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

DANIEL WEAGLEY

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 User Risk Exposure and 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.

The end users in the weather derivatives market are predominately energy utilities. 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] The temperature indices (heating degree day and cooling degree day) originated in the energy sector and are highly correlated with energy demand.

For energy suppliers, there are opposing cost and volume risks associated with temperature outcomes. If temperatures are mild, then energy sales usually fall because firms and households use less natural gas or electricity for heating or cooling. If temperatures are extreme, demand for energy is high and input costs usually rise (the supply of inputs is relatively fixed in the short-run). 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 mild temperatures can be quite large. For example, in justifying the decline in DTE 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 year's second quarter operating earnings were boosted

[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.

by record-setting (extreme) temperatures, we are on track to realize our financial and operational goals for this year."[2]

Most energy utilities are more exposed to mild temperature shocks. Pérez-González and Yun (2013) (henceforth, 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. Following the same procedure as PGY, I find 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).

For multiple reasons the 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. 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. Additionally, the exposure of utilities to cost fluctuations can be partially diminished by passing through changes in costs to consumers (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.

Not all utilities will find it beneficial to use weather derivatives to hedge volume risks though. 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

[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/`.

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 changes in revenue, effectively shifting temperature risk to customers. In flat fee programs, 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:

> 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

[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.

were 2 to 3 times more likely to use weather derivatives after their introduction than less exposed energy companies.

End User Risk Exposure:

To provide evidence that end users are significantly exposed to mild temperature risks, I estimate the risk exposure of energy utilities. I use quarterly firm-level observations of energy utilities (SIC codes: 4911, 4923, 4924, 4931, & 4932). For a firm to be in the sample, it must have at least 10 years of data pre-1997. This filter allows me to measure the firm's weather risk exposure before the introduction of weather derivative contracts. I obtain daily temperature data for 344 climate divisions in the continental U.S. from the National Climatic Data Center (NCDC). I match each firm to the climate division that covers the county of the firm's headquarters.[5] There are 264 firms in the sample. Summary statistics on firm financials and matching quarterly degree days are presented in Panel A of Table I. All firm variables are winsorized at the 1% level to minimize the effect of outliers.

I calculate a firm's weather risk exposure following a similar procedure to PGY. I regress the firm's quarterly revenue to assets on quarterly energy (heating, cooling) degree days controlling for the logarithm of total assets using data from 1977 to 1996. Energy degree days are the sum of HDDs and CDDs during the quarter. The coefficient on the degree days measure is the firm's energy (heating, cooling) degree day beta. The HDD (CDD) beta is calculated during quarters 1 and 4 (2 and 3) because heating (cooling) degree days will drive consumer demand in these quarters. The EDD beta captures exposure to both hot and cold temperature shocks.

Panel B of Table I provides summary statistics for the measures of temperature risk exposure. Eighty percent of firms have positive energy degree day exposure. The number is highly skewed; the mean is 0.023 and the median is 0.008. Mild temperature risk is much more prevalent in the winter months (i.e., for HDDs than CDDs). Eighty-seven percent of utilities have a positive HDD beta, while only sixty-five percent have a positive CDD beta. The vast majority of energy utilities will want to short HDD contracts to hedge their temperature risk, while less than two-thirds will

[5] A small number of counties are in multiple climate divisions. For these cases, I match the lowest numbered climate division.

want to short CDD contracts. The strong asymmetry in the direction of hedging demand for HDD contracts is the motivation for focusing on HDD contracts in the analysis.

Table I
Summary Statistics for End Users

This table presents summary statistics for energy utilities weather risk exposure (SIC codes: 4911, 4923, 4924, 4931, & 4932). There are 264 firms in the sample. Financial information from Compustat is matched with temperature data from NCDC. Panel A presents quarterly financial and temperature (degree day) variables. Total assets and revenue are in thousands of March 2008 dollars (adjusted using the Consumer Price Index). *Heating (Cooling) Degree Days* is the quarterly heating (cooling) degree days. *Energy Degree Days* is the sum of heating and cooling degree days. Panel B presents firm weather exposure information. *EDD (HDD, CDD) Beta* is the the coefficient from a regression of revenue-to-assets on energy (heating, cooling) degree days (in ten-thousands) controlling for the logarithm of total assets. I present the number of observations (N), mean (Mean), standard deviation (Std. Dev.), 10th percentile (10th), median (Median), and 90th percentile (90th).

Panel A: Quarterly Firm and Degree Days Information

Variables	N	Mean	Std. Dev.	10th	Median	90th
Total Assets	31,321	6,263	8,274	420	3,072	16,690
Revenue	31,321	637	763	62	335	1,682
Heating Degree Days	31,321	1,309	1,178	41	921	3,072
Cooling Degree Days	31,321	264	381	0	84	802
Energy Degree Days	31,321	1,573	965	609	1,153	3,075

Panel B: Firm Weather Exposure Information

Variables	N	Mean	Std. Dev.	10th	Median	90th
HDD Beta (β_i^{HDD})	264	0.288	0.421	-0.021	0.107	0.896
CDD Beta (β_i^{CDD})	264	-0.099	0.913	-1.256	0.199	0.573
EDD Beta (β_i^{EDD})	264	0.279	0.439	-0.042	0.112	0.929

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[6]:

  "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

[6] http://www.globalcapital.com/article/k663ldzls40n/banks-enter-weather-derivatives-market

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[7]:

  "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 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 II. 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 temperature just greater than 70, while Minneapolis has the lowest estimate with mean temperature slightly less than 50. The magnitude of seasonality in temperature is captured by parameter β_1. The locations exhibiting the most seasonality are Kansas City, Chicago, and Salt Lake City with estimates slightly

[7] `http://www.institutionalinvestor.com/article.aspx?articleID=1024914`

greater than 24. 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 II
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 the relationship between systematic risk and 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 a long position in monthly temperature futures, 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 drop the financial crisis months from the sample when estimating the contract beta (results are similar if included).

I find the portfolio of monthly temperature futures has an insignificant CAPM beta of -0.601. If financial institutions have systematic risk exposure from going long HDD contracts, it is likely negative. The negative systematic risk exposure partially explains the willingness of financial institutions to go long HDD contracts even though expected returns are near zero and realized returns are negative. Importantly, the R^2 is only 0.0156, which is much smaller than what is found for other financial assets and, especially, portfolios of financial assets. For comparison, over the years 1999-2012 the Goldman Sachs Commodity Index (GSCI) and the GSCI Agriculture Index have R^2 over five times larger (10.5% and 9.3%, respectively) and positive and significant (p-value$\leq$.001) CAPM-betas (0.47 and 0.41, respectively).

Second, I examine systematic risk at the location level. In Table III, I present results from location-level CAPM-style regressions. 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 beta is negative (-0.28) and significant (p-value=0.012). None of the location's individual beta estimates are significant.

The correlation between a location's average expected return and estimated beta is -0.0451 with a p-value of 0.86, which provides further evidence that the systematic risk exposure in this market is not driving risk premiums. The negative average beta implies that the average contract should have experienced a decrease in the risk premium during the crisis when the price of systematic risk increased. This would lead to an increase in contract prices, which is the opposite of what is observed, making it highly unlikely systematic risk is driving the main result.

Third, I control for each location's estimated beta in the cross-sectional price regressions. Results are presented in Table IV. I I include an interaction between the stress variable of interest and the location beta. The coefficient on the beta and stress interaction term is near zero in all specifications and insignificant. The margin and total risk coefficients remain statistically and economically significant.[8] In sum, the margin and total risk results cannot be explained by an increase in the price of systematic risk.

[8]The coefficient on the beta and stress interaction is likely underestimated due to an errors-in-variables problem. Even so, the inclusion of noisy beta estimates should affect the capital-intensity coefficient estimates if systematic risk is the main driver of risk premiums. The capital-intensity coefficients are virtually unchanged by the inclusion of the beta estimates providing further evidence that systematic risk is not driving the shift in risk premiums during periods of financial sector stress.

Table III
Systematic Risk By Location

This table reports the β estimates 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. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

City	β	s.e.	R^2
Atlanta	-0.78	1.02	0.009
Baltimore	-0.19	0.57	0.002
Boston	-0.35	0.48	0.009
Chicago	-0.39	0.47	0.01
Cincinnati	-0.28	0.65	0.003
Dallas	-0.44	1.39	0.002
Des Moines	-0.59	0.6	0.015
Detroit	-0.2	0.46	0.003
Houston	-1.16	2.19	0.006
Kansas City	-0.27	0.76	0.003
Las Vegas	0.84	1.74	0.002
Minneapolis	-0.57	0.47	0.021
New York	-0.06	0.69	0
Philadelphia	-0.17	0.59	0.001
Portland	0.16	0.42	0.003
Sacramento	0.25	1	0.001
Salt Lake City	-0.3	0.66	0.009
Tucson	-0.58	4.27	0
Mean	-0.28***	0.1	0.006

Correlation($\overline{E[r_i]}$,$\hat{\beta}_i$) = -0.0451, p-value=0.86

Table IV
The Effect of Financial Sector Stress on Contract Prices (Controlling for Systematic Risk Exposure)

This table reports the results of an examination of the effect of financial sector stress on contract prices controlling for systematic risk exposure. The dependent variable is the logarithm of the contract price. The four measures of financial sector stress are: (1) *Financial Crisis*, a dummy variable equal to one during the financial crisis period (October 2008-May 2009 contract months) (columns (1) and (2)), (2) *TED*, the TED spread (columns (3) and (4)), (3) Δ *VIX*, the monthly change in the VIX (columns (5) and (6)), and (4) –*Capital*, the negative of the capital ratio of active financial institutions (columns (7) and (8)). *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 = Financial Crisis		*Stress = TED*		*Stress =* Δ *VIX*		*Stress = –Capital*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*
Stress	0.1469***	0.1744***	0.0679***	0.0705***	0.0010	0.0051***	1.0861***	1.3068***
	(0.0384)	(0.0305)	(0.0176)	(0.0130)	(0.0020)	(0.0019)	(0.2528)	(0.2944)
*Stress*Margin*	-0.0335***		-0.0178***		-0.0005		-0.2475***	
	(0.0092)		(0.0041)		(0.0004)		(0.0583)	
*Stress*CV*		-0.9272***		-0.4415***		-0.0358***		-7.1227***
		(0.1590)		(0.0642)		(0.0098)		(1.5152)
*Stress*Beta*	-0.0164	-0.0177	-0.0036	0.0003	0.0005	-0.0004	-0.1793	-0.1301
	(0.0132)	(0.0184)	(0.0089)	(0.0081)	(0.0006)	(0.0008)	(0.1228)	(0.1445)
Margin	-0.0012	-0.0017	0.0025	-0.0040	-0.0047	-0.0019	-0.0564***	0.0001
	(0.0051)	(0.0042)	(0.0057)	(0.0048)	(0.0059)	(0.0054)	(0.0136)	(0.0047)
Observations	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5329	0.6086	0.5550	0.6090	0.5023	0.5388	0.5223	0.5759

Appendix E. Additional Results

In this section, I provide the results of additional robustness tests.

Different Financial Crisis End Dates:

In Table V, I examine the effect of the financial crisis on contract prices while varying the crisis end date. In Columns 1-3 (4-6), the crisis indicator variable is equal to one for the contract months of October 2008 to December 2008 (October 2008 to December 2009). The results are large and significant in both specifications. The effect of the crisis is greatest in the first few months after the collapse of Lehman Brothers.

Sensitivity to Controls:

In Table VI, I test the robustness of the price results to changing the regression specification and controls. In the first column, I drop the stress variable to document the explanatory power of the control variables. 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. In columns (6) and (11), I do not include contract fixed effects and additionally control for total risk and the square of total risk. The coefficient on the stress variable remains negative in all specifications. For the TED spread, the coefficient remains significant in all specifications. For the financial crisis dummy, the coefficient is robust to controlling for the realized index and not controlling for the previous month's index. In the regression without any controls, the coefficient on the financial crisis dummy is of similar magnitude, but is not statistically significant. Not controlling for forecasts increases the standard errors since greater variation in price is left unexplained. The effect of the TED spread remains significant even without controls.

In the specification without fixed effects, the coefficient on the financial crisis dummy is much larger at -0.0424, but has a p-value of 0.12. The decline in statistical significance is not surprising considering the heterogeneity in the cross-section of contract prices that is unexplained in this specification. Additionally, this specification is not comparing price movements within contract and may suffer from a potential bias in the types of contracts traded at each point in time.

Controlling for Energy Demand:

Are the observed price movements related to the decline in economic activity and energy demand during the crisis? Although the decrease in prices and open interest during the crisis provide strong evidence that increases in hedging demand are not driving the results, there may still be concerns that price movements are related to changes in local economic activity or energy demand. To further rule out the economic activity or energy demand channel, I run additional regressions controlling for electricity and natural gas consumption at the state-year 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 using demand data from the U.S. Energy Information Association. If local economic activity or energy demand is driving the results, then including energy demand at the location level should weaken the results. Results for contract prices are presented in Table VII. The coefficients of interest are very similar to the main specification and remain significant. I also examine if the decline in open interest during the crisis can be explained by local economic activity or energy demand. In Table VIII, I include the energy consumption variables as controls in the open interest regressions. I find the results become slightly stronger after controlling for energy consumption. Although the measures of energy demand are noisy, there is no evidence a decline in energy demand is driving either the price or open interest results.

Additional Return Regressions:

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 IX presents the results using Δ *VIX*. Table X 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.

Table V
The Effect of Financial Sector Stress on Contract Prices (Varying Crisis End Date)

This table presents the results of an examination of the effect of the financial crisis on contract prices in the weather derivatives market with varying end dates for the crisis. The dependent variable is the logarithm of contract price one-month before contract maturity. *Financial Crisis* is a dummy variable equal to one during the financial crisis period, which is defined as October 2008-December 2008 in columns (1)-(3) and October 2008-December 2009 in columns (4)-(6). *Margin* is the contract-specific margin requirement. *CV* is the coefficient of variation of the contract's index calculated over the years 1974-2011 (total risk). 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. 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 * $p < 0.1$.

	Ending Month: December 2008			Ending Month: December 2009		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*
Financial Crisis	-0.0442**	0.1165***	0.1559***	-0.0218*	0.1217***	0.1634***
	(0.0197)	(0.0431)	(0.0242)	(0.0127)	(0.0376)	(0.0305)
*Financial Crisis*Margin*		-0.0301**			-0.0266***	
		(0.0116)			(0.0087)	
*Financial Crisis*CV*			-0.9594***			-0.8365***
			(0.1113)			(0.1518)
Margin	-0.0043	-0.0026	-0.0029	-0.0046	-0.0017	-0.0018
	(0.0057)	(0.0055)	(0.0053)	(0.0056)	(0.0053)	(0.0043)
Observations	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4871	0.5036	0.5430	0.4822	0.5184	0.5917

Table VI
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 combinations of controls and specifications. The dependent variable is the logarithm of contract price one-month before contract maturity. The two measures of financial sector stress are: (1) *Financial Crisis*, a dummy variable equal to one during the financial crisis period (October 2008-May 2009 contract months) (columns (2)-(6)), and (2) *TED*, the TED spread (columns (7)-(11)). *Margin* is the contract-specific margin requirement. *CV* is the coefficient of variation of the contract's index calculated over the years 1974-2011 (total risk). *Log(E[Index])* is the logarithm of the forecasted degree day index. *Log(Index)* is the logarithm of the realized degree day index. *Log($Index_{m-1}$)* the logarithm of the previous month's degree day index. Regressions include contract fixed effects (at the location-month level) in all columns except columns (6) and (11). 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 = Financial Crisis					*Stress = TED*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*	*Log(Price)*
Stress		-0.0286**	-0.0354*	-0.0347*	-0.0266	-0.0424	-0.0254***	-0.0338***	-0.0340***	-0.0304***	-0.0164**
		(0.0144)	(0.0189)	(0.0193)	(0.0203)	(0.0272)	(0.0054)	(0.0082)	(0.0084)	(0.0088)	(0.0076)
Log(E[Index])	0.4819***	0.4945***				0.9236***	0.4836***				0.9257***
	(0.0662)	(0.0626)				(0.0280)	(0.0633)				(0.0298)
Log(Index)			0.1355***	0.1367***				0.1363***	0.1377***		
			(0.0311)	(0.0329)				(0.0299)	(0.0313)		
Log($Index_{m-1}$)	0.0267*		0.0496**			-0.0328**		0.0487**			-0.0351**
	(0.0136)		(0.0224)			(0.0144)		(0.0207)			(0.0153)
Margin		-0.0037	-0.0090	-0.0082		-0.0022	-0.0054	-0.0110	-0.0102		-0.0019
		(0.0056)	(0.0072)	(0.0077)		(0.0040)	(0.0058)	(0.0074)	(0.0079)		(0.0042)
CV						-1.8945***					-1.9329***
						(0.5122)					(0.5277)
CV^2						2.0034**					2.0203**
						(0.8173)					(0.8460)
Observations	644	644	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
R^2	0.4711	0.4734	0.1551	0.1074	0.0128	0.9755	0.4967	0.2003	0.1545	0.0553	0.9753

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

This table presents the results of an examination 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. *Financial Crisis* is a dummy variable equal to one during the financial crisis period (October 2008-May 2009 contract months). *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. 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	-0.0314**	0.1194***	0.1652***
	(0.0141)	(0.0377)	(0.0272)
*Financial Crisis*Margin*		-0.0278***	
		(0.0091)	
*Financial Crisis*CV*			-0.8679***
			(0.1383)
Margin	-0.0082	-0.0046	-0.0041
	(0.0064)	(0.0059)	(0.0051)
Log(Residential)	0.1678	0.1496	0.1363
	(0.1070)	(0.1044)	(0.1022)
Log(Industrial)	-0.1134***	-0.1001***	-0.1006***
	(0.0301)	(0.0286)	(0.0251)
Log(Commercial)	-0.2858***	-0.2397***	-0.2395***
	(0.0698)	(0.0614)	(0.0533)
Log(Natural Gas)	0.0751	0.0524	0.0465
	(0.0459)	(0.0420)	(0.0384)
Observations	644	644	644
Contract FEs	Yes	Yes	Yes
R^2	0.5195	0.5532	0.6292

Table VIII

The Effect of Financial Sector Stress on Open Interest (Controlling for Electricity Sales and Natural Gas Consumption)

This table reports the results of an examination of the effect of financial sector stress on open interest controlling for local electricity sales and natural gas consumption. The dependent variable is the logarithm of contract open interest. The four measures of financial sector stress are: (1) *Financial Crisis*, a dummy variable equal to one during the financial crisis period (October 2008-May 2009 contract months) (columns (1)-(3)), (2) *TED*, the TED spread (columns (4) and (5)), (3) Δ *VIX*, the monthly change in the VIX (columns (6) and (7)), and (4) *–Capital*, the negative of the capital ratio of active financial institutions (columns (8) and (9)). *Margin* is the contract-specific margin requirement. *CV* is the coefficient of variation of the contract's index calculated over the years 1974-2011 (total risk). 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. Year-month fixed effects are included in all regressions. In column (1), fixed effects for the months of January 2007-May 2009 are omitted. All regressions include contract fixed effects. Standard errors are clustered at the year-month level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

		Stress = Financial Crisis		*Stress = TED*		*Stress =* Δ *VIX*		*Stress = -Capital*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*	*Log(O.I.)*
Financial Crisis	-0.6874***								
	(0.1162)								
*Stress*Margin*		-0.0133		-0.0096		0.0011		-1.0543**	
		(0.0543)		(0.0280)		(0.0020)		(0.4940)	
*Stress*CV*			-0.1465		-0.1227		-0.0525		-13.6060
			(1.5245)		(0.7443)		(0.0659)		(14.2718)
Margin		-0.3142***		-0.3107***		-0.3160***		-0.5522***	
		(0.0826)		(0.0863)		(0.0797)		(0.1296)	
Log(Residential)	-1.2876	0.8703	-1.2302	0.8493	-1.2371	0.8386	-1.1544	1.5853	-0.8676
	(2.5697)	(2.3709)	(2.4613)	(2.3365)	(2.4477)	(2.3368)	(2.4529)	(2.4206)	(2.5061)
Log(Industrial)	-1.5609***	-1.5181***	-1.5012***	-1.5146***	-1.4984***	-1.5295***	-1.4933***	-1.4011***	-1.4330***
	(0.4883)	(0.4423)	(0.4668)	(0.4468)	(0.4679)	(0.4458)	(0.4678)	(0.4412)	(0.4642)
Log(Commercial)	-0.2996	-0.7619	-0.1942	-0.7791	-0.1955	-0.7761	-0.1980	-0.3821	0.0411
	(1.1363)	(1.0578)	(1.1258)	(1.0488)	(1.1153)	(1.0581)	(1.1100)	(1.0564)	(1.1218)
Log(Natural Gas)	0.5395	0.1236	0.5509	0.1117	0.5486	0.1524	0.5439	-0.0827	0.4569
	(0.6948)	(0.6860)	(0.6826)	(0.7029)	(0.6795)	(0.6656)	(0.6672)	(0.6747)	(0.6794)
Observations	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.7359	0.7519	0.7416	0.7519	0.7416	0.7519	0.7418	0.7540	0.7422

Table IX
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 expected return ($E[r]$), expected return on margin ($E[r \times \frac{1}{m}]$), and realized return (r). 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 (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 * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$E[r]$	$E[r]$	$E[r]$	$E[r \times \frac{1}{m}]$	$E[r \times \frac{1}{m}]$	$E[r \times \frac{1}{m}]$	r	r	r
Δ *VIX*	0.1002*	-0.2050	-0.5077***	1.7723*	-1.9210	-7.3943***	0.1928	-0.5380*	-0.6738
	(0.0527)	(0.2073)	(0.1679)	(1.0050)	(3.8808)	(2.7264)	(0.1788)	(0.2945)	(0.4871)
Δ *VIX*Margin*		0.0565			0.6842			0.1354**	
		(0.0392)			(0.6636)			(0.0531)	
Δ *VIX*CV*			3.0367***			45.7889***			4.3289*
			(0.8681)			(12.2077)			(2.2250)
Margin	-0.1751	-0.1897	-0.4097	-6.8938	-7.0697	-10.4310	-0.3247	-0.3595	-0.6591
	(0.5918)	(0.5809)	(0.5545)	(13.2994)	(13.1816)	(12.5791)	(1.0993)	(1.0899)	(1.1330)
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	0.0164	0.0510	0.0106	0.0139	0.0410	0.0077	0.0166	0.0265

Table X
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 expected return ($E[r]$), expected return on margin ($E[r \times \frac{1}{m}]$), and realized return (r). 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 May 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 * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	$E[r]$	$E[r]$	$E[r]$	$E[r \times \frac{1}{m}]$	$E[r \times \frac{1}{m}]$	$E[r \times \frac{1}{m}]$	r	r	r
Financial Crisis	2.1147	-10.1294*	-15.3586***	27.1582	-144.5647*	-214.2863***	6.6121*	-3.8512	-6.8373
	(1.7189)	(5.2888)	(4.2099)	(29.3918)	(77.2548)	(65.6218)	(3.4395)	(9.7171)	(8.2217)
*Financial Crisis*Margin*		2.2664*			31.7866*			1.9368	
		(1.2192)			(17.1103)			(2.1752)	
*Financial Crisis*CV*			77.5152***			1,071.0971***			59.6644
			(22.6134)			(340.6122)			(39.9381)
Margin	-0.1856	-0.4153	-0.4117	-7.1073	-10.3294	-10.2314	-0.3378	-0.5341	-0.5118
	(0.5870)	(0.6056)	(0.5174)	(13.3716)	(13.1579)	(12.6779)	(1.1173)	(1.1811)	(1.1412)
Observations	644	644	644	644	644	644	644	644	644
Contract FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0110	0.0416	0.1285	0.0071	0.0265	0.0794	0.0236	0.0285	0.0390

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