of Rev/assets	EDD weather Ind. vol	Vol. of Rev/assets	EDD weather Ind. vol	Vol. of Rev/assets	EDD Weather Ind. Vol
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,490	4,490	3,080	3,080	3,080	3,080	4,490	4,490
R^2	0.729	0.728	0.302	0.303	0.488	0.478	0.332	0.329

of weather exposure are subject to a 3% to 4% discount in terms of value. In contrast, the value difference between firms in quartiles 2 and 3 and those in quartile 1, although negative and increasing in absolute value, are not robustly significant. The effects of profitability and investment growth on M–B are both positive as expected.

To assess whether the differences in market values reported above reflect distortions in operating decisions, in Columns III and IV of Table IV we examine the impact of weather exposure on the ratio of capital expenditures to assets. The results cast doubt on the idea that weather exposure affects firms' investment decisions, at least before 1997.

In Table IV, we also test for the effect of weather exposure on leverage (Columns V and VI) and payout policies (Columns VII and VIII). The evidence shows that firms in the most weather-exposed quartile have two to four percentage points lower debt ratios than their peers (6% to 11% differences). This is consistent with the idea that creditors care about left-tail cash flow events. Similarly, we find that highly weather-exposed firms have lower dividend ratios than other firms. The differences are in the 0.003 to 0.004 range, significant at conventional levels. In contrast, firms in quartiles 2 and 3 do not exhibit robust differences in their leverage or dividend ratios across specifications.

These results show that financial distortions may be important to understanding weather exposure effects on value. The presence of sizeable weather risk exposures may lead firms to use conservative financial structures, which can limit tax or incentive debt-based benefits. Similarly, although the average level of investments is not affected, weather-exposed firms exhibit less aggressive payout policies, consistent with the presence of external financing costs.

Overall, the results provide empirical support for the idea that, absent weather hedges, weather-exposed firms are less valuable and adopt more conservative financial policies than their peers. We now test whether these distortions were relaxed by financial innovation.

VI. Hedging and Firm Value: Evidence from Weather Derivatives

A. Differences-in-Differences Specifications

Before implementing the main IVs specifications, we test for the effect of hedging on value using differences-in-differences specifications. Intuitively, the introduction of weather derivatives after 1997 would be expected to disproportionately benefit those firms with substantial ex ante weather exposures. To conduct these tests, we interact the pre-1997 weather exposure groupings with an indicator variable equal to one in the post-1997 period. We expect firms in quartile 4 in terms of weather exposure to gain in value. Given our interest in testing for weather effects, we present tests based on weather exposure measures as the key quantity risk variables, rather than relying on proxies for total revenue volatility.

Table V, Columns I and II show the results using firm-fixed effects specifications with and without firm controls, respectively. The results show that

Table V

Weather Exposure Effects on Value and Profitability Around 1997

This table reports changes in market-to-book ratios as a function of weather risk exposure variables (Columns I–V), and net income weather sensitivity (Columns VI–IX), around 1997. Measures of weather risk exposure are: (a) *EDD quantity risk quartiles*, and (b) *EDD weather-based quantity risk indicator*, which is equal to one whenever the pre-1997 EDD quarterly beta was significant. *Weather shock* is an indicator variable equal to one if (a) the annual EDD values are in the lowest quintile, zero otherwise (Columns VI and VI), or (b) the annual EDD values are below 90% of the average in the 1977–1997 period (Columns VIII and IX). Results from fixed effects (firm) specifications are shown in Columns I, II, and IV and Columns VI to IX. Estimates from lagged dependent variables (M–B) specifications are shown in Columns III and V. All specifications include a post-1997 dummy variable, year dummies, and controls for the natural logarithm of lagged assets and lagged *OROA* (results not shown). Columns II and IV include controls for lagged investment rates, and Columns III and V include controls for each of the quantity risk exposure variables (results not shown). Columns I–V report results for all sample firms with relevant data, and Columns VI–IX split the sample into two groups based on EDD quantity risk quartiles. Results for EDD risk quartiles 3 and 4 (quartiles 1 and 2) are shown in Columns VI and VIII (Columns VII and IX). Standard errors are clustered at the firm level and are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables	Market-to-Book Ratio					Ln Net Income			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
EDD quantity risk quartile 4*Post	0.1153***	0.1305***	0.0172**						
	(0.032)	(0.030)	(0.008)						
EDD quantity risk quartile 3*Post	−0.0023	0.0145	0.0157*						
	(0.028)	(0.030)	(0.008)						
EDD quantity risk quartile 2*Post	0.0163	0.0178	0.0080						
	(0.034)	(0.032)	(0.011)						
EDD weather-based quantity risk indicator*Post				0.0693***	0.0196***				
				(0.024)	(0.007)				
Lagged M–B ratio			0.8464***		0.8464***				
			(0.011)		(0.010)				
Weather shock						−0.0624***	0.0076	−0.0808**	−0.0082
						(0.019)	(0.023)	(0.036)	(0.038)
Weather derivatives						−0.0178	−0.0017	0.0086	0.0122
						(0.079)	(0.078)	(0.075)	(0.069)

(*Continued*)

Table V—*Continued*

Dependent Variables	Market-to-Book Ratio					Ln Net Income			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Weather derivatives *Weather shock						0.1481**	0.0029	0.1329**	−0.0547
						(0.073)	(0.084)	(0.067)	(0.118)
Sample	All firms	All firms	All firms	All firms	All firms	Quantity risk Quartiles 3–4	Quantity risk Quartiles 1–2	Quantity risk Quartiles 3–4	Quantity risk Quartiles 1–2
Year controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Observations	5,226	5,226	5,226	5,226	5,226	3,779	3,837	3,779	3,837
R^2	0.721	0.762	0.904	0.756	0.904	0.928	0.911	0.928	0.911

quartile 4 firms in terms of EDD weather exposure increase their valuations following the introduction of weather derivatives. The estimated coefficient is large: M–B ratios increase by 11–13 percentage points, significant at the 1% level. As in the pre-1997 period, firms in weather exposure quartiles 2 and 3 do not exhibit differential value effects.

One concern with fixed effects specifications is that they may not adequately control for time-varying omitted variables that differentially affect firms based on their historical weather exposure. To address this concern, in Column III of Table V, we report results from a lagged dependent variables model. The results again indicate that firms in the most weather-sensitive quartile increase in value after 1997: the estimated effect is 1.7 percentage points, significant at the 5% level. Also, as expected, lagged M–B ratios are important determinants of M–B values.

Columns IV and V of Table V show that even a noisy proxy variable for historical weather exposure, such as a statistically significant EDD weather beta before 1997 (which holds for 71% of the sample firms), is correlated with meaningful gains in M–B ratios after the introduction of weather derivatives. The value gains are in the 2% to 7% range depending on the specification. These results confirm that weather-exposed firms increased in value after 1997, which is consistent with the idea that weather derivatives have a positive effect on firm value.

An alternative difference-in-differences test for the importance of weather derivatives is to investigate whether the correlations between weather shocks and net income change around 1997 for firms with and without weather derivatives. If firms hedge their weather exposures with derivatives, these contracts should pay in periods of low energy demand, reducing the volatility of profits. As a result, we would expect the interaction of weather derivatives and weather shocks to be positive and significant.

Table V, Column VI presents the results for the top half of the sample firms in terms of weather exposure, which, according to the data in Table II, Panel C, account for the bulk of weather hedging. Consistent with the evidence presented in Table III, the profits of highly weather-exposed firms decline in the presence of weather shocks. The estimated coefficient on weather derivatives is negative but insignificant, consistent with the idea that firms are primarily using these contracts to shift cash flows across states of the world. Interestingly, the interaction term between weather derivatives and weather shocks is positive and significant, and the estimated coefficient overcomes the effect of the weather shock variable. This result implies that weather-sensitive firms using derivatives are able to eliminate the negative consequences of weather shocks and that weather hedge ratios are statistically indistinguishable from 100%. More broadly, these results are important in view of the Guay and Kothari (2003) observation that derivative positions are typically relatively small and unlikely to significantly affect firm value. Our results show that weather derivatives have a statistically significant and economically meaningful effect on profits for weather-sensitive firms.

To further investigate the implicit hedge ratios, we introduce an alternative net income smoothing test based on anecdotal evidence that suggests utilities seek weather insurance contracts with strike prices that are in the 5% to 10% range of historical (10–20 year) weather levels. We incorporate these features by (1) setting the weather shock to one in years where annual EDD values are 90% or less than historical values, and (2) testing for the impact of the interaction between this alternative weather shock dummy and the weather derivatives variable. The results, presented in Table V, Column VIII, confirm the two findings above: hedging smoothes weather shocks, and implicit hedge ratios are consistently large.

Table V, Columns VII and IX, in contrast, show that weather shocks and their interactions with weather derivatives have insignificant effects on net income for the bottom half of the sample in terms of weather exposure.

Overall, Table V provides evidence consistent with the notion that weather derivatives benefit those firms with high ex ante weather exposure. After 1997, weather-exposed firms increase in value. Furthermore, the profits of weather-sensitive firms that rely on weather derivatives after 1997 become isolated from weather shocks. This latter evidence suggests that, if abnormally low cash flow realizations limit debt capacity or investments, weather hedging may allow firms to overcome those constraints and increase firm value.

B. IVs Specifications

If weather derivatives explain the difference-in-differences results in Table V, we would also expect weather-sensitive firms to be more likely to use weather derivatives after 1997.

We test this conjecture formally using an IVs framework. Columns I and II of Table VI present the results. In both specifications, the dependent variable is an indicator variable that, in the post-1997 period, is equal to one for weather derivative users, and zero for both nonusers and all pre-1997 observations. The evidence confirms that weather-exposed firms are significantly more likely to use weather derivatives after 1997. Using EDD weather-induced volatility, we show in Column I of Table VI that weather exposure quartiles 3 and 4 are 23.9 and 24.4 percentage points, respectively, more likely to use weather derivatives than quartile 1 firms. Only 12% of firms in quartile 1 use weather derivatives. These differences are statistically significant at the 10% and 5% levels, respectively. Economically, these results show that firms in the most weather-sensitive quartile are 2.9 times more likely to use weather derivatives than those in quartile 1. Interestingly, this differential variation is likely to capture the insurance, as opposed to the speculative, demand for derivatives.[28]

Table VI, Column II relies on a noisy measure of weather exposure, namely, a dummy variable equal to one whenever the firm shows a statistically significant EDD weather beta before 1997. The results show that firms with significant

[28] For evidence on speculation with derivatives, see, for example, Géczy, Minton, and Schrand (2007) and Adam and Fernando (2006).

Table VI

Weather Derivatives and Firm Value

This table presents 2SLS-IV estimates on the impact of weather derivatives on firm value (market-to-book ratio). Columns I and II report first-stage estimates of the effect of pre-1997 weather exposure measures and a post-1997 indicator variable on weather derivative use. Columns III to IX report 2SLS-IV estimates on the impact of weather derivatives on market-to-book ratios. Weather derivatives were introduced in 1997. The instrumental variables for weather derivatives are based on measures of pre-1997 weather exposure, namely, (a) *EDD quantity risk quartiles* (Columns I, III, and V-IX), and (b) *EDD weather-based quantity risk indicator* (Columns II and IV). Results from fixed effects (firm) specifications are shown in Columns I to IV, VI, and VIII. Estimates from lagged dependent variables (M–B) specifications are shown in Columns V, VII, and IX. Specifications in Columns VI–IX include year dummies and controls for the natural logarithm of lagged assets, lagged *OROA*, and lagged investment rates; those in Columns V, VII, and IX also control for lagged M–B ratios, and for each of the quantity risk quartiles (estimated coefficients are omitted). Deregulation electricity (natural gas, access to retail, industry, and all electricity consumers, NG pilot, partial, and all consumers) are indicator variables equal to one for the observations where the relevant state-year has experienced deregulation, and zero otherwise. Standard errors are clustered at the firm level and are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variables	Weather Derivatives (I)	Weather Derivatives (II)	Market-to-Book Ratio (III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Weather derivatives			0.2442***	0.2452***	0.1177***	0.3124**	0.0635**	0.2959*	0.0834*
			(0.055)	(0.055)	(0.024)	(0.154)	(0.030)	(0.172)	(0.044)
EDD quantity risk quartile 4*Post	0.2437**								
	(0.110)								
EDD quantity risk quartile 3*Post	0.2387*								
	(0.123)								
EDD quantity risk quartile 2*Post	0.1464								
	(0.123)								
EDD weather-based quantity risk indicator*Post		0.1989**							
		(0.088)							
Post	0.1242*	0.1441**							
	(0.064)	(0.065)							
Deregulation electricity						−0.0459	0.0204	−0.0585*	0.0176
						(0.033)	(0.012)	(0.031)	(0.013)
Dereg. elect. retail consumers						−0.0845*	−0.0347	−0.0950*	−0.0441*
						(0.049)	(0.024)	(0.051)	(0.026)

(*Continued*)

Table VI—*Continued*

Dependent Variables	Weather Derivatives (I)	Weather Derivatives (II)	Market-to-Book Ratio (III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
Dereg. elect. industrial consumers						0.0561	0.0060	0.0646	0.0182
						(0.049)	(0.018)	(0.054)	(0.019)
Dereg. elect. all consumers						0.0628**	0.0356*	0.0600*	0.0294
						(0.032)	(0.020)	(0.035)	(0.022)
Deregulation natural gas						−0.0094	−0.0133	−0.0052	−0.0213
						(0.049)	(0.022)	(0.050)	(0.024)
Deregulation NG pilot program						−0.0246	−0.0051	−0.0211	0.0013
						(0.048)	(0.022)	(0.045)	(0.023)
Deregulation NG partial program						0.0687	0.0258	0.0727	0.0295
						(0.054)	(0.021)	(0.053)	(0.024)
Deregulation NG all consumers						−0.0074	−0.0181	−0.0120	−0.0188
						(0.068)	(0.022)	(0.065)	(0.025)
Ln CDD								0.0346***	0.0003
								(0.010)	(0.001)
Ln HDD								0.0084	−0.0008
								(0.023)	(0.002)
Interest rate derivatives								−0.0510	−0.0270
								(0.050)	(0.017)
Natural gas derivatives								0.0018	0.0021
								(0.037)	(0.012)
Single state utility*Post								0.0266	0.0175
								(0.048)	(0.013)
Firm-fixed effects	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No
Year controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,226	5,226	5,226	5,226	5,226	5,226	5,226	5,226	5,226

weather betas are 20 percentage points more likely to use weather derivatives than other firms. In economic terms, this difference implies that weather-sensitive firms are 2.4 times more likely to use weather derivatives than other firms. Furthermore, the *F*-test in these specifications is 9.8 (Column I) and 19.2 (Column II), which shows that these variables provide meaningful variation in weather derivatives.

Consistent with Hypothesis 1, the results provide empirical support for the notion 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 hedging tools more frequently than other firms.

Having shown that weather exposure begets usage of weather derivatives, we now present the main results on the consequences of risk management for firm value (M–B ratios). Columns III and IV of Table VI present 2SLS-IV estimates of the effect of weather derivatives on value corresponding to the first-stage specifications in Columns I and II. These fixed effects specifications show a positive and arguably causal effect of derivatives on value. The point estimates are in the 24% to 25% range, and are significant at the 1% level. To assess the robustness of the results to time-varying omitted variables, we also report results from an IV-2SLS lagged M–B model. The results indicate that weather derivatives lead to an increase in value of 12%, significant at the 1% level.

Overall, these results provide empirical support for Hypothesis 2, which predicts that weather derivatives lead to economically large and statistically significant effects on value.

Although the introduction of weather derivatives was arguably exogenous to individual firms, in Table VI, Columns VI–IX we examine the robustness of our results against alternative hypotheses. Inference may be confounded, for example, by a combination of changing business prospects because of deregulation, variation in climate conditions because of global warming, or a reduction in exposure driven by other hedging technologies.

We use information from the Energy Information Administration (EIA; 2003) to test whether state-level deregulation of electricity and natural gas markets drives the reported effects. In Table VI, Columns VI–IX, we include dummy variables equal to one for observations in which the relevant state-year experiences deregulation actions. We also include detailed indicator variables to control for specific electricity (Fabrizio, Rose, and Wolfram (2007)) and natural gas deregulation events. These include having access to retail, industrial, or all electricity consumers, and having pilot, partial, or complete choice in natural gas markets. Each indicator variable is set to one for the observations in which, according to the EIA, the relevant state-year experiences deregulation.[29] Although we find that (1) access to all consumers in electricity leads to an increase in M–B ratio of 3% to 6%, and (2) access to retail clients has a negative

[29] 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.

effect on value in the 3% to 10% range (other effects are insignificant or not robust across specifications), we do not find that such detailed deregulation indicator variables affect the key coefficients of interest.

In Table VI, Columns VIII and IX, we provide results of further tests on whether changing weather conditions and alternative hedging technologies affect the key results of this paper. To this end, we include controls for CDD or HDD values. The estimated coefficient of CDD on M–B ratios is positive and significant, showing that higher cooling demand leads to higher firm value. The effect of HDD, in contrast, is insignificant. We also investigate whether the post-1997 effects are related to the use of other financial contracts. We fail to find significant effects on the interaction between the use of interest rate and natural gas derivatives and the post-1997 indicator variable. Interpreting these latter coefficients is challenging, however, given the endogeneity between hedging decisions and firm value, which we cannot overcome in the case of interest rate and natural gas derivatives. Finally, to investigate whether the differential effects of regional diversification have a bearing on the results, we assess the differential post-1997 behavior of those utilities that, as of 1997, operated only within one state, relative to multiple-jurisdiction firms. This additional interaction is insignificant.

Overall, the evidence presented in Table VI shows that, after controlling for a wide array of alternative variables, the effect of weather derivatives on value remains positive and significant, bolstering the case for the causal interpretation of the effect of weather derivatives on value. As is common with IV estimates, the standard errors are significantly large in some specifications because these estimates rely on relatively fewer observations. However, the most precisely estimated coefficients are in the 6% to 8% range, consistent with prior estimates in the literature (Allayannis and Weston (2001), Carter, Rogers, and Simkins (2006)).

In the Internet Appendix we present additional robustness tests that investigate the sensitivity of the results to: (1) using alternative econometric specifications, (2) excluding firms from one state at a time, (3) using size matching techniques using pre-1997 revenue information, (4) using pre-1997 firm size as placebo IV, (5) dropping the 10-year data requirement for the sample firms, (6) using an out-of-sample measure of weather exposure, (7) relying on alternative weather-based IVs, and (8) using alternative dependent variables to capture firm value. In addition, we examine the effect of hedging within subsamples. Specifically, we test for the impact of weather derivatives if: (1) we exclude the 1997 to 2002 period, (2) we only focus on post-1994 data, (3) we separately analyze firms with and without WNA clauses, and (4) we separately use firms with relatively low (high) leverage levels before 1997. These alternative tests confirm the main results of the paper.

C. Specific Channels

The evidence presented thus far demonstrates that weather-exposed utilities use weather derivatives more frequently than other firms, and that weather derivatives lead to significant gains in firm value. But what, exactly, changes inside firms with risk management? Previous studies emphasize the role of hedging for investment and capital structure decisions. Furthermore, as argued above, financing policies are shown to be at least partially distorted by weather exposure before weather derivatives were available. We examine these and other alternative channels in Table VII.

Table VII reports both difference-in-differences (Panel A) and fixed effects 2SLS-IV (Panel B) estimates, where the IVs are EDD weather exposure quartiles. We investigate whether revenue, financing, investment, and payout policies react differentially for firms in distinct weather quartiles after 1997 in response to weather derivative use.

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

The consequences for financing decisions are investigated in Table VII, Columns II (net debt), III (book leverage), and IV (cash to assets). Irrespective of the measure used, differences-in-differences estimates (Panel A) indicate that, after 1997, quartile 4 firms rely more heavily on debt financing. Book leverage increases by 3.3 percentage points whereas cash ratios decline by 0.7 percentage points. The effect on net debt is four percentage points, significant at the 1% level. Consistent with trade-off theories of capital structure, we find that weather-sensitive firms were able to use more debt and hold less cash whenever they use financial derivatives.

The IV estimates on the effect of weather derivatives shown in Table VII, Panel B reflect the same signs as the reduced-form correlations in Panel A. The IVs' estimate of the effect of derivatives on net debt is 7.1 percentage points, significant at the 10% level because of the larger estimated standard errors associated with IV specifications. Such large standard errors make the effect of hedging on book leverage significant only at the 15% level. Lastly, despite the larger standard errors, Column IV shows that risk management policies lead to lower cash holdings. The estimated coefficient is −1.5 percentage points, significant at the 10% level.

Beyond these IVs specifications, an alternative test for the effect of risk management on leverage is to evaluate, in the cross-section, whether weather risk characteristics matter for capital structure after 1997. When we repeat the same net debt specification as reported in Table IV, Column VI after 1997, we find that the estimated coefficient on the highest risk quartile group of firms is no longer negative and significant, but positive and indistinguishable from zero at conventional levels.

Having shown that weather risk exposure affects debt financing policies before 1997, and that weather derivatives reduce the volatility of profits and enhance value after 1997, a potential issue is whether changes in leverage

Table VII

Weather Derivatives: Revenue, Financing, Investment, and Dividend Effects

This table examines the effect of weather derivatives on (a) revenue (natural logarithm of revenue) (Column I), (b) financing (net debt/assets (Column II), book leverage/assets (Column III), and cash/assets (Column IV)), (c) investment (CAPEX/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, financing, investment, and dividend policies. The instrumental variables for weather derivatives use in the post-1997 period are based on pre-1997 weather exposure or *EDD quantity risk quartiles*Post*. Quartile 1 is the omitted category. *EDD quantity risk quartiles*Post* captures the differential evolution of each outcome variable for each quartile of firms after 1997. Weather derivatives were introduced in 1997. 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. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent Variables					
	Ln revenue (I)	Net debt/assets (II)	Book leverage/assets (III)	Cash/assets (IV)	CAPEX/assets (V)	Dividends/assets (VI)
Panel A. Differences-in-Differences Specifications						
EDD quantity risk	0.0091	0.0402***	0.033**	−0.0072**	0.0113***	0.0020
quartile 4*Post	(0.093)	(0.014)	(0.014)	(0.003)	(0.004)	(0.002)
EDD quantity risk	0.0932	0.0014	−0.00004	−0.0015	0.0034	0.0018
quartile 3*Post	(0.086)	(0.015)	(0.014)	(0.003)	(0.004)	(0.002)
EDD quantity risk	0.0809	−0.0145	−0.0130	0.0015	0.0025	−0.0005
quartile 2*Post	(0.074)	(0.014)	(0.014)	(0.003)	(0.004)	(0.002)
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 (IV) Specifications. Instruments: EDD Weather-Induced Volatility Quartiles*Post						
Weather	0.4044	0.0712*	0.0560	−0.0152*	0.0461***	−0.0056
derivatives	(0.249)	(0.040)	(0.038)	(0.009)	(0.014)	(0.006)
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

alone can contribute to the reported increases in value. The arguably least controversial method to examine the effect of leverage on value is to estimate the tax-related savings from debt financing, a likely lower bound of the contribution of leverage to value.[30] Using cross-sectional and IV-2SLS estimates of Tables IV and VII, we find that hedging may allow firms to increase their leverage ratio by two to seven percentage points of assets. Assuming a perpetual increase in debt and a tax rate of 35%, those estimates suggest a contribution of debt to value in the 0.8% to 2.5% range, which is consistent with the estimates of Graham and Rogers (2002). In other words, although tax shields provide an important contribution to firm value, they do not fully account for the total increase in M–B ratios reported in this paper.

To further explore the effects of hedging inside firms, we investigate the impact of weather derivatives on investment. Table VII, Column V examines the effect of risk management on the ratio of capital expenditures to assets. The difference-in-differences estimates of Panel A indicate that firms in quartile 4 increased their capital expenditures by one percentage point of assets after 1997, which is significant at the 5% level. The resulting IV estimates, shown in Panel B, indicate that weather derivatives lead to a positive and significant effect on investment: the IV estimate is 0.046, significant at the 5% level.

The fact that capital expenditures respond to risk management is consistent with the insight of Froot, Scharfstein, and Stein (1993) that risk management can enhance value through firms' investment policy. Higher investment, however, is also potentially consistent with overinvestment stories because of agency concerns (Jensen (1986), Tufano (1998)). Although this paper does not provide a structural model that concurrently encompasses and quantifies these financing and incentive (among other) frictions, the reduced-form correlation between investment and value suggests that the net effect of overcoming financial frictions is positive for firm value.[31]

Lastly, Table VII, Column VI examines the effect of weather derivatives on dividend ratios. We do not report significant effects on dividend payouts.

D. Interpretation

This paper examines the effect of active risk management on firm value. To test for this effect, we rely on an empirical strategy that emphasizes a plausibly exogenous source of variation in the use of derivatives. In our tests, we compare the relative valuation of weather-exposed firms with and without weather derivatives, and rely on historical weather exposures to provide arguably causal estimates on the effect of hedging on value.

[30] Increasing leverage reduces tax obligations (Leland (1998), Graham and Rogers (2002)), but may also enhance managers' incentives (Jensen (1986)), leading to improved outcomes from existing and new investments. Higher debt financing also raises asset substitution concerns (Jensen and Meckling (1976)), increases the costs of financial distress (Warner (1977), Weiss (1990)), and the possibility of asset fire sales (Shleifer and Vishny (1992)), among other margins.

[31] See, for example, Hennessy and Whited (2007) for an illustration of a structural model of optimal financial and investment policy in the presence of a broad set of frictions.

Our main results demonstrate that hedging leads to a positive and significant effect on firm value. We also show that risk management allows firms to increase their debt capacity, invest more, and enjoy smoother earnings. Overall, we interpret the evidence as supportive of the idea that financial derivatives have a positive effect on firm value.

VII. Concluding Remarks

Financial derivatives lie at the heart of Miller's (1986) "revolution" in financial innovation. Derivatives are powerful tools for shifting or hedging risks. They also reduce the cost of engaging in speculative transactions. However, as Rajan (2005) predicted, financial innovation can exacerbate both firm and systemic risk exposures. Not surprisingly, derivatives have played a central role in recent financial crises.

Despite the prominence of financial derivatives, we know surprisingly little about the causal effect of hedging on firm value. In this paper, we address this question by exploiting the introduction of weather derivatives as a plausible exogenous shock to firms' costs of hedging weather-related risks. Using this natural experiment and data from utilities, we find evidence consistent with the idea that derivatives lead to higher value, investments, and leverage.

Overall, the results demonstrate that financial innovation that is targeted to meaningful economic risks can significantly affect firm decisions.

An important limitation of our analysis is that it only focuses on one industry, and within this sector weather hedging tools are used only by a subset of firms. Whether our results extend to other industries and other financial products are interesting areas for further research. Similarly, studies quantifying the magnitude of the specific channels through which hedging affects firm value seem promising. Our evidence casts doubt on the idea that tax-driven capital structure gains that result from hedging can explain the observed gains in firm value. We leave the analysis of this conjecture for future research.

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