Internet Appendix to "Financial Sector Stress and Risk Sharing: Evidence from the Weather Derivatives Market"

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I do not tabulate all of my results in the paper for brevity. This appendix contains additional details on the weather derivatives market and its participants and additional results not reported in the paper. I have provided captions to each table to make them self-explanatory.

Appendix A. End Users and Their Hedging Tactics

In this section, I provide evidence that the net hedging position of end users is short in the monthly futures market due to the large presence of energy companies and their desire to hedge against mild temperatures. This asymmetry in hedging demand is necessary for a shift in hedging demand or capital supply to affect the price and quantity of contracts.

In 2004-2005, the Weather Risk Management Association documented that 69% of OTC weather derivative end users were energy companies. This number has hovered around 50% over time and is likely greater on the CME, where energy companies helped structure the market.[1] For energy suppliers, there are opposing cost and volume risks associated with temperature outcomes. Energy sales usually fall if temperatures are mild because firms and households use less natural gas or electricity for heating or cooling. Concomitantly, input costs usually rise during a period of extreme temperatures when demand for energy is high and the supply of inputs is relatively fixed. The exposure of utilities to cost fluctuations can be partially diminished by passing through changes in costs to consumers (Pérez-González and Yun (2013, henceforth PGY)). Every state in the U.S. has purchased gas adjustments for natural gas utilities (American Gas Association (2007)). Purchased gas adjustments adjust rates based on the price of natural gas, which helps mitigate utilities' exposure to fluctuations in the price of natural gas.

Although the costs due to a temporary spike in temperatures are more salient for customers (e.g., summer blackouts or high natural gas prices) the costs to energy suppliers and distributors of long-term mild temperatures can be quite large. For example, in justifying the decline in DTE

[1] The year-by-year OTC percentage of end user demand attributed to the energy sector was: 56% in 2003-2004, 69% in 2004-2005, 46% in 2005-2006, 47% in 2006-2007, 36% in 2007-2008, 59% in 2008-2009, 58% in 2009-2010, and 46% in 2010-2011.

Energy's earnings from $147M in the second quarter of 2012 to $109M in the second quarter of 2013, executive vice president David Meador explained "while last years second quarter operating earnings were boosted by record-setting (extreme) temperatures, we are on track to realize our financial and operational goals for this year."[2] PGY find that energy firms that are most exposed to mild temperature risks have valuations approximately 4% lower than other energy firms and have lower revenues, return on assets, and operating income. The exposure to mild temperatures is wide spread in the energy utility industry. I find that 80% of Compustat energy utilities have revenues that are positively correlated with quarterly energy degree days (the sum of heating and cooling degree days) in the years 1977-1996 (i.e., lower revenues when temperatures are less extreme).

There are multiple reasons why monthly temperature futures are better suited to hedge the quantity risk associated with mild temperatures than the spike in input costs due to a few hours or days of extreme temperatures. First, energy companies can hedge the cost of inputs through traditional futures or by switching between energy sources, if possible, and use monthly temperature futures to hedge low sales. Second, risks of a spike in input prices due to a few days of extreme temperature are better hedged using other, shorter-duration contracts, such as critical day options or daily weather contingent power options, not a contract on the monthly aggregate of daily temperature deviations. Third, call options on monthly or seasonal degree days can be purchased on the CME, which pay out when temperatures are extreme over the month or season, respectively. These option contracts will better capture extreme temperature events that will lead to a shortage in the supply of natural gas.

Not all utilities will find it beneficial to use weather derivatives to hedge volume risks. The sensitivity of revenue to temperature and the fluctuations in temperature will vary across locations and utilities. In addition, the utility's regulatory body may allow for rate changes based on volume fluctuations either through full or partial decoupling of revenues and sales volume or a flat fee structure. Decoupling mechanisms have been introduced by regulators to incentivize energy utilities to promote energy efficiency and to share volume risks between customers and shareholders. Full decoupling adjusts rates to keep revenue per customer relatively constant over time. Partial decoupling, or weather normalization adjustments, adjust rates in response to weather-driven

[2] "DTE Energy Earnings Fall Due To Cooler Weather." CBS Detroit, July 2013 `http://detroit.cbslocal.com/2013/07/28/dte-energy-earnings-fall-due-to-cooler-weather/`.

changes in revenue, effectively shifting temperature risk to customers. There are also flat free programs, where customers pay a flat monthly fee for their energy.[3] In 2009, natural gas utilities in 36 states had non-volumetric rate designs and electric utilities in only nine states had decoupling mechanisms.[4] Utilities with these adjustments may still be exposed to volume risks either because the rate adjustment is not contemporaneous with the weather shock, revenues are only adjusted for non-weather related revenue changes, there is regulatory risk or the adjustment is only for the regulated portion of the utility's business (see PGY for a more complete discussion). Even with the prevalence of regulatory mechanisms, PGY find that one-quarter of utilities use weather derivatives, while the CME reports that 35% of energy companies used weather derivative instruments in 2008 (Myers (2008)).

An example of a utility using weather derivatives to hedge against low revenue due to mild temperature is Washington Gas Light Company, a natural gas distributor in the District of Columbia, Maryland and Virginia. In its 2012 10-K filing, Washington Gas describes its weather derivative usage as:

> During the fiscal years ended September 30, 2012, 2011 and 2010, Washington Gas used HDD weather-related instruments to manage its financial exposure to variations from normal weather in the District of Columbia. Under these contracts, Washington Gas purchased protection against net revenue shortfalls due to warmer-than-normal weather and sold to its counterparty the right to receive the benefit when weather is colder than normal.

Washington Gas' is a prime example of a utility hedging mild temperature risks with weather derivatives. Consistent with weather derivatives being used by utilities to hedge mild temperatures, PGY find that energy companies that were especially sensitive to mild temperature outcomes were 2 to 3 times more likely to use weather derivatives after their introduction than less exposed energy companies.

Energy companies with positive revenue to degree day correlations will sell monthly futures to hedge their risk exposure. In the main paper, I show that 87% of energy utilities have revenues

[3] http://www.aga.org/SiteCollectionDocuments/RatesReg/Issues/Revenue%20Decoupling%20and%20other%20Non-Volumetric%20Rate%20Designs/2009%20Aug%20Accounting%20Presentation.pdf.

[4] http://switchboard.nrdc.org/blogs/rcavanagh/decouplingreportMorganfinal.pdf.

positively correlated with HDDs, while only 65% have revenues positively correlated with CDDs. In the price analysis, I focus on the HDD contract market, where the hedging direction is relatively clear (utilities short, financial institutions long). A short position will have a positive return if temperatures are sufficiently mild. If energy companies are the main end users in the market and their desire to hedge leads them to sell the monthly contract, then there will be a net short hedging position on average. This asymmetry creates an active role for financial institutions to bear risk in the market, where a direct exchange between hedgers is uncommon (PGY; Brix and Jewson (2005)). On net, these financial intermediaries should be long the monthly temperature futures. Consistent with financial institutions being net long, Bellini (2005) estimates a positive risk premium for three U.S. locations over January 2002 to February 2004. Similarly, I find a positive average expected return for HDD contracts. I maintain the assumption that financial institutions are net long in the market throughout my analysis.

Appendix B. Financial Institution Participation

Below I provide a few selected excerpts documenting the participation of large investment banks and hedge funds in the weather derivatives market .

- Banks Enter Weather Derivatives Market, *Global Capital*, January 7, 2002[5]:

  > "Investment banks entering the weather derivatives market gave the nascent industry a seal of approval just before Enron, one of its pioneers, filed for bankruptcy. Among the firms to enter were Barclays Capital (DW, 1/15), Dresdner Kleinwort Wasserstein (DW, 5/7), Credit Suisse First Boston, Deutsche Bank (DW, 5/20) and Italy's IntesaBci (DW, 7/16)."

- Hedge Funds Warm to Weather Derivatives, *Institutional Investor*, January 26, 2005[6]:

  > "Hedge funds are increasingly looking to trade weather derivatives either as a non-correlated play or as an investment strategy. Behemoth Citadel Investment Group is set to join the mix and plans to start trading weather derivatives this year. It closely follows fellow hedge fund giant D.E. Shaw & Co., which started

[5] `http://www.globalcapital.com/article/k663ldzls40n/banks-enter-weather-derivatives-market`
[6] `http://www.institutionalinvestor.com/article.aspx?articleID=1024914`

trading weather derivatives in October, according to Derivatives Week, a sister publication. Officials at Citadel, which manages roughly $11 billion, confirmed the plan but declined further comment... In the fall, Jeff Bortniker former CEO of XL Weather & Energy, set up Pyrenees Capital Management in Stamford, Conn., with two partners specifically to trade weather derivatives."

Appendix C. Estimating Expected Index Values

In the Appendix of the main paper I detail the modeled temperature process and the parameter estimation procedure. Here, I present the parameter estimates in Table I. The mean reversion parameter (κ) has a mean value of 0.33, which corresponds to a $\rho = e^{-\kappa}$ of 0.72. The speed of mean reversion is inversely related to κ, so Boston has the slowest speed of reversion, while the warmer climates (Las Vegas and Tucson) have the fastest mean reversion. In column 3, I present the amount of long-term drift in temperature (μ_0). The parameter can be interpreted as the yearly increase in the mean temperature for each location (I present the drift term multiplied by 365). The mean drift is greater than 0 and ranges between 0.000 and 0.004. There appears to be a modest amount of warming over time at 17 of the 18 locations, although I do not test for the significance of these parameters. The long-run mean temperature (β_0) varies as expected across cities. Houston and Tucson have the highest estimates with mean temperatures just greater than 70, while Minneapolis has the lowest estimate with mean temperatures slightly less than 50. The magnitude of seasonality in temperature is captured by parameter β_1. The most seasonal locations are Kansas City, Chicago, and Salt Lake City with estimates slightly greater than 24. As discussed in the previous paragraph, additional sine functions are added when the introduction of the additional parameters is significant at the 10% level. When P=2, there is an additional sine function that captures semi-annual variation in mean temperatures. There is significant semi-annual variation in temperature in 13 of the 18 cities. For 8 cities, there is significant variation in mean temperature at the tri-annual frequency. Turning to the parameters for the standard deviation process, the estimates for the mean level of variation (γ_0) align with expectations. Locations in the Southwest (Las Vegas, Tucson, and Sacramento) have parameter estimates less than 4, while some locations in the Midwest (Chicago, Cincinnati, Kansas City, and Minneapolis) have parameter

estimates greater than 6. All but 2 locations have at least 2 significant seasonal frequencies in the standard deviation ($Q \geq 2$), 6 cities have at least 3, and Tucson has 4 seasonal frequencies in the standard deviation.

The forecasted temperature on day T-21 plus the random error is the initial value for the temperature simulations. From the forecasted and simulated temperatures, I apply the degree day index temperature formulas to calculate the payoff of the contract for each path. The expected index is the average of the simulated contract payoffs. Specifically,

$$E[HDDPayoff] = \frac{1}{1,000} \sum_{s=1}^{1,000} \sum_{t=\text{1st Day of Month}}^{T-21} \max(0, 65-(Temp_{forecast,t}+\epsilon_s)) + \sum_{t=T-20}^{T} \max(0, 65-Temp_{s,t}), \tag{C1}$$

where T is the last day of the month, $Temp_{forecast,t}$ is the forecasted temperature on day t, ϵ_s is the forecast error randomly drawn from the forecast error distribution, and $Temp_{s,t}$ is the simulated temperature for day t and path s.

Table I
Temperature Process Parameter Estimates

This table reports parameter estimates from a maximum likelihood estimation of each city's temperature process. The discrete time representation of the temperature process is an AR(1) process with time-varying mean temperature and time-varying standard deviation of temperature: $T(t) = e^{-\kappa}[T(t-1)-\theta(t-1)]+\theta(t)+s(t)\epsilon(t)$, where $\theta(t) = \beta_0+\delta t+\sum_{p=1}^{P} \beta_p \sin(\frac{2\pi}{365}pt+\phi_p)$ and $\sigma(t) = \gamma_0+\sum_{q=1}^{Q} \gamma_p \sin(\frac{2\pi}{365}qt+\psi_p)$.

Location	κ	μ_0	β_0	β_1	ϕ_1	β_2	ϕ_2	β_3	ϕ_3	γ_0	γ_1	ψ_1	γ_2	ψ_2	γ_3	ψ_3	γ_4	ψ_4
Atlanta	0.29	0.001	62.87	18.54	-1.86	-1.56	2.14	-	-	4.65	2.37	-5.09	-	-	-	-	-	-
Baltimore	0.38	0.001	55.95	21.98	-1.92	-	-	-	-	5.78	1.74	-5.31	0.38	-2.38	-	-	-	-
Boston	0.44	0.001	52.10	21.86	-2.00	-	-	-	-	6.11	1.09	-5.30	0.35	-3.85	-	-	-	-
Chicago	0.34	0.001	50.51	24.83	-1.92	-1.65	1.63	-1.38	0.63	6.21	1.67	-5.28	0.45	-3.01	0.23	-5.43	-	-
Cincinnati	0.31	0.001	54.60	22.63	-1.88	-1.62	1.85	-	-	6.01	2.64	-5.12	0.26	-1.96	-	-	-	-
Dallas	0.32	0.001	67.37	20.25	-1.88	-1.84	2.31	-	-	5.45	2.78	-5.02	0.41	-1.96	-	-	-	-
Des Moines	0.33	0.002	51.43	26.52	-1.87	-1.71	1.35	-0.82	0.44	6.42	2.27	-5.08	0.31	-1.93	-	-	-	-
Detroit	0.33	0.000	50.76	24.19	-1.93	-	-	-	-	5.78	1.53	-5.33	0.44	-2.38	-	-	-	-
Houston	0.34	0.002	70.29	16.32	-1.83	-2.00	1.68	-	-	4.89	2.96	-4.92	0.30	-3.39	0.26	-2.96	-	-
Kansas City	0.34	0.000	55.28	24.67	-1.86	-1.88	1.86	-1.35	0.32	6.53	2.52	-5.06	0.38	-1.28	-	-	-	-
Las Vegas	0.24	0.001	69.65	22.74	-1.86	-2.70	3.07	-0.70	2.17	3.72	0.58	-6.17	0.49	-2.25	0.24	-5.04	-	-
Minneapolis	0.29	0.001	47.31	28.85	-1.88	-1.85	1.33	-1.09	0.36	6.11	1.70	-5.11	0.05	-2.23	0.39	-6.13	-	-
New York	0.38	0.001	56.44	22.28	-1.99	-	-	-	-	5.49	1.34	-5.34	0.26	-3.32	-	-	-	-
Philadelphia	0.36	0.001	56.52	22.55	-1.94	-	-	-	-	5.44	1.63	-5.28	0.30	-2.47	-	-	-	-
Portland	0.34	0.001	54.28	14.36	-1.95	-2.59	2.95	-	-	3.84	-0.10	-4.57	0.25	-3.60	-	-	-	-
Sacramento	0.29	0.002	61.10	14.54	-1.94	-1.95	2.56	-1.07	2.55	3.47	0.23	-7.41	-	-	-	-	-	-
Salt Lake City	0.31	0.004	53.10	24.53	-1.88	-3.38	3.06	-0.64	0.82	5.27	0.59	-5.87	0.69	-2.38	0.52	-5.44	-0.01	-0.01
Tucson	0.28	0.001	70.17	18.51	-1.90	-1.22	2.59	-1.70	2.74	3.89	1.05	-5.38	0.31	-2.10	0.34	-3.12	-	-
Mean	0.33	0.001	58.58	20.67	-1.91	-1.82	2.28	-1.06	1.28	5.24	1.71	-5.30	0.38	-2.49	0.34	-4.41	-0.01	-0.01
Std. Dev.	0.05	0.001	7.16	4.57	0.06	0.60	0.59	0.36	0.98	1.04	0.88	0.55	0.16	0.65	0.11	1.41	-	-

Appendix D. Systematic Risk Results

I conduct multiple analyses on the amount of systematic risk in the weather derivatives market and its role in affecting contract prices. First, I run a CAPM-style regression of the form:

$$r_p - r_f = \beta * (r_m - r_f) + \alpha,$$

where r_p is the return on an equal-weighted portfolio of monthly weather derivative contracts, r_f is the monthly risk-free rate, and r_m is the monthly market return. Contract returns are calculated using "physical" returns to going long the contract. The physical returns are $\frac{Index}{E[Index]} - 1$, where $Index$ is the realized index of the contract and $E[Index]$ is the expected index. The physical return proxies for contract returns if contracts are priced at their actuarially fair value. I include a location-month in the portfolio return calculation if a contract was ever open 31 days before maturity for that location and month. I use physical returns because it increases the number of observations since I do not need contract prices. This will allow for a less noisy estimate of the relationship between market returns and temperature innovations at a location. I find a CAPM alpha of 5.268% and beta of -0.557. The beta is insignificant and the constant term is significant at the 5% level.[7] Financial institutions enjoy positive alpha from going long HDD contracts. This likely explains the willingness of financial institutions to go long HDD contracts even though expected returns are near zero and realized returns are negative.

In Table II, I present results from CAPM-style regressions of weather derivative return on the market return. Regressions are run for for each location separately. The weather derivative return is the "physical" return. For a month and location (e.g., New York City, February) to be included, an HDD contract for the relevant contract month and location must trade at least once between January 2000 to January 2012. I find the average alpha is positive and significant and the average beta is negative and significant.

In Table III, I control for each location's beta in the cross-sectional price regressions. I include an interaction between the stress variable of interest and the location beta. The coefficient on the interaction term is never significant and near zero. The margin and total risk coefficients remain statistically and economically significant. The margin and total risk results cannot be explained by an increase in the price of systematic risk.

[7] I calculate White standard errors as there is likely heteroscedasticity in returns.

Table II
Systematic Risk By Location

This table reports results for CAPM-style regressions of the form:

$$r_i - r_f = \beta * (r_m - r_f) + \alpha,$$

where r_i is the weather derivative return for location i, r_f is the monthly risk-free rate and α is the intercept. The weather derivative return is calculated as: $r_{it} = \frac{Index_{it}}{E[Index_{it}]} - 1$, where $Index_{it}$ is the realized degree index value and $E[Index_{it}]$ is the expected index. For a month and location (e.g., New York, February) to be included, an HDD contract for the relevant contract month and location must trade at least once between January 2000 and January 2012. The regression includes all such months from January 2000 to January 2012. All regressions are standard OLS regressions. Standard errors are White standard errors.

City	β	s.e.	α	s.e.	N	R^2
Atlanta	-1.5*	0.90	4.86	3.9	84	0.047
Baltimore	-0.25	0.39	-3.29*	1.79	60	0.006
Boston	-0.43	0.33	-0.52	1.51	84	0.022
Chicago	-0.59*	0.30	-0.33	1.53	84	0.040
Cincinnati	-0.48	0.43	0.20	2	84	0.015
Dallas	-0.15	1.06	5.76	5.35	84	0.000
Des Moines	-0.70 *	0.40	-0.42	2	84	0.033
Detroit	-0.66*	0.35	-0.74	1.54	72	0.058
Houston	-2.47	3.28	37.93**	16.21	84	0.008
Kansas City	-0.55	0.56	1.77	2.36	84	0.015
Las Vegas	0.81	1.08	5.84	5.66	84	0.006
Minneapolis	-0.69**	0.30	-2.11	1.54	84	0.053
New York	-0.42	0.56	-1.21	2.04	84	0.011
Philadelphia	-0.48	0.48	-0.96	1.91	84	0.018
Portland	-0.07	0.29	0.64	1.34	84	0.001
Sacramento	0.29	0.65	5.46 *	3	84	0.003
Salt Lake City	0.61	0.78	3.04	3.91	12	0.036
Tucson	-0.96	2.42	29.07**	13.01	84	0.002
Mean	-0.48**	0.17	4.72*	2.58	78.00	0.021

Correlation($\overline{WRP_i}$,$\hat{\beta}_i$) = -0.15, p-value=0.56

Table III
Systematic Risk and Stress

This table reports the results of an examination of the effect of financial sector stress on contract prices controlling for systematic risk. The dependent variable is the logarithm of the contract price. The two measures of financial sector stress are: (1) *TED*, the TED spread one month before contract maturity, and (2) Δ *VIX*, the monthly change in the VIX one month before the contract month. *Beta* is a location specific beta. *Margin* is the contract-specific margin requirement. *CV* is the coefficient of variation of the contract's index (calculated over the years 1974-2011). The logarithm of the forecasted degree day index (*Log(E[Index])*) and the logarithm of the previous month's degree day index ($Log(Index_{m-1})$) are included as control variables (coefficients not reported). All regressions include contract fixed effects (at the location-month level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

	Stress = TED			*Stress = Δ VIX*		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*
Stress	-0.0201***	0.0712***	0.0689***	-0.0015***	-0.0014***	-0.0012***
	(0.0055)	(0.0180)	(0.0130)	(0.0004)	(0.0003)	(0.0004)
*Stress*Beta*	0.0094	-0.0128	-0.0062	0.0007	0.0007	0.0006
	(0.0076)	(0.0084)	(0.0059)	(0.0005)	(0.0004)	(0.0004)
*Stress*Margin*		-0.0196***			-0.0001**	
		(0.0044)			(0.0001)	
*Stress*CV*			-0.4509***			-0.0044***
			(0.0662)			(0.0015)
Margin	-0.0055	0.0028	-0.0044	-0.0048	-0.0007	-0.0031
	(0.0057)	(0.0058)	(0.0049)	(0.0058)	(0.0061)	(0.0055)
Observations	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5125	0.5578	0.6098	0.4978	0.5093	0.5191

Appendix E. Financial Institution Capital Ratio and Contract Prices

In this section, I present results from tests of the effect of shifts in the aggregate capital ratio of financial institutions participating in the weather derivatives market on the prices of weather futures and the implied volatility of weather options. I focus on financial institutions that mention weather derivatives in their 2008 10-K. The capital ratio of the financial secto is calculated: $\frac{\text{Aggregate Market Value of Equity}}{\text{Aggregate Market Value of Equity + Aggregate Book Value of Debt}}$. I calculate the aggregate value-weighted capital ratio of the firms using quarterly data from Compustat and CRSP. I use the capital ratio prevailing at the end of the quarter and match based on the trade month (e.g., the October 2008 contract is priced in September 2008, so it is matched to the capital ratio at the end of the third quarter of 2008.)[8] The capital ratio measure has a mean of 0.22 and a standard deviation of .05. The ratio reaches it's nadir in the first quarter of 2009 at 0.128.

I report results of regressions of contract price on the capital ratio measure in Table IV. I find that contract price is significantly positively correlated with the capital ratio measure. A one standard deviation decrease in the capital ratio leads to a decline in prices of approximately 1%. Higher margin contracts and contracts with greater total risk are especially sensitive to changes in the capital ratio of these financial institutions. The interaction between margin and capital is positive and significant at the 1% level. Similarly, the interaction term between total risk and capital is positive and highly significant. The less capitalized the financial institutions, the less willing they are to bear risk and the lower contract prices, especially for higher margin and higher total risk contracts.

To examine the relationship between implied volatility and capital, I regress the implied volatility of options on the capital ratio measure. I average the implied volatility (and moneyness) of options at the location-month-year-put/call level. I include contract fixed effects at the location-month-put/call level. This test will compare the implied volatility of approximately the same option during periods with different levels of financial institution capital. The identifying assumption is that the volatility of the underlying temperature for the same location and month is exogenous to the capital ratio of the financial institutions. I control for option moneyness and its square to ease concerns that options of different moneyness may be traded during periods of financial sector stress.

[8] Results are robust to using one quarter lagged capital ratios.

I report results of regressions of option implied volatility on the capital ratio measure in Table V. I include an interaction between the capital ratio and an indicator variable for a call option ($Capital * Call$) since it is common for end users to create a collar strategy by buying a put option and selling a call. I find that implied volatility is significantly negatively related to the capital of the financial institutions. The results are concentrated in the put options, which are the contracts end users are most likely to use to hedge mild temperatures. The results are similar if option moneyness and its square are not included as control variables.

These results are consistent with the tests using aggregate measures of financial sector stress: when financial institutions are under stress, they become less willing to bear risk in the weather derivatives market and risk premiums rise.

Table IV
Financial Institution Capital Ratio and Contract Prices

This table presents the results of an examination of the effect of financial institution capital on contract prices in the weather derivatives market. Financial institution capital (*Capital*) is the ratio of aggregate market value of equity to total value (market value of equity plus book value of debt) of the financial institutions active in the weather derivatives market in 2008. The dependent variable is the logarithm of contract price one-month before contract maturity. *CV* is the coefficient of variation of the contract's index calculated over the years 1974-2011 (total risk). *Margin* is the contract-specific margin requirement. The logarithm of the forecasted degree day index (*Log(E[Index])*) and the logarithm of the previous month's degree day index ($Log(Index_{m-1})$) are included to control for market payoff expectations (results not shown). All regressions include contract fixed effects (at the location-month level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

	(1)	(2)	(3)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*
Capital	0.1943**	-1.0211***	-1.3055***
	(0.0971)	(0.2629)	(0.2944)
*Capital*Margin*		0.2247***	
		(0.0605)	
*Capital*CV*			6.9201***
			(1.4526)
Margin	-0.0022	-0.0512***	0.0002
	(0.0054)	(0.0137)	(0.0047)
Observations	644	644	644
Contract FEs	Yes	Yes	Yes
R^2	0.4834	0.5211	0.5752

Table V
Financial Institution Capital Ratio and Implied Volatility

This table presents the results of an examination of the effect of financial institution capital on the implied volatility of weather derivative options. Financial institution capital (*Capital*) is the ratio of aggregate market value of equity to total value (market value of equity plus book value of debt) of the financial institutions active in the weather derivatives market in 2008. The dependent variable is the implied volatility of options on weather derivative futures. *Call*, is an indicator variable for a call option. *Money*, the option's moneyness ($\frac{K}{S}$), and $Money^2$ are included as control variables in Columns (1) and (2). All regressions include contract fixed effects (at the location-month-put/call level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

	(1)	(2)	(3)	(4)
VARIABLES	*Imp. Vol.*	*Imp. Vol.*	*Imp. Vol.*	*Imp. Vol.*
Capital	-0.6607*	-0.8908*	-0.7706*	-0.9636*
	(0.3736)	(0.4794)	(0.4401)	(0.5059)
*Capital*Call*		0.4148		0.3536
		(0.4932)		(0.4770)
Money	-3.2227**	-3.0956**		
	(1.5136)	(1.5168)		
$Money^2$	1.6450**	1.5937**		
	(0.7051)	(0.7085)		
Observations	222	222	222	222
Contract FEs	Yes	Yes	Yes	Yes
R^2	0.1775	0.1806	0.0469	0.0493

Appendix F. Additional Results

In this section, I provide the results of additional robustness tests. I re-run the expected return, expected return on margin, and realized returns analysis with the the one month change in the VIX, Δ *VIX*, and the financial crisis dummy, *Financial Crisis*, as the proxies for financial sector stress. Table VI presents the results using Δ *VIX*. Table VII presents the results using *Financial Crisis*. The results are broadly consistent with the results using the TED spread. The coefficient on the stress variable is positive in all specifications. The two interaction terms are positive in all specifications as well. The results are statistically less significant than the TED spread regression, especially for the Δ *VIX* specification.

An alternative explanation for the main results is that during the financial crisis the demand for energy declined, which led to a decrease in hedging demand. The decline in hedging demand led to a decline in open interest, which led to a decline in liquidity in the market and an increase in the

risk premium. In other words, a decline in hedging demand led to an increase in the risk premium even though there is less risk being shared. To alleviate this concern I run additional regressions controlling for energy demand at the location level. Specifically, I match contract locations to annual energy demand within a state. I control for residential, industrial and commercial electricity sales and natural gas consumption at the state-year level.[9] If energy demand is driving the results, then energy demand at the location level should explain the decline in prices. Results are presented in Table VIII. The coefficients of interest are very similar to the main specification and remain significant. Although the measures of energy demand are noisy, there is no evidence a decline in energy demand is driving the results.

In Table IX, I re-run the main price regression controlling for market expectations using alternative controls. In the main tests I control for market expectations using the logarithm of the expected index value and the logarithm of the previous month's index value. In these tests, I include the realized index in some specifications and alternate which of the control variables I include. The coefficient on the stress variable remains negative and significant in all specifications. In the first column, I drop the stress variable to document the explanatory power of the control variables.

In Table X, I run two-stage least squares regressions examining the relative effect of the financial crisis on weather derivative users. The first stage regresses weather derivative usage on temperature risk quartiles and a post-1997 indicator variable. The second stage examines the relative effect of the crisis on weather derivative users. I regress the firm outcome variable of interest on the instrumented weather derivative indicator interacted with a post-introduction indicator (1 in all years post-1997 outside of the crisis) and interacted with the crisis dummy (1 in the quarters 2008:Q4 through 2009). The difference between coefficients on the two interaction terms captures the relative effect of the crisis on weather derivative users. Columns (1)-(6), include estimates from a firm fixed effects specification. Similar to PGY, I find that weather derivative usage is positively related to temperature risk exposure measured in the pre-1997 period and weather derivative users are able to take on more leverage, hold less cash, invest more and have higher valuations after weather derivative introduction. In the crisis, weather derivative users see a decline in investment (at a 5% level of significance) and leverage (at a 1% level of significance). Cash and market-to-book do not significantly change during the crisis for weather derivative users. In columns (7) and (8), I

[9] I obtain energy demand data from the U.S. Energy Information Association.

estimate a lagged dependent variable two stage least squares, which includes lagged market-to-book values instead of firm fixed effects. I find an insignificant change in relative valuations for weather derivative users under this specification.

In Table XI, I present results for difference-in-difference tests of the relative effect of the financial crisis on firms highly exposed to temperature risk. The tests are identical to those presented in Table IX of the main text except observations are at the firm-year level instead of firm-quarter. Results are similar to the results using quarterly observations. Firms most exposed to weather risk increase investment and leverage, hold less cash, and experience significantly higher valuation after weather derivative introduction. During the financial crisis, most of the positive effects of weather derivative markets are diminished. High-risk firms have significantly lower relative investment and leverage in the crisis than in the rest of the post-introduction period. I find that cash holdings remain about the same during the crisis. The relative difference in the market-to-book ratio actually decreases slightly during the crisis, although the difference in coefficients is insignificant with a p-value of 0.81.

Table VI
The Effect of Changes in the VIX on Expected and Realized Returns

This table reports the results of an examination of the effect of financial sector stress on the expected return ($E[r]$), expected return on margin ($E[r \times \frac{1}{m}]$), and realized return (r) on a long position. The dependent variable in columns (1)-(3) is the expected return calculated as: $100 \times (\frac{E[Index]}{Price} - 1)$. The dependent variable in columns (4)-(6) is the the expected return on margin calculated as the expected return multiplied by the inverse of the percentage margin requirement. The dependent variable in columns (7)-(9) is the realized return. The measure of financial sector stress is the monthly change in the VIX one month before the contract month (Δ *VIX*). *CV* is the coefficient of variation of the contract's index (calculated over the years 1974-2011). *Margin* is the contract-specific margin requirement. All regressions include contract fixed effects (at the location-month level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

VARIABLES	(1) *E[r]*	(2) *E[r]*	(3) *E[r]*	(4) $E[r \times \frac{1}{m}]$	(5) $E[r \times \frac{1}{m}]$	(6) $E[r \times \frac{1}{m}]$	(7) *r*	(8) *r*	(9) *r*
Δ *VIX*	0.1002*	0.0921*	0.0765	1.7723*	1.6429	1.4273	0.1928	0.1521	0.1138
	(0.0527)	(0.0543)	(0.0596)	(1.0050)	(1.0612)	(1.1236)	(0.1788)	(0.1185)	(0.1242)
Δ *VIX*Margin*		0.0088			0.1401			0.0441**	
		(0.0081)			(0.1354)			(0.0170)	
Δ *VIX*CV*			0.3427			4.9810			1.1409**
			(0.2460)			(3.9300)			(0.4493)
Margin	-0.1751	-0.4481	-0.3112	-6.8938	-11.2642	-8.8716	-0.3247	-1.6989	-0.7777
	(0.5918)	(0.6892)	(0.6113)	(13.2994)	(14.1852)	(13.2347)	(1.0993)	(1.2765)	(1.1828)
Observations	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0094	0.0159	0.0264	0.0106	0.0160	0.0222	0.0077	0.0444	0.0497

Table VII
The Effect of the Financial Crisis on Expected and Realized Returns

This table reports the results of an examination of the effect of financial sector stress on the expected return ($E[r]$), expected return on margin ($E[r \times \frac{1}{m}]$), and realized return (r) on a long position. The dependent variable in columns (1)-(3) is the expected return calculated as: $100 \times (\frac{E[Index]}{Price} - 1)$. The dependent variable in columns (4)-(6) is the the expected return on margin calculated as the expected return multiplied by the inverse of the percentage margin requirement. The dependent variable in columns (7)-(9) is the realized return. The measure of financial sector stress is a dummy for the financial crisis period from October 2008 to December 2009 (*Financial Crisis*). *CV* is the coefficient of variation of the contract's index (calculated over the years 1974-2011). *Margin* is the contract-specific margin requirement. All regressions include contract fixed effects (at the location-month level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

VARIABLES	(1) $E[r]$	(2) $E[r]$	(3) $E[r]$	(4) $E[r \times \frac{1}{m}]$	(5) $E[r \times \frac{1}{m}]$	(6) $E[r \times \frac{1}{m}]$	(7) r	(8) r	(9) r
Financial Crisis	1.4095	-8.9776*	-14.3983***	14.6007	-138.9453*	-202.4383***	6.5450*	-3.6176	-6.7113
	(1.6112)	(4.8358)	(4.2224)	(27.4871)	(70.2684)	(66.2634)	(3.4565)	(8.7807)	(8.1134)
*Financial Crisis*Margin*		1.9291*			28.5167*			1.8874	
		(1.1224)			(15.6277)			(1.9179)	
*Financial Crisis*CV*			71.3744***			979.9625***			59.8540
			(22.7703)			(343.5082)			(38.6121)
Margin	-0.1749	-0.3782	-0.3947	-7.0115	-10.0156	-10.0290	-0.2794	-0.4783	-0.4637
	(0.5894)	(0.6095)	(0.5231)	(13.4419)	(13.2545)	(12.8161)	(1.1203)	(1.1822)	(1.1438)
Observations	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0058	0.0308	0.1115	0.0033	0.0210	0.0675	0.0266	0.0319	0.0431

Table VIII
The Effect of the Financial Crisis on Contract Prices (Controlling for Electricity Sales and Natural Gas Consumption)

This table presents of the effect of financial sector stress on contract prices controlling for electricity sales and natural gas consumption. The dependent variable is the logarithm of contract price one-month before contract maturity. The three measures of financial sector stress are: (1) *Financial Crisis*, a dummy variable equal to one during the financial crisis period (October 2008-December 2009), (2) *TED*, the TED spread one month before contract maturity, and (3) Δ *VIX*, the monthly change in the VIX one month before the contract month. *Margin* is the standardized within degree-day index contract-specific margin requirement. The logarithm of the forecasted degree day index (*Log(E[Index])*) and the logarithm of the previous month's degree day index (*Log(Index*$_{m-1}$*)*) are included as control variables. The logarithm of natural gas sales (*Log(Natural Gas)*) in millions of cubic feet in the contract state during the year is included as a control. The logarithm of electricity sales (total KwH) in the contract state to residential (*Log(Residential)*), commercial (*Log(Commercial)*) and industrial (*Log(Industrial)*) uses are included as additional controls. All regressions include contract fixed effects (at the location-month level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

	(1)	(2)	(3)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*
Financial Crisis	-0.0253*	0.0973***	0.1526***
	(0.0129)	(0.0365)	(0.0281)
*Financial Crisis*Margin*		-0.0227***	
		(0.0085)	
*Financial Crisis*CV*			-0.7983***
			(0.1441)
Margin	-0.0083	-0.0054	-0.0047
	(0.0065)	(0.0061)	(0.0053)
Log(Residential)	0.1719	0.1611	0.1500
	(0.1085)	(0.1065)	(0.1035)
Log(Industrial)	-0.1189***	-0.1036***	-0.1008***
	(0.0311)	(0.0287)	(0.0256)
Log(Commercial)	-0.2907***	-0.2472***	-0.2455***
	(0.0710)	(0.0631)	(0.0544)
Log(Natural Gas)	0.0724	0.0505	0.0420
	(0.0458)	(0.0421)	(0.0385)
Observations	644	644	644
Contract FEs	Yes	Yes	Yes
R^2	0.5149	0.5400	0.6132

Table IX
The Effect of Financial Sector Stress on Contract Prices: Alternative Controls

This table reports the results of an examination of the effect of financial sector stress on contract prices in the weather derivatives market using different controls for forecasted weather. The dependent variable is the logarithm of contract price one-month before contract maturity. The two measures of financial sector stress are: (1) *TED*, the TED spread one month before contract maturity and (2) Δ *VIX*, the monthly change in the VIX one month before the contract month. The logarithm of the forecasted degree day index (*Log(E[Index])*), the logarithm of the realized degree day index (*Log(Index)*) and the logarithm of the previous month's degree day index (*Log(Index$_{m-1}$)*) are included to control for market payoff expectations. *Margin* is the contract-specific margin requirement. All regressions include contract fixed effects (at the location-month level). R^2 is the within R^2. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

		Stress = TED				*Stress = Δ VIX*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*
Stress		-0.0254***	-0.0338***	-0.0340***	-0.0304***	-0.0018***	-0.0025***	-0.0023***	-0.0023***
		(0.0054)	(0.0082)	(0.0084)	(0.0088)	(0.0005)	(0.0008)	(0.0007)	(0.0007)
Log(E[Index])	0.4819***	0.4836***				0.4855***			
	(0.0662)	(0.0633)				(0.0671)			
Log(Index)			0.1363***	0.1377***			0.1267***	0.1282***	
			(0.0299)	(0.0313)			(0.0318)	(0.0335)	
Log(Index$_{m-1}$)	0.0267*		0.0487**				0.0521**		
	(0.0136)		(0.0207)				(0.0219)		
Margin		-0.0054	-0.0110	-0.0102		-0.0041	-0.0095	-0.0086	
		(0.0058)	(0.0074)	(0.0079)		(0.0060)	(0.0078)	(0.0083)	
Observations	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4711	0.4967	0.2003	0.1545	0.0553	0.4801	0.1755	0.1233	0.0379

Table X
Weather Exposure Effect on Investment and Financing of End Users During the Crisis: 2SLS-IV

This table reports the estimates from 2SLS-IV examinations of the relative effect of the financial crisis on utilities that use weather derivatives. Columns (1) and (7) report first stage estimates of the effect of pre-1997 temperature exposure and a post-introduction indicator on firm weather derivative usage. *Derivative* is an indicator variable equal to one if the firm used weather derivatives post-introduction and zero otherwise. The instrumental variables are quartile risk grouping based on pre-introduction temperature exposure ($|\beta_{EDD}| \times \sigma_{EDD}$). The dependent variables are: *CAPEX/Assets* (the ratio of quarterly capital expenditures to total assets) in column (2), *Book Leverage/Assets* (the ratio of long-term debt plus debt in current liabilities to total assets) in column (3), *Net Debt/Assets* (the ratio of long-term debt plus debt in current liabilities minus cash and short-term investments to total assets) in column (4), *Cash/Assets* (the ratio of cash to assets) in column (5), and *M-B Ratio* (the ratio of book value of total assets plus market value of equity minus book value of common equity minus book value of deferred taxes to book value of total assets) in columns (6) and (8). *Post-Intro* is an indicator variable equal to one if the year is 1997 (the year of weather derivative introduction) or later excluding the financial crisis. *Financial Crisis* is an indicator variable equal to one if the year-quarter is during the financial crisis time period (Q4 2008 to Q4 2009). Regressions in columns (1) through (6) include firm fixed effects. Estimates from lagged dependent variables specifications are shown in columns (7) and (8). Lagged market-to-book is included in the regressions in Columns (7) and (8) (results not shown). Regressions in Columns (2)-(6) and (8) include year-quarter fixed effects (results not shown). R^2 is the within R^2. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

VARIABLES	(1) Derivative	(2) *CAPEX/ Assets*	(3) *Book Leverage/ Assets*	(4) *Net Debt/ Assets*	(5) *Cash/ Assets*	(6) *M-B Ratio*	(7) Derivative	(8) M-B Ratio
Post-Intro.	0.1850***						0.2541***	
	(0.0045)						(0.0080)	
*Risk quartile 2*Post-Intro.*	-0.0542***						-0.0773***	
	(0.0064)						(0.0115)	
*Risk quartile 3*Post-Intro.*	0.0501***						-0.0248**	
	(0.0063)						(0.0107)	
*Risk quartile 4*Post-Intro.*	0.1132***						0.0292***	
	(0.0067)						(0.0111)	
*Derivative*Post-Intro.*		0.1063***	0.2264***	0.2762***	-0.0536***	0.2644*		0.0579***
		(0.0315)	(0.0675)	(0.0695)	(0.0108)	(0.1482)		(0.0182)
*Derivative*Financial Crisis*		0.0883***	0.0375	0.0795	-0.0467**	0.2642		0.0725**
		(0.0328)	(0.0945)	(0.1011)	(0.0203)	(0.1825)		(0.0360)
Wald Test p-value		0.0301	0.0025	0.0045	0.8033	0.6346		0.5597
Observations	31,323	8,034	31,323	31,323	31,323	18,532	17,814	17,814
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year-Quarter FEs	No	Yes	Yes	Yes	Yes	Yes	No	Yes
R^2	0.2262	0.1278	0.1927	0.1931	0.0392	0.3483	0.1809	0.9232

Table XI
Weather Exposure Effect on Value, Investment, and Financing of End Users During the Crisis: Annual Observations

This table reports the results of an examination of the relative effect of the financial crisis on utilities with high temperature risk exposure versus those with less temperature risk exposure. The dependent variables are: (1) *CAPEX/Assets* (the ratio of quarterly capital expenditures to total assets), (2) *Book Leverage/Assets* (the ratio of long-term debt plus debt in current liabilities to total assets), (3) *Net Debt/Assets* (the ratio of long-term debt plus debt in current liabilities minus cash and short-term investments to total assets), (4) *Cash/Assets* (the ratio of cash to assets), and (5) the *M-B Ratio* (the ratio of book value of total assets plus market value of equity minus book value of common equity minus book value of deferred taxes to book value of total assets). *High Risk* is a dummy variable equal to one for firms with absolute weather-induced volatility in the top 25% of firms. Absolute weather-induced volatility is the product of the absolute value of the firm's energy degree days beta and energy degree days volatility ($|\beta_{EDD}| \times \sigma_{EDD}$); calculated in the years pre-1997. *Post-Intro* is an indicator variable equal to one if the year is 1997 (the year of weather derivative introduction) or later excluding the financial crisis. *Financial Crisis* is an indicator variable equal to one if the firm reports between October 2008 and December 2009. All regressions include firm fixed effects and year fixed effects (results not shown). R^2 is the within R^2. Standard errors are clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

VARIABLES	(1) *CAPEX/ Assets*	(2) *Book Leverage/ Assets*	(3) *Net Debt/ Assets*	(4) *Cash/ Assets*	(5) *M-B Ratio*
*High Risk*Post-Intro.*	0.0100**	0.0226**	0.0399***	-0.0088***	0.0960***
	(0.0039)	(0.0105)	(0.0104)	(0.0016)	(0.0274)
*High Risk*Financial Crisis*	-0.0083	-0.0097	-0.0002	-0.0037	0.0901***
	(0.0088)	(0.0148)	(0.0157)	(0.0048)	(0.0325)
Wald Test p-value	0.0117	0.0070	0.0014	0.3097	0.8124
Observations	8,945	11,205	7,860	7,860	7,457
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.2226	0.4376	0.3079	0.0479	0.6528

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